# The Limits of Fundamental Arbitrage: Evidence from Detailed Hedge Fund Transaction Data

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**Abstract**

We study the limits of fundamental arbitrage using detailed transaction and position data for long-short equity hedge funds. We document that these funds are skilled but constrained. Their opening trades are followed by significant risk-adjusted returns, but they close their positions too early and thereby forgo about a third of the total profitability of their trading opportunities. We show that funds close positions early in order to reallocate their limited risk capital to more profitable investments. Consistently, we find more premature position closures when arbitrage constraints tighten (e.g., after negative fund returns, increases in volatility, or increases in funding costs).

**JEL classification: G11, G12, G14, G15**

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> "[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." — Lee Ainslee III., quoted from Pedersen (2015)

Fundamental trading—i.e., trading on information acquired through fundamental research—resembles an arbitrage: while “standard” (relative-value) arbitrage exploits price discrepancies between (almost) identical assets, “fundamental arbitrage” exploits the difference between an asset’s market price and its fundamental value. Moreover, like other forms of arbitrage, fundamental trading is crucial for price efficiency. Indeed, without it, prices could be far away from fundamentals even though they might look “right” relative to each other.[1] Yet, we know very little about fundamental trading—about its constraints, how severe they are, and how they affect actual trading behaviour. Indeed, fundamental arbitrage opportunities are notoriously difficult to observe and fundamental investors are secretive in trading on them, making it difficult to identify the limits of fundamental arbitrage in practice. After all, the negligence to trade on a fundamental arbitrage opportunity can always be explained by not being aware of it.

In this paper, we conduct the first detailed study on the limits of fundamental arbitrage by exploiting a rich proprietary transaction dataset for a sample of 21 hedge funds over a ten-year period. Two features make the data uniquely suitable for our purpose. First, it exclusively covers discretionary long-short equity hedge funds, which routinely undertake independent long and short investments (“directional bets”)—making them archetypical fundamental arbitrageurs. Second, our data comprises the funds’ *entire equity trading histories as well as daily position updates*, allowing us to exactly pinpoint the dates when they enter and close their arbitrage positions. This level of detail is crucial: By studying post-opening returns, we confirm that our sample hedge funds are skilled fundamental traders. By studying post-closure returns, we gain insight into the nature and severity of their constraints. Indeed, we argue that constrained fundamental arbitrageurs often close stock positions early in order to redeploy their scarce capital into other, more

[1] See Brunnermeier (2005) and Weller (2016) on the importance of fundamental arbitrage vis-à-vis standard (relative-value) arbitrage.

profitable opportunities. Importantly, such early position closures, unlike postponed position openings, cannot be explained by lack of awareness, because the hedge fund did enter the position before. This makes foregone profits from prematurely closed arbitrage positions a gauge that allows us to quantify the severity of arbitrage constraints.

We find that the long-short equity hedge funds in our sample indeed behave like informed but constrained fundamental investors. Specifically, we show that their openings of long and short positions are followed by significant benchmark-adjusted returns with an absolute magnitude of about 1% (1.5%) over the next 60 (125) trading days, suggesting that these hedge funds are informed. When measured over the holding period (i.e., from opening to close), the difference in benchmark-adjusted returns between long and short positions amounts to 2.7%. Turning to position closures, we find that stock returns continue to drift upward after the closure of a long position and downwards after the closure of a short position. When we design a trading strategy that goes long in stocks in which hedge funds closed a long position and short in stocks in which they closed a short positions, we obtain a significant benchmark-adjusted return of about 1.3% over the next six months (125 trading days). Compared to the return difference between long and short positions over the holding period, this figure implies that the hedge funds in our sample forego about a third of the potential profitability of their trades (we obtain similar results for DGTW returns and 4-factor alphas). We thus establish that the constraints faced by long-short equity hedge funds are economically important as they force them to "leave substantial money on the table."

We explain with a simple trading model (presented in the appendix) that early position closures naturally flow from the existence of arbitrage constraints. Our model rests on three assumptions: First, there is a hedge fund that faces a risk constraint, preventing it from taking too large a position in any mispriced stock. This mirrors standard practice in the hedge fund industry (see, e.g., Pedersen (2015)).[2] Second, the hedge fund incurs a fixed cost for each open position in its portfolio, which can be loosely interpreted as a fixed

[2] Alternatively, we can also assume that the hedge fund faces a margin capital constraint.

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 fund to limit the number of open positions, consistent with what is observed in the data.[3] Third, we assume that new investment opportunities (stock mispricings) emerge each period, whose alphas decay gradually over time. This "alpha decay" arises naturally in models of informed trading with multiple speculators (Foster and Viswanathan (1996), Back, Cao, and Willard (2000), Bernhardt and Miao (2004)) and is confirmed empirically (e.g., Chen, Da and Huang (2016), Di Mascio, Lines and Naik (2016)). It is also evident in our data as two-thirds (1%/1.5%) of the six-months benchmark-adjusted return is earned within the first three months after opening the position.

We show that, under these 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 funds' limited risk capital and monitoring capacity into these more profitable opportunities, explaining why hedge funds close positions that continue to generate alpha going forward. In this sense, our model precisely captures the intuition behind Lee Ainslee III's quote from above. We then derive a number of additional predictions from the model: 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 large number of new positions, (2) has suffered poor past performance, (3) when the risk constraint tightens due to a surge in fund return volatility, and (4) when funding costs increase.

We test and confirm these additional predictions in the data. We begin by comparing post-trade returns between position openings and closings made by the same fund in the same month. We find that, over the 125 trading days following the order, newly initiated long (short) positions yield a benchmark-adjusted return that is 0.6% larger (smaller) than that following closed long (short) positions. Thus, we document

[3] For instance, the average hedge fund in our sample has less than 80 open positions at any time. See also Pedersen (2015).

that, within the same month, hedge funds generate more returns with their opening trades than they forego by closing their positions prematurely, showing 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 yields an estimate of how much return 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. We find that the strategy yields a highly significant benchmark-adjusted return of 2.0% over the next half year after an increase in the number of open positions (our proxy for the number of trading opportunities), while we observe a return of only 0.7% after a decrease in the number of open positions. Second, we conduct a sample split based on whether the fund had a positive or negative return over the prior week. The idea 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 a benchmark-adjusted return of 2.2% over the next half year, while it only delivers 0.6% following a positive fund return. Third, we split the sample based on whether there was an increase in fund return 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. As predicted, we find that trading against closing orders following an increase in fund volatility yields a benchmark-adjusted return of 1.8% over the next half year, versus only 0.9% after a decrease in fund volatility. Last, we split the sample by changes in the TED spread, a well-known measure of funding costs for financial intermediaries. We find that the (benchmark-adjusted) return difference between closed long and short positions amounts to 1.9% after an increase in the TED spread, compared to 0.4% after a decrease in the TED spread.

Taken together, these findings provide strong evidence that early position closures—which are associated with foregone risk-adjusted returns—occur in response to binding arbitrage constraints. Indeed, as we explain in the robustness section, alternative explanations for early position closures that center on hedge funds' rebalancing motives, biased beliefs, or the disposition effect are not able to explain the entirety of our findings.

One key advantage of our data is that it only includes discretionary long-short equity hedge funds. Long-short equity is the most popular hedge fund strategy, accounting for 40% of funds and 27% of assets-under-management in the Lipper Tass database (Fung and Hsieh (2011)). Even more importantly, this strategy resembles fundamental arbitrage: First, long-short equity hedge funds take directional bets on individual stocks (e.g. Pedersen (2015)) and thus their long and short trades in different stocks should not be part of a long-short trading strategy. Consistent with this view, we show that our hedge funds do not open positions for mere hedging reasons and rarely engage in popular relative-value arbitrage strategies such as pairs trading or merger arbitrage. Second, discretionary long-short equity hedge funds are known to spend a lot of resources on research in order to distill an information advantage from public and private sources. Indeed, we document that the trades of our sample hedge funds predict subsequent earnings surprises, suggesting that they trade on fundamental information. In summary, long-short equity hedge funds such as those in our sample are the real-world equivalent of fundamental arbitrageurs, making them the ideal laboratory to study the limits of fundamental arbitrage.

While focus and detail are clear advantages of our data, we acknowledge that the relatively small number of hedge funds (21) raises questions about the selection and representativeness of our sample. We try to allay such concerns to the best of our ability. First, we compare the factor loadings of our hedge funds' portfolio returns with those obtained for a comprehensive dataset of hedge fund returns (Kruttli, Patton and Ramodorai (2015)) as well as with those for the Credit Suisse long-short equity hedge fund index and find them to be very similar. Second, we note that our funds represent a variety of different sizes, trade across industries and invest in equity markets worldwide with a tilt toward larger stocks. All this is typical for long-short equity hedge funds. Third, as we explain and corroborate in the robustness section, our data is unlikely to be plagued by common sample problems such as survivorship bias or back-filling bias. Finally, we emphasize that a key part of our analysis is about describing how long-short equity hedge funds respond to the existence of risk/funding constraints. To the degree that such constraints are pervasive in the hedge fund industry, one can expect these results to be generalizable to the broader population.

In conclusion, our paper provides an in-depth study of how the trading behavior of fundamental investors—such as the long-short equity funds in our sample—is affected by the presence of arbitrage constraints. We show that their opening trades are clearly profitable, but that they close their positions prematurely in order to accommodate tightened constraints and/or to recycle their capital into more profitable investment opportunities. The latter result implies that the emergence of a new investment opportunity, by raising the opportunity cost of arbitrage capital, can further constrain the trading in an existing arbitrage position. Thus, arbitrage can become more constrained not only due to a tightening of the funding costs (perhaps triggered by trading losses) but also due to high expected profits elsewhere. To the best of our knowledge, we are the first to document this interdependence of trading positions at the micro level, thereby providing support for recent multi-asset models on the limits of arbitrage (e.g., Gromb and Vayanos (2017)). More broadly, our results have important implications for the efficiency of financial markets. Indeed, early position closures will slow down the information incorporation in market prices, rendering them less informative. Moreover, when many hedge funds decide to close their positions at the same time, their behavior can exacerbate the very mispricing that they had set out to correct.

Our paper contributes to several strands of research. First and foremost, we contribute to the literature on the limits of arbitrage. Theoretical papers in this field have highlighted different channels as to why arbitrageurs may be forced to liquidate their positions (Shleifer and Vishny (1997), Kyle and Xiong (2001), Gromb and Vayanos (2002, 2017), Brunnermeier and Pedersen (2009), Acharya and Viswanathan (2011)).[4] We contribute by documenting how these frictions affect the trading activity of fundamental investors. We thereby complement existing empirical work that is mostly at the macro-level and explores, for example, how liquidity, price dislocations and risk premia respond to aggregate funding shocks (Hameed, Kang and

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

Viswanathan (2010), Nagel (2011), Adrian, Etula and Muir (2014), Pasquariello (2014), He, Kelly and Manela (2016)). Another strand focuses on how the 2007-09 Financial Crisis has forced hedge funds to delever and curb back their liquidity provision (Ang, Gorovyy and van Inwegen (2011), Khandani and Lo (2011), Aragon and Strahan (2012), Ben-David, Franzoni and Moussawi (2012), Franzoni and Plazzi (2015)). 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.

Our second contribution is to the literature on hedge funds. Many papers examine hedge fund skill using databases on self-reported hedge fund returns (see, e.g., Agarwal, Mullally, and Naik (2015) for a survey), but are hampered by different biases of these databases (e.g. Agarwal, Fos, and Jiang (2013)). More recent papers examine hedge fund skill using quarterly 13F filings data on long positions and reach mixed conclusions: While Cao et al. (2016) and Grinblatt et al. (2017) find that at least some hedge funds are able to predict returns, Griffin and Xu (2009) find no such predictive power. Jank and Smajlbegovic (2015) find evidence for predictability from hedge funds' mandatory disclosures of large short positions. We add to this debate by examining trading skill in both long and short positions. We find that the opening of positions predicts stock returns for over six months and more, thereby complementing previous work that focuses on hedge funds' short-term profits from liquidity provision (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 and 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 more complete[5] and, perhaps more

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

importantly, covers the trading activity for one particular class of hedge funds—long-short equity. We find long-term predictability for these hedge funds, which matches their description as fundamental arbitrageurs.

