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

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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 hedge funds exhibit skill in opening positions, but that they close their positions too early, thereby forgoing about one-third of the trades' potential profitability. We explain this behavior with the limits of arbitrage: hedge funds close positions early in order to reallocate their capital to more profitable investments and/or to accommodate tightened financial constraints. Consistent with this view, we document that hedge funds leave more money on the table after opening new positions, negative returns, or increases in funding constraints and volatility. (*JEL* G11, G12, G14, G15)

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

—Lee Ainslee III, quoted from Pedersen (2015)

Fundamental trading, that is, trading on information acquired through fundamental research, resembles arbitrage: while "standard" (relative-value) arbitrage exploits price discrepancies between (almost) identical assets, "fundamental arbitrage" exploits the difference between an asset's market price and its fundamental value. Like other forms of arbitrage, fundamental trading is crucial for price efficiency. Indeed, without it, prices could be far away from fundamentals even though they might look "right" relative to each other.[1] While several papers have studied relative-value arbitrage (e.g., Pontiff 1996; Gagnon and Karolyi 2010; Fleckenstein, Longstaff, and Lustig 2014), we know very little about fundamental trading—about its constraints, how severe they are, and how they affect actual trading behavior. Indeed, fundamental arbitrage opportunities are notoriously difficult to observe, and fundamental investors are secretive in trading on them, making it difficult to identify the limits of fundamental arbitrage in practice.

In this paper, we conduct the first detailed study on the limits of fundamental arbitrage by exploiting a rich proprietary transaction data set for a sample of 21 hedge funds over a 10-year period.[2] Two features make the data uniquely suitable for our purpose. First, it exclusively covers discretionary long-short equity hedge funds, which routinely undertake independent long and short investments ("directional bets"), making them archetypical fundamental arbitrageurs. Second, our data comprise the funds' *entire equity trading histories as well as daily position updates*, allowing us to exactly pinpoint the dates when they enter and close their arbitrage positions. This level of detail is crucial: By studying post-opening returns, we confirm that our sample hedge funds are skilled fundamental traders. By studying post-closure returns, we gain insight into the nature and severity of their constraints. Indeed, we argue that, as suggested by Lee Ainslee III's quote above, constrained fundamental arbitrageurs close stock positions early in order to redeploy their scarce capital into other, more profitable opportunities.[3] This

1 See Brunnermeier (2005) and Weller (2018) on the importance of fundamental arbitrage vis-à-vis standard (relative-value) arbitrage.

2 Given their secretive nature, large micro-level data sets describing hedge funds' trading behavior do not exist (one exception is the ANcerno data set, which also includes some hedge funds; in Internet Appendix B.1, we show that these data lack the detail needed for our analysis; see also footnote 5). Other small-sample studies on institution investors have made important contributions to the literature. For example, Keim and Madhavan (1997) use data on 21 institutional investors, while Ang, Gorovyy, and van Inwegen (2011) use data from a single fund of funds and Geczy, Musto, and Reed (2002) use data from a single equity lender.

3 In Internet Appendix F, we formally make this argument by solving a trading model in which an informed but risk-constrained investor decides how to allocate his capital over different investment opportunities that exhibit

makes forgone profits from prematurely closed arbitrage positions a gauge that allows us to quantify the severity of arbitrage constraints.

We find that the long-short equity hedge funds in our sample behave like informed but constrained fundamental investors. Specifically, we show that their openings of long and short positions are followed by significant four-factor alphas with an absolute magnitude of about 1% over the next 125 trading days, suggesting that these hedge funds are skilled. When measured over the holding period (i.e., from opening to close), the difference in four-factor alpha between long and short positions amounts to 2%. In stark contrast, we find that closing trades are followed by 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 four-factor alpha of about 0.9% over the next 125 trading days. This figure implies that the hedge funds in our sample forgo about one-third ($\approx$0.9%/(2%+0.9%)) of the trade's potential profitability. We thus establish that the constraints faced by long-short equity hedge funds are economically important as they force them to "leave substantial money on the table."

Early position closures arise from the limits of arbitrage in a world in which investment opportunities exhibit alpha decay: as the expected profitability of an existing position declines, new trading opportunities become more attractive. This triggers a reallocation of the funds' limited risk capital into these more profitable opportunities, explaining why hedge funds close positions that continue to generate alpha going forward. An immediate implication of our argument is that, at any point in time, the profits from newly opened positions should exceed the profits from older existing positions, which should in turn exceed the forgone profits from closed positions. We test and confirm these predictions in our data: over the next 125 trading days, the forgone alphas from closed positions are 0.4% lower than the alphas of positions held by the same fund at the same point in time that are not closed; and they are 0.6% lower than the alphas of newly opened positions.

Having established that hedge funds profitably reallocate their capital across positions, we next investigate the nature of the constraints that give rise to this behavior. To this end, we conduct multiple sample splits for the trading strategy built around hedge funds' closing trades, that is, 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 experience a tightening of funding constraints. First, financial constraints should tighten when hedge funds face higher opportunity costs in the form of new trading opportunities. Indeed, we find that our sample hedge funds forgo

"alpha decay" (i.e., returns that dissipate over time). We will discuss the underlying assumptions and intuitions of the model in Section 1.

substantially more return after an increase rather than after a decrease in the number of open positions. Next, we conduct sample splits based on past returns for the specific stock and the rest of the hedge fund's portfolio. We find that in both cases funds leave more money on the table after negative returns. Interestingly, this effect is slightly stronger for past returns of the specific stock, suggesting that hedge funds' financing constraints operate both at the fund *and* at the position level. Finally, we examine a split by fund flows over the prior month as redemption risk is considered an important limit to arbitrage (Shleifer and Vishny 1997). We only find a modest difference in this sample split, suggesting that long-short equity hedge funds successfully mitigate redemption risk, presumably by means of advance notice periods and/or holding cash buffers.

Our next set of sample splits investigates whether certain fund characteristics are associated with larger forgone post-closing returns. We start by examining leverage as a direct measure of the severity of hedge funds' financial constraints. We find that highly levered funds leave more money on the table, thereby providing micro-level evidence in support of theories of financially constrained arbitrage (e.g., Gromb and Vayanos 2002; Brunnermeier and Pedersen 2009). Next, we analyze two characteristics—a fund's track record and portfolio liquidity—that can help alleviate financial constraints stemming from agency frictions (e.g., Kreps et al. 1982; Hart and Moore 1994). Consistent with this argument, we find that funds engage in fewer premature position closures if they have a longer track record, a more successful track record, or more liquid assets. We then test a recent idea by Gupta and Sachdeva (2018): hedge funds with high inside ownership (by their managers) may not want to dilute the returns on this inside capital and may thus be reluctant to raise additional equity capital from investors. We indeed find that hedge funds with high inside capital leave more money on the table, in line with these funds choosing to operate on a smaller scale.

Our results on leverage hint at the importance of debt as a funding source for hedge funds. To corroborate this view, we conduct several sample splits by changes in marketwide funding constraints in the financial intermediary sector. Using four different measures of funding constraints (the TED spread, the He, Kelly, and Manela (2017) intermediary risk factor, VIX, and primary dealer stock returns), we consistently find that hedge funds leave more money on the table after marketwide funding constraints tighten. Overall, our results suggest that, for the hedge funds in our sample, funding constraints feeding through the lending channel appear to be more important than equity outflows.

We then move on to study the role of risk for explaining early position closures. If hedge funds operate under a risk constraint, we would expect them to close positions earlier after an increase in volatility and this is indeed what we find. We also examine whether hedge funds pay particular attention to industry risk exposures or a specific position's contribution to overall portfolio risk. We find that post-closure returns are larger for stocks in industries to which the hedge fund recently increased its exposure, as well as for stocks that contribute positively to portfolio risk. These findings suggest that hedge funds use sophisticated risk management strategies to guide their position closure decisions.

To summarize, we find that our hedge funds' opening trades are profitable, but that they close their positions prematurely in response to tightened constraints. We provide an in-depth study of the sources of these constraints and show that they are related to both fund-specific characteristics and market-wide funding squeezes and that both cash flow shocks (such as negative returns) and changes in volatility matter. We also show that the emergence of new investment opportunities, by raising the opportunity cost of capital, can constrain the trading in existing positions. To the best of our knowledge, we are the first to document this interdependence of trading positions, thereby providing support for recent multiasset models on the limits of arbitrage (e.g., Gromb and Vayanos 2018; Dow, Han, and Sangiorgi 2020). Moreover, 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 the limits of fundamental arbitrage are economically severe as they force hedge funds to forgo one-third of the potential profitability of their trades.

In supplementary analyses, we discuss the representativeness and potential biases of our data as well as alternative explanations for our results. 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 studied in 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 that our sample hedge funds rarely engage in popular relative-value arbitrage strategies, such as pairs trading or merger arbitrage, and that their trades predict subsequent earnings surprises. Hence, the long-short equity hedge funds in our sample behave as fundamental traders. Fourth, we show that our data are unlikely to be plagued by survivorship or back-filling bias. Fifth, 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. As such constraints are pervasive, we expect these qualitative results to generalize to the broader population. Finally, we entertain the possibility that our results, instead of being due to the limits of arbitrage, are driven by the disposition effect, biased beliefs, lack of skill, or price pressure effects in illiquid stocks. As we will argue in detail in the robustness section, neither of these alternative explanations is able to explain our collective results.

Our paper contributes to several strands of research. First and foremost, we contribute to the literature on the limits of arbitrage. Theoretical papers in this field have highlighted different channels as to why arbitrageurs may be forced to liquidate their positions (De Long et al. 1990; Shleifer and Vishny 1997; Kyle and Xiong 2001; Gromb and Vayanos 2002, 2018; Brunnermeier and Pedersen 2009; Acharya and Viswanathan 2011; Liu and Mello 2011).[4] We contribute by documenting how these frictions affect the trading activity of fundamental investors. We thereby complement existing empirical work that is mostly at the macro level and explores, for example, how liquidity, price dislocations, and risk premiums respond to aggregate funding shocks (Hameed, Kang, and Viswanathan 2010; Nagel 2012; Adrian, Etula, and Muir 2014; Pasquariello 2014; He, Kelly, and Manela 2017). Another strand focuses on how the 2007–2009 Financial Crisis has forced hedge funds to deliver and curb their liquidity provision (Ang, Gorovyy, and van Inwegen 2011; Khandani and Lo 2011; Aragon and Strahan 2012; Ben-David, Franzoni, and Moussawi 2012; Çötelioğlu, Franzoni, and Plazzi 2020). We contribute to this literature by providing evidence for the limits of arbitrage at the *transaction* level. Our study thereby offers a unique glimpse into the process by which hedge funds "recycle" their limited arbitrage capital, that is, how and when they close existing positions and redeploy their capital.

