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

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Abstract

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

JEL classification: G11, G12, G14, G15

Keywords: Hedge funds, Short selling, Profitability, Limits of arbitrage

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

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

In stark contrast, we find that closing trades are not informed. To the contrary, long sells and short buys tend to be followed, respectively, by positive and negative returns; that is, returns in the opposite direction of the closing trade. When we design a trading strategy that goes long in stocks in which hedge funds just closed a long position (long sells) and shorts stocks from closed short

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

positions (short buys) we obtain a significant alpha of about 1% over the next six months (125 trading days). This implies that the hedge funds in our sample close their positions too early in the sense that they "leave money on the table."

To understand this finding, we draw on a simple trading model (presented in the appendix) in which a hedge fund decides whether and how much to invest in mispriced stocks. We embed three important—and as we believe realistic—features into the model: First, the hedge fund is assumed to face a risk constraint, which prevents it from taking too large a position in any mispriced stock. Second, the hedge fund incurs a monitoring cost for each open position in its portfolio. The first assumption mirrors standard practice in the hedge fund industry (see, for instance, Pedersen (2015)) and should thus be uncontroversial. The second assumption can be interpreted loosely as a fixed transaction, monitoring or attention cost for maintaining the position and checking whether a previous trading signal has not lost its allure. Such a cost naturally leads the investor to focus on a limited number of open positions, consistent with what we empirically observe for the long-short equity hedge funds in our sample.[2] Finally, we assume that new investment opportunities (stock mispricings) emerge each period, whose alphas partially decay over time. This "alpha decay" is again consistent with prior empirical evidence (e.g., Chen, Da and Huang (2016), Di Mascio, Lines and Naik (2016)) and is also evident in our data, where roughly 75% (=1.5%/2%) of the alpha is earned within the first six months after the initiation of a stock position.

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

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

Our model is designed to capture this intuition. Indeed, we show that, under the abovementioned assumptions, the hedge fund's optimal trading rule involves early position closures: as the expected profitability of an investment decays, other trading opportunities become more attractive. This triggers a reallocation of the limited risk capital and monitoring capacity into these more promising opportunities, explaining why we find that hedge funds close positions that continue to generate alpha going forward. We then use the model to derive a number of additional predictions: First, at any point in time, the profits from newly opened positions should exceed the profits that hedge funds

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

forego by closing existing ones. Second, the return continuation following position closures should be more pronounced—meaning that the hedge fund leaves more money on the table—when the fund (1) simultaneously opens a lot of new positions (that require capital), (2) has suffered from poor past performance, and (3) when the risk constraint becomes more binding due to a surge in fund return volatility.

We test and confirm these additional predictions in the data. We begin by comparing returns after opening and closing orders within the same month. We find that, over the 125 trading days following the order, newly initiated long (short) positions yield an alpha that is 0.6% larger (smaller) than the alpha following closed long (short) positions. Thus, we document that, within the same month, hedge funds generate more alpha with their opening trades than they forego by closing their positions prematurely, proving that hedge funds recycle their limited risk capital into more profitable trading opportunities.

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

these findings suggest that early position closures—which are associated with foregone risk-adjusted returns—occur in response to binding (risk) capital and monitoring constraints.[3]

As mentioned before, one key advantage of our data is that it comprises the complete transaction and position records for a subset of hedge funds *all* belonging to the same investment class: discretionary long-short equity. 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, we argue that they constitute an ideal laboratory to study the limits to *fundamental* arbitrage: First, long-short equity hedge funds take *directional* bets on individual stocks. Thus, their long and short positions are not part of a combined trading strategy as in, for example, merger arbitrage, allowing us to directly examine the profits of individual positions. Second, discretionary long-short equity hedge funds spend a lot of time and effort on research in order to distill an information advantage from public and private sources (Pedersen (2015)). We provide evidence that the hedge funds in our data meet these descriptions. On the first point, we note 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 and merger arbitrage. On the second point, we document that the position openings of our sample hedge funds predict subsequent earning announcement surprises, suggesting that they trade on fundamental information. In summary, long-short equity funds such as those in our sample closely resemble the textbook case of informed arbitrageurs trading on fundamental mispricing.

Exploiting our data, we provide an in-depth study of how the trading behavior of these fundamental investors is affected by the presence of arbitrage constraints. We find that the long-short equity hedge funds in our sample are skilled but constrained investors: While their opening trades are clearly profitable, they do not hold on to their positions until the alpha is fully exploited. Rather, they close their positions prematurely in order to recycle their capital and/or accommodate tightened risk constraints. These results have important implications for the literature on the limits of arbitrage—and in particular for a recent strand studying how constrained arbitrageurs simultaneously trade in multiple arbitrage opportunities (Brunnermeier and Pedersen (2009) and Gromb and Vayanos (2017)). These models show how arbitrageurs' funding constraints lead to an interrelation between otherwise unrelated assets, which can be a source of additional comovement

[3] In additional tests, we reject the alternative hypothesis that early position closures can be explained by hedge funds' rebalancing motives.

and fragility. To the best of our knowledge, we are the first to document this interdependence of trading positions at the micro level. One important implication of our results—which we feel existing models have not emphasized enough—is that the emergence of a new investment opportunity, by raising the opportunity cost of arbitrage capital, further constrains 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. Our partial equilibrium model in the spirit of Brunnermeier and Pedersen (2009) and Gromb and Vayanos (2017) helps clarify this point.

While the level of detail is a clear advantage 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 hedge funds' returns dataset (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. On many dimensions, we have no reasons to believe that the funds in our sample are markedly different from a typical long-short equity hedge fund. 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 studying the post-trade performance differences between opening and closing trades, which we rationalize with the help of a stylized trading model. Thus, to the degree that our model—and in particular the assumptions on risk limits and position monitoring costs—capture features that are common in the hedge fund industry, one would expect our results to be generalizable to the broader population.

Our paper contributes to several strands of research. First and foremost, we contribute to the literature on informed trading and the limits of arbitrage. Using transaction data for a sample of active mutual funds from the same data provider, Di Mascio, Lines and Naik (2016) provide an in-depth analysis on the opening of long arbitrage positions. Like us, they find abnormal returns of about 1.5% following the opening of a long position (but over a longer horizon of 18 months). They further document that the mutual funds gradually build up their positions over a horizon of up to 6 months, consistent with them trying to strategically limit their price impact. We complement their

study by including short sales and by focusing on and explaining the returns following position closures. We thereby link with the (mostly theoretical) literature on the limits of arbitrage that emphasizes different channels as to why arbitrageurs may be forced to close their positions too early (Shleifer and Vishny (1997), Gromb and Vayanos (2002, 2017), Brunnermeier and Pedersen (2009), Acharya and Viswanathan (2011)).[4] Existing empirical work in this area 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 Viswanathan (2010), Nagel (2011), Adrian, Etula and Muir (2014), Pasquariello (2014), He, Kelly and Manela (2016)). Another strand studies hedge funds' deleveraging behavior in the wake of the 2007-09 Financial Crisis (Ang, Gorovyy and van Inwegen (2011), Khandani and Lo (2011), Aragon and Strahan (2012), Ben-David, Franzoni and Moussawi (2012)). We contribute to this literature by providing evidence for the limits of arbitrage at the *transaction*-level. Our study thereby offers a unique glimpse into the process by which hedge funds "recycle" their limited arbitrage capital—i.e., how and when they close existing positions and redeploy their capital.

Second, we speak to the literature on hedge funds—and in particular on their trading and performance. Many papers examine hedge fund skill using databases on self-reported hedge fund returns, but are hampered by different biases of these databases (see, e.g., Agarwal, Mullally, and Naik (2015) for a survey). More recent papers try to examine hedge fund skill using quarterly 13F filings data and reach mixed conclusions: While Cao et al. (2016) find that hedge fund holdings predict future returns, Griffin and Xu (2009) find no such predictive power. Grinblatt et al. (2017) document long-term predictability for a subset of contrarian hedge funds. Jank and Smajlbegovic (2015) use data from hedge funds' mandatory disclosure of large short positions and find evidence for predictability. We add to the debate on hedge fund performance by examining trading skill using detailed trading and position records for *both* long and short positions of the same funds. Furthermore, our data has the advantage of covering *all* equity positions of the hedge funds in the sample. We find strong evidence of hedge fund outperformance for up to one year after the opening of positions. This shows that long-short equity funds in our sample possess the skill to identify mispriced stocks, thereby complementing previous work that emphasize hedge funds' role as liquidity providers (Aragon and Strahan (2012), Ben-David, Franzoni and Moussawi (2012), Jylhä, Rinne and Suominen (2014), Franzoni and Plazzi (2015), Jame (2016)). Finally, our work is closely

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

related to Choi, Pearson and Sandy (2016), who study hedge fund short positions gleaned from merging institutional transaction data from ANcerno with quarterly holdings from 13F. They find that the position openings by hedge funds in their sample do *not* predict long-term returns. Instead, they find that their short positions are profitable only over the short-term (up to 5 trading days), suggesting that these funds make the bulk of their profits from liquidity provision. Our data is more comprehensive[5] and, perhaps more importantly, covers the trading activity for *one particular class* of hedge funds—long-short equity—as opposed to the trading by a mix of different hedge funds belonging to the same hedge fund family. This may explain why our results for the long-term predictability of stock trades are markedly different.

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

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

I. Hypotheses

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

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

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

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

Our modeling assumptions are supposed to reflect realistic features of the trading environment for long-short equity hedge funds: The risk constraint is meant to capture, in a simplified way, common risk management practices such as risk parity investment (see Pedersen (2005)). A straightforward implication of this constraint is that position sizes are bounded and inversely related to the volatility of the underlying stock.[6] The position monitoring cost is a placeholder for any type of fixed cost that is associated with holding a stock position. For instance, it can represent a fixed transaction cost or a fixed attention cost for monitoring a given position (the hedge fund may want to check, for example, whether the trading signal, which induced the opening of the position, is still valid after the arrival of new information). Without this assumption, the hedge fund would always smoothly scale back position sizes all the way to zero until the alpha is fully exploited.[7] 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 wealthier funds have more open positions—a prediction for which we find strong support in the data.[8]

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 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

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[6] 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.

[7] 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.

[8] 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.

past performance, and (3) when the funds' stock positions become more volatile or (4) when funding constraints tighten.

Before testing these predictions, we introduce our data in the next section.

II. Data and Variable Construction

A. Inalytics data

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

Our data contain *complete* trading and portfolio information for the equity holdings of 21 hedge funds. For each fund, we are thus able to track both their long and short portfolios. Specifically, we have access to two datasets: The first is a transaction-level dataset containing all trades. Variables in this dataset include stock identifiers (ISIN, SEDOL, and CUSIP), the date of the trade, the number of shares traded, and the execution price. The second dataset is a stock-day level dataset of each funds' portfolio holdings. This dataset contains stock identifiers, the number of shares held, and the price of the stock at the end of the day. All prices are expressed in the base currency of the fund and in the local currency of the stock.

We use a merged dataset that combines the holdings and trading data (details on merging these two datasets can be found in Section A of the Internet Appendix). Hedge funds often split their orders into several trades that are executed on different days to reduce the market impact of their orders. To avoid double counting, we follow Di Mascio, Lines, and Naik (2016) and aggregate the trades belonging to one investment decision into orders. We assume that trades belong to one order if they trade the same stock in the same direction and the distance between two trades of the order is two days or less. Seventy-three percent of the orders consist of only one trade.

B. Summary statistics

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

In Table 1, Panel A, we display summary statistics by fund. Funds hold on average 50 long positions and 24 short positions (median values are 36 and 19). The fewer number of short positions is further reflected by the fact that short positions make up about 30% by USD value. Having a larger long than short portfolio is seen as typical for long-short equity hedge funds (Fung and Hsieh (2004)). The funds conduct on average 6 orders per day. Compared to an average of 74 positions this corresponds to a new order for a given stock position every 12 trading days. The daily fund turnover (trading volume over total portfolio holdings) is on average 5.4% (median 2.8%). Our funds 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 funds in our data are larger on average than funds in the commonly used Lipper Tass database. 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)).

The investment areas of the funds vary as shown in Figure 2. We have 7 Europe-focused funds, 3 US, 3 UK and 2 Australia-focused funds, as well as 6 funds that invest world-wide. Hence, European stocks are somewhat overrepresented in our sample (they make up 29% of stocks held, compared to making up 17% of world market capitalization in Worldscope). Additional fund-level statistics are provided in Subsection C.1 in the Internet Appendix. There, we document that our hedge funds, similar to other institutional investors (e.g., Lee, Shleifer and Thaler (1991)), overweigh large

companies in their portfolios. Otherwise, they split their investments relatively evenly across different industries and value vs. growth stocks.

[Insert Table 1 about here.]

In Panel B, we display summary statistics by position. A position lasts from its opening—i.e., the first buy for long positions or the first sell for short positions—to its close—i.e., the moment when the stock holding goes back to zero. After being closed, a new position can be established in the same stock. However, this does not happen very often: on average there are only 2 positions in a given stock over the lifetime of the fund. Our data contains about 16,000 positions; 6.9% of them are already open when the fund enters the database, while 11% are still open when the fund leaves the database. Due to this censoring, the length of positions will be biased downwards. The investment horizon of the funds seems to be fairly long: on average position are open for 104 trading days (about half a year), although the median is only 35 trading days (about 2 months). Over the lifetime of a position, funds conduct on average 6 orders (median 3) and change the direction of trading on average 2.5 times (median 1).