Third, 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. The only other paper examining returns following the closing of short positions is Boehmer, Duong, and Huszar (2015). Contrary to us, they show evidence of positive return predictability for closing trades. However, their analysis is based on the mandatory disclosure of very large positions and may thus be influenced by price impact and signaling effects.

Finally, we note that our paper is related to Di Mascio, Lines and Naik (2016), who study a transaction dataset for a sample of long-only mutual funds from the same data provider. While they find a similar abnormal return following the opening of a long position, their focus differs from ours in that they show how their sample funds strategically build up their positions in order to limit their price impact. We focus instead on position closures and show how they relate to the limits of arbitrage.

## I. Hypotheses

We think of the discretionary long-short equity hedge funds in our sample as fundamental arbitrageurs. Indeed, this hedge fund strategy consists of taking a number of long and short bets on individual stocks based on a fundamental analysis. The starting point of our empirical investigation is 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

to identify the trading institution (up to 2011), but not the individual fund. Thus, the hedge fund trades in ANcerno are from a mix of different hedge funds belonging to the same hedge fund family.

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 data studied to date, our performance analysis constitutes a valuable contribution in its own right.

Next, we investigate how and when hedge funds close their positions. We argue that position closures are particularly revealing about the constraints faced by fundamental arbitrageurs. Indeed, when they 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 on average. In practice, however, we expect them 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 their fundamental research is time and effort intensive, implying that long-short equity hedge funds focus on a limited number of open positions (directional bets). Being cognizant of these constraints, we expect hedge funds to allocate their limited resources on the basis of a cost-benefit analysis. Each period, they 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.[6] 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 appear every period but gradually decay over time (in a way that displays "alpha decay"). In

[6] It is also possible that constrained hedge funds delay the opening of a new arbitrage position. However, it is always possible that a position was not opened because the hedge fund was not aware of a given arbitrage opportunity. For position closures, this concern should be less relevant. After all, the hedge fund must have been aware of the opportunity at the time it opened its position.

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. "Alpha decay" arises naturally in models of informed trading with multiple speculators (Foster and Viswanathan (1996), Back, Cao, and Willard (2000), Bernhardt and Miao (2004)), has been documented empirically (Chen, Da and Huang (2016), Di Mascio, Lines and Naik (2016)) and is also present in our data (see Section 3.A for more details). 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.[7] 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.[8] 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 assumption is that larger funds have more open positions—a prediction for which we find strong support in the data.[9]

Our model identifies four 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

[7] In our model, the risk constraint can also be understood as a short-hand for a leverage or funding constraint, such as modeled in Gromb and Vayanos (2002, 2017). Indeed, like a margin constraint, the risk constraint ensures that both long and short positions consume from the overall risk budget, thereby preventing the hedge fund from leveraging up his positions without bounds.

[8] Gromb and Vayanos (2017) show that early position closures also occur under a margin constraint when cross-netting is not allowed. In their setting, there are no diversification benefits and hedge funds forego trading on investment opportunities below some minimum return.

[9] 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.

some positions when better investment opportunities arise. Second, as the hedge fund's wealth decreases (e.g., because of trading losses), the hedge fund is forced to scale back its positions. Third, as the hedge fund's stock positions become more volatile, it must again downscale its positions in order to satisfy the risk limit constraint. Fourth, position sizes also need to be reduced as funding constraints tighten. In all these cases, the reduced position sizes are traded off with the fixed monitoring cost, leading the hedge fund to optimally decrease the number of open positions. As the hedge fund always closes the least profitable position first, more closures imply that more profitable positions are closed. 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 or (4) when funding constraints tighten.

## 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 study. 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. As such, there are two ways in which a hedge fund can enter our database: Either a hedge fund submits its trading data directly to Inalytics to obtain feedback on and verification of its trading performance, or an institutional client, e.g. a plan sponsor, asks Inalytics to monitor the hedge fund's trades and performance on its behalf. In both cases, funds are obligated to submit their complete equity trades and position updates to Inalytics. Furthermore, Inalytics verifies the data carefully for its accuracy.

Our dataset covers the years 2005 to 2015 and contains *complete* trading and holding information for the equity portfolios of 21 distinct hedge funds.[10] 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 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. Our data does not cover derivative positions, but conversations with Inalytics suggest that hedge funds in our sample use them little and, if they do, mostly for hedging their market exposure (for example using index options). Thus, their equity trades likely offer a comprehensive reflection of the fundamental bets that they engage in.

We use a merged dataset that combines the holdings and trading data (details on merging these two datasets can be found Internet Appendix A). 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 trades likely belonging to the same investment decision into orders. Specifically, we assume that trades belong to the same order if a hedge fund trades the same stock in the same direction and the distance between them is two trading days or less. Seventy-three percent of the orders consist of only one trade.

### *B. Summary statistics*

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

[10] The data that comes closest to ours in its level of detail is obtained via a fuzzy name-matching between the hedge fund trades contained in the ANcerno institutional transaction data and 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 from quarterly holdings is bound to be noisy. Finally, while our data is at the fund-level, the ANcerno data is at the fund-family level. In the aggregate, these families appear to 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)).

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 (Fung and Hsieh (2004)). Our 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 5.4% on average (median 2.8%). Our funds span a large range of different sizes. The median fund holds about USD 350 million in assets, while the 10$^{th}$ and 90$^{th}$ percentile funds range from USD 115 million to USD 6,400 million. These numbers suggest that the funds in our data are above average in terms of size. For instance, assuming an average leverage of 2.13 as reported in Ang, Gorovyy, and van Inwegen (2011), we estimate that our median fund has about USD 164 million of assets under management, which is slightly above the USD 130 million reported for the 75$^{th}$ percentile in the Lipper Tass database (see Lim, Sensoy and Weisbach (2016)).

[Insert Table 1 about here.]

The investment areas of our funds are shown in Figure 1. We have 7 Europe-focused funds, 3 US, 3 UK and 2 Australia-focused funds, as well as 6 funds that invest world-wide. In line with their investment focus, the funds mainly invest in North America, Europe and Asia-Pacific (mainly Australia). The EME and Japan region both make up less than 1% of the sample. Additional descriptive statistics are provided in Internet Appendix B. There, we report summary statistics for each individual fund and further document that they overweigh large companies in their portfolios, similar to other institutional investors (e.g., Lee, Shleifer and Thaler (1991)). Otherwise, they split their investments relatively evenly across different industries and value vs. growth stocks.

We display gross fund profitability computed from holdings in Figure 2. In Panel A, we display the actual profitability of the funds by year. 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 experience their best year. To get a better idea of the fund's stock-picking skill, we display profitability based on benchmark-adjusted returns in Panel B. Our funds display positive benchmark-adjusted returns in every year of the sample, suggesting that they exhibit skill.

In Table 1 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 (or when our sample period ends). Due to this censoring, the length of the holding period for positions is biased downwards. Despite of this, 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: 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 15.5% (median 8.5%). Thus, position openings and closings are the more important investment decisions, justifying why we focus on these two types of orders in our main analyses. Follow-up orders, while making up 70% of orders in our sample, are small and more likely to be based on hedging or rebalancing motives rather than on information. We confirm this intuition in Subsection V.C below, where we show that follow-up orders are not predictive of future stock returns, suggesting that they are not information-driven trades.

Finally, we note that hedge funds do not 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 Internet Appendix C.6 that our results are robust if we only use return data from Datastream. We use three types of risk-adjusted returns: (1) benchmark-adjusted returns with respect to the fund-specified benchmark, (2) characteristics-adjusted returns 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 Internet Appendix A; here we provide only a brief summary description.

Benchmark-adjusted returns are computed as returns minus the return of the fund-specified benchmark. Since this risk-adjustment depends on the fund, benchmark-adjusted 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 the Internet Appendix A.1. 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 (value-weighted) 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 constitutes 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. Following the recommendations by Levi and Welch (2016), we estimate stock betas with respect to these factors using daily regressions over the prior 12 months and shrink the resulting betas toward their cross-sectional average as in Vasicek (1973). We then 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 winsorize all our return measures at the 1% level on both sides.

## III. Profitability Results

### *A. Profitability of opening and closing trades*

As shown in Figure 2, our sample hedge funds appear to trade profitably on average. We now examine their 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 3. We show cumulative benchmark-adjusted returns in the 200 trading days 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 3 reveals clear evidence of informed trading for the opening of positions: in the first half-year (125 days) following the initiation of a long (short) position, cumulative benchmark-adjusted returns are slightly above (below) 1.5% (-1.5%). After that, the return drift is fairly muted. Moreover, on both the long and the short side, two-thirds of these returns (1%) is realized in the first 60 trading days (3 months) following the opening order, while the remaining third is realized in the 3 months after that. In other words, the post-opening alphas (per unit of time) decay over time: they are highest immediately after the position is established and then gradually shrink as time progresses.[11]

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 200 days following the closing of a long position cumulative benchmark-adjusted returns are about 1%. Similarly, the closing of a short position is followed by negative benchmark-adjusted returns (-1% after 200 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 Panel A, we focus on position openings and run a regression of risk-adjusted returns following the order on *D(Long Position)*, a dummy variable equal to one if the order initiates a long position (and zero if it initiates a short 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 choose these holding periods because they straddle the average holding period (see Table 1 Panel B) and Figure 2 reveals that most of the trade profitability accrues by this time. Returns are measured from the date following the last date of the order so as to 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 long 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.]

[11] 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(Long Position)* 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 Panel A, show that this return difference is economically and statistically significant. For instance, for benchmark-adjusted returns, long positions outperform short positions by about 1.8% over 60 days and 2.4% over 125 days. For DGTW returns and alphas the effect is slightly smaller at about 1.6% over 60 days and 1.9% over 125 days. These results are all statistically significant at the 1% level.

In Panel B, we repeat our regression analysis for holding-period returns; i.e., cumulated returns from the last day of the opening order to the first day of the closing order. This is a conservative estimate because it excludes within-order profits, which on average are positive (unreported). As before, we find that long positions outperform short positions over the holding period. For instance, the coefficient on the *D(Long Position)* dummy for benchmark-adjusted returns indicates that the return difference between long and short positions amounts to 2.7%. For DGTW returns and alphas, the return difference is slightly smaller but remains strongly statistically significant. [12] These findings confirm that our sample hedge funds possess investment skill.

In Table 2 Panel C, we examine post-trade returns for closing orders. To this end, we regress cumulated risk-adjusted returns over the 60 and 125 trading days following position closures on our *D(Long Position)* dummy (including the fund and month fixed effects as before). We again find a positive coefficient for the *D(Long Position)* dummy, albeit with a smaller economic magnitude. For benchmark-adjusted returns, the return difference between closed long and closed short positions equals 0.7% over 60 days and 1.3% over 125 days. For DGTW returns and alphas the effect is 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.

[12] We confirm in Internet Appendix C.1 that we find similar predictability when we focus on average returns during the holding period.

Taken together, Panels B and C allow us to assess what fraction of cumulated returns the sample hedge funds forgo by closing early. For instance, in terms of benchmark-adjusted returns, long positions outperform short ones by 4 percentage points (=2.7%+1.3%) from opening to 125 trading days after the close. However, our hedge funds only capture about 68% (=2.7%/4%) of the trade's total worth, implying that they leave 32% "on the table." For DGTW returns and alphas, the corresponding figures amount to 37% and 31%, respectively. As argued before, we interpret early position closures as arising from the presence of arbitrage constraints and corroborate this interpretation below. Our back-of-the-envelope calculation suggests that these arbitrage constraints are economically important.