Our second contribution is 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.[5] 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 that long-short equity funds in our sample possess the skill to identify mispriced stocks, thereby complementing previous work that emphasizes hedge funds' role as liquidity providers (Aragon and Strahan 2012; Ben-David, Franzoni, and Moussawi 2012; Jylhä, Rinne, and Suominen 2014; Çötelioğlu, Franzoni, and Plazzi 2020; Jame 2018). 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 position openings in their sample do not predict long-term returns and that short positions are profitable only over the short-term (up to 5 trading days), suggesting that these hedge funds make the bulk of their profits from liquidity provision. Our data, while comprising fewer funds, is more

[4] See Gromb and Vayanos (2010) for a survey of the limits of arbitrage literature. See Pontiff (1996) for evidence of the noise trader risk channel in the realm of closed-end mutual funds.

[5] 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 (2009), Patton and Ramodarai (2013), Aragon and Martin (2012), Agarwal, Fos, and Jiang (2013), Bali, Brown, and Demirtas (2013), and Bali, Brown, and Caglayan (2011, 2012, 2014). For studies based on quarterly holdings, see Griffin and Xu (2009), Cao et al. (2018), and Grinblatt et al. (2020). For comprehensive surveys, see Agarwal, Mullally, and Naik (2015) or Getmansky, Lee, and Lo (2015).

comprehensive and 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.[6] We argue that our focus on (long-term) fundamental traders explains why we find different results for the long-term predictability of stock trades.

Third, we contribute to the literature on short selling. Several papers focus on the opening of short positions or the change in short interest and find that both predict future returns.[7] We contribute by examining the profitability of both the *opening* and *closing* of short positions. The only other paper examining returns following the closing of short positions is Boehmer, Duong, and Huszar (2018). Contrary to us, they show evidence of positive return predictability for closing trades. However, their analysis is based on the mandatory disclosure of very large positions and may thus be influenced by price impact and signaling effects.

Finally, we note that our paper is related to Di Mascio, Lines and Naik (2016), who study a transaction data set for a sample of long-only mutual funds from the same data provider. They focus on how mutual funds open and strategically build up their positions in order to limit price impact, whereas we focus on position closures and show how they relate to the limits of arbitrage. Notably, their findings for long-only mutual funds are consistent with ours. Indeed, they similarly find positive returns after both the opening and closing of long positions, but do not explain the latter.

1. Hypotheses

Discretionary long-short equity hedge funds resemble fundamental traders; that is, they take on a limited number of long and short bets on individual stocks based on fundamental analyses. 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 [forthcoming]). Given the novelty and granularity of our data, our performance analysis constitutes a valuable contribution in its own right. The focus of our analysis, however, lies on studying hedge funds' position closures. Indeed, we argue that the returns following position closures are particularly revealing about the nature and severity of

6 In Internet Appendix B.1, we describe in detail why the ANcerno data are not suitable for the purpose of studying the limits of fundamental arbitrage. First, we show that the hedge funds in ANcerno, unlike the funds in our data, are not representative of long-short equity funds in terms of portfolio size and average holding period. Second, we demonstrate the impossibility of accurately measuring the timing of hedge funds' position openings and closings with the ANcerno data; thus, these data are ill-suited for our 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), and Engelberg, Reed, and Ringgenberg (2012).

hedge funds' arbitrage constraints. We review—and ultimately dismiss—alternative interpretations for post-closing returns in Section 5.

To understand why position closures are driven by arbitrage constraints, we develop in Internet Appendix F a simple trading model in which a hedge fund (1) faces a risk constraint, (2) incurs position monitoring costs, and (3) new investment opportunities exhibit alpha decay. These assumptions are realistic and enjoy empirical support. Alpha decay, that is, a declining profitability of available trading opportunities, arises naturally in models of informed trading with multiple speculators (Foster and Viswanathan 1996; Back, Cao, and Willard 2000; Bernhardt and Miao 2004) and appears in our data (Internet Appendix E.1) as well as elsewhere (Chen, Da, and Huang 2016; Di Mascio, Lines, and Naik 2016). The risk constraint captures, in a simplified way, common risk management practices, such as risk parity investment (see Pedersen 2015).[8] A straightforward implication of this constraint is that position sizes are inversely related to changes in portfolio volatility; a prediction that we confirm empirically (Internet Appendix E.2). The position monitoring cost represents a fixed attention cost for monitoring a given position (the hedge fund may want to check, for example, whether the trading signal that induced the opening of the position is still valid after the arrival of new information).[9] A natural implication of this assumption is that larger funds have more open positions; a prediction that we again verify in the data (Internet Appendix E.3).

Our model predicts that hedge funds trade off diversification benefits with position monitoring costs: because hedge funds do not want to spread their limited capital too thinly, they close existing stock positions even though they are still expected to be profitable when more promising investment opportunities arrive.[10] Put differently, we expect our hedge funds to reallocate their capital efficiently; that is, we expect newly opened positions (or positions that are kept open) to be followed by higher risk-adjusted returns than closed positions.

In follow-up analysis, we carefully dissect forgone post-closing returns in order to shed light on the question where the limits of arbitrage ultimately come from. The predominant view in the literature emphasizes the importance of *financial constraints* for understanding why arbitrage is limited (for a survey, see, e.g., Gromb and Vayanos 2010). Our model predicts that a

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[8] In our model described in Internet Appendix F, the risk constraint can also be understood as a shorthand for a leverage or a funding constraint as in Gromb and Vayanos (2002, 2018).

[9] Alternatively, our fixed monitoring cost can be seen as a placeholder for any other fixed cost or incentive to limit the number of positions (coming from, e.g., the information acquisition technology; see Van Nieuwerburgh and Veldkamp 2010).

[10] Because of alpha decay, hedge funds should prefer to close an existing position early rather than to delay opening a new one. Moreover, even if opening delays do occur, they will be difficult to identify empirically as it is always possible that a position was not opened because hedge funds were not aware of a given arbitrage opportunity. This concern is not relevant for position closures. After all, hedge funds must have been aware of the opportunity at the time they opened the position.

tightening of financial constraints forces hedge funds to close their positions earlier, thereby leading to higher forgone post-closing returns. We therefore predict that hedge funds leave more money on the table after negative past fund (or position-level) returns, fund outflows, and increases in funding costs for hedge funds' prime brokers.

A deeper question is why hedge funds fail to raise the capital that would allow them to exploit all the alpha potential in their positions. Here, the literature commonly points to agency frictions. For example, in Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009) moral hazard concerns are assumed to force arbitrageurs to collateralize their positions, effectively constraining their ability to raise capital. In this spirit, we expect hedge funds to leave more money on the table when agency frictions are more severe (e.g., when their leverage is high, their reputation is low, and or when their assets are less liquid). A complementary point of view is proposed by Gupta and Sachdeva (2018). They argue that there is an important difference between inside and outside equity capital. To see this, consider a market for delegated asset management in which managerial skill is in short supply, investment opportunities exhibit decreasing returns to scale, and outside investors—if drawn on—competitively allocate their capital to fund managers. Without inside capital, managers just want to grow their funds up to the point at which outside investors earn zero returns after fees. With inside capital, managers may instead choose a smaller fund size in order to avoid diluting the return on this capital. Gupta and Sachdeva (2018) find strong support for this idea in the cross-section of hedge fund returns.[11] Taking this argument to the trade level, we predict that hedge funds with high inside capital display a larger shadow cost of capital as indicated by higher (forgone) post-closing returns.

Concerns for risk are another important driver of position closing decisions. Specifically, our model implies that, when portfolios become more volatile, hedge funds must downscale their positions in order to satisfy the risk constraint. Because of the fixed monitoring costs, this downscaling leads to additional position closings and thus to larger forgone post-closing returns. In addition, we expect hedge funds to close earlier positions with a large contribution to overall portfolio risk and/or after increases in the position's industry risk exposure.

[11] Specifically, Gupta and Sachdeva (2018) explore data on inside ownership gleaned from SEC form ADV filings and find that hedge funds with high inside ownership exhibit a lower flow-performance sensitivity (suggesting that these funds are more reluctant to accept outside capital) and deliver higher and more persistent risk-adjusted returns.

2. Data and Variable Construction

2.1 Analytics data

Our data on long-short equity hedge funds is provided by Inalytics Ltd., a company that provides portfolio monitoring services for institutional asset owners as well as consulting services for asset managers. Inalytics mostly works with long-only equity mutual funds, and this data has been previously studied in Di Mascio, Lines and Naik (2016). In addition, Inalytics has obtained data from a small number of long-short equity hedge funds, and we are the first to obtain and work with this data.

A hedge fund can enter our database in two ways: either the hedge fund submits its trading data directly to Inalytics to obtain feedback on and verification of its trading performance or an institutional client, for example, 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 carefully verifies the data for accuracy.

Our data set covers the years 2005 to 2015 and contains *complete* trading and holding information for the equity portfolios of 21 distinct hedge funds, allowing us to precisely track their long and short stock positions over time. This ability to precisely identify hedge fund trades is a unique feature of our data and crucial for our analyses.[12] Specifically, we have access to two data sets: The first is a transaction-level data set containing all trades. Variables in this data set include stock identifiers (ISIN, SEDOL, and CUSIP), the date of the trade, the number of shares traded, and the execution price. The second data set consists of each funds' portfolio holdings at the stock-day-level. This data set 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 (e.g., using index options).[13] Thus, their equity trades likely offer a comprehensive reflection of the fundamental bets that they engage in.

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[12] The data that come 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 inventory positions is thus very noisy, a fact that we demonstrate in Internet Appendix B.1. Moreover, while our data are at the fund level, the ANcerno data are at the fund-family level. Consequently, we find that hedge fund portfolios in ANcerno are substantially larger and not representative of the portfolios of long-short equity hedge funds (Internet Appendix B.1). Finally, prior work finds that hedge fund families in ANcerno make the most of their profits from short-term liquidity provision as opposed to long-term trading (Çötelioğlu, Franzoni, and Plazzi 2020; Jame 2018; Choi, Pearson, and Sandy 2016), which is again untypical behavior for long-short equity hedge funds.

