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

Bastian von Beschwitz*
Federal Reserve Board

Sandro Lunghi**
Inalytics

Daniel Schmidt***
HEC Paris

December 21, 2017

Abstract

We exploit detailed transaction and position data for a sample of long-short equity hedge funds to study the trading activity of fundamental investors. We find that opening trades are followed by significant risk-adjusted returns, suggesting that the hedge funds possess investment skill. In contrast, closing trades are followed by return continuation, implying that hedge funds close their positions too early and forgo about a third of the trades' potential profitability. We show that funds close positions early in order to reallocate their capital to more profitable investments. Consistently, we find more premature position closures when financial constraints tighten (e.g., after negative fund returns and increases in volatility or funding costs).

JEL classification: G11, G12, G14, G15

Keywords: Hedge funds, Short selling, Profitability, Fundamental Trading

* Bastian von Beschwitz, Federal Reserve Board, International Finance Division, 20th Street and Constitution Avenue N.W., Washington, D.C. 20551, USA, tel. +1 202 475 6330, e-mail: bastian.vonbeschwitz@gmail.com.
** Sandro Lunghi, Inalytics, 9th Floor, Corinthian House, 17 Lansdowne Road, Croydon CR0 2BX, UK, tel. +44 (0)20 3675 2904, e-mail: alunghi@inalytics.com
*** Daniel Schmidt, HEC Paris, 1 Rue de la Libération, 78350 Jouy-en-Josas, France, tel. +33 (0)139 67 9408, e-mail: schmidt@hec.fr.

We thank Chris Collins and Laura Kane for excellent research assistance and Inalytics Ltd. for providing the data. We thank Vikas Agarwal, Laurent Barras, John Cochrane, Jean-Edouard Colliard, Richard Evans, Francesco Franzoni, Denis Gromb, Russell Jame, Petri Jylhä, Augustin Landier, Hugues Langlois, Alberto Manconi, Asaf Manela, Oguzhan Ozbas, Joël Peress, Elena Pikulina, Tarun Ramadorai, Adam Reed, Ioanid Rosu, Yu Wang, and seminar participants at the Federal Reserve Board, HEC Paris, INSEAD, McGill, the University of Kentucky, the ESSFM Gerzensee, EFA, NFA, FMA, SFA, the 4th Conference on Recent Advances in Mutual Fund and Hedge Fund Research, the 9th Annual Hedge Fund and Private Equity Research Conference, and the 15th Paris December Finance Meeting for helpful comments. We further thank Matthias Kruttli for sharing his hedge fund return data for comparison. The views in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System.

Fundamental trading—i.e., trading on information acquired through fundamental research—plays a critical role for market efficiency as it helps to align individual stock prices with their (ever elusive) "fair" values. Arguably the most important group of fundamental traders are discretionary long-short equity hedge funds. Indeed, these type of hedge funds routinely undertake independent long and short investments ("directional bets") and are known to invest in equity research. Moreover, long-short equity accounts for 40% of hedge funds in the Lipper TASS database (Fung and Hsieh (2011)), making it by far the most popular hedge fund strategy with investors. Despite their importance, we know very little about their actual trading behavior and, by extension, about fundamental trading in practice.

In this paper, we shed light on fundamental trading by analyzing a novel, proprietary transaction dataset for a sample of 21 discretionary long-short equity hedge funds over a ten-year period. Our data comprises the entire trading history as well as daily position updates for both long and short positions. This level of detail allows us 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 positive and negative benchmark-adjusted returns with an absolute magnitude of about 1% (1.5%) over the next 60 (125) trading days. When measured over the holding period (i.e., from opening to close), the difference in benchmark-adjusted returns between long and short positions amounts to 2.7%. This shows 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 are followed by negative returns and short buys by positive returns; that is, returns in the opposite direction of the closing trade. When we design a trading strategy that goes long in stocks in which hedge funds just closed a long position (long sells) and shorts stocks from closed short positions (short buys), we obtain a significant benchmark-adjusted return of about 1.3% over the next six months (125 trading days). This figure implies that the hedge funds in our sample forgo about a third of the trade's potential profitability,[1] suggesting that they "leave substantial money on the table."

Why do hedge funds close their positions too early? We argue that this behavior arises naturally from the existence of financial constraints. To illustrate this point, 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. This mirrors standard practice in the hedge fund industry (see, e.g., Pedersen (2015)). Second, the hedge fund incurs a fixed cost for each open position in its portfolio, which can be loosely interpreted 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 fund to limit the number of open positions, consistent with what is observed in the data.[2] Third, we assume that new investment opportunities (stock mispricings) emerge each period, whose alphas decay gradually over time. This "alpha decay" arises naturally in models of informed trading with multiple speculators (Foster and Viswanathan (1996), Back, Cao, and Willard (2000), Bernhardt and Miao (2004)) and is confirmed empirically (e.g., Chen, Da and Huang (2016), Di Mascio, Lines and Naik (2016)). It is also evident in our data as two-thirds (1%/1.5%) of the six-months benchmark-adjusted return is earned within the first three months after opening the position.

We show that, under these assumptions, the hedge fund's optimal trading rule involves early position closures: as the expected profitability of an investment decays, other trading opportunities become more attractive. This triggers a reallocation of the funds' limited risk capital and monitoring capacity into these

[1] Our hedge funds forgo 1.3% return out of a total trade profitability of 4% (2.7% over the holding period plus the 1.3% to be had over the next 125 trading days).

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

more profitable opportunities, explaining why hedge funds close positions that continue to generate alpha going forward. In the words of hedge fund manager Lee Ainslee III:

> "[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)

We derive and test a number of additional predictions in order to corroborate our explanation for early position closures. First, our model predicts that, at any point in time, the profits from newly opened positions should exceed the profits that hedge funds forgo by closing existing ones. We thus compare post-trade returns between position openings and closings made by the same fund around the same point in time. We find that, over the 125 trading days following the order, newly initiated long (short) positions yield a benchmark-adjusted return that is 0.6% larger (smaller) than that following closed long (short) positions. Thus, we document that hedge funds generate more returns with their opening trades than they forgo by closing their positions prematurely, showing that hedge funds recycle their limited risk capital into more profitable trading opportunities.

Second, the return continuation following position closures should be more pronounced—meaning that the hedge fund leaves more money on the table—when the fund (1) simultaneously opens a large number of new positions, (2) has suffered poor past performance, (3) when the risk constraint tightens due to a surge in fund return volatility, and (4) when funding costs increase. To test these predictions, 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, which yields an estimate of how much return hedge funds forgo by closing early. We start by examining whether this strategy is more profitable when hedge funds have higher opportunity costs due to facing more trading opportunities. Indeed, we find that our sample hedge funds forgo almost three times as much return after an increase in the number of open positions than after a decrease. Next, we conduct a sample split based on the fund's portfolio return over the prior week. Negative returns reduce the available (risk) capital of the fund, forcing it to close down some existing stock positions. Consistent with this idea, we find that funds leave more money on the table after negative returns. Finally, we conduct two sample splits—by changes in fund return volatility and the TED spread—to test whether our hedge funds forgo more return after a tightening of their volatility or funding constraints. Again we document confirming evidence, showing that our hedge funds close their positions earlier when they become more constrained.

We also consider, and ultimately dismiss, several alternative explanations for early position closures. Specifically, we show that our hedge funds do not exhibit the dispositions effect and further argue that rebalancing motives or biased beliefs are not able to explain the entirety of our findings. We then provide additional support for the view that long-short equity hedge funds are fundamental traders: they do not open positions for mere hedging reasons and rarely engage in popular relative-value arbitrage strategies such as pairs trading or merger arbitrage. Moreover, their trades predict subsequent earnings surprises, suggesting that they trade on fundamental information. In summary, discretionary long-short equity hedge funds such as those in our sample are archetypical fundamental traders and we show how their trading activity is impeded by the presence of financial constraints.

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

In conclusion, our paper provides an in-depth study on how fundamental investors trade in practice. We show that their opening trades are profitable, but that they close their positions prematurely in response to tightened constraints and/or to recycle their capital into more profitable investment opportunities. The latter result implies that the emergence of a new investment opportunity, by raising the opportunity cost of capital, can further constrain the trading in an existing position. To the best of our knowledge, we are the first to document this interdependence of trading positions, thereby providing support for recent multi-asset models on the limits of arbitrage (e.g., Gromb and Vayanos (2017)). Perhaps more importantly, our approach allows us to provide a first *quantitative estimate* for the severity of the constraints faced by real-world arbitrageurs—a task usually made impossible by the inability to observe the would-be trades prevented by the constraints. We find that these constraints are economically important as they force hedge funds to forgo one third of the potential profitability of their trades. More broadly, our results have important implications for the efficiency of financial markets. Indeed, early position closures slow down the information incorporation in market prices, rendering them less informative.

Our paper contributes to several strands of research. First, we speak to the literature on hedge funds. Existing research mostly focuses on self-reported returns or quarterly snapshots of long-only holdings data and reaches mixed conclusions about hedge fund performance.[3] However, these approaches have their limitations: studying returns is a very indirect way of examining hedge fund behavior and studying long holdings is bound to give an incomplete picture as hedge funds routinely go short. We add to this literature by examining hedge funds' trading skill using complete equity trading and position records for both long and short positions. 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

[3] For studies based on returns, see for example Ackermann, McEnally, and Ravenscraft (1999), Amin and Kat (2003), Kosowski, Naik, and Teo (2007), Jagannathan, Malakhov, and Novikov (2010), Agarwal, Boyson and Naik (2011), Patton and Ramodarai (2013), Agarwal, Fos, and Jiang (2013), Bali, Brown, and Demirtas (2013), Bali, Brown and Caglayan (2011, 2012, 2014). For studies based on quarterly holdings, see Griffin and Xu (2009), Cao et al. (2016), Grinblatt et al. (2017). For comprehensive surveys, see Agarwal, Mullally, and Naik (2015) or Getmansky, Lee, and Lo (2015).

providers (Aragon and Strahan (2012), Ben-David, Franzoni and Moussawi (2012), Jylhä, Rinne and Suominen (2014), Franzoni and Plazzi (2015), Jame (2016)). Finally, our work is closely related to Choi, Pearson and Sandy (2016), who study hedge fund short positions gleaned from merging institutional transaction data from ANcerno with quarterly holdings from 13F. They find that the position openings by hedge funds in their sample do not predict long-term returns and 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, while comprising fewer funds, is arguably more comprehensive and,[4] perhaps more importantly, covers the trading activity for one particular class of hedge funds—discretionary long-short equity—as opposed to the trading by different hedge funds belonging to the same hedge fund family. This could explain why we find different results for the long-term predictability of stock trades.

Second, we contribute to the literature on the limits of arbitrage. Theoretical work in this field has highlighted different channels as to why arbitrageurs may be forced to liquidate their positions,[5] which have been subsequently confirmed in numerous empirical studies.[6] Given this wealth of evidence, our contribution is not to show that arbitrage is limited, but rather to document precisely how arbitrage frictions affect the trading behavior of fundamental investors at the micro-level. Moreover, by measuring forgone profits from prematurely closed positions, we are able to quantify the economic importance of hedge funds' arbitrage constraints. Such quantifiable estimates are still rare as one normally does not observe which potential trades are impeded by the presence of arbitrage constraints.

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

[5] See for example Shleifer and Vishny (1997), Kyle and Xiong (2001), Gromb and Vayanos (2002, 2017), Brunnermeier and Pedersen (2009), Acharya and Viswanathan (2011), Liu and Mello (2011). For a survey of this literature see Gromb and Vayanos (2010).

