

Investor Interest and Hedge Fund Returns.*

Tarun Ramadorai[†]

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[†]Saïd Business School, Oxford-Man Institute of Quantitative Finance, and CEPR. Park End Street, Oxford OX1 1HP, UK. Tel: 44-1865-278816, email: tarun.ramadorai@sbs.ox.ac.uk.

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Abstract

Employing a new dataset of over 8,000 expressed demands for over 700 hedge funds from a secondary market for hedge funds, this paper finds evidence that hedge fund investors rationally anticipate future hedge fund performance. Both demand and supply indications of interest arrive following periods of fund outperformance. Demand (supply) indications forecast increases (decreases) in strategy-adjusted hedge fund returns over the subsequent year, and large dollar-amount indications are better forecasters than small-dollar amount indications. Indication-based capital allocation strategies are potentially useful to real-world investors: they yield high alphas when implemented using calendar-time portfolios.

1. Introduction

Hedge fund assets under management have exploded over the past decade, and declined significantly in the past few months. Concurrently, press reports are full of anecdotes about the stellar – or more recently, dreadful – performance of hedge funds. These observations are closely connected: The allocation of capital to hedge funds responds to hedge fund returns, and if hedge fund investors rationally anticipate future returns, their capital allocation decisions may forecast hedge fund performance. Since investors in hedge funds are either wealthy individuals or large institutions, it might naturally be presumed that they are rational decision makers.¹ However in theories by DeLong et al. (1990), Barberis and Shleifer (2003), and Hong and Stein (2003), “trend-chasing” – where capital allocation decisions follow recent patterns in returns – is the behaviour of naive investors that follow simple rules of thumb.

Many authors have discovered that capital flows to hedge funds chase past hedge fund returns and past hedge fund alphas (see Baquero and Verbeek (2008), Fung, Hsieh, Naik and Ramadorai (2008), Wang and Zheng (2008) and Ding, Liang, Getmansky and Wermers (2009)). Furthermore, capital flows chase funds with high imputed managerial deltas, suggesting that investors are interested in fund managers with high incentives to perform in the future (Agarwal, Daniel and Naik (2009)). In light of the strong evidence for hedge fund performance persistence (see Kosowski, Naik and Teo (2006) and Jagannathan and Novikov (2008)²), these findings suggest that hedge fund investors are rational trend-chasers, with the ability to anticipate hedge fund performance. If this is true, and such rational investors compete to allocate capital to purchase managerial talent, then in the presence of capacity constraints in implementing hedge fund strategies, Berk and Green (2004) predict that in equilibrium, hedge fund alphas will shrink to zero, and performance persistence will disappear.

¹See Cohen, Gompers and Vuolteenaho (2002) and Campbell, Ramadorai and Schwartz (2008) for evidence that institutional investors make rational trading decisions. Hvidjkaer (2006) and Malmendier and Shanthikumar (2007) identify the size of transactions - and hence the wealth of the investors engaging in them - with the sophistication of these investors.

²A partial list of other work on hedge fund performance includes Fung and Hsieh (1997, 2004 a,b), Ackermann, McEnally and Ravenscraft (1999), Liang (1999), Agarwal and Naik (2004), Chen and Liang (2007), Patton (2009).

Before accepting this conclusion, it is worth noting that the evidence of hedge fund investor rationality is almost exclusively derived from regressions that condition capital flows and hedge fund returns on one another. This is problematic for at least three reasons: First, flows are an imperfect measure of investor interest, as they are calculated from assets under management and return data, employing assumptions about the timing of the arrival of money into the fund at a particular time within the month. The well-documented biases inherent in hedge fund returns (see Fung and Hsieh (2000) and Liang (2000)) are inherited by flows imputed from these calculations, making them a noisy measure of investors' true allocation decisions. Second, the combination of lockup and redemption notice periods in hedge funds, and the ability for funds to close to new investments breaks the link between investors' desires and the observed behavior of flows. Flows are only partial signals of the expectations of investors in the presence of these constraints on investors' ability to enter and exit hedge funds (see Ding, Getmansky, Liang and Wermers (2009) for an in-depth analysis of this issue). Third, flows have been found to forecast future declines in hedge fund returns and alphas, consistent with the presence of capacity constraints in the implementation of hedge fund strategies.³ This complicates assessments of investors' rationality using such forecasting regressions. The observed negative sign in the forecasting relationship of flows for hedge fund returns is consistent with two possibilities: Either investors are getting it wrong about future hedge fund returns; or hedge fund managers accept unreasonably high amounts of capital from rational investors, and succumb to capacity constraints, which are revealed in subsequent declines in their future returns.

This paper adopts a different approach to ascertain whether hedge fund investors rationally anticipate hedge fund returns, analyzing a large dataset of indications of investor interest to purchase and sell hedge funds between 2002 and 2009, from Hedgebay, one of the only known venues for secondary trading of ownership stakes in hedge funds.⁴ The data comprises over 8,000 indications of interest over the period, in over 500 hedge funds.

³See Naik, Ramadorai and Stromqvist (2007), Fung, Hsieh, Naik and Ramadorai (2008), Teo (2008), Zhong (2008) and Avramov et al. (2009).

⁴See "How hedge funds are bought and sold online", *The Economist*, August 4, 2005; and "All locked-up", *The Economist*, August 2, 2007.

These indications of interest arrive at Hedgebay, and are mailed out to their client base periodically; the information contained in these mailings are dollar amounts demanded or supplied in each hedge fund that is listed. The indications occasionally translate into transactions between investors, but are not associated with new capital infusions into funds.⁵ This ensures that the forecasting ability of these indications is insulated from concerns about capacity constraints. Furthermore, the use of these indications does away with the need to impute flows from potentially noisy return and AUM information. Finally, since indications on the secondary market arise from a desire to *surmount* lockup and redemption notice periods, such restrictions do not affect inferences derived from this source.

Analysis of these data confirms that prospective hedge fund investors rationally anticipate hedge fund returns. Indications of interest to buy hedge funds forecast increases in future abnormal (strategy-adjusted) hedge fund returns, and conversely, indications of interest to sell forecast declines in future abnormal hedge fund returns. This forecasting power is more pronounced when the dollar size of the indication is taken into account. Expressed desires to engage in large dollar-size transactions, in general, appear to be better forecasters of future performance. This finding has interesting similarities with the literature on equity trading (see Hvidjkaer (2006) and Malmendier and Shanthikumar (2007)) which seeks to identify the size of a transaction with the sophistication of the investor engaging in it. If we adopt the same classification of smaller-sized indications as coming from less sophisticated investors, this might explain why larger-sized indications have greater forecasting power. There is also the possibility that size-based classifications are simply picking up different investor groups with different motivations for trade: Liquidity demands for selling may co-exist in the data with more information-driven motivations for trade.

The predictability of hedge fund abnormal returns by indications of interest survives the introduction of several controls into the forecasting regressions. Indications forecast abnormal returns over and above lagged returns, suggesting that performance persistence is not the only source of information available to hedge fund investors. Indications

⁵Ramadorai (2009) analyzes these completed transactions.

also forecast abnormal returns over and above lagged flows, and computed managerial compensation deltas (computed using the method of Agarwal, Daniel and Naik (2009)). Taken together, these findings suggest that investors possess private information about the future return prospects of hedge funds.

It is also worth noting that when both capital flows and indications of interest are included in the return forecasting regression simultaneously, capital flows negatively forecast hedge fund abnormal returns, while indications of interest positively forecast returns. This appears to confirm the co-existence of hedge fund investor rationality and capacity constraints in hedge funds. The forecasting power is also attenuated, but not eliminated, by the introduction of a control for selection bias, computed using the method of Heckman (1979). Finally, the results are confirmed by the construction of calendar-time portfolios based on demand and supply indications, holding funds experiencing such indications for a period of 12 calendar months. The resulting 'investor demand' portfolios outperform the aggregate hedge fund portfolio in terms of alpha from a Fung-Hsieh seven factor model, while the resulting 'investor supply' portfolios underperform the aggregate hedge fund portfolio, suggesting that the demand and supply indications are useful conditioning information for a real-world investor contemplating investments into hedge funds.

Finally, the much-noted trend-chasing behavior of hedge fund flows also shows up in indications of interest, with one twist: Both demand indications of interest and supply indications of interest follow periods of abnormally high hedge fund performance. The fact that run-ups in abnormal hedge fund returns precede indications of interest to buy echoes the findings in the literature of alpha-chasing by hedge fund investors. The fact that sell indications are also preceded by run-ups in abnormal hedge fund returns suggests that portfolio rebalancing may be one underlying motivation for these indications.

The remainder of this paper is organized as follows: the next section describes the data employed in the study, the third section describes the methodology and the results, the fourth section conducts robustness checks, and the final section concludes.