[13] Aragon and Martin (2012) study derivative positions disclosed in 13F filings for a subsample of hedge fund management companies and find evidence of return predictability. However, as they note, "the raw required filings are at the level of the advisor and do not contain entire portfolios at the fund level. A single filing might,

We use a merged data set of holdings and trading data (details on merging these two data sets can be found Internet Appendix A). Institutional traders, such as hedge funds, often split their orders into several trades that are executed on different days to reduce the market impact of their orders (Keim and Madhavan 1995; Chan and Lakonishok 1995). To avoid double counting, we follow Di Mascio, Lines, and Naik (2016) and aggregate trades likely belonging to the same investment decision into orders. Specifically, we assume that trades belong to the same order if a hedge fund trades the same stock in the same direction and the distance between them is 2 trading days or less. Seventy-three percent of the orders comprise only one trading day, and we show in Internet Appendix D.9 that our results are robust to not aggregating trades into orders.

2.2 Summary statistics

Table 1, panel A, displays summary statistics by fund. Funds hold on average 50 long positions and 24 short positions (median values are 36 and 19). In terms of USD, short positions make up about 30% of the combined portfolio value, suggesting that the funds are not market neutral. Having a larger long than short portfolio is typical for long-short equity hedge funds (see, e.g., Fung and Hsieh 2011). Our funds conduct on average six orders per day. Compared to an average of 74 positions this corresponds to a new order per 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 US\$350 million in assets, while funds in the 10th and 90th percentiles range from US\$115 million to US\$6,400 million, respectively. 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 US\$164 million of assets under management, which is slightly above the 75th percentile of the size distribution in the Lipper TASS database (see Lim, Sensoy, and Weisbach 2016).

Figure 1 charts the investment areas for our funds. We have 7 European-, 3 U.S.-, 3 U.K.-, and 2 Australian-focused funds, as well as 6 funds that invest worldwide. In line with their investment focus, funds mainly invest in North America, Europe, and Australia (included in Asia-Pacific). The EME and Japanese regions both make up less than 1% of the sample. Additional descriptive statistics are provided in Internet Appendix B, where we compare Analytics to Ancerno data, report summary statistics for each individual fund, and document that funds overweigh large companies in their portfolios, similar to other institutional investors (e.g., Lee, Shleifer, and Thaler 1991).

therefore, correspond to several hedge funds with different strategies under management and even by mixed with mutual funds" (p. 438).

Table 1.
Summary statistics

A. Averages by fund

Variable	Mean	10^{th} percentile	Median	90^{th} percentile	SD
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				

B. Statistics by position

Variable	Mean	10^{th} percentile	Median	90^{th} percentile	SD
Length (trading days)	104.4	4	35	275	188.9
Length of long positions (trading days)	126.3	5	44	337	219.8
Length of short positions (trading days)	77.4	4	27	198	137.0
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	16,241				

C. Statistics by order: Opening orders

Variable	Mean	10th percentile	Median	90th Percentile	SD
Number of trading days	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	13,759				

D. Statistics by order: Follow-up orders

Variable	Mean	10th percentile	Median	90th Percentile	SD
Number of trading days	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	62,502				

E. Statistics by order: Closing orders

Variable	Mean	10th percentile	Median	90th percentile	SD
Number of trading days	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	12,432				

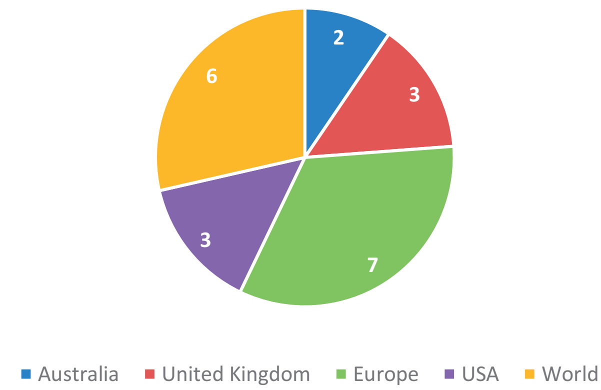
Panel A displays summary statistics by fund. *Number of long (short) positions* is the average number of long (short) positions held by the fund. *Short fraction* is the average fraction of short positions over total fund holdings (measured in USD). *Orders per day* is the average number of orders executed 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. *Length of long (short) positions* is the average number of trading days for which long (short) positions remain 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 trading days* is the average number of trading days 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.

Otherwise, they split their investments relatively evenly across different industries and value versus growth stocks.

Figure 2 displays gross fund profitability computed from portfolio holdings. Panel A shows the average fund profitability by year. We measure profitability as the position-weighted average signed return; that is, returns multiplied by -1 in case of a short position. Because most funds have more long than short positions, this profitability comoves with the market. The worst year is 2008, when equity markets worldwide crashed in the wake of the Lehman bankruptcy. In 2009, equity markets recovered, and our sample hedge funds experienced their best year. To get a better idea of their risk-adjusted performance, panel B shows average signed four-factor Carhart (1997) alphas. Our funds display positive signed four-factor alphas in every year of the sample, except 2008, suggesting that they exhibit persistent stock-picking skill.

Table 1, panel B, displays summary statistics by position. A position lasts from its opening (i.e., the first buy (sell) for long (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 two 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). For positions that are opened and closed during our sample period, the average position length amounts to 104 trading days (about half a year), suggesting that these hedge funds trade on long-term information. Long positions are kept open longer (126 trading days) than short positions (77 trading days). 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).

A Investment area of fund as specified by their benchmark



B Region of stocks held by funds (%)

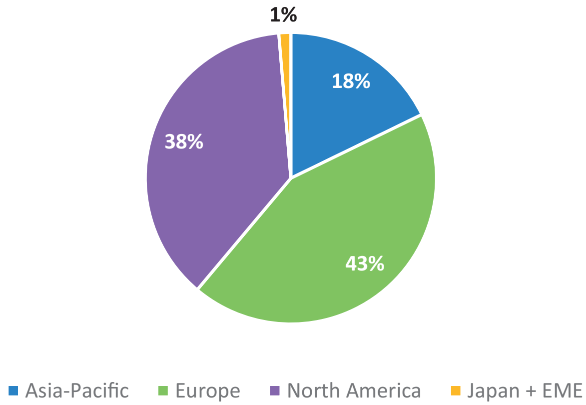


Figure 1.
Investment areas of funds
Panel A shows the investment areas of our sample of funds. We base these areas on their chosen benchmark, but verify that the funds indeed predominantly invest in these areas. Panel B depicts the regions of the stocks held by the funds. We compute this average over the number of positions over the entire sample period. Internet Appendix A.1 defines the regions.
(A) Investment area of fund as specified by their benchmark
(B) Region of stocks held by funds (%)

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 adjust the size of the position in between. Panels C to E display summary statistics for each type of order separately. When measured against the maximum position size, opening and closing orders are significantly larger than follow-up orders: while opening and closing orders on average make up around 77% of the maximum position size (median 100), follow-up orders make up only 15.5%

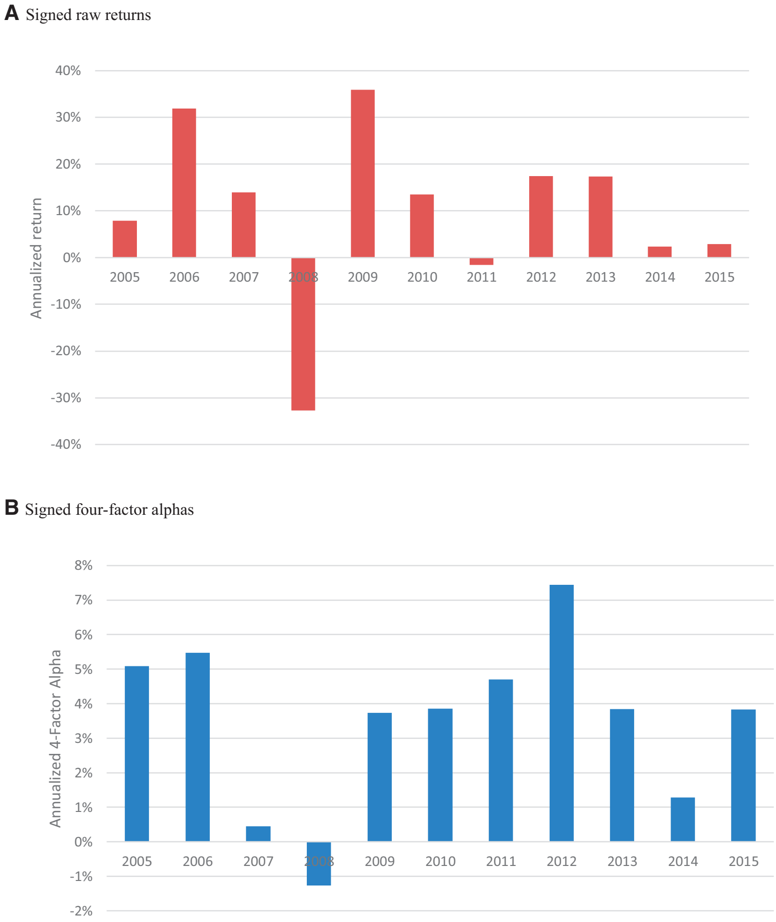


Figure 2.
Fund returns and alphas
This figure displays the fund returns and alphas by year. In panel A, we use raw returns. In panel B, we use four-factor alphas. Specifically, for each fund, we first compute the (position-weighted) daily average signed return of positions the fund holds (for panel B, we compute the daily average signed four-factor alpha 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 four-factor alphas are equal to the alpha according to the Carhart (1997) model estimated at the regional level for long positions and the four-factor alpha times minus one for short positions.
(A) Signed raw returns
(B) Signed four-factor alphas

(median 8.5%).[14] In our analyses, we focus on position opening and closing decisions, because the former are most likely to be driven by information while the latter allow us to precisely measure the forgone profits arising from

[14] In dollar terms, the difference between opening/closing and follow-up orders appears smaller. The reason is that larger positions are accompanied by more rebalancing trades; hence, the average dollar volume of rebalancing trades overweighs large positions.

early position closures.[15] Finally, we note that hedge funds do not split orders over multiple days very often: the average number of trading days per order is only about 1.6 (median 1) for each order type.

2.3 Datastream and Worldscope data

We obtain international stock return and balance sheet data from Datastream and Worldscope, respectively. We complement Datastream with stock return information provided by Analytics (this affects approximately 14% of our stocks).[16] To adjust returns for risk, we implement a regional version of the Carhart (1997) four-factor model. Following Karolyi and Wu (2014), we categorize stock markets into five regions (Japan, North America, Europe, Asia-Pacific, and Emerging Markets). The assignment of countries into regions is displayed in Internet Appendix A.1. We use a market factor, a High-minus-Low Book to Market Factor (HML), a Small-minus-Big (SMB) factor, and a Momentum (MOM) factor of winners minus losers. For America, Asia-Pacific, Europe, and Japan, we obtain daily factors from Kenneth French's website; for the emerging market region, we compute the factors ourselves (as detailed in Internet Appendix A.5).[17] We use the U.S. 1-month Treasury-bill rate as the risk-free rate. Returns and all other variables are measured in U.S. dollars.

