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ABSTRACT

The Secondary Market for Hedge Funds and the Closed-Hedge Fund Premium*

Employing data from a new secondary market for hedge funds, this paper documents the existence of a closed-hedge fund premium, analogous to the closed-end mutual fund premium which has been extensively studied in the literature. Over the past decade, the two premia comove with one another at high and low frequencies, which is surprising given the numerous differences between the two markets. Rational theories put forward to explain the closed-end mutual fund premium are strongly supported as explanations for the variation in closed-hedge fund premia. These results are robust to correction for potential selection bias.

JEL Classification: G11, G12 and G23
Keywords: alpha, closed-end funds, hedge funds, liquidity and secondary market

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1. Introduction

Closed-end mutual funds raise a fixed sum of capital at the time of their initial public offering, and do not permit capital withdrawals by their investors. Instead, these funds are traded on a secondary market, and their prices diverge, often substantially, from the net asset values (NAVs) of their underlying portfolios. This leads to the well-known closed-end fund premium puzzle – if investors can access the assets directly rather than via the fund, and if arbitrage is working well, then why does the premium (the difference between a fund's price and its NAV) exist and vary over time? A number of authors have attributed the behaviour of closed-end fund premia to individual investor sentiment.[1] Rational explanations of closed-end mutual fund premia have relied on taxes (Malkiel (1977), Brickley, Manaster and Schallheim (1991), fund holdings of restricted stock (Lee, Shleifer, and Thaler (1991)), private benefits of managerial control (Barclay, Holderness and Pontiff (1993)), the illiquidity of funds' shares and their underlying asset holdings (Cherkes, Sagi and Stanton (2008)), and expectations of future fund performance and fees (Boudreaux (1973), Chay and Trzcinka (1999), Gemmill and Thomas (2002), Ross (2002), and Berk and Stanton (2007)).

In recent years, the literature on active investment management has moved towards analyzing hedge funds as well as mutual funds. Hedge funds often close to new investments to avoid the negative impact of capacity constraints (Naik, Ramadorai and Stromqvist (2007) and Fung, Hsieh, Naik and Ramadorai (2008)), and simultaneously impose lockup and redemption notice periods on investors seeking to withdraw capital (Aragon (2005), Liang and Park (2008), and Ding, Getmansky, Liang and Wermers (2008)), effectively closing funds for the duration that these constraints bind. When hedge fund investors pay to get in and out of these closed hedge funds, is there a "closed-hedge fund premium," analogous to its equivalent in the mutual fund industry? If so, are the determinants of such a premium

[1] A partial list of papers exploring the role of sentiment in closed-end fund premia includes Zweig (1973), Brauer (1988), DeLong, Shleifer, Summers and Waldmann (1990), Lee, Shleifer, and Thaler (1991), Chopra, Lee, Shleifer, and Thaler (1993), Bodurtha, Kim, and Lee (1995), Pontiff (1996), and Baker and Wurgler (2006, 2007). Dimson and Minio-Kozerski (1999) provide a comprehensive survey of the closed-end fund literature.

sentiment-based or rational?

This paper analyzes all completed transactions from Hedgebay, the only known secondary market for hedge funds.[2] Transactions on this market occur in funds that are closed to new investments, and existing investors of the funds trade stakes with one another at premia and discounts to the end-of-month NAV reported by funds. These premia and discounts are conceptually similar to the premia and discounts on closed-end mutual funds. However, several important differences must be emphasized: first, closed-end equity mutual funds and the shares held in their portfolios are both traded on stock exchanges. In contrast, hedge funds hold and trade a wide variety of assets, including currencies, commodities and bonds, and Hedgebay is an over-the-counter (OTC) market, rather than a public stock exchange. Second, while the hedge funds traded on Hedgebay are primarily closed to new investments, this is not an irreversible or legally binding decision unlike in closed-end mutual funds, which are not permitted to accept additional capital after their initial establishment.[3] Third, the investors in hedge funds that transact on Hedgebay are primarily institutional investors (such as funds-of-funds and banks), and family offices that manage the investments of wealthy individuals, rather than the small investors that have been documented as the primary clientele for closed-end mutual funds (Lee, Shleifer and Thaler (1991)).

Despite these differences, however, the closed-end mutual fund premium and the closed-hedge fund premium comove strongly. The correlation between the monthly average closed-hedge fund premium and the closed-end mutual fund premium is a surprising 54% over the ten year period beginning in 1998. While this relationship is in part driven by the tendency for both series to comove (negatively) with state variables such as the short-term interest rate and the price-earnings ratio, the two series are also related to one another at higher frequencies – the correlation between their first differences is a statistically significant 17%. This gives rise to the intriguing possibility that there may be common factors determining investors' decisions to allocate capital to active investment vehicles, regardless of whether

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

[3] However, closed-end mutual funds can be taken over and liquidated.

these are hedge funds or mutual funds.

In the cross-section of closed-hedge fund premia, rational theories that have been put forward to explain closed-end mutual fund premia receive strong support. First, premia are negatively related to liquidity restrictions in hedge funds. Funds that impose lengthy redemption notice periods and lower redemption frequencies on their investors are traded at lower premia on average. This result is consistent with the prediction of Cherkes, Sagi and Stanton (2008). However, premia are unrelated to the Getmansky, Lo and Makarov (2004) coefficient of fund return-smoothing estimated over the twelve months prior to a transaction. This suggests either that investors are not necessarily willing to pay more for funds investing in illiquid underlying investments, that other variables in the empirical model are better at capturing the illiquidity of funds' investments, or that buyers and sellers of funds have similar expectations about the extent of return-smoothing by fund managers.

Second, premia are positively and nonlinearly related to past performance. The higher the average return, alpha, or information ratio of a fund over the twelve months prior to the transaction on Hedgebay, the higher the premium at which the fund is traded. When fund information ratios are very high, however, fund premia decline. This finding supports the theory of Berk and Stanton (2007), who predict a nonlinear relationship between managerial ability and premia, driven by the likelihood that managers will demand greater compensation at high levels of ability. Furthermore, premia are negatively related to the volatility of past performance – the lower the standard deviation of fund returns over the twelve months prior to the transaction, the higher the premium paid to acquire it.

Third, premia are lower for larger funds, and for funds with high management fees, although the level of incentive fees do not appear to have a significant relationship to transactions premia. This relationship is consistent with the predictions of Gemmill and Thomas (2002), Ross (2002), Berk and Stanton (2007) and Cherkes, Sagi and Stanton (2008) that emphasize fees as important factors that drive closed-end mutual fund premia down.

Fourth, the premia at which funds are traded on Hedgebay help to predict future hedge fund performance over the 12 month period subsequent to trades. The sign of this pre-

dictive relationship depends on the level of the premium, and whether past performance is included as a conditioning variable. Without accounting for the relationship between past performance and future performance, high premia forecast that funds will deliver better risk-adjusted performance in the future. However, when performance persistence is accounted for, a very high premium is a negative indicator of future performance, while more moderate premia positively forecast future performance.[4]

All of these results are robust to correction for potential selection bias using a first stage probit regression, which seeks to explain the determinants of a fund being traded on Hedgebay. In this probit exercise, the sample of hedge funds which is traded on Hedgebay is compared with the entire universe of hedge funds and funds-of-funds in the consolidated TASS, HFR, CISDM and MSCI database.