2. Data

2.1. Secondary Market Data

The data employed in this study come from Hedgebay, the longest-running trading venue for hedge funds. Transactions are conducted as follows: indications of interest for buying and selling hedge funds are either posted on Hedgebay's website by interested parties, or phoned in to Hedgebay directly. These indications are either matched to countervailing and pre-existing indications of interest in the same fund on the website, or are disseminated to prospective buyers or sellers in Hedgebay's client list via phone. Once an interested party on the other side of the transaction has been identified, bargaining is conducted by both parties engaging in unilateral negotiations with Hedgebay. Strict anonymity is preserved in these transactions about the identities of the counterparties involved. Once agreement has been reached about the terms of the deal (trade amount and discount or premium to end-of-month NAV), the approval of the fund manager is required to complete the transaction. While transactions are conducted throughout the month, they are settled during the last few days of the month, just following the report of the fund's NAV at the end of each month. Thus, these are technically short-dated forward contracts entered into mid-month, which are legally binding between counterparties once approval of the fund manager has been obtained. The existence of this market allows investors to transact in closed share classes of funds, i.e., funds closed to new investments, or specific share classes which fund managers have stopped issuing. It also offers an opportunity for investors to liquidate their holdings within the lock-up or redemption notice period. The premia and discounts from these transactions exhibit similar behavior to closed-end fund discounts and premia in mutual funds (see Ramadorai (2009)).

The secondary market data used in this paper comprise 8,656 expressions of interest to buy or sell in 713 funds that are identified from a consolidated dataset compiled from TASS, HFR, CISDM and Morningstar (details on the consolidated dataset are in the Appendix), over the period from January 2002 to February 2009. The coverage (compiled from mailings sent out to Hedgebay's client list which were saved by the data provider) is somewhat patchy in the early years of the data sample. Furthermore, in the early period

of the data, there are often multiple report dates per month. The frequency of mailings depended on the amount of new interest put forward by investors on Hedgebay's website in any given month. However in the more recent years, Hedgebay has begun sending out these mailings roughly once a month, resulting on average in 12 mailings per year from 2006 onwards. Table I shows some basic details about these indications. On average, both demand and supply indications are quite large, at approximately U.S.\$ 5 million per indication, which translates roughly to around 4% of the AUM of the funds for which they are issued. Both demand and supply indication distributions are skewed to the right, there are several very large indications in both sets.

Table II breaks these indications down by the year in which they arrive. This table shows that the total dollar amount of indications, as well as the number of funds for which indications came into the market have been steadily increasing over the 2002 to 2009 period. However, there is not much growth in the normalized amounts, which suggests that the growth in the secondary market has roughly mirrored the well-documented rate of growth in the size of the average hedge fund over the same period. Table II also shows that the average number of indications per fund was very high at the beginning of the sample, with approximately 16 (9) indications per fund on the demand (supply) sides. As the market grew, the number of funds for which indications were issued went up, but the total number of indications did not.

The rows labelled 'N(Premium)' and 'N(Discount)' refer to data that Hedgebay recorded during the first three years of the data sample, namely whether the indications were accompanied by expressions of willingness to trade at premia or discounts to end-of-month NAV. Unfortunately Hedgebay do not have any records of these premium/discount indicators from 2005 to 2009. Finally, it appears that the number of demand indications fell in 2008, relative to the number of supply indications. This roughly mirrors the difficulties that hedge funds experienced in generating returns in that year.

2.2. Hedge Fund Returns and Characteristics, and Factor Data

2.2.1. Characteristics of the Sample

All transactions are matched (by name and management company) to the consolidated TASS, HFR, CISDM and Morningstar database, for administrative information, returns, and AUMs of funds around the time of transactions. Appendix A lists details of this matching procedure. There are 9,305 funds in the combined universe. Funds' vendor-provided strategies are consolidated to a list of nine – Security Selection; Macro; Relative Value; Directional Traders; Emerging Markets; Fixed Income; Multi-Strategy; Funds of Funds and Other. Details about the mappings between vendor-provided styles and the list of nine strategies are provided in Appendix Table A.1. Strategy average returns and other aggregate statistics are compiled from indices created using these 9,305 funds.

Table III below shows the characteristics of the matched sample relative to the universe of hedge funds. The statistics reveal that the matched funds have more severe investment restrictions in the form of lockups, and longer redemption restrictions than the remainder of the hedge fund universe. They also charge higher incentive fees, and are more likely to be domiciled in offshore financial centres than the remainder of the hedge fund universe. Interestingly, the strategy composition of the sample is very similar to that of the universe, with three main exceptions. There are far fewer funds-of-funds and directional traders for which there are indications of interest in the data relative to their frequency in the hedge fund universe, and far more multi-process funds represented in the data relative to the universe. This may be a consequence of the relatively high (low) liquidity offered by most funds-of-funds and directional traders (multi-process funds).

2.2.2. Fung-Hsieh Factors

Apart from strategy-adjustment, the main method of risk adjustment used in the paper is the Fung and Hsieh (2004) seven-factor model. The Fung and Hsieh factors have been shown to have considerable explanatory power for fund-of-fund and hedge fund returns. The set of factors comprises the excess return on the S&P 500 index (SNPMRF); a small minus big factor (SMB) constructed as the difference between the Wilshire small and large

capitalization stock indices (I use the SMB factor obtained from Kenneth French’s website as a proxy for this); the excess returns on portfolios of lookback straddle options on currencies (PTFSFX), commodities (PTFSCOM), and bonds (PTFSBD), which are constructed to replicate the maximum possible return to trend-following strategies on their respective underlying assets; the yield spread of the U.S. 10-year Treasury bond over the 3-month T-bill, adjusted for the duration of the 10-year bond (BD10RET); and the change in the credit spread of Moody’s BAA bond over the 10-year Treasury bond, also appropriately adjusted for duration (BAAMTSY).

The next section introduces the methodology and discusses the results.

3. Methodology and Results

3.1. Is There Information Content in the Indications?

As a first step, standard event-study methodology is employed. First, abnormal returns are created for a fund i at event date t :

$$AR_{it} = R_{it} - R_{Sit}, \quad (3.1)$$

where R_{Sit} is the return on the strategy to which the fund belongs (using the nine strategy classifications).

Second, these abnormal returns are averaged across all funds, to generate mean abnormal returns at each event date:

$$MAR_t = \frac{1}{N_t} \sum_{i=1}^{N_t} AR_{it} \quad (3.2)$$

Finally, these abnormal returns are cumulated to generate the total abnormal return on the portfolio up until any specific date:

$$CAR_t = \sum_{k=1}^t MAR_k \quad (3.3)$$

The red dashed lines in figures, where they appear, indicate ± 2 standard error bounds for the CARs, constructed using the non-parametric delete-cross-section jackknife method, in the spirit of Shao and Wu (1989) and Shao (1989). The jackknife does not require normality, is consistent in the presence of heteroskedasticity and, in this specific implementation, cross-correlation in calendar time at each event date.⁶

Figure 1 plots the CAR's from 24 months prior to a buy indication of interest to 24 months after the buy indication of interest. The figure reveals a pronounced pattern in the CAR's prior to the arrival of the indication of interest. They rise to approximately 13% by the time the indication arrives. This corresponds to a roughly 54 basis point per month out-performance of the fund relative to the average return of the strategy over the period prior to the indication. This is consistent with the findings in the literature that connect flows to past hedge fund returns and hedge fund alphas. However, what is also interesting in this figure is the behavior of the CARs following the arrival of the buy indication of interest. Over the 24 month period, the out-performance of the fund relative to the strategy continues, and at the end of the 24 month period, the CAR stands at 17.22%, a rise of close to 4% subsequent to the indication of interest. The lower confidence interval is higher than 13% by the end of the window, showing that this result is statistically significant. Figure 2 plots the CAR's following sell indications of interest, and the associated confidence intervals for these CARs. The figure reveals another interesting pattern. Again, there appears to be statistically significant out-performance of these funds relative to the strategy prior to the arrival of the indication. This is, however, far smaller than in the case of the buy indications of interest, with the CAR at 4.6% over the 24 month period prior to the arrival of the sell indication. However, following the sell indication, there is an economically significant decline in the CAR - by the end of the 24 month period, the CAR is at 2.72%. This decline is also statistically significant in the 6 month period following the sell indication.

Table IV and Table V conduct a more formal test, regressing the strategy-adjusted re-

⁶To compute the jackknife standard error for an estimator, we form the estimator for T delete-cross-section jackknife data samples, constructed by deleting all funds i for each calendar time period t in T . The standard deviation of the resulting jackknife trials, appropriately scaled, is the jackknife standard error of the estimator at each event date.

turns on the demand and supply indicators in event time, and controlling for additional regressors that may be expected to affect these returns. Table IV employs a short window of -12 to +12 months surrounding the arrival of the indication, and Table V looks at returns in a -24 to +24 month window surrounding the indication. Table IV reveals that on average, strategy-adjusted returns have the expected sign in the year following the arrival of demand (positive) and supply (negative) indications across all specifications, but that the statistical significance of the results is weak in the short window, especially once the persistence of strategy-adjusted returns is controlled for. Table V shows that the result is stronger for the longer two year window, mimicking the result seen in Figure 1, with the buy indication forecasting increases in the strategy-adjusted return. Note that the intercept in the specification is introduced to account for the handful of fund-dates on which both buy and sell indications are observed for funds. Note also that the introduction of the managerial option delta and total delta measures (constructed using the method of Agarwal, Daniel and Naik (2009), see Appendix B) eliminate the statistical significance of the demand indication, suggesting that on average, investors may be using signals embedded in past returns to gauge the alignment of the incentives of the manager with outside investors. However, as we will see in the next section, once we condition on the size of the indication, there is additional forecasting power provided by the indications of interest that is not available from using return, flow and fee-based signals.