[6] See Hameed, Kang and Viswanathan (2010), Nagel (2011), Adrian, Etula and Muir (2014), Pasquariello (2014), and He, Kelly and Manela (2016) for macro-level evidence. See Ang, Gorovyy and van Inwegen (2011), Khandani and Lo (2011), Aragon and Strahan (2012), Ben-David, Franzoni and Moussawi (2012), and Franzoni and Plazzi (2015) for micro-level evidence on how hedge funds were forced to delever and curb back their liquidity provision during the 2007-09 Financial Crisis.

Third, we contribute to the literature on short selling. Several papers find that short selling predicts future returns.[7] 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. Our paper is thus related to Boehmer, Duong, and Huszar (2015), who examine stock returns around short covering trades identified from mandatory disclosures of large short positions. While they show evidence of positive returns around covering trades, their analysis may be influenced by signaling effects and the data, unlike ours, doesn't allow to observe precise position closure dates.[8]

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

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 on long-short equity funds as fundamental traders. Section VI provides robustness checks and discusses representativeness and selection concerns. Section VII concludes.

I. Hypotheses

Discretionary long-short equity hedge funds resemble fundamental traders. Indeed, this hedge fund strategy consists of taking a number of long and short bets on individual stocks based on a fundamental analysis.

[7] See for example 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), Jank and Smajlbegovic (2015).

[8] In their data, a hedge fund will stop disclosing a short position as soon as it falls below 0.25% of stocks' shares outstanding, but positions below this threshold can still be quite substantial.

The starting point of our empirical investigation is to see whether the long and short stock positions opened by hedge funds in our sample deliver risk-adjusted returns (alpha). Prior research on hedge fund performance and managerial skill are hampered by data constraints and reach mixed conclusions (see, for instance, the survey by Agarwal, Mullally, and Naik (2015)). Given that our data, while covering only 21 funds, is the most detailed hedge fund transaction data studied to date, our performance analysis constitutes a valuable contribution in its own right.

Next, we investigate how and when hedge funds close their positions. We argue that position closures are particularly revealing about the constraints faced by fundamental investors. Indeed, when they were unconstrained, we would expect them to hold on to their positions until all the alpha is reaped, implying that post-closure risk-adjusted returns should be zero on average. In practice, however, we expect them to be capital and/or attention constrained: while they can take leverage, their ability to do so depends on banks willingness to provide it, and their fundamental research is time and effort intensive, implying that long-short equity hedge funds focus on a limited number of open positions (directional bets). Being cognizant of these constraints, we expect hedge funds to allocate their limited resources on the basis of a cost-benefit analysis. Each period, they decide how many positions to maintain, which ones to open and which ones to close. An important implication is that, when constraints are binding, the hedge fund may decide to close a stock position before its alpha is fully exploited.[9] Thus, if our sample hedge funds are constrained, 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 (1) faces a risk constraint, (2) incurs position monitoring costs, and

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

(3) new stock mispricings appear every period but gradually decay over time (in a way that displays "alpha decay").[10] 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. "Alpha decay"—i.e., a gradual decline in the profitability of available trading opportunities—has been documented empirically (Chen, Da and Huang (2016), Di Mascio, Lines and Naik (2016); see also our evidence presented in Section 3.A) and arises naturally in models of informed trading with multiple speculators (Foster and Viswanathan (1996), Back, Cao, and Willard (2000), Bernhardt and Miao (2004)). The risk constraint captures, 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.[11] The position monitoring cost is a placeholder for any type of fixed cost that is associated with holding a stock position. For instance, it can represent a fixed transaction cost or a fixed attention cost for monitoring a given position (the hedge fund may want to check, for example, whether the trading signal, which induced the opening of the position, is still valid after the arrival of new information). Without this assumption, the hedge fund would always smoothly scale back position sizes all the way to zero until the alpha is fully exploited. Thus, there would be no early position closures. With a fixed monitoring cost, early position closures do occur as it is not economical to hold on to a position below a certain minimum position size. A natural implication of this assumption is that larger funds have more open positions. Indeed, in our data, funds with an above-median portfolio value hold on average 94 distinct stocks, while those below median hold only 61.

[10] Our model borrows from the limits of arbitrage literature (e.g., Gromb and Vayanos, 2002, 2017; Brunnermeier and Pedersen, 2009). Indeed, fundamental trading promises positive (risk-adjusted) returns and thus resembles a (statistical) arbitrage. We view our model's contribution in clarifying which precise assumptions are needed in order to give rise to early position closures in a dynamic setting.

[11] 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). Alternatively, we can assume that the hedge fund is risk averse.

Our model identifies four potential reasons for why a hedge fund may close a position before its alpha is fully exploited:[12] 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 past performance,[13] and (3) when the funds' stock positions become more volatile or (4) when funding constraints tighten.

II. Data and Variable Construction

A. Analytics data

Our data on long-short equity hedge funds is provided by Inalytics Ltd. and this is the first time it is used in an academic study. A different subset of the Inalytics database, for long-only equity funds, has been previously studied in Di Mascio, Lines and Naik (2016). Inalytics provides portfolio monitoring services for institutional asset owners as well as investment and process management consulting for asset and hedge fund managers. As such, there are two ways in which a hedge fund can enter our database: Either a hedge

[12] We emphasize that a test of any of the following predictions must be understood as a joint test of our three modelling assumptions (risk constraint, monitoring costs, and alpha decay). Indeed, our model only predicts early position closures when all three assumptions are met: without the risk constraint, the hedge fund would want to take unbounded long-short positions; without the monitoring cost, the hedge fund would split his capital very thinly to invest in all available trading opportunities (no matter how small their alpha); without alpha decay, the hedge fund would be as likely to forgo entering a new position as to close an existing one. An alternative setting, which yields identical predictions to our model, is to assume that the hedge fund faces margin constraints at the position-level (i.e., there is no cross-netting of margins across positions) as in Gromb and Vayanos (2017).

[13] In practice, this effect is further exacerbated by investors' tendency to withdraw their money after poor performance (Baquero and Verbeek (2008), Fung, Hsieh, Naik, and Ramadorai (2008), Wang and Zheng (2008), and Ding, Getmansky, Liang, and Wermers (2009)).

fund submits its trading data directly to Inalytics to obtain feedback on and verification of its trading performance, or an institutional client, e.g. a plan sponsor, asks Inalytics to monitor the hedge fund's trades and performance on its behalf. In both cases, funds are obligated to submit their complete equity trades and position updates to Inalytics. Furthermore, Inalytics verifies the data carefully for its accuracy.

Our dataset covers the years 2005 to 2015 and contains *complete* trading and holding information for the equity portfolios of 21 distinct hedge funds.[14] For each fund, we are thus able to track both their long and short portfolios. Specifically, we have access to two datasets: The first is a transaction-level dataset containing all trades. Variables in this dataset include stock identifiers (ISIN, SEDOL, and CUSIP), the date of the trade, the number of shares traded, and the execution price. The second dataset is a stock-day level dataset of each funds' portfolio holdings. This dataset contains stock identifiers, the number of shares held, and the price of the stock at the end of the day. All prices are expressed in the base currency of the fund and in the local currency of the stock. Our data does not cover derivative positions, but conversations with Inalytics suggest that hedge funds in our sample use them little and, if they do, mostly for hedging their market exposure (for example using index options). Thus, their equity trades likely offer a comprehensive reflection of the fundamental bets that they engage in.

We use a merged dataset that combines the holdings and trading data (details on merging these two datasets can be found Internet Appendix A). Hedge funds often split their orders into several trades that are executed on different days to reduce the market impact of their orders. To avoid double counting, we follow Di Mascio, Lines, and Naik (2016) and aggregate trades likely belonging to the same investment decision into orders. Specifically, we assume that trades belong to the same order if a hedge fund trades the same stock

[14] The data that comes closest to ours in its level of detail is obtained via a fuzzy name-matching between the hedge fund trades contained in the ANcerno institutional transaction data and quarterly equity holdings reported in 13F filings. However, funds covered by ANcerno only make available a subset of their transaction records and identifying long and short positions from quarterly holdings is bound to be noisy. Finally, while our data is at the fund-level, the ANcerno data is at the fund-family level. In the aggregate, these families appear to make most of their profits from liquidity provision and their trades do not predict long-term alpha (Franzoni and Plazzi (2015), Jame (2016), Choi, Pearson and Sandy (2016)).

in the same direction and the distance between them is two trading days or less. Seventy-three percent of the orders consist of only one trade.

B. Summary statistics

In Table 1 Panel A, we display summary statistics by fund. Funds hold on average 50 long positions and 24 short positions (median values are 36 and 19). The fewer number of short positions is further reflected by the fact that short positions make up about 30% by USD value, implying that the funds are not market neutral. Having a larger long than short portfolio is seen as typical for long-short equity hedge funds. For instance, Fung and Hsieh (2011) document that long-short equity hedge funds in the Lipper TASS database have an average market beta of 0.5. Our funds conduct on average 6 orders per day. Compared to an average of 74 positions this corresponds to a new order for a given stock position every 12 trading days. The daily fund turnover (trading volume over total portfolio holdings) is 5.4% on average (median 2.8%). Our funds span a large range of different sizes. The median fund holds about USD 350 million in assets, while the 10^{th} and 90^{th} percentile funds range from USD 115 million to USD 6,400 million. These numbers suggest that the funds in our data are above average in terms of size. For instance, assuming an average leverage of 2.13 as reported in Ang, Gorovyy, and van Inwegen (2011), we estimate that our median fund has about USD 164 million of assets under management, which is slightly above the USD 130 million reported for the 75^{th} percentile in the Lipper TASS database (see Lim, Sensoy and Weisbach (2016)).

[Insert Table 1 about here.]

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

Thaler (1991)). Otherwise, they split their investments relatively evenly across different industries and value vs. growth stocks.

We display gross fund profitability computed from holdings in Figure 2. In Panel A, we display the actual profitability of the funds by year. Because most funds have more long than short positions, this profitability co-moves a lot with the market. The worst year is 2008 when equity markets crashed worldwide in the wake of the Lehman bankruptcy. In 2009, equity markets recovered and our sample hedge funds experience their best year. To get a better idea of the fund's stock-picking skill, we display profitability based on benchmark-adjusted returns in Panel B. We compute benchmark-adjusted returns as stock returns minus the fund-specific benchmark. For short positions, we then multiply these benchmark-adjusted returns by minus one before averaging across positions. Thus, the more the funds' long (short) positions overperform (underperform) relative to the benchmark, the larger is the fund's benchmark-adjusted returns. We find that our funds display positive benchmark-adjusted returns in every year of the sample, suggesting that they exhibit persistent stock-picking skill.

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

Next, we examine summary statistics at the order-level. We distinguish between three types of orders: Opening orders that initiate the position, closing orders that close the position and follow-up orders that change the size of the position in between. We display summary statistics for each type of order separately in Panels C to E. The opening and closing orders are much larger than the follow-up orders: when standardized by the maximum size of a given position, opening and closing orders on average make up around 77% of this maximum position size (median 100), while the follow-up orders make up only 15.5% (median 8.5%). Thus, position openings and closings are the more important investment decisions, justifying why we focus on these two types of orders in our main analyses. Follow-up orders, while making up 70% of orders in our sample, are smaller and more likely to be based on hedging or rebalancing motives rather than on information. We confirm this intuition in Subsection V.C below, where we show that follow-up orders are not predictive of future stock returns, suggesting that they are not information-driven trades. Finally, we note that hedge funds do not split orders into separate trades very often: the average number of trades per order is only about 1.6 and the median is 1 for each order type.