This paper, the first to document and analyze the properties of the closed-hedge fund premium, makes three main contributions. First, the existence of this premium, and its variation over time, offers a counterpoint to the closed-end mutual fund market, which is dominated by individual investors. In contrast, in the secondary market for hedge funds, market participants are primarily institutional investors. This gives rise to the presumption that rational theories should explain movements in the closed-hedge fund premium if financial wealth and financial sophistication are correlated (see Campbell (2006)). Confirming this intuition, the results in this paper confirm that closed-hedge fund premia are well-explained by the rational theories that have been put forward to explain the behaviour of closed-end mutual fund premia. Second, the paper documents that there is a link between the time-series behaviour of the closed-hedge fund premium and that of the closed-end mutual fund premium, raising the intriguing possibility that common factors govern the decision to allocate capital to actively managed investment vehicles. Third, the results confirm aspects of hedge fund investor behaviour heretofore inferred from more indirect sources such as hedge fund flows, which are constructed from information on fund assets under management

[4] These results are similar to Chay and Trzcinka (1999), who find that closed-end mutual fund premia forecast future NAV returns. However they find that premia positively forecast the future performance of funds over and above past performance and expense ratios.

(AUM) and returns, and rely on assumptions about the timing of flows into hedge funds (see Baquero and Verbeek (2005), Aragon (2006), Agarwal, Daniel and Naik (2007), Fung, Hsieh, Naik and Ramadorai (2008), Wang and Zheng (2008), Ding, Liang, Getmansky and Wermers (2008)).

The organization of the paper is as follows. Section 2 describes the data. Section 3 presents stylized facts about the behaviour of the closed-hedge fund premium over time, and estimates the relationship between premia, fund characteristics and past performance. Section 4 describes the implementation of the selection bias correction. Section 5 relates the hedge fund premium to future hedge fund performance, and Section 6 concludes.

2. Data

2.1. Secondary Market Transactions

The secondary market data come from Hedgebay, an OTC secondary market 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. Almost every completed transaction (except for the disaster transactions, details below) is conducted between pre-existing investors of the funds. Furthermore, every completed non-disaster transaction in the data arose from an initial indication of interest to sell (liquidity is harder to find on the sell side than the buy side over the sample period from August 1998

to March 2007, according to Hedgebay).

Over the sample period, transactions almost exclusively occurred in closed share classes of offshore domiciled funds, i.e., either the funds were closed to new investments, or fund managers were not issuing additional shares in the specific share classes that were transacted on Hedgebay. While transactions are conducted thoughout 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.

I denote by $PREM_{i,t,\tau}$ the percentage premium in excess of NAV agreed on between the buyer and the seller of the fund i on Hedgebay in month t in transaction τ. Note that the total payment made by the buyer comprises the premium *and* the commission ($COMM$) charged by Hedgebay, which is only charged to buyers for transactions occurring at premia, and only to sellers on transactions taking place at discounts. Thus,

$$HFPREM_{i,t,\tau} = PREM_{i,t,\tau} + COMM_{i,t,\tau}, \text{when } PREM_{i,t,\tau} \geq 0, \tag{2.1}$$

where $COMM_{i,t,\tau}$ is the commission paid to Hedgebay on the transaction). In the analysis, I present explanatory regressions for both $HFPREM$ and $PREM$, to check that the results are not just driven by changes in the commission paid to acquire funds.

Table I shows summary statistics about all transactions conducted on Hedgebay between August 1998 and March 2007. There data comprise a total of 935 transactions in a total of 220 funds. The data is split into non-disaster transactions, which form the main focus of the analysis, and disaster transactions, which occur in funds that suffered heavy and publicly reported losses and are either liquidated, or likely candidates for liquidation (such as Amaranth and Absolute Capital); or have been implicated in the press for fraud (such as Sphinx). For non-disaster transactions, the number of funds traded in each year, and the average transaction amounts traded, have both grown over time. In 1999, the dollar value of the average non-disaster transaction (not reported in the table) was around half

a million dollars, and by 2007, this number was up to 3.85 million dollars per transaction. The table reports transaction amounts as percentages of fund AUM, and shows that these transactions represent a non-trivial and growing fraction of total AUM, from around 30 basis points of AUM in 1999 to approximately 1.5% of AUM in 2007. These percentages are AUM-weighted across all funds each year, suggesting that the observed growth is not driven by trades in small funds. Non-disaster transactions also predominantly occur at premia to reported fund NAV at the end of the month, rather than discounts, the norm in closed-end mutual funds.[5] Furthermore, the annual cross-sectional standard deviation of premia is 2.4%, which is lower than that exhibited by closed-end mutual fund premia. This relatively smaller standard deviation can be attributed to the fact that the interval prior to open-ending is effectively smaller than the equivalent for closed-end mutual funds – when selling, for example, the maximum period over which the hedge fund is closed is the tenor of the lockup plus redemption notice period of the fund (or the redemption frequency in case of periodic redemptions).

For the disaster transactions, several facts stand out. First, they all occur at discounts, and the average discount is 50% to reported end-of-month fund NAV. Second, transaction numbers and the amounts transacted in disaster funds have grown appreciably since the inception of the marketplace in 1998. This may reflect the increasing public awareness of Hedgebay as a venue for such types of transactions.

The investors transacting via Hedgebay are primarily funds-of-funds, banks and family offices, domiciled in over 30 countries, with investment pools sourced mainly from the US and Europe. Initially, investors were exclusively based offshore, as regulatory issues for trading on the secondary market differ for offshore and onshore investors. However, since 2006, both onshore and offshore investors have traded on Hedgebay, following Hedgebay's efforts to open the onshore segment of the market.

[5] The fact that every transaction in these funds occurs between pre-existing investors in the fund partly assuages concerns that asymmetric information should generate discounts to compensate buyers against adverse selection risk.

2.2. Hedge Fund Characteristics

In order to study the behaviour of premia and discounts at which hedge funds are traded in the secondary market, these data must first be matched to the characteristics of the hedge funds, including their returns. The funds are matched by their names (the identifier on Hedgebay) to a combined database of hedge funds and funds-of-funds from HFR, CISDM, TASS and MSCI. This combined database comprises 10,790 funds of funds and hedge funds for which returns and administrative information about withdrawal restrictions and fees are available. This number includes data on 44 funds for which administrative information and returns are obtained from Hedgebay. The database includes multiple share classes of funds on account of different currencies and lock-up and redemption restrictions, which is useful, as occasionally, only particular share classes of funds are traded on Hedgebay.

The set of 220 funds traded on Hedgebay is matched to the consolidated database, and several requirements are imposed on the data. These are the availability of all fields of administrative information (including lockup periods and redemption notice periods) for funds; the restriction of the sample to non-disaster transactions; and the availability of measures of performance for 12 months prior to each transaction. This results in a final sample of 380 transactions in 95 funds. This constitutes the main sample used for most of the analysis.[6]

The funds come from a broad range of strategies, which can be consolidated into nine main strategies from the bewildering variety of vendor classifications. These nine strategies are: Security Selection, Global Macro, Relative Value, Directional Traders, Funds of Funds, Multi-Process, Emerging Markets, Fixed Income, and Other. Table A.1. in the Appendix shows the mapping from the vendor classifications to these nine strategy groups.

Table II, Panel A shows the characteristics of the matched set of non-disaster transactions, which look very similar to the summary statistics for the entire set of funds reported in

[6] The main reason for the attrition of the sample is that many of the funds traded on Hedgebay do not report to database vendors. Details about the matching and database consolidation procedures are provided in Appendix 1.