3.2. Conditioning on the Size of the Indication

A standard assumption in the literature that seeks to identify institutional trading in equities is that the size of the transaction is a good proxy for the size/sophistication of the investor (see Hvidkjaer (2006) and Malmendier and Shanthikumar (2007) among others). This insight is based on using a wealth constraint to separate investor types – for example, large institutional investors or wealthy individuals can trade in large dollar sizes. Others dispute this logic, finding that institutional investors' trading is associated with very small trades as well (some refer to this as 'stealth-trading', see Barclay and Warner (1993), Chakravarty (2001), and Campbell, Ramadorai and Schwartz (2008)). This latter perspective is more related to Kyle (1985) logic, namely that informed traders will at-

tempt to disguise their trading behavior in order to avoid tipping off their counterparties about the information contained in their transactions. Either way, the size of the indication should be useful conditioning information when assessing the forecasting ability of indications of interest for future hedge fund returns.

Tables VI and VII use the sizes of the indications to separate their forecasting power for future returns. The indications are divided into those buy and sell indications larger than or equal to the 75th percentile of buy and sell indications ('Big' demand and supply indicators), and those smaller than or equal to the 25th percentile of buy and sell indications ('Small' demand and supply indicators), where size is simply the indication dollar amount. Both tables show that using information about the size of the indication significantly improves the forecasting power of the indications for future strategy-adjusted returns. On the buy side, larger indications are followed by larger movements in CAR's relative to smaller sized indications. On the sell side, small indications are more reliable forecasters of declines in future CARs than larger indications. On the buy side, larger indications do appear to be more informative about future returns than smaller indications. This is consistent with larger investors in hedge funds either having better information about the future, or processing available information more efficiently than smaller investors, with the caveat that the size-based separation of indications is assumed to be an accurate representation of the size of the investors putting them in.

On the sell side, the 'stealth-trading' logic seems to apply. These differences suggest that there may be different motivations for wanting to trade that are showing up in the analysis of the aggregate set of indications. For example, liquidity-based motivations for large sales could co-exist with information-driven smaller sell indications. The other coefficients in the regressions are also worth highlighting. First, strategy-adjusted returns are very persistent: The coefficient on lagged, non-overlapping strategy-adjusted returns is always significant when included. Second, lagged flows come in negative and statistically significant when the option delta variables are included, echoing the findings of capacity constraints in hedge fund documented by several authors (Naik et al. (2007), Zhong (2008)). The coexistence of predictability from indications and the negative forecasting power of flows for future returns suggests that hedge fund investor rationality

co-exists with hedge fund managers taking on excessive capital in the presence of capacity constraints in hedge funds. Finally, the manager's option delta is a useful indicator of future excess hedge fund returns, in line with the findings in Agarwal et al. (2009).

These findings point strongly towards the notion that prospective hedge fund investors rationally anticipate the future return prospects of hedge funds. Moreover, they appear to possess information that is not merely contained in past returns, or the fund characteristics that appear as controls in the forecasting regressions. However, two concerns remain about these specifications. The first is that there may be special features about the sample of funds that appear on Hedgebay, relative to their counterparts in the universe, causing the results of these forecasting regressions to be unrepresentative of wider hedge fund investor rationality. The second concern is that the use of strategy-adjustment of excess returns does not appropriately control for the risks underlying hedge fund returns. The next section presents robustness checks of the results in response to these concerns.

4. Robustness Checks

4.1. What Determines Whether a Fund is Traded on the Market?

Specifications estimated on indications of interest sourced from Hedgebay employ a relatively small fraction of funds from the entire hedge fund universe. These funds, as outlined above, have several characteristics that look different from those of their counterparts in the broader universe of funds. Therefore, the sample may not be representative of the population of funds. These differences lead to questions about the results in Table VI and VII: Are they representative of the 'true' behavior of hedge fund investors when they are making investment decisions? Any coefficients purporting to explain the behavior of the future returns of funds solicited on Hedgebay may be contaminated by correlation between the residuals in these explanatory regressions, and the unobserved determinants of the selection of a fund to trade on the market. This necessitates the use of controls to ensure that the results are not biased by this correlation. Consequently, I apply Heckman's (1979) two-stage procedure to correct for possible selection bias. In this pro-

cedure, a first-stage probit regression is estimated on the entire universe of hedge funds and funds-of-funds to capture the determinants of selection. The inverse Mills ratio is then computed from this first stage probit, and incorporated into the explanatory regression for the strategy-adjusted excess returns as the selection bias correction. A useful set of insights is also provided by the probit regression: It helps us understand when and what kinds of funds are most likely to be the objects of interest for hedge fund investors. Technical details about estimation are in Appendix C.

4.1.1. The Exclusion Restriction

An important identifying assumption when applying the Heckman correction is that there are some variables that explain selection, but not the level of transactions premiums. If there is no such “exclusion restriction,” the model is identified only by distributional assumptions about the residuals, which could lead to problems in estimating the parameters of the model (see Sartori (2003)). The exclusion restriction that I employ is $OFFSHORE_i$, a dummy variable that takes the value of 1 if the fund is domiciled in an offshore financial centre such as Bermuda or the Cayman Islands. Using the domicile of a fund as the exclusion restriction is justifiable if its domicile status affects the propensity of a fund to be traded on Hedgebay, but does not affect the strategy-adjusted returns of a fund.

There are numerous tax benefits to being located offshore, and the tax implications of a fund’s changing hands on Hedgebay are less complicated if the fund is offshore. This is the main reason why, reading from Table III, 70% of the funds traded on Hedgebay are offshore. This makes the domicile of a fund a useful instrument to explain the propensity of a fund to be traded on Hedgebay. It is worth noting that the onshore-offshore classifications employed by the vendors are likely to be noisy indicators of the true domicile of funds, as funds headquartered in offshore centres such as Bermuda are occasionally classified as onshore funds by vendors, and vice versa. However, since this noise should affect the onshore-offshore ratios in the universe of funds and the sample of Hedgebay funds similarly, it should not affect the use of $OFFSHORE$ as a determinant of selection. As far as the determinants of the premium are concerned, Liang and Park (2008)

present evidence that the main channel through which the domicile of the fund affects its performance is the presence of share restrictions. These authors document that offshore domiciled funds impose less severe lockup restrictions than onshore funds on their investors, but that these restrictions are more binding when they are employed. Therefore a useful proxy for the illiquidity of a fund's shares is the interaction between the presence of a lockup restriction and the *OFFSHORE* dummy. To make sure that the *OFFSHORE* dummy is not capturing this potential joint determinant of selection and the expected future returns of a fund, I include this interaction term in the selection equation along with the *OFFSHORE* dummy.

To balance concerns of sample size and inclusiveness, I estimate the selection equation as a fund-year panel, with average returns measured over the previous calendar year to December, and the rank variables computed as of December prior to the year in which the indication appears for the fund on Hedgebay. The final set of variables in the selection equation comprises the strategy dummies; the entire set of static variables employed in Table III; three dynamic variables, namely: average returns over the previous year, the size of the fund captured by its rank in the cross-sectional distribution each year, and the minimum investment level of the fund, also measured by its percentile rank each year; and finally *OFFSHORE*.

4.1.2. Results: Probit Selection Equation

Table VIII presents results from estimating the probit model for selection. The panel regression is estimated using a total of 32,746 fund-year observations comprising both hedge funds and funds-of-funds, of which there are 1,114 fund-years in which trades occurred on Hedgebay. The Chi-squared statistic from a Wald test of the null hypothesis that all coefficients are jointly zero is 986.21, a rejection of the null that none of the variables employed in the probit are useful for explaining selection at the 1% level of significance. The table presents marginal effects of each continuous right-hand side variable, that is, the change in the probability of selection that results from an infinitesimal change in each variable. They reveal that the continuous variables in the specification (the mean returns of the funds over the year prior to the year of the transaction and the fund size) are both

positive and significant determinants of selection. Clearly past performance and the size of the fund (and indication of past performance over a longer term) are both significant determinants of indications of interest arriving for funds. Furthermore, the management fees and incentive fees are positively associated with the arrival of indications of interest. These results confirm the anecdotal evidence that highly successful funds raise their fees. The funds are also likely to be demanded on Hedgebay when they have high total redemption restrictions (lockup + redemption frequency + redemption notice period), which accords with the fact that Hedgebay is an important venue for the acquisition or disposal of funds that do not easily permit capital withdrawal.