For each stock and each month, we estimate betas by regressing daily excess returns on the regional factors over the past 12 months:

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

where $r_{c,t}$ is the daily company return, $r_{m,t}$ is the daily market return and $r_{f,t}$ is the daily risk-free rate. We only keep betas that are based on at least 50 days of nonmissing return data. As recommended by Levi and Welch (2016), we shrink the resultant beta estimates toward their cross-sectional mean:

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

for $j \in \{m, HML, SMB, MOM\}$ and where $\bar{\beta}_{j,t}$ is the equal-weighted average of $\beta_{j,t}$ estimated in stock c's region. We then compute daily alphas as

[15] Internet Appendix E.4 presents our analyses on follow-up orders.

[16] We show in Internet Appendix D.7 that our results are robust if we only use return data from Datastream.

[17] Our results are also robust to excluding the EME region completely; see Internet Appendix D.6. Furthermore, some stocks cannot be assigned to a region. In this case, we compute alphas relative to the global factors provided by Kenneth French, but we show in Internet Appendix D.6 that our results are robust to excluding these stocks.

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

Finally, we winsorize four-factor alphas at the 1% level on both sides.

In Internet Appendix C, we show that our results are robust to using characteristics-adjusted returns following the methodology of Daniel, Grinblatt, Titman, and Wermers (1997). In Internet Appendix D.2, we further show that they are robust to using benchmark-adjusted returns with respect to the self-reported fund-specific benchmark.

2.4 Other data

For additional cross-sectional tests, we employ data from a variety of sources: we use fund flows, leverage, and track record from the HFR hedge fund database, and data on hedge funds' insider ownership from SEC form ADV. These data sources force us to work with a subset of our data (e.g., 14 of 21 funds in the case of HFR) as they rely on determining hedge funds' identities. In Internet Appendix A.9, we describe in detail our process of establishing hedge funds' identities in the Inalytics data.

3. Profitability Results

3.1 Profitability of opening and closing trades

As shown in Figure 2, our sample hedge funds are profitable on average. We now examine their trading skill in more detail. We start with a simple graphical analysis presented in Figure 3, in which we show cumulative four-factor alphas in the 125 trading days following opening or closing orders (as noted before, follow-up orders are excluded from our analysis). To be conservative, we always measure cumulative returns starting on the trading day following the last day of the order.[18]

Figure 3 reveals clear evidence of informed trading for position openings: in the first half-year (125 days) following the initiation of a long (short) position, cumulative benchmark-adjusted returns are slightly above (below) 1% (-1%).[19] Moreover, on both the long and the short side, most of these returns are realized in the first 60 trading days (3 months) following the opening order. In other words, the post-opening alphas (per unit of time) decay over time: they are highest immediately after the position is established and

[18] In Internet Appendix D.8, we measure returns from actual transaction prices and show that this only strengthens our results.

[19] This number may seem small given that the average of yearly returns in Figure 2, panel B, is 3.5%. This difference is driven by two facts. First, the number of orders per year does not stay constant over time. Thus, a simple average over yearly values in Figure 2 is not representative for the whole sample. Second, many fund positions are kept open for less than 125 trading days and due to alpha decay the annualized returns over these shorter holding periods is much higher. For example, after 60 trading days, the average cumulative alpha is about 0.7%, which is 3.0% annualized.

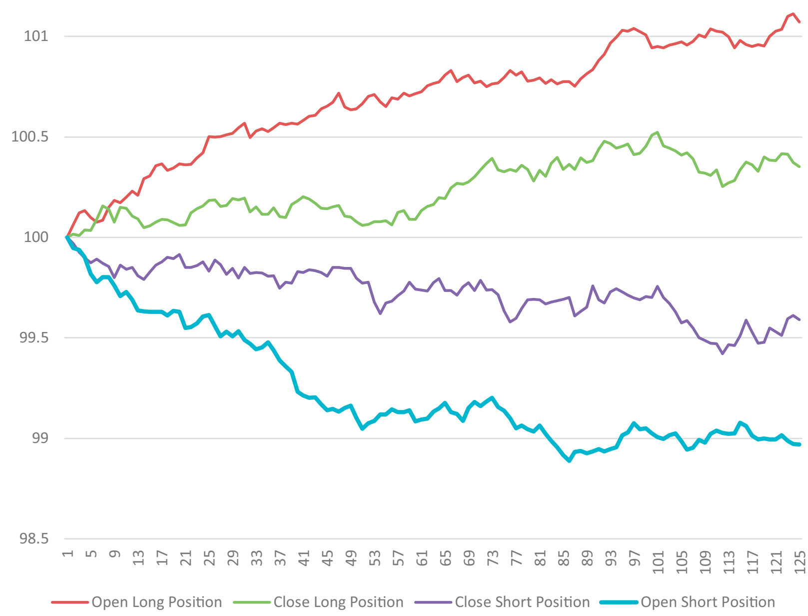


Figure 3.
Alpha following orders
This figure displays cumulative four-factor alphas for 125 trading days following orders that open or close a position. *Open long position* is the buy order establishing a long position ("long buy"). *Open short position* is the sell order establishing a short position ("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"). Four-factor alpha is the alpha according to the Carhart (1997) model estimated at the regional level. The return index is set to 100 at the last day of the order.

then gradually shrink as time progresses.[20] In contrast to position openings, closings of long and short positions do not seem to be informed. Long sells, for instance, are not followed by negative alphas, but rather by positive ones. In the 125 trading days following the closing of a long position cumulative four-factor alphas are about 0.5%. Similarly, the closing of a short position is followed by negative alphas of about -0.5% over 125 trading days.

Table 2, panel A, shows the results for a regression analysis of the significance of the return difference between long and short positions. Specifically, in columns 1 to 3, we focus on position openings and run a regression of four-factor alphas following the order on *D(Long position)*, a dummy variable equal to one if the order opens a long position (and zero if it opens a short position). In columns 1 and 2, we examine alphas for holding periods of 60 and 125 trading days, respectively. We choose these holding periods because they straddle the average holding period (see Table 1, panel B), and Figure 3 reveals that most of the trade profitability accrues in this time. We include

[20] We show further evidence of alpha decay in Internet Appendix E.1.

fund fixed effects to ensure that we compare long and short position openings by the same fund; we include month fixed effects to control for macroeconomic conditions. Standard errors are two-way clustered by stock and the last date of the order.

Given our specification, the coefficient estimate for the *D(Long position)* dummy can be interpreted as the return difference between long and short positions. This return difference is 1.6% over 60 days and 2.0% over 125 days and it is statistically significant at the 1% level. In column 3, we repeat the regression for holding-period alphas; that is, alphas from the day following the opening order to the day prior to the closing order. As noted before, this approach is conservative because it excludes within-order profits; results including within-order profits are even larger (Internet Appendix D.8). The difference in holding period four-factor alphas between long and short positions amounts to 2.0% and is significant at the 1% level.[21] These findings confirm that our sample hedge funds possess investment skill.

In Table 2, panel A, columns 4 and 5, we examine post-trade returns for closing orders using the same regression setup as in columns 1 and 2. We find that the four-factor alpha difference between closed long and closed short positions is again positive at 0.5% over 60 days and 0.9% over 125 days, significant at the 10% and 5% level, respectively. In Section 4, we will show that the post-closing return difference becomes substantially larger (and statistically more significant) when we focus on subsamples of constrained hedge funds.

In Table 2, panel B, we repeat our analysis after controlling for various stock characteristics. These controls address the concern that hedge funds open or close positions in response to past returns or changes in stock liquidity and/or volatility, and that these stock characteristics are responsible for the return predictability. The results show that the long-short return difference for opened and closed positions is barely affected by the inclusion of controls for past stock returns, share turnover, Amihud illiquidity, and return volatility (measured over the previous 60 trading days), perhaps because our left-hand-side variable (four-factor alphas) already controls for these effects. We therefore omit these controls in our subsequent analyses.

Taken together, our results imply that the hedge funds in our sample close their positions too early in the sense that they forgo a substantial fraction of the trade's potential profitability. Specifically, while long positions outperform short positions by about 2.9 percentage points (=2.0%+0.9%) from opening to 125 trading days after the close, we find that our hedge funds only capture about 68% (=2.0%/2.9%) of this return, implying that they leave a staggering 32% "on the table." This back-of-the-envelope calculation shows that early position closures are economically important.

[21] We confirm in Internet Appendix D.1 that we find similar predictability for the average returns during the holding period.

Table 2.
Returns following the opening and closing of positions

A. Difference between long and short positions

Sample:	Opening orders			Closing orders	
Dependent variable:	*Four-factor alpha t+1, t+60* (1)	*Four-factor alpha t+1, t+125* (2)	*Four-factor alpha (open-to-close)* (3)	*Four-factor alpha t+1, t+60* (4)	*Four-factor alpha t+1, t+125* (5)
D(Long position)	1.57***	2.03***	2.03***	0.46*	0.89**
	(5.72)	(4.82)	(6.17)	(1.68)	(2.08)
Observations	13,053	12,527	11,231	12,299	11,730
Adjusted R^2	.03	.04	.03	.04	.05
Fund fixed effects	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes

B. Difference between long and short positions, with added controls

Sample:	Opening orders			Closing orders	
Dependent variable:	*Four-factor alpha t+1, t+60* (1)	*Four-factor alpha t+1, t+125* (2)	*Four-factor alpha (open-to-close)* (3)	*Four-factor alpha t+1, t+60* (4)	*Four-factor alpha t+1, t+125* (5)
D(Long position)	1.59***	2.13***	1.98***	0.51*	1.04**
	(5.71)	(4.98)	(6.10)	(1.81)	(2.38)
Return (past 60 days)	−0.72	−0.94	−0.37	0.46	0.05
	(-0.57)	(-0.57)	(-0.29)	(0.40)	(0.03)
Turnover (past 60 days)	−26.11	21.79	20.41	27.96	49.91
	(-1.04)	(0.55)	(0.74)	(1.16)	(1.12)
Illiquidity (past 60 days)	−0.00	−0.00**	−0.00***	−0.00	−0.00
	(-1.15)	(-2.12)	(-2.76)	(-0.22)	(-0.59)
Volatility (past 60 days)	546.91	911.62	−459.25	−178.33	162.12
	(1.06)	(1.19)	(-0.95)	(-0.30)	(0.20)
Observations	12,312	11,809	10,489	11,593	11,034
Adjusted R^2	.04	.04	.03	.04	.05
Fund fixed effects	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes

This table examines returns following opening and closing orders. In panel A, we regress average four-factor alphas following the order on a dummy variable whether the order is related to a long position. In panel B, we add additional controls for past stock returns, share turnover, Amihud illiquidity, and return volatility (measured over the past 60 trading days). In columns 1 to 3, we include only opening orders. In columns 4 and 5, we include only closing orders. In columns 1, 2, 4, and 5, the dependent variable is the cumulative four-factor alpha expressed as a percentage for 60 and 125 trading days following the last day of the order. In column 3, the dependent variable is the cumulative alpha from the day after the last day of the opening order to the day before the first day of the closing order (i.e., the holding period). We include fund fixed effects and month fixed effects (based on the month of the last day of the order). Details on variable constructions can be found in Table A1 in the appendix. All standard errors are two-way clustered by stock and the last date of the order. We report t-statistics below the coefficients in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

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

3.2 Profitable capital reallocation

We argue that early position closures arise because constrained hedge funds want to free up capital in order to invest in 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. We test this prediction in Table 3, panel A.