C. Datastream and Worldscope data

Because the hedge funds in our sample trade stocks internationally, we require international stock market and balance sheet data. We use the datasets most commonly used in the international context: Datastream for stock returns and Worldscope for balance sheet data. For stocks that appear in our transaction and holdings data but are not covered in Datastream, we add stock return information provided by Inalytics (this affects approx. 14% of our stocks). We show in Internet Appendix C.6 that our results are robust if we only use return data from Datastream. We use three types of risk-adjusted returns: (1) benchmark-adjusted returns with respect to the fund-specified benchmark, (2) characteristics-adjusted returns following the methodology of Daniel, Grinblatt, Titman, and Wermers (1997), hereafter DGTW, and (3) alphas estimated using the four-factor model of Carhart (1997). The details of the risk-adjustments are explained in Internet Appendix A; here we provide only a brief summary description.

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

As a second methodology, we compute DGTW returns on a regional level. We categorize stock markets into 5 regions (Japan, North America, Europe, Asia-Pacific and Emerging Markets) following Karolyi and Wu (2014). The assignment of countries into regions is displayed in the Internet Appendix A.1. Within each region, we sort stocks into quintiles by market capitalization, market-to-book ratio and past-12 month returns, thus forming 625 portfolios (125 per region). We compute DGTW returns as stock returns minus the (value-weighted) returns of the respective benchmark portfolio. Given prior evidence suggesting that local factors are better able in pricing risk (Griffin (2002)), our approach to compute portfolios on a regional level constitutes a reasonable compromise between a desirable granularity and the need to sufficiently populate 125 portfolios.

As a third methodology, we implement a regional version of the Carhart (1997) 4-factor model, which includes a market factor, a High-minus-Low Book to Market Factor (HML), a Small-minus-Big (SMB) factor and a Momentum (MOM) factor of winners minus losers. Following the recommendations by Levi and Welch (2016), we estimate stock betas with respect to these factors using daily regressions over the prior 12 months and shrink the resulting betas toward their cross-sectional average as in Vasicek (1973). We then compute alphas on the daily level as:

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

All returns are winsorized at the 1% level on both sides.

We use these risk-adjusted stock returns for our profitability analysis below. A long (short) position will be considered profitable if it has positive (negative) risk-adjusted returns. As this approach ignores short lending fees, it arguably overstates the profitability for short positions. In unreported analysis, we find that the median lending fee for stocks in our sample is only about 18 basis points per year,[15] confirming that the bias introduced by ignoring lending fees should be small.

III. Profitability Results

A. Profitability of opening and closing trades

As shown in Figure 2, our sample hedge funds appear to trade profitably on average. We now examine their trading skill in more detail by studying the post-trade returns for the stocks they buy and sell. We start with a simple graphical analysis presented in Figure 3. We show cumulative benchmark-adjusted returns in the 200 trading days following an order. We include only orders that either open or close a position (that is, we exclude follow-up orders). We further separate between orders that are related to long or short positions.

Figure 3 reveals clear evidence of informed trading for the opening of positions: in the first half-year (125 days) following the initiation of a long (short) position, cumulative benchmark-adjusted returns are slightly above (below) 1.5% (-1.5%). After that, the return drift is fairly muted. Moreover, on both the long and the short side, two-thirds of these returns (1%) is realized in the first 60 trading days (3 months) following the opening order, while the remaining third is realized in the 3 months after that. In other words, the post-opening alphas (per unit of time) decay over time: they are highest immediately after the position is established and then gradually shrink as time progresses.

In contrast, the closing of long and short positions does not seem to be informed. Long sells are not followed by negative returns, but rather by positive returns. In the 200 days following the closing of a long position cumulative benchmark-adjusted returns are about 1%. Similarly, the closing of a short position is followed

[15] This figure corresponds to the average lending fee across sample stocks for the years 2005-2010, for which we have access to equity lending data from Markit.

by negative benchmark-adjusted returns (-1% after 200 days). In both cases, most of the cumulative return is realized in the first half year (125 trading days) following the order.

Next, we investigate the statistical significance of these findings. In Table 2 Panel A, we focus on position openings and run a regression of risk-adjusted returns following the order on *D(Long Position)*, a dummy variable equal to one if the order initiates a long position (and zero if it initiates a short position). We examine all three measures of risk-adjusted returns for holding periods of 60 and 125 trading days (approximately 3 and 6 months) following the order. We choose these holding periods because they straddle the average holding period (see Table 1 Panel B) and Figure 2 reveals that most of the trade profitability accrues by this time. To be conservative, we report results for returns measured from the price at the end of the last date of the order. In Internet Appendix C.10, we instead measure returns from actual transaction prices and show that this only strengthens our results. We include fund fixed effects to control for any differences in post-trade profitability across funds that could correlate with their propensity to enter a long position. We also include month fixed effects to ensure that our results are not driven by a particular time period. Finally, we cluster standard errors two-way by stock and last date of order. Clustering by stock accounts for correlation due to overlapping returns and clustering by date accounts for correlation in the cross-section of stock returns.

[Insert Table 2 about here.]

Given our specification, the coefficient estimate for the *D(Long Position)* dummy can be interpreted as the return difference between long and short positions that have been opened in the same month. The results, presented in Panel A, show that this return difference is economically and statistically significant. For instance, for benchmark-adjusted returns, long positions outperform short positions by about 1.8% over 60 days and 2.4% over 125 days. For DGTW returns and alphas the effect is slightly smaller at about 1.6% over 60 days and 1.9% over 125 days. These results are all statistically significant at the 1% level.

In Panel B, we repeat our regression analysis for holding-period returns; i.e., cumulated returns from the last day of the opening order to the first day of the closing order. This is a conservative estimate because it excludes within-order profits, which on average are positive (unreported). As before, we find that long positions outperform short positions over the holding period. For instance, the coefficient on the *D(Long Position)* dummy for benchmark-adjusted returns indicates that the return difference between long and short positions amounts to 2.7%. For DGTW returns and alphas, the return difference is slightly smaller but remains strongly statistically significant.[16] These findings confirm that our sample hedge funds possess investment skill.

In Table 2 Panel C, we examine post-trade returns for closing orders. To this end, we regress cumulated risk-adjusted returns over the 60 and 125 trading days following position closures on our *D(Long Position)* dummy (including the fund and month fixed effects as before). We again find a positive coefficient for the *D(Long Position)* dummy, albeit with a smaller economic magnitude. For benchmark-adjusted returns, the return difference between closed long and closed short positions equals 0.7% over 60 days and 1.3% over 125 days. For DGTW returns and alphas the effect is slightly smaller. Over the 125 days horizon, the return difference is statistically significant for all measures of risk-adjusted returns. These results suggest that the hedge funds in our sample close their positions too early in the sense that these positions would have earned significant risk-adjusted returns going forward.

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

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

from the presence of financial constraints and corroborate this interpretation below. Our back-of-the-envelope calculation suggests that these constraints are economically important.

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

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

We have established that both the opening and the closure of a long (short) position is followed by positive (negative) returns. As argued in the hypotheses section, a natural explanation for this is the presence of a risk capital (or margin capital) constraint: a constrained hedge fund may want to close an existing stock position even though it still offers some alpha in order to free-up capital that can be invested into new, more promising trading opportunities. Of course, this argument only makes sense when these new investments deliver higher returns than those that are forgone by closing existing positions. A casual inspection of Figure 3 suggests that this is indeed the case: newly established positions earn most of their alpha in the first weeks/months after the opening trade. After some time, alphas peter out and so it could 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. By including these fixed effects, we compare openings and closures undertaken by the same fund, on the same side (either long or short), and at roughly the same point in time—where it is thus likely that the closure provided the capital for the new position opening.[17] The key variable of interest is *D(Position Opening)*, a dummy variable that takes the value one when the order opens a (long or short) position and zero when it closes the position (follow-up orders are again excluded from this analysis).

Table 3 shows the results. In Panel A, we focus on long positions only. The significantly positive coefficient for the *D(Position Opening)* dummy implies that newly initiated long positions are indeed more profitable than the previous long positions that are closed within the same month by about 0.5-0.8% depending on the risk-adjustment and the holding horizon. For short positions (Panel B), the coefficient flips sign, meaning that initiated short positions are followed by more negative returns than closed short positions (although it is not always significant). In Panel C, we examine long and short positions together, which requires us to use signed returns as the dependent variable. Signed returns are defined as risk-adjusted returns for long positions and minus one times the risk-adjusted returns for short positions. We find about 0.5-0.7% higher signed returns following the opening of positions. Because combining short and long positions improves statistical power, these tests are all statistically significant at the 1% level.

[Insert Table 3 about here.]

The results so far show that hedge funds are on average right when they reallocate their capital from an old stock position to a new one. Going one step further, we can also test whether funds are right when they decide which stock position to close. Indeed, if our funds are informed but constrained as we argue, one would expect them to first close the positions which they expect to be least profitable. As such, the stock positions that they keep holding-on to should on average outperform those that they decide to close. To test this, we construct a sample of all fund portfolio holdings on days when the fund closes an existing stock position. We then regress future signed returns on *D(Position not Closed)*, a dummy variable taking the value one when the fund holds on to the position. We now include fund×portfolio×date fixed effects because we want to compare positions that have and have not been closed by the same fund on the same day. Table

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

3 Panel D shows the results. As predicted, we find that the positions that are kept open outperform those that are closed by about 0.4-0.5% depending on the horizon (this difference is statistically significant at the 5% level in four out of the six regressions). Note that this return difference is less than the one between closed and newly opened positions (see Panel C). This makes sense: newly opened positions should promise larger returns than existing ones, for otherwise the fund would have preferred to increase the existing position rather than to open a new one.

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

IV. Explaining Post-Closure Returns

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

The first prediction states that existing stock positions should be closed earlier at times when more new trading opportunities emerge that result in a large number of newly opened positions. A larger number of early position closures in turn implies that hedge funds "leave more money on the table"—i.e., the return difference between closed long and closed short positions should increase. In Table 4, we test this prediction by splitting the sample of closing orders by whether the hedge fund increased or decreased the number of open positions over the previous five days (Panel A) or over the previous ten days (Panel B). We then repeat our regression analysis from Table 2 Panel B for these different subsamples.[18] The results broadly confirm our prediction: whereas the benchmark-adjusted return difference between closed long and short positions

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

after increases in the number of open positions over the previous five days is 2%, it is only 0.7% and insignificant after decreases in the number of open positions. The results for DGTW returns and 4-factor alphas are similar with 1.7% vs. 0.5%, and 1.5% vs. 0.4%. These results are robust to using the change over the previous ten trading days instead of five trading days (Table 4, Panel B). In summary, our results suggest that early position closures are more common when hedge funds simultaneously seize new trading opportunities.

[Insert Table 4 about here.]

The second prediction concerns the relation between past portfolio profits and subsequent position closures. The intuition is that hedge funds (which are often highly levered) will be forced to close positions after experiencing portfolio losses. In our model, this prediction is driven by the hedge fund's optimal number of open positions, which is pinned down by the fund's equity and position monitoring costs. This fixed monitoring cost makes it uneconomical to hold positions below a certain minimum position size. As such, funds with more equity naturally hold a larger number of open positions and, when a given fund suffers losses, it responds by closing existing positions. We thus check whether the returns from the post-closure investment strategy from Table 2 Panel B are more pronounced after times in which the fund has experienced negative (position-weighted) portfolio returns. The results, shown in Table 5, support this prediction. When we split closing orders by prior fund returns over the previous five trading days, the benchmark-adjusted return difference between closed long and short positions is 2.2% in the subsample with negative prior fund returns and only 0.6% in the subsample with positive prior fund returns. For the other risk-adjusted return measures, the difference is smaller but goes in the same direction. When we split the sample based on fund returns over the previous 10 trading days, we again obtain similar results. These findings suggest that trading losses force funds to close some of their positions earlier, thereby leaving more money on the table.