The marginal effects of the binary right-hand side variables are differences in the probability of selection when the variable takes the value of 1 rather than 0. Of these binary variables, most of the strategy dummies are significant at the 5% level. This reflects the fact that the strategy mix of the sample under consideration in this study differs significantly from that in the universe of all hedge funds and funds of funds. Turning to the other binary variables, the high-water mark/hurdle rate dummy does appear to be a significant determinant of selection: Funds which employ these provisions to align the interests of managers and investors are more often demanded or supplied by outside investors. However the interaction between the presence of a lockup restriction and the offshore dummy is not statistically significant, which suggests that concerns about the exclusion restriction *OFFSHORE* capturing liquidity restrictions may not be warranted in this sample. Finally, the exclusion restriction *OFFSHORE* is a statistically significant determinant of selection.

The next section incorporates the inverse Mills ratio computed from the selection equation into the regression which explains the premium, to correct for possible selection bias in the results.

4.1.3. Results: Incorporating the Selection Bias Correction

The coefficient on the inverse Mills ratio takes the sign of the correlation between the residuals in the regressions that explain selection and the premium (equations (D.2) and (D.1) in Appendix C). If this sign is estimated to be positive (negative), this suggests that

funds that are solicited on Hedgebay are more likely (less likely) to exhibit high unexplained strategy-adjusted returns. In Table IX, the coefficient on the inverse Mills ratio is negative and statistically significant across all specifications. One possible interpretation of this result is that over the sample period (and especially towards the end), funds expected to underperform are more often the subject of indications of interest than those expected to outperform.

The inclusion of the inverse Mills ratio also seems to have important effects on the explanatory regression for the premium – it kills off the (admittedly weak) forecasting power of the large supply indication. Nevertheless, there is still strong and statistically significant forecasting power across all specifications for the small supply indications, and for five out of the six specifications for the large demand indication as well. In the final specification, the inclusion of the inverse Mills ratio also makes the large demand indication statistically insignificant, suggesting that the detected forecasting power of large demand indications is related to managerial option delta, a relationship which is undetectable when selection bias is not controlled for.

In Table IX, virtually all of the other determinants of the premium that were significant in Table VI (other than the size of the fund) continue to be statistically significant at the same level as before, with the same signs, and virtually the same coefficient magnitudes as before. This finding and the fact that the forecasting power of indications survives the correction for selection bias is reassuring, and suggests that the results are not contaminated by selection bias. However the concern about risk-adjustment using the strategy-excess returns still remains. The next section employs a calendar-time regression approach and the Fung-Hsieh seven factor model to verify the robustness of the results.

4.2. Calendar-Time Portfolio Approach

Can the information in demand and supply indications be used to help a real-world investor allocate capital to hedge funds? In this section, the analysis takes the perspective of such an investor, and employs the indications to construct a capital allocation strategy. The strategy is implemented as follows: First, take each indication during the month it arrives, and track the returns of the hedge fund i for which the indication arrives in month

t , and add it to the portfolio, holding it for the subsequent 12 months following the arrival of the indication, i.e., for months $t + 1$ to $t + 12$. Separate portfolios are constructed for demand indications, supply indications, and big and small demand and supply indications (constructed as outlined in the analysis above). For comparison and benchmarking purposes, I also use the same strategy to construct an 'unconditional' hedge fund portfolio, using all available funds in the consolidated database of funds in each month, and hold the portfolio for 12 months. I then regress the resulting portfolios on the Fung-Hsieh seven factors and an intercept, and correct the standard errors from the regressions using the Newey-West procedure, using 12 lags of the residuals to clean the standard errors for any autocorrelation induced by overlapping returns in the portfolios.

Figure 3 presents a graphical representation of the cumulative raw returns from the aggregate portfolio, and the demand indication and supply indication portfolios. The figure shows that the demand portfolio significantly outperforms both the aggregate and the supply portfolio in raw return terms, especially during the downturn experienced in the most recent period of the data. The performance of the supply portfolio is close to that of the aggregate portfolio, but towards the end of the data, the aggregate portfolio outperforms it, suggesting that supply indications are more informative during significant aggregate downturns in hedge fund returns. However to make any conclusive statements, we need to go further, and risk-adjust these returns.

Table X conducts the calendar-time portfolio analysis over the period from February 2002 to December 2008 (January 2002 is the first date in the sample, but since the portfolios are constructed out of sample, we drop that observation). The first column of the table reveals that despite the troubles of the hedge fund sector, the aggregate hedge fund portfolio has generated 40 basis points of alpha per month after fees (this should of course be viewed in light of the biases inherent in reported hedge fund returns that have been extensively documented by authors such as Liang (2000) and Fung and Hsieh (2000)). The demand indications portfolio has slightly higher alpha, of approximately 50 basis points per month, an improvement of around 1.2% per annum after fees. The supply indications portfolio, on the other hand, has statistically insignificant alpha, with a point estimate of 17 basis points per month. Clearly by overweighting the funds in the demand portfo-

lio and underweighting those in the supply portfolio, a real-world investor could have benefited.

The remaining columns of Table X use the size of the demand and supply indications as additional information in the calendar-time portfolio regressions. The main important result here is the statistically significant 75 basis point per month alpha of the big demand portfolio, a large improvement of 4.2 percent per annum over the aggregate hedge fund portfolio. What is also interesting is that the point estimate of alpha on the large supply portfolio is -15 basis points per month (although this is statistically insignificant). Clearly conditioning on the size of the indication provides additional gain to a real-world investor using this information to construct a portfolio of hedge funds. Taken together, the calendar-time approach confirms the findings from the strategy-adjusted hedge fund returns analyzed in event-time.

5. Conclusions

This paper employs data on investors' expressed indications of interest to buy or sell hedge funds to ascertain whether hedge fund investors rationally anticipate future hedge fund returns. Using both standard event-time and calendar-time portfolio analysis techniques, even after controlling for other well-known determinants of hedge fund returns such as flows, lagged returns and managerial option deltas, indications of interest on the secondary market provide useful signals of future hedge fund returns. Furthermore, the information contained in these indications would be of use of a real-world investor considering an allocation of capital to hedge funds. I conclude not only that hedge fund investors are rational, but also that there is evidence of private information about future hedge fund returns contained in their expressed demands. The results offer strong support to the hypothesis that capital is provided to hedge funds by rational, well-informed investors. This has implications for the future risk-adjusted performance of the hedge fund sector as a whole.

Appendix A

Matching Hedgebay Data to the Consolidated Hedge Fund Database

The final combined database used in this paper comprises 9,305 funds of funds and hedge funds for which comprehensive information on returns and fund characteristics such as minimum investment amounts, the presence of high water mark or hurdle rate provisions, redemption frequencies and fees are available. This number includes data on 8 funds for which administrative information and returns are obtained from Hedgebay. This appendix describes how this combined database was created.

The hedge fund and fund of funds data span four different sources: TASS, HFR, Morningstar and CISDM, all from December 2008. There are a total of 20,823 live and dead funds across all four databases, for which both administrative information (including fund characteristics) and returns information were available. This number is misleading, since an individual fund can appear multiple times from different vendors, resulting in duplication. The information available in the administrative files of the databases are used to systematically remove duplicates. The criteria used for elimination are:

1. Key name: different funds from different database sources occasionally name the same fund differently. A "Key name" is created for each unique fund using a name-matching algorithm that eliminates differences on account of hyphenation, misspellings and punctuation.

2. Currency: funds that have the same Key names might offer shares to investors in multiple different currencies. These differences are preserved, as occasionally, on Hedgebay, only one share class in a particular currency is traded.

3. Strategy: there are 78 different strategies listed in the consolidated administrative information file coming from the four different database sources. Using the classification system employed in Naik, Ramadorai and Stromqvist (2007), these 78 strategies are condensed into nine broad categories. The correspondence between the strategies encountered in the administrative file, and the broad categories is presented in the Table A.1. below.

4. Management Company: since the information came from four different sources, the names of the management companies of funds are also occasionally differently spelled.

The names of management companies are standardized in the same way as the creation of key names (point 1. above).

5. Length of History: the administrative files include information such as from- and to-dates, which provide the start and end date of when information about the hedge fund or fund-of-funds was recorded in the database source. If there are two or more funds that are completely identical in terms of key name, currency, strategy, and management company, the fund for which the longest period of information is available is selected.

This process reduces the list of funds to 16,659 funds-of-funds and hedge funds. Next, additional criteria from the administrative files are used to remove any remaining duplicates. Funds with identical key names, currencies, and from-dates are compared based on their reported minimum investment, redemption notice periods and lock-up periods. If, within these subgroups, all of the three administrative fields are the same, the funds are assumed to be the same. In cases of duplicates, those with the greatest length of history are chosen, as before. This procedure results in the elimination of an additional 1,732 names, leaving administrative information on 14,927 unique hedge funds and funds-of-funds. Finally, I require that the funds have information available for every one of the fields employed in the selection analysis (complete administrative information). This eliminates a total of 5,650 funds, leaving a total of 9,305 funds from the consolidated database. Of these funds, 713 funds have indications of interest on Hedgebay, of which 518 have return information available for 12 months prior to and 12 months following the arrival of the indication of interest on Hedgebay. The sources of these funds and the percentage that are alive and defunct (either liquidated or closed to new investments) are shown in Table A.2.

