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ABSTRACT

Investor Interest and Hedge Fund Returns*

Employing a new dataset of over 9,000 expressed demands for over 700 hedge funds from a secondary market for hedge funds, this paper finds evidence suggesting that hedge fund investors rationally anticipate future hedge fund performance. Both buy and sell indications of interest arrive following periods of fund outperformance. Buy (sell) indications have some forecasting power for increases (decreases) in hedge fund performance, over and above other well-known forecasting variables. This information in investor demand co-exists with the presence of capacity constraints in hedge fund returns, confirming two main assumptions of Berk and Green (2004).

JEL Classification: G11, G12 and G23
Keywords: capacity constraints, flows, hedge funds, information

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1. Introduction

Hedge fund assets under management have exploded over the past decade, and declined significantly in the recent past. 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 correctly 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 sophisticated decision makers.[1] However in behavioral 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.[2] 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, for example, Kosowski, Naik and Teo (2006) and Jagannathan and Novikov (2008)),[3] these findings suggest that hedge fund investors may indeed be rational decision makers, with the ability to anticipate future hedge fund performance. Accepting this view of hedge fund investors as rational and well-informed has important implications: if such sophisticated 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)

[1] See 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.

[2] See Baquero and Verbeek (2008), Fung, Hsieh, Naik and Ramadorai (2008), Wang and Zheng (2008) and Ding, Liang, Getmansky and Wermers (2009).

[3] A 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).

predict that in equilibrium, hedge fund alphas will shrink to zero, and performance persistence will disappear.

Before we accept this view and its attendant consequences, it is worth noting that the evidence about hedge fund investors is almost exclusively derived from regressions that condition capital flows and hedge fund returns on one another. This is problematic for a number of reasons. First, flows have been found to forecast hedge fund returns and alphas with a negative sign.[4] 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 at least two possibilities: one is that 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. Another, more consistent with the behavioral theories, is that hedge fund investors trend-chase returns, and shower successful hedge funds with new capital. These funds commit capital to assets that become overpriced and subsequently fall in value.[5] Flow-return regressions would be hard-pressed to disentangle these two explanations.

A second problem with flow-return regressions is that 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. Third, 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

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

[5]See Coval and Stafford (2007), Lou (2010) and Jotikasthira, Lundblad and Ramadorai (2010) among others for evidence that mutual fund flows temporarily impact the valuations of underlying assets held by these funds.

issue).

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.[6] The data comprises over 9,000 indications of interest over the period, in over 700 hedge funds. 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.[7] 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.[8] These features of the indications of interest make them a useful instrument for helping to shed light on the relationships between capacity constraints, the information available to investors, and future hedge fund returns.

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 or factor-model-adjusted) hedge fund returns, and conversely, indications of interest to sell forecast declines in future abnormal hedge fund returns. This forecasting power 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

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

[7]Ramadorai (2010) analyzes these completed transactions.

[8]When hedge funds are traded on Hedgebay, they are closed to new investments and withdrawals – but usually for a relatively short duration (inside the lockup and redemption notice period, or for a period of time before re-opening to new investments). Capital flows to these funds would normally take longer to get in or out than in an open fund, but unlike closed-end mutual funds, there is no legal obligation to restrict capital infusions or redemptions.

to hedge fund investors. Indications also forecast abnormal returns over and above managerial compensation deltas (computed using the method of Agarwal, Daniel and Naik (2009)) and variation in aggregate liquidity proxies. When measures of capital constraints (such as capital flows, fund size, and new fund launches by the same management company) are included in the forecasting regressions simultaneously with indications of interest, these measures negatively forecast hedge fund abnormal returns, while indications of interest positively forecast returns. Taken together, these findings confirm the co-existence of hedge fund investor rationality and capacity constraints in hedge funds, two key assumptions of Berk and Green (2004). It is worth noting that these results all survive the introduction of a control for selection bias, computed using the method of Heckman (1979).

Interesting additional variation in forecasting power is detected when the size of the indication (relative to fund AUM) is taken into account. Large and small sell indications and small buy indications are reliable positive forecasters of hedge fund returns over short (12-month) and longer (24-month) horizons. However, expressed desires to engage in large buy transactions appear to forecast hedge fund returns negatively, especially when other forecasting variables are simultaneously included in the model. This suggests that investors wishing to buy large hedge fund stakes may be systematically overoptimistic about the outperformance of hedge funds over longer time periods, over and above forecasting variables that the academic literature has identified. There is also the possibility that size-based classifications are simply picking up different investor groups with different motivations for trade: Liquidity demands for buying or selling may co-exist in the data with more information-driven motivations for trade.

Finally, the much-noted trend-chasing behavior of hedge fund flows also shows up in indications of interest, with one twist: both buy indications of interest and sell indications of interest follow periods of abnormally high hedge fund performance (although in the case of sell indications, the longer run outperformance is accompanied by shorter-term underperformance). The fact that run-ups in abnormal hedge fund returns precede indications of interest to buy echoes the findings in the literature of return-chasing by hedge fund investors. The fact that sell indications are also preceded by longer-term run-ups in abnormal hedge fund returns suggests that portfolio rebalancing may be one underlying motivation for trade.

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, 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. 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 that 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 (2010)). Appendix A contains more details about Hedgebay, and the trading process on the market.

The secondary market data used in this paper comprise 9,338 expressions of interest to buy or sell 751 funds that are identified from a consolidated dataset compiled from TASS, HFR, CISDM and Morningstar (details on the consolidated dataset are in Appendix B), 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 between 3% and 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 17 (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. 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

Funds with indications on Hedgebay 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 B lists details of this matching procedure. There are 10,895 funds in the combined universe. Funds' vendor-provided strategies are consolidated to a list of ten – Security Selection; Macro; Relative Value; Directional Traders; Emerging Markets; Fixed Income; Multi-Strategy; Funds of Funds, CTAs and Other. Details about the mappings between vendor-provided styles and the list of nine strategies are provided in Appendix Table B.1. Strategy average returns and other aggregate statistics are compiled from indices created using these 10,895 funds.