Specifically, in columns 1 and 2, we regress post-opening and post-closing returns on *D(Position Opening)*, a dummy variable that takes the value one for opening orders and zero otherwise. We use *signed* four-factor alphas as the dependent variable, which are defined as alphas for long positions and minus one times alpha for short positions. Hence, for both long and short positions, a larger value implies a larger profitability. By including fund-portfolio-month fixed effects, we compare openings and closures undertaken by the same fund, on the same side of the portfolio (long or short), and in the same month; that is, when it is likely that the closure provided the capital for the new position opening. We find a significantly positive coefficient of about 0.5%–0.6% for *D(Position opening)*, implying that newly opened positions are indeed more profitable than existing positions that are closed within the same month.

In columns 3 and 4 of panel A, we complement our regression approach with an even finer matching analysis. Specifically, we match every position closing with position openings by the same fund between the *first* day of the closing order and up to *3* trading days after the last day of the closing order. We show the average return difference between matched openings and closings for the following 60 and 125 trading days, respectively. Newly opened positions outperform recently closed positions by 0.65% (0.65%) over the next 60 (125) trading days. The fact that our results get slightly stronger as we tighten the time link between openings and closings confirms that hedge funds redeploy their capital profitably.

In panel B, we repeat our analysis after adding large position increases and decreases to our sample of opening and closing orders. We define large positions increases (decreases) as orders that at least double (halve) a position. The premise is that the capital freed up by large position decreases could be used to open or substantially increase a more profitable position. For both the regression analysis (columns 1 and 2) and the matching analysis (columns 3 and 4), we again find strong evidence for profitable capital reallocation by hedge funds: position-increasing orders are followed by 0.5%–0.6% larger

Table 3.
Do hedge funds reallocate their capital optimally?

A. Position opening versus closing

Regression analysis			Matching analysis [0, 3]	
Dependent variable:	*Signed four-factor alpha t+1, t+60* (1)	*Signed four-factor alpha t+1, t+125* (2)	*Mean difference in signed four-factor alpha t+1, t+60* (3)	*Mean difference in signed four-factor alpha t+1, t+125* (4)
D(Position opening)	0.51***	0.62***	0.65***	0.65**
	(3.59)	(3.09)	(3.22)	(2.05)
Observations	25,352	24,257	10,044	9,540
Adjusted R^2	.11	.11	–	–
Fund×Portfolio×Month FE	Yes	Yes	–	–

B. Large increases versus large decreases

Regression analysis			Matching analysis [0, 3]	
Dependent variable:	*Signed four-factor alpha t+1, t+60* (1)	*Signed four -factor alpha t+1, t+125* (2)	*Mean difference in signed four-factor alpha t+1, t+60* (3)	*Mean difference in signed four-factor alpha t+1, t+125* (4)
D(Position increase)	0.51***	0.65***	0.59***	0.56*
	(3.74)	(3.20)	(3.35)	(1.88)
Observations	32,681	31,131	13,738	12,996
Adjusted R^2	.11	.12	–	–
Fund×Portfolio×Date FE	Yes	Yes	–	–

C. Position not closed versus closed

Regression analysis			Matching analysis [0]	
Dependent variable:	*Signed four-factor alpha t+1, t+60* (1)	*Signed four-factor alpha t+1, t+125* (2)	*Mean difference in signed four-factor alpha t+1, t+60* (3)	*Mean difference in signed four-factor alpha t+1, t+125* (4)
D(Position not closed)	0.38***	0.49**	0.32**	0.42**
	(2.83)	(2.18)	(2.35)	(2.03)
Observations	452,907	452,907	14,311	14,311
Adjusted R^2	.07	.09	–	–
Fund×Portfolio×Date FE	Yes	Yes	–	–

This table examines whether hedge funds reallocate their capital optimally. In panel A, we compare returns following the opening and closing of (long and short) positions. In columns 1 and 2, the dependent variables are signed four-factor alphas (equal to the alpha for long positions and the alpha times minus one for short positions), which we regress on a dummy variable equal to one if it is an opening order. We include fund-portfolio-month fixed effects in these regressions (where portfolio distinguishes between the hedge fund's long and short portfolio). In columns 3 and 4, we present results for a matching analysis in which position closings are matched with position openings made by the same fund between the first day of the closing order and 3 trading days after the last day of the closing order. The columns report the mean difference between matched openings and closings in signed cumulative four-factor alphas for 60 and 125 trading days, respectively. In panel B, we redo our analyses after adding large position increases (defined as orders that at least double the position) and large position decreases (defined as orders that decrease the position by at least 50%) to our sample of opening and closing orders. In panel C, we compare returns following positions closed and positions kept open for long and short positions together. In columns 1 and 2, the sample contains all positions a fund holds at the beginning of a day on which a position is closed (last day of order). For this sample, we regress signed position alphas on a dummy variable equal to one if the position is kept open (not closed) on that day. We include fund-portfolio-date fixed effects in these regressions. In columns 3 and 4, we present results for a matching analysis in which position closings are matched with all positions that the fund did not close on the same trading day. The columns report the mean difference between matched positions that are not closed and those that are closed in signed cumulative four-factor alphas for 60 and 125 trading days, respectively. Details on variable constructions can be found in Table A1 in the appendix. All standard errors are two-way clustered by stock and the last date of the order. We report *t*-statistics below the regression coefficients (mean difference in the matching analyses) in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

signed returns than position-decreasing orders undertaken by the same fund around the same point in time.

The results so far show that newly opened positions outperform recently closed positions. Going one step further, we examine whether stock positions that are kept open outperform those that are closed. 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 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 or have not been closed by the same fund on the same day. Columns 1 and 2 of Table 3, panel C, show 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 (statistically significant at the 5% level). The results for the corresponding matching analysis (columns 3 and 4) are very similar. The return difference between closed and kept-open positions is smaller than the one between closed and newly opened positions (confer panel A). This makes sense: newly opened positions should promise larger returns than existing ones, for otherwise the fund should have preferred to increase the existing positions 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 further where these constraints come from.

4. Examining Constraints to Fundamental Arbitrage

Our stylized trading model in Internet Appendix F shows that early position closures are driven by opportunity costs in the form of new investment opportunities, a tightening of funding constraints, and an increase in risk exposure. In this section, we examine the empirical relevance of these predictions.[22]

4.1 Sample splits by changes in fund-specific funding constraints

Our first set of tests relates to changes in fund-specific funding constraints. When funds become more financially constrained, we expect them to close positions earlier, leading to higher forgone post-closing returns. In Table 4, we test this prediction by splitting the sample of closing orders along several dimensions of fund-specific funding constraints. Since we do not observe hedge funds' actual borrowing activity and/or cash positions, we rely on empirical proxies of funding constraints for this analysis.

Funding constraints tighten when more new trading opportunities emerge that require additional capital. Accordingly, we split the sample by whether the hedge fund increased or decreased the number of open positions over the previous 5 or 10 days. For each of these subsamples, we then regress post-closing returns over the following 125 trading days on the *D(Long Position)* dummy (as in Table 2, panel A). The results in Table 4, panel A, confirm our prediction: whereas the four-factor alpha difference between closed long and short positions after an increase in the number of open positions over the previous 5 days is 1.5%, it is only 0.4% and insignificant after a decrease in the number of open positions (columns 1 and 2). Results for changes in the number of open positions over the previous 10 trading days are similar (columns 3 and 4). Compared to long-short return difference over the holding period, these results suggest that hedge funds leave more than 40% of existing positions' profitability on the table after opening new positions.

Next, we study a tightening of funding constraints due to negative prior returns, which can force levered hedge funds to close existing positions. To tease out whether hedge funds' funding constraints operate at the position or at the fund level, we separately examine losses on the particular position and on the hedge fund portfolio as a whole (excluding the specific position). Specifically, in Table 4, panels B and C, we split the sample of closing orders by whether returns on the specific position (or the portfolio excluding that position) were positive or negative over the prior 5 or 10 trading days. As expected, we find that hedge funds leave more money on the table after negative returns of both the specific stock and their overall portfolio.

[22] Unfortunately, our relatively small sample doesn't give us enough statistical power to test for significance of the difference in coefficient estimates across subsamples. Instead, we investigate for which subsample of hedge fund trades post-closing returns are statistically and economically significant.

Table 4.