Next, we examine summary statistics at the order-level. We distinguish between three types of orders: Opening orders that initiate the position, closing orders that close the position and follow-up orders that change the size of the position in between. We display summary statistics for each type of order separately in Panels C to E. The opening and closing orders are much larger than the follow-up orders: when standardized by the maximum size of a given position, opening and closing orders on average make up around 77% of this maximum position size (median 100), while the follow-up orders make up only 15.8% (median 8.7%). Thus, position openings and closings are the more important investment decisions, explaining why we focus on these two types of orders in our main analyses. Follow-up orders, while making up 69% 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 the Internet Appendix in Subsection B.6 that our results are robust if we only use return data from Datastream. We use three methodologies to risk-adjust returns: (1) excess returns computed with respect to the fund-specified benchmark, (2) risk-adjusted returns computed following the methodology of Daniel, Grinblatt, Titman, and Wermers (1997), hereafter DGTW, and (3) alphas estimated using the four-factor model of Carhart (1997). The details of the risk-adjustments are explained in Section A of the Internet Appendix; here we provide only a brief summary description.

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

As a second methodology, we compute DGTW returns on a regional level. We categorize stock markets into 5 regions (Japan, North America, Europe, Asia-Pacific and Emerging Markets) following Karolyi and Wu (2014). The assignment of countries into regions is displayed in the Internet Appendix in Table 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 returns of the respective benchmark portfolio. Given prior evidence suggesting that local factors are better able in pricing risk (Griffin (2002)), our approach to compute portfolios on a regional level provides for a reasonable compromise between a desirable granularity and the need to sufficiently populate 125 portfolios.

As a third methodology, we implement a regional version of the Carhart (1997) 4-factor model, which includes a market factor, a High-minus-Low Book to Market Factor (HML), a Small-minus-Big (SMB) factor and a Momentum (MOM) factor of winners minus losers. For each stock, we

compute betas with respect to these factors using daily regressions over the prior 12 months. We then shrink these betas to their cross-sectional average following Vasicek (1973). This implementation follows the suggestions of Levi and Welch (2016) who find that for predicting betas the best results are obtained by daily regressions over 1 year horizons and after shrinking the estimated betas. Finally, we compute alphas on the daily level as:

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

Finally, we winsorize all our return measures at the 1% level on both sides.

III. Profitability Results

A. Profitability of opening and closing trades

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

We now examine hedge funds' trading skill in more detail by studying the post-trade returns for the stocks they buy and sell. We start with a simple graphical analysis presented in Figure 4. We show cumulative returns in excess of the fund-specified benchmark in the 250 trading days (approximately 1 year) following an order. We include only orders that either open or close a position (that is, we exclude follow-up orders). We further separate between orders that are related to long or short positions.

Figure 4 reveals clear evidence of informed trading for the opening of positions: in the 250 days following the initiation of a long (short) position, cumulative excess returns are around 2% (-2%). Moreover, on both the long and the short side, a large fraction of these returns is realized in the first

125 trading days (6 months) following the opening order, after which the return drift appears to be more muted. In other words, the post-trade alphas (per unit of time) for initiated positions decay over time: they are highest immediately after the position is established and then gradually shrink as time progresses.[9]

In contrast, the closing of long and short positions does not seem to be informed. Long sells are not followed by negative returns, but rather by positive returns. In the 250 days following the closing of a long position cumulative excess returns are about 1%. Similarly, short buys are followed by negative excess returns (-1% after 250 days). In both cases, most of the cumulative return is realized in the first 125 trading days following the order.

Next, we investigate the statistical significance of these findings. In Panel A of Table 2, we focus on position openings and run a regression of risk-adjusted returns following the order on *D(Short)*, a dummy variable equal to one if the order initiates a short position (and zero if it initiates a long position). We examine all three measures of risk-adjusted returns for holding periods of 60 and 125 trading days (approximately 3 and 6 months) following the order. We measure returns from the date following the last date of the order; i.e., we do not account for within order returns. We include fund fixed effects to control for any differences in post-trade profitability across funds that could correlate with their propensity to enter a short position. We also include month fixed effects to ensure that our results are not driven by a particular time period. Finally, we cluster standard errors two-way by stock and last date of order. Clustering by stock accounts for correlation due to overlapping returns and clustering by date accounts for correlation in the cross-section of stock returns.

[Insert Table 2 about here.]

Given our specification, the coefficient estimate for the *D(Short)* dummy can be interpreted as the return difference between long and short positions that have been opened in the same month. The results, presented in Panel A, show that this return difference is economically and statistically significant. For instance, for excess returns, long positions outperform short positions by about 1.8% over 60 days and 2.5% over 125 days. For DGTW returns and alphas the effect is slightly smaller at about 1.6% over 60 days and 2% over 125 days. These results are all statistically significant at the

[9] 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.

1% level. In short, hedge funds' position openings are clearly profitable, suggesting that the fund managers in our sample possess investment skill.

In Table 2 Panel B, we repeat our analysis for closing orders. We again find a negative coefficient for the *D(Short)* dummy, albeit with a smaller economic magnitude. For excess returns, the return difference between closed long and closed short positions equals 0.7% over 60 days and 1.5% over 125 days. For DGTW returns and alphas the effect is again slightly smaller. Over the 125 days horizon, the return difference is statistically significant for all measures of risk-adjusted returns. These results suggest that the hedge funds in our sample close their positions too early in the sense that these positions would have earned significant risk-adjusted returns going forward. However, such early position closures don't have to be suboptimal. Indeed, we argue below that they can be explained by the presence of (risk) capital constraints and position monitoring costs faced by the hedge funds in our sample.

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

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

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

established positions earn most of their alpha in the first weeks/months after the opening trade. After some time, alphas peter out and so it could to be more attractive to open a new position.

We now test 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.[10] The key variable of interest is *D(Opening)*, a dummy variable that takes the value one when the order opens a (long or short) position and zero when it closes the position (follow-up orders are again excluded from this analysis).

Table 3 shows the results. In Panel A, we focus on long positions only. The significantly positive coefficient for the *D(Opening)* dummy implies that newly initiated long positions are indeed more profitable than the previous long positions that are closed within the same month by about 0.5-0.7% depending on the risk-adjustment and the holding horizon. For short positions (Panel B), the coefficient flips sign, meaning that initiated short positions are followed by more negative returns than closed short positions (although it is not always significant). In Panel C, we examine both long and short positions jointly. To be able to combine long and short positions, we use signed returns instead of returns as the dependent variable. Signed returns are defined as returns for long positions and minus one times the returns for short positions. We find about 0.5-0.7% higher signed returns following the opening of positions. Because combining short and long positions improves statistical power, these tests are all highly statistically significant.

[Insert Table 3 about here.]

The results so far show that hedge funds are on average right when they reallocate their capital from on old stock position into 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 would expect them to close first their positions which they expect to be least profitable. As such, the stock positions that they keep holding on to should outperform those that

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

they decide to close. To test this, we construct a sample of all fund portfolio holdings on days when the fund does close an existing portfolio position. We then regress future realized 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 0.3-0.4% 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 positions and newly opened ones (see Panel C) which 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 so that they are able to recycle their capital into new investment opportunities. In the next section, we investigate position closures in greater detail.

IV. Explaining Post-Closure Returns

In Appendix B, we show with the help of a stylized trading model that early position closures can be explained by funds being subject to risk capital constraints and position monitoring costs. In this section, we 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, which manifests itself in many newly opened positions. A larger number of early position closures in turn implies that hedge funds "leave more money on the table"—i.e., the return difference between closed long and closed short positions should increase. In Table 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 5 days (Panel A) or over the previous 10 days (Panel B). We then repeat our regression analysis from Table 2 Panel B for these

different subsamples.[11] The results broadly confirm our prediction: whereas the excess return difference between closed long and short positions after increases in the number of open positions over the previous 5 days is 2.2%, it is only 0.8% and insignificant after decreases in the number of open positions over the previous 5 days. The results for DGTW returns and 4-factor alphas are similar with 1.7% vs. 0.5%, and 1.7% vs. 0.3%. These results are robust to using the change over the previous 10 trading days instead of 5 trading days (Table 4, Panel B). In summary, our results suggest that early position closures appear to be more common when hedge funds simultaneously seize new trading opportunities.

[Insert Table 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 wealth (or total net asset value) relative to the position monitoring cost. Intuitively, this fixed cost makes it uneconomical to hold positions below a certain minimum position size. As such, wealthier funds naturally hold a larger number of open positions, and when a given fund suffers portfolio losses it may respond by closing existing positions. We thus check whether the returns from the post-closure investment strategy from Table 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 excess return difference between closed long and short positions is 2.5% in the subsample with negative prior fund returns and only 0.7% in the subsample of positive prior fund returns. For the other risk-adjusted return measures, the difference is smaller but goes in the same direction. When we split the sample based on fund returns over the previous 10 trading days, we again obtain similar results. These findings suggest that trading losses force funds to close some of their positions earlier, leaving more money on the table.

[Insert Table 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 may again cause the premature closure of existing stock

[11] Throughout this section, we 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.

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 excess returns over a 125-days horizon, we see that the return difference between closed long and short positions amounts to more than 2% 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 He, Kelly, and Manela (2016, henceforth HKM) intermediary risk factor and the TED spread.[12] Specifically, in Panels A and B, we split the sample by the HKM intermediary risk factor aggregated over the previous 5 and 10 trading days, respectively. He, Kelly, and Manela (2016) find that this factor, which essentially captures changes in the capital ratios of financial intermediaries (primary dealer counterparties of the New York Federal Reserve), has significant explanatory power for the cross-section of returns in various asset classes. In Panels C and D, we look at changes in the TED spread (three-month LIBOR minus and the three-month T-Bill rate), a widely-used (e.g., Brunnermeier (2009)) and theoretically-motivated (e.g., Garleanu and Pedersen (2011)) bellwether of the financial sector's health. 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 HKM factor decreases or when the

[12] In the Internet Appendix in Subsection B.1, 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).

TED spread increases), especially when the tightening is measured over the previous 10 trading days (Panels B and D). This suggests that funding constraints in the intermediary sector feed through and affect the trading activity of our sample hedge funds.

[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.

A. Long-short equity funds as fundamental investors

We have argued that long-short equity funds are the archetype fundamental investor 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 year 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 show that the trades by our sample hedge funds 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 data 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.[13,14] 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.]

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 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

[13] 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.

[14] 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.

long in that industry). The results, reported in Subsection C.2 in the Internet Appendix, 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. 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 therefore 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. 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 Subsection C.3 of the Internet Appendix, 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 firm fundamentals.

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 69% 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 columns 1 and 2, we only include follow up orders related to long positions. If follow-up orders were to contain additional information, we would expect more positive returns after follow-up buys (which increase the long position). We find a positive coefficient, but it is very small and not statistically significant. Similarly, in columns 3 and 4, we find more negative returns following orders that increase short positions (follow-up sells) but the magnitude remains small and insignificant. Finally, in columns 5 and 6, we combine long and short positions and use signed returns as the dependent variable. Once again the coefficients are very close to zero and insignificant.

[Insert Table 9 about here.]

These results suggest that hedge funds' follow-up trades are not informed, because post-trade returns are independent of the direction of the follow-up order. In other words, in contrast to opening and closing trades, the capital freed from decreasing some existing positions is not more profitably employed by increasing other existing positions. 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. Data Representativeness, Selection Concerns and Robustness

A) Representativeness

Our data comprises the complete transaction and holding records for a sample of 21 long-short equity hedge funds. While this level of detail is unprecedented,[15] we acknowledge that the relatively small number of funds raises questions about the representativeness of our data.

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 with. The best we can do 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 gross in the sense that they neither incorporate funds' leverage nor their fees nor any derivative positions that may be used to hedge some of the risk exposure.

Our comparison proceeds as follows: for each fund, we compute position-weighted portfolio returns at the monthly frequency. We take the equal-weighted average across funds to obtain a monthly return series for the hedge funds in our sample, which we then 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), (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 regress all four return series over our sample period on the 8 Fung and Hsieh factors (Fung and Hsieh (2001)).[16]

[15] The data that comes closest to ours in its level of detail is obtained via a fuzzy name-matching approach between the hedge fund trades contained in the ANcerno institutional transaction data and their quarterly equity holdings reported in 13F filings. However, funds covered by ANcerno only make available a subset of their transaction records and identifying long and short positions—a crucial element of our study—from quarterly holdings is bound to be noisy. Finally, while our data is on long-short equity hedge funds (for which we document clear evidence of stock-picking ability), the ANcerno data only allows to identify trades by different hedge fund families. 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)).

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

[Insert Table 10 about here.]

The results are displayed in Table 10. 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 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.

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 (negatively) on HML. Overall, these results suggest 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 should not be an issue.

One important remaining concern with our data is self-selection into the sample. Here, the biggest worry is that successful hedge funds strategically engage with Inalytics in order to advertise their trading success—implying that the documented trade profitability would be biased upward. Alternatively, it could be that institutional clients demand from poorly-performing hedge funds to submit their trades to Inalytics for monitoring and verification purposes. 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 excess returns as we believe that these are the returns hedge funds would be selected upon, but we confirm in the Internet Appendix in Subsection B.2 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 excess 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 these qualitative results should thus apply more generally.