2.2.1. Fung-Hsieh Factors

Apart from strategy-adjustment, the main methods of risk adjustment used in the paper are the market model and 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; a small minus big factor (the SMB factor obtained from Kenneth French's website); the excess returns on portfolios of lookback straddle options on currencies, commodities, and bonds, which are constructed to replicate the maximum possible return to trend-following strategies on their respective underlying assets (obtained from David Hsieh's website); 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; and the change in the credit spread of Moody's BAA bond over the 10-year Treasury bond, also appropriately adjusted for duration. The next section introduces the methodology and discusses the results.

3. Methodology and Results

3.1. A Naïve Approach

As a first step, I plot cumulative abnormal returns from simply using the indications as indicator variables. This suppresses all information other than the timing of the indications, but is useful as a first look at the information content of the indications, and the relationship of the arrival of indications to past returns. To do so, I begin by creating abnormal returns for a fund i at event date t (the event date is the arrival of a buy or sell indication), i.e., $AR_{it} = R_{it} - R_{Sit}$, where R_{Sit} is the average date t return to all funds in the strategy to which the fund belongs (using the ten strategy classifications). Next, these abnormal returns are averaged across all funds, to generate mean abnormal returns at each event date, i.e., $MAR_t = \frac{1}{N_t}\sum_{i=1}^{N_t} AR_{it}$. Finally, these abnormal returns are cumulated to generate the total abnormal return on the portfolio up until any specific date, i.e., $CAR_t = \sum_{k=1}^{t} MAR_k$.

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.[9] The figure reveals a set of interesting patterns in the CARs. Prior to the arrival of the indication of interest, they rise to 12.63% by the time the indication arrives. This corresponds to a roughly 54 basis point per month outperformance 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 outperformance of the fund relative to the strategy continues, and at the end of the 24 month period, the CAR stands at 15.15%, a rise of close to 3% subsequent to the indication of interest. The lower confidence interval is just below 12.63% by the end of the window, suggesting marginal statistical significance. Figure 2 plots the CARs 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 outperformance of these funds (with a recent dip in performance prior to the indication) prior to the arrival of the indication. The CAR stands at 4.98% 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 2.42%. This decline is also statistically significant in a 9 month period following the sell indication.

Before we turn to more sophisticated regression models to analyze the forecasting power of indications and the impacts of capacity constraints on hedge fund returns, we need to consider potentially important sample selection issues. This is the topic of the next subsection.

[9]The red dashed lines in the figure indicate 90% confidence intervals for the CARs, constructed using the non-parametric delete-cross-section jackknife method, in the spirit of Shao and Wu (1989) and Shao (1989). All standard errors in this paper have standard errors constructed using this method unless otherwise stated. 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. To 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.

3.2. Selection Bias

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).

The funds solicited on Hedgebay have several characteristics that look different from those of their counterparts in the broader universe of funds. This means that results that are estimated from this sample may not be representative of behavior in the broader population of funds. 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 be solicited on the market. This necessitates the use of controls to ensure that the results are not biased by this correlation. The first set of controls employed are strategy-specific fixed effects in the panel regressions. If the unobserved determinants of selection are solely strategy-specific, e.g., if there is a propensity for some strategies to be more frequently solicited on the secondary market because they are more prone to being closed to new investments, or disproportionately represented on Hedgebay for other reasons, the use of strategy fixed effects in the estimated specifications will capture this channel, and the remaining coefficient estimates will be unbiased (see Campa and Kedia (2002) for a similar argument employed in a different context). However, this does leave the concern that fund-specific and time-varying reasons exist for funds to be solicited on Hedgebay.

Consequently, the second control is to apply Heckman's (1979) two-stage procedure to correct for possible selection bias. In this procedure, 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 D.

3.2.1. 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 $OFFSHORE$, 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, 76% 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; four 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, the minimum investment level of the fund, also measured by its percentile rank each year, and a dummy variable that takes the value of one if a fund's management company launched a new fund, or the fund launched a new share class in the previous year; and finally *OFFSHORE*.

3.2.2. Probit Selection Equation

Table IV presents results from estimating the probit model for selection. The panel regression is estimated using a total of $35,786$ fund-year observations comprising both hedge funds and funds-of-funds, of which there are $1,050$ 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 887.52, 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 two of 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 are do not easily permit capital withdrawal. The dummy variable capturing new launches by the management company or fund is estimated to have a negative coefficient (although the coefficient is significant at the 10.5% level at best). That is, when a new fund or series is launched, there is a lower probability that a fund will be solicited on Hedgebay. This is easily interpreted – a new launch suggests additional supply of the fund's shares (or of a close substitute) is available on the primary market, reducing demand for the fund on the secondary market.

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 also a statistically significant determinant of selection.

The next section incorporates the inverse Mills ratio computed from the selection equation into regressions which condition future fund returns on indications of interest, to correct for possible selection bias in those results.

3.3. A More Sophisticated Approach

Tables V and VI use the information in the indications more intelligently than in the naïve event time plots, regressing raw returns, strategy-adjusted returns and alphas from market and Fung-Hsieh factor models on the indications as a percentage of fund assets under management. The tables show results from a simple model in which the indication information is used on its own (along with the selection bias correction estimated as described above), and an augmented model which includes categories of variables that are of interest in light of the hypotheses put forward in the literature. These categories are capacity constraints (past flows, fund size, and a dummy variable that indicates whether the fund's management company launched a new fund or the fund launched a new share class in the year prior to the arrival of the indication); performance persistence (which contains the lagged fund performance measures); fund manager incentives (the Agarwal, Daniel and Naik (2009) measures of managerial option delta and total compensation delta), and variables capturing variation in aggregate liquidity (Sadka's (2010) hedge fund liquidity risk premium and the 3-month T-Bill rate, which is detrended up to time $t-1$ in each period t). Table V employs a short window of 12 months following the arrival of the indication, and Table VI looks at returns 24 months after the indication.