Our results also offer an important insight for researchers studying the informativeness of individual buy and sell transactions. Indeed, they suggest that at least for the long-short equity hedge funds in our sample, only opening trades are informative, whereas closing trades are not only uninformative but rather predict returns in the opposite direction of the closing trade. This shows that it is important to determine whether individual trades open or close a stock position, which is only possible with access to portfolio data such as we use here. Without this distinction, opening and closing trades are lumped together, causing a downward bias when assessing investors' trading skills.

### *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 deliver higher returns than those that are foregone by closing existing positions. A casual inspection of Figure 3 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 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×portfolio×month fixed effects, where the portfolio indicator separately captures a fund's long and short portfolio. This approach allows us to compare openings and closures undertaken by a fund on the same side (either long or short) at roughly the same point in time—and where it is thus likely that the closure provided the capital for the new position opening.[13] The key variable of interest is *D(Position 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 3 shows the results. In Panel A, we focus on long positions only. The significantly positive coefficient for the *D(Position 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 0.5-0.8% 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 long and short positions together, which requires us to use signed 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 statistically significant at the 1% level.

[Insert Table 3 about here.]

The results so far show that hedge funds are on average right when they reallocate their capital from an old stock position to a new one. Going one step further, we can also test whether funds are right when they decide which stock position to close. Indeed, if our funds are informed but constrained as we argue, one

[13] Our results are virtually unchanged if we use coarser fund×month fixed effects.

would expect them to first close the positions which they expect to be least profitable. As such, the stock positions that they keep holding-on to should outperform those that they decide to close. To test this, we construct a sample of all fund portfolio holdings on days when the fund closes an existing stock position. We then regress future signed returns on *D(Position not Closed)*, a dummy variable taking the value one when the fund holds on to the position. We now include fund×portfolio×date fixed effects because we want to compare positions that have and have not been closed by the same fund on the same day. Table 3 Panel D shows the results. As predicted, we find that the positions that are not closed outperform those that are by about 0.4-0.5% depending on the horizon (this difference is statistically significant at the 5% level in four out of the six regressions). Note that this return difference is less than the one between closed and newly opened positions (see Panel C). This makes sense: newly opened positions should promise larger returns than existing ones, for otherwise the fund would have preferred to increase the existing position rather than to open a new one.

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 in order 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 provide further support for this mechanism by testing four 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 that result in a large number of 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 4, 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 five days (Panel A) or over the previous ten days (Panel B). We then repeat our regression analysis from Table 2 Panel B for these different subsamples.[14] The results broadly confirm our prediction: whereas the benchmark-adjusted return difference between closed long and short positions after increases in the number of open positions over the previous five days is 2%, it is only 0.7% and insignificant after decreases in the number of open positions. The results for DGTW returns and 4-factor alphas are similar with 1.7% vs. 0.5%, and 1.5% vs. 0.4%. These results are robust to using the change over the previous ten trading days instead of five trading days (Table 4, Panel B). In summary, our results suggest that early position closures are more common when hedge funds simultaneously seize new trading opportunities.

[Insert Table 4 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 (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, funds with more equity 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 2 Panel B are more pronounced after times in which the fund has experienced negative (position-weighted) portfolio returns. The results, shown in Table 5, support this prediction. When we split closing orders by prior fund returns over the previous five trading days, the benchmark-adjusted return difference between closed long and short positions is 2.2% in the subsample with negative prior fund returns and only 0.6% in the subsample with positive prior fund returns. For the other risk-adjusted return measures, the difference is smaller but goes in the same direction. When we split

[14] Throughout this section, we group unchanged values with increases when conducting sample splits. We further focus on sample split results for a holding period of 125 trading days. The results for 60 days go in the same direction but are of smaller magnitude.

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, thereby leaving more money on the table.

[Insert Table 5 about here.]

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 can again cause the premature closure of existing stock positions. To test this prediction, we conduct two sample splits for different volatility measures. In Table 6 Panel A, we look at the change in fund return volatility, where volatility is measured as the sum of squared fund portfolio returns over the previous 20 trading days. In Panel B, we split the sample based on the change in the average stock position volatility, defined as the position-weighted average of individual stock volatilities measured over the previous 20 trading days. The results shown in Table 6 confirm our prediction. Focusing on benchmark-adjusted returns over a 125-days horizon, we see that the return difference between closed long and short positions amounts to 1.8% at times when fund volatility goes up, while it is less than 1% and insignificant when volatility goes down. This holds regardless of whether we measure volatility by the volatility of fund portfolio returns (Panel A) or by the average stock position volatility (Panel B). We again obtain very similar retults for DGTW returns and 4-factor alphas.

[Insert Table 6 about here.]

Finally, we test whether our sample hedge funds leave more money on the table after a tightening of their funding constraints. This is a straightforward prediction of arbitrage models under funding constraints (e.g., Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009)) and it also obtains in our setting as we show that our risk constraint is closely related to a margin constraint (see Appendix B for details). Because our funds remain anonymous, we cannot tell the identity of their prime brokers, and we thus have to conduct sample splits by *market-wide* measures of funding constraints. In Table 7, we report results for two such measures: the TED spread and the intermediary risk factor of He, Kelly, and Manela (2016, henceforth HKM).[15] Specifically, in Panels A and B, we split the sample by changes in the TED spread (three-month LIBOR minus three-month T-Bill rate), a bellwether of the financial sector's health that is both widely-used (e.g., Brunnermeier (2009)) and theoretically-motivated (e.g., Garleanu and Pedersen (2011)). In Panels C and D, we split the sample by the HKM intermediary risk factor aggregated over the previous 5 and 10 trading days, respectively. This factor reflects changes to the capital ratios of primary dealer counterparties of the New York Federal Reserve and HKM find that it has significant explanatory power for the cross-section of returns in various asset classes. For both measures, our results paint a consistent picture: The return gap between closed long and short positions opens up after a tightening of funding constraints (i.e., when the TED spread increases or when the HKM intermediary risk factor is negative). This shows that tighter funding constraints in the intermediary sector are passed on to our sample hedge funds, forcing them to close their arbitrage positions prematurely.

[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. Additional Results

In this section, we present additional results supporting the view that the trades by our long-short equity funds can be considered as independent bets on firm fundamentals. We also document that their follow-up orders are not informative, thereby justifying our choice to exclude them from the main analyses.

[15] In Internet Appendix C.2, we report similar results using alternative proxies for funding constraints (e.g,. changes in VIX and stock returns to publicly traded holding companies of primary dealers of the New York Federal Reserve).

*A. Long-short equity funds as fundamental investors*

We have argued that long-short equity funds are archetypical fundamental investors as they are said to make discretionary long and short bets based on a fundamental analysis (Pedersen (2015), Getmansky, Lee and Lo (2015)). The fact that hedge funds' opening trades are followed by abnormal returns over the subsequent 6 months (and more) is consistent with this view. We also note that our hedge funds have an average holding period of 6 months, so they seem to be trading on long-lived information.

In this subsection, we provide further evidence that our funds trade on fundamentals by showing that their trades predict future earnings surprises. Indeed, if our hedge funds are able to identify fundamentally under- or overvalued stocks, the direction of their trades should predict future earnings news over and above what is anticipated by the market and/or already embedded in the consensus forecast. We test this premise using two popular measures of earnings surprises. The first measure is based on the difference between the actual earnings and analysts' consensus earnings forecast calculated from I/B/E/S data (e.g., Della Vigna and Pollet (2009)), whereas the second measure uses Worldscope data and compares the actual earnings to the past earnings in the same calendar quarter of the previous fiscal year (e.g., Sadka (2006)). In both cases, we scale the resulting earnings surprise by the standard deviation of the surprise in the previous 8 quarters. The resulting measures, called $SUE_{IBES}$ and $SUE_{Worldscope}$, are the dependent variable of our analysis. The key independent variable, called HF imbalance, takes the value 1 (-1) when our sample hedge funds, in the aggregate, buy (sell) the stock in the window 20 to 5 trading days before to the announcement date.[16,17] We include standard control variables (see table description) as well as firm and month fixed effects. Standard errors are two-way clustered by stock and earnings announcement date.

[Insert Table 8 about here.]

[16] HF imbalance is 1 (-1) in only 3.16% (3.11%) of all observations and thus equals zero most of the time. As such, it is really the fact whether our hedge funds trade at all that matters rather than how much they trade conditional on trading.

[17] We choose to end the window a few days prior to the announcement date as these dates are frequently misreported (Della Vigna and Pollet (2009)) and we want to be sure that the position was opened before the announcement. If we instead use a window of 20 to 1 days prior to the announcement, we get very similar but statistically slightly weaker results.

The results, shown in Table 8, suggest that the hedge funds in our sample are indeed able to predict future fundamental news: when they go long (short), the subsequent earnings announcements exceeds (falls below) expectations by 6% of a standard deviation. This effect is statistically significant regardless of whether controls are added and which earnings surprise measure is being used. In particular, they hold even after controlling for the cumulative return and stock turnover in the same window over which HF imbalance is measured. This shows that trades by our hedge funds predict future earnings surprises over and above what is predicted by the stock market at large, suggesting that our hedge funds trade on fundamental information rather than just technical signals (such as past returns or valuation ratios).

*B. Hedge funds' trades as independent bets*

Our trade-level analysis treats different trades as representing independent trading decisions. In this subsection, we briefly describe additional tests, detailed in our Internet Appendix, that support this implicit assumption.

First, we find that new position openings appear to be unrelated to the exposure from outstanding positions in the same industry. Specifically, for each new position opening, we regress its sign (i.e., whether it is a long or short position) on a dummy variable that captures the direction of the aggregate industry exposure from outstanding stock positions (i.e., whether the hedge funds is more short or long in that industry). The results, reported in Internet Appendix D.1, reveal that there is no significant correlation between the two. Thus, our funds neither bet on the over- or underperformance of whole industries, nor do they try to hedge their industry exposure. Similarly, we find no relation between the sign of new positions and aggregate risk exposure from stock positions in the same DGTW benchmark portfolio.

Second, we document that our hedge funds rarely engage in merger arbitrage or pairs trading—two of the most popular convergence strategies involving equities. Since such convergence trades involve pairs of long and short trades, the stock trades by our hedge funds could hardly be considered as independent if they did engage in these strategies. Merger arbitrage typically involves purchasing the target and short selling the acquirer, thereby betting on completion of the merger. We thus examine how often our hedge funds establish both a long position in the target and a short position in the acquirer in the two weeks following the announcement of a merger. Out of a total of 17,593 relevant merger events listed in SDC Platinum, we find that there is only 1 merger event in which this is the case. Furthermore, we show in Internet Appendix C.8 that our results are robust to excluding hedge funds' orders around merger events. Pairs trading consists of finding two highly correlated stocks and then going long (short) the relatively under- (over-)valued stock of the pair. We therefore test whether our hedge funds often open both a long and a short position in a pair of highly correlated stocks. As we report in Internet Appendix D.2, we find that our hedge funds, rather than going long-short, on average trade in the same direction for such high-correlation pairs.

Taken together, these results suggest that the funds in our sample do not engage in merger arbitrage or pairs trading and that new positions are not opened in order to hedge the risk exposure from outstanding stock positions. In other words, consistent with the textbook description of long-short equity hedge funds, the different stock trades by our funds appear to represent independent discretionary bets on individual firms.

*C) Are follow-up orders profitable?*

In our main analysis, we study the profitability of opening and closing orders. This means that we exclude follow-up orders, even though they make up about 70% of all orders in our sample. Apart from ruling out rebalancing-based explanations (see below), 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).