Table A.1.
Vendor Provided Strategies and Mapped Strategies

This table shows the fund strategies provided by HFR, TASS, CISDM and MSCI data vendors in the first column, and the nine strategies to which these are mapped in the second column.

Strategy in Consolidated Database	Mapped Strategy
Arbitrage	Relative Value
Capital Structure Arbitrage	Relative Value
Convertible Arbitrage	Fixed Income
CPO-Multi Strategy	Other
CTA – Commodities	Other
CTA-Systematic/Trend-Following	Other
Dedicated Short Bias	Directional Traders
Directional Traders	Directional Traders
Discretionary Trading	Other
Distressed Securities	Multi-Process
Emerging	Emerging
Emerging Markets	Emerging
Emerging Markets: Asia	Emerging
Emerging Markets: E. Europe/CIS	Emerging
Emerging Markets: Global	Emerging
Emerging Markets: Latin America	Emerging
Equity Hedge	Security Selection
Equity Long Only	Directional Traders
Equity Long/Short	Security Selection
Equity Market Neutral	Security Selection
Equity Non-Hedge	Directional Traders
Event Driven	Multi-Process
Event Driven Multi Strategy	Multi-Process
Event-Driven	Multi-Process
Fixed Income	Fixed Income
Fixed Income – MBS	Fixed Income
Fixed Income Arbitrage	Fixed Income
Fixed Income: Arbitrage	Fixed Income
Fixed Income: Convertible Bonds	Fixed Income
Fixed Income: Diversified	Fixed Income
Fixed Income: High Yield	Fixed Income
Fixed Income: Mortgage-Backed	Fixed Income
FOF-Conservative	Funds of Funds
FOF-Invest Funds in Parent Company	Funds of Funds
FOF-Market Neutral	Funds of Funds
FOF-Multi Strategy	Funds of Funds
FOF-Opportunistic	Funds of Funds
FOF-Single Strategy	Funds of Funds
Foreign Exchange	Global Macro
Fund of Funds	Funds of Funds
Global Macro	Global Macro
HFRI	Other
Index	Other
Long Bias	Directional Traders

Table A.1. (Continued)

Strategy in Consolidated Database	Mapped Strategy
Long/Short Equity Hedge	Security Selection
Long-Short Credit	Fixed Income
Macro	Global Macro
Managed Futures	Other
Market Timing	Directional Traders
Merger Arbitrage	Relative Value
Multi Strategy	Multi-Process
Multi-Process	Multi-Process
Multi-Strategy	Multi-Process
No Bias	Relative Value
Option Arbitrage	Relative Value
Other Relative Value	Relative Value
Private Placements	Multi-Process
Regulation D	Relative Value
Relative Value	Relative Value
Relative Value Arbitrage	Relative Value
Relative Value Multi Strategy	Multi-Process
Sector	Directional Traders
Sector: Energy	Directional Traders
Sector: Financial	Directional Traders
Sector: Health Care/Biotechnology	Directional Traders
Sector: Miscellaneous	Directional Traders
Sector: Real Estate	Directional Traders
Sector: Technology	Directional Traders
Security Selection	Security Selection
Short Bias	Directional Traders
Short Selling	Directional Traders
Statistical Arbitrage	Relative Value
Strategy	Other
Systematic Trading	Directional Traders
Tactical Allocation	Directional Traders
UNKNOWN STRATEGY	Other
Variable Bias	Directional Traders
(blank)	Other

Table A.2. Data Sources

This table shows the number of funds from each of the five sources (HFR, TASS, CISDM, MSCI and Hedgebay), and the number of these funds that are alive and defunct (either liquidated or closed) in the consolidated universe of hedge fund data.

Source Dataset	Number of Funds	Alive	Defunct	% Defunct
TASS	3489	1823	1666	47.750%
HFR	3770	2288	1482	39.310%
MSCI	1823	1113	710	38.947%
CISDM	215	196	19	8.837%
Proprietary/Hedgebay	8	0	8	100.000%
Total	9305	5420	3885	41.752%

Appendix B

Measuring Managerial Incentives

To compute measures of managerial option delta and managerial investment for the funds in the sample, I employ the Black-Scholes option calculation method outlined in the Appendix of Agarwal, Daniel and Naik (2009), with one modification, namely, I assume that investors' money flows occur at the end of each year-end working backwards from the month prior to the transaction-month, and that incentive fees are paid according to the same schedule. This stands in contrast to Agarwal et al.'s use of December as the end of each calendar year. That is, if the transaction occurred in November of 1996, I assume that money flows and incentive fees occurred in October of each year, and work through the calculations of delta with all other facets of the Agarwal et al. calculation unchanged. This modification is to ensure that I have the maximum number of observations of option delta and managerial investment, a necessity given the desire to avoid losing observations in the sample. Note that as in Agarwal et al., I lag all computed variables by a month to avoid any mechanical association. The correlation between the total deltas computed with this modification and total deltas calculated using the calendar year assumption of Agarwal et al. is 96.78% in the panel of fund-months.

Appendix C The Selection Bias Correction

Formally, the determinants of selection are modelled as:

$$\begin{aligned} z_{i,t}^* &= \mathbf{w}'_{i,t-1} \gamma + u_{i,t} \\ z_{i,t} &= 1 \text{ if } z_{i,t}^* > 0 \\ z_{i,t} &= 0 \text{ if } z_{i,t}^* \leq 0. \end{aligned} \tag{D.1}$$

Here, $z_{i,t}$ is a ‘selection’ variable that takes the value of 1 if an indication arrives for fund i in year t on Hedgebay, and 0 otherwise. $z_{i,t}^*$ is an unobserved latent variable, and $\mathbf{w}'_{i,t-1}$ is a set of variables that determine whether a fund is traded in a year.⁷ Next, consider the previously employed regression equation to explain the strategy-adjusted excess returns for a fund i at time t ($STRATRET_{i,t}$), written with a generic right-hand side vector of determinants of these returns, $\mathbf{x}_{i,t}$ (which contains some of the same constituents as $\mathbf{w}_{i,t-1}$):

$$STRATRET_{i,t} = \mathbf{x}'_{i,t} \beta + \varepsilon_{i,t}. \tag{D.2}$$

Note that (D.2) is observed only if $z_{i,t} = 1$. I assume that the errors in equations (D.1) and (D.2) have a bivariate normal distribution:⁸

$$(\varepsilon_{i,t}, u_{i,t}) \sim N \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_\varepsilon^2 & \rho\sigma_\varepsilon \\ \rho\sigma_\varepsilon & 1 \end{bmatrix} \right). \tag{D.3}$$

Then, using the moments of the incidentally truncated bivariate normal distribution, following Greene (2003):

$$E[STRATRET_{i,t} \mid z_{i,t} = 1, \mathbf{x}_{i,t}, \mathbf{w}_{i,t-1}] = \mathbf{x}'_{i,t} \beta + \delta \lambda(\mathbf{w}'_{i,t-1} \gamma), \tag{D.4}$$

where $\delta = \rho\sigma_\varepsilon$, which will have the sign of the correlation (ρ) between the residual in the selection equation (D.1) and in the explanatory equation (D.2), that is, δ is informative about whether funds that are traded on Hedgebay have higher or lower strategy-adjusted excess returns as a consequence of selection.

$\lambda(\mathbf{w}'_{i,t-1} \gamma)$ is known as the inverse Mills ratio, and it can be computed from the estimated coefficients of equation (D.1). To estimate γ , I employ maximum likelihood and a probit model on the entire universe of hedge funds and funds-of-funds.⁹ Once this is done, $\hat{\lambda}(\mathbf{w}'_{i,t-1} \hat{\gamma}) = \frac{\phi(\mathbf{w}'_{i,t-1} \hat{\gamma})}{\Phi(\mathbf{w}'_{i,t-1} \hat{\gamma})}$ (where $\phi(\cdot)$ is the standard normal density function, and

⁷The $t - 1$ time subscript captures the fact that the time-varying variables in the set are lagged – as explained in the subsection on the exclusion restriction.

⁸I model equation (D.1) as a probit, and normalize $u_{i,t} \sim N(0, 1)$. This is innocuous, since z is 0 or 1 depending on the sign, not the scale of z^* (see Greene (2003)).

⁹When estimating the probit, I treat multiple share classes of fund as separate funds in order to make the selection bias correction robust to the variations in liquidity restrictions, fee structures and returns that often characterize different share classes of the same fund.