The results from the different risk-adjustment models (ranging from raw to factor-model adjusted) can be viewed in light of the central question of the paper, namely, whether hedge fund investors are informed about the return prospects of the funds in which they invest – and whether that information survives over and above capacity constraints and other relevant conditioning variables. Each risk-adjustment method raises the hurdle for the investors, in the sense that forecasting the future raw performance of the fund is less difficult than forecasting the outperformance of the fund in relation to the returns of the funds in its strategy, and the most difficult of all is to forecast the outperformance of the fund with respect to a more sophisticated factor model such as the Fung-Hsieh model. The three sets of results are broadly consistent with one another up to statistical precision, with the alpha results being the most precisely estimated, in the sense that indications are more informative about alphas than about raw or strategy-adjusted returns. This suggests that the information investors have about future hedge fund returns pertains to the outperformance of funds rather than simply to raw returns, and that evaluating their information using raw or strategy-adjusted returns makes it more difficult to detect their signal since raw returns are essentially alpha plus noise. It is also the case that over the shorter forecasting horizon (Table V), both demand and supply indications are better on their own at forecasting future returns than over the longer, 24 month window. However, once the other conditioning variables in the model are included, it appears that both demand and supply indications forecast declines in future hedge fund performance over the longer horizon. This suggests that investors desiring to buy funds in the sample are systematically over-optimistic about the outperformance of hedge funds over longer time periods, over and above the other conditioning variables in the model.

The other conditioning variables in the model are interesting in light of the ability of these regressions to disentangle investor information from fund capacity constraints. Past fund flows, both over the 12 month and 24 month horizons, are reliable negative forecasters of future hedge fund returns, regardless of the method of risk-adjustment employed. Fund size also significantly and negatively impacts future returns. Finally, if capacity constraints exist in hedge fund returns, then one useful measure of this should be the impact on the returns of pre-existing funds when a fund family launches a new fund, or when a fund launches a new share class.[10] It appears that a new launch of a fund or share class does reduce the returns for pre-existing funds in the future, but only for raw fund returns and strategy-adjusted returns. However, there are no real effects on the alphas of the funds in the future. 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 capi-

[10]Thanks to an anonymous referee for this very useful suggestion.

tal in the presence of capacity constraints in hedge funds. 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 in the fund attributes that appear as controls in the forecasting regressions.

Of the other conditioning variables in the model, 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 D). 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 Tables V and VI, 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 remaining variables in the model are not consistently signed or significant in the specifications, suggesting that their effects may be captured by other time-varying variables in the model, or by the strategy-specific fixed effects (for variables with cross-sectional variation). The next section turns to understanding the information contained in indications of different sizes.

3.4. 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 attempt to disguise their trading behavior in order to avoid tipping off their counterparties about the information contained in their transactions. Yet another possibility is that large transaction sizes are associated with overoptimism about the future prospects of a fund. Regardless of the underlying logic, 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 VII and VIII 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 median buy and sell indication ('big' demand and supply indicators), and those smaller than or equal to the median buy and sell indication ('small' demand and supply indicators), where all indications are measured relative to the assets under management of the fund, and percentiles are computed each month across demand and supply indications.[11]

Both tables show that using information about the size of the indication helps the forecasting power of the indications for future strategy-adjusted returns. However there do not appear to be great differences between the coefficient sizes contingent on the sizes of the transactions in the simple models. Nevertheless, in the augmented models, more interesting findings are obtained. These augmented models essentially compare the information that hedge fund investors employ to forecast returns with information that the econometrician can compute. Over and above that information (such as capital flows or fund size), small buys, and large and small supply indications contain some positive forecasting power (depending on the performance measure employed, and the horizon). Large demand indications, on the other hand, seem to be systematically over-optimistic about the outperformance of hedge funds over longer time periods, over and above the other conditioning variables in the model. This is true regardless of the risk-adjustment method for returns.

[11] All indications are normalized by their standard deviations in the panel, to enable easy interpretation, and to avoid the inflation of coefficients because different transaction sizes have mechanically different variances. Therefore a one unit movement in a buy (large buy or small buy) indication represents a one standard deviation movement relative to all buys (large buys or small buys); and similarly for sells, large sells and small sells.

4. 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, and to confirm the presence of capacity constraints in hedge fund returns. After controlling for other well-known determinants of hedge fund returns, indications of interest on the secondary market provide useful signals of future hedge fund returns. I conclude not only that hedge fund investors are rational, but also that their information about future hedge fund returns exists over and above commonly employed forecasting variables for hedge fund returns. In addition, the specifications reveal that variables commonly employed to measure capacity constraints, such as capital flows and fund size, are reliably negative forecasters of hedge fund returns. The results offer strong support to the hypothesis that capital is provided to hedge funds by rational, well-informed investors, and that capacity constraints exist in hedge funds, the two assumptions that underpin the model of Berk and Green (2004). The findings in this paper therefore have important implications for the future risk-adjusted performance of hedge funds.

Appendix A

How Transactions are Conducted on Hedgebay

Hedgebay has been in business since 1998, however they only began capturing information on the indications of interest since 2002, hence the beginning of the sample in the paper. Only accredited and qualified investors are allowed to transact on Hedgebay, i.e., those that can claim exemption from the public registration requirements for securities offerings under Rule 506 of Regulation D of the U.S. Securities Act of 1933. This is the usual requirement for hedge fund investors, and broadly means that participants on Hedgebay are required to be institutional investors or high-net-worth individuals, the usual clientele for hedge funds. While the identities of these participants are kept strictly confidential, Hedgebay estimates that approximately 60-70% of the transactions (and indications) come from funds-of-funds. The remainder come from other institutions such as family offices, banks, pension funds and consultants, and some from high-net-worth individuals. General partners of hedge funds are allowed to use Hedgebay, but they account for a very small minority of the transactions.

Prospective transactors send in indications of interest for buying and selling hedge funds, either by posting them on Hedgebay's website, or phoning them in to Hedgebay directly. These indications do not need to be firm in the sense that if a price is not agreed (price discovery occurs through negotiations between the counterparties conducted anonymously through Hedgebay), then there is no requirement to transact. However, Hedgebay personally contacts each new prospective participant on the website and monitors users. This means that there are significant reputational sanctions (such as being barred from the market) for parties that put in a lot of indications but are not serious about transacting. Furthermore, there is no index or structured product that is contingent on the indications of interest on Hedgebay (or for that matter, on the premiums and discounts on the completed transactions, which are only reported to Hedgebay's clients in aggregated, capital-weighted form).[12]

[12]Occasionally fund shareholders are interested in understanding the liquidity of their holdings, but generally obtain this information by requesting quotes from Hedgebay (i.e., querying what sort of premium or discount has a particular fund most recently traded at, or soliciting Hedgebay brokers' thoughts about

The 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 telephone. 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. There are some circumstances under which transactions in offshore funds are much easier to conduct than transactions in onshore funds because the legal and regulatory processes are far less onerous in the former set of funds. This sometimes creates issues for fund managers approval of transactions, and hence I attempt to control for it in the selection analysis that I conduct. The second circumstance is more idiosyncratic and usually involves the desire of the fund manager to avoid possible control issues with the fund. 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.