Table I. Table II Panel B shows some comparisons between these statistics and those for the 10,666 funds in the consolidated database that are not traded on Hedgebay, with the associated 95% confidence interval from the total universe of 10,790 funds. The average minimum investment requirement imposed by funds traded on Hedgebay is $1.75 million, the average redemption frequency across funds each year is 2.76 months on average, and approximately 32% of the funds impose lockup restrictions on their investors. These numbers are very similar to the characteristics of the remaining sample of 10,666 funds, in which the redemption frequency is 2.41 months on average, and 31% of funds impose lockup restrictions on investors. However, the minimum investment amount is $3.46 million on average across all funds, which is higher than that in the Hedgebay sample (although not significantly so, as many offshore funds have low minimum investment requirements). Several of these differences, however, are statistically significant, such as the redemption notice period, the redemption frequency, the average management and incentive fee, and the percentage of funds traded on Hedgebay that are domiciled in offshore financial centres. This raises the possibility of sample selection issues, a possibility that I attempt to correct for later in the analysis.

2.3. Hedge Fund Performance

Several different hedge fund performance measures are employed in the paper, all estimated over 12 month periods prior to and following transactions on Hedgebay. The first is the simple average of the returns reported by the hedge fund over these periods. The second is alpha (α):

$$r_{i,t} = \alpha_i + \sum_j \beta_j F_{j,t} + \varepsilon_{i,t} \tag{2.2}$$

Assume there is a transaction for fund i in period h. Then, (2.2) is estimated for fund i over the interval between $h-12$ and $h-1$ to obtain past risk-adjusted performance, and between $h+1$ and $h+12$ to obtain future risk-adjusted performance. Two different

factor models are employed: the first is a single-factor market model, in which F is the return on the CRSP value-weighted portfolio. The second is Carhart's (1997) four factor model, comprising excess returns on the three Fama-French factors (Rm-Rf, SMB and HML), and the returns on a momentum portfolio (UMD). The estimated past (future) alphas from these two models for a fund i with a transaction at time h are, respectively, denoted $MKTALPHA_{h-1}$, $FFALPHA_{h-1}$ ($MKTALPHA_{h+1}$, $FFALPHA_{h+1}$).[7]

Finally, I also use the estimated t-statistics of $MKTALPHA$ and $FFALPHA$ as performance measures (denoted $MKTTALPHA$ and $FFTALPHA$). The t-statistic of alpha is closely related to the "information ratio" of a fund (Treynor and Black (1973)), a commonly employed performance measure in the investment management industry. This measure has been employed for mutual fund and hedge fund performance evaluation in recent papers by Kosowski, Timmerman, Wermers and White (2006), Kosowski, Naik and Teo (2006), and Fung, Hsieh, Naik and Ramadorai (2007).[8]

Several of the specifications incorporate a measure of the illiquidity of a fund's underlying investments, computed using the methodology of Getmansky, Lo and Makarov (2004). Using maximum likelihood, a moving average model is estimated on the demeaned returns $X_{t-1} = R_{t-1} - \mu$, of each fund with return data available for a 12 month period prior to it being traded on Hedgebay:

$$X_{t-1} = \eta_{t-1} + \theta_1 \eta_{t-2} + ... + \theta_k \eta_{t-k-1} \tag{2.3}$$

Here the assumption is that η_k is mean-zero and distributed normally with variance σ_η^2. The next step is to apply the Getmansky, Lo and Makarov (2004) normalization, to create:

$$GLMTHETA0 = \frac{1}{1 + \sum_k \theta_k}. \tag{2.4}$$

[7] I also check the robustness of the results to the use of Fung and Hsieh's (2004) seven-factor model and 24 months of return data prior to and following transactions. The results are qualitatively similar despite the sample size reducing greatly as a consequence of the increased data requirement.

[8] Both Kosowski, Timmerman, Wermers and White (2006) and Kosowski, Naik and Teo (2006) prefer this measure to alpha, especially over short periods in which alphas are estimated with less precision, potentially generating outliers. By normalizing the estimated alpha by its precision, the alpha t-statistic provides a correction for these potentially spurious outliers.

When estimating, k is set to 2, and $GLMTHETA0$ for a fund i estimated over the ($h-1$ to $h-12$) months prior to a trade in month h is denoted as $GLMTHETA0_{i,h-1}$. $GLMTHETA0_{i,h-1}$ can be interpreted as the percentage of the true current month returns that are reported in the month, with the remainder distributed over the subsequent two months (since $k=2$). Thus, a value of $\widehat{\theta}_0 = 0.5$ represents a higher level of illiquidity of the fund's assets than a value of $\widehat{\theta}_0 = 0.75$, under the assumption that return smoothing is solely driven by underlying asset illiquidity (and not earnings smoothing by the manager). I winsorize $GLMTHETA0$, setting values > 1 or < 0, to 1 and 0 respectively, as it is difficult to interpret the values as percentages of smoothing otherwise.[9] The next section analyzes the time series behaviour of the hedge fund premium.

3. Explaining the Hedge Fund Premium

3.1. Stylized Facts in the Time Series

The literature has highlighted that closed-end fund premia vary over the business cycle, and comove with aggregate stock returns. For example, Brickley, Manaster and Schallheim (1991) find that premia on 17 closed-end funds over the 1969 to 1978 period are procyclical, and Lee, Shleifer and Thaler (1990) document that premia are positively correlated with contemporaneous stock returns. Brickley et. al. attribute this cyclicality to the tax-timing option value of closed-end funds (since stock return variances are countercyclical, premia are likely to be lower when these variances are higher if tax-timing options are driving closed-end fund premia). Lee et. al. suggest that the positive correlation with contemporaneous stock returns is evidence of sentiment driving both equity returns and closed-end fund premia. Both these explanations suggest that the aggregate variation in the closed-hedge fund premium may be related to movements in stock and other asset returns. The sentiment-based explanation also suggests that commonly employed sentiment proxies

[9] This is similar to the approach of Aragon (2005). Winsorizing $GLMTHETA0_{i,t-1}$ at the 5th and 95th percentiles of the pooled distribution yields virtually identical results.

may be related to time-series variation in the closed-hedge fund premium. Finally, illiquidity-based explanations of closed-end fund premia suggest that an aggregate proxy for illiquidity could be related to the closed-hedge fund premium.

As a first step, therefore, I relate the average equal-weighted closed-hedge fund premium $HFPREM_t$ across all transactions (τ) in all funds (f) in each month (t) to a set of market covariates, estimating a set of univariate specifications:

$$\begin{aligned} HFPREM_t &= a + bMKTCOVARIATE_t + u_t, \qquad (3.1) \\ HFPREM_t &= \frac{1}{N_t}\sum_{\tau=1}^{N_t} HFPREM_{i,t,\tau} \end{aligned}$$

Note that the average is taken over N_t, the total number of transactions occurring across all funds in month t.

$MKTCOVARIATE_t$ is successively the value-weighted closed-end fund premium across all US general equity closed-end mutual funds found in the CRSP database ($CEFPREM$); Baker and Wurgler's (2007) sentiment index, which is based on the first principal component of six (standardized) sentiment proxies, where each of the proxies has first been orthogonalized with respect to a set of macroeconomic conditions ($SENT^{\perp}$)[10]; the University of Michigan's consumer sentiment index ($MICHSENT$); the level of equity market illiquidity ($PSLIQLEVEL$) obtained from WRDS, and computed as in Pastor and Stambaugh (2003); the 3-month US Treasury Bill rate ($RF3M$), obtained from Kenneth French's website; the level of the credit spread measured as Moody's average BAA yield less the yield on a 10-year constant maturity Treasury bond ($BAAMTSY$); the ratio of the S&P 500 price level to a ten-year moving average of earnings ($PE10Y$) obtained from Robert Shiller's website; and the return on the CRSP value-weighted market portfolio (Rm). Left- and right-hand side variables in these regressions are first normalized by their standard deviations prior to

[10]Both $SENT^{\perp}$ and $CEFPREM$ are obtained from Jeff Wurgler's website. $CEFPREM$ is updated from 2006:01 to 2007:03 using data from Compustat, CRSP and Barron's.

estimating equation (3.1), so as to estimate correlation coefficients between the variables.