C) Can rebalancing explain our results?

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

risk exposure to a single stock, the hedge fund may want to rebalance the position by selling some stocks. Such rebalancing trades appear to leave additional money on the table.[17]

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

In the Internet Appendix in Subsection C.4, we report results for an additional test that confirm this argument. Specifically, we examine a sample split of post-closure returns by the underlying stock's return over the prior 10 trading days. Rebalancing trades that close a position should be more likely to occur after a positive return because positive returns increase the size of a position. Thus, if the alpha following closing orders was explained by rebalancing, we would expect a larger alpha if the closing happens after a positive stock return. However, we find very similar returns following closing orders after positive and negative stock returns. If anything, hedge funds seem to leave slightly more money on the table when they close positions after negative stock returns, which is the exact opposite of what we would expect if closing orders were due to rebalancing.

VII. Conclusion

The question to which extent rational arbitrageurs remove mispricings and thus promote efficient prices is of crucial importance in asset pricing. Many arbitrageurs (and academics) focus on relative-value arbitrage; i.e., the process of exploiting relative price differences between two assets with comparable payoffs. However, a group of assets can be priced correctly relative to each other, while still being jointly mispriced when all assets are far away from their fundamental value. Thus, relative-value arbitrage in and of itself is not sufficient to ensure that prices reflect fundamental values. Similarly, while relative-value arbitrageurs arguably make prices more efficient (in the sense that they faster incorporate public information), they don't necessarily make prices more informative (in the sense that prices summarize a higher absolute level of information).[18] In financial markets,

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

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

this important void is filled by what we call *fundamental arbitrageurs*—traders that produce new and synthesize existing information in order to trade on deviations of asset prices from their fundamental values. Long-short equity hedge funds are presumably the most important group of investors belonging to this category. They spend substantial resources to gain an informational advantage and then take directional (long or short) bets in relatively small number of stocks about which they have strong convictions.

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

We 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 (1) in order to invest their limited capital in even more profitable trading opportunities or (2) in response to tightened funding or volatility constraints. We document supporting evidence for these predictions in the data.

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

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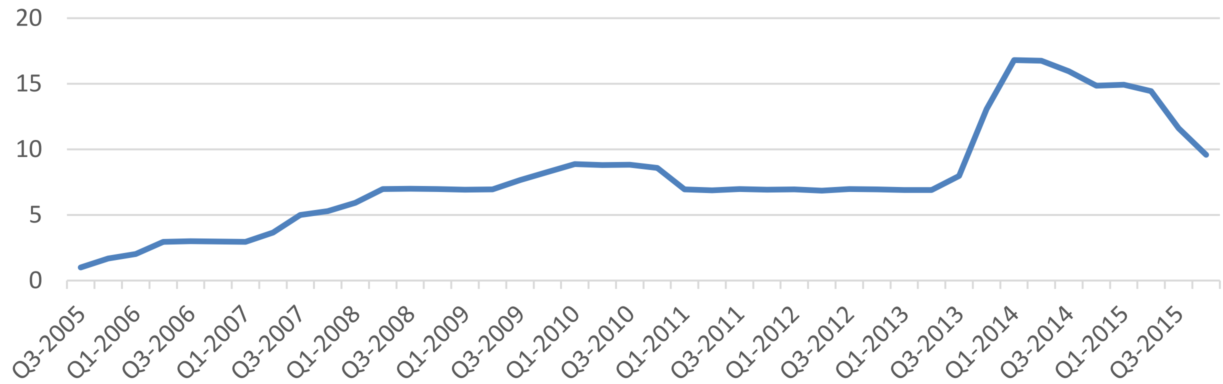
Figure 1: Coverage over sample period

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

Panel A: Number of funds in the sample



Panel B: Number of orders and positions per day

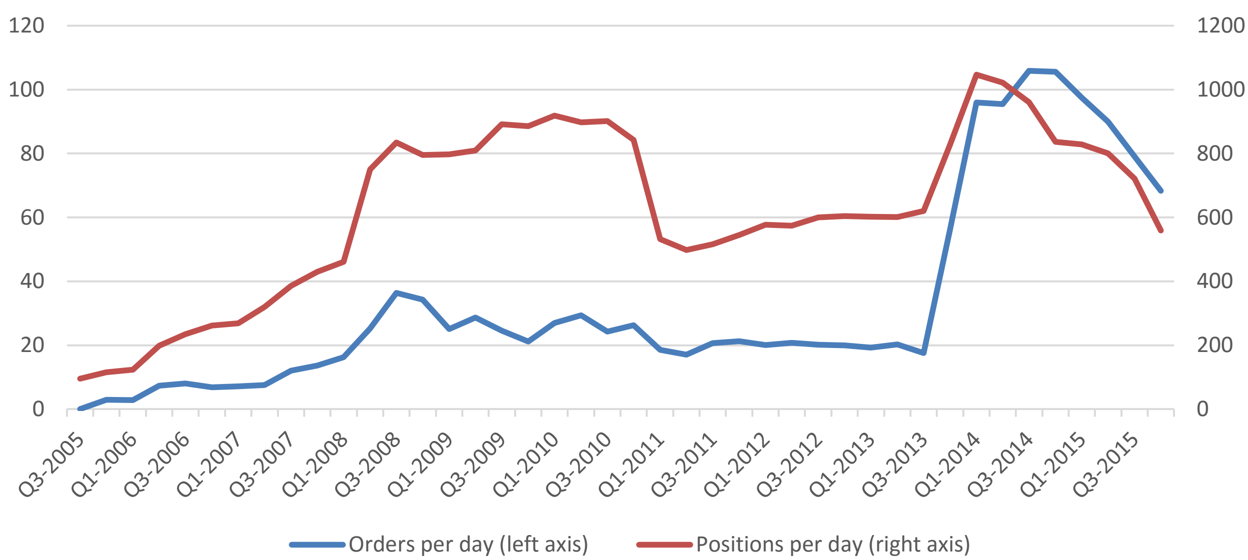
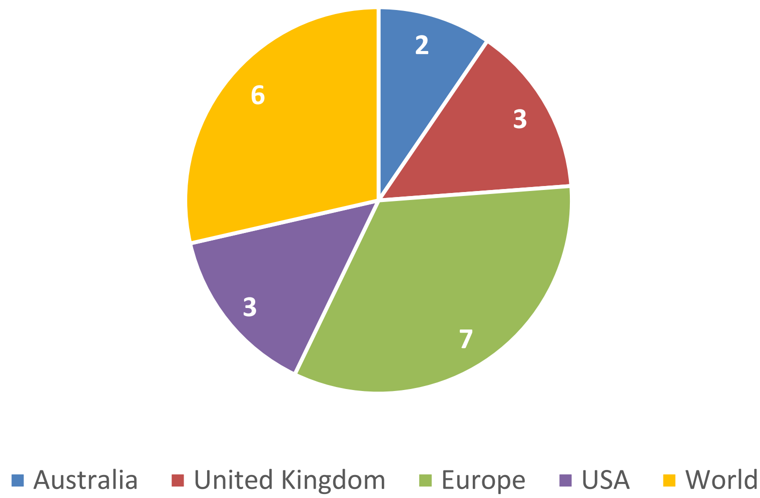


Figure 2: Investment areas of funds

Panel A shows the investment areas of our sample of funds. We base these areas on their chosen benchmark, but verify that the funds indeed invest predominantly in these regions. Panel B depicts the regions of the stocks held by the funds. We compute this average over the number of positions over the entire sample period. The definition of the regions are displayed in the Internet Appendix in Subsection A.1.

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



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

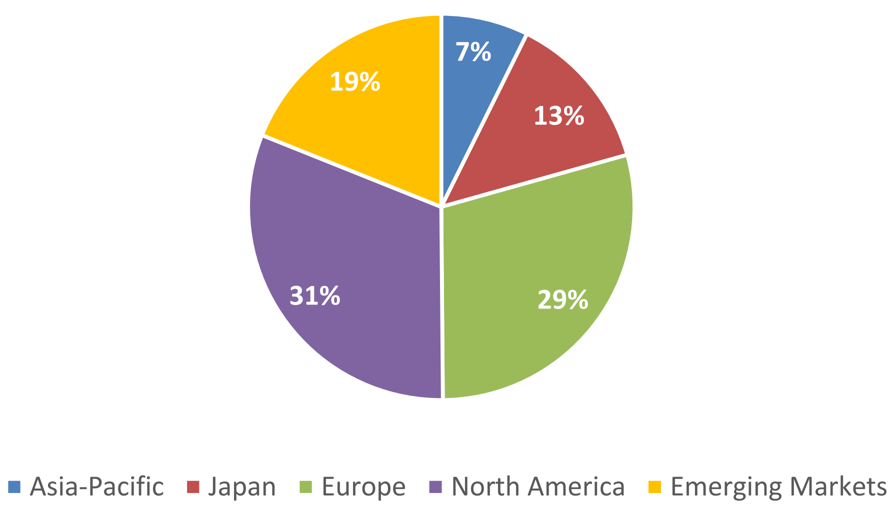


Figure 3: Fund returns

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

Panel A: Fund return

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

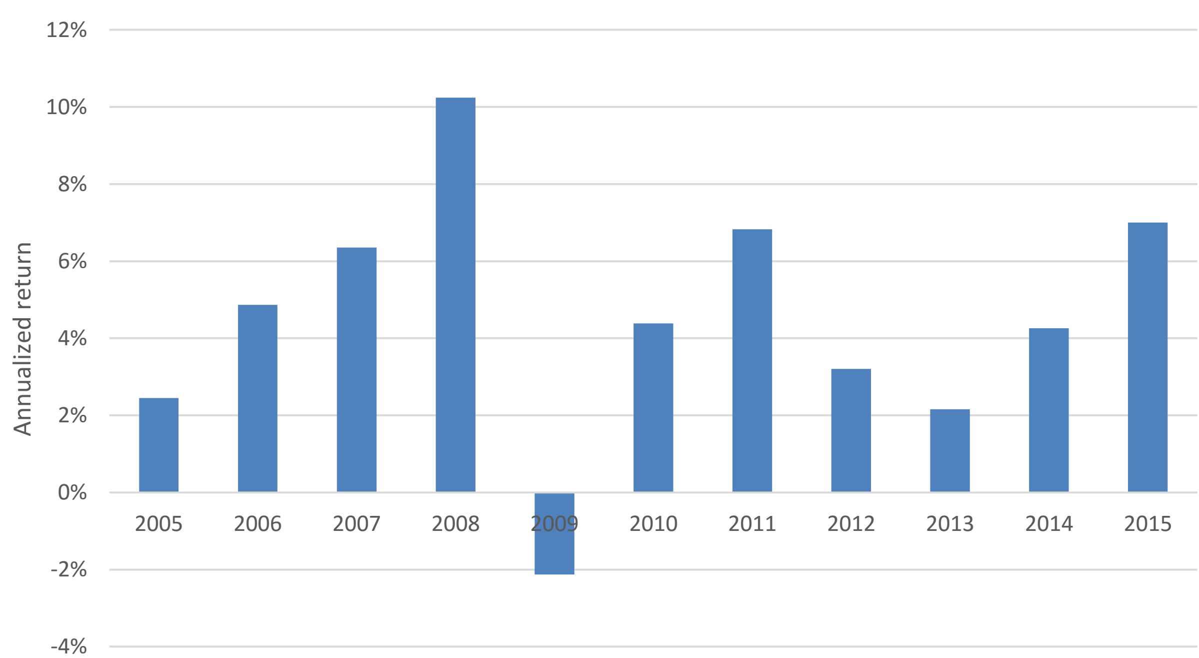


Figure 4: Excess returns following orders

This figure displays cumulative excess return indices for 250 trading days following orders that open or close a position. *Open Long Position* is the buy order establishing a long position ("long buy"). *Open Short Position* is the sell order establishing a short position ("short sale"). *Close Short Position* is the buy order closing a short position ("short buy"). *Close Long Position* is the sell order closing a long position ("long sell"). *Excess return* is the return of the stock minus the return of the fund-specified benchmark. The return index is set to 100 at the last day of the order.