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the prices at which the fund could be traded) rather than putting in indications for trading. Such telephonic requests do not get translated into indications, so would not show up in the data that I employ.

Appendix B

Matching Hedgebay Data to the Consolidated Hedge Fund Database

The final combined database used in this paper comprises $10,895$ 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 9 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).[13] This eliminates a total of 4,032 funds, leaving a total of 10,895 funds from the consolidated database. Of these funds, 751 funds have indications of interest on Hedgebay, of which 364 have return information available for a complete 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 B.2

[13]In cases in which some administrative information for funds is missing, I attempt to acquire it from all available sources. Take as an example, a fund from TASS selected from the consolidation procedure, with no available information on, say, its management fee. If management fee information is available (and identical) for funds that are identified as its duplicates, say from HFR and CISDM, I use this management fee information for the fund.

Table B.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	CTA
CTA – Commodities	CTA
CTA-Systematic/Trend-Following	CTA
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
Long/Short Equity Hedge	Security Selection
Long-Short Credit	Fixed Income
Macro	Global Macro

Table B.1 (Continued)

Strategy in Consolidated Database	Mapped Strategy
Managed Futures	CTA
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	CTA
Tactical Allocation	Directional Traders
UNKNOWN STRATEGY	Other
Variable Bias	Directional Traders
(blank)	Other

Table B.2
Data Sources

This table shows the number of funds from each of the five sources (HFR, TASS, CISDM, Morningstar 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	4114	2015	2099	51.02%
HFR	4655	2761	1894	40.69%
Morningstar	1841	1123	718	39.00%
CISDM	276	257	19	6.88%
Proprietary/Hedgebay	9	0	9	100.00%
Total	10895	6156	4739	43.50%

Appendix C
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 D
The Selection Bias Correction

Formally, the determinants of selection are modelled as:

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

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 $\mathrm{w}'_{i,t-1}$ is a set of variables that determine whether a fund is traded in a year.[14] Next, consider the previously employed regression equation to explain the returns (raw, strategy-adjusted or alpha) for a fund i from t to $t+k$ ($RET_{i,t,t+k}$), written with a generic right-hand side vector of determinants of these returns, $\mathrm{x}_{i,t-1}$ (which contains some of the same constituents as $\mathrm{w}_{i,t-1}$):

$$RET_{i,t,t+k} = \mathrm{x}'_{i,t-1}\beta + \varepsilon_{i,t,t+k}. \tag{D.2}$$

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:[15]

$$(\varepsilon_{i,t,t+k}, u_{i,t}) \sim N\left(\left[\begin{array}{c} 0 \\ 0 \end{array}\right], \left[\begin{array}{cc} \sigma^2_\varepsilon & \rho\sigma_\varepsilon \\ \rho\sigma_\varepsilon & 1 \end{array}\right]\right). \tag{D.3}$$

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

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

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.

$\lambda(\mathrm{w}'_{i,t-1}\gamma)$ 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.[16] Once this is done, $\hat{\lambda}(\mathrm{w}'_{i,t-1}\hat{\gamma}) = \frac{\phi(\mathrm{w}'_{i,t-1}\hat{\gamma})}{\Phi(\mathrm{w}'_{i,t-1}\hat{\gamma})}$ (where $\phi(.)$ is the standard normal density function, and

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

[15]I 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)).

[16]When 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.

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

$$RET_{i,t,t+k} = \mathrm{x}_{i,t-1}^{'}\beta + \delta\hat{\lambda}(\mathrm{w}_{i,t-1}^{'}\hat{\gamma}) + v_{i,t,t+k}. \tag{D.5}$$

References

[1] Agarwal, V, Daniel, N. and Naik, N.Y., 2009. Role of managerial incentives and discretion in hedge funds, Journal of Finance, forthcoming.

[2] Baquero, G., and M., Verbeek, 2008. A portrait of hedge fund investors: flow, performance and smart money, Erasmus University Rotterdam Working Paper.

[3] Barberis, Nicholas, and Andrei Shleifer. 2003. "Style Investing." Journal of Financial Economics 68:2, 161-199.

[4] Barclay, M., Warner, J. B., 1993. Stealth trading and volatility: which trades move prices?. Journal of Financial Economics 34, 281–305.

[5] Berk, J. B., and R. Green, 2004, Mutual fund flows and performance in rational markets, Journal of Political Economy 112, 1269–1295.

[6] Campbell, John Y., Tarun Ramadorai, and Allie Schwartz. 2008. "Caught on Tape: Institutional Trading, Stock Returns, and Earnings Announcements." Journal of Financial Economics 92:1, 66-91.

[7] Chakravarty, S., 2001. Stealth-trading: which traders' trades move stock prices?. Journal of Financial Economics 61, 289–307.

[8] Cohen, Randolph, Paul Gompers, and Tuomo Vuolteenaho. 2002. "Who Underreacts to Cashflow News? Evidence from Trading between Individuals and Institutions." Journal of Financial Economics 66:2-3, 409-462.

[9] Coval, Joshua, and Erik Stafford, 2007, Asset fire sales (and purchases) in equity markets, Journal of Financial Economics 86, 479-512.

[10] DeLong, J. Bradford, Andrei Shleifer, Lawrence Summers, and Robert J. Waldmann. 1990. "Positive Feedback Investment Strategies and Destabilizing Rational Speculation." Journal of Finance 45:2, 379-395.

[11] Ding, B., Getmansky, M., Liang, B. and Wermers, R., 2009. Investor flows and share restrictions in the hedge fund industry. Unpublished working paper.