As these variables are all quite persistent, I conduct an augmented Dickey-Fuller (ADF) test of the residuals u_t from the above regressions, to check that the correlations are not spurious (see Engle and Granger (1987)). Finally, I regress the first difference of $HFPREM$ on the first difference in each of these covariates (with the exception of Rm). Newey-West (1983) standard errors, robust to heteroskedasticity and autocorrelation, are employed in all time-series regressions.

Table III shows the results from this exercise. The first striking result from the table is that the closed-hedge fund premium is highly correlated with the closed-end mutual fund premium over time. The correlation coefficient between the two series is 54%. Figure 1 plots the two series over the period from August 1998 to March 2007. The figure suggests that the correlation is not merely driven by low frequency movements in the two variables. This is confirmed by the fact that the correlation between the first differences of the two series is 17% over the same period, and statistically significant at the 10% level. Second, hedge fund premia are highly *negatively* correlated with $SENT^{\perp}$ and $MICHSENT$ (the correlations are -48% and -36%). However, these correlations exist only in levels, rather than first differences.

Third, the relationship between $HFPREM$ and $RF3M$ is strongly negative over the period. Figure 2 plots $RF3M$, $HFPREM$ and the Hodrick-Prescott trend (using the recommended monthly smoothing parameter) of $HFPREM$ over the 1998 to 2007 period. While $RF3M$ is highly persistent, the residual from the regression of $HFPREM$ on $RF3M$ is stationary, suggesting that the relationship is not spurious (the ADF t-statistic is -12.973, rejecting the null of a unit root at the 1% level of confidence). While a longer time series of $HFPREM$ is unavailable, Appendix 2 shows that the relationship between $CEFPREM$ and $RF3M$ is negative over the 1965:07 to 2007:03 period.

These features of the time series of the hedge fund premium are intriguing. It appears that there are sources of common variation in $HFPREM$ and $CEFPREM$. Furthermore, unlike the results for $CEFPREM$ detected in the earlier studies of Lee, Shleifer and Thaler

(1991) and Brickley, Manaster and Schallheim (1991), $HFPREM$ appears to be unrelated to movements in aggregate stock returns, and move in the opposite direction to $RF3M$, a state variable that has often been linked to variation in the business cycle (see Ferson and Harvey (1991) and Hodrick and Prescott (1997)). Additionally, the relationship between $HFPREM$ and both measures of sentiment over the sample period is negative, rather than positive as predicted by sentiment-based theories of the closed-end fund premium. This might not be surprising, given that $HFPREM$ arises in a market in which institutional investors, rather than individual investors, transact with one another.[11] The next section investigates whether rational theories that have been used to explain the closed-end mutual fund premium are useful for explaining the behaviour of $HFPREM$ in the cross-section.

3.2. The Cross-Section of Hedge Fund Premia

To evaluate whether variation in $HFPREM$ is well-explained by the rational theories put forward to explain closed-end mutual fund premia, I regress it on a set of fund characteristics, and hedge fund performance measures. The choice of regressors is motivated primarily by the recent theories of Cherkes, Sagi and Stanton (2008), and Berk and Stanton (2007), as well as by empirical studies on hedge funds such as Aragon (2005). A convenient null hypothesis in all these regressions is that measures of liquidity and performance are unrelated to cross-sectional variation in the premia across funds, and to changes in this cross-sectional variation over time. The alternative hypothesis in each case is outlined along with a brief explanation of the theory.

3.2.1. Liquidity Based Explanations

In the model of Cherkes, Sagi and Stanton (2008), the underlying driver of premia is that funds provide access to illiquid assets, with high expected returns. This tends to drive closed-end fund premia up. However, if the shares of the fund themselves are illiquid, this

[11] A large and recent body of literature provides evidence that institutional investors accurately interpret cashflow relevant news, in contrast to the behaviour of individual investors. See Cohen, Gompers and Vuolteenaho (2002), Campbell, Ramadorai and Schwartz (2008) and references therein.

drives premia down. Aragon (2005) documents that hedge funds with lock-up provisions and other such restrictions outperform those that do not have them, by 4 to 7% per annum. This leads him to conclude that share restrictions allow hedge funds more flexibility in managing illiquid assets, and that positive expected returns in such funds are required compensation to investors for holding illiquid fund shares.

Both studies suggest that lock-up restrictions should be utilized as explanatory variables for $PREM$ and $HFPREM$, and both suggest that lengthier investment restrictions in funds (such as the lockup, redemption notice period and the frequency at which redemptions are permitted from funds) should drive $HFPREM$ down. This would result in negative regression coefficients when cross-sectional premia are regressed on the length of the lockup, redemption notice period and redemption frequency of funds. Both explanations also suggest that funds with more illiquid underlying assets should have higher $HFPREM$, which would lead to a *negative* regression coefficient of $HFPREM$ on a measure of underlying asset *liquidity* (such as $GLMTHETA0$). These predicted signs serve as the alternative hypothesis in the following regression:

$$\begin{aligned} HFPREM_{i,t,\tau} = \alpha_s + \beta_1 LOCK_i + \beta_2 REDEMP_i + \beta_3 REDFREQ_i \\ + \beta_4 AMT_{i,t,\tau} + \beta_5 GLMTHETA0_{i,t-1} + \beta_6 RF3M_t + u_{i,t,\tau} \end{aligned} \quad (3.2)$$

In regression (3.2), $LOCK_i$ is a dummy variable which signifies whether or not fund i has a lock-up restriction on capital withdrawals, $REDEMP_i$ is the length in months of the redemption notice period which the investor needs to give fund i prior to capital withdrawal, $MININV_i$ is the minimum investment requirement to get into the fund, in millions of U.S. dollars, $REDFREQ_i$ is the frequency in months at which redemptions are allowed to take place (i.e., if redemptions are only allowed at the end of each calendar quarter, $REDFREQ_i = 3$), $AMT_{i,t,\tau}$ is the transaction amount normalized by the fund's assets under management in the month of the trade ($AUM_{i,t}$),[12] $GLMTHETA0_{i,t-1}$ is estimated

[12] $AMT_{i,t}$ is normalized by the average AUM in the strategy of the fund when the AUM of the fund is

over $t-1$ to $t-12$ prior to the transaction month, and $RF3M_t$ is included to capture the low-frequency variation in $HFPREM$ documented in the previous section. α_s denotes the use of strategy-specific fixed effects in estimation, see Section 3.3 below for more details about estimation.

3.2.2. Performance Based Explanations

Berk and Stanton (2007) present a model in which the closed-end fund premium is related positively to expectations about managerial ability in generating performance, and negatively to the level of fees that must be paid to fund managers. Their model shows that under an 'insurance contract' (in which the manager of the fund is entrenched, and given pay increases commensurate with his ability to generate high risk-adjusted performance), at low levels of managerial ability, premia are linearly and positively related to ability. As managerial ability rises, the likelihood rises that the manager will demand a pay increase, resulting in reductions in premia at very high levels of ability.