Returns following the closure of positions: Split by change in fund-specific funding constraints

A. Split by position changes

Dependent variable:	*Four-factor alpha t+1, t+125*			
Sample	More positions (5 days) (1)	Fewer positions (5 days) (2)	More positions (10 days) (3)	Fewer positions (10 days) (4)
D(Long position)	1.52**	0.39	1.30**	0.72
	(2.45)	(0.68)	(2.28)	(1.25)
Observations	5,228	6,490	5,627	6,091
Adjusted R^2	.05	.05	.06	.04
Fund fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes

B. Split by stock specific signed return

Dependent variable:	*Four-factor alpha t+1, t+125*			
Sample	Negative signed return (5 days) (1)	Positive signed return (5 days) (2)	Negative signed return (10 days) (3)	Positive signed return (10 days) (4)
D(Long position)	1.84***	0.43	2.22***	0.47
	(2.81)	(0.69)	(3.40)	(0.72)
Observations	5,545	5,622	5,468	5,699
Adjusted R^2	.06	.04	.07	.04
Fund fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes

C. Split by fund returns (excluding specific stock)

Dependent variable:	*Four-factor alpha t+1, t+125*			
Sample	Negative fund return (5 days) (1)	Positive fund return (5 days) (2)	Negative fund return (10 days) (3)	Positive fund return (10 days) (4)
D(Long position)	1.39**	0.48	1.27*	0.60
	(2.13)	(0.92)	(1.92)	(1.11)
Observations	5,131	6,599	4,993	6,737
Adjusted R^2	0.05	0.05	0.05	0.05
Fund fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes

D. Fund flow

Dependent variable:	*Four-factor alpha t+1, t+125*	
Sample	Outflow (prior month) (1)	Inflow (prior month) (2)
D(Long position)	2.41**	1.91*
	(2.39)	(1.94)
Observations	1,747	1,340
Adjusted R^2	.09	.06
Fund fixed effects	Yes	Yes
Month fixed effects	Yes	Yes

In this table, we examine returns following closing orders (as in Table 2, panel A, column 5), but split the sample by changes in fund-specific funding constraints. For the different subsamples, we regress the cumulative four-factor alphas expressed as a percentage for 125 trading days following the last day of the order on a dummy variable whether the order is related to a long position. In panel A, we split the sample by the change in the number of positions in the 5 or 10 days prior to the order. In panel B, we split the sample by the stock-specific signed stock return in the 5 or 10 days prior to the order. In panel C, we split the sample by the signed fund return (excluding the specific stock) in the 5 or 10 days prior to the order. In panel D, we split the sample by fund flows over the prior month computed from HFR data. Details on variable constructions can be found in Table A1 in the appendix. 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 the last date of the order. We report t-statistics below the coefficients in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

Interestingly, the effect of the stock-specific return appears to be somewhat stronger than the effect of the portfolio return, suggesting that funding constraints operate both at the position and at the fund level.

Investor redemptions may constitute another important source of funding constraints (e.g., Shleifer and Vishny 1997). We examine this idea in Table 4, panel D, by splitting closing orders by whether the fund experienced an outflow or an inflow in the prior month.[23] We find that the direction of past fund flow does not seem to be very important as the post-closure alpha difference between long and short positions in the two subsamples is fairly similar. This suggests that hedge funds successfully manage redemption risk by means of advance notice periods and/or holding cash buffers.

4.2 Sample splits by level in fund-specific funding constraints

In this section, we examine sample splits by the *level* of fund-specific funding constraints. Funds with higher leverage, worse track records, and less liquid assets may find it more difficult to obtain additional financing, forcing them to close positions earlier.

In Table 5, panel A, we start with a sample split by hedge fund leverage. In columns 1 and 2, we compute leverage as the ratio of the total portfolio value in Analytics over the net asset value reported in HFR. In columns 3 and 4, we instead use the coarse but more widely available leverage classification provided in HFR. In both cases, the post-closing return difference between long and short positions is higher for funds with high leverage. When put in perspective with the long-short return difference over the holding period, highly levered hedge funds leave approximately 40%50% of the trades' potential profitability on the table, in line with the intuition that they are more constrained.[24]

Next, we look at portfolio liquidity. There are two reasons owning a liquid portfolio can alleviate funding constraints. First, prime brokers look at liquidity in order to determine the haircut for the fund's portfolio. The more

[23] Monthly fund flows are obtained from HFR data (see Appendix A.9 for more detail). Since we cannot match all funds to HFR, the sample size is reduced for this test.

[24] The funds that match to HFR have a higher open-to-close return differential of 3.9 percentage points. Thus, the coefficient of 3.55 suggests that they leave about 48% (=3.55/(3.55 + 3.9)) of profitability on the table.

Table 5.

Returns following the closure of positions: Split by level of fund-specific funding constraints

A. Split by fund leverage

Dependent variable:	*Four-factor alpha t+1, t+125*			
Sample	High leverage (computed) (1)	Low leverage (computed) (2)	High leverage (reported) (3)	Low leverage (reported) (4)
D(Long position)	3.55***	1.56*	1.34**	0.62
	(3.17)	(1.67)	(2.09)	(0.69)
Observations	1,396	1,645	4,792	2,139
Adjusted R^2	.05	.11	.06	.07
Fund fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes

B. Split by portfolio liquidity

Dependent variable:	*Four-factor alpha t+1, t+125*			
Sample	Illiquid portfolio (60 days) (1)	Liquid portfolio (60 days) (2)	Illiquid portfolio (125 days) (3)	Liquid portfolio (125 days) (4)
D(Long position)	1.18**	0.70	1.23**	0.66
	(2.03)	(1.16)	(2.08)	(1.10)
Observations	5,824	5,900	5,783	5,941
Adjusted R^2	.06	.04	.06	.04
Fund fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes

C. Split by fund track record

Dependent variable:	*Four-factor alpha t+1, t+125*			
Sample	Short track record (1)	Long track record (2)	Unsuccessful track record (3)	Successful track record (4)
D(Long position)	2.15***	0.16	1.45**	0.53
	(3.17)	(0.19)	(2.01)	(0.79)
Observations	3,298	3,633	2,686	5,045
Adjusted R^2	.08	.06	.09	.05
Fund fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes

D. Insider ownership

Dependent variable:	*Four-factor alpha t+1, t+125*	
Sample	High insider ownership (1)	Low insider ownership (2)
D(Long position)	2.58***	0.21
	(3.05)	(0.17)
Observations	2,374	2,043
Adjusted R^2	.08	.01
Fund fixed effects	Yes	Yes
Month fixed effects	Yes	Yes

In this table, we examine returns following closing orders (as in Table 2, panel A, column 5), but split the sample by the level of fund-specific funding constraints. For the different subsamples, we regress cumulative four-factor alphas expressed as a percentage for 125 trading days following the last day of the order on a dummy variable whether the order is related to a long position. In panel A, we split the sample by fund leverage. In columns 1 and 2 of panel A, we split the sample by whether the computed fund leverage, defined as the ratio of the fund's portfolio value over its net asset value, is above or below median. In columns 3 and 4 of panel A, we use leverage as reported in HFR. We treat "2-5" and "unspecified" leverage as high leverage and "1-2" as low leverage (if we exclude observations with "unspecified" leverage, the economic difference between the two groups is even larger). In panel B, we split the sample by the portfolio's value-weighted average liquidity of the funds' stock positions measured using the Amihud Illiquidity measure over the previous 60 or 125 trading days. In panel C, we split the sample by fund track record. In columns 1 and 2 of panel B, we split the sample by whether the time since fund inception is above or below median. In columns 3 and 4 of panel C, we split the sample by whether the average fund return (taken from HFR) since inception was above or below median. In panel D, we split the sample by whether the fund's insider ownership, according to ADV data, is above or below the median. Details on variable constructions can be found in Table A1 in the appendix. 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 the last date of the order. We report *t*-statistics below the coefficients in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

liquid the portfolio, the more pledgeable it is, which alleviates funding constraints by serving as collateral (e.g., Hart and Moore 1994). Second, hedge funds with a liquid portfolio may be willing to borrow more money because they know that they can easily divest these assets if needed. We therefore expect hedge funds with more liquid portfolios to be less constrained, which should coincide with lower post-closing returns. To examine this prediction, Table 5, panel B, reports results for a sample split by the portfolio average of the stock-level Amihud illiquidity measure (computed over the past 60 or 125 trading days). A high Amihud illiquidity measure indicates low liquidity. Consistent with our expectation, we find that funds that hold less liquid portfolios leave more money on the table (amounting to 40% of the position's total profitability). This finding highlights the importance of debt-financing for hedge funds, thereby complementing our earlier results on fund leverage.

Reputation is another way hedge funds can mitigate agency frictions that give rise to financial constraints (e.g., Kreps et al. 1982; Kreps 1990). We examine this idea by looking at hedge funds' track records in Table 5, panel C. Specifically, we split the sample by whether the length of the track record (columns 1 and 2) or the average return since fund inception (columns 3 and 4) is above or below the median. We find that a good reputation in the form of a positive track record helps to reduce financial constraints: the return difference between closed long and short positions amounts to 2.2% (1.5%) for funds with short (unsuccessful) track records, while it is only 0.2% (0.5%) for funds with long (successful) track records.[25]

Finally, we consider inside ownership by hedge fund managers. The premise is that hedge fund managers with large personal stakes may be reluctant to

[25] While the economic magnitude appears to be relatively large, we note that our sample is relatively small. Indeed, we only have track record information for 13 of the 21 hedge funds in our sample. Thus, the standard errors are relatively large, and the economic magnitude should be interpreted with caution.

accept outside equity capital because, facing decreasing returns to scale, they do not want to dilute the returns on their inside capital. Consistent with this view, Gupta and Sachdeva (2018) show that funds with large inside ownership have higher and more persistent alphas. At the trade level, we would then expect these fund managers to close positions earlier in order to focus their limited capital on the most attractive bets. In panel D, we therefore split the sample by the level of inside ownership, which we obtain from SEC Form ADV. We indeed find that the post-closure alpha difference between long and short positions is 2.6% for funds with high insider ownership while it is only 0.2% for funds with low insider ownership.[26] This finding is consistent with high-inside-ownership funds deliberately operating on a smaller scale, forcing them to close existing positions earlier (thereby leaving about half of the position's profitability on the table).[27]

4.3 Sample splits by change in marketwide funding constraints

Our previous results underscore the importance of debt financing for hedge funds. In this case, we expect portfolio closure decisions to be sensitive to changes in prime brokers' funding constraints. In Table 6, we test this prediction by offering sample splits along four widely used measures of market wide funding constraints: changes in the TED spread, the intermediary risk factor of He, Manela, and Kelly (2016) (henceforth HKM intermediary factor), changes in the VIX, and stock returns of primary dealers.[28] In addition to proxying for prime brokers' funding constraints, the TED spread may also capture arbitrageurs' opportunity cost of capital (Pontiff 1996).

For all four measures, our results paint a consistent picture. The return gap between closed long and short positions opens up after a tightening of funding constraints measured over the previous 5 or 10 trading days (i.e., when the TED spread increases, the HKM intermediary risk factor is negative, the VIX increases, or stock returns of primary dealers are 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

[26] Consistent with Gupta and Sachdeva (2018), we also find that hedge funds with high insider ownership have larger post-opening alphas compared to funds with low insider ownership (results available on request).

[27] Alternatively, these hedge funds may for some reason be unable to attract outside capital, implying that they involuntarily remain more constrained.