[Insert Table 5 about here.]

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

[Insert Table 6 about here.]

Finally, we test whether our sample hedge funds leave more money on the table after a tightening of their funding constraints. This is a straightforward prediction of arbitrage models under funding constraints (e.g., Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009)) and it also obtains in our setting as we show that our risk constraint is closely related to a margin constraint (see Appendix B for details). Because our funds remain anonymous, we cannot tell the identity of their prime brokers, and we thus have to conduct sample splits by *market-wide* measures of funding constraints. In Table 7, we report results for two such measures: the TED spread and the intermediary risk factor of He, Kelly, and Manela (2016, henceforth HKM).[19] Specifically, in Panels A and B, we split the sample by changes in the TED spread (three-month LIBOR minus three-month T-Bill rate), a bellwether of the financial sector's health that is both widely-

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

used (e.g., Brunnermeier (2009)) and theoretically-motivated (e.g., Garleanu and Pedersen (2011)). In Panels C and D, we split the sample by the HKM intermediary risk factor aggregated over the previous 5 and 10 trading days, respectively. This factor reflects changes to the capital ratios of primary dealer counterparties of the New York Federal Reserve and HKM find that it has significant explanatory power for the cross-section of returns in various asset classes. For both measures, our results paint a consistent picture: The return gap between closed long and short positions opens up after a tightening of funding constraints (i.e., when the TED spread increases or when the HKM intermediary risk factor is negative). This shows that tighter funding constraints in the intermediary sector are passed on to our sample hedge funds, forcing them to close their positions prematurely.

[Insert Table 7 about here.]

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

In this subsection, we provide further evidence that our funds trade on fundamentals by showing that their trades predict future earnings surprises. Indeed, if our hedge funds are able to identify fundamentally under- or overvalued stocks, the direction of their trades should predict future earnings news over and above what is anticipated by the market and/or already embedded in the consensus forecast. We test this premise using two popular measures of earnings surprises. The first measure is based on the difference between the actual earnings and analysts' consensus earnings forecast calculated from I/B/E/S data (e.g., DellaVigna 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.[20,21] 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 earnings surprises over and above

[20] 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.

[21] We choose to end the window a few days prior to the announcement date as these dates are frequently misreported (DellaVigna 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.

what is predicted by the stock market at large, suggesting that our hedge funds trade on fundamental information.

B. Hedge funds' trades as independent bets

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

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

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

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

C) Are follow-up orders profitable?

In our main analysis, we study the profitability of opening and closing orders. This means that we exclude follow-up orders, even though they make up about 70% of all orders in our sample. Apart from ruling out rebalancing-based explanations (see below), this choice is motivated by the intuition that, out of all trading orders, opening orders should be the most informed (as they capture the point in time when a hedge fund started acting on its trading signal), whereas closing orders should in principle be the least informed (as an unconstrained hedge fund will only close after fully exploiting its trading signal).

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

To this end, we focus on the sample of follow-up orders and regress post-order returns on a dummy variable indicating whether the order increased or decreased the position. The results are shown in Table 9. In essence, our test is the analogue of Table 3 where we studied whether position openings outperform position closures (and we similarly include fund-portfolio-month fixed). In Panel A, we only include follow-up orders related to long positions. If follow-up orders were to contain additional information, we would expect more positive returns after follow-up buys (which increase the long position). We indeed find coefficients that are mostly positive, but they are small and not statistically significant. Similarly, in Panel B, we find more negative returns following orders that increase short positions (follow-up sells) but the magnitude remains small and insignificant. Finally, in Panel C, we combine long and short positions and use signed returns as the dependent variable. Once again the coefficients are small and insignificant (with the exception of one marginally significant coefficient).

[Insert Table 9 about here.]

These results suggest that hedge funds' follow-up trades are not informed, because post-trade returns are independent of the direction of the follow-up order. In other words, in contrast to opening and closing trades, the capital freed from decreasing some existing positions is not more profitably employed by increasing other existing positions. Follow-up trades thus appear to be caused by different underlying reasons, justifying why we focus on opening and closing orders in our main analysis.

VI. Robustness

A) Representativeness

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

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

We start by regressing all four return series over our sample period on the 8 Fung and Hsieh factors (Fung and Hsieh (2001)).[22] The results are displayed in Table 10 Panel A. We find that our fund returns load on the same factors as the benchmark return indexes. Specifically, they all load strongly positively on the Equity Market Factor and the Emerging Market Factor and somewhat negatively on the Credit Spread Factor. The other factors are insignificant. We also note that the average alpha of our funds is similar to those from KPR and the Broad Credit Suisse Long/Short Equity index. The alpha of the investable Credit Suisse index is much lower but this comparison is likely not appropriate as some of our funds may well be closed for new investors.

[Insert Table 10 about here.]

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

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

B) Potential data biases and selection concerns

In this subsection, we discuss potential data biases and selection concerns. We begin by noting that several sample biases that have been identified in the literature should not be of major concern here. For instance, since hedge funds that engage with Inalytics provide most of their transaction data in real time, there should be little incentives for window dressing and little scope for back-filling bias. Moreover, since our data includes funds that have already been terminated, survivorship bias is not an issue.

One important remaining concern with our data is self-selection into the sample. Here, the biggest worry is that successful hedge funds strategically engage with Inalytics in order to advertise their trading success—implying that the documented trade profitability would be biased upward. Alternatively, it could be that institutional clients demand from poorly-performing hedge funds to submit their trades to Inalytics for monitoring and verification purposes or that poorly performing funds engage with Inalytics to learn how they can improve their trading processes. In this case, the trade profitability documented above could be understood as a lower bound estimate of the average trade profitability for the class of long-short equity hedge funds.

These considerations lead us to examine our fund returns for any signs of fund selection. The idea is that, since we cannot observe fund returns prior to them entering our sample, we can at least test whether funds with poor returns are more likely to drop out of the sample. Similarly, we can test whether fund returns appear to be elevated shortly after entering the sample. This would be indicative of a backfilling bias since—to the extent that it occurs—backfilling should be more pronounced for returns at the beginning of the sample. We therefore regress daily fund returns (i.e., position-weighted portfolio returns of all outstanding stock positions) on dummy variables that equal one during the first (last) 60 (or 125) days that the fund is in our sample. We focus on raw and benchmark-adjusted returns as we believe that these are the returns hedge funds would be selected upon, but we confirm in Internet Appendix C.3 that we find similar results for DGTW returns and alphas.

[Insert Table 11 about here.]

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

Finally, we argue that any remaining selection concerns only affect the inference about the representativeness of the average trade performance that we document. However, that they should not invalidate our micro evidence on how financial constraints affect the trading behavior of long-short equity funds. Indeed, financial constraints are ubiquitous and thus our qualitative results on early position closures and hedge funds' capital reallocations should apply more generally.

C) Alternative explanations

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

We first consider an alternative explanation based on portfolio rebalancing; i.e., hedge fund trades aimed at maintaining a certain risk exposure for a given stock position. For long positions, rebalancing has indeed the potential to explain why hedge funds reduce their positions before alphas are fully exploited. To see this, consider a hedge fund with a long position in a stock whose price is expected to go up over time. As the stock price starts increasing, the position size grows and, being concerned about the risk exposure to a single stock, the hedge fund may want to rebalance the position by selling some stocks. Such rebalancing trades appear to leave additional money on the table. However, this argument does not work for short positions, because they shrink in (absolute) size as the stock price decreases (assuming shorted stocks continue to go down on average). More importantly, rebalancing cannot explain why we find return continuation after position *closures*. This is because rebalancing trades by definition never close a position entirely, but only reduce it to the desired size. Position closing decisions should thus be independent of rebalancing considerations. In Internet Appendix D.3, we present an additional test that confirms this intuition.[23]

The second alternative explanation we consider involves the disposition effect; i.e., investors' tendency to close winning positions too early while holding on to losing positions for too long (Odean (1998), Jin and Scherbina (2011)). Indeed, if our hedge fund managers close winning positions too early due to the disposition effect, this could explain the average return continuation we observe after closing trades. Other results are, however, at odds with this explanation. In particular, the disposition effect cannot explain why we find an association between post-closure returns and hedge funds' financial constraints (Tables 4-7) and is hard to square with our finding that positions that our hedge funds keep open outperform those that they close (see Table 3 Panel D). In Internet Appendix D.4, we further test whether our hedge funds display the disposition effect and find that they do not. In fact, they are more likely to close positions trading at a loss rather than those trading at a gain, which is the exact opposite of the disposition effect. Hence, our results cannot be explained by the disposition effect.

Finally, we discuss the possibility that early position closures can be explained by biased beliefs. More precisely, it is conceivable that hedge funds systematically underestimate the precision of their trading

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

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

VII. Conclusion

Fundamental investors play an important role in financial markets: through their research, they acquire and synthesize value-relevant information and, through their trading, they ensure that this information finds its way into prices. As a consequence, market prices become more informative and better reflect fundamental values.[24] Yet, like other real-world arbitrageurs, fundamental investors face constraints that impede their trading activity.

In this paper, we provide an in-depth study on such limits of "fundamental arbitrage." More specifically, we exploit proprietary trading data for a sample of discretionary long-short equity hedge funds—presumably the most important fundamental investors in todays' markets—to offer a microscopic analysis of their trading activity. We first establish that positions opened by these funds predict risk-adjusted returns over a horizon of six months, suggesting that their trades are informed. We then show that their closing trades are not only uninformed, but rather predict returns in the opposite direction of the closing trade; that is, our sample hedge funds close their positions too early. In this way, they forgo about a third of the total trade profitability, implying that they "leave substantial money on the table."

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

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

Our findings have profound implications for what we call the limits to fundamental arbitrage. Indeed, we believe that we are the first to provide micro-level evidence on how fundamental investors decide to abandon a profitable trading opportunity in order to recycle their capital or to accommodate tightened constraints. As the trading opportunity is not fully exploited, mispricing persists. Thus, despite the presence of informed fundamental traders, market prices can remain removed from their fundamental values.

References

Acharya, Viral V., and S. Viswanathan, 2011, Leverage, Moral Hazard, and Liquidity, *Journal of Finance* 66, 99-138.

Ackermann, Carl, Richard McEnally, and David Ravenscraft, 1999, The performance of hedge funds: risk, return, and incentives, *Journal of Finance* 54, 833-874.

Adrian, Tobias, Erkko Etula, and Tyler Muir, 2014, Financial Intermediaries and the Cross-Section of Asset Returns, *Journal of Finance* 69, 2557-2596.

Agarwal, Vikas, Nicole M. Boyson, and Narayan Y. Naik, 2009, Hedge funds for retail investors? An examination of hedged mutual funds, *Journal of Financial and Quantitative Analysis* 44, 273-305.

Agarwal, Vikas, Vyacheslav Fos, and Wei Jiang, 2017, Inferring Reporting-Related Biases in Hedge Fund Databases from Hedge Fund Equity Holdings, *Management Science* 56, 1271-1289.

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

Amin, Gaurav S. and Harry M. Kat, 2003b, Hedge fund performance 1990-2000: Do the “money machines” really add value? *Journal of Financial and Quantitative Analysis* 38, 251-274.