Excess returns around orders

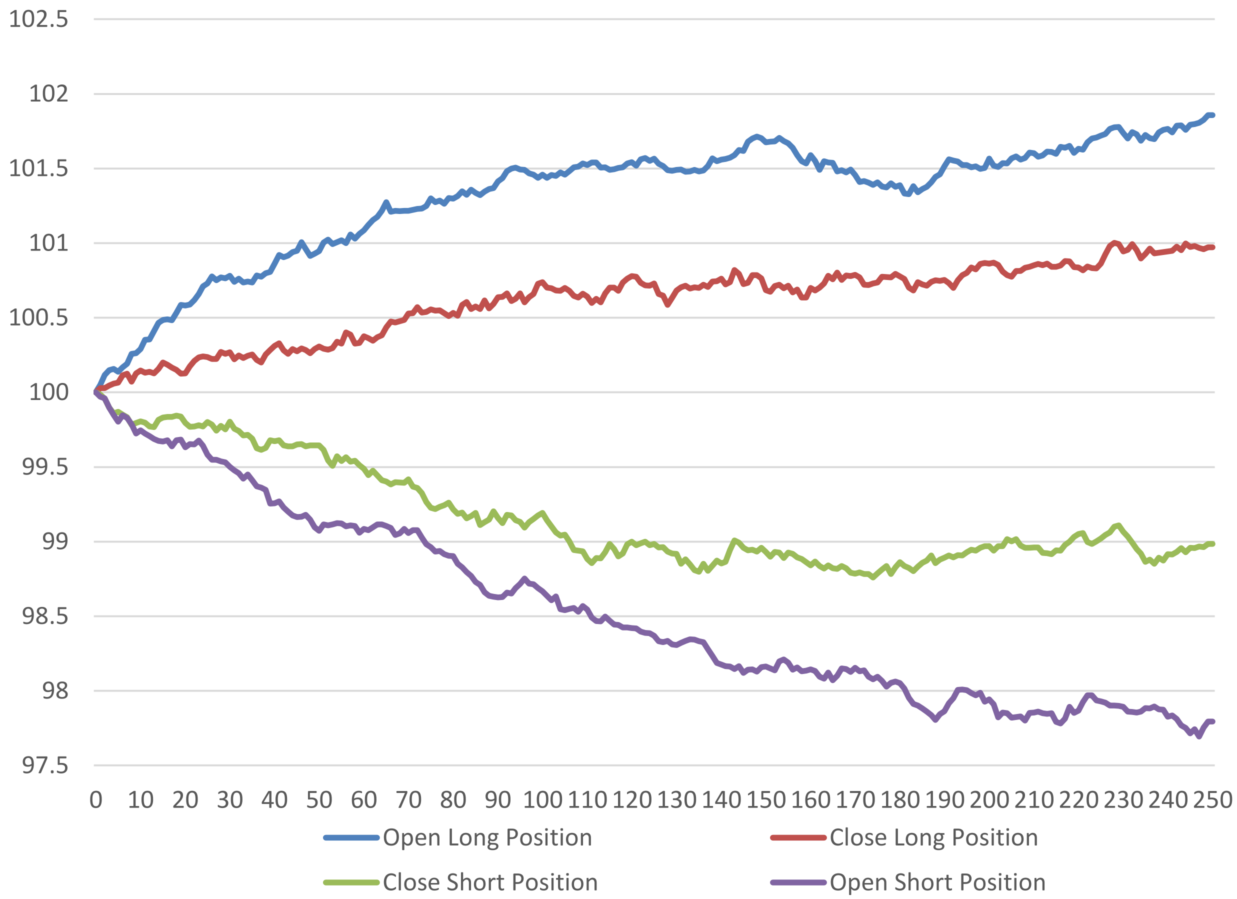


Table 1: Summary statistics

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	10th Percentile	Median	90th Percentile	Standard Deviation
Number of Long Positions	49.8	16.9	36.1	74.9	43.4
Number of Short Positions	23.9	10.8	18.6	46.3	14.2
Short Fraction (%)	30.2	15.8	26.4	48.7	19.2
Orders per Day	5.81	1.54	5.60	10.5	3.58
Trade Fraction (%)	5.37	0.82	2.75	14.0	5.36
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	10th Percentile	Median	90th Percentile	Standard Deviation
Length (trading days)	104.4	4	35	275	188.9
Number of Orders	5.92	2	3	12	8.89
Number of Direction Changes	2.50	1	1	5	5.06
Open Start	0.069	0	0	0	0.25
Open End	0.11	0	0	1	0.32
Observations	16241				

Panel C: Statistics by order – opening orders

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

Panel D: Statistics by order – follow-up orders

Variable	Mean	10th Percentile	Median	90th Percentile	Standard Deviation
Number of Trades	1.49	1	1	3	1.30
USD volume (million USD)	7.66	0.085	1.70	17.1	31.5
Size as fraction of largest holding (%)	15.8	0.92	8.65	42.6	18.3
Observations	66700				

Panel E: Statistics by order – closing orders

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

Table 2: Returns following the opening and closing of positions

This table examines returns following the opening of positions (Panel A) and the closing of positions (Panel B). We regress average returns following the order on a dummy variable whether the order is related to a short position. The dependent variable is the cumulative return expressed in percent for 60 and 125 trading days following the last day of the order. *Excess return* is the return of the stock minus the return of the fund-specified benchmark. *DGTW return* is the return of the stock minus the average return of a portfolio sorted by region, size, book-to-market and momentum. *Four-factor alpha* is the alpha according to the Carhart (1997) model estimated at the regional level. Details on variable constructions can be found in Appendix 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:	Excess Return t+1, t+60	Excess Return t+1, t+125	DGTW Return t+1, t+60	DGTW Return t+1, t+125	4-Factor Alpha t+1, t+60	4-Factor Alpha t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-1.81***	-2.46***	-1.58***	-1.90***	-1.58***	-2.06***
	(-6.39)	(-5.70)	(-5.95)	(-4.95)	(-5.68)	(-5.00)
Observations	13050	12409	11700	11214	12598	12074
Adjusted R^2	0.06	0.09	0.04	0.05	0.03	0.04
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Returns following the closing of positions

Dependent Variable:	Excess Return t+1, t+60	Excess Return t+1, t+125	DGTW Return t+1, t+60	DGTW Return t+1, t+125	4-Factor Alpha t+1, t+60	4-Factor Alpha t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-0.74**	-1.46***	-0.40	-1.09***	-0.52*	-1.02**
	(-2.57)	(-3.28)	(-1.40)	(-2.63)	(-1.87)	(-2.39)
Observations	11952	11320	11027	10469	11860	11262
Adjusted R^2	0.07	0.10	0.04	0.06	0.04	0.05
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 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 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:	Excess Return t+1, t+60	Excess Return t+1, t+125	DGTW Return t+1, t+60	DGTW Return t+1, t+125	4-Factor Alpha t+1, t+60	4-Factor Alpha t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Opening)	0.55^{**}	0.72^{**}	0.69^{***}	0.55^{**}	0.46^{**}	0.71^{**}
	(2.54)	(2.28)	(3.83)	(2.21)	(2.28)	(2.55)
Observations	13419	12779	11980	11457	13050	12484
Adjusted R^2	0.13	0.16	0.11	0.14	0.11	0.13
Fund×Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes

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

Dependent Variable:	Excess Return t+1, t+60	Excess Return t+1, t+125	DGTW Return t+1, t+60	DGTW Return t+1, t+125	4-Factor Alpha t+1, t+60	4-Factor Alpha t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Opening)	-0.45^{**}	-0.36	-0.63^{***}	-0.47^{*}	-0.52^{**}	-0.40
	(-2.05)	(-1.22)	(-3.08)	(-1.75)	(-2.35)	(-1.42)
Observations	11583	10950	10747	10226	11408	10852
Adjusted R^2	0.14	0.16	0.11	0.12	0.11	0.10
Fund×Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes

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

Dependent Variable:	Signed Excess Return t+1, t+60	Signed Excess Return t+1, t+125	Signed DGTW Return t+1, t+60	Signed DGTW Return t+1, t+125	Signed 4-Factor Alpha t+1, t+60	Signed 4-Factor Alpha t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Opening)	0.51^{***}	0.56^{**}	0.66^{***}	0.52^{**}	0.49^{***}	0.57^{***}
	(3.26)	(2.37)	(4.70)	(2.55)	(3.22)	(2.65)
Observations	25002	23729	22727	21683	24458	23336
Adjusted R^2	0.13	0.16	0.11	0.13	0.11	0.12
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 Excess Return t+1, t+60	Signed Excess Return t+1, t+125	Signed DGTW Return t+1, t+60	Signed DGTW Return t+1, t+125	Signed 4-Factor Alpha t+1, t+60	Signed 4-Factor Alpha t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Position not Closed)	0.39^{**}	0.46^{*}	0.44^{***}	0.41^{**}	0.34^{**}	0.37
	(2.51)	(1.78)	(3.40)	(2.00)	(2.34)	(1.56)
Observations	416070	416070	416070	416070	416070	416070
Adjusted R^2	0.13	0.15	0.08	0.10	0.07	0.10
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:	Excess Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	More Positions	Less Positions	More Positions	Less Positions	More Positions	Less Positions
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-2.21***	-0.77	-1.74***	-0.54	-1.67***	-0.50
	(-3.39)	(-1.31)	(-2.93)	(-0.98)	(-2.69)	(-0.86)
Observations	5079	6228	4715	5744	5059	6191
Adjusted R^2	0.11	0.10	0.06	0.06	0.05	0.05
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

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

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

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

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

Table 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:	Excess Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	Higher Volatility	Lower Volatility	Higher Volatility	Lower Volatility	Higher Volatility	Lower Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-2.21***	-0.98	-1.78***	-0.69	-1.57***	-0.69
	(-3.53)	(-1.59)	(-3.22)	(-1.14)	(-2.70)	(-1.13)
Observations	5432	5500	5017	5088	5407	5472
Adjusted R^2	0.10	0.11	0.08	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:	Excess Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	Higher Volatility	Lower Volatility	Higher Volatility	Lower Volatility	Higher Volatility	Lower Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-2.10***	-0.93	-1.74***	-0.38	-1.46**	-0.57
	(-3.52)	(-1.49)	(-2.99)	(-0.65)	(-2.49)	(-0.94)
Observations	5592	5721	5198	5268	5574	5682
Adjusted R^2	0.10	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 above or below median. In Panels A and B, our proxy for funding constraints is the HKM intermediary risk factor developed in He, Kelly and Manela (2016). The HKM intermediary risk factor measures innovations to the capital ratio of financial intermediaries (primary dealer counterparties of the New York Federal Reserve). The data is available at http://apps.olin.wustl.edu/faculty/manela/data.html. In Panels C and D, the proxy for funding constraints is the TED spread, defined as the difference between the three-month LIBOR and the three-month T-bill interest rate. 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 HKM intermediary risk factor change over prior 5 trading days

Dependent Variable:	Excess Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	Above median	Below median	Above median	Below median	Above median	Below median
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-0.62	-2.37***	-1.05*	-1.18**	-0.63	-1.29**
	(-1.02)	(-3.80)	(-1.78)	(-2.09)	(-1.06)	(-2.21)
Observations	5622	5572	5202	5149	5513	5477
Adjusted R^2	0.10	0.11	0.06	0.07	0.02	0.04
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Split by HKM intermediary risk factor change over prior 10 trading days

Dependent Variable:	Excess Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	Above median	Below median	Above median	Below median	Above median	Below median
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-0.64	-2.34***	-0.74	-1.54***	-0.40	-1.50***
	(-1.03)	(-3.85)	(-1.23)	(-2.76)	(-0.66)	(-2.66)
Observations	5568	5622	5134	5215	5449	5537
Adjusted R^2	0.10	0.11	0.07	0.05	0.03	0.03
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Split by TED spread change over prior 5 trading days

Dependent Variable:	Excess Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	Above median	Below median	Above median	Below median	Above median	Below median
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-2.12**	-1.17**	-1.47*	-0.98**	-1.30	-0.80
	(-2.38)	(-2.25)	(-1.88)	(-2.03)	(-1.58)	(-1.62)
Observations	3611	7431	3341	6874	3547	7291
Adjusted R^2	0.10	0.11	0.05	0.07	0.02	0.03
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

Dependent Variable:	Excess Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	Above median	Below median	Above median	Below median	Above median	Below median
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-2.77***	-0.64	-1.84***	-0.71	-2.26***	-0.14
	(-3.72)	(-1.12)	(-2.72)	(-1.31)	(-3.24)	(-0.26)
Observations	4340	6659	4042	6134	4273	6522
Adjusted R^2	0.10	0.11	0.05	0.06	0.03	0.03
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. In Regressions 1 and 2, we only include follow-up orders for long positions. In Regressions 3 and 4, we only include follow-up orders for short positions. In Regressions 5 and 6, we include all follow-up orders and study signed position returns (equal to the stock return for long positions and the stock return times minus one for short positions). 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 Regression 1 to 4 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.

Sample:	Long Positions		Short Positions		Long and Short Positions	
Dependent Variable:	Excess Return t+1, t+60	Excess Return t+1, t+125	Excess Return t+1, t+60	Excess Return t+1, t+125	Signed Excess Return t+1, t+60	Signed Excess Return t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Increasing)	0.02	0.23	-0.15	-0.19	0.07	0.22
	(0.14)	(0.97)	(-0.76)	(-0.64)	(0.55)	(1.17)
Observations	39328	37148	19764	18468	59092	55616
Adjusted R^2	0.12	0.15	0.16	0.18	0.14	0.16
Fund×Month F.E.	Yes	Yes	Yes	Yes	No	No
Fund×Portfolio×Month F.E.	No	No	No	No	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 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	38.78***	9.98***	26.27***	18.84***
	(8.84)	(3.02)	(7.18)	(4.26)
Size Spread Factor	3.64	-2.44	0.78	1.66
	(0.77)	(-0.67)	(0.15)	(0.33)
Emerging Market Factor	24.48***	24.01***	13.83***	16.28***
	(9.28)	(10.99)	(4.92)	(5.53)
Bond Market Factor	-0.28	0.10	-0.16	0.78
	(-0.50)	(0.27)	(-0.32)	(1.57)
Credit Spread Factor	-1.83***	-0.91*	-1.40**	-0.75
	(-3.17)	(-1.97)	(-2.40)	(-1.19)
Bond Trend-Following Factor	-1.38*	0.16	0.03	0.01
	(-1.74)	(0.30)	(0.03)	(0.02)
Currency Trend-Following Factor	0.43	0.47	0.26	0.50
	(0.57)	(0.89)	(0.42)	(0.81)
Commodity Trend-Following Factor	0.43	0.03	-1.06	-0.29
	(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 return of positions the fund holds. In Panel B, the dependent variable is the (position-weighted) daily excess return relative to the fund-specified benchmark 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: Excess Returns

Dependent Variable:	Daily Fund Excess 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. All return measures are winsorized at the 1% level on both sides.