[28] The TED spread is defined as the 3-month LIBOR minus the 3-month Treasury-bill rate and is a bellwether of the financial sector's health (e.g., Brunnermeier 2009; Garleanu and Pedersen 2011). The HKM intermediary risk factor reflects changes to the capital ratios of primary dealer counterparties of the New York Federal Reserve and He, Manela, and Kelly (2016) find that it has significant explanatory power for the cross-section of returns in various asset classes. The VIX index is a measure of the implied volatility of S&P 500 index options, calculated and published by the Chicago Board Options Exchange (CBOE). Increases in the VIX are generally interpreted as reflecting an increase in risk aversion and tighter funding constraints. The intermediary stock returns, described in He, Manela, and Kelly (2016), are value-weighted portfolio returns of all publicly traded holding companies of primary dealer counterparties of the New York Federal Reserve. Negative returns signal that primary dealers have less capital and are more likely to tighten funding constraints for client hedge funds.

Table 6.

Returns following the closure of positions: Split by the change in marketwide funding constraints

A. Split by TED spread change

Dependent variable:	*Four-factor alpha t+1, t+125*			
Sample	Higher TED spread (5 days) (1)	Lower TED spread (5 days) (2)	Higher TED spread (10 days) (3)	Lower TED spread (10 days) (4)
D(Long position)	1.17**	0.35	1.84***	−0.41
	(2.01)	(0.56)	(3.28)	(-0.61)
Observations	6,379	5,078	6,580	4,833
Adjusted R^2	.06	.04	.06	.04
Fund fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes

B. Split by HKM intermediary risk factor

Dependent variable:	*Four-factor alpha t+1, t+125*			
Sample	Negative HKM Factor (5 days) (1)	Positive HKM Factor (5 days) (2)	Negative HKM Factor (10 days) (3)	Positive HKM Factor (10 days) (4)
D(Long position)	1.54**	0.45	1.49***	0.42
	(2.54)	(0.80)	(2.59)	(0.71)
Observations	5,284	6,318	5,676	5,926
Adjusted R^2	.05	.05	.05	.05
Fund fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes

C. Split by VIX change

Dependent variable:	*Four-factor alpha t+1, t+125*			
Sample	Higher VIX (5 days) (1)	Lower VIX (5 days) (2)	Higher VIX (10 days) (3)	Lower VIX (10 days) (4)
D(Long position)	0.93	0.83	1.44**	0.29
	(1.49)	(1.49)	(2.39)	(0.49)
Observations	5,905	5,697	5,915	5,686
Adjusted R^2	.05	.05	.05	.04
Fund fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes

D. Split by intermediary stock return

Dependent variable:	*Four-factor alpha t+1, t+125*			
Sample	Negative intermediary return (5 days) (1)	Positive intermediary return (5 days) (2)	Negative intermediary return (10 days) (3)	Positive intermediary return (10 days) (4)
D(Long position)	1.48**	0.42	1.27**	0.66
	(2.49)	(0.74)	(2.12)	(1.15)
Observations	5,186	6,416	5,112	6,490
Adjusted R^2	.05	.04	.05	.05
Fund fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes

In this table, we examine returns following closing orders (as in Table 2, panel A, column 5), but split the sample by changes in marketwide funding constraints. For the different subsamples, we regress cumulative four-factor alphas expressed as a percentage for 125 trading days following the last day of the order on a dummy variable whether the order is related to a long position. In panel A, we split the sample by whether the TED spread, defined as the difference between the 3-month LIBOR and the 3-month Treasury-bill interest rate, has increased or decreased over the prior 5 or 10 trading days. In panel B, 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 2017). A negative risk factor implies lower capital ratios and thus tighter funding constraints. In panel C, our proxy for funding constraints is the change in the VIX index over the prior 5 or 10 trading days. In panel D, we split the sample by the cumulative intermediary stock return, which is the value-weighted portfolio return of all publicly traded holding companies of primary dealer counterparties of the New York Fed. Details on variable constructions can be found in Table A1 in the appendix. 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 the last date of the order. We report *t*-statistics below the coefficients in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

(resulting in forgone profits of about 40% of the position's potential profitability).

4.4 Sample splits by risk management variables

Our model shows that, in addition to financial constraints, risk considerations should be an important determinant of position closure decisions. We now test this hypothesis.

We start by examining changes to the volatility of hedge fund returns. Our model predicts that, when the volatility of portfolio stocks increases, hedge funds' risk constraints tighten, forcing them to close positions prematurely. Table 7, panel A, presents the results of two sample splits for different volatility measures. In columns 1 and 2, we look at the change in portfolio return volatility, which is measured as the sum of squared fund portfolio returns over the previous 20 trading days. In columns 3 and 4, we split the sample based on the change in the average stock position volatility, defined as the position-weighted average of the sum of squared stock returns over the previous 20 trading days. The results confirm our prediction for both volatility measures. The alpha difference between closed long and short positions amounts to a significant 1.3% after an increase in fund volatility, while it is 0.6% or less after a decrease in volatility.

Next, we examine whether funds are more willing to forgo high post-closing returns in stocks that add more risk to their portfolio. Pontiff (1996, 2006) shows that institutional investors like our sample hedge funds trade off idiosyncratic risk with alpha in order to determine how much to invest in a particular stock position. When idiosyncratic risk goes up, the position becomes less attractive and should be reduced or even closed. In columns 1 and 2 of panel B, we therefore test whether funds are more willing to close a position prematurely if it exhibited an increase in idiosyncratic volatility. Indeed, we find that hedge funds leave more money on the table when they close positions that exhibited an increase in idiosyncratic volatility, confirming that idiosyncratic volatility is an important arbitrage cost as

Table 7.
Returns following the closure of positions: Split by risk management variables

A. Split by change in fund volatility

Dependent variable:	*Four-factor alpha t+1, t+125*			
Sample	Higher fund return volatility (1)	Lower fund return volatility (2)	Higher average position volatility (3)	Lower average position volatility (4)
D(Long position)	1.28**	0.63	1.32**	0.39
	(2.26)	(1.05)	(2.24)	(0.67)
Observations	5,666	5,681	5,790	5,934
Adjusted R^2	.07	.04	.05	.06
Fund fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes

B. Split by how the individual stock position affects portfolio volatility

Dependent variable:	*Four-factor alpha t+1, t+125*			
Sample	Higher idiosyncratic stock volatility (1)	Lower idiosyncratic stock volatility (2)	Position increases portfolio volatility (1)	Position decreases portfolio volatility (2)
D(Long position)	1.19**	0.60	2.07***	−0.08
	(2.10)	(1.06)	(2.67)	(-0.11)
Observations	6,131	5,426	5,564	5,799
Adjusted R^2	.04	.06	.05	.05
Fund fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes

C. Split by whether there is increase or decrease in industry exposure

Dependent variable:	*Four-factor alpha t+1, t+125*			
Sample	Increase in same industry (12 FF) (1)	Decrease in same industry (12 FF) (2)	Increase in same industry (SIC 2) (3)	Decrease in same industry (SIC 2) (4)
D(Long position)	1.22**	0.82	1.31*	0.58
	(2.03)	(1.27)	(1.95)	(0.92)
Observations	5,579	5,076	4,839	5,085
Adjusted R^2	.06	.06	.05	.08
Fund fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes

In this table, we examine returns following closing orders (as in Table 2, panel A, column 5), but split the sample by several risk management variables. For the different subsamples, we regress cumulative four-factor alphas expressed as a percentage for 125 trading days following the last day of the order on a dummy variable whether the order is related to a long position. In panel A, we split the sample by change in fund return volatility. In columns 1 and 2 of panel A, we measure fund return volatility as the sum of squared fund returns over the previous 20 trading days. In columns 3 and 4 of panel A, we measure fund return volatility as the average 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. In panel B, we split our sample by how the individual stock position affects portfolio volatility. In columns 1 and 2 of panel B, we split by the change in idiosyncratic stock volatility, where idiosyncratic volatility is measured as the sum of squared four-factor alphas over the previous 20 trading days. In columns 3 and 4 of panel B, we split the sample by whether the position closure decreases or increases the volatility of the fund's portfolio. We determine this by comparing the squared fund returns over the previous 60 trading days between two portfolios: the (actual) portfolio excluding the closed stock position and the (hypothetical) portfolio that the fund would have had if it had not closed the position. In panel C, we split the sample by whether there is an increase or a decrease in the fund's long (or short) exposure in the same industry relative to 20 trading days prior. In columns 1 and 2 of panel C, we use Fama-French 12 industry classification. In columns 3 and 4 of panel C, we use two-digit SIC codes. Details on variable constructions can be found in Table A1 in the appendix. 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 the last date of the order. We report t-statistics below the coefficients in parentheses. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

shown by Pontiff (1996). Our finding is also consistent with that of Duan, McLean, and Hu (2009), who find that mutual fund managers have higher stock picking ability for stocks with large idiosyncratic volatility.

Our detailed portfolio data allows us to measure more precisely how much an individual stock position contributes to overall portfolio volatility. Indeed, given that our hedge funds also hold many short positions, how much risk a position actually adds to the portfolio may deviate from idiosyncratic risk. To assess how much an individual stock position contributes to portfolio volatility, we compare the squared fund returns over the previous 60 trading days between two hypothetical portfolios: the current portfolio including the stock position that was closed and the portfolio excluding that position. We then split the sample of post-closing returns by whether the stock position increases or decreases portfolio volatility. As shown in columns 3 and 4 of panel B, we find that positions that increase portfolio volatility (whose closure thus decreases fund volatility) are followed by a long-short alpha difference of about 2.0%, while the difference is close to 0% for positions that increase portfolio volatility (whose closure thus increases fund volatility).

Finally, in panel C, we examine risk at the industry level. We conjecture that hedge funds may try to avoid being overly exposed to a specific industry. Thus, after experiencing an increase in exposure to a certain industry, they may be more willing to prematurely close positions in that industry. To examine this prediction, we conduct sample splits by whether hedge funds increased or decreased their exposure to the industry of the closed stock over the prior 20 trading days. Using industry groupings based on 12 Fama-French industries and two-digit SIC codes, we find a higher long-short difference in post-closure returns after an increase in industry exposure, suggesting that hedge funds are wary of taking on too much industry risk.

Taken together, these results suggest that hedge funds engage in active risk management, which leads them to close positions that are still profitable in order to reduce their risk exposure.

5. Additional Results and Robustness Checks

In this section, we summarize additional results and robustness checks that are presented in the Internet Appendix.