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 study whether follow-up orders, on balance, appear to be informed; that is, whether position-increasing orders are followed by higher (signed) 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 3 where we studied whether position openings outperform position closures (and we similarly include fund-portfolio-month fixed). In Panel A, 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 indeed find coefficients that are mostly positive, but they are small and not statistically significant. Similarly, in Panel B, we find more negative returns following orders that increase short positions (follow-up sells) but the magnitude remains small and insignificant. Finally, in Panel C, we combine long and short positions and use signed returns as the dependent variable. Once again the coefficients are small and insignificant (with the exception of one marginally significant coefficient).

[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. Follow-up trades thus appear to be caused by different underlying reasons, justifying why we focus on opening and closing orders for our analysis of the limits of fundamental arbitrage.

## VI. Robustness

### *A) Representativeness*

While the level of detail is a clear strength of our data, we acknowledge that the relatively small number of funds raises questions about its representativeness. Given that our data is the first of its kind, we obviously lack a transaction sample of other long-short equity funds that we could compare it to. The best we can do therefore is to compare our *imputed* hedge fund returns to the fund returns reported in standard hedge fund databases such as Lipper Tass or HFR. One caveat to bear in mind is that, since we do not observe the actual net returns of our hedge funds, we are forced to work with their portfolio returns instead. These returns are a noisy proxy for hedge funds' net returns because they neither incorporate funds' leverage, nor their fees, nor any derivative positions that they may be using to hedge some of the market-wide risk exposure.

Our comparison proceeds as follows: for each fund, we compute position-weighted portfolio returns at the monthly frequency. We then take the equal-weighted average across funds to obtain a monthly return series for the hedge funds in our sample, which we compare to 3 benchmark return indexes: (1) the average return (net-of-fees, equal-weighted) by long-short equity funds in the Kruttli, Patton, and Ramodarai (2015) dataset (henceforth KPR), which consolidates data from BarclayHedge, CISDM, HFR, Morningstar, and TASS, (2) the Credit Suisse AllHedge Long/Short Equity Index, which includes only investable long-short equity funds, (3) the Broad Credit Suisse Long/Short Equity Index, which also includes funds that are closed for investment. Both Credit Suisse indices are weighted by assets under management and returns are net of fees.

We start by regressing all four return series over our sample period on the 8 Fung and Hsieh factors (Fung and Hsieh (2001)).[18] The results are displayed in Table 10 Panel A. We find that our fund returns load on the same factors as the benchmark return indexes. Specifically, they all load strongly positively on the Equity Market Factor and the Emerging Market Factor and somewhat negatively on the Credit Spread

[18] We obtain the factors from https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm.

Factor. The other factors are insignificant. We also note that the average alpha of our funds is similar to those from KPR and the Broad Credit Suisse Long/Short Equity index. The alpha of the investable Credit Suisse index is much lower but this comparison is likely not appropriate as some of our funds may well be closed for new investors.

[Insert Table 10 about here.]

In Panel B, we repeat the analysis for the Carhart (1997) 4 Factor Model. All hedge fund returns load positively on the market factor and SMB. Our fund returns do not load on either HML or WML, while both Credit Suisse indices load negatively on them. However, the funds in KPR do not load on WML either and only at the 10% significance level (negatively) on HML. We conclude that the hedge funds in our sample appear to be similar to long-short equity funds that report to standard databases.

*B) Potential data biases and selection concerns*

In this subsection, we discuss potential data biases and selection concerns. 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 most of their transaction data in real time, there should be little incentives for window dressing and little scope for back-filling bias. Moreover, since our data includes funds that have already been terminated, survivorship bias is not 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. Alternatively, it could be that institutional clients demand from poorly-performing hedge funds to submit their trades to Inalytics for monitoring and verification purposes or that poorly performing funds engage with Inalytics to learn how they can improve their trading processes. In this case, the trade profitability documented above could be understood as a lower bound estimate of the average trade profitability for the class of long-short equity hedge funds.

These considerations lead us to examine our fund returns for 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 test whether funds with poor returns are more likely to drop out of the sample. Similarly, we can test whether fund returns appear to be elevated shortly after entering the sample. This would be indicative of a backfilling bias since—to the extent that it occurs—backfilling should be more pronounced for returns at the beginning of the sample. We therefore regress daily fund returns (i.e., position-weighted portfolio returns of all outstanding stock positions) on dummy variables that equal one during the first (last) 60 (or 125) days that the fund is in our sample. We focus on raw and benchmark-adjusted returns as we believe that these are the returns hedge funds would be selected upon, but we confirm in Internet Appendix C.3 that we find similar results for DGTW returns and alphas.

[Insert Table 11 about here.]

The results are presented in Table 11. For both raw and benchmark-adjusted returns (Panels A and B), the coefficients are statistically insignificant and economically small compared to the average return of 2.5 basis points per day (approximately 6.25% per year). If anything, performance seems to be slightly lower (higher) during the first (last) days of the sample. Hence, we do not detect any signs of backfilling bias or sample selection in our transaction data.

Finally, we argue that any remaining selection concerns 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 on how limits of arbitrage affect the trading behavior of the long-short equity funds in our sample. Indeed, limits of arbitrage exist for all fundamental traders and our qualitative results on early position closures and hedge funds' capital reallocations should thus apply more generally.

*C) Alternative explanations*

In this subsection, we discuss alternative explanations for early position closures and explain why they do not fit the data.

We first consider an alternative explanation based on portfolio rebalancing; i.e., hedge fund trades aimed at maintaining a certain risk exposure for a given stock position. For long positions, rebalancing has indeed 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. However, this argument does not work for short positions, because they shrink in (absolute) size as the stock price decreases (assuming shorted stocks continue to go down on average). More importantly, rebalancing 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. Position closing decisions should thus be independent of rebalancing considerations. In Internet Appendix D.3, we present an additional test that confirms this intuition.[19]

The second alternative explanation we consider involves the disposition effect; i.e., investors' tendency to close winning positions too early while holding on to losing positions for too long (Odean (1998), Jin and Scherbina (2011)). Indeed, if our hedge fund managers close winning positions too early due to the disposition effect, this could explain the average return continuation we observe after closing trades. Other results are, however, at odds with this explanation. In particular, the disposition effect cannot explain why we find an association between post-closure returns and hedge funds' arbitrage constraints (Tables 4-7) and

[19] Specifically, we conduct a sample split of post-closure returns by the underlying stock's return over the prior 10 trading days. Under the view that rebalancing can trigger position closures one would expect more closures to occur after positive returns because positive returns increase the (absolute) size of both short and long positions. Thus, if the alpha following closing orders was explained by rebalancing, there should be a larger alpha after a positive stock return. If anything, we find the opposite.

is hard to square with our finding that positions that our hedge funds keep open outperform those that they close (see Table 3 Panel D). In Internet Appendix D.4, we further test whether our hedge funds display the disposition effect and find that they do not. In fact, they are more likely to close positions trading at a loss rather than those trading at a gain, which is the exact opposite of the disposition effect. Hence, our results cannot be explained by the disposition effect.

Finally, we discuss the possibility that early position closures can be explained by biased beliefs. More precisely, it is conceivable that hedge funds systematically underestimate the precision of their trading signals, so that they end up closing positions under the impression that their information is already exploited when in fact it is not. We first note that such a bias would be the opposite of overconfidence—a trait that is believed to be common among investors (Odean (1999), Barber and Odean (2000)), including professional ones (Griffin and Tversky (1992), Puetz and Ruenzi (2011)). Moreover, a belief-based explanation cannot explain our sample split results; that is, our finding that hedge funds close their positions even earlier when they become more constrained. Biased beliefs are therefore unlikely to drive our results.

## VII. Conclusion

Fundamental arbitrageurs play an important role in financial markets: through their research, they acquire and synthesize value-relevant information and, through their trading, they ensure that this information finds its way into prices. As a consequence, market prices become more informative and better reflect fundamental values.[20] Yet, this important corrective action will be impeded by the presence of arbitrage constraints.

In this paper, we provide an in-depth study on such limits of fundamental arbitrage. More specifically, we exploit proprietary trading data for a sample of discretionary long-short equity hedge funds—presumably

[20] Of course, other types of arbitrageurs are also important for price efficiency, by ensuring for example that markets are liquid or that prices quickly summarize the available public information. However, their actions do not necessarily make price more informative (in the sense that prices summarize *more* information; see Brunnermeier (2005) and Weller (2016)). For this, someone must expend resources in order to acquire new information—and this is what fundamental traders do.

the most important fundamental arbitrageurs in todays' markets—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 six months, suggesting that their trades are informed. We then show that their closing trades are not only uninformed, but rather predict returns in the opposite direction of the closing trade. Thus, our sample hedge funds close positions that would have otherwise earned risk-adjusted returns going forward. Indeed, we estimate that they leave about a third of the total trade profitability "on the table."

We argue that this behavior can be rationalized with the help of a simple trading model in which trading opportunities exhibit alpha decay and in which hedge funds are subject to risk constraints and position monitoring costs. Under these assumptions, funds rationally decide to close positions that are still expected to generate profits in order to invest their limited capital in even more profitable trading opportunities. As predicted by the model, we find that funds engage in more premature position closures when new trading opportunities arise or when arbitrage constraints tighten due to negative fund returns, increases in volatility, or increases in funding costs.

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 fundamental 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.[21] Thus, despite the presence of informed and rational arbitrageurs, market prices can remain inefficient.

[21] Another reason as to why mispricing can persist despite the presence of rational arbitrageurs is that these arbitrageurs may occasionally want to bet on a further increase of the mispricing (see Abreu and Brunnermeier (2003)). Indeed, Brunnermeier and Nagel (2004) document that hedge funds were riding the dot-com bubble instead of trading against it.

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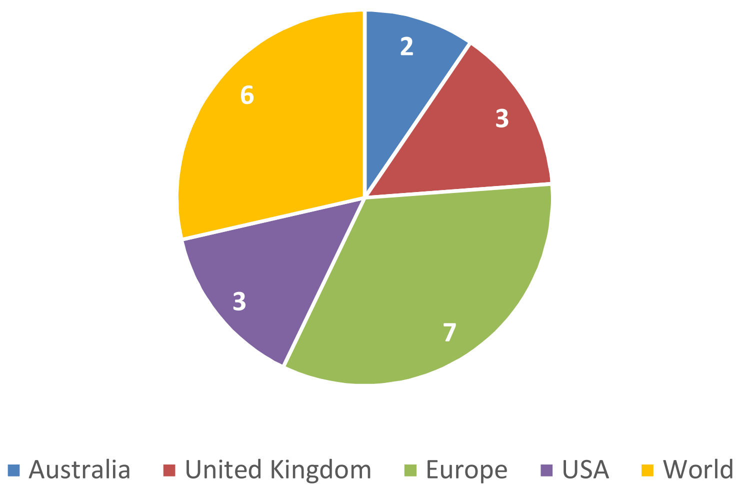
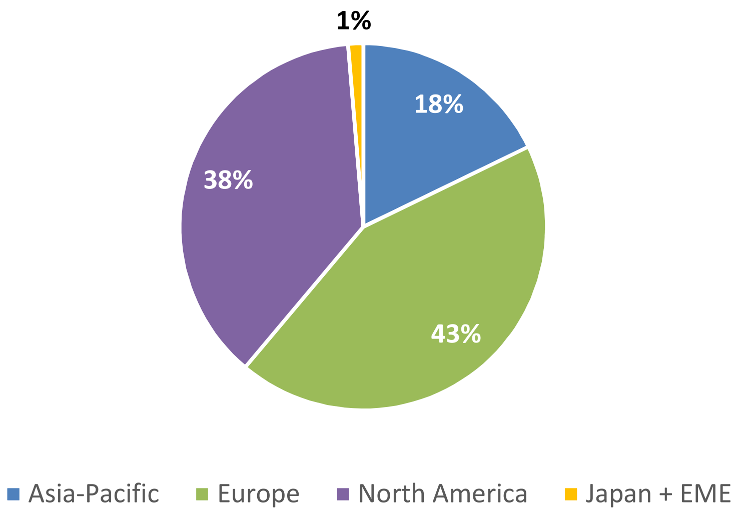
## Figure 1: Investment areas of funds

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 areas. 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 Internet Appendix A.1.