Variable Name	Definition
Excess Return	$Stock\ Return - \ Benchmark\ Return$
Stock Return	Return in USD from Datastream or Analytics.
Benchmark Return	USD return of the benchmark specified by the fund. The benchmark is specific for the fund, but is the same for both long and short positions of the fund. Data is provided by Analytics.
DGTW Return	$Stock\ Return - \ Return\ of\ portfolio\ of\ similar\ stocks$ Similar stocks are stocks in the same quintile of market capitalization, book-to-market ratio and past 12 month stock return within the same region. For more details see Section A of the Internet Appendix.
4-Factor Alpha	$r_{c,t} - r_{f,t} - \beta_m * (r_{m,t} - r_{f,t}) - \beta_{HML} * HML_t - \beta_{SMB} * SMB_t - \beta_{MOM} * MOM_t$ For more details see Section A of the Internet Appendix.
Signed Excess Return	Excess Return for long positions and Excess 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	4-Factor Alpha for long positions and 4-Factor Alpha multiplied by minus one for short positions.
D(Short)	Dummy variable equal to one if the order is related to a short position (i.e., a short sell or a short buy) and zero if it is related to a long position (i.e., a long buy or a long sell).
D(Opening)	Dummy variable equal to one if the order is related to a position opening (i.e., a long buy or a short sell) and zero if the order is related to a position closure (i.e., a long sell or a short buy).
D(Position non Closed)	Dummy variable equal to one if the position is kept open and equal to zero if it is closed on that day.
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 Excess Return	Position-weighted average signed excess return of all positions of the fund, where the weight is the dollar value of the position. Daily stock-level excess 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$_{[1,20]}$	$$\sum_{1}^{20} Daily\ fund\ return^2$$ 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$_{[1,20]}$	$$Weighted\ Average[\sum_{1}^{20} Daily\ stock\ return^2]$$ 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.
VIX	A measure of implied volatility of S&P500 index options, calculated and published by the Chicago Board Options Exchange (CBOE).
Intermediary stock returns	The intermediary stock returns, described in He, Manela and Kelly (2016), are value-weighted portfolio returns of all publicly-traded holding companies of primary dealer counterparties of the New York Federal Reserve. The data are available at http://apps.olin.wustl.edu/faculty/manela/data.html.
SUE$_{IBES}$	$$\frac{Actual\ Earnings_t - \ Median\ of\ analyst\ earnings\ forecast_t}{Standard\ Deviation\ _{t-8,t-1}(Actual\ Earnings_\tau - Median\ of\ analyst\ earnings\ forecast_\tau)}$$ 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$_{Worldscope}$	$$\frac{Actual\ Earnings_t - \ Actual\ Earnings_{t-4}}{Standard\ Deviation\ _{t-8,t-1}(Actual\ Earnings_\tau - Actual\ Earnings_{\tau-4})}$$ 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	$\frac{Market\ value\ of\ equity\ (5\ days\ before\ earnings\ annoucement)}{Book\ value\ of\ equity\ (at\ the\ end\ of\ the\ previous\ quarter)}$
D(Short exposure by 2-digit SIC code)	Dummy variable equal to one if the other holdings of the fund in this 2-digit SIC industry code are more short than long (by dollar value).
D(Short exposure by 49 FF industry)	Dummy variable equal to one if the other holdings of the fund in this 49 Fama French industry are more short than long (by dollar value).
D(Short exposure by DGTW portfolio)	Dummy variable equal to one if the other holdings of the fund in this triple quintile of market capitalization, book-to-market ratio and past 12 month stock return are more short than long (by dollar value).
D(Short exposure by DGTW portfolio * region)	Dummy variable equal to one if the other holdings of the fund in this triple quintile of market capitalization, book-to-market ratio and past 12 month stock return by region are more short than long (by dollar value).
Correlation Coefficient	Correlation Coefficient between the two stocks over the prior 250 trading days.
D(Correlation Coefficient > 0.50)	Dummy variable equal to one if Correlation Coefficient is above 0.50.
D(Correlation Coefficient > 0.75)	Dummy variable equal to one if Correlation Coefficient is above 0.75.
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.
D(Increasing)	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).
D(Long-Short)	Dummy variable equal to one if the positions in the two stocks are opened in different directions (long-short or short-long) and zero if they are opened in the same direction (long-long or short-short).

Appendix B: A simple hedge fund trading model

1) General setup

Time is discrete. In a given period t, a hedge fund has W_t units of capital and faces different investment opportunities: it can invest in a riskless asset with a net return of $r_f = 0$ or into N risky stocks that are all assumed to be uncorrelated with each other (and over time). Any stock i is either fairly priced or mispriced. If it is fairly priced, then its return from one period to the next is given by $r_{it} = \varepsilon_{it}$ where ε_{it} is a zero-mean noise term with variance σ_t^2 (constant for all i).[19] 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 Δ_{it} decays over subsequent periods. That is, if the mispricing of stock i occurs in period t and lasts for τ periods, then we have $|\Delta_{it}| > |\Delta_{it+1}| > \cdots > |\Delta_{it+\tau}| = 0$. The hedge fund is assumed to know which stocks are mispriced and by how much.

The stock return component ε_{it} represents fluctuations in the stock's fair value driven by public news. There are two ways to think about the mispricing in this setup: First, it could be that, occasionally, a stock price movement ε_{it} occurs that is not justified by fundamentals. After such an occurrence, the hedge fund learns about this mispricing and expects it to revert over time.[20] 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.[21]

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:

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

$$\boldsymbol{w}_t' \mathbf{1}_N + w_{ft} = 1 \qquad (1)$$
$$\boldsymbol{w}_t' \boldsymbol{w}_t \sigma_t^2 \leq \bar{\sigma}^2 \qquad (2)$$
$$\mathbb{I}_{\boldsymbol{w}_t}' \mathbf{1}_N = N_{Pt} \qquad (3)$$

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

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

[21] 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.[22] 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 Δ ($-\Delta$). In the following period, the mispricing reduces to $|\Delta(1-\delta)|$ with $0 < \delta < 1$ being the rate of alpha decay. After two periods, the mispricing is assumed to have disappeared. We further assume that every period t, a random number M_t of new stocks becomes mispriced (some positive, some negative). The number of mispriced stocks is small relative to the total number of stocks, $M_t \ll N$. It follows that in any period t, there are M_t "newly mispriced stocks" with an expected alpha of $|\Delta|$, M_{t-1} "previously mispriced stocks" with an alpha of $|\Delta(1-\delta)|$, and M_{t-2} stocks

[22] 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.[23] 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*

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

[23] 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 $N_{At} \leq M_t$, and $N_{Bt} = w_{Bt} = 0$. In this case, the Lagrangian of the fund's optimization problem becomes

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

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

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

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

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

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

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

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

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

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

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

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

The unique solution is given by

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

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

3) Life-cycle of a round-trip trade

We now describe the life-cycle of a round-trip trade—i.e., its *opening*, the *rebalancing* and its *closure*. Consider a new mispricing in stock i occurring in period t. In that period, the hedge fund *opens* the trade by investing $W_t \times w_{At}$ of risk capital into that stock.[24] 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.[25] (These rebalancing trades will typically result in a gradual downscaling of the position concomitant to the decay in alpha.)

4) Empirical predictions

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

In period *t*, the hedge fund closes all the N_{Bt-1} positions in stocks that become 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 $N_{Bt} < N_{At-1}$.[26] Each of these prematurely closed positions is followed by a positive expected return ($\Delta(1-\delta)$). As such, the average return after closing trades in period t is given by $X_t\Delta(1-\delta)$, where X_t is defined as

[24] 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.

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

[26] 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.

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

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

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

The following empirical predictions follow immediately:

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

Proof: Opening trades in any period *t* are followed by an average return close to Δ.[27] Closing trades are followed by an average return of $X_t\Delta(1-\delta)$, where $0 \leq X_t \leq 1$ (see above). ■

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

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

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

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

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

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

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

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

[27] 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).

Internet Appendix

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

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This internet appendix collects supplementary results and data descriptions for our paper. In Section A, we provide additional information on variable construction and on how we define investment regions. In Section B, we provide robustness checks to some regressions in the paper. In Section C, we show additional results that are referenced in the paper.

Section A: Additional Information on Dataset Construction

1) Regions

Following Karolyi and Wu (2014), we estimate DGTW returns and 4-factor alphas at the regional level as this provides for a reasonable compromise between a desirable granularity and the need to sufficiently populate 125 portfolios. As in Karolyi and Wu (2014), we categorize stock markets into 5 regions (Japan, North America, Europe, Asia-Pacific and Emerging Markets). All but the EME region are identical to Fama and French (2012). The assignment of countries into regions is displayed below in Table A.1.

Table A.1: Regions

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

2) Merging of datasets

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

We treat as a mistake if a holding disappears from the data and then reappears shortly afterwards *without a trade being recorded*. In these cases we fill in the missing dates in between with the old holding quantity. Reappearing shortly afterwards means within 22 trading days (one month); or within 70 trading days (one quarter) if the position reappears with the exact same number of stocks. In total we identify 637 of these mistakes (compared to 150,000 trades in the full sample).

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

In total, we have about 150,000 (inferred) trades according to the holdings data. For about 90% of these trades, we have a corresponding trade in the trading data. However, for only about 83% of these trades does the number of stocks traded according to the trading data match the change in the number of stocks held in the holding data. In these cases we follow Inalytics' advice and assume the holdings data to be correct. In Table B.3 of this internet appendix, we show that our results are very similar if we only use those observations where the holdings and trade data perfectly agree.

3) Stock universe

To compute DGTW returns (and regional factors for the emerging market region, see below), we need a universe of stocks. We construct this stock universe by matching Worldscope and Datastream data. We

only keep stocks that are covered in both databases. We only keep one stock per company (we identify companies using the Worldscope Permanent Identifier). We only keep stocks from the countries listed in Appendix A.1 (we take the country information from Worldscope). We require stocks to have a positive book value, information on market capitalization in Worldscope and a stock price of at least USD 0.20.

If funds trade stocks that are outside this stock universe (e.g., because they cannot be assigned to one of the regions or have no information on book value), we still include these trades in our sample. For such trades, we can only compute excess returns and alphas (as described below) but we cannot compute DGTW returns. Our results are unchanged if we (1) exclude trades of stocks with a stock price of less than USD 1 (see Internet Appendix Table B.4) or (2) include only trades of stocks that are in the stock universe used to compute DGTW returns and factors (see Internet Appendix Table B.5).

4) Stock returns and balance sheet data

We download daily returns for stocks in our stock universe from Datastream using ISINs (and then using SEDOLs if we do not find a match using ISINs). We download returns in local currency and convert them to USD using the exchange rates on Datastream. Using local currency returns minimizes the errors due to rounding for stocks with low stock prices. When stocks are delisted, Datastream continues to report zero returns for these stocks. Following Busse, Goyal, Wahal (2014), we remove these trailing zeros, as well as any period with consecutives zero-return days that is at least 20 trading days long. When computing returns for the DGTW portfolios and Carhart (1997) factor, we remove returns in the top and bottom 0.25% by region following the instructions on the website of Kenneth French.

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

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

5) Excess returns

Excess returns are defined as the stock return minus the return of the fund-specific benchmark index. The benchmark indexes are the benchmark returns against which hedge funds mark their own performance (for

which they are then compensated). They are self-reported by the funds and do not change over the lifetime of a fund in our sample. Benchmark returns are provided to us by Inalytics.

6) Four-Factor alphas

To compute alphas, we use daily factor returns of the Carhart (1997) model for each of our 5 regions (see Table A.1 above). We use daily factors for America, Asia-Pacific, Europe, and Japan provided on Kenneth French's website. Because he does not provide factors for the emerging market region, we compute the emerging market factors ourselves following the instructions given on his website. We use the U.S. 1-month T-bill rate as the risk free rate and all returns are in U.S. dollars. We compute market returns as value-weighted average returns for our stock universe in the EME region. To construct the SMB and HML factors, we sort stocks in the emerging market region into two market cap and three book-to-market equity (B/M) groups at the end of each June. Big stocks are those in the top 90% of (cumulative) market capitalization for the region, and small stocks are those in the bottom 10%. Fama and French (2012) use this method because for North America it roughly corresponds to the NYSE median used in Fama French (1993). According to Fama and French (2012), big stocks are more reliable for identifying B/M breakpoints. We follow their recommendation and set the B/M breakpoints for the emerging market region to the 30th and 70th percentiles of B/M for the big stocks in this region. For the 6 portfolios thus formed, we compute value-weighted returns for each day and then compute the factors as:

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

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

The 2×3 sorts on size and lagged momentum to construct the MOM factor are formed monthly. For portfolios formed at the end of month t–1, the lagged momentum return is a stock's cumulative return for month t–12 to month t–2. The momentum breakpoints for the emerging market region are the 30th and 70th percentiles of the lagged momentum returns of the big stocks in the region. For the 6 portfolios thus formed, we compute value-weighted returns for each day and then compute the momentum factor as:

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

For each stock and each month, we then compute the beta with respect to their regional factors from a daily regression over the past year:

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

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

For stocks that cannot be assigned to a region (either because country information is missing or the country is not included in any regions), we compute alphas relative to the global factors provided by Kenneth French. We remove returns from the regression that are in the top and bottom 0.25% by region. Furthermore, we only keep betas that are based on at least 50 days of non-missing return data.