Ang, Andrew, Sergiy Gorovyy, and Gregory B. van Inwegen, 2011, Hedge Fund Leverage, *Journal of Financial Economics* 102, 102-126.

Aragon, George O., and Philip E. Strahan, 2012, Hedge Funds as Liquidity Providers: Evidence from the Lehman Bankruptcy, *Journal of Financial Economics* 103, 570-587.

Asquith, Paul, Parag A. Pathak, and Jay R. Ritter, 2005, Short Interest, Institutional Ownership, and Stock Returns, *Journal of Financial Economics* 78, 24-276.

Back, Kerry, C. Henry Cao, and Gregory A. Willard, 2000, Imperfect Competition among Informed Traders, *Journal of Finance* 55, 2117-2155.

Bali, Turan G., Stephen J. Brown, and Mustafa Onur Caglayan, 2011, Do hedge funds' exposures to risk factors predict their future returns?, *Journal of Financial Economics* 101, 36-68.

Bali, Turan G., Stephen J. Brown, and Mustafa Onur Caglayan, 2012, Systematic risk and the cross section of hedge fund returns, *Journal of Financial Economics* 106, 114-131.

Bali, Turan G., Stephen J. Brown, and Mustafa Onur Caglayan, 2014, Macroeconomic risk and hedge fund returns, *Journal of Financial Economics* 114, 1-19.

Bali, Turan G., Stephen J. Brown, and K. Ozgur Demirtas, 2013, Do hedge funds outperform stocks and bonds?, *Management Science* 59, 1887-1903.

Baquero, Guillermo and Marno Verbeek, 2015, Hedge fund flows and performance streaks: how investors weigh information, *Working paper*.

Barber, Brad M., and Terrance Odean, 2000, Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors, *Journal of Finance* 55, 773-806.

Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi, 2012, Hedge Funds Stock Trading during the Financial Crisis of 2007-2009, *Review of Financial Studies* 25, 1-54.

Bernhardt, Dan, and Jianjun Miao, 2004, Informed Trading when Information becomes Stale, *Journal of Finance* 59, 339-390.

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

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

Brunnermeier, Markus K., 2005, Information Leakage and Market Efficiency, *Review of Financial Studies* 18, 417-457.

Brunnermeier, Markus K., 2009, Deciphering the Liquidity and Credit Crunch 2007-2008, *Journal of Economic Perspectives* 23, 77-100.

Brunnermeier, Markus K., and Lasse H. Pedersen, 2009, Market Liquidity and Funding Liquidity, *Review of Financial Studies* 22, 2201- 2238.

Cao, Charles, Yong Chen, William N. Goetzmann, and Bing Liang, 2016, The Role of Hedge Funds in the Security Price Formation Process, *Working paper*.

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

Chen, Yong, Zhi Da, and Dayong Huang, 2016, Arbitrage Trading: The Long and the Short of It, *Working paper*.

Choi, Jaewon, Neil D. Pearson, and Shastri Sandy, 2016, A First Glimpse into the Short Side of Hedge Funds, *Working Paper*.

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

DellaVigna, Stefano and Joshua M. Pollet, 2009, Investor Inattention and Friday Earnings Announcements, *Journal of Finance* 64, 709-749.

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

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

Ding, Bill, Mila Getmansky, Bing Liang, and Russ Wermers, 2009, Share restrictions and investor flows in the hedge fund industry, *Working Paper*.

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

Engelberg, Joseph E., Adam V. Reed, and Matthew C. Ringgenberg, 2012, How are Shorts Informed? Short Sellers, News, and Information Processing, *Journal of Financial Economics* 105, 260-278.

Fama, Eugene F. and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

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

Foster, F. Douglas, and S. Viswanathan, 1996, Strategic Trading when Agents Forecast the Forecasts of others, *Journal of Finance* 51, 1437-1478.

Franzoni, Francesco and Alberto Plazzi, 2015, What Constrains Liquidity Provision? Evidence from Hedge Fund Trades, *Working Paper*.

Frazzini, Andrea and Lasse Heje Pedersen, 2014, Betting against Beta, *Journal of Financial Economics* 111, 1-25.

Fung, William and David A. Hsieh, 2001, The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers, *Review of Financial Studies* 14, 313-341.

Fung, William and David A. Hsieh, 2004, Extracting portable alphas from equity long/short hedge funds, *Journal of Investment Management* 2, 57-75.

Fung, William and David A. Hsieh, 2011, The risk in hedge fund strategies: Theory and evidence from long/short equity hedge funds, *Journal of Empirical Finance* 18, 547-569.

Fung, William, David A. Hsieh, Narayan Y. Naik, and Tarun Ramadorai, 2008, Hedge funds: performance, risk, and capital formation, *Journal of Finance* 63, 1777-1803.

Garleanu, Nicolae, and Lasse H. Pedersen, 2011, Margin-based Asset Pricing and Deviations from the Law of One Price, *Review of Financial Studies* 24, 1980-2022.

Getmansky, Mila, Peter A. Lee, and Andrew W. Lo, 2015, Hedge Funds: A Dynamic Industry In Transition, *Annual Review of Financial Economics* 7, 483-577.

Griffin, Dale, and Amos Tversky, 1992, The Weighing of Evidence and the Determinants of Confidence, *Cognitive Psychology* 24, 411-435.

Griffin, John M. and Jun Xu, 2009, How Smart are the Smart Guys? A Unique View from Hedge Fund Stock Holdings, *Review of Financial Studies* 22, 2332-2370.

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

Grinblatt, Mark, Gergana Jostova, Lubomir Petrasek and Alexander Philipov, 2017, Style and Skill: Hedge Funds, Mutual Funds, and Momentum, *Working Paper*.

Gromb, Denis, and Dimitri Vayanos, 2002, Equilibrium and Welfare in Markets with Financially Constrained Arbitrageurs, *Journal of Financial Economics* 67, 361-407.

Gromb, Denis, and Dimitri Vayanos, 2010, Limits of Arbitrage, *Annual Review of Financial Economics* 2, 251-275.

Gromb, Denis, and Dimitri Vayanos, 2017, The Dynamics of Financially Constrained Arbitrage, *Journal of Finance*, forthcoming.

Hameed, Allaudeen, Wenjin Kang, and S. Viswanathan, 2010, Stock Market Declines and Liquidity, *Journal of Finance* 65, 257-293.

He, Zhiguo, Bryan Kelly, and Asaf Manela, 2016, Intermediary Asset Pricing: New Evidence from Many Asset Classes, *Journal of Financial Economics*, forthcoming.

Jagannathan, Ravi, Alexey Malakhov, and Dmitry Novikov, 2010, Do hot hands exist among hedge fund managers? An empirical evaluation, *Journal of Finance* 65, 217-255.

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

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

Jylha, Petri, Kalle Rinne, and Matti Suominen, 2013, Do Hedge Funds Supply or Demand Liquidity, *Review of Finance* 18, 1259-1298.

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

Khandani, Amir E., and Andrew W. Lo, 2011, What Happened to the Quants in August 2007? Evidence from Factors and Transactions Data, *Journal of Financial Markets* 14, 1-46.

Kosowski, Robert, Narayan Y. Naik, and Melvyn Teo, 2007, Do hedge funds deliver alpha? A Bayesian and bootstrap analysis, *Journal of Financial Economics* 84, 229-264.

Kruttli, Mathias S., Andrew Patton, and Tarun Ramadorai, 2015, The Impact of Hedge Funds on Asset Markets, *Review of Asset Pricing Studies* 5, 185-226.

Kyle, Albert S., 1985, Continuous Auctions and Insider Trading, *Econometrica* 53, 1315-1335.

Kyle, Albert S. and Wei Xiong, 2001, Contagion as a Wealth Effect, *Journal of Finance* 56, 1401-1440.

Jin, Li, and Anna Scherbina, 2011, Inheriting Losers, *Review of Financial Studies* 24, 786-820.

Lan, Yingcong, Neng Wang and Jinqiang Yang, 2013, The Economics of Hedge Funds, *Journal of Financial Economics* 110, 300-323.

Lee, Charles M.C., Andrei Shleifer, and Richard Thaler, 1991, Investor Sentiment and the Closed-End Fund Puzzle, *Journal of Finance* 46, 75-109.

Liu, Xuewen and Antonio S. Mello, 2011, The fragile capital structure of hedge funds and the limits to arbitrage, *Journal of Financial Economics* 102, 491-506.

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

Nagel, Stefan, 2012, Evaporating Liquidity, *Review of Financial Studies* 25, 2005-2039.

Odean, Terrance, 1998, Are Investors Reluctant to Realize Their Losses? *Journal of Finance* 53, 1775-1798.

Odean, Terrance, 1999, Do Investors trade too much? *American Economic Review* 89, 1279-1298.

Pasquariello, Paolo, 2014, Financial Market Dislocations, *Review of Financial Studies* 27, 1868-1914.

Patton, Andrew J. and Tarun Ramadorai, 2013, On the high-frequency dynamics of hedge fund risk exposures, *Journal of Finance* 68, 597-635.

Pedersen, Lasse H., 2015, Efficiently Inefficient: How Smart Money invests and Market Prices are determined, *Princeton University Press*.

Puetz, Alexander, and Stefan Ruenzi, 2011, Overconfidence among Professional Investors: Evidence from Mutual Fund Managers, *Journal of Business Finance and Accounting* 38, 684-712.

Sadka, Ronnie, 2006, Momentum and Post-earnings-announcement Drift Anomalies: The Role of Liquidity Risk, *Journal of Financial Economics* 80, 309-349.

Shleifer, Andrei, and Robert W. Vishny, 1997, The Limits of Arbitrage, *Journal of Finance* 52, 35-55.

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

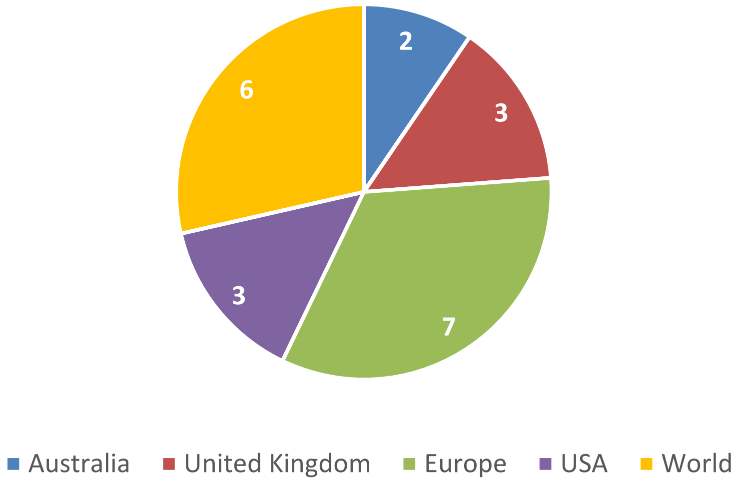
Wang, Ashley and Lu Zheng, 2008, Aggregate Hedge Fund Flows and Asset Returns, *Working Paper*.

Weller, Brian M., 2016, Does Algorithmic Trading Deter Information Acquisition, *Working Paper*.