[12] Fama, E.F., and MacBeth, J.D., 1973. Risk, return, and equilibrium: Empirical tests, Journal of Political Economy, 81 (3), 607–636.

[13] Fung, W., and Hsieh, D.A., 2000, Performance characteristics of hedge funds and CTA funds: Natural versus spurious biases, Journal of Financial and Quantitative Analysis 35, 291–307.

[14] Fung, William, and David A. Hsieh, 2004, Hedge fund benchmarks: A risk based approach, Financial Analysts Journal 60, 65-80.

[15] Fung, William, David A. Hsieh, Narayan Y. Naik and Tarun Ramadorai, 2008, Hedge funds: Performance, risk and capital formation, Journal of Finance, 63, 1777–1803.

[16] Heckman, James J., 1979, Sample selection bias as a specification error, Econometrica 47, 153-161.

[17] Hong, Harrison, and Jeremy C. Stein. 2003. "Differences of Opinion, Short-sales Constraints, and Market Crashes." Review of Financial Studies 16:2, 487-525.

[18] Hvidkjaer, S., 2006. A trade-based analysis of momentum. Review of Financial Studies 19, 457–491.

[19] Jagannathan, R., and Novikov, D., 2007. Do hot hands persist among hedge fund managers? An empirical investigation. Unpublished working paper.

[20] Jotikasthira, C., Lundblad, C., and T. Ramadorai, 2010. Asset fire sales and purchases and the international transmission of financial shocks, Unpublished working paper.

[21] Kosowski, R, Naik, N, Teo, M, 2007. Do hedge funds deliver alpha? A Bayesian and bootstrap analysis. Journal of Financial Economics, 84, 229–264

[22] Kyle, A. S. 1985. Continuous auctions and insider trading. Econometrica 53, 1315–1335.

[23] Liang, Bing, 2000, Hedge funds: The living and the dead, Journal of Financial and Quantitative Analysis 35, 309–326.

[24] Liang, Bing and Hyuna Park, 2008, Share restrictions, liquidity premium, and offshore hedge funds, Unpublished working paper.

[25] Lou, Dong, 2010, A flow based explanation for return predictability, Unpublished working paper.

[26] Malmendier, U., Shanthikumar, D., 2007. Are small investors naive about incentives?. Journal of Financial Economics 85, 457–489.

[27] Naik, N., Ramadorai, T., and Stromqvist, M., 2007. Capacity constraints and hedge fund strategy returns. European Financial Management, 13(2), 239–256.

[28] Ramadorai, T., 2010. The secondary market for hedge funds and the closed-hedge fund premium. Journal of Finance, forthcoming.

[29] Sadka, R., 2010, Liquidity risk and the cross-section of hedge-fund returns, Journal of Financial Economics 98, 54-71.

[30] Shao, J., 1989. The efficiency and consistency of approximations to the jackknife variance estimators. Journal of the American Statistical Association 84, 114–119.

[31] Shao, J., Wu, C.F.J., 1989. A general theory for jackknife variance estimation. Annals of Statistics 17, 1176–1197.

[32] Sirri, E.R., and Tufano, P., 1998. Costly search and mutual fund flows, Journal of Finance, 53, 1589–1622.

[33] Teo, M., 2008. Does size matter in the hedge fund industry? Unpublished working paper.

[34] Wang, Ashley W. and Zheng, Lu, 2008, Aggregate hedge fund flows and asset returns. SSRN working paper 1081475

[35] Zhong, Z., 2008. Why does hedge fund alpha decrease over time? Evidence from individual hedge funds. Unpublished working paper.

Table I
Overview of Indications of Interest

This table shows the percentiles of the distribution of both demand and supply indications of interest in the dataset. The first two rows of numbers present these statistics for the demand indications of interest, while the last two rows of numbers in the table show them for the supply indications of interest. These are shown in dollar terms as well as in percentage points of the funds' assets under management (AUM). Where fund AUM is unavailable, the average AUM across funds in the strategy is utilized instead.

Demand	**Mean**	**Min**	**5 Pctile**	**Median**	**95 Pctile**	**Max**
Amount(Dollars)	5,336,970	34,000	500,000	3,000,000	16,000,000	100,000,000
Amount/AUM	3.614	0.007	0.080	0.999	11.625	53.280
Supply						
Amount(Dollars)	4,230,217	50,000	437,000	2,300,000	15,000,000	50,400,000
Amount/AUM	2.774	0.002	0.067	0.960	10.633	33.157

Table II
Summary Statistics of Demand and Supply Indications of Interest Over Time

This table shows summary statistics over time for the sample of demand and supply indications of interest on Hedgebay that can be matched to specific funds in the consolidated dataset of hedge funds. The first block of numbers shows the summary statistics for the matched demand indications, and the second block for the supply indications. The columns show the evolution of the statistics over the years in the sample period. The statistics presented are the number of matched indications, the number of unique funds represented by these matched indications, the mean indication size in percentage points of fund AUM, the median indication size in percentage points of fund AUM, and the mean indication size in dollars.

Demand	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**
N(Indications)	751	805	273	709	1134	1001	207	68
N(Funds)	45	67	63	114	131	222	115	55
Mean(% Amount/AUM)	3.939	4.962	4.077	2.837	3.604	3.069	2.369	2.280
Median(% Amount/AUM)	0.745	0.941	1.295	0.908	1.108	1.161	0.934	1.228
Mean(Dollar Amount)	3,780,692	3,410,832	5,247,852	4,963,326	5,446,702	7,557,618	8,049,329	6,804,368
Supply	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**
N(Indications)	688	798	239	738	810	566	445	106
N(Funds)	74	99	76	163	173	203	205	80
Mean(% Amount/AUM)	3.939	4.962	4.077	2.837	3.604	3.069	2.369	2.280
Median(% Amount/AUM)	0.745	0.941	1.295	0.908	1.108	1.161	0.934	1.228
Mean(Dollar Amount)	1,757,214	2,332,294	4,004,923	4,660,164	5,186,036	6,581,501	5,717,290	5,982,340

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 (column labelled 'Solicited') and computed across all observations in the consolidated dataset of funds (column labelled 'Universe'). The rows labelled 'Strategies' show the percent of funds in the set of solicited funds and the universe of funds that are in each of the detailed strategies represented in the rows. The means of the variables are computed across all unique funds appearing in the set of solicited funds and the universe of funds, respectively. The t-statistic that reported for the difference in means in each case is computed using the White heteroskedasticity-consistent estimator.