Following Frazzini and Pedersen (2014), we shrink the resulting beta estimates toward their cross sectional mean by computing:

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

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

$$\begin{aligned} &Four\ factor\ alpha_{c,t} \\ &\quad = r_{c,t} - r_{f,t} - \beta_m * (r_{m,t} - r_{f,t}) - \beta_{HML} * HML_t - \beta_{SMB} * SMB_t - \beta_{MOM} * MOM_t \end{aligned}$$

7) DGTW returns

To compute DGTW returns, we split the stocks in our universe into 625 portfolios. First, we split the universe into the 5 geographic region (see Table A.1 above). Second, each year, within each region we sort stocks into 5 portfolios by market capitalization. Third, within each of these 25 size-region portfolios we sort stocks by book-to-market. Fourth, within each of these 125 region-size-book to market portfolios, we sort stocks into 5 portfolios by returns over months t-12 to t-2. While splits for market cap and market-to-book happen once a year, splits by past return are executed every month.

We then compute the benchmark return for each of the 625 portfolio on each day as the value-weighted average return of all portfolio stocks (in USD). Finally, we compute DGTW returns as stock return minus the return of the respective benchmark portfolio.

8) Return winsorization

Since the international stock return data contains large outliers (Ince and Porter (2004)), we winsorize all our return measures at the 1% level on both sides.

Section B: Robustness Checks

1) Different measures of market-wide financial constraints

In Table 7 of the paper, we show that hedge funds leave more money on the table when market-wide funding constraints tighten. We measure these constraints with the HKM intermediary risk factor and the TED spread. In Table B.1 below, we show that we obtain comparable results when we split the sample instead by *change in the VIX* or by *intermediary stock returns*. The VIX index is a measure of the implied volatility of S&P 500 index options, calculated and published by the Chicago Board Options Exchange (CBOE). Increases in the VIX are generally interpreted as reflecting an increase in risk aversion and tighter funding constraints. In Panel A and B, we show that the direction of a closing trade predicts future returns better after increases of the VIX over the past 5 (or 10) trading days. This finding suggests that funds exhibit more early position closures after increases in the VIX. Similarly, in Panel C and D, we show that there are more early position closures after negative intermediary stock returns. The intermediary stock returns, described in He, Manela and Kelly (2016), are value-weighted portfolio returns of all publicly-traded holding companies of primary dealer counterparties of the New York Federal Reserve. Negative returns signal that primary dealers have less capital and are more likely to tighten funding constraints for their client hedge funds. Both results suggest that hedge funds engage in more premature position closures when financial constraints tighten.

Table B.1: Robustness check for Table 7 (split by market-wide funding constraints)

This table examines whether returns following the closure of positions depend on changes in (market-wide) funding constraints. In Panels A and B, our proxy for funding constraints is the change in the VIX index over the prior 5 or 10 trading days. In Panels C and D, the proxy for funding constraints is the cumulative intermediary stock return, which is the value-weighted portfolio return of all publicly-traded holding companies of primary dealer counterparties of the New York Federal Reserve. These returns are available at http://apps.olin.wustl.edu/faculty/manela/data.html. 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 in the paper. 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 VIX change over prior 5 trading days

Dependent Variable:	Excess Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	Above median	Below median	Above median	Below median	Above median	Below median
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-2.24^{***}	-0.79	-1.22^{**}	-1.09^{*}	-1.14^{*}	-0.88
	(-3.58)	(-1.28)	(-2.17)	(-1.85)	(-1.92)	(-1.55)
Observations	5476	5715	5079	5269	5375	5612
Adjusted R^2	0.11	0.11	0.07	0.05	0.04	0.03
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Split by VIX change over prior 10 trading days

Dependent Variable:	Excess Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	Above median	Below median	Above median	Below median	Above median	Below median
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-1.93^{***}	-0.91	-1.07^{*}	-1.13^{**}	-1.16^{*}	-0.76
	(-2.87)	(-1.51)	(-1.75)	(-1.97)	(-1.82)	(-1.31)
Observations	5452	5739	5042	5305	5361	5626
Adjusted R^2	0.11	0.10	0.07	0.06	0.03	0.03
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Split by intermediary stock return over prior 5 trading days

Dependent Variable:	Excess Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	Above median	Below median	Above median	Below median	Above median	Below median
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-0.60	-2.40^{***}	-0.93	-1.38^{**}	-0.49	-1.49^{**}
	(-0.99)	(-3.81)	(-1.58)	(-2.44)	(-0.83)	(-2.56)
Observations	5639	5555	5203	5145	5535	5453
Adjusted R^2	0.09	0.12	0.06	0.06	0.02	0.04
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel D: Split by intermediary stock return over prior 10 trading days

Dependent Variable:	Excess Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	Above median	Below median	Above median	Below median	Above median	Below median
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-0.93	-2.14^{***}	-0.95	-1.37^{**}	-0.48	-1.43^{**}
	(-1.42)	(-3.53)	(-1.54)	(-2.44)	(-0.76)	(-2.55)
Observations	5532	5659	5098	5249	5424	5563
Adjusted R^2	0.10	0.11	0.07	0.05	0.03	0.03
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

2) Testing for backfill bias using DGTW returns and 4-factor alphas

In Table 11 in the paper, we show that funds do not exhibit statistically significantly different raw returns or excess returns just after they enter or just before they leave the sample. In this subsection, we extend this test by studying DGTW returns and 4-factor alphas as dependent variables. We report the results in Table B.2 below. Generally, they confirm that returns are not significantly different at the beginning or the end of a fund being covered. The only exception is the positive and marginally significant coefficient for DGTW returns in the first 125 trading days. However, this result is likely random given that the comparable coefficients for alphas, excess returns, and raw returns are far from being significant and sometimes even negative. In summary, these results do not indicate any evidence of backfill bias or sample selection.

Table B.2: Robustness check for Table 10 (testing for backfill bias and sample selection)

This table reports the same analysis as in Table 10 in the paper but using DGTW returns and 4-Factor Alphas as dependent variables. We examine 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) average daily DGTW return of the funds' portfolio stocks. In Panel B, the dependent variable is the (position-weighted) average daily 4-factor alpha of the funds' portfolio stocks. 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 (and thus enters our sample). 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: DGTW Returns

Dependent Variable:	Daily Fund DGTW Return (in basis points)			
	(1)	(2)	(3)	(4)
D(First 60 days in sample)	0.48			
	(0.35)			
D(First 125 days in sample)		1.74*		
		(1.66)		
D(Last 60 days in sample)			0.72	
			(0.42)	
D(Last 125 days in sample)				0.36
				(0.36)
Constant	1.04***	0.85***	1.03***	1.02***
	(3.88)	(3.00)	(3.83)	(3.62)
Observations	21257	21257	21257	21257
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

Panel B: 4 Factor Alphas

Dependent Variable:	Daily Fund 4 Factor Alpha (in basis points)			
	(1)	(2)	(3)	(4)
D(First 60 days in sample)	-0.38			
	(-0.24)			
D(First 125 days in sample)		0.52		
		(0.43)		
D(Last 60 days in sample)			-0.61	
			(-0.30)	
D(Last 125 days in sample)				-0.77
				(-0.64)
Constant	1.33***	1.24***	1.34***	1.40***
	(3.12)	(2.84)	(3.15)	(3.26)
Observations	21260	21260	21260	21260
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

3) Only using trades where holding and trade data agree

There are some inconsistencies between the holdings and trades data provided by Inalytics. Specifically, there are sometimes holding changes that are not accompanied by a matching trade. In the paper, we follow Inalytics' advice and assume that the holdings data are correct. That is, if there is a holding change but no recorded trade, we impute a trade that corresponds to the holding change. In Table B.3 below, we run a robustness check where we remove all trades inferred from the holdings data for which we do not have a trade that matches exactly in terms of stocks traded. In Panel A, we show robustness checks for the main specifications of Tables 2 and 3. In Panel B, we show robustness checks for the main specifications of Tables 4 to 6. Our results remain very similar, implying that they are not driven by errors in the Inalytics data.

Table B.3: Robustness check – Only trades where holding and trade data agree

This table shows a robustness check in which we remove all trades from our data for which the change in the holdings data does not exactly match the trade data. In Panel A, we show robustness checks for Tables 2 and 3. Regressions 1 and 2 are run on opening orders and provide robustness to Table 2 Panel A. Regressions 3 and 4 are run on closing orders and provide robustness to Table 2 Panel B. Regressions 5 and 6 are run on both closing and opening orders and provide robustness to Table 3 Panel C. In Panel B, we display robustness checks for the sample splits in Tables 4 to 6. Regressions 1 and 2 splits the sample based on the change in number of positions in the 5 days prior to the order. Regressions 3 and 4 split the sample based on whether the fund return in the 5 days prior to the order was positive. Regressions 5 and 6 split the sample by whether fund return volatility, measured as the sum of squared fund returns over the previous 20 trading days increased or decreased relative to the 20 trading days before that. 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), except for regressions 5 and 6 in Panel A which have fund×portfolio×month fixed effects instead. All standard errors are two-way clustered by stock and last date of order. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Panel A: Robustness for Tables 2-3

Sample:	Opening Orders		Closing Orders		Opening and Closing Orders	
Dependent Variable:	Excess Return t+1, t+60	Excess Return t+1, t+125	Excess Return t+1, t+60	Excess Return t+1, t+125	Excess Return t+1, t+60	Excess Return t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-1.81***	-2.68***	-0.73**	-1.38***		
	(-5.65)	(-5.51)	(-2.13)	(-2.60)		
D(Opening)					0.60***	0.78***
					(3.09)	(2.69)
Observations	11337	10799	8588	8160	19925	18959
Adjusted R^2	0.06	0.09	0.07	0.09	0.13	0.15
Fund Fixed Effects	Yes	Yes	Yes	Yes	No	No
Month Fixed Effects	Yes	Yes	Yes	Yes	No	No
Fund×Portf.×Month F.E.	No	No	No	No	Yes	Yes

Panel B: Robustness for Tables 4-6 (sample splits)

Dependent Variable:	Excess Return t+1, t+125					
Sample	More Positions	Less Positions	Positive Fund Return	Negative Fund Return	Higher Volatility	Lower Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-1.60**	-1.09	-0.55	-2.61***	-1.80**	-1.21
	(-2.06)	(-1.53)	(-0.84)	(-3.26)	(-2.42)	(-1.64)
Observations	3849	4311	4506	3654	3945	3913
Adjusted R^2	0.09	0.10	0.07	0.13	0.10	0.11
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

4) Excluding trades with stock prices below $1

In our analysis, we remove any stocks below a stock price of USD 0.20. We choose this relatively low cut-off because international stocks often have low prices when converted to USD (without there being a rounding issue with the stock return in the local currency) and we want to exclude as few stocks as possible that are actually traded by our hedge funds. To show that our results are not driven by this low cut-off, we exclude all stocks with prices below USD 1 in the robustness check in Table B.4 below. Our results remain very similar.

Table B.4: Robustness check – Excluding trades with stock prices below $1

This table shows a robustness check in which we remove all trades of stocks with a price below USD 1. In Panel A, we show robustness checks for Tables 2 to 3. Regressions 1 and 2 are run on opening orders and provide robustness to Table 2 Panel A. Regressions 3 and 4 are run on closing orders and provide robustness to Table 2 Panel B. Regressions 5 and 6 are run on both closing and opening orders and provide robustness to Table 3 Panel C. In Panel B, we display robustness checks for the sample splits in Tables 4 to 6. Regressions 1 and 2 splits the sample based on the change in number of positions in the 5 days prior to the order. Regressions 3 and 4 split the sample based on whether the fund return in the 5 days prior to the order was positive. Regressions 5 and 6 split the sample by whether fund return volatility, measured as the sum of squared fund returns over the previous 20 trading days increased or decreased relative to the 20 trading days before that. 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), except for regressions 5 and 6 in Panel A which have fund×portfolio×month fixed effects instead. All standard errors are two-way clustered by stock and last date of order. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Panel A: Robustness for Tables 2-3

Sample:	Opening Orders		Closing Orders		Opening and Closing Orders	
Dependent Variable:	Excess Return t+1, t+60	Excess Return t+1, t+125	Excess Return t+1, t+60	Excess Return t+1, t+125	Excess Return t+1, t+60	Excess Return t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-1.90***	-2.67***	-0.76***	-1.53***		
	(-6.67)	(-6.18)	(-2.59)	(-3.44)		
D(Opening)					0.54***	0.63***
					(3.48)	(2.70)
Observations	12776	12141	11677	11054	24453	23195
Adjusted R^2	0.06	0.09	0.07	0.10	0.13	0.15
Fund Fixed Effects	Yes	Yes	Yes	Yes	No	No
Month Fixed Effects	Yes	Yes	Yes	Yes	No	No
Fund×Portf.×Month F.E.	No	No	No	No	Yes	Yes

Panel B: Robustness for Tables 4-6 (sample splits)

Dependent Variable:	Excess Return t+1, t+125					
Sample	More Positions	Less Positions	Positive Fund Return	Negative Fund Return	Higher Volatility	Lower Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-2.29***	-0.79	-0.78	-2.53***	-2.25***	-1.12*
	(-3.51)	(-1.33)	(-1.47)	(-3.74)	(-3.57)	(-1.81)
Observations	4957	6084	6193	4861	5316	5353
Adjusted R^2	0.10	0.10	0.08	0.12	0.10	0.10
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

5) Excluding trades of stocks outside stock universe

If funds trade stocks that are outside our stock universe used to compute DGTW returns (e.g. because they cannot be assigned to one of the regions or have no information on book value), we still include these trades in our sample (see Subsection A.3 of this internet appendix). For such trades, we only have access to excess returns and alphas. In this robustness check, we limit our sample to stocks that are in our stock universe; that is, to stock trades for which we have excess returns, alphas and DGTW returns. The results, reported in Table B.5 below, are very similar to those reported in the paper.