$\Phi(\cdot)$ is the standard normal cumulative distribution function) can be incorporated into (D.2) as a selection bias correction:

$$STRATRET_{i,t} = \mathbf{x}'_{i,t}\beta + \delta\hat{\lambda}(\mathbf{w}'_{i,t-1}\hat{\gamma}) + v_{i,t}. \quad (\text{D.5})$$

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Table I
Overview of Indications of Interest by Year

This table shows the percentiles of the distribution of both demand and supply indications of interest in the dataset. The statistics are shown in dollar terms as well as in terms of the percentages of the funds' assets under management (AUM). Where fund AUM is unavailable, the average AUM across funds in the strategy is utilized.

Demand	Mean	Minimum	5th. Percentile	50th. Percentile	95th. Percentile	Maximum
Amount(Dollars)	5,226,390	34,000	500,000	3,000,000	16,000,000	76,000,000
Amount/AUM	3.902%	0.066%	0.097%	1.269%	16.156%	38.895%
Supply						
Amount(Dollars)	4,253,852	100,000	437,000	2,250,000	15,000,000	50,400,000
Amount/AUM	3.843%	0.041%	0.062%	1.147%	18.395%	41.042%

Table II
Summary Statistics of Demand and Supply Indications of Interest

This table shows summary statistics over time for both demand and supply indications of interest in the dataset. The rows in columns show the number of matched indications, the number that are demanded or supplied at a premium, neither a premium nor a discount, and at a discount (this information is only available for the early years of the data), the mean indication size as a percentage of AUM, the median indication size as a percentage of AUM, and the mean indication size in dollars.

Demand	2002	2003	2004	2005	2006	2007	2008	2009
N(Indications)	743	765	260	641	1056	887	196	61
N(Premium)	247	336	115	0	0	0	0	0
N(No Premium/Discount)	350	348	132	641	1056	887	196	61
N(Discount)	146	81	13	0	0	0	0	0
N(Funds)	43	63	61	106	124	201	109	51
Mean(Amount/AUM)	3.895%	4.636%	5.902%	2.841%	3.883%	3.883%	2.843%	1.422%
Median(Amount/AUM)	1.279%	1.369%	1.695%	1.019%	1.260%	1.426%	0.834%	0.810%
Mean(Dollar Amount)	3,813,324	3,520,915	5,133,321	4,694,225	5,338,883	7,512,374	8,067,403	5,498,770
Supply	2002	2003	2004	2005	2006	2007	2008	2009
N(Indications)	646	742	210	684	748	507	412	98
N(Premium)	334	457	90	0	0	0	0	0
N(No Premium/Discount)	255	229	91	684	748	507	412	98
N(Discount)	57	56	29	0	0	0	0	0
N(Funds)	73	92	69	153	161	183	194	74
Mean(Amount/AUM)	4.108%	3.654%	4.159%	3.488%	4.750%	3.591%	3.011%	3.204%
Median(Amount/AUM)	0.973%	1.298%	1.289%	0.979%	1.191%	1.491%	1.097%	1.120%
Mean(Dollar Amount)	1,775,833	2,277,103	3,912,556	4,861,617	5,157,793	6,775,101	5,713,456	5,965,367

Table III
Characteristics of the Hedgebay Sample

This table compares the mean of each of the variables listed in rows first computed in the sample of funds for which indications arrive on Hedgebay (Solicited) and second, computed across all observations in the consolidated dataset of funds (Universe). The means of the variables are computed across all unique funds appearing in the sample and the universe, respectively. The t-statistic reported for the difference in means is computed using the White heteroskedasticity-consistent estimator.

	SOLICITED	UNIVERSE	T-Stat of Difference
NUMBER	713	10790	
MININV (\$MM)	1.561	1.058	2.949
LOCK (%)	38.149	31.112	4.016
REDEMP (Months)	1.539	1.164	10.207
REDFREQ (Months)	2.861	2.412	3.882
MGMTFEE (%)	1.479	1.435	2.121
INCFEE (%)	19.219	17.025	12.777
OFFSHORE (%)	69.425	59.778	4.771
STRATEGIES			
Security Selection	32.118	24.625	4.458
Global Macro	4.769	5.496	0.938
Relative Value	6.732	7.183	0.496
Directional Traders	8.696	14.764	5.832
Funds of Funds	6.171	20.009	14.993
Multi-Process	19.355	8.721	7.571
Emerging Markets	6.311	4.745	1.795
Fixed Income	12.482	6.886	4.749
Other	3.366	7.572	6.197

Table IV
Strategy-Adjusted Returns One Year After Indications of Interest

This table regresses average strategy-adjusted hedge fund returns over the (+1,+12) month window following an indication of interest on a number of different regressors. Specification (1) regresses these strategy adjusted returns on an intercept, a demand (supply) indicator variable that takes the value of 1 for a demand (supply) indication; (1) without the intercept, but with strategy specific fixed effects – (2); (2) adding lagged strategy adjusted returns – (3); (3) adding lagged flows into the fund – (4); (4) adding the manager’s option delta, the total compensation delta (computed using the method of Agarwal, Daniel and Naik (2009)), and the rank of the fund’s lagged AUM in the set of all live funds – (5). Coefficients significant at the 5% (10%) level are in underlined bold (underlined).

	Specifications				
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.063				
	0.153				
Demand Indicator	0.221	<u>0.240</u>	0.187	0.187	0.136
	0.154	0.146	0.142	0.142	0.151
Supply Indicator	-0.101	-0.084	-0.067	-0.067	-0.078
	0.136	0.150	0.153	0.153	0.163
Strat. Adj Rets (-12,-1)			<u>0.145</u>	<u>0.145</u>	<u>0.137</u>
			0.034	0.034	0.036
Flow(-12,-1)				-0.043	<u>-1.771</u>
				0.432	0.489
Mgr Option Delta (-1)					<u>4.803</u>
					0.956
log(Total Delta (-1))					-0.003
					0.011
Rank(AUM(-1))					<u>0.268</u>
					0.146
R-Squared	0.011	0.019	0.030	0.030	0.043
N	6280	6280	6210	6210	5838
N(Funds)	518	518	512	512	492
Strategy Dummies?	No	Yes	Yes	Yes	Yes

Table V
Strategy-Adjusted Returns Two Years After Indications of Interest

This table regresses average strategy-adjusted hedge fund returns over the (+1,+24) month window following an indication of interest on a number of different regressors. Specification (1) regresses these strategy adjusted returns on an intercept, a demand (supply) indicator variable that takes the value of 1 for a demand (supply) indication; (1) without the intercept, but with strategy specific fixed effects (2); (2) adding lagged strategy adjusted returns (3); (3) adding lagged flow into the fund (4); (4) adding the manager's option delta, the total compensation delta (computed using the method of Agarwal, Daniel and Naik (2009)), and the rank of the fund's lagged AUM in the set of all live funds (5). Coefficients significant at the 5% (10%) level are in underlined bold (underlined).

	Specifications				
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.062				
	0.148				
Demand_Indicator	<u>0.262</u>	<u>0.295</u>	<u>0.263</u>	<u>0.262</u>	0.167
	0.148	0.146	0.141	0.141	0.147
Supply_Indicator	-0.113	-0.079	-0.046	-0.046	-0.078
	0.132	0.151	0.152	0.152	0.160
Strat Adj Rets (-24,-1)			<u>0.149</u>	<u>0.149</u>	<u>0.180</u>
			0.029	0.030	0.029
Flow(-24,-1)				-0.075	<u>-1.889</u>
				0.451	0.499
Mgr Option Delta (-1)					<u>4.909</u>
					1.042
log(Total Delta (-1))					<u>-0.022</u>
					0.010
Rank(AUM(-1))					<u>0.342</u>
					0.115
R-Squared	0.017	0.027	0.037	0.037	0.058
N	6310	6310	6210	6210	5838
N(Funds)	520	520	512	512	492
Strategy Dummies?	No	Yes	Yes	Yes	Yes

Table VI
Strategy-Adjusted Returns One Year After Large and Small Indications of Interest

This table regresses average strategy-adjusted hedge fund returns over the (+1,+12) month window following an indication of interest on a number of different regressors. Specification (1) regresses these strategy adjusted returns on an intercept, a large demand (large supply) indicator variable that takes the value of 1 for a demand (supply) indication that is greater than or equal to the 75th percentile of demand (supply) indications, and a small demand (small supply) indicator variable that takes the value of 1 for a demand (supply) indication less than or equal to the 25th percentile of demand (supply) indications; (1) without the intercept, but with strategy specific fixed effects – (2); (2) adding lagged strategy adjusted returns – (3); (3) adding lagged flows into the fund – (4); (4) adding the manager’s option delta, the total compensation delta (computed using the method of Agarwal, Daniel and Naik (2009)), and the rank of the fund’s lagged AUM in the set of all live funds – (5). Coefficients significant at the 5% (10%) level are in underlined bold (underlined).