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




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

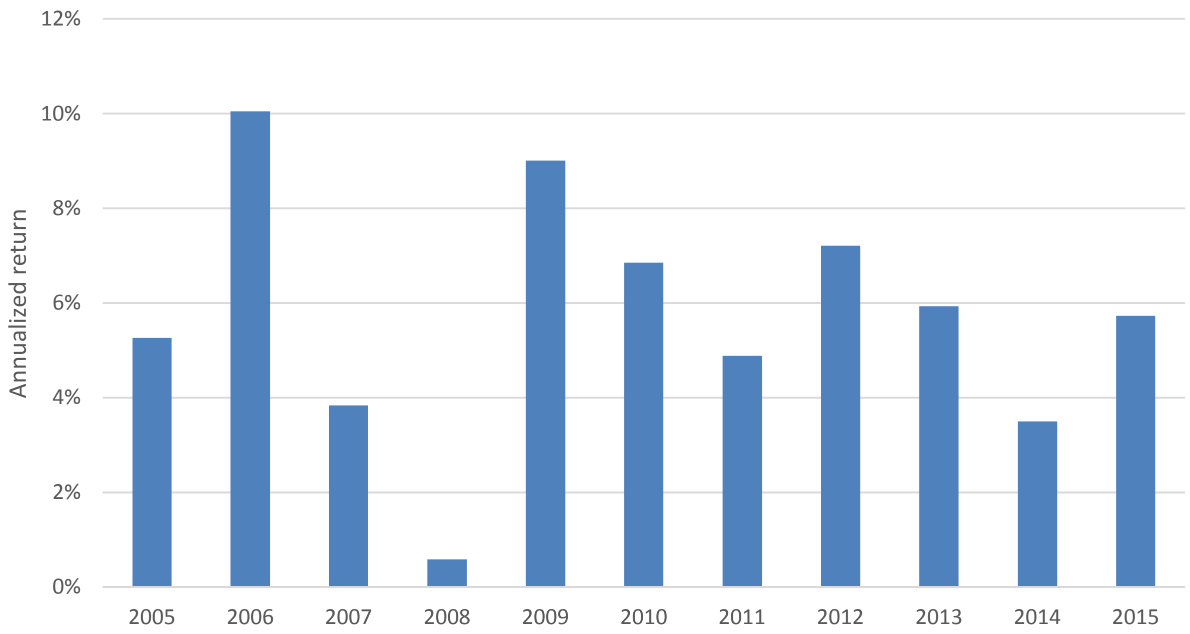


# Figure 2: Fund returns

In this figure, we display fund returns by year. For each fund, we first compute the (position-weighted) daily average signed return of positions the fund holds. Then on each day, we compute the (equal-weighted) average across funds. Finally, we compound these returns over the year. Signed returns are equal to the stock return for long positions and the stock return times minus one for short positions. In Panel A, we use raw returns. In Panel B, we use benchmark-adjusted returns relative to the fund-specified benchmark.

*Panel A: Fund return*

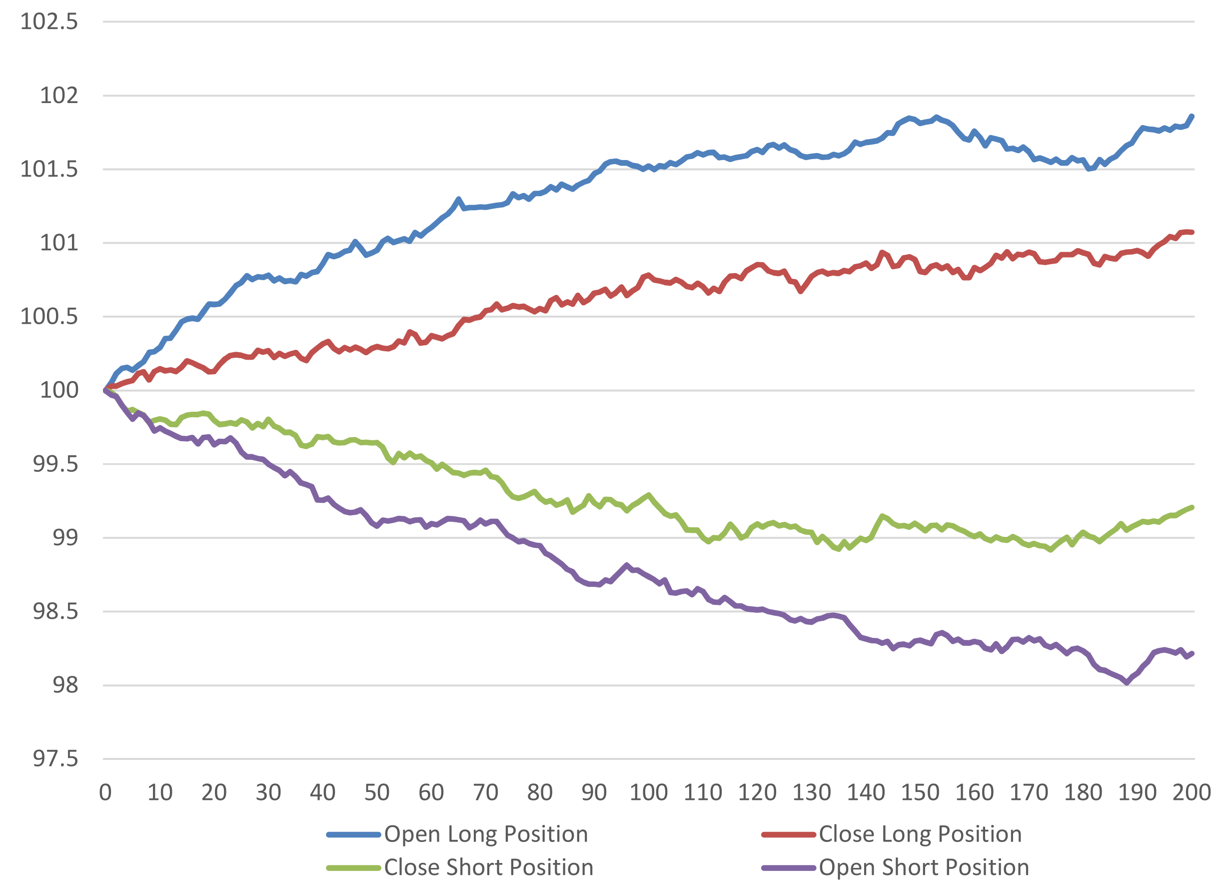

*Panel B: Fund benchmark-adjusted return*



# Figure 3: Benchmark-adjusted returns following orders

This figure displays cumulative benchmark-adjusted return indices for 200 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"). *Benchmark-adjusted 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.

*Benchmark-adjusted returns around orders*



# Table 1: Summary statistics

Panel A displays summary statistics by fund. *Number of Long (Short) Positions* is the average number 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* is 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. *Total Asset Value* is the average dollar value of all open stock 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 | $10^{th}$ Percentile | Median | $90^{th}$ 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 |
| Total Asset Value (million USD) | 2,054 | 115 | 347 | 6,410 | 3,629 |
| Positions per Stock | 1.96 | 1.37 | 1.90 | 2.70 | 0.61 |
| Observations | 21 | | | | |

*Panel B: Statistics by position*

| Variable | Mean | $10^{th}$ Percentile | Median | $90^{th}$ 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 | $10^{th}$ Percentile | Median | $90^{th}$ Percentile | Standard Deviation |
|---|---|---|---|---|---|
| Number of Trades | 1.63 | 1 | 1 | 3 | 1.58 |
| USD Volume (million USD) | 11.6 | 0.27 | 3.75 | 23.4 | 41.8 |
| Size as Fraction of Largest Holding (%) | 76.3 | 23.7 | 100.0 | 100 | 31.3 |
| Observations | 13759 | | | | |

*Panel D: Statistics by order – follow-up orders*

| Variable | Mean | $10^{th}$ Percentile | Median | $90^{th}$ Percentile | Standard Deviation |
|---|---|---|---|---|---|
| Number of Trades | 1.50 | 1 | 1 | 3 | 1.32 |
| USD Volume (million USD) | 7.88 | 0.089 | 1.78 | 17.8 | 31.9 |
| Size as Fraction of Largest Holding (%) | 15.5 | 0.93 | 8.48 | 41.7 | 18.0 |
| Observations | 62502 | | | | |

*Panel E: Statistics by order – closing orders*

| Variable | Mean | $10^{th}$ Percentile | Median | $90^{th}$ Percentile | Standard Deviation |
|---|---|---|---|---|---|
| Number of Trades | 1.64 | 1 | 1 | 3 | 1.99 |
| USD Volume (million USD) | 11.3 | 0.24 | 3.48 | 23.2 | 34.1 |
| Size as Fraction of Largest Holding (%) | 78.1 | 25.7 | 100 | 100 | 31.0 |
| Observations | 12432 | | | | |

# Table 2: Returns following the opening and closing of positions

This table examines returns following the opening of positions (Panel A and B) and the closing of positions (Panel C). We regress average returns following the order on a dummy variable whether the order is related to a short position. In Panels A and C, the dependent variable is the cumulative return expressed in percent for 60 and 125 trading days following the last day of the order. In Panel B, the dependent variable is the cumulative return from the last day of the opening order to the first day of the closing order (i.e., the holding period). In Panel B, we only include positions that are both opened and closed while the fund is in our sample. *Benchmark-adjusted 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. 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: Returns following the opening of positions*

| Dependent Variable: | Benchmark-Adj. Return t+1, t+60 | Benchmark-Adj. 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(Long Position) | 1.81*** | 2.41*** | 1.57*** | 1.90*** | 1.57*** | 2.03*** |
| | (6.53) | (5.44) | (5.99) | (4.76) | (5.72) | (4.82) |
| Observations | 13759 | 13047 | 11753 | 11309 | 13053 | 12527 |
| Adjusted $R^2$ | 0.06 | 0.08 | 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 |

*Panel B: Cumulative holding-period returns*

| Dependent Variable: | Benchmark-Adjusted Return (open-to-close) | DGTW Return (open-to-close) | 4-Factor Alpha (open-to-close) |
|---|---|---|---|
| | (1) | (2) | (3) |
| D(Long Position) | 2.74*** | 1.71*** | 2.03*** |
| | (8.29) | (5.49) | (6.17) |
| Observations | 12452 | 9985 | 11231 |
| Adjusted $R^2$ | 0.03 | 0.03 | 0.03 |
| Fund Fixed Effects | Yes | Yes | Yes |
| Month Fixed Effects | Yes | Yes | Yes |

*Panel C: Returns following the closing of positions*

| Dependent Variable: | Benchmark-Adj. Return t+1, t+60 | Benchmark-Adj. 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(Long Position) | 0.66** | 1.29*** | 0.38 | 1.04** | 0.46* | 0.89** |
| | (2.34) | (2.89) | (1.37) | (2.48) | (1.68) | (2.08) |
| Observations | 12432 | 11839 | 11078 | 10582 | 12299 | 11730 |
| 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 3: Do hedge funds reallocate their capital optimally?