The theory predicts a nonlinear relationship between the premium and managerial ability, especially at high levels of ability. While it is impossible to measure ability directly, I use measures of past hedge fund performance (raw returns and risk-adjusted returns) as signals of managerial ability. If hedge performance is persistent (see Agarwal and Naik (2000), Kosowski, Naik and Teo (2006) and Jagannathan, Malakhov and Novikov (2007) for evidence that this is the case), investors in hedge funds will extract information about managerial ability from past performance, resulting in higher premia paid to acquire funds with better past performance.

The Berk and Stanton model suggests the following regression specification:

$$HFPREM_{i,t,\tau} = \alpha_s + \beta_1 \overline{PERF}_{i,t-1} + \beta_2 \overline{PERF}^2_{i,t-1} + \beta_3 \overline{RM}_{t-1} + \beta_4 STDPERF_{i,t-1}$$
$$+ \beta_5 MGMTFEE_i + \beta_6 INCFEE_i + \beta_7 AMT_{i,t,\tau} + \beta_8 AUM_{i,t} + \beta_9 RF3M_t + u_{i,t,\tau}. \quad (3.3)$$

unavailable. The normalization is done to ensure that $AMT_{i,t}$ is not merely picking up the effect of fund size on returns.

In regression (3.3), $\overline{PERF}_{i,t-1}$ is the average return of the fund in percent, estimated over $t-1$ to $t-12$ prior to the transaction month, and $\overline{PERF}^2_{i,t-1}$ is its square. $\overline{RM}_{t-1}$ is the average equity return in percent, measured using the CRSP value-weighted market portfolio, over the same prior 12 month period. $STDPERF_{i,t-1}$ is the standard deviation of fund returns in percent in the 12 months prior to it being traded on Hedgebay. $MGMTFEE_i$ and $INCFEE_i$ are the fixed management fee and the incentive fee charged by the fund, both in percent. AMT and $RF3M$ are as described above, and $AUM_{i,t}$ is the AUM of fund i at time t, in billions of US dollars.

In regression (3.3), the alternative hypotheses from the Berk and Stanton model are $\beta_1 > 0$, $\beta_2 < 0$ (non-linear relationship between premium and ability); $\beta_2 < 0$ (high standard deviation of returns suggests higher risk-taking by the manager, and therefore lower risk-adjusted performance); $\beta_5 < 0$ and $\beta_6 < 0$ (fees). Additionally, if dollar fees rather than percentage fees are important to investors, the larger the fund, the higher the level of management fees investors in the fund will pay, hence $\beta_8 < 0$.

The regression (3.3) is then rerun, successively replacing $\overline{PERF}_{i,t-1}$ with the estimated alpha and t-statistic of alpha of the fund, estimated using the market model and Carhart (1997) four-factor models over the same prior 12 month period (computed as described in the Data section). For example, the regression with $MKTALPHA$ is:

$$\begin{aligned} HFPREM_{i,t,\tau} = \alpha_s &+ \beta_1 MKTALPHA_{i,t-1} + \beta_2 MKTALPHA^2_{i,t-1} \\ &+ \beta_3 \overline{RM}_{t-1} + \beta_4 STDPERF_{i,t-1} + \beta_5 MGMTFEE_i \\ &+ \beta_6 INCFEE_i + \beta_7 AMT_{i,t,\tau} + \beta_8 AUM_{i,t} + \beta_9 RF3M_t + u_{i,t,\tau} \end{aligned} \quad (3.4)$$

3.2.3. Liquidity and Performance

Finally, a consolidated specification is estimated, which incorporates both liquidity and performance variables as explanators of $PREM$. The consolidated specification is:

$$\begin{aligned} HFPREM_{i,t,\tau} = \alpha_s + \beta_1 LOCK_i + \beta_2 REDEMP_i + \beta_3 REDFREQ_i \\ + \beta_4 TALPHA_{i,t-1} + \beta_5 TALPHA^2_{i,t-1} + \beta_6 STDPERF_{i,t-24,t-1} \\ + \beta_7 AMT_{i,t,\tau} + \beta_8 AUM_{i,t} + +\beta_9 MGMTFEE_i + \\ \beta_{10} INCFEE_i + \beta_{11} GLMTHETA0_{i,t-1} + \beta_{12} RF3M_t + u_{i,t,\tau}. \quad (3.5) \end{aligned}$$

The expected signs of the coefficients follow directly from the subsections above.

3.3. A Note on Estimation

Specifications (3.2)-(3.5) contain fund-specific variables, time-period specific variables, and variables that vary across funds, time and transactions. The data for all transactions are stacked, and specifications are estimated using pooled OLS. In all estimated specifications, the left-hand side variables are, successively, $PREM$, and $HFPREM$, which explain both the contracted premium between buyer and seller, as well as the total percentage paid over NAV by the buyer, including commission. The intercepts in the pooled regressions are denoted α_s, since I use strategy-specific fixed effects – subtracting strategy-specific means from both left-and right-hand side variables. The regressions aim to capture the sources of fund and time variation in premia, rather than strategy-level variation. There are nine strategies represented in the data, details on these are provided in the Data section of the paper and in Table A.1. in the Appendix.

Heteroskedasticity is likely to affect the regressions, especially since there are concerns about the possibility of selection issues. Furthermore, there may be unexplained commonalities in the movement of the residuals in the regressions. These may occur across time, if premia are unexpectedly high across all funds at the same time or if premia are persistent. They may also occur at the level of funds, if multiple transactions occur for the same fund

quite close together in time, and they are driven by common determinants. Therefore, the standard errors are additionally corrected using a Rogers (1983, 1993) covariance matrix, which is robust to heteroskedasticity, contemporaneous correlation of the residuals across all transactions each month, and autocorrelation of the residuals (both own and cross) of up to one month. These are preferred to the Fama-MacBeth procedure, since they allow pooled OLS estimation, allowing for the possibility of using common time-series regressors such as $RF3M$ in the specifications.[13] The next subsection describes the results from estimating equations (3.2) to (3.5).

3.4. Cross-Sectional Results

Table IV shows the results from estimating equation (3.2). The adjusted R-squared of the regression for $PREM$ and $HFPREM$ is around 16% (including the strategy fixed effects). The contemporaneous level of $RF3M$ is negatively related to premia, in keeping with the strong negative relationship between $HFPREM$ and $RF3M$ detected at the aggregate level. The table also shows, consistent with the predictions of Cherkes, Sagi and Stanton (2008), that the level of illiquidity of the fund's shares is negatively related to the premium paid to acquire it. The liquidity restrictions that seem important here are the length of the redemption notice period and the redemption frequency of the fund, which are short-term restrictions on capital withdrawal, rather than a longer-term restriction such as $LOCK$. The magnitude of the coefficients indicate that a one-month increase in the redemption notice period of the fund is associated with a 45 (52) basis point reduction in $PREM$ ($HFPREM$). Given the variation of $REDEMP$ across the set of funds, this translates into a one standard deviation shock to $REDEMP$ being associated with a movement of around 25% of a standard deviation of $PREM$ ($HFPREM$).

In addition to the withdrawal restrictions, the regressors include $GLMTHETA0_{i,t-1}$,

[13] Cohen, Polk and Vuolteenaho (2003) discuss that the method can also be interpreted as an application of Hansen's (1982) generalized method of moments or as a multivariate generalization of Hansen and Hodrick (1980) standard errors. Standard errors are also computed using White's (1980) method, and the delete-1-jackknife method of Shao and Wu (1989) and Shao (1989), with comparable results. The jackknife estimator is robust to heteroskedasticity and non-normality of the errors.