5.1 Long-short equity hedge funds as fundamental arbitrageurs

Long-short equity funds are described as fundamental investors that make independent long and short bets based on a fundamental analysis (Pedersen 2015; Getmansky, Lee, and Lo 2015). Our finding that hedge funds' opening trades are followed by abnormal returns over the subsequent 6 months (and more) is consistent with informed trading on long-lived information. In Internet Appendix E.5, we provide further evidence that our funds trade on fundamentals by showing that their trades predict future earnings surprises. This finding suggests that our hedge funds are able to identify fundamentally under- or overvalued stocks. In Internet Appendix E.6, we further show that our hedge funds rarely engage in merger arbitrage or pairs trading, two of the most popular convergence strategies involving equities. This suggests that hedge fund trades in different stocks represent independent speculative bets as implicitly assumed by our analysis.

5.2 Follow-up orders are different from opening and closing orders

Our analysis focuses on opening and closing orders, as follow-up orders are likely to be driven by different considerations. For example, Di Mascio, Lines, and Naik (2016) show how mutual funds gradually build up their stocks positions as a function of price impact and competition. In Internet Appendix E.4, we confirm that follow-up orders are different by showing that (with the exception of large follow-up orders) position-increasing orders do not predict higher future returns than position-decreasing orders. Hence, unlike what we find for closing orders, the capital freed from decreasing an existing position is on average not more profitably employed by increasing another position.

5.3 Representativeness

We acknowledge that the relatively small number of funds raises questions about the representativeness of our data. Given that similar data for a comparison is not available, the best we can do is to compare our imputed hedge fund returns to the returns reported in standard hedge fund databases, such as Lipper TASS or HFR. We find broadly consistent factor loadings across the different hedge fund return series (see Internet Appendix E.7). We thus conclude that the hedge funds in our sample appear to be similar to long-short equity funds that report to standard databases. Moreover, the trading behavior displayed in our sample looks consistent with what is commonly assumed for long-short equity hedge funds: hedge funds' trades predict fundamentals (Internet Appendix E.5), are independent (Internet Appendix E.6), and are spread over different industries with a tilt toward large stocks (Internet Appendix B.4).

5.4 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 for standard hedge fund databases are not a major concern for us. Indeed, hedge funds that engage with Inalytics provide most of their transaction data in real time, limiting the scope for window dressing and back-filling. Moreover, since our data include already-terminated funds, survivorship bias is not an issue.

One potential concern is sample selection. Here, the biggest worry is that successful hedge funds strategically engage with Inalytics in order to advertise their trading success. Should this be the case, 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 would be biased downward.

We study the extent of sample selection in Internet Appendix E.8. We find that fund returns are not elevated (reduced) shortly after entering (before leaving) the sample. Hence, hedge funds do not opportunistically enter (leave) the sample in order to advertise (hide) their performance, suggesting that sample selection is not a big concern for our data. Finally, we argue that selection should only affect the magnitude of the documented trade performance. However, it 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 we expect our qualitative results on early position closures and hedge funds' capital reallocations to apply more generally.[29]

5.5 Alternative explanations

Here, we briefly discuss three alternative explanations and explain why they are unlikely to drive early position closures. First, we study how our results relate to the disposition effect; that is, investors' tendency to close winning

[29] Consistent with this point, we note that Di Mascio, Lines, and Naik (2016) also find positive abnormal returns after the closure of long positions (but they do not explain this result).

positions too early and hold losing position too long (Odean 1998; Jin and Scherbina 2011). In Internet Appendix E.9, we show that our hedge funds do not exhibit the disposition effect. 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. Thus, our findings are not explained by the disposition effect.

Second, we study whether early position closures can be explained by lack of skill or biased beliefs. In Internet Appendix E.10, we show that average post-opening and post-closing returns are significantly positively correlated across managers; that is, the same hedge funds that leave more money on the table are also those that open more profitable positions. This is consistent with Table 3, which shows that, *within a given fund*, the forgone profits from early position closures are outweighed by the profits from new position openings. Hence, early closures do not appear to be mere trading errors, but rather conscious decisions to reallocate funds into more profitable investment opportunities.

Finally, we address the concern that post-closure returns are due to price pressure in illiquid stocks. We first note that this explanation fails to explain our numerous sample split results (Tables 4–7). For example, there is little reason to think that the track record of an individual hedge fund affects the liquidity condition of the stock market. Hence, price pressure cannot explain why only hedge funds with poor track records exhibit a significant post-closure return difference (Table 5, panel C). In Internet Appendix D.10, we further show that our results for forgone post-closing returns are robust to measuring cumulative alphas starting 3 trading days after the last day of the closing order; that is, after leaving out the trading days that are expected to be most contaminated by price pressure originating from the closing trade.

5.6 Other robustness checks

In Internet Appendix D, we report additional robustness checks. For instance, we show there that our results are robust to using benchmark-adjusted returns instead of alphas (D.2), excluding stocks with converted prices of less than $1 (D.3), excluding trades around merger events (D.5), excluding stocks from emerging markets or without regional assignment (D.6), only using return data from Datastream (D.7), including within-order returns (D.8), or not aggregating trades into orders (D.9).

6. Conclusion

Fundamental investors play a vital role in financial markets: they acquire and synthesize value-relevant information through their research and impound it into prices through their trading. 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." Specifically, we exploit proprietary trading data for a sample of discretionary long-short equity hedge funds—presumably the most important fundamental investors in today's 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 6 months, suggesting that their trades are informed. We then show that their closing trades predict returns in the opposite direction of the closing trade. In other words, our sample hedge funds close their positions too early, thereby forgoing about one-third of the total trade profitability.

We argue that this behavior naturally arises from the limits of arbitrage (we show this formally with the help of a simple trading model in Internet Appendix F): hedge funds rationally decide to close positions that are still expected to generate profits in order to accommodate tightened financial constraints and/or to invest their limited capital in even more profitable trading opportunities. Our results broadly confirm this view: 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 marketwide funding costs. Similarly, hedge funds with short track records, high leverage, or less liquid assets engage in more premature position closures. Interestingly, investor outflows matter less for portfolio closing decisions, suggesting that—at least for the long-short equity funds in our sample—redemption risk is a less important impediment to arbitrage as theory predicts (Shleifer and Vishny 1997), perhaps because they mitigate this risk with the help of advance notice and lockup periods. Finally, we also find that hedge funds with large inside ownership leave more money on the table, consistent with the argument that large inside-ownership funds choose to accept less outside capital in order to not dilute their returns (Gupta and Sachdeva 2018).

To the best of our knowledge, our paper is the first to provide micro-level evidence on how constrained fundamental investors decide to abandon a profitable trading opportunity in order to recycle their capital. 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.

Appendix

Table A1.
Variable definitions

Variable name	Definition
Stock return	Return in USD from Datastream or Analytics
Four-factor alpha	• $r_{c,t} - r_{f,t} - \beta_m * (r_{m,t} - r_{f,t}) - \beta_{HML} * HML_t - \beta_{SMB} * SMB_t - \beta_{MOM} * MOM_t$ • For more details, see Section 2.3
DGTW return	• *Stock return – Return of portfolio of similar stocks* • Similar stocks are stocks appearing in the same quintile of market capitalization, book-to-market ratio, and past 12 months stock return within the same region. For more details, see Daniel et al. (1997) and Internet Appendix A.6
Benchmark-adjusted return	• *Stock return – Benchmark return* • For more details, see Internet Appendix A.6
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 are provided by Inalytics
Signed four-factor alpha	Four-factor alpha for long positions and four-factor alpha 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 benchmark-adj. return	Benchmark-adjusted return for long positions and benchmark-adjusted return 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 four-factor alpha	Position-weighted average signed four-factor alpha of all positions of the fund, where the weight is the dollar value of the position. Daily stock-level four-factor alphas are winsorized at 10% and -10%
Fund flow	• Computed from (monthly) HFR data as • $(NAV_t - NAV_{t-1}) - (NAV_{t-1} * Ret_t)$, • where NAV is the net asset value and Ret is the fund return (both from HFR data)
Leverage (computed)	• Computed as • $Total\ asset\ value\ (Inalytics) / Net\ asset\ value (HFR)$, • where total asset value is the some of the value of all long and short positions (from the Inalytics data) and net asset value is taken from HFR
Track record (length)	• *Current date – Inception date* • The inception date is reported in HFR
Track record (average return)	Average fund return (taken from HFR) since fund inception
Amihud illiquidity	$mean\left(\frac{ret_{daily}}{dollar\ \ volume_{daily}}\right)$

(continued)

Table A1.
Continued

Variable name	Definition
	Measured over the previous 60 or 125 trading days
Insider ownership	Fraction of inside ownership as reported to the SEC in Form ADV in response to the question: "What is the approximate percentage of the private fund beneficially owned by you and your related persons"
TED spread	$LIBOR3_{month} - Tbill3_{month}$
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 (2017) calculate aggregate dealer capital ratios as • $\eta_t = \frac{\sum_i Market\ Equity_{i,t}}{\sum_i \left(Market\ Equity_{i,t} + Book\ Debt_{i,t}\right)}$ • 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: • $HKM\ intermediary\ risk\ factor_t = \frac{u_t}{\eta_{t-1}}$
VIX index	CBOE volatility index
Intermediary stock return	Value-weighted portfolio return of all publicly traded holding companies of primary dealer counterparties of the New York Federal Reserve. The data are available at http://apps.olin.wustl.edu/faculty/manela/data.html
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
Idiosyncratic volatility$_{[1,20]}$	• $\sum_1^{20} Daily\ four\ factor\ alpha^2$ • It is set to missing if there are 16 or fewer daily fund observations available in the last 20 trading days. Alpha is based on nonshrunk betas to stay consistent with the prior literature
Average position return volatility$_{[1,20]}$	• $Weighted\ Average[\sum_1^{20} Daily\ stock\ return^2]$ • Weights refer to 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
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 are 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 are 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 directions, 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	$log(Total\ assets)$ Measured at the end of the previous quarter

(continued)

Table A1.
Continued

Variable name	Definition
#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	• $\frac{Long-term\ debt}{Total\ assets}$ • Measured at the end of the previous quarter
Market-to-book	$\frac{Market\ value\ of\ equity\ (5\ days\ before\ earnings\ annoucement)}{Book\ value\ of\ equity\ (at\ the\ end\ of\ the\ previous\ quarter)}$
Cash flow-to-price	• $\frac{Cash\ flow}{Share\ price}$ • Measured at the end of the previous quarter
Sales growth	• $\frac{Sales\ revenue-Prior\ quarter\ sales\ revenue}{Prior\ quarter\ sales\ revenue}$ • Measured at the end of the previous quarter
Equity market factor	The Standard & Poor's 500 index monthly total return [Datastream code: S&PCOMP(RI)]
Size spread factor	Russell 2000 index monthly total return - Standard & Poor's 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 nonmissing 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

This table defines the 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.

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