	SOLICITED	UNIVERSE	T-Stat of Difference
NUMBER	751	10,895	
MININV ($MM)	1.524	1.069	2.799
LOCK (%)	37.284	31.143	3.618
REDEMP (Months)	1.571	1.170	10.973
REDFREQ (Months)	2.920	2.422	4.253
MGMTFEE (%)	1.494	1.437	2.186
INCFEE (%)	19.204	17.043	12.553
OFFSHORE (%)	76.165	60.211	7.299
STRATEGIES			
Security Selection	30.093	24.580	3.429
Global Macro	5.060	5.498	0.566
Relative Value	6.658	7.150	0.559
Directional Traders	9.321	14.713	5.176
Funds of Funds	5.726	19.862	16.169
Multi-Process	19.441	8.857	7.737
Emerging Markets	6.125	4.727	1.670
Fixed Income	13.981	7.031	5.792
CTA	0.133	0.009	1.001
Other	3.462	7.572	6.142

Table IV
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 nine strategy dummy variables employed in estimation: the tenth, for 'Other' funds is dropped to avoid perfect collinearity. The CTA coefficient is rescaled because of the small percentage of CTA funds in the data. 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).

	dF/dX	Clustered t-statistic
Mean Monthly Return (previous year)	**0.140**	6.490
Size (AUM) (percentile rank)	**4.724**	19.080
Minimum Investment (percentile rank)	**0.789**	3.830
Management Fee	**0.199**	2.770
Incentive Fee	**0.073**	7.680
Redemption Restrictions	**0.002**	6.440
Subscription Restrictions	**-0.009**	-4.250
Hurdle Rate/High Water Mark Provision	**0.002**	4.110
Lock*Offshore Dummy	0.000	-1.210
New Fund or Share Class Launch (previous year)	-0.176	-1.620
EXCLUSION RESTRICTION		
Offshore Dummy	**1.040**	7.080
STRATEGIES		
Security Selection	**2.502**	5.590
Global Macro	**1.060**	2.200
Relative Value	**1.911**	3.100
Directional Traders	**2.818**	4.530
Funds of Funds	-0.229	-0.610
Multi-Process	**3.143**	5.530
Emerging Markets	**3.162**	4.890
Fixed Income	**3.740**	5.920
CTA	**0.373**	3.190
Observed Probability	0.029	
Pseudo R-Squared	0.163	
Chi2(20)	887.520	
P-value(Chi2)	0.000	
N(Fund-Years)	35,786	

Table V
Fund Returns One Year Following 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. Columns labelled 'Simple Model' only condition future returns on the demand and supply indication amounts (as a percentage of AUM), while columns labelled 'Augmented Model' add in regressors that have been shown to forecast hedge fund returns in the academic literature. These variables are classified into categories; 'Selection' contains the invesrse Mills ratio from the probit analysis in Table IV; 'Capacity' adds capital flows over the previous 12 months, the AUM of the fund in the month prior to the indication, measured as a fractional rank across all funds in the universe, and a dummy variable for whether the fund's management company launched a new fund, or the fund launched a new share class in the previous year; 'Persistence' adds in the lagged performance measure (over the previous 12 months); 'Incentives' adds in the manager's option delta, and the total compensation delta (computed using the method of Agarwal, Daniel and Naik (2009)); and finally 'Liquidity' adds in Sadka's (2010) hedge fund liquidity factor and the U.S. 3-month T-Bill rate (detrended up to time t-1 in each period t using the Hodrick-Prescott filter). Within each of the simple and augmented models, the results are presented for raw returns, strategy-adjusted returns and abnormal returns from a single-factor market model.

		Simple Model			Augmented Model		
Category	**Variable**	**Raw**	**Strategy**	**Market**	**Raw**	**Strategy**	**Market**
Information	**Demand**	**0.069**	**0.061**	**0.052**	0.029	0.002	0.017
		0.026	0.022	0.026	0.030	0.026	0.034
	Supply	-0.041	-0.038	**-0.063**	-0.028	-0.022	**-0.049**
		0.022	0.020	0.019	0.023	0.020	0.021
Selection	**Inverse Mills Ratio**	-0.064	-0.100	**-0.106**	**-0.251**	**-0.346**	**-0.294**
		0.061	0.054	0.052	0.126	0.119	0.101
Capacity	**Flow(-12,-1)**				**-0.011**	-0.006	-0.005
					0.004	0.003	0.003
	Rank(AUM(-1))				**-0.370**	**-0.373**	-0.186
					0.185	0.169	0.152
	New Launch Prior Year				**-0.155**	-0.022	0.011
					0.035	0.037	0.035
Persistence	**Lagged Performance**				**0.078**	**0.095**	-0.021
					0.037	0.026	0.032
Incentives	**Mgr Option Delta (-1)**				-0.346	-0.783	-0.144
					0.405	0.615	0.303
	Log(Total Delta (-1))				-0.006	**0.036**	0.042
					0.023	0.017	0.030
Liquidity	**Sadka Hedge Fund Liquidity**				0.040	**0.094**	-0.060
					0.090	0.032	0.044
	Risk Free Rate				-0.093	**0.134**	-0.035
					0.068	0.025	0.036
	R-Squared	0.034	0.031	0.034	0.055	0.064	0.040
	N	4809	4809	4809	4544	4544	4544
	N(Funds)	364	364	364	342	342	342
	Strategy Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table VI
Fund Returns Two Years Following 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. Columns labelled 'Simple Model' only condition future returns on the demand and supply indication amounts (as a percentage of AUM), while columns labelled 'Augmented Model' add in regressors that have been shown to forecast hedge fund returns in the academic literature. These variables are classified into categories; 'Selection' contains the invesrse Mills ratio from the probit analysis in Table IV; 'Capacity' adds capital flows over the previous 24 months, the AUM of the fund in the month prior to the indication, measured as a fractional rank across all funds in the universe, and a dummy variable for whether the fund's management company launched a new fund, or the fund launched a new share class in the previous year; 'Persistence' adds in the lagged performance measure (over the previous 24 months); 'Incentives' adds in the manager's option delta, and the total compensation delta (computed using the method of Agarwal, Daniel and Naik (2009)); and finally 'Liquidity' adds in Sadka's (2010) hedge fund liquidity factor and the U.S. 3-month T-Bill rate (detrended up to time t-1 in each period t using the Hodrick-Prescott filter). Within each of the simple and augmented models, the results are presented for raw returns, strategy-adjusted returns and abnormal returns from the Fung-Hsieh seven-factor model.