Getmansky, Lo and Makarov's (2004) measure of the smoothness of the returns of fund i, measured over months $t-1$ to $t-12$. This can be interpreted as a measure of the illiquidity of the fund's assets, or as evidence of earnings management by the manager. There is no evidence to indicate that this variable helps explain the premium that is paid for funds. Given that transactions occur between pre-existing owners of funds, it could be that different owners of a given fund have similar expectations on average about the extent of performance-smoothing by the hedge fund manager, or it could represent that underlying asset illiquidity does not affect the premium paid to acquire funds.

Table V relates $PREM$ and $HFPREM$ to the past performance of the fund, and to the levels of management and incentive fees that the fund charges (equation (3.3)). The average raw returns of a fund over the previous 12 months positively forecasts both $PREM$ and $HFPREM$. An increase of one percent per month (around one standard deviation of $\overline{PASTPERF}_{i,t-1}$) is associated with an increase in $PREM$ ($HFPREM$) of 38 (43) basis points. The relationship is statistically significant at the 5% level.

There are several other interesting results in Table V. First, the past 12 months' average equity market return has a significant and negative coefficient in the regression, suggesting that there may be some benchmarking by hedge fund investors, or some form of substitution in institutional portfolios between equity assets and hedge funds. Second, the standard deviation of performance over the past 12 months also has a negative and statistically significant relationship with $PREM$ and $HFPREM$. Investors in hedge funds seem to like high mean returns, but dislike volatile hedge fund performance. A one percent increase in fund return standard deviation measured over the 12 months prior to a transaction reduces the premium by approximately 25 basis points. Third, the level of management fees that hedge funds charge investors appear to be strong drivers of transactions premia. Holding performance constant, an increase of one percent in a fund's management fees results in a 1.13% reduction in the transactions premium (the standard deviation of management fees in the cross-section of funds is approximately 60 basis points). Fourth, the coefficient on AUM is negative and statistically significant. Larger funds have lower future returns. This

may be a result of incubation bias (see Liang (2000) and Fung and Hsieh (2000)), which would cause the returns on small, young funds to be higher. It may also be evidence that capacity constraints hurt the ability of larger hedge funds to continue to generate high future performance (see Fung, Hsieh, Naik and Ramadorai (2008)).

The positive coefficient on past hedge fund returns and the negative coefficient on the lagged equity market return suggests that the specifications be refined further. Table VI Panel A shows the results when $\overline{PASTPERF}_{i,t-1}$ and $\overline{RM}_{t-1}$ are replaced by $MKTALPHA_{i,t-1}$, the intercept from regressing hedge fund returns over the $t-1$ to $t-12$ period on the CRSP value-weighted portfolio return over the same period. The coefficient on $MKTALPHA$ is statistically significant and positive, and the coefficient magnitude indicates that an additional percent of $ALPHA$ is associated with a hike in $HFPREM$ of 56 basis points. Table VI Panel B substitutes the fund's information ratio $MKTTALPHA_{i,t-1}$ for $MKTALPHA_{i,t-1}$, and the results remain strong and statistically significant. In addition, $MKTTALPHA^2_{i,t-1}$ is now statistically significant and negative in this regression, as predicted by the model of Berk and Stanton (2007) – at very high levels of $MKTTALPHA$, the premium paid to acquire a fund begins to decline. The level of management fees also continues to be an important determinant of $PREM$ and $HFPREM$, and the adjusted R-squared statistics across the specifications in Tables V and VI range from $24-31\%$, higher than that for the regressions in Table IV.

Taken together, the results from Tables V and VI provide strong support for the theory of Berk and Stanton (2007), in which performance expectations and fees are the proximate determinants of $HFPREM$. If performance is persistent, hedge fund investors on Hedgebay rationally pay high premia to acquire funds with better past performance. The non-linear relationship detected between $HFPREM$ and $MKTTALPHA$ is also consonant with the predictions of the Berk and Stanton theory, although the nonlinearity is not evident for the other performance measures such as $PASTPERF$ and $MKTALPHA$.[14] Of course,

[14] As highlighted in section 2.3, this may be a result of the greater noise in these measures relative to the $TALPHA$ measure, which normalizes estimated risk-adjusted performance by the estimation precision (see Kosowski, Timmerman, White and Wermers (2005)).

a better test of the Berk and Stanton (2007) theory would be to check that $HFPREM$ correctly forecasts *future* performance, a test implemented for closed-end funds by Chay and Trzcinka (1999), with positive results. Section 5 below conducts this test.

Table VII explains $PREM$ and $HFPREM$ using all of the performance and liquidity related variables, estimating equation (3.5). Both performance and liquidity related variables continue to be strong and statistically significant determinants of both left-hand side variables. While these results suggest that both performance and liquidity related variables have a role in explaining premia on the secondary market for hedge funds, concerns about the generalizability of the results remain, especially given that the sample on Hedgebay may not be representative of the universe of hedge funds (recall the difference between several of the attributes of Hedgebay-traded funds and those of the broader universe in Table II). The next section presents Heckman's (1979) approach to correct for the presence of selection bias, and implements it on the data.

4. Correcting For Possible Selection Bias

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

This section presents a method to uncover the determinants of a fund's being traded on Hedgebay. Specifications estimated on data from Hedgebay employ a small fraction of funds from the entire hedge fund universe. This fraction is also composed of funds that are closed to new investments. Therefore, the sample may not be representative of the population of funds. These reasons may lead us to suspect that the results from any regressions we run will not be representative of the 'true' behaviour of hedge fund investors when they are making investment decisions. Indeed, any coefficients purporting to explain the behaviour of premia on Hedgebay may be contaminated by correlation between the residuals in these explanatory regressions, and the unobserved determinants of the fund's being traded on Hedgebay.

More formally, following Heckman (1979), let z_i be a 'selection' variable that takes the value of 1 if a trade occurs for fund i on Hedgebay, and 0 otherwise. Let w_i be a vector of

determinants of selection, such that:

$$z_i = \mathrm{w}_i^{'}\gamma + \varepsilon_i \tag{4.1}$$

Now, consider a regression equation that purports to explain the premia at which funds are traded on Hedgebay ($HFPREM$), and consider a generic vector of determinants of these premia, $\mathrm{x}_{i,t}$, which will contain many of the same constituents as w_i, in each period t:

$$HFPREM_{i,t} = \mathrm{x}_{i,t}^{'}\beta + u_{i,t} \tag{4.2}$$

Assume that the selection equation (4.1) is time-invariant, that is, that the selection of funds to be traded on Hedgebay does not vary across time, but only in the cross-section of funds.[15]

Note that (4.2) is observed only if $z_i = 1$. Assume also that in each period t:

$$(\varepsilon_{it}, u_i) \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho\sigma_\varepsilon \\ \rho\sigma_\varepsilon & \sigma_\varepsilon \end{bmatrix}\right) \tag{4.3}$$

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

$$\mathrm{E}[HFPREM_{i,t} \mid z_i = 1, \mathrm{x}_{i,t}, \mathrm{w}_i] = \mathrm{x}_{i,t}^{'}\beta + \delta\lambda(\mathrm{w}_i^{'}\gamma), \tag{4.4}$$

where $\delta = \rho\widehat{\sigma}_\varepsilon$, which will have the sign of the correlation (ρ) between the residual in the selection equation (4.1) and in the explanatory equation (4.2), that is, δ is informative about whether funds that are closed to new investments have higher or lower premia as a consequence of this attribute.