Table B.5: Robustness check – Excluding trades of stocks outside stock universe

This table shows a robustness check in which we remove all trades of stocks which are not within the stock universe (e.g., because region information or book value data is missing, etc.). In Panel A, we show robustness checks for Tables 2 to 3. Regressions 1 and 2 are run on opening orders and provide robustness to Table 2 Panel A. Regressions 3 and 4 are run on closing orders and provide robustness to Table 2 Panel B. Regressions 5 and 6 are run on both closing and opening orders and provide robustness to Table 3 Panel C. In Panel B, we display robustness checks for the sample splits in Tables 4 to 6. Regressions 1 and 2 splits the sample based on the change in number of positions in the 5 days prior to the order. Regressions 3 and 4 split the sample based on whether the fund return in the 5 days prior to the order was positive. Regressions 5 and 6 split the sample by whether fund return volatility, measured as the sum of squared fund returns over the previous 20 trading days increased or decreased relative to the 20 trading days before that. 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), except for regressions 5 and 6 in Panel A which have fund×portfolio×month fixed effects instead. All standard errors are two-way clustered by stock and last date of order. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Panel A: Robustness for Tables 2-3

Sample:	Opening Orders		Closing Orders		Opening and Closing Orders	
Dependent Variable:	Excess Return t+1, t+60	Excess Return t+1, t+125	Excess Return t+1, t+60	Excess Return t+1, t+125	Excess Return t+1, t+60	Excess Return t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-1.64***	-2.17***	-0.58*	-1.32***		
	(-5.61)	(-4.87)	(-1.95)	(-2.92)		
D(Opening)					0.54***	0.47*
					(3.42)	(1.94)
Observations	11729	11219	11036	10452	22765	21671
Adjusted R^2	0.06	0.09	0.07	0.10	0.13	0.16
Fund Fixed Effects	Yes	Yes	Yes	Yes	No	No
Month Fixed Effects	Yes	Yes	Yes	Yes	No	No
Fund×Portf.×Month F.E.	No	No	No	No	Yes	Yes

Panel B: Robustness for Tables 4-6 (sample splits)

Dependent Variable:	Excess Return t+1, t+125					
Sample	More Positions	Less Positions	Positive Fund Return	Negative Fund Return	Higher Volatility	Lower Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-1.73***	-0.88	-0.64	-2.24***	-2.16***	-0.84
	(-2.66)	(-1.42)	(-1.18)	(-3.22)	(-3.33)	(-1.34)
Observations	4702	5740	5851	4601	5005	5086
Adjusted R^2	0.10	0.10	0.08	0.12	0.10	0.11
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

6) Excluding return data from Inalytics

For some trades, we cannot find matching return data in Datastream. In these cases, we use return data provided by Inalytics instead (see Subsection A.4 above). In Table B.6 below, we provide a robustness check using only return data from Datastream. The results remain very similar to those reported in the paper.

Table B.6: Robustness check – Exclude return data from Inalytics

This table shows a robustness check in which we remove all stock trades for which we do not have return data from Datastream. In Panel A, we show robustness checks for Tables 2 to 3. Regressions 1 and 2 are run on opening orders and provide robustness to Table 2 Panel A. Regressions 3 and 4 are run on closing orders and provide robustness to Table 2 Panel B. Regressions 5 and 6 are run on both closing and opening orders and provide robustness to Table 3 Panel C. In Panel B, we display robustness checks for the sample splits in Tables 4 to 6. Regressions 1 and 2 splits the sample based on the change in number of positions in the 5 days prior to the order. Regressions 3 and 4 split the sample based on whether the fund return in the 5 days prior to the order was positive. Regressions 5 and 6 split the sample by whether fund return volatility, measured as the sum of squared fund returns over the previous 20 trading days increased or decreased relative to the 20 trading days before that. 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), except for regressions 5 and 6 in Panel A which have fund×portfolio×month fixed effects instead. All standard errors are two-way clustered by stock and last date of order. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Panel A: Robustness for Tables 2-3

Sample:	Opening Orders		Closing Orders		Opening and Closing Orders	
Dependent Variable:	Excess Return t+1, t+60	Excess Return t+1, t+125	Excess Return t+1, t+60	Excess Return t+1, t+125	Excess Return t+1, t+60	Excess Return t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-1.77***	-2.43***	-0.72**	-1.51***		
	(-6.17)	(-5.59)	(-2.45)	(-3.40)		
D(Opening)					0.53***	0.53**
					(3.45)	(2.28)
Observations	12526	11991	11698	11077	24224	23068
Adjusted R^2	0.06	0.09	0.07	0.10	0.14	0.16
Fund Fixed Effects	Yes	Yes	Yes	Yes	No	No
Month Fixed Effects	Yes	Yes	Yes	Yes	No	No
Fund×Portf.×Month F.E.	No	No	No	No	Yes	Yes

Panel B: Robustness for Tables 4-6 (sample splits)

Dependent Variable:	Excess Return t+1, t+125					
Sample	More Positions	Less Positions	Positive Fund Return	Negative Fund Return	Higher Volatility	Lower Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-2.25***	-0.84	-0.74	-2.51***	-2.22***	-1.09*
	(-3.43)	(-1.44)	(-1.39)	(-3.72)	(-3.49)	(-1.78)
Observations	4980	6084	6214	4863	5293	5400
Adjusted R^2	0.11	0.10	0.08	0.12	0.10	0.11
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

7) Excluding trades around mergers events

A common hedge fund strategy is to engage in merger arbitrage; i.e., purchasing the target and short selling the acquirer of an announced stock merger, thereby betting on its completion. We show in Subsection C.3 below that our funds almost never engage in merger arbitrage. Nonetheless, one may wonder whether our results can be confounded by merger events. In this subsection, we therefore provide a robustness check in which we exclude the days around a merger event. Specifically, we exclude from our sample all stock-days for both the acquirer and the target starting from a week before the announcement of a merger until one week after the merger is either completed or withdrawn. Table B.7 below shows that our results remain very similar after excluding these observations.

Table B.7: Robustness check – Exclude days around mergers

This table shows a robustness check in which we remove all stock-days for both the target and the acquirer stock starting from 7 days before the announcement of the merger to 7 days after the merger is either completed or withdrawn. If we do not have information on merger completion, we assume that the merger completes 30 days after its announcement. In Panel A, we show robustness checks for Tables 2 to 3. Regressions 1 and 2 are run on opening orders and provide robustness to Table 2 Panel A. Regressions 3 and 4 are run on closing orders and provide robustness to Table 2 Panel B. Regressions 5 and 6 are run on both closing and opening orders and provide robustness to Table 3 Panel C. In Panel B, we display robustness checks for the sample splits in Tables 4 to 6. Regressions 1 and 2 splits the sample based on the change in number of positions in the 5 days prior to the order. Regressions 3 and 4 split the sample based on whether the fund return in the 5 days prior to the order was positive. Regressions 5 and 6 split the sample by whether fund return volatility, measured as the sum of squared fund returns over the previous 20 trading days increased or decreased relative to the 20 trading days before that. 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), except for regressions 5 and 6 in Panel A which have fund×portfolio×month fixed effects instead. All standard errors are two-way clustered by stock and last date of order. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Panel A: Robustness for Tables 2-3

Sample:	Opening Orders		Closing Orders		Opening and Closing Orders	
Dependent Variable:	Excess Return t+1, t+60	Excess Return t+1, t+125	Excess Return t+1, t+60	Excess Return t+1, t+125	Excess Return t+1, t+60	Excess Return t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-1.88***	-2.59***	-0.78***	-1.51***		
	(-6.51)	(-5.81)	(-2.68)	(-3.43)		
D(Opening)					0.51***	0.58**
					(3.16)	(2.47)
Observations	12525	11932	11435	10869	23960	22801
Adjusted R^2	0.06	0.09	0.07	0.10	0.14	0.16
Fund Fixed Effects	Yes	Yes	Yes	Yes	No	No
Month Fixed Effects	Yes	Yes	Yes	Yes	No	No
Fund×Portf.×Month F.E.	No	No	No	No	Yes	Yes

Panel B: Robustness for Tables 4-6 (sample splits)

Dependent Variable:	Excess Return t+1, t+125					
Sample	More Positions	Less Positions	Positive Fund Return	Negative Fund Return	Higher Volatility	Lower Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-2.25***	-0.79	-0.88*	-2.28***	-2.21***	-1.11*
	(-3.46)	(-1.36)	(-1.68)	(-3.40)	(-3.61)	(-1.78)
Observations	4868	5989	6109	4760	5212	5280
Adjusted R^2	0.11	0.10	0.09	0.12	0.10	0.12
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Section C: Additional Results

1) What stocks do our hedge funds invest in?

In this subsection, we study in more detail which type of stocks the hedge funds in our sample invest in. In In Figure C.1 Panel A, we plot the average fraction of shares outstanding held by our hedge funds for different market capitalization deciles. We see that this fraction is monotonically increasing with company size for long positions. For short positions, it is also generally increasing but peaks at the 9^{th} decile. Also, short positions in small stocks (deciles 1 to 4) seem to be very rare, likely due to the difficulty of borrowing these stocks. In summary, similar to institutional investors in general (Gompers and Metrick (2001)), the hedge funds in our sample tend to focus on larger stocks.

Next, we examine whether our funds tend to concentrate their holdings in certain industries. In Figure C.1 Panel B, we plot the fraction of long and short positions that is held in each of the 12 Fama French industries. As a comparison, we also plot the fraction of total market capitalization concentrated in these industries. By and large, funds invest in all 12 industries in proportion to their market capitalization weights. If anything, funds tend to somewhat overweigh more traditional industries such as manufacturing, business equipment and retail, while they underweigh industries like finance and utilities that are subject to special rules and regulation.

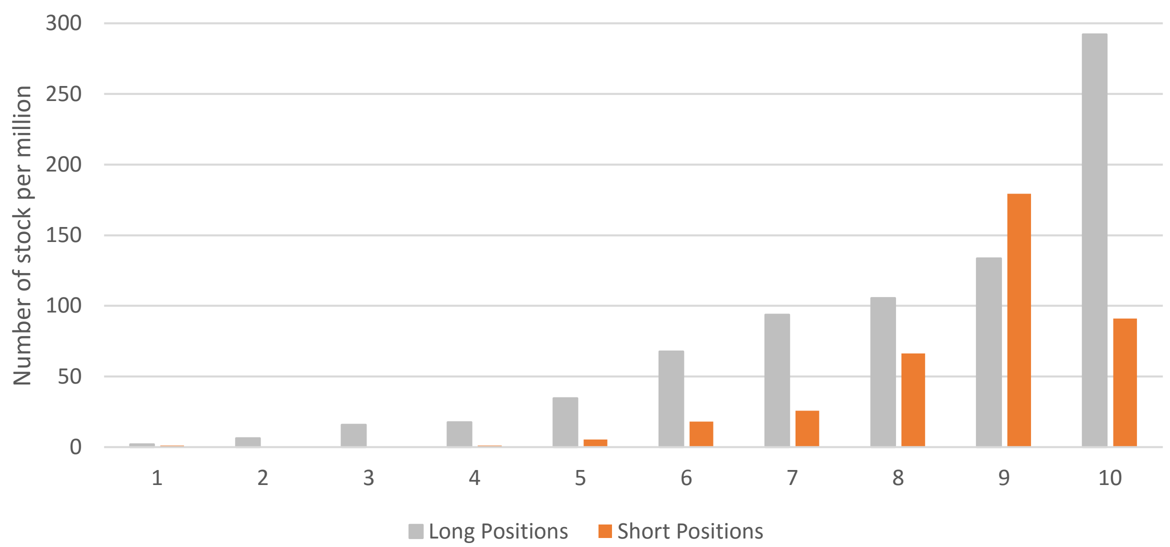
In Panel C, we present a similar plot for different deciles in terms of book-to-market ratio. Once again, the long and short position weights are fairly close to the market capitalization weights, although funds tend to somewhat overweigh growth stocks especially in long positions. Next, in Panel D, we present a plot for the different deciles of past 12-months return. Here, we observe a tendency of our funds to overweigh stocks with positive past returns in their long positions and to overweigh stocks with negative past returns in their short positions. This suggests that our funds engage in some momentum trading.

To conclude, we show that the long-short hedge funds in our sample spread their investments over many industries and different types of stocks. They tend to overweigh larger companies and engage in some momentum trading, but split fairly evenly across different industries and value vs. growth stocks.