	Specifications				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.009				
	0.037				
Big Demand_Indicator	<u>0.308</u>	<u>0.309</u>	<u>0.282</u>	<u>0.282</u>	<u>0.212</u>
	0.054	0.056	0.056	0.056	0.054
Small Demand_Indicator	<u>0.076</u>	0.058	-0.025	-0.025	-0.017
	0.042	0.040	0.040	0.040	0.041
Big Supply_Indicator	<u>-0.224</u>	<u>-0.225</u>	<u>-0.192</u>	<u>-0.192</u>	-0.185
	0.116	0.114	0.115	0.114	0.120
Small Supply_Indicator	<u>-0.231</u>	<u>-0.241</u>	<u>-0.194</u>	<u>-0.193</u>	<u>-0.165</u>
	0.054	0.052	0.054	0.054	0.060
Strat Adj Rets (-12,-1)			<u>0.152</u>	<u>0.152</u>	<u>0.140</u>
			0.034	0.034	0.036
Flow(-12,-1)				-0.082	<u>-1.920</u>
				0.420	0.476
Mgr Option Delta (-1)					<u>5.098</u>
					0.978
log(Total Delta (-1))					-0.005
					0.010
Rank(AUM(-1))					<u>0.294</u>
					0.146
R-Squared	0.012	0.019	0.032	0.032	0.044
N	6280	6280	6210	6210	5838
N(Funds)	518	518	512	512	492
Strategy Dummies?	No	Yes	Yes	Yes	Yes

Table VII
Strategy-Adjusted Returns Two Years After Large and Small Indications of Interest

This table regresses average strategy-adjusted hedge fund returns over the (+1,+12) month window following an indication of interest on a number of different regressors. Specification (1) regresses these strategy adjusted returns on an intercept, a large demand (large supply) indicator variable that takes the value of 1 for a demand (supply) indication that is greater than or equal to the 75th percentile of demand (supply) indications, and a small demand (small supply) indicator variable that takes the value of 1 for a demand (supply) indication less than or equal to the 25th percentile of demand (supply) indications; (1) without the intercept, but with strategy specific fixed effects – (2); (2) adding lagged strategy adjusted returns – (3); (3) adding lagged flows into the fund – (4); (4) adding the manager’s option delta, the total compensation delta (computed using the method of Agarwal, Daniel and Naik (2009)), and the rank of the fund’s lagged AUM in the set of all live funds – (5). Coefficients significant at the 5% (10%) level are in underlined bold (underlined).

	Specifications				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.029				
	0.029				
Big Demand_Indicator	<u>0.167</u>	<u>0.166</u>	<u>0.155</u>	<u>0.153</u>	0.024
	0.044	0.043	0.045	0.046	0.045
Small Demand_Indicator	<u>0.120</u>	<u>0.089</u>	0.018	0.017	0.041
	0.041	0.037	0.033	0.033	0.037
Big Supply_Indicator	<u>-0.199</u>	<u>-0.201</u>	-0.139	-0.139	-0.166
	0.116	0.114	0.116	0.115	0.115
Small Supply_Indicator	<u>-0.204</u>	<u>-0.223</u>	<u>-0.198</u>	<u>-0.197</u>	<u>-0.181</u>
	0.049	0.047	0.049	0.049	0.054
Strat Adj Rets (-24,-1)			<u>0.164</u>	<u>0.166</u>	<u>0.189</u>
			0.029	0.030	0.029
Flow(-24,-1)				-0.210	<u>-2.114</u>
				0.433	0.487
Mgr Option Delta (-1)					<u>5.233</u>
					1.056
log(Total Delta (-1))					<u>-0.019</u>
					0.010
Rank(AUM(-1))					<u>0.384</u>
					0.117
R-Squared	0.007	0.017	0.030	0.030	0.055
N	6310	6310	6210	6210	5838
N(Funds)	520	520	512	512	491
Strategy Dummies?	No	Yes	Yes	Yes	Yes

Table VIII
Time-Varying Probit Model for Indications

This table presents results from a probit selection equation, estimated using maximum likelihood, for the probability of the arrival of an indication of interest for a hedge fund on Hedgebay. The column dF/dX shows the marginal effect, that is, the change in this probability for an infinitesimal change in each independent, continuous variable and the discrete change in the probability for dummy variables, all reported in percent. The marginal effects are calculated when variables are set to their mean values in the sample. The next column reports the t-statistic for the associated coefficient estimate of the marginal effect (from the underlying probit equation), computed from standard errors that are clustered by calendar year. The rows list the variables used in the selection equation. Note that there are eight strategy dummy variables employed in estimation: the ninth, for 'Other' funds is dropped to avoid perfect collinearity. The last few rows show the observed probability, i.e., the percentage of fund-years in the consolidated database in which there are trades on Hedgebay; the Pseudo R-squared statistic from Probit estimation; the Chi-squared statistic from a Wald test of the null hypothesis that all coefficients are jointly zero, and the p-value at which the null hypothesis is rejected. Coefficients significant at the 5% (10%) level are in underlined bold (underlined).

	<u>dF/dX</u>	Clustered t-statistic
Mean Monthly Return (previous year)	<u>0.111</u>	4.460
Size (AUM) (percentile rank)	<u>6.081</u>	24.810
Minimum Investment (percentile rank)	-0.037	-0.210
Management Fee	<u>0.246</u>	3.660
Incentive Fee	<u>0.072</u>	7.390
Redemption Restrictions	<u>0.001</u>	5.090
Subscription Restrictions	<u>-0.008</u>	-4.380
Hurdle Rate/High Water Mark Provision	<u>0.736</u>	7.180
Lock*Offshore Dummy	0.015	0.100
EXCLUSION RESTRICTION		
Offshore Dummy	<u>0.451</u>	3.740
STRATEGIES		
Security Selection	<u>2.113</u>	5.250
Global Macro	<u>1.008</u>	2.330
Relative Value	<u>0.960</u>	2.350
Directional Traders	<u>0.686</u>	1.930
Funds of Funds	-0.441	-1.460
Multi-Process	<u>2.556</u>	5.360
Emerging Markets	<u>1.835</u>	3.710
Fixed Income	<u>2.567</u>	4.970
Observed Probability	0.034	
Pseudo R-Squared	0.214	
Chi2(17)	986.210	
P-value(Chi2)	0.000	
N(Fund-Years)	32,746	

Table IX
Strategy-Adjusted Returns One Year After Large and Small Indications of Interest, Corrected for Selection Bias

This table regresses average strategy-adjusted hedge fund returns over the (+1,+12) month window following an indication of interest on a number of different regressors. Specification (1) regresses these strategy adjusted returns on an intercept, a large demand (large supply) indicator variable that takes the value of 1 for a demand (supply) indication that is greater than or equal to the 75th percentile of demand (supply) indications, and a small demand (small supply) indicator variable that takes the value of 1 for a demand (supply) indication less than or equal to the 25th percentile of demand (supply) indications; (1) without the intercept, but with strategy specific fixed effects – (2); (2) adding lagged strategy adjusted returns – (3); (3) adding lagged flows into the fund – (4); (4) adding the manager’s option delta, the total compensation delta (computed using the method of Agarwal, Daniel and Naik (2009)), and the rank of the fund’s lagged AUM in the set of all live funds – (5). Coefficients significant at the 5% (10%) level are in underlined bold (underlined). All specifications contain the inverse Mills ratio (IMILLS) from the time-varying probit model estimated in Table VIII. Coefficients significant at the 5% (10%) level are in underlined bold (underlined).

	Specifications				
	(1)	(2)	(3)	(4)	(5)
Intercept	<u>0.232</u> 0.088				
Big Demand_Indicator	<u>0.139</u> 0.052	<u>0.144</u> 0.051	<u>0.113</u> 0.052	<u>0.113</u> 0.052	0.023 0.055
Small Demand_Indicator	0.019 0.041	-0.019 0.042	<u>-0.074</u> 0.040	<u>-0.074</u> 0.040	-0.054 0.039
Big Supply_Indicator	-0.144 0.118	-0.143 0.118	-0.113 0.115	-0.112 0.114	-0.122 0.112
Small Supply_Indicator	<u>-0.230</u> 0.054	<u>-0.249</u> 0.053	<u>-0.202</u> 0.055	<u>-0.202</u> 0.055	<u>-0.179</u> 0.060
IMILLS	<u>-0.121</u> 0.038	<u>-0.216</u> 0.070	<u>-0.204</u> 0.070	<u>-0.204</u> 0.070	<u>-0.293</u> 0.122
Strat Adj Rets (-12,-1)			<u>0.161</u> 0.035	<u>0.160</u> 0.035	<u>0.146</u> 0.036
Flow(-12,-1)				0.070 0.451	<u>-1.523</u> 0.488
Mgr Option Delta (-1)					<u>4.865</u> 1.007
log(Total Delta (-1))					-0.003 0.011
Rank(AUM(-1))					-0.203 0.232
R-Squared	0.006	0.015	0.030	0.030	0.042
N	6156	6156	6156	6156	5831
N(Funds)	520	520	512	512	491
Strategy Dummies?	No	Yes	Yes	Yes	Yes

Table X
Calendar-Time Portfolio Analysis

This table regresses the returns on several calendar-time portfolios on the Fung-Hsieh seven factors. The first (aggregate portfolio) uses all funds in the consolidated database, and for each month follows the returns of the live funds in that month for the next 12 months. This is done for every month in the data. The demand (supply) portfolio does the same for all funds that have a demand (supply) indication on Hedgebay; the small (big) demand and supply portfolios the same for funds with greater than or equal to 75th percentile (less than or equal to 25th percentile) demand or supply indications. Newey-West standard errors with 12 lags are utilized to correct for heteroskedasticity and autocorrelation induced by the overlapping portfolio construction. Coefficients significant at the 5% (10%) level are in underlined bold (underlined). The number of observations across portfolios occasionally differs owing to the non-availability of categorized indications at certain periods of time.