Thus, once $\lambda(\mathrm{w}_i^{'}\gamma)$ has been computed, it can be incorporated into (4.2) as a selection

[15] This assumption is likely to be satisfied if rates of hedge funds' closing to new investments are similar over time, or if the choice of which funds are traded on Hedgebay is driven primarily by static, rather than dynamic attributes of these funds.

bias correction:

$$HFPREM_{i,t} = \mathrm{x}_{i,t}^{'}\beta + \delta\lambda(\mathrm{w}_i^{'}\gamma) + \upsilon_{i,t}. \tag{4.5}$$

$\lambda(\mathrm{w}_i^{'}\gamma)$ is known as the inverse Mills ratio, and is computed using the coefficients from the probit equation (4.1), which in turn is estimated using maximum likelihood. The sample on which (4.1) is estimated is the entire universe of hedge funds and funds-of-funds. Once this is done:

$$\lambda(\mathrm{w}_i^{'}\gamma) = \frac{\phi(\mathrm{w}_i^{'}\gamma)}{\Phi(\mathrm{w}_i^{'}\gamma)},$$

where $\phi(.)$ is the standard normal density function, and $\Phi(.)$ is the standard normal cumulative distribution function.

A crucial identifying assumption here is that at least some of the elements of w_i are not contained in $\mathrm{x}_{i,t}$, that is, that there are some variables that explain selection, but not the level of transactions premia.[16] Therefore:

$$\begin{aligned}\mathrm{w}_i = [&LOCK_i, REDEMP_i, MININV_i, REDFREQ_i, ... \\ &INCFEE_i, MGMTFEE_i, STRATDUM_{i1} - STRATDUM_{i9}, OFFSHORE_i]\end{aligned} \tag{4.6}$$

Here, $STRATDUM_{i1} - STRATDUM_{i9}$ are nine strategy dummy variables, which take the value of 1 if fund i is in the strategy and 0 otherwise (Table A.1. in the Appendix documents the classification of the numerous vendor provided strategies into the nine groups employed),.and $OFFSHORE_i$ is 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.[17] The variable $OFFSHORE$ shows up only in the selection equation, and not in the regression used to explain transactions premia. Using the domicile of a fund as the exclusion restriction

[16] If there is no such exclusion restriction, the model is identified only by distributional assumptions about the residuals, which can lead to problems in estimating the parameters of the model (see Sartori (2003))

[17] In practice, the MSCI, TASS, HFR and CISDM databases provide domicile information for most, but not all funds. For the Hedgebay traded funds for which there is no domicile information provided, the headquarters of the fund were looked up manually, and $OFFSHORE$ is set to 1 when the headquarters of the fund is located in an offshore financial centre. This is done for 4 of the 124 funds in the sample.

is justifiable if its domicile status affects the propensity of a fund to be traded on Hedgebay, but does not much affect the premium at which the fund changes hands. There are numerous tax benefits to being located offshore, and the tax implications of a fund's changing hands on Hedgebay are dramatically simpler if the fund is an offshore fund. This is the main reason why, reading from Table II, Panel B, 83% of the funds traded on Hedgebay are offshore funds. 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 investment restrictions (such as lockup and redemption notice periods) than onshore funds on their investors, and that underlying asset illiquidity is therefore lower in offshore funds. To the extent that share restrictions affect the premium at which a fund is traded on Hedgebay, therefore, $OFFSHORE$ will be a useful determinant of the premium. However, the explanatory regressions for $HFPREM$ include $LOCK$, $REDEMP, MININV$ and $REDFREQ$ as regressors. Under the assumption that the incremental impact of $OFFSHORE$ over and above its use as a proxy for the presence of these share restrictions is minor, $OFFSHORE$ serves as a useful exclusion restriction. When estimating the cross-sectional selection equation (4.1), maximum likelihood and a probit model are employed, and the standard errors are corrected for heteroskedasticity using White's (1980) procedure.

4.2. Results: Probit Selection Equation

Table VIII presents results from estimating (4.1). The cross-sectional regression is run on a total of $10,790$ hedge funds and funds-of-funds, of which 124 (only including funds in which non-disaster transactions occurred), or 1.15% of the entire sample, were traded on Hedgebay. The Chi-squared statistic from a Wald test of the null hypothesis that all coefficients are jointly zero is 116.27, which rejects the null hypothesis (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 $INCFEE, REDFREQ$ and $REDEMP$ are the most important continuous selection variables. All three variables have positive coefficients, which shows that the sub-sample of funds traded on Hedgebay has higher incentive fees and higher redemption notice periods than the average hedge fund or fund-of-funds. The positive coefficient on $INCFEE$ in particular, fits well with the anecdotal evidence that highly successful funds raise their fees and close to new investments. These results accord roughly with the results in Panel B of Table II, except for the fact that $MGMTFEE$ is not statistically significant in the probit estimation. This suggests that the higher management fees of funds traded on Hedgebay are not important independent determinants of selection once other fund characteristics are controlled for.

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, three of the strategy dummies, namely those for Security Selection, Global Macro and Multi-Process, are significant at the 5% level, and one of them, for Fixed-Income funds, is significant at the 10% level. The coefficient estimates show that there is a 1.25% greater chance of selection if the fund is in the Security Selection strategy, a 1.5% greater probability of selection if the fund is a Global Macro fund, and a 1.1% increase in the probability of selection for a Multi-Process fund. Security Selection comprises primarily equity funds that concentrate on long-short bets, while Global Macro includes funds that primarily trade in

global currencies and bonds. The Global Macro strategy represented a disproportionate share of the hedge fund industry in the early and mid-1990s, and Multi-Process funds tend to be larger on average than their counterparts in other strategies. Finally, the exclusion restriction $OFFSHORE$ is a statistically significant determinant of selection. An offshore fund has an approximately 1% greater chance of being traded on Hedgebay once all the other determinants of trading are accounted for. The next section incorporates the inverse Mills ratio computed from the selection equation into (3.5) to correct for possible selection bias in the results.

4.3. Results: Incorporating the Selection Bias Correction

The coefficient on the inverse Mills ratio takes the sign of ρ, that is, the correlation between the residuals in (4.2) and (4.1). If positive, this suggests that funds that are closed to new investments are more likely to exhibit high unexplained transactions premia. If negative, controlling for the variables in (4.2) this suggests that all else equal, a fund's being closed to new investment is likely to be associated with a lower premium. In Table IX, the coefficient on $IMILLS$ is positive in the explanatory regressions for $PREM$ and $HFPREM$, although it is not statistically significant. Simply interpreting the sign, it appears as if, all else equal, market participants are willing to pay higher premia to get into funds which are closed to new investments. This may be because closing is a signal of high future earnings prospects, or there may be benefits from closing to avoid capacity constraints' effects on future performance.

In Table IX, several of the determinants of $PREM$ and $HFPREM$ in Table VIII, namely $MKTTALPHA$, $MKTTALPHA^2$, $MGMTFEE$, AUM and $RF3M$ remain statistically significant at the 5% level, with the same signs, and virtually the same coefficient magnitudes as before. However, $REDEMP$, the redemption notice period of the fund, is no longer statistically significant once $IMILLS$ is included, suggesting that the result in Table VIII of the effect of this liquidity restriction was driven by sample selection of funds with higher redemption notice periods. However, $REDFREQ$ continues to be statistically significant.