Figure 1: Investment areas of funds

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

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



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

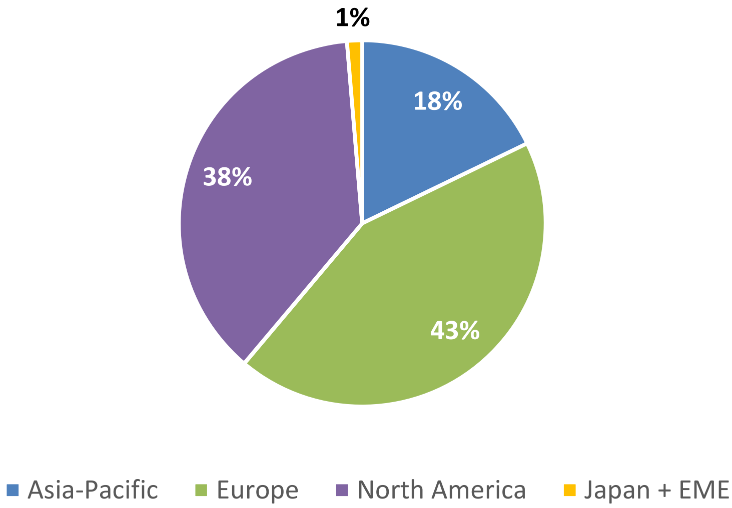


Figure 2: Fund returns

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

Panel A: Raw returns

Panel B: Benchmark-adjusted returns

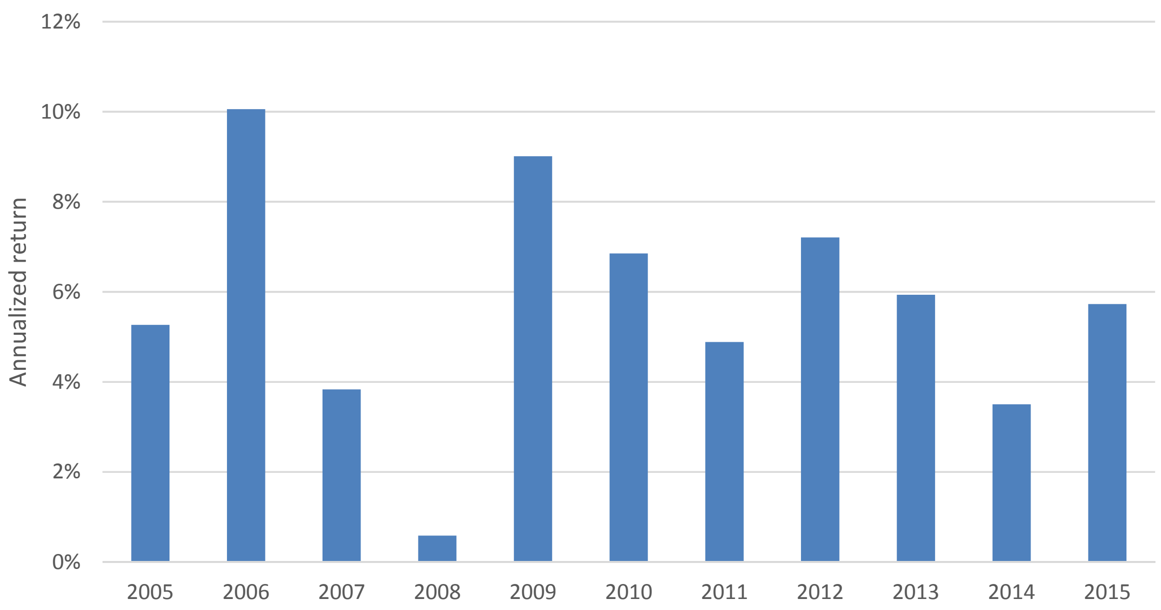


Figure 3: Benchmark-adjusted returns following orders

This figure displays cumulative benchmark-adjusted return indices for 200 trading days following orders that open or close a position. *Open Long Position* is the buy order establishing a long position ("long buy"). *Open Short Position* is the sell order establishing a short position ("short sale"). *Close Short Position* is the buy order closing a short position ("short buy"). *Close Long Position* is the sell order closing a long position ("long sell"). *Benchmark-adjusted return* is the return of the stock minus the return of the fund-specified benchmark. The return index is set to 100 at the last day of the order.

Benchmark-adjusted returns around orders

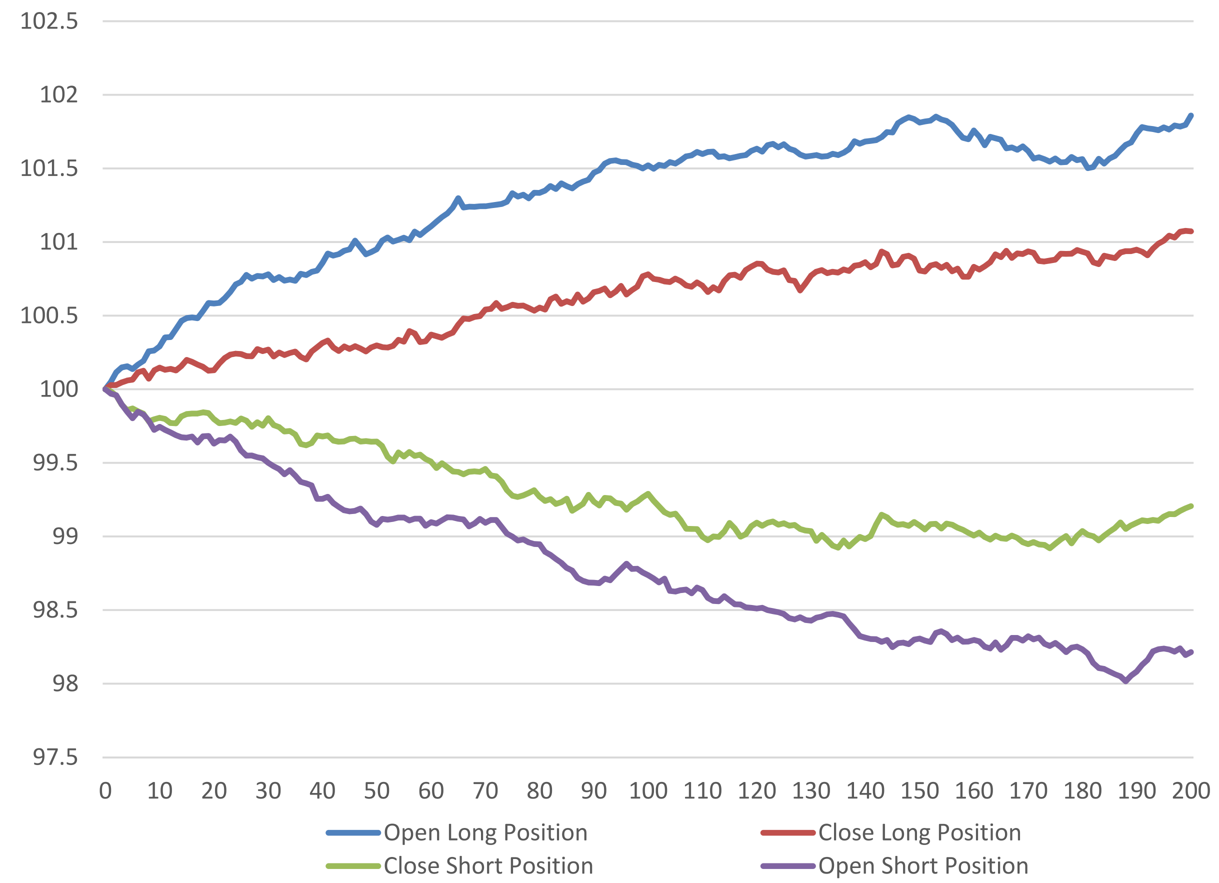


Table 1: Summary statistics

Panel A displays summary statistics by fund. *Number of Long (Short) Positions* is the average number of long (short) positions held by the fund. *Short Fraction* is the average fraction of short positions over total fund holdings (measured in USD). *Orders per Day* is the average number of orders executed per day. *Trade Fraction* is the average of the funds trading volume divided by the value of its holdings. *Total Asset Value* is the average dollar value of all open stock positions (long and short positions added together). *Positions per Stock* is the average number of times the fund establishes a position in a given stock. Panel B displays summary statistics by position. A position lasts from its opening (first buy for long positions or first sell for short positions) to its close (i.e., the moment the holding of the stock goes back to zero). *Length* is the average number of trading days for which the position remains open. *Number of Orders* is the average number of trading orders per position. *Number of Direction Changes* is the number of times the orders move from buy to sell orders or from sell to buy orders while the position is open. *Open Start* is a dummy variable equal to one if the position is open already at the time the fund enters the database. *Open End* is a dummy variable equal to one if the position is still open when the fund leaves the database. Panel C-E display summary statistics by order. We split the orders by whether they open a position, close a position or simply change the size of a position ("follow-up orders"). *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	1.63	1	1	3	1.58
USD Volume (million USD)	11.6	0.27	3.75	23.4	41.8
Size as Fraction of Largest Holding (%)	76.3	23.7	100.0	100	31.3
Observations	13759				

Panel D: Statistics by order – follow-up orders

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

Panel E: Statistics by order – closing orders

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

Table 2: Returns following the opening and closing of positions

This table examines returns following the opening of positions (Panel A and B) and the closing of positions (Panel C). We regress average returns following the order on a dummy variable whether the order is related to a short position. In Panels A and C, the dependent variable is the cumulative return expressed in percent for 60 and 125 trading days following the last day of the order. In Panel B, the dependent variable is the cumulative return from the last day of the opening order to the first day of the closing order (i.e., the holding period). In Panel B, we only include positions that are both opened and closed while the fund is in our sample. *Benchmark-adjusted return* is the return of the stock minus the return of the fund-specified benchmark. *DGTW return* is the return of the stock minus the average return of a portfolio sorted by region, size, book-to-market and momentum. *Four-factor alpha* is the alpha according to the Carhart (1997) model estimated at the regional level. Details on variable constructions can be found in Appendix A. We include fund fixed effects and month fixed effects (based on the month of the last day of the order). All standard errors are two-way clustered by stock and last date of order. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Panel A: Returns following the opening of positions

Dependent Variable:	Benchmark-Adj. Return t+1, t+60	Benchmark-Adj. Return t+1, t+125	DGTW Return t+1, t+60	DGTW Return t+1, t+125	4-Factor Alpha t+1, t+60	4-Factor Alpha t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Long Position)	1.81^{***}	2.41^{***}	1.57^{***}	1.90^{***}	1.57^{***}	2.03^{***}
	(6.53)	(5.44)	(5.99)	(4.76)	(5.72)	(4.82)
Observations	13759	13047	11753	11309	13053	12527
Adjusted R^2	0.06	0.08	0.04	0.05	0.03	0.04
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Cumulative holding-period returns

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

Panel C: Returns following the closing of positions

Dependent Variable:	Benchmark-Adj. Return t+1, t+60	Benchmark-Adj. Return t+1, t+125	DGTW Return t+1, t+60	DGTW Return t+1, t+125	4-Factor Alpha t+1, t+60	4-Factor Alpha t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Long Position)	0.66^{**}	1.29^{***}	0.38	1.04^{**}	0.46^{*}	0.89^{**}
	(2.34)	(2.89)	(1.37)	(2.48)	(1.68)	(2.08)
Observations	12432	11839	11078	10582	12299	11730
Adjusted R^2	0.07	0.10	0.04	0.06	0.04	0.05
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: Do hedge funds reallocate their capital optimally?