		Simple Model			Augmented Model		
Category	**Variable**	**Raw**	**Strategy**	**Fung-Hsieh**	**Raw**	**Strategy**	**Fung-Hsieh**
Information	Demand	**0.072**	**0.060**	0.034	-0.049	**-0.084**	**-0.057**
		0.021	0.020	0.019	0.027	0.029	0.029
	Supply	-0.027	-0.030	**-0.054**	-0.037	-0.038	-0.036
		0.034	0.027	0.021	0.022	0.021	0.021
Selection	Inverse Mills Ratio	**-0.175**	**-0.150**	**-0.090**	**-0.604**	**-0.657**	**-0.450**
		0.064	0.051	0.044	0.105	0.090	0.090
Capacity	Flow(-24,-1)				-0.004	**-0.014**	**-0.014**
					0.005	0.004	0.003
	Rank(AUM(-1))				**-0.981**	**-0.936**	**-0.461**
					0.171	0.135	0.146
	New Launch Prior Year				**-0.146**	**-0.131**	0.028
					0.032	0.031	0.032
Persistence	Lagged Performance				**0.177**	**0.189**	0.003
					0.031	0.020	0.039
Incentives	Mgr Option Delta (-1)				-0.394	-0.134	0.128
					0.397	0.447	0.185
	Log(Total Delta (-1))				-0.002	0.010	**-0.110**
					0.025	0.021	0.022
Liquidity	Sadka Hedge Fund Liquidity				0.043	**0.062**	-0.025
					0.055	0.020	0.029
	Risk Free Rate				**-0.513**	**0.093**	0.032
					0.075	0.022	0.030
	R-Squared	0.054	0.047	0.063	0.251	0.123	0.075
	N	4322	4322	4322	3961	3961	3961
	N(Funds)	299	299	299	271	271	271
	Strategy Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table VII
Fund Returns One Year Following 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. Columns labelled 'Simple Model' only condition future returns on the large and small demand and supply indication amounts (as a percentage of AUM, where 'large' and 'small' are defined each month as above and below the monthly median sized demand and supply indications), while columns labelled 'Augmented Model' add in regressors that have been shown to forecast hedge fund returns in the academic literature. These variables are classified into categories; 'Selection' contains the invesrse Mills ratio from the probit analysis in Table IV; 'Capacity' adds capital flows over the previous 12 months, the AUM of the fund in the month prior to the indication, measured as a fractional rank across all funds in the universe, and a dummy variable for whether the fund's management company launched a new fund, or the fund launched a new share class in the previous year; 'Persistence' adds in the lagged performance measure (over the previous 12 months); 'Incentives' adds in the manager's option delta, and the total compensation delta (computed using the method of Agarwal, Daniel and Naik (2009)); and finally 'Liquidity' adds in Sadka's (2010) hedge fund liquidity factor and the U.S. 3-month T-Bill rate (detrended up to time t-1 in each period t using the Hodrick-Prescott filter). Within each of the simple and augmented models, the results are presented for raw returns, strategy-adjusted returns and abnormal returns from a single-factor market model.

		Simple Model			Augmented Model		
Category	**Variable**	**Raw**	**Strategy**	**Fung-Hsieh**	**Raw**	**Strategy**	**Fung-Hsieh**
Information	**Big Demand**	**0.066**	**0.064**	**0.052**	0.027	0.005	0.018
		0.025	0.022	0.026	0.029	0.026	0.034
	Small Demand	0.012	**0.053**	**0.039**	0.008	**0.044**	**0.046**
		0.016	0.015	0.013	0.017	0.013	0.012
	Big Supply	**-0.043**	-0.034	**-0.061**	-0.030	-0.019	**-0.047**
		0.021	0.020	0.019	0.023	0.020	0.021
	Small Supply	-0.059	-0.019	**-0.042**	-0.051	-0.017	**-0.047**
		0.031	0.018	0.021	0.038	0.014	0.021
Selection	**Inverse Mills Ratio**	-0.057	-0.091	-0.098	-0.244	**-0.339**	**-0.286**
		0.061	0.055	0.052	0.127	0.119	0.102
Capacity	**Flow(-12,-1)**				**-0.011**	-0.006	-0.005
					0.004	0.003	0.003
	Rank(AUM(-1))				-0.364	**-0.371**	-0.184
					0.188	0.169	0.154
	New Launch Prior Year				**-0.149**	-0.023	0.014
					0.033	0.037	0.035
Persistence	**Lagged Performance**				0.073	**0.088**	-0.028
					0.039	0.027	0.032
Incentives	**Mgr Option Delta (-1)**				-0.314	-0.770	-0.111
					0.419	0.625	0.311
	Log(Total Delta (-1))				-0.008	0.034	0.037
					0.023	0.017	0.030
Liquidity	**Sadka Hedge Fund Liquidity**				0.043	**0.094**	-0.058
					0.091	0.032	0.044
	Risk Free Rate				-0.093	**0.134**	-0.036
					0.068	0.024	0.036
	R-Squared	0.036	0.034	0.037	0.057	0.066	0.044
	N	4809	4809	4809	4544	4544	4544
	N(Funds)	364	364	364	342	342	342
	Strategy Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table VIII
Fund Returns Two Years Following Large and Small 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. Columns labelled 'Simple Model' only condition future returns on the large and small demand and supply indication amounts (as a percentage of AUM, where 'large' and 'small' are defined each month as above and below the monthly median sized demand and supply indications), while columns labelled 'Augmented Model' add in regressors that have been shown to forecast hedge fund returns in the academic literature. These variables are classified into categories; 'Selection' contains the invesrse Mills ratio from the probit analysis in Table IV; 'Capacity' adds capital flows over the previous 24 months, the AUM of the fund in the month prior to the indication, measured as a fractional rank across all funds in the universe, and a dummy variable for whether the fund's management company launched a new fund, or the fund launched a new share class in the previous year; 'Persistence' adds in the lagged performance measure (over the previous 24 months); 'Incentives' adds in the manager's option delta, and the total compensation delta (computed using the method of Agarwal, Daniel and Naik (2009)); and finally 'Liquidity' adds in Sadka's (2010) hedge fund liquidity factor and the U.S. 3-month T-Bill rate (detrended up to time t-1 in each period t using the Hodrick-Prescott filter). Within each of the simple and augmented models, the results are presented for raw returns, strategy-adjusted returns and abnormal returns from the Fung-Hsieh seven factor model.