This table examines if hedge funds reallocate their capital optimally. In Panels A to C, we compare 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 it 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. In Panel D, we compare returns following the closing of positions to returns of positions that were kept open. For Panel D, the sample contains all positions a fund holds at the beginning of a day on which a position is closed (last day of order). The explanatory variable is a dummy variable equal to one if the position is kept open (not closed) on that day and zero otherwise. Details on variable constructions can be found in Appendix A. In Panels A to C, we include fund-portfolio-month fixed effects based on the month of the last day of the order (in Panel A and B they are equivalent to fund-month fixed effects because we include only the long or the short portfolio). In Panel D, we include fund-portfolio-date fixed effects (based on 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: Closed Positions vs. Opened Positions - Long Positions*

| Dependent Variable: | Benchmark-Adj. Return t+1, t+60 | Benchmark-Adj. 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(Position Opening) | 0.56*** | 0.77** | 0.69*** | 0.55** | 0.47** | 0.75*** |
| | (2.76) | (2.52) | (3.96) | (2.25) | (2.45) | (2.83) |
| Observations | 14141 | 13518 | 12008 | 11579 | 13602 | 13088 |
| Adjusted $R^2$ | 0.12 | 0.15 | 0.11 | 0.14 | 0.10 | 0.12 |
| Fund×Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |

*Panel B: Closed Positions vs. Opened Positions - Short Positions*

| Dependent Variable: | Benchmark-Adj. Return t+1, t+60 | Benchmark-Adj. 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(Position Opening) | -0.51** | -0.46 | -0.63*** | -0.46* | -0.56*** | -0.46* |
| | (-2.36) | (-1.56) | (-3.12) | (-1.73) | (-2.65) | (-1.68) |
| Observations | 12050 | 11368 | 10823 | 10312 | 11750 | 11169 |
| Adjusted $R^2$ | 0.14 | 0.15 | 0.11 | 0.11 | 0.11 | 0.10 |
| Fund×Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |

*Panel C: Closed Positions vs. Opened Positions – Long and Short Positions*

| Dependent Variable: | Signed Benchmark-Adj. Ret. t+1, t+60 | Signed Benchmark-Adj. Ret. t+1, t+125 | Signed DGTW Ret. t+1, t+60 | Signed DGTW Ret. 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(Position Opening) | 0.54*** | 0.63*** | 0.67*** | 0.51*** | 0.51*** | 0.62*** |
| | (3.67) | (2.78) | (4.92) | (2.58) | (3.59) | (3.09) |
| Observations | 26191 | 24886 | 22831 | 21891 | 25352 | 24257 |
| Adjusted $R^2$ | 0.13 | 0.15 | 0.11 | 0.13 | 0.11 | 0.11 |
| Fund×Portfolio×Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |

*Panel D: Closed Positions vs. Positions Kept Open– Long and Short Positions*

| Dependent Variable: | Signed Benchmark-Adj. Ret. t+1, t+60 | Signed Benchmark-Adj. Ret. t+1, t+125 | Signed DGTW Ret. t+1, t+60 | Signed DGTW Ret. 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(Position not Closed) | 0.43*** | 0.54** | 0.38*** | 0.36* | 0.38*** | 0.49** |
| | (2.86) | (2.18) | (3.21) | (1.91) | (2.83) | (2.18) |
| Observations | 452907 | 452907 | 452907 | 452907 | 452907 | 452907 |
| Adjusted $R^2$ | 0.12 | 0.14 | 0.07 | 0.09 | 0.07 | 0.09 |
| Fund×Portfolio×Date F.E. | Yes | Yes | Yes | Yes | Yes | Yes |

# Table 4: 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 2 Panel B but split the sample by whether the fund increased or decreased the number of open positions before the first day of the order. That is, for the different subsamples, we regress average returns following the closing order on a dummy variable whether the order is related to a short position. 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. The dependent variable is the cumulative return expressed in percent for 125 trading days following the last day of the order. Details on variable constructions can be found in Appendix A. 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: | Benchmark-Adj. 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(Long Position) | 2.01*** | 0.65 | 1.73*** | 0.47 | 1.52** | 0.39 |
| | (3.10) | (1.12) | (2.87) | (0.86) | (2.45) | (0.68) |
| Observations | 5279 | 6547 | 4757 | 5815 | 5228 | 6490 |
| Adjusted $R^2$ | 0.10 | 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: | Benchmark-Adj. 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(Long Position) | 1.69*** | 1.18** | 1.48*** | 0.84 | 1.30** | 0.72 |
| | (2.82) | (1.99) | (2.66) | (1.48) | (2.28) | (1.25) |
| Observations | 5683 | 6143 | 5134 | 5438 | 5627 | 6091 |
| Adjusted $R^2$ | 0.10 | 0.10 | 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 5: 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 2 Panel B but split the sample by whether the fund had negative or positive returns before the first day of the order. That is, for the different subsamples, we regress average returns following the closing order on a dummy variable whether the order is related to a short position. 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. The dependent variable is the cumulative return expressed in percent for 125 trading days following the last day of the order. Details on variable constructions can be found in Appendix A. 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: | Benchmark-Adj. Return t+1, t+125 | | DGTW Return t+1, t+125 | | 4-Factor Alpha t+1, t+125 | |
|---|---|---|---|---|---|---|
| Sample | Negative Fund Return | Positive Fund Return | Negative Fund Return | Positive Fund Return | Negative Fund Return | Positive Fund Return |
| | (2) | (1) | (4) | (3) | (6) | (5) |
| D(Long Position) | 2.18*** | 0.62 | 1.59** | 0.71 | 1.44** | 0.46 |
| | (3.21) | (1.17) | (2.42) | (1.40) | (2.21) | (0.90) |
| Observations | 5213 | 6626 | 4665 | 5917 | 5180 | 6550 |
| Adjusted $R^2$ | 0.11 | 0.09 | 0.07 | 0.05 | 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 fund return over prior 10 trading days*

| Dependent Variable: | Benchmark-Adj. Return t+1, t+125 | | DGTW Return t+1, t+125 | | 4-Factor Alpha t+1, t+125 | |
|---|---|---|---|---|---|---|
| Sample | Negative Fund Return | Positive Fund Return | Negative Fund Return | Positive Fund Return | Negative Fund Return | Positive Fund Return |
| | (2) | (1) | (4) | (3) | (6) | (5) |
| D(Long Position) | 2.09*** | 0.61 | 1.56** | 0.58 | 1.45** | 0.48 |
| | (3.12) | (1.09) | (2.49) | (1.13) | (2.26) | (0.88) |
| Observations | 5032 | 6807 | 4462 | 6120 | 4989 | 6741 |
| Adjusted $R^2$ | 0.12 | 0.08 | 0.07 | 0.06 | 0.05 | 0.05 |
| 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 change in return volatility

This table examines whether returns following the closure of positions depend on changes in return volatility (opening and follow-up orders are excluded). We run the same regression as in Table 2 Panel B but split the sample by whether the fund experienced an increase or a decrease in return volatility. That is, for the different subsamples, we regress average returns following the closing order on a dummy variable whether the order is related to a short position. In Panel A, we measure return volatility as the sum of squared fund returns over the previous 20 trading days. In Panel B, we measure return volatility as the (position-weighted) average stock return volatility of all portfolio stocks, where the stock return volatility is defined as the sum of squared stock returns over the previous 20 trading days. In both cases, we compare our volatility measures to their values over a 20-day window before that. The dependent variable is the cumulative return expressed in percent for 125 trading days following the last day of the order. Details on variable constructions can be found in Appendix A. 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 fund return volatility over prior 20 trading days*

| Dependent Variable: | Benchmark-Adj. 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(Long Position) | 1.82*** | 0.94 | 1.67*** | 0.71 | 1.28** | 0.63 |
| | (2.97) | (1.54) | (3.05) | (1.15) | (2.26) | (1.05) |
| Observations | 5718 | 5721 | 5115 | 5103 | 5666 | 5681 |
| Adjusted $R^2$ | 0.10 | 0.11 | 0.07 | 0.05 | 0.07 | 0.04 |
| Fund Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Month Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |

*Panel B: Split by change in average position return volatility over prior 20 trading days*

| Dependent Variable: | Benchmark-Adj. 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(Long Position) | 1.86*** | 0.75 | 1.64*** | 0.41 | 1.32** | 0.39 |
| | (3.07) | (1.22) | (2.80) | (0.70) | (2.24) | (0.67) |
| Observations | 5835 | 5997 | 5252 | 5327 | 5790 | 5934 |
| Adjusted $R^2$ | 0.09 | 0.11 | 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 7: Returns following the closure of positions – Split by change in funding constraints

This table examines whether returns following the closure of positions depend on changes in (market-wide) funding constraints. That is, we run the same regression as in Table 2 Panel B but split the sample by whether the change in funding constraints is positive or negative. In Panels A and B, we split the sample by whether the TED spread, defined as the difference between the three-month LIBOR and the three-month T-bill interest rate, has increased or decreased over the prior 5 or 10 trading days. In Panels C and D, we split our sample by whether the HKM intermediary risk factor aggregated over the past 5 or 10 trading days is negative or positive. The HKM intermediary risk factor measures innovations to the capital ratio of financial intermediaries (He, Kelly and Manela (2016)). A negative risk factor implies lower capital ratios and thus higher risk. In Panels A and C, we split by changes over the 5 days prior to the order. In Panels B and D, we split by changes over the 10 days prior to the order. The dependent variable is the cumulative return expressed in percent for 125 trading days following the last day of the order. Details on variable constructions can be found in Appendix A. 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 TED spread change over prior 5 trading days*

| Dependent Variable: | Benchmark-Adj. Return t+1, t+125 | | DGTW Return t+1, t+125 | | 4-Factor Alpha t+1, t+125 | |
|---|---|---|---|---|---|---|
| Sample | Higher TED Spread | Lower TED Spread | Higher TED Spread | Lower TED Spread | Higher TED Spread | Lower TED Spread |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| D(Long Position) | 1.94*** | 0.36 | 1.65*** | 0.23 | 1.17** | 0.35 |
| | (3.13) | (0.55) | (2.89) | (0.38) | (2.01) | (0.56) |
| Observations | 6452 | 5111 | 5771 | 4565 | 6379 | 5078 |
| Adjusted $R^2$ | 0.10 | 0.10 | 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 |

*Panel B: Split by TED spread change over prior 10 trading days*

| Dependent Variable: | Benchmark-Adj. Return t+1, t+125 | | DGTW Return t+1, t+125 | | 4-Factor Alpha t+1, t+125 | |
|---|---|---|---|---|---|---|
| Sample | Higher TED Spread | Lower TED Spread | Higher TED Spread | Lower TED Spread | Higher TED Spread | Lower TED Spread |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| D(Long Position) | 2.46*** | -0.32 | 1.89*** | 0.09 | 1.84*** | -0.41 |
| | (4.10) | (-0.47) | (3.39) | (0.14) | (3.28) | (-0.61) |
| Observations | 6637 | 4882 | 5940 | 4355 | 6580 | 4833 |
| 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 |

*Panel C: Split by HKM intermediary risk factor over prior 5 trading days*

| Dependent Variable: | Benchmark-Adj. Return t+1, t+125 | | DGTW Return t+1, t+125 | | 4-Factor Alpha t+1, t+125 | |
|---|---|---|---|---|---|---|
| Sample | Negative HKM Factor | Positive HKM Factor | Negative HKM Factor | Positive HKM Factor | Negative HKM Factor | Positive HKM Factor |
| | (2) | (1) | (4) | (3) | (6) | (5) |
| D(Long Position) | 2.33*** | 0.45 | 1.24** | 0.95* | 1.54** | 0.45 |
| | (3.66) | (0.78) | (2.08) | (1.69) | (2.54) | (0.80) |
| Observations | 5331 | 6380 | 4787 | 5678 | 5284 | 6318 |
| Adjusted $R^2$ | 0.11 | 0.09 | 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 D: Split by HKM intermediary risk factor over prior 10 trading days*

| Dependent Variable: | Benchmark-Adj. Return t+1, t+125 | | DGTW Return t+1, t+125 | | 4-Factor Alpha t+1, t+125 | |
|---|---|---|---|---|---|---|
| Sample | Negative HKM Factor | Positive HKM Factor | Negative HKM Factor | Positive HKM Factor | Negative HKM Factor | Positive HKM Factor |
| | (2) | (1) | (4) | (3) | (6) | (5) |
| D(Long Position) | 2.16*** | 0.60 | 1.49** | 0.79 | 1.49*** | 0.42 |
| | (3.49) | (0.98) | (2.54) | (1.37) | (2.59) | (0.71) |
| Observations | 5720 | 5991 | 5117 | 5348 | 5676 | 5926 |
| Adjusted $R^2$ | 0.11 | 0.10 | 0.05 | 0.07 | 0.05 | 0.05 |
| Fund Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Month Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |

# Table 8: Hedge fund trading and earnings surprises

This table examines whether hedge funds' opening of long and short positions predicts the standardized unexpected earnings (SUE) of subsequent earnings announcements. We regress two different measures of SUE on HF $imbalance_{[5,20]}$, a variable that takes the value 1 (-1) when our sample hedge funds, in the aggregate, buy (sell) the stock in the window 20 to 5 trading days before to the announcement date and zero otherwise, and a number of controls. In columns 1-3, the dependent variable is $SUE_{IBES}$, defined as the difference between the actual earnings (per share) and the median earnings forecast made by analysts following the stock, scaled by the standard deviation of this difference over the previous 8 quarters. In columns 4-6, the dependent variable is $SUE_{Worldscope}$, defined as the difference between the actual earnings (per share) and the earnings announced for the same calendar quarter of the previous year, scaled by the standard deviation of this difference over the previous 8 quarters. Controls include: the cumulated return and cumulated share turnover over the 15 trading days prior to the announcement week; firm size, defined as the logarithm of total assets in USD at the end of the previous quarter; #analysts, defined as the number of analysts issuing earnings forecasts for a given announcement; leverage, defined as the ratio of long-term debt over total assets at the end of the previous quarter; and market-to-book, defined as the ratio of market value of equity (measured 5 days prior to the announcement) over the book value of equity at the end of the previous quarter. 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 earnings announcement date. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

| Dependent Variable: | | $SUE_{IBES}$ | | | $SUE_{Worldscope}$ | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| HF $imbalance_{[5,20]}$ | 0.0583** | 0.0541** | 0.0589** | 0.0646*** | 0.0592** | 0.0515** |
| | (2.55) | (2.36) | (2.23) | (2.71) | (2.48) | (2.03) |
| Stock $Return_{[5,20]}$ | | 0.7857*** | 0.8430*** | | 0.8882*** | 0.9204*** |
| | | (5.91) | (5.92) | | (6.57) | (6.65) |
| $Turnover_{[5,20]}$ | | -0.1817 | -0.2867** | | -0.0024** | -0.0029*** |
| | | (-1.53) | (-2.26) | | (-2.46) | (-3.85) |
| Firm size | | | -0.0827** | | | -0.1516*** |
| | | | (-2.37) | | | (-7.02) |
| #Analysts | | | -0.0270 | | | -0.1102*** |
| | | | (-1.51) | | | (-8.98) |
| Leverage | | | 0.2136* | | | -0.2157** |
| | | | (1.77) | | | (-2.46) |
| Market-to-book | | | -0.0008 | | | 0.0006 |
| | | | (-1.34) | | | (0.70) |
| Observations | 83414 | 83414 | 63431 | 110033 | 110033 | 77080 |
| Adjusted $R^2$ | 0.09 | 0.10 | 0.09 | 0.03 | 0.04 | 0.04 |
| 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). We regress returns following the order on a dummy variable equal to one if it is an order that increases the position (i.e., long buys and short sells). 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. We include fund-portfolio-month fixed effects based on the month of the last day of the order (in Panel A and B they are equivalent to fund-month fixed effects because we include only the long or the short portfolio). 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: Position Increase vs. Position Decrease - Long Positions*

| Dependent Variable: | Benchmark-Adj. Return t+1, t+60 | Benchmark-Adj. 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(Position Increase) | -0.04 | 0.19 | 0.06 | 0.16 | 0.04 | 0.28 |
| | (-0.23) | (0.79) | (0.43) | (0.80) | (0.27) | (1.27) |
| Observations | 41808 | 39677 | 34720 | 33338 | 40074 | 38452 |
| Adjusted $R^2$ | 0.12 | 0.15 | 0.11 | 0.14 | 0.10 | 0.13 |
| Fund×Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |

*Panel B: Position Increase vs. Position Decrease - Short Positions*

| Dependent Variable: | Benchmark-Adj. Return t+1, t+60 | Benchmark-Adj. 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(Position Increase) | -0.16 | -0.27 | -0.05 | -0.32 | -0.30 | -0.35 |
| | (-0.81) | (-0.95) | (-0.27) | (-1.19) | (-1.60) | (-1.23) |
| Observations | 20694 | 19377 | 18310 | 17353 | 20082 | 18946 |
| Adjusted $R^2$ | 0.16 | 0.17 | 0.13 | 0.15 | 0.11 | 0.11 |
| Fund×Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |

*Panel C: Position Increase vs. Position Decrease – Long and Short Positions*

| Dependent Variable: | Signed Benchmark-Adj. Ret. t+1, t+60 | Signed Benchmark-Adj. Ret. t+1, t+125 | Signed DGTW Ret. t+1, t+60 | Signed DGTW Ret. 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(Position Increase) | 0.03 | 0.22 | 0.06 | 0.22 | 0.13 | 0.30* |
| | (0.25) | (1.19) | (0.52) | (1.34) | (1.10) | (1.74) |
| Observations | 62502 | 59054 | 53030 | 50691 | 60156 | 57398 |
| Adjusted $R^2$ | 0.14 | 0.16 | 0.12 | 0.15 | 0.11 | 0.13 |
| Fund×Portfolio×Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |

# Table 10: Comparing factor loadings to other hedge fund databases

This table compares the factor loadings of the hedge fund returns in our data to the loadings of other hedge fund indices. In Regression 1, we use hedge fund returns computed from our data as the dependent variable. We compute monthly returns of each fund by computing the combined returns of all long and short positions (position-weighted) per fund. Then we compute the equal-weighted average across funds (in percentage points). In Regression 2, the dependent variable is the average fund return (equal-weighted, net of fees) in the Kruttli, Patton, and Ramodarai (2015) dataset including only long-short equity funds. In Regression 3, the dependent variable is the Credit Suisse AllHedge Long/Short Equity Index, which includes only investable long-short equity funds. In Regression 4, the dependent variable is the Broad Credit Suisse Long/Short Equity, which also includes funds that are closed for investment. All returns are excess returns with respect to the 1-month T-bill rate. In Panel A, we report factor loadings of the Fung and Hsieh 8 factor model. In Panel B, we report factor loadings of the Carhart/Fama French Global 4 factor model. Details on variable constructions can be found in Appendix A. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

*Panel A: Fung and Hsieh 8 Factor Model*

| Dependent Variable: | Hedge Fund Returns based on Our Data | Kruttli, Patton, Ramodarai (2015) | Credit Suisse Only Investable | Credit Suisse All Funds |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Equity Market Factor | 0.39*** | 0.10*** | 0.26*** | 0.19*** |
| | (8.84) | (3.02) | (7.18) | (4.26) |
| Size Spread Factor | 0.04 | -0.02 | 0.01 | 0.02 |
| | (0.77) | (-0.67) | (0.15) | (0.33) |
| Emerging Market Factor | 0.24*** | 0.24*** | 0.14*** | 0.16*** |
| | (9.28) | (10.99) | (4.92) | (5.53) |
| Bond Market Factor | -0.00 | 0.00 | -0.00 | 0.01 |
| | (-0.50) | (0.27) | (-0.32) | (1.57) |
| Credit Spread Factor | -0.02*** | -0.01* | -0.01** | -0.01 |
| | (-3.17) | (-1.97) | (-2.40) | (-1.19) |
| Bond Trend-Following Factor | -0.01* | 0.00 | 0.00 | 0.00 |
| | (-1.74) | (0.30) | (0.03) | (0.02) |
| Currency Trend-Following Factor | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.57) | (0.89) | (0.42) | (0.81) |
| Commodity Trend-Following Factor | 0.00 | 0.00 | -0.01 | -0.00 |
| | (0.57) | (0.05) | (-1.33) | (-0.42) |
| Alpha | 0.18 | 0.13 | -0.12 | 0.21** |
| | (1.43) | (1.47) | (-1.18) | (1.99) |
| Observations | 123 | 123 | 123 | 123 |
| Adjusted $R^2$ | 0.89 | 0.85 | 0.79 | 0.76 |

*Panel B: Carhart 4 Factor Model*

| Dependent Variable: | Hedge Fund Returns based on Our Data | Kruttli, Patton, Ramodarai (2015) | Credit Suisse Only Investable | Credit Suisse All Funds |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Global Market minus risk-free rate | 0.74*** | 0.44*** | 0.51*** | 0.47*** |
| | (33.37) | (21.25) | (21.51) | (21.41) |
| Global SMB | 0.21*** | 0.26*** | 0.15*** | 0.22*** |
| | (3.80) | (4.88) | (3.28) | (4.50) |
| Global HML | -0.03 | -0.11* | -0.18*** | -0.18*** |
| | (-0.44) | (-1.80) | (-3.12) | (-2.87) |
| Global WML | 0.00 | 0.03 | 0.11*** | 0.12*** |
| | (0.06) | (1.15) | (4.88) | (5.53) |
| Alpha | 0.25** | 0.08 | -0.18** | 0.13 |
| | (2.56) | (1.04) | (-2.23) | (1.63) |
| Observations | 123 | 123 | 123 | 123 |
| Adjusted $R^2$ | 0.92 | 0.86 | 0.89 | 0.88 |

# Table 11: Testing for backfill bias

This table examines whether hedge funds have different returns shortly after they enter or before they exit the sample. We run OLS regressions at the fund-date level. In Panel A, the dependent variable is the (position-weighted) daily average signed return of all positions the fund holds. In Panel B, the dependent variable is the (position-weighted) daily average signed benchmark-adjusted return of all positions the hedge fund holds. The independent variables are dummy variables equal to one in the first (or last) 60 (or 120) days that the fund is reporting to Inalytics. Details on variable constructions can be found in Appendix A. We include fund fixed effects and month fixed effects. All standard errors are clustered by date. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

*Panel A: Raw Returns*

| Dependent Variable: | Daily Fund Return (in basis points) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| D(First 60 days in sample) | -0.05 | | | |
| | (-0.02) | | | |
| D(First 125 days in sample) | | -0.02 | | |
| | | (-0.01) | | |
| D(Last 60 days in sample) | | | 1.97 | |
| | | | (0.52) | |
| D(Last 125 days in sample) | | | | 0.36 |
| | | | | (0.16) |
| Constant | 2.46** | 2.46** | 2.34* | 2.42* |
| | (1.98) | (1.97) | (1.88) | (1.94) |
| Observations | 21266 | 21266 | 21266 | 21266 |
| Adjusted $R^2$ | 0.02 | 0.02 | 0.02 | 0.02 |
| Fund Fixed Effects | Yes | Yes | Yes | Yes |
| Month Fixed Effects | Yes | Yes | Yes | Yes |

*Panel B: Benchmark-Adjusted Returns*

| Dependent Variable: | Daily Fund Benchmark-Adjusted Return (in basis points) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| D(First 60 days in sample) | -0.02 | | | |
| | (-0.01) | | | |
| D(First 125 days in sample) | | 0.75 | | |
| | | (0.60) | | |
| D(Last 60 days in sample) | | | 0.60 | |
| | | | (0.35) | |
| D(Last 125 days in sample) | | | | 0.43 |
| | | | | (0.37) |
| Constant | 2.25*** | 2.15*** | 2.21*** | 2.19*** |
| | (6.86) | (6.34) | (6.93) | (6.74) |
| Observations | 21265 | 21265 | 21265 | 21265 |
| Adjusted $R^2$ | 0.00 | 0.00 | 0.00 | 0.00 |
| Fund Fixed Effects | Yes | Yes | Yes | Yes |
| Month Fixed Effects | Yes | Yes | Yes | Yes |