This table examines if hedge funds reallocate their capital optimally. In Panels A to C, we compare returns following the opening and closing of positions. We regress returns following the order on a dummy variable equal to one if it is an opening order. In Panel A, we only include orders related to long positions (i.e., long buys and long sells). In Panel B, we only include orders related to short positions (i.e., short sells and short buys). In Panel C, we include orders related to both long and short positions. In Panel C, the dependent variables are signed position returns (equal to the stock return for long positions and the stock return times minus one for short positions). The dependent variable is the cumulative return expressed in percent for 60 and 125 trading days following the last day of the order. In Panel D, we compare returns following the closing of positions to returns of positions that were kept open. For Panel D, the sample contains all positions a fund holds at the beginning of a day on which a position is closed (last day of order). The explanatory variable is a dummy variable equal to one if the position is kept open (not closed) on that day and zero otherwise. Details on variable constructions can be found in Appendix A. In Panels A to C, we include fund-portfolio-month fixed effects based on the month of the last day of the order (in Panel A and B they are equivalent to fund-month fixed effects because we include only the long or the short portfolio). In Panel D, we include fund-portfolio-date fixed effects (based on the last day of the order). All standard errors are two-way clustered by stock and last date of order. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Panel A: Closed Positions vs. Opened Positions - Long Positions

Dependent Variable:	Benchmark-Adj. Return t+1, t+60	Benchmark-Adj. Return t+1, t+125	DGTW Return t+1, t+60	DGTW Return t+1, t+125	4-Factor Alpha t+1, t+60	4-Factor Alpha t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Position Opening)	0.56***	0.77**	0.69***	0.55**	0.47**	0.75***
	(2.76)	(2.52)	(3.96)	(2.25)	(2.45)	(2.83)
Observations	14141	13518	12008	11579	13602	13088
Adjusted R^2	0.12	0.15	0.11	0.14	0.10	0.12
Fund×Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes

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

Dependent Variable:	Benchmark-Adj. Return t+1, t+60	Benchmark-Adj. Return t+1, t+125	DGTW Return t+1, t+60	DGTW Return t+1, t+125	4-Factor Alpha t+1, t+60	4-Factor Alpha t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Position Opening)	-0.51**	-0.46	-0.63***	-0.46*	-0.56***	-0.46*
	(-2.36)	(-1.56)	(-3.12)	(-1.73)	(-2.65)	(-1.68)
Observations	12050	11368	10823	10312	11750	11169
Adjusted R^2	0.14	0.15	0.11	0.11	0.11	0.10
Fund×Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes

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

Dependent Variable:	Signed Benchmark-Adj. Ret. t+1, t+60	Signed Benchmark-Adj. Ret. t+1, t+125	Signed DGTW Ret. t+1, t+60	Signed DGTW Ret. t+1, t+125	Signed 4-Factor Alpha t+1, t+60	Signed 4-Factor Alpha t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Position Opening)	0.54***	0.63***	0.67***	0.51***	0.51***	0.62***
	(3.67)	(2.78)	(4.92)	(2.58)	(3.59)	(3.09)
Observations	26191	24886	22831	21891	25352	24257
Adjusted R^2	0.13	0.15	0.11	0.13	0.11	0.11
Fund×Portfolio×Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes

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

Dependent Variable:	Signed Benchmark-Adj. Ret. t+1, t+60	Signed Benchmark-Adj. Ret. t+1, t+125	Signed DGTW Ret. t+1, t+60	Signed DGTW Ret. t+1, t+125	Signed 4-Factor Alpha t+1, t+60	Signed 4-Factor Alpha t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Position not Closed)	0.43***	0.54**	0.38***	0.36*	0.38***	0.49**
	(2.86)	(2.18)	(3.21)	(1.91)	(2.83)	(2.18)
Observations	452907	452907	452907	452907	452907	452907
Adjusted R^2	0.12	0.14	0.07	0.09	0.07	0.09
Fund×Portfolio×Date F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Returns following the closure of positions – Split by position changes

This table examines whether returns following the closure of positions depend on changes in the number of positions of the fund. We run the same regression as in Table 2 Panel C but split the sample by whether the fund increased or decreased the number of open positions before the first day of the order. That is, for the different subsamples, we regress average returns following the closing order on a dummy variable whether the order is related to a short position. In Panel A, we split by change in number of positions in the 5 days prior to the order. In Panel B, we split by change in number of positions in the 10 days prior to the order. The dependent variable is the cumulative return expressed in percent for 125 trading days following the last day of the order. Details on variable constructions can be found in Appendix A. We include fund fixed effects and month fixed effects (based on the month of the last day of the order). All standard errors are two-way clustered by stock and last date of order. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Panel A: Split by change in number of positions relative to 5 trading days before

Dependent Variable:	Benchmark-Adj. Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	More Positions	Less Positions	More Positions	Less Positions	More Positions	Less Positions
	(1)	(2)	(3)	(4)	(5)	(6)
D(Long Position)	2.01***	0.65	1.73***	0.47	1.52**	0.39
	(3.10)	(1.12)	(2.87)	(0.86)	(2.45)	(0.68)
Observations	5279	6547	4757	5815	5228	6490
Adjusted R^2	0.10	0.10	0.06	0.06	0.05	0.05
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

Dependent Variable:	Benchmark-Adj. Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	More Positions	Less Positions	More Positions	Less Positions	More Positions	Less Positions
	(1)	(2)	(3)	(4)	(5)	(6)
D(Long Position)	1.69***	1.18**	1.48***	0.84	1.30**	0.72
	(2.82)	(1.99)	(2.66)	(1.48)	(2.28)	(1.25)
Observations	5683	6143	5134	5438	5627	6091
Adjusted R^2	0.10	0.10	0.07	0.05	0.06	0.04
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Returns following the closure of positions – Split by fund returns

This table examines whether returns following the closure of positions depend on the profitability of the fund before the order. We run the same regression as in Table 2 Panel C but split the sample by whether the fund had negative or positive returns before the first day of the order. That is, for the different subsamples, we regress average returns following the closing order on a dummy variable whether the order is related to a short position. In Panel A, we split by fund return in the 5 days prior to the order. In Panel B, we split by fund return in the 10 days prior to an order. The dependent variable is the cumulative return expressed in percent for 125 trading days following the last day of the order. Details on variable constructions can be found in Appendix A. We include fund fixed effects and month fixed effects (based on the month of the last day of the order). All standard errors are two-way clustered by stock and last date of order. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Panel A: Split by fund return over prior 5 trading days

Dependent Variable:	Benchmark-Adj. Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	Negative Fund Return	Positive Fund Return	Negative Fund Return	Positive Fund Return	Negative Fund Return	Positive Fund Return
	(2)	(1)	(4)	(3)	(6)	(5)
D(Long Position)	2.18***	0.62	1.59**	0.71	1.44**	0.46
	(3.21)	(1.17)	(2.42)	(1.40)	(2.21)	(0.90)
Observations	5213	6626	4665	5917	5180	6550
Adjusted R^2	0.11	0.09	0.07	0.05	0.05	0.05
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

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

Table 6: Returns following the closure of positions – Split by change in return volatility

This table examines whether returns following the closure of positions depend on changes in return volatility. We run the same regression as in Table 2 Panel C but split the sample by whether the fund experienced an increase or a decrease in return volatility. That is, for the different subsamples, we regress average returns following the closing order on a dummy variable whether the order is related to a short position. In Panel A, we measure return volatility as the sum of squared fund returns over the previous 20 trading days. In Panel B, we measure return volatility as the (position-weighted) average stock return volatility of all portfolio stocks, where the stock return volatility is defined as the sum of squared stock returns over the previous 20 trading days. In both cases, we compare our volatility measures to their values over a 20-day window before that. The dependent variable is the cumulative return expressed in percent for 125 trading days following the last day of the order. Details on variable constructions can be found in Appendix A. We include fund fixed effects and month fixed effects (based on the month of the last day of the order). All standard errors are two-way clustered by stock and last date of order. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Panel A: Split by change in fund return volatility over prior 20 trading days

Dependent Variable:	Benchmark-Adj. Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	Higher Volatility	Lower Volatility	Higher Volatility	Lower Volatility	Higher Volatility	Lower Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
D(Long Position)	1.82***	0.94	1.67***	0.71	1.28**	0.63
	(2.97)	(1.54)	(3.05)	(1.15)	(2.26)	(1.05)
Observations	5718	5721	5115	5103	5666	5681
Adjusted R^2	0.10	0.11	0.07	0.05	0.07	0.04
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

Dependent Variable:	Benchmark-Adj. Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	Higher Volatility	Lower Volatility	Higher Volatility	Lower Volatility	Higher Volatility	Lower Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
D(Long Position)	1.86***	0.75	1.64***	0.41	1.32**	0.39
	(3.07)	(1.22)	(2.80)	(0.70)	(2.24)	(0.67)
Observations	5835	5997	5252	5327	5790	5934
Adjusted R^2	0.09	0.11	0.06	0.06	0.05	0.06
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Returns following the closure of positions – Split by change in funding constraints

This table examines whether returns following the closure of positions depend on changes in (market-wide) funding constraints. That is, we run the same regression as in Table 2 Panel C but split the sample by whether the change in funding constraints is positive or negative. In Panels A and B, we split the sample by whether the TED spread, defined as the difference between the three-month LIBOR and the three-month T-bill interest rate, has increased or decreased over the prior 5 or 10 trading days. In Panels C and D, we split our sample by whether the HKM intermediary risk factor aggregated over the past 5 or 10 trading days is negative or positive. The HKM intermediary risk factor measures innovations to the capital ratio of financial intermediaries (He, Kelly and Manela (2016)). A negative risk factor implies lower capital ratios and thus higher risk. In Panels A and C, we split by changes over the 5 days prior to the order. In Panels B and D, we split by changes over the 10 days prior to the order. The dependent variable is the cumulative return expressed in percent for 125 trading days following the last day of the order. Details on variable constructions can be found in Appendix A. We include fund fixed effects and month fixed effects (based on the month of the last day of the order). All standard errors are two-way clustered by stock and last date of order. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

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

Dependent Variable:	Benchmark-Adj. Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	Higher TED Spread	Lower TED Spread	Higher TED Spread	Lower TED Spread	Higher TED Spread	Lower TED Spread
	(1)	(2)	(3)	(4)	(5)	(6)
D(Long Position)	1.94***	0.36	1.65***	0.23	1.17**	0.35
	(3.13)	(0.55)	(2.89)	(0.38)	(2.01)	(0.56)
Observations	6452	5111	5771	4565	6379	5078
Adjusted R^2	0.10	0.10	0.07	0.05	0.06	0.04
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

Dependent Variable:	Benchmark-Adj. Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	Higher TED Spread	Lower TED Spread	Higher TED Spread	Lower TED Spread	Higher TED Spread	Lower TED Spread
	(1)	(2)	(3)	(4)	(5)	(6)
D(Long Position)	2.46***	-0.32	1.89***	0.09	1.84***	-0.41
	(4.10)	(-0.47)	(3.39)	(0.14)	(3.28)	(-0.61)
Observations	6637	4882	5940	4355	6580	4833
Adjusted R^2	0.10	0.11	0.07	0.05	0.06	0.04
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

Dependent Variable:	Benchmark-Adj. Return t+1, t+125		DGTW Return t+1, t+125		4-Factor Alpha t+1, t+125	
Sample	Negative HKM Factor	Positive HKM Factor	Negative HKM Factor	Positive HKM Factor	Negative HKM Factor	Positive HKM Factor
	(2)	(1)	(4)	(3)	(6)	(5)
D(Long Position)	2.33***	0.45	1.24**	0.95*	1.54**	0.45
	(3.66)	(0.78)	(2.08)	(1.69)	(2.54)	(0.80)
Observations	5331	6380	4787	5678	5284	6318
Adjusted R^2	0.11	0.09	0.06	0.06	0.05	0.05
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