		Simple Model			Augmented Model		
Category	**Variable**	**Raw**	**Strategy**	**Fung-Hsieh**	**Raw**	**Strategy**	**Fung-Hsieh**
Information	**Big Demand**	**0.069**	**0.060**	0.032	-0.047	**-0.085**	-0.055
		0.022	0.020	0.019	0.027	0.028	0.029
	Small Demand	-0.001	**0.035**	0.019	-0.015	**0.028**	**0.031**
		0.012	0.012	0.013	0.016	0.014	0.014
	Big Supply	-0.029	-0.029	**-0.054**	-0.038	-0.040	-0.038
		0.034	0.028	0.021	0.022	0.021	0.021
	Small Supply	-0.048	**-0.041**	**-0.039**	-0.041	-0.032	**-0.042**
		0.025	0.017	0.017	0.023	0.018	0.016
Selection	**Inverse Mills Ratio**	**-0.171**	**-0.138**	-0.082	**-0.549**	**-0.645**	**-0.409**
		0.064	0.051	0.045	0.111	0.095	0.087
Capacity	**Flow(-24,-1)**				**-0.015**	-0.009	**-0.017**
					0.006	0.005	0.004
	Rank(AUM(-1))				**-0.883**	**-0.948**	**-0.420**
					0.192	0.154	0.147
	New Launch Prior Year				**-0.145**	**-0.130**	0.028
					0.030	0.031	0.032
Persistence	**Lagged Performance**				**0.188**	**0.180**	0.002
					0.032	0.021	0.038
Incentives	**Mgr Option Delta (-1)**				-0.330	-0.222	0.081
					0.407	0.482	0.191
	Log(Total Delta (-1))				-0.012	0.028	**-0.100**
					0.028	0.022	0.021
Liquidity	**Sadka Hedge Fund Liquidity**				0.046	**0.068**	-0.018
					0.054	0.020	0.028
	Risk Free Rate				**-0.517**	**0.099**	0.037
					0.076	0.023	0.031
	R-Squared	0.055	0.050	0.065	0.254	0.121	0.078
	N	4322	4322	4322	3961	3961	3961
	N(Funds)	299	299	299	271	271	271
	Strategy Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Figure 1
Demand Indications and Strategy-Adjusted Hedge Fund Returns

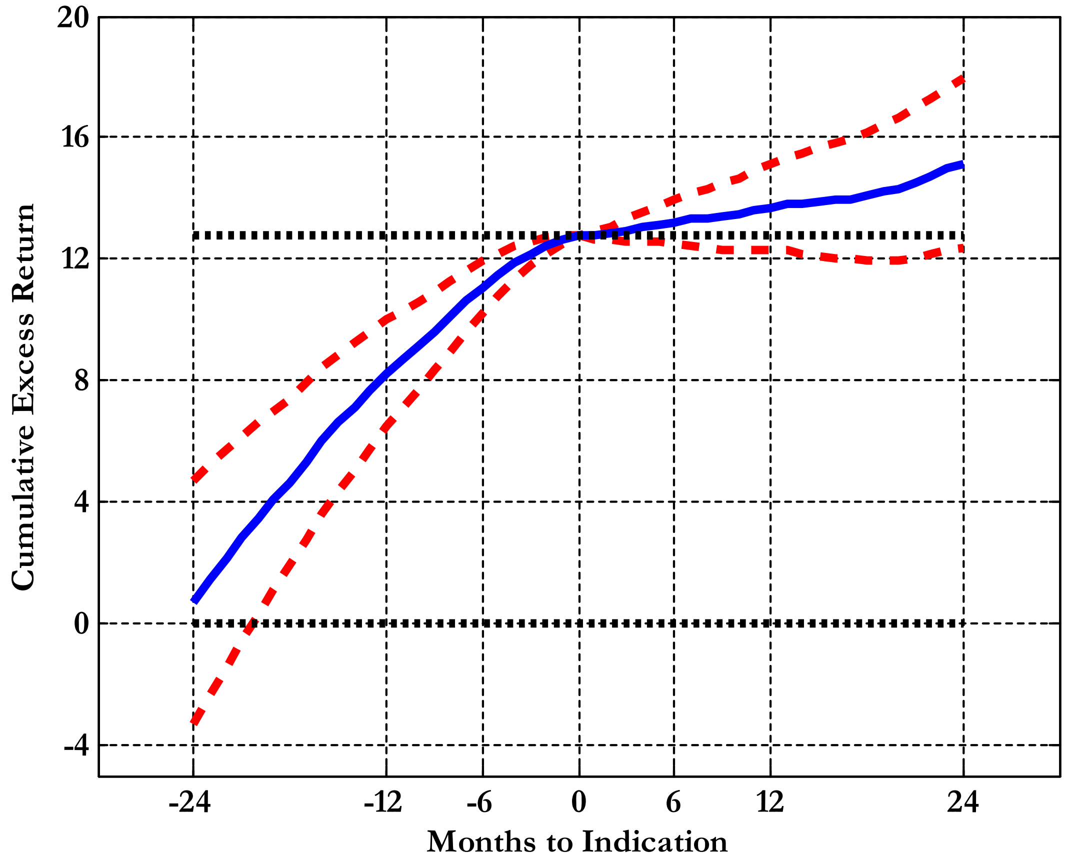

Figure 2
Supply Indications and Strategy-Adjusted Hedge Fund Returns