# Appendix A: Variable definitions

This table displays the variable definitions for all variables used in the regressions. Return measures over the 60 trading days following the order are set to missing if we have less than 50 daily return observations. Returns measures over the 125 trading days following the order are set to missing if we have less than 100 daily return observations. Cumulative holding period returns are set to missing if more than 10% of the daily return observations are missing. All return measures are winsorized at the 1% level on both sides.

| Variable Name | Definition |
|---|---|
| Benchmark-Adjusted 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 | $Stock\ Return - \ Return\ of\ portfolio\ of\ similar\ stocks$<br>Similar stocks are stocks in the same quintile of market capitalization, book-to-market ratio and past 12 month stock return within the same region. For more details see Internet Appendix A. |
| 4-Factor Alpha | $r_{c,t} - r_{f,t} - \beta_m * (r_{m,t} - r_{f,t}) - \beta_{HML} * HML_t - \beta_{SMB} * SMB_t - \beta_{MOM} * MOM_t$<br>For more details see Internet Appendix A. |
| Signed Benchmark-Adj. Return | Benchmark-adjusted return for long positions and benchmark-adjusted return multiplied by minus one for short positions. |
| Signed DGTW Return | DGTW return for long positions and DGTW return multiplied by minus one for short positions. |
| Signed 4-Factor Alpha | Four-factor alpha for long positions and 4-factor alpha multiplied by minus one for short positions. |
| D(Long Position) | Dummy variable equal to one if the order is related to a long position (i.e., a long buy or a long sell) and zero if it is related to a short position (i.e., a short sell or a short buy). |
| D(Position 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). |
| D(Position not Closed) | Dummy variable equal to one if the position is kept open and equal to zero if it is closed on that day. |
| D(Position Increase) | Dummy variable equal to one if a follow-up order increases a position (long-buy or short-sell) and equal to zero if it decreases a position (long-sell or short-buy). |
| Daily Fund return | Position-weighted average signed return of all positions of the fund, where the weight is the dollar value of the position. Daily stock-level returns are winsorized at 10% and -10%. |
| Daily Fund Benchmark-Adjusted Return | Position-weighted average signed benchmark-adjusted return of all positions of the fund, where the weight is the dollar value of the position. Daily stock-level benchmark-adj. returns are winsorized at 10% and -10%. |
| Daily Fund DGTW Return | Position-weighted average signed DGTW return of all positions of the fund, where the weight is the dollar value of the position. Daily stock-level DGTW return returns are winsorized at 10% and -10%. |
| Daily Fund 4-Factor Alpha | Position-weighted average signed 4-factor alpha of all positions of the fund, where the weight is the dollar value of the position. Daily stock-level 4-factor alphas are winsorized at 10% and -10%. |
| Fund return volatility$_{[1,20]}$ | $$\sum_{1}^{20} Daily\ fund\ return^2$$<br>It is set to missing if there are 16 or fewer daily fund observations available in the last 20 trading days. |
| Average position return volatility$_{[1,20]}$ | $$Weighted\ Average[\sum_{1}^{20} Daily\ stock\ return^2]$$<br>The weights is the dollar value invested. Daily stock returns are winsorized at 10% and -10%. A stocks volatility is set to missing if there are 16 or fewer daily stock return observations available in the last 20 trading days. |
| TED spread | $LIBOR_{3\ month} - Tbill_{3\ month}$ |
| HKM intermediary risk factor | Measures innovations to the capital ratio of financial intermediaries (primary dealer counterparties of the New York Federal Reserve). The data are available at http://apps.olin.wustl.edu/faculty/manela/data.html.<br><br>More specifically, He, Kelly, and Manela (2016) calculate aggregate dealer capital ratios as<br>$$\eta_t = \frac{\sum_i Market\ Equity_{i,t}}{\sum_i(Market\ Equity_{i,t} + Book\ Debt_{i,t})}$$<br>and compute innovations in this variable using an AR(1) process<br>$$\eta_t = \rho_0 + \rho\eta_{t-1} + u_t\ .$$<br>The risk factor is then defined as the growth rate of these innovations:<br>$$HKM\ intermediary\ risk\ factor_t = \frac{u_t}{\eta_{t-1}}$$ |
| SUE$_{IBES}$ | $$\frac{Actual\ Earnings_t - \ Median\ of\ analyst\ earnings\ forecast_t}{Standard\ Deviation\ _{t-8,t-1}(Actual\ Earnings_\tau - Median\ of\ analyst\ earnings\ forecast_\tau)}$$<br>Analyst forecasts are taken from I/B/E/S detail history North America file for U.S. and Canadian companies and from the I/B/E/S detail history International file for other companies. For each analyst, only the last forecast is retained if it has been issued no more than 60 days prior to the earnings announcement date. The data is quarterly. |
| SUE$_{Worldscope}$ | $$\frac{Actual\ Earnings_t - \ Actual\ Earnings_{t-4}}{Standard\ Deviation\ _{t-8,t-1}(Actual\ Earnings_\tau - Actual\ Earnings_{\tau-4})}$$<br>Quarterly earnings data is taken from Worldscope. |
| HF imbalance$_{[5,20]}$ | This variable takes the value one (minus one) if sample hedge funds open a long (short) position from t-20 to t-5 days prior to the earnings announcement and zero if there is no newly opened position. If there are opened |

| | |
|---|---|
| | positions in both direction, the variable takes the value one (minus one) if the newly opened long (short) positions are larger in terms of the number of traded stocks. |
| Turnover | $\frac{Shares\ traded}{Shares\ outstanding}$ |
| Firm size | $Log\ (Total\ assets)$ |
| #Analysts | Number of analysts issuing forecasts for this earnings announcement. For each analyst, only the last forecast is retained if it has been issued no more than 60 days prior to the earnings announcement date. |
| Leverage | $\frac{Long-term\ debt}{Total\ assets}$ At the end of the previous quarter |
| Market-to-book | $\frac{Market\ value\ of\ equity\ (5\ days\ before\ earnings\ annoucement)}{Book\ value\ of\ equity\ (at\ the\ end\ of\ the\ previous\ quarter)}$ |
| Equity Market Factor | The Standard & Poors 500 index monthly total return [Datastream code: S&PCOMP(RI)] |
| Size Spread Factor | Russell 2000 index monthly total return - Standard & Poors 500 monthly total return. [Datastream code: FRUSS2L(RI)] |
| Emerging Market Factor | MSCI Emerging Market index monthly total return [Datastream code: MSEMKF$(RI)] |
| Bond Market Factor | Monthly change in the 10-year U.S. treasury constant maturity yield (month end-to-month end) |
| Credit Spread Factor | Monthly change in the Moody's Baa yield less 10-year treasury constant maturity yield (month end-to-month end) |
| Bond Trend-Following Factor | Downloaded at https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm |
| Currency Trend-Following Factor | Downloaded at https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm |
| Commodity Trend-Following Factor | Downloaded at https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm |
| 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. |
| Global Market minus risk-free rate | Global market factor downloaded at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research |
| Global SMB | Global small minus big factor downloaded at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research |
| Global HML | Global high minus low book to market factor downloaded at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research |
| Global WML | Global momentum factor downloaded at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research |
| D(First 60 days in sample) | Dummy variable equal to one in the first 60 days that a fund is in our sample. |
| D(First 125 days in sample) | Dummy variable equal to one in the first 125 days that a fund is in our sample. |
| D(Last 60 days in sample) | Dummy variable equal to one in the last 60 days that a fund is in our sample. |
| D(Last 125 days in sample) | Dummy variable equal to one in the last 125 days that a fund is in our sample. |

## 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 $\varepsilon_{it}$ is a zero-mean noise term with variance $\sigma_t^2$ (constant for all $i$).[22] 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 fact that such trading opportunities disappear over time (Chen, Da and Huang (2016), Di Mascio, Lines and Naik (2016)), we assume that the mispricing $\Delta_{it}$ decays over subsequent periods. That is, if the mispricing of stock $i$ occurs in period $t$ and lasts for $\tau$ 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 $\varepsilon_{it}$ 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 $\varepsilon_{it}$ 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.[23] 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.[24]

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:

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

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

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

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

[22] 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 $\alpha$; i.e., any return in excess of the market risk premium.

[23] 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 $\tau$ 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.

[24] 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). Such a risk constraint may itself stem from a leverage or margin constraint and we indeed argue below that both types of constraints closely resemble each other and lead to very similar predictions.[25] 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 allows for an explicit, simple solution. A more general structure leads to similar predictions as long as the stock mispricing satisfies the assumption on alpha decay.

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 $\Delta$ $(-\Delta)$. 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

[25] Margin constraints are modelled, for instance, in Gromb and Vayanos (2002, 2017) and Brunnermeier and Pedersen (2009). They take the form of a fraction of the arbitrage position that needs to be kept as a margin. This makes them very similar to a risk constraint which also imposes an upper bound on the arbitrage position.

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.[26] 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*

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

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

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

- *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*

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

[26] 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.

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

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

**Proof**: We start with assuming that the hedge fund only invests into newly mispriced stocks. That is $N_{At} \le M_t$, 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 $\lambda$ 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, $N_{At} \le M_t$ and so this solution is only valid for $M_t \ge \kappa_t \left(\frac{W_t \Delta}{2c}\right)^2 \equiv \bar{M}_{3t}$.

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

Since $\bar{M}_{2t} < \bar{M}_{3t}$, there is a range for $M_t$ in which neither solution applies. This means that, for $\bar{M}_{2t} \le M_t < \bar{M}_{3t}$, 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 $\kappa_t$, 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 $\delta$, volatility limit $\kappa_t$, 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.[27] 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.[28] These rebalancing trades will typically result in a gradual downscaling of the position concomitant to the decay in alpha. Nevertheless, in our model, all rebalancing trades are followed by the same expected return, $\Delta(1-\delta)$. Thus, whether or not a rebalancing trade increases or decreases the position is uninformative about its future return.

## 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 mispriced 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 mispriced in *t-1*. Specifically, out of the $N_{At-1}$ positions, it will only want to hold on to $N_{Bt}$ positions, where typically $N_{Bt} < N_{At-1}$.[29] Each of these prematurely closed positions is

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[27] 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.

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

[29] 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.

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., $0 \le X_t \le 1$. The fraction becomes zero if $N_{At-1} \le N_{Bt}$, 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 $\mathrm{N}_{Bt}$.

Finally, note that all terms entering $X_t$ except for $\mathrm{N}_{Bt}$ are pre-determined (i.e., depend on parameters from period *t-1*). Thus, only $\mathrm{N}_{Bt}$ 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 $\Delta$.[30] Closing trades are followed by an average return of $X_t\Delta(1-\delta)$, where $0 \le X_t \le 1$ (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 $\mathrm{N}_{Bt}$, 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 $\mathrm{N}_{Bt}$, 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 or when funding constraints tighten.*

**Proof**: $X_t$ is decreasing in $\mathrm{N}_{Bt}$, which is increasing in $\kappa_t$ and thus decreasing in $\sigma_t$. ■

[30] 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 $\Delta(1-\delta)$.

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. 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. Finally, prediction 5 can also be reinterpreted as meaning that early position closures are more likely to occur when the hedge fund's funding constraint tightens. This is because, as mentioned before, the risk constraint closely resembles a leverage constraint. Indeed, in our model, the hedge fund's leverage, defined as its dollar investments in risky stocks over its capital, is given by $N_{At}w_{At} + N_{Bt}w_{Bt}$. Plugging in the expressions from the proposition, it is straightforward to see that leverage is linearly increasing in the risk limit $\bar{\sigma}^2$. Thus, apart from reflecting actual risk management practice, our risk constraint can also be thought off as a short-hand for a leverage constraint. We therefore expect hedge funds' position closures to be affected by changes in overall funding constraints of financial intermediaries (such as hedge funds' prime brokers).