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

Table 8: Hedge fund trading and earnings surprises

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

Dependent Variable:		SUE$_{IBES}$			SUE$_{Worldscope}$	
	(1)	(2)	(3)	(4)	(5)	(6)
HF imbalance$_{[5,20]}$	0.0583**	0.0541**	0.0589**	0.0646***	0.0592**	0.0515**
	(2.55)	(2.36)	(2.23)	(2.71)	(2.48)	(2.03)
Stock Return$_{[5,20]}$		0.7857***	0.8430***		0.8882***	0.9204***
		(5.91)	(5.92)		(6.57)	(6.65)
Turnover$_{[5,20]}$		-0.1817	-0.2867**		-0.0024**	-0.0029***
		(-1.53)	(-2.26)		(-2.46)	(-3.85)
Firm size			-0.0827**			-0.1516***
			(-2.37)			(-7.02)
#Analysts			-0.0270			-0.1102***
			(-1.51)			(-8.98)
Leverage			0.2136*			-0.2157**
			(1.77)			(-2.46)
Market-to-book			-0.0008			0.0006
			(-1.34)			(0.70)
Observations	83414	83414	63431	110033	110033	77080
Adjusted R^2	0.09	0.10	0.09	0.03	0.04	0.04
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

This table studies the post-trade returns for follow-up orders (i.e., all orders that neither open nor close a stock position). We regress returns following the order on a dummy variable equal to one if it is an order that increases the position (i.e., long buys and short sells). In Panel A, we only include orders related to long positions (i.e., long buys and long sells). In Panel B, we only include orders related to short positions (i.e., short sells and short buys). In Panel C, we include orders related to both long and short positions. In Panel C, the dependent variables are signed position returns (equal to the stock return for long positions and the stock return times minus one for short positions). The dependent variable is the cumulative return expressed in percent for 60 and 125 trading days following the last day of the order. Details on variable constructions can be found in Appendix A. We include fund-portfolio-month fixed effects based on the month of the last day of the order (in Panel A and B they are equivalent to fund-month fixed effects because we include only the long or the short portfolio). All standard errors are two-way clustered by stock and last date of order. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Panel A: Position Increase vs. Position Decrease - Long Positions

Dependent Variable:	Benchmark-Adj. Return t+1, t+60	Benchmark-Adj. Return t+1, t+125	DGTW Return t+1, t+60	DGTW Return t+1, t+125	4-Factor Alpha t+1, t+60	4-Factor Alpha t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Position Increase)	-0.04	0.19	0.06	0.16	0.04	0.28
	(-0.23)	(0.79)	(0.43)	(0.80)	(0.27)	(1.27)
Observations	41808	39677	34720	33338	40074	38452
Adjusted R^2	0.12	0.15	0.11	0.14	0.10	0.13
Fund×Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes

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

Dependent Variable:	Benchmark-Adj. Return t+1, t+60	Benchmark-Adj. Return t+1, t+125	DGTW Return t+1, t+60	DGTW Return t+1, t+125	4-Factor Alpha t+1, t+60	4-Factor Alpha t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Position Increase)	-0.16	-0.27	-0.05	-0.32	-0.30	-0.35
	(-0.81)	(-0.95)	(-0.27)	(-1.19)	(-1.60)	(-1.23)
Observations	20694	19377	18310	17353	20082	18946
Adjusted R^2	0.16	0.17	0.13	0.15	0.11	0.11
Fund×Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes

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

Dependent Variable:	Signed Benchmark-Adj. Ret. t+1, t+60	Signed Benchmark-Adj. Ret. t+1, t+125	Signed DGTW Ret. t+1, t+60	Signed DGTW Ret. t+1, t+125	Signed 4-Factor Alpha t+1, t+60	Signed 4-Factor Alpha t+1, t+125
	(1)	(2)	(3)	(4)	(5)	(6)
D(Position Increase)	0.03	0.22	0.06	0.22	0.13	0.30*
	(0.25)	(1.19)	(0.52)	(1.34)	(1.10)	(1.74)
Observations	62502	59054	53030	50691	60156	57398
Adjusted R^2	0.14	0.16	0.12	0.15	0.11	0.13
Fund×Portfolio×Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Comparing factor loadings to other hedge fund databases

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

Panel A: Fung and Hsieh 8 Factor Model

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

Panel B: Carhart 4 Factor Model

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

Table 11: Testing for backfill bias

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

Panel A: Raw Returns

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

Panel B: Benchmark-Adjusted Returns

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

Appendix A: Variable definitions

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

Variable Name	Definition
Benchmark-Adjusted Return	$Stock\ Return - \ Benchmark\ Return$
Stock Return	Return in USD from Datastream or Analytics.
Benchmark Return	USD return of the benchmark specified by the fund. The benchmark is specific for the fund, but is the same for both long and short positions of the fund. Data is provided by Analytics.
DGTW Return	$Stock\ Return - \ Return\ of\ portfolio\ of\ similar\ stocks$ Similar stocks are stocks in the same quintile of market capitalization, book-to-market ratio and past 12 month stock return within the same region. For more details see Internet Appendix A.
4-Factor Alpha	$r_{c,t} - r_{f,t} - \beta_m * (r_{m,t} - r_{f,t}) - \beta_{HML} * HML_t - \beta_{SMB} * SMB_t - \beta_{MOM} * MOM_t$ For more details see Internet Appendix A.
Signed Benchmark-Adj. Return	Benchmark-adjusted return for long positions and benchmark-adjusted return multiplied by minus one for short positions.
Signed DGTW Return	DGTW return for long positions and DGTW return multiplied by minus one for short positions.
Signed 4-Factor Alpha	Four-factor alpha for long positions and 4-factor alpha multiplied by minus one for short positions.
D(Long Position)	Dummy variable equal to one if the order is related to a long position (i.e., a long buy or a long sell) and zero if it is related to a short position (i.e., a short sell or a short buy).
D(Position Opening)	Dummy variable equal to one if the order is related to a position opening (i.e., a long buy or a short sell) and zero if the order is related to a position closure (i.e., a long sell or a short buy).
D(Position not Closed)	Dummy variable equal to one if the position is kept open and equal to zero if it is closed on that day.
D(Position Increase)	Dummy variable equal to one if a follow-up order increases a position (long-buy or short-sell) and equal to zero if it decreases a position (long-sell or short-buy).
Daily Fund return	Position-weighted average signed return of all positions of the fund, where the weight is the dollar value of the position. Daily stock-level returns are winsorized at 10% and -10%.
Daily Fund Benchmark-Adjusted Return	Position-weighted average signed benchmark-adjusted return of all positions of the fund, where the weight is the dollar value of the position. Daily stock-level benchmark-adj. returns are winsorized at 10% and -10%.
Daily Fund DGTW Return	Position-weighted average signed DGTW return of all positions of the fund, where the weight is the dollar value of the position. Daily stock-level DGTW return returns are winsorized at 10% and -10%.
Daily Fund 4-Factor Alpha	Position-weighted average signed 4-factor alpha of all positions of the fund, where the weight is the dollar value of the position. Daily stock-level 4-factor alphas are winsorized at 10% and -10%.
Fund return volatility[1,20]	$$\sum_{1}^{20} Daily\ fund\ return^2$$ 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. More specifically, He, Kelly, and Manela (2016) calculate aggregate dealer capital ratios as $$\eta_t = \frac{\sum_i Market\ Equity_{i,t}}{\sum_i (Market\ Equity_{i,t} + Book\ Debt_{i,t})}$$ and compute innovations in this variable using an AR(1) process $$\eta_t = \rho_0 + \rho\eta_{t-1} + u_t\ .$$ The risk factor is then defined as the growth rate of these innovations: $$HKM\ intermediary\ risk\ factor_t = \frac{u_t}{\eta_{t-1}}$$
SUE~IBES~	$$\frac{Actual\ Earnings_t - \ Median\ of\ analyst\ earnings\ forecast_t}{Standard\ Deviation_{\ t-8,t-1}(Actual\ Earnings_\tau - Median\ of\ analyst\ earnings\ forecast_\tau)}$$ 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	$\frac{Market\ value\ of\ equity\ (5\ days\ before\ earnings\ annoucement)}{Book\ value\ of\ equity\ (at\ the\ end\ of\ the\ previous\ quarter)}$
Equity Market Factor	The Standard & Poors 500 index monthly total return [Datastream code: S&PCOMP(RI)]
Size Spread Factor	Russell 2000 index monthly total return - Standard & Poors 500 monthly total return. [Datastream code: FRUSS2L(RI)]
Emerging Market Factor	MSCI Emerging Market index monthly total return [Datastream code: MSEMKF$(RI)]
Bond Market Factor	Monthly change in the 10-year U.S. treasury constant maturity yield (month end-to-month end)
Credit Spread Factor	Monthly change in the Moody's Baa yield less 10-year treasury constant maturity yield (month end-to-month end)
Bond Trend-Following Factor	Downloaded at https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm
Currency Trend-Following Factor	Downloaded at https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm
Commodity Trend-Following Factor	Downloaded at https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm
Fund volatility	Monthly standard deviation of daily fund returns. Volatility is set to missing when we have fewer than 15 non-missing daily return observations for a given month.
Global Market minus risk-free rate	Global market factor downloaded at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research
Global SMB	Global small minus big factor downloaded at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research
Global HML	Global high minus low book to market factor downloaded at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research
Global WML	Global momentum factor downloaded at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research
D(First 60 days in sample)	Dummy variable equal to one in the first 60 days that a fund is in our sample.
D(First 125 days in sample)	Dummy variable equal to one in the first 125 days that a fund is in our sample.
D(Last 60 days in sample)	Dummy variable equal to one in the last 60 days that a fund is in our sample.
D(Last 125 days in sample)	Dummy variable equal to one in the last 125 days that a fund is in our sample.

Appendix B: A simple hedge fund trading model

1) General setup

Time is discrete. In a given period t, a hedge fund has W_t units of capital and faces different investment opportunities: it can invest in a riskless asset with a net return of $r_f = 0$ or into N risky stocks that are all assumed to be uncorrelated with each other (and over time). Any stock i is either fairly priced or mispriced. If it is fairly priced, then its return from one period to the next is given by $r_{it} = \varepsilon_{it}$ where ε_{it} is a zero-mean noise term with variance σ_t^2 (constant for all i).[25] 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.[26] 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.[27]

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:

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

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

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

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

[25] 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.

[26] 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.

[27] 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.[28] 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

[28] 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.[29] 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

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

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*

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

[29] 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.[30] 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.[31] These rebalancing trades will typically result in a gradual downscaling of the position concomitant to the decay in alpha. Nevertheless, in our model, all rebalancing trades are followed by the same expected return, $\Delta(1-\delta)$. Thus, whether or not a rebalancing trade increases or decreases the position is uninformative about its future return.

4) Empirical predictions

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

In period *t*, the hedge fund closes all the N_{Bt-1} positions in stocks that become mispriced in *t-2* (because they stop being mispriced). In addition, the hedge fund may need to close some (and perhaps all) of its N_{At-1} positions in stocks that become mispriced in *t-1*. Specifically, out of the N_{At-1} positions, it will only want to hold on to N_{Bt} positions, where typically $N_{Bt} < N_{At-1}$.[32] Each of these prematurely closed positions is

[30] 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.

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

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

followed by a positive expected return ($\Delta(1-\delta)$). As such, the average return after closing trades in period t is given by $X_t\Delta(1-\delta)$, where X_t is defined as

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

Note that X_t is a fraction; i.e., $0 \leq X_t \leq 1$. 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.[33] 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. ■

---

[33] 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.[34] 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).

[34] See Lan, Wang, Yang (2013) for a model of hedge fund leverage. However, their model does not feature multiple investment opportunities with alpha decay. Thus, it does not make any predictions about hedge funds' capital recycling which is at the core of our model.