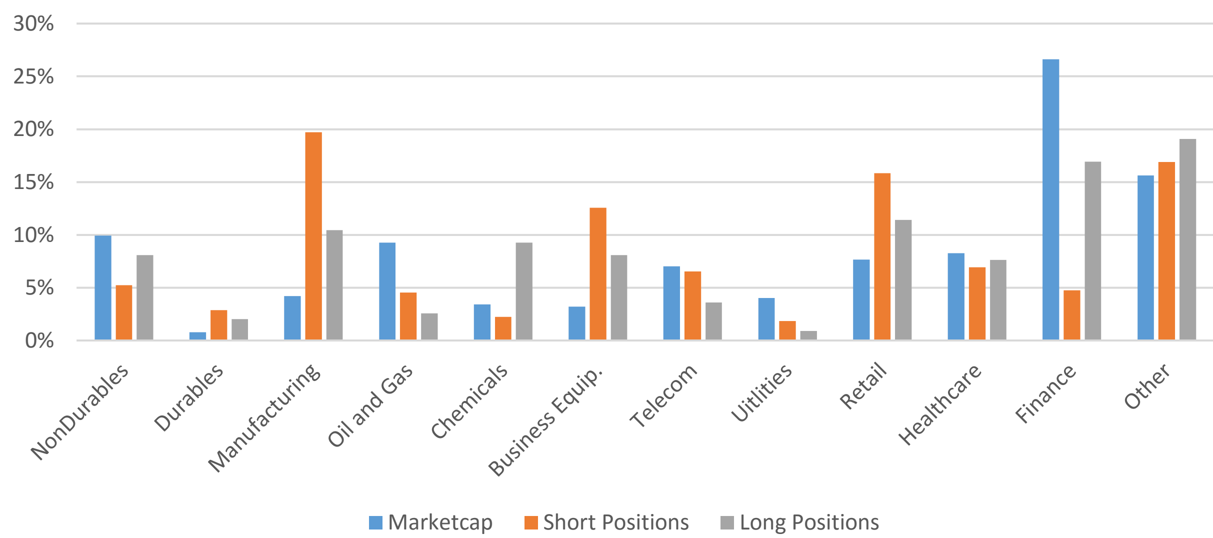
Figure C.1: Which stocks do the funds invest in?

This figure examines which stocks are more or less held by the hedge funds in our sample. In Panel A, we display the fraction of shares outstanding held by our hedge funds as long or short positions across different deciles of stocks in terms of market capitalization. The fraction is displayed in number of shares held per million of shares outstanding. We compute this fraction for each stock-month observation and then compute averages of this fraction. In Panel B, we display stock holdings by industry (using the 12 Fama French industry classification). Here, we display holding fractions separately for long and short positions. For comparison, we include the fraction of total market capitalization concentrated in each industry. We base the fraction of long and short positions on a sum over all funds and all months (i.e. these results are asset-weighted in the sense that they put more weight on larger funds). In Panel C and Panel D, we display similar results for deciles by book-to-market and past 12-months stock return. Deciles are formed each month.

Panel A: Holdings by size decile (1=small) – Fraction of shares outstanding

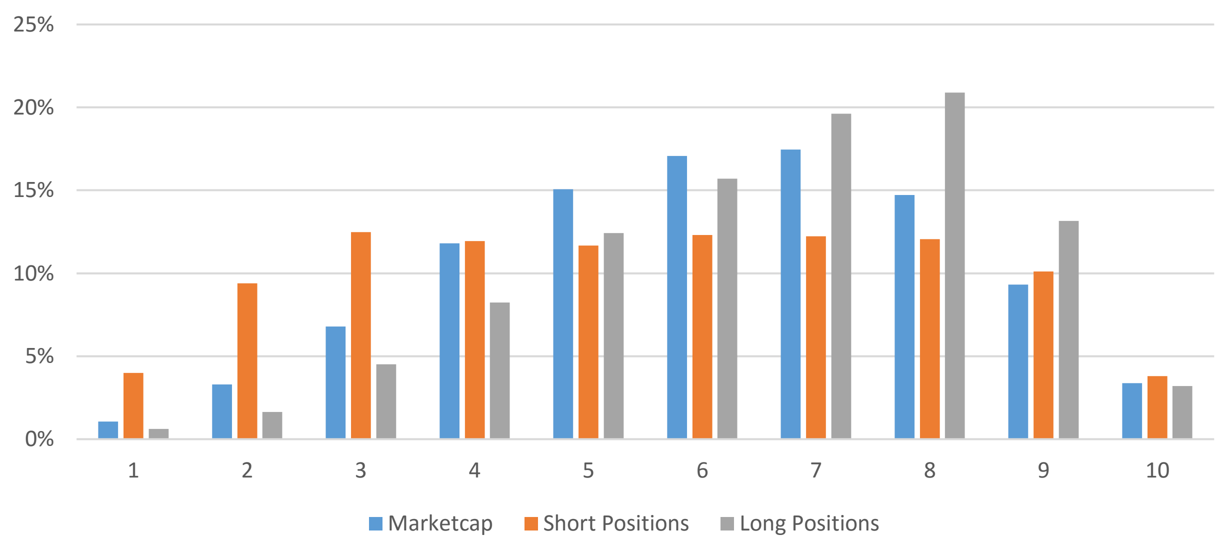


Panel B: Holdings by industry



Panel C: Holdings by book-to-market deciles (1=low book to market value)

Panel D: Holdings by past 12 month return (1=most negative return)



2) Do funds hedge their industry exposure?

In this subsection, we study whether our funds engage in industry hedging; i.e., whether they attempt to limit their industry exposure by going short and long different stocks of the same industry. To this end, we group stock positions for every fund and every day by 2-digit SIC codes. For each newly opened stock position, we create the dummy variable *D(Short exposure by 2-digit SIC code)* that equals one if the other holdings of the fund in the same industry on the previous day are more short than long (in terms of dollar value). We then regress *D(Short)* on *D(Short exposure by 2-digit SIC code)*. We report the results in regression 1 of Table C.2 below. If hedge funds engaged in industry hedging, we would expect significant negative coefficients. Instead, the coefficient is positive but very close to zero and statistically insignificant. Regression 2 documents similar results for the 49 Fama-French industry classification, even though now the coefficient is slightly negative. These findings suggest that hedge funds do not hedge their industry exposure. As shown in regression 3, there seems to be no hedging by DGTW portfolios (quintiles based on size, market-to-book and past returns) either. Finally, we also do not find any significant results when interacting these industry and DGTW groups with the investment region in regressions 4-6. Taken together, these findings suggest that stock positions are not meant to hedge away existing risk exposures to specific industries or stock characteristic.

Table C.2: Industry hedging

This table examines whether hedge funds concentrate their short and long positions in certain industries and DGTW portfolios. The sample includes only opening orders. The dependent variable is D(Short), which is a dummy variable equal to one if the newly opened position is a short position and zero if it is a long position. The explanatory variable is *D(Short exposure by group)*, which is a dummy variable equal to one if the *existing* holdings of the fund in this group are more short than long (by dollar value) on the day before the first day of the order. We use 6 groups: 2-digit SIC industries, 49 Fama-French industries, DGTW portfolios (quintiles by size, market-to-book and past returns) and each of these groups interacted with the investment region. Details on variable constructions can be found in Appendix A of the paper. We include fund fixed effects, month fixed effects and group fixed effects based on the specific group. All standard errors are two-way clustered by group and date. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Dependent Variable:	D(Short)					
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short exposure by 2-digit SIC code)	0.01					
	(0.18)					
D(Short exposure by 49 FF industry)		-0.03				
		(-0.29)				
D(Short exposure by DGTW portfolio)			0.02			
			(0.48)			
D(Short exposure by 2-digit SIC code * region)				-0.02		
				(-0.29)		
D(Short exposure by 49 FF industry * region)					-0.06	
					(-0.67)	
D(Short exposure by DGTW portfolio * region)						-0.01
						(-0.29)
Observations	11479	11981	9030	9288	9635	8173
Adjusted R^2	0.08	0.07	0.06	0.09	0.07	0.07
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

3) Pairs trading and merger arbitrage

In this subsection, we investigate whether our sample hedge funds systematically engage in merger arbitrage or pairs trading. Both of these popular arbitrage strategies involve pairs of long and short trades; and thus such stock trades could hardly be considered as independent. Merger arbitrageurs usually purchase the target and short sell the acquirer, thereby betting on completion of the merger. This leads us to examine whether our hedge funds tend to hold positions of opposite directions in the acquirer and target between the announcement and the completion of an acquisition. For this purpose, we collect from SDC Platinum all acquisitions where both the acquirer and the target are publicly listed. We obtain a total of 17,593 merger events. In only 96 of those, one of our sample hedge funds holds a stake in both the acquirer and the target and in 60% of these cases, the positions have the same direction (i.e., they are not long-short). Restricting the analysis to stock positions that are established in the two weeks after a merger announcement, we find that there is only 1 merger event in which a sample fund opened both a long position in the target and a short position in the acquirer.

Turning to pairs trading, we note that this strategy consists of finding two highly correlated stocks and then going long (short) the relatively under- (over-)valued stock of the pair. As such, pairs trading should show up in the data as the opening of both a long and a short position in a pair of highly correlated stocks. We use this insight to test for the extent of pairs trading in our trading data. Specifically, we consider all position pairs that each fund opens on the same day and compute the correlation of the pairs' stocks over the past 250 trading days. We then check whether pairs with a high return correlation are indeed more likely to be opened as a long-short trade (that is, whether hedge funds go long in one stock of the pair and short in the other). This test takes the form of regressing *D(Long-Short)*, a dummy variable equal to one for long-short trades, on the correlation coefficient.

The results are reported in Table C.3 below. We find a significantly negative coefficient, showing that funds are less likely to open long-short positions if the two stocks of the pair are more strongly correlated. We find similar results when we replace the correlation coefficient by dummy variables that flag correlations above 50% or 75%; that is, for stock pairs that are particularly well-suited for a pairs trading strategy. Taken together, these results suggest that the funds in our sample do not engage in merger arbitrage or pairs trading.

Table C.3: Pairs trading

This table examines whether hedge funds are more likely to take positions with opposite direction in highly correlated stocks. The sample consists of all stock pairs in which a hedge fund initiates a position on the same day. The dependent variable is *D(Long-Short)*, which is a dummy variable equal to one if the opened positions go in opposite directions, i.e. one is a long and the other a short position. The explanatory variables are *Correlation Coefficient*, which is the correlation coefficient between the two stocks of the pair over the previous 250 trading days, as well as *D(Correlation Coefficent > 0.50)* and *D(Correlation Coefficient > 0.75)*, which are dummy variables equal to one if the correlation coefficient is above 50% or 75%, respectively. We include fund fixed effects and month fixed effects. We cluster standard errors by date. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Dependent Variable:	D(Same Direction)		
	(1)	(2)	(3)
Correlation Coefficient	-0.17***		
	(-4.00)		
D(Correlation Coefficient > 0.50)		-0.05***	
		(-4.52)	
D(Correlation Coefficient > 0.75)			-0.08**
			(-2.56)
Observations	31509	31509	31509
Adjusted R^2	0.05	0.05	0.05
Fund Fixed Effects	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes

4) Can rebalancing explain our results?

As we argue in the paper, rebalancing should not affect closing trades because by definition a rebalancing trade never closes a position completely.

In this subsection, we present an additional test to confirm this argument. Specifically, we examine a sample split for post-closure returns by the underlying stock's return over the prior 10 trading days. If one were to believe that rebalancing trades can close a position, one would expect such rebalancing trades to be more likely to occur after a positive return because positive returns increase the size of a position. Thus, if the alpha following closing orders was explained by rebalancing, we would expect a larger alpha if the closing happens after a positive stock return. Our regression setup is identical to the sample splits provided in the paper (Tables 4-7), except that we now split by the closing order's prior stock return. The results are presented below in Table C.4. We find very similar returns following closing orders after positive and negative stock returns. If anything, hedge funds seem to leave slightly more money on the table when they close positions after negative stock returns, which is the exact opposite of what we one would expect if closing orders were due to rebalancing. This finding confirms our argument that portfolio rebalancing cannot explain early position closures.

Table C.4: Returns after the closure of positions – Split by past stock return

This table examines whether returns following the closure of positions depend on the stocks prior return. We run the same regression as in Table 3 but split the sample by whether the stock had a positive or negative return in the 10 trading days prior to the first day of the order. We regress average returns following the order on a dummy variable whether the order is related to a short position (and is thus a short buy). The dependent variable is the cumulative return expressed in percent for 60 and 125 trading days following the last day of the order. Details on variable constructions can be found in Appendix A.1. We include fund fixed effects and month fixed effects (based on the month of the last day of the order). All standard errors are two-way clustered by stock and last date of order. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Dependent Variable:	Excess Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	Positive Stock Return	Negative Stock Return	Positive Stock Return	Negative Stock Return	Positive Stock Return	Negative Stock Return
	(1)	(2)	(3)	(4)	(5)	(6)
D(Short)	-1.09*	-1.59**	-1.03*	-1.00*	-0.97*	-1.01*
	(-1.87)	(-2.56)	(-1.87)	(-1.76)	(-1.74)	(-1.66)
Observations	5671	5401	5348	5119	5675	5395
Adjusted R^2	0.09	0.12	0.06	0.06	0.05	0.06
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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