	Aggregate Portfolio	Demand Portfolio	Supply Portfolio	Small Demand Portfolio	Big Demand Portfolio	Small Supply Portfolio	Big Supply Portfolio
Alpha	<u>0.406</u>	<u>0.496</u>	0.166	0.218	<u>0.754</u>	0.374	-0.148
	0.187	0.175	0.203	0.260	0.270	0.262	0.283
RmRf	0.654	0.216	-0.387	-0.535	0.979	0.094	-0.934
	0.898	0.803	0.839	0.848	1.142	1.160	1.035
SMB	11.608	10.670	5.085	11.311	13.221	-1.342	10.661
	7.816	9.866	7.579	11.087	12.581	8.701	10.806
TCM10Y	<u>-0.979</u>	-0.411	-0.543	-1.133	0.103	-0.556	-0.880
	0.556	0.899	0.532	1.038	1.140	0.636	0.553
BAAMTSY	<u>-5.460</u>	<u>-4.165</u>	<u>-5.689</u>	<u>-6.089</u>	<u>-3.641</u>	<u>-7.631</u>	<u>-6.126</u>
	0.390	0.642	0.524	0.470	1.084	1.107	0.708
PTFSBD	<u>-1.771</u>	<u>-3.129</u>	<u>-2.280</u>	<u>-3.233</u>	<u>-4.629</u>	<u>-2.383</u>	<u>-1.957</u>
	0.817	1.061	0.956	1.044	1.597	1.244	0.865
PTFSFX	0.147	0.416	<u>-1.117</u>	0.717	0.740	-1.542	-0.490
	0.541	0.612	0.579	0.861	0.762	1.053	0.729
PTFSCOM	0.806	1.362	0.819	1.023	2.210	2.073	0.110
	1.197	1.551	1.160	1.621	1.976	1.956	1.326
R-Squared	0.528	0.365	0.563	0.464	0.290	0.528	0.555
N	83	83	83	83	83	83	78

Figure 1
Demand Indications and Strategy-Adjusted Hedge Fund Returns in Event Time

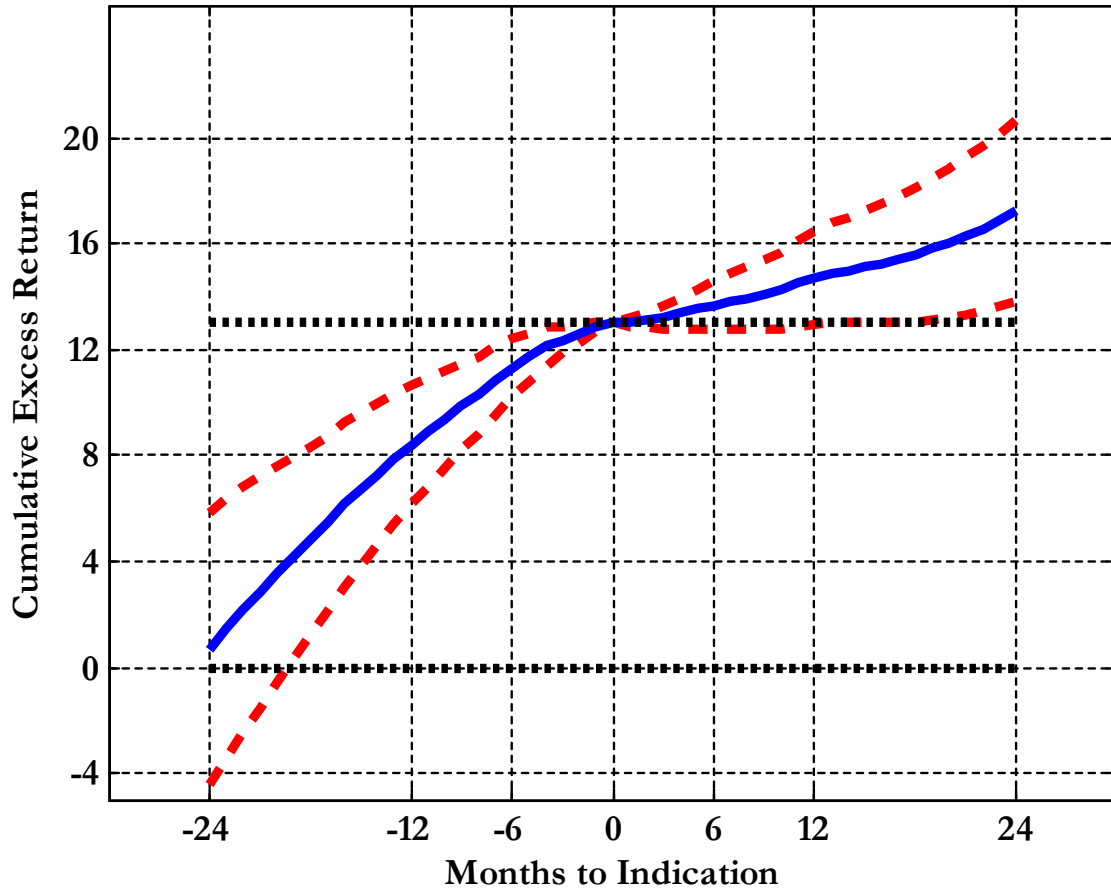


Figure 2
Supply Indications and Strategy-Adjusted Hedge Fund Returns in Event Time

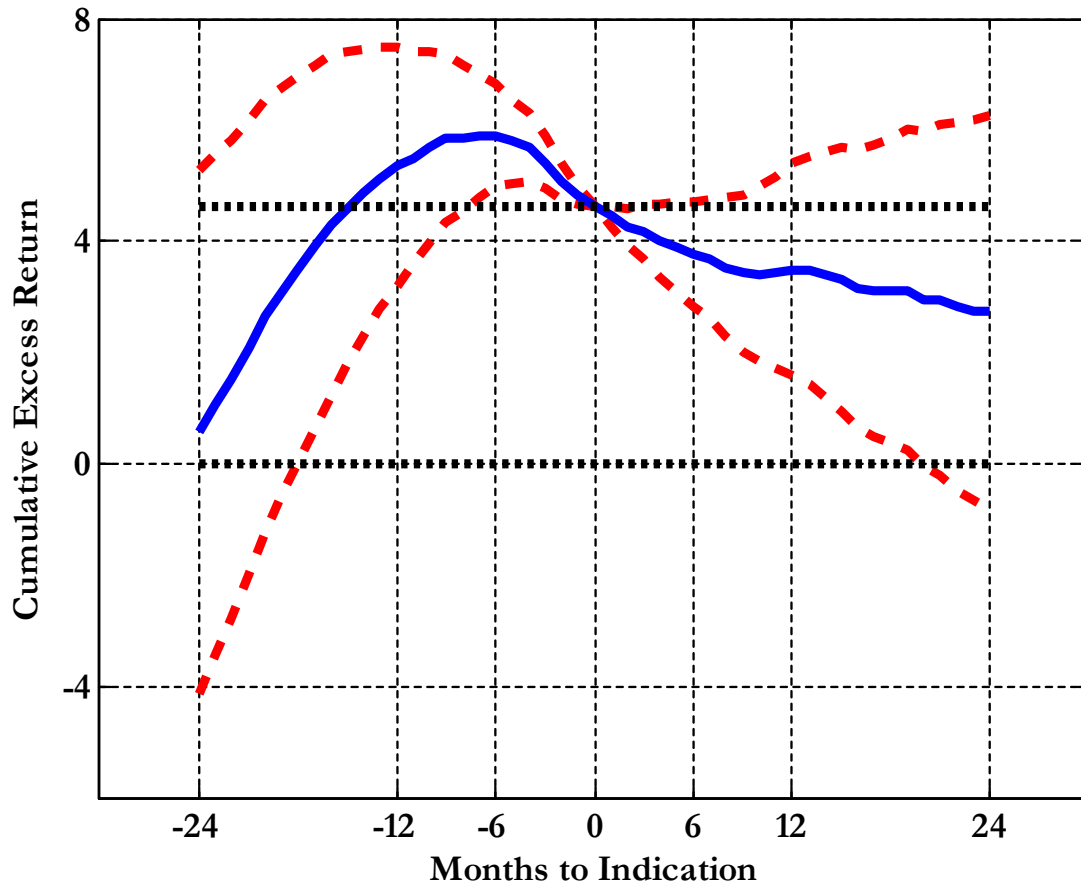


Figure 3
Demand and Supply Calendar-Time Portfolios