The positive coefficient of $HFPREM$ on past performance suggests that hedge fund investors are engaged in return-chasing behaviour, that is, they seem willing to pay high prices for funds exhibiting high past performance. This is rational if hedge fund performance is persistent, i.e., if premia in this market chase past performance in rational anticipation that past performance is a reliable indicator of future performance. This suggests that we can use $HFPREM$ as a forecasting variable for future hedge fund performance, if the expectations of market participants are correct on average. The next section investigates this hypothesis.

5. The Premium and Future Hedge Fund Performance

5.1. Does the Premium Have Predictive Power for Future Hedge Fund Returns?

First, I forecast several future performance measures using $HFPREM$, $IMILLS$, and a number of other conditioning variables that have been used both in the hedge fund literature and the closed-end mutual fund literature to explain expected future hedge fund returns:

$$\begin{aligned}\overline{FUTPERF}_{i,t+1,t+12} = \alpha_s + \beta_1 \overline{HFPREM}_{i,t} + \beta_2 \overline{AMT}_{i,t} + \beta_3 AUM_{i,t} \\ + \beta_4 MGMTFEE_i + \beta_5 INCFEE_i + \beta_6 LOCK_i \\ + \beta_7 IMILLS_i + \beta_8 RF3M_t + e_{i,t} \quad (5.1)\end{aligned}$$

Here $\overline{FUTPERF}_{i,t+1,t+12}$ and $\overline{PASTPERF}_{i,t-1,t-12}$ are, successively, average hedge fund returns and the alpha and information ratio (t-statistic of alpha) of funds computed using three different factor models, over the period $t+1$ to $t+12$, in the case of $FUTPERF$, and $t-1$ to $t-12$ for $PASTPERF$. The factor models are the single factor market model and the Fama-French (1993) three factor model, augmented using Carhart's (1997) momentum factor. Note also that the right-hand side variable is:

$$HFPREM_{i,t} = \frac{1}{N_{i,t}} \sum_{\tau=1}^{N_{i,t}} HFPREM_{i,t,\tau},$$

the average premium across all transactions conducted for fund i in month t, rather than $HFPREM_{i,t,\tau}$. This is done in the interest of reducing measurement error.[18] The null hypothesis here is that the hedge fund premium has no relationship with future performance, i.e., $\beta_1 = 0$. The alternative is that $\beta_1 > 0$.

Note that specification (5.1) incorporates fund characteristics as controls on the right hand side, but not past performance measures. This suggests a modification to (5.1), and the alternative hypothesis is that $\beta_1 > 0$ in the regression:

$$\begin{aligned}\overline{FUTPERF}_{i,t+1,t+12} &= \alpha_s + \beta_1 \overline{HFPREM}_{i,t} + \beta_2 \overline{PASTPERF}_{i,t-1,t-12} \\ &+ \beta_3 STDPERF_{i,t-1,t-12} + \beta_4 \overline{AMT}_{i,t} + \beta_5 AUM_{i,t} + \beta_6 MGMTFEE_i \\ &+ \beta_7 INCFEE_i + \beta_8 LOCK_i + \beta_9 IMILLS_i + \beta_{10} RF3M_t + e_{i,t} \quad (5.2)\end{aligned}$$

5.2. Results: The Premium and Future Hedge Fund Performance

Tables X and XI present estimates of equations (5.1), and (5.2), when $FUTPERF$ is successively estimated as the average of hedge fund returns in the 12 months following a transaction on Hedgebay; the alpha over the same period; and the t-statistic of alpha, measured using two different factor models. The sample size reduces when we impose the additional requirement of data availability for 24 months surrounding each transaction – there are now 325 transactions from 80 funds in the sample, which when averaged across all transactions for each fund in each month, results in 267 fund-month observations .

Table X shows that $HFPREM$ has a positive coefficient in all the regressions, which suggests that that market participants anticipate future performance correctly. However, the coefficients on $HFPREM$ are significant at the 10% level at best, and only for the alpha t-statistic measures from the market model and the Carhart model. Table X also shows that the management fee level of the fund strongly forecasts the future net-of-fee returns of the funds. This may be because $MGMTFEE$ is higher for funds with better past performance,

[18] The results are virtually unaffected if I use the transactions-level premia to forecast $FUTPERF$ rather than the average premium across all transactions in each fund-month.

and is picking up some of the effects of performance persistence.

Table XI reveals that the sign on $HFPREM$ turns negative (in the alpha t-statistic regressions), once past performance and the standard deviation of past performance are included in the regressions. This suggests that hedge fund investors on Hedgebay don't seem to have information about future performance over and above past performance. Indeed, this might indicate that they are overpaying for high past hedge fund returns. Table XI also shows that performance persistence in hedge funds only shows up when performance is measured using the alpha t-statistic of funds.[19] When performance is measured using raw returns, or alpha, there seems to be some reversion in performance. This suggests that there may be some return smoothing in the underlying asset holdings. Another interesting result in this table is that $STDPERF$ negatively forecasts future performance in this sample of funds.[20]

To refine the investigation in Table XI further, I check the difference between the predictive ability of premia that are higher than the cross-sectional median premium in each month and those that are lower than the median. It may be that when hedge fund investors pay high transactions premia, they overbid for funds, and are subsequently disappointed with the future performance of these funds, while transactions occurring at discounts, or low premia, may anticipate future performance more accurately. I estimate:

$$\begin{aligned}\overline{FUTPERF}_{i,t+1,t+12} = \alpha_s + \beta_1\overline{HIPREM}_{i,t} + \beta_2\overline{LOPREM}_{i,t} + \beta_3\overline{PASTPERF}_{i,t-1,t-12} \\ + \beta_4 STDPERF_{i,t-1,t-12} + \beta_5\overline{AMT}_{i,t} + \beta_6 AUM_{i,t} + \beta_7 MGMTFEE_i \\ + \beta_8 INCFEE_i + \beta_9 LOCK_i + \beta_{10} IMILLS_i + \beta_{11} RF3M_t + e_{i,t} \quad (5.3)\end{aligned}$$

[19] Kosowski, Naik and Teo (2006) show that performance persistence is most accurately estimated when the t-statistic of alpha is employed as the performance measure.

[20] Wang and Zheng (2008) find that hedge fund flows react negatively to past return volatility, and that this relationship is significant for the event-driven, macro and multi-process funds. Given that hedge fund flows and returns are positively correlated (see Naik, Ramadorai and Stromqvist (2007)), and that a large fraction of the funds in the sample are macro and multi-process funds (see Table VIII) this result is perhaps unsurprising.

where

$$
\begin{aligned}
HIPREM_{i,t} &= HFPREM_{i,t} * I_{\{HFPREM_{i,t} > median(HFPREM_{i,t})\}}, \\
LOPREM_{i,t} &= HFPREM_{i,t} * I_{\{HFPREM_{i,t} <= median(HFPREM_{i,t})\}}
\end{aligned}
$$

where $I_{\{.\}}$ is an indicator variable which takes the value of 1 when the condition is satisfied and 0 otherwise.

Table XII shows that when we separately consider transactions occurring at high and low premia as predictors of future performance, the picture is more nuanced. High premium transactions continue to negatively forecast future hedge fund returns, and the coefficients are measured with greater precision than in Table XI. The coefficients are significant at the 5% level for both the t-statistic of alpha estimated from the market model, and the t-statistic of alpha from the Carhart four-factor model. This suggests that there is at least some overbidding for hedge fund performance at high levels of transactions premia. In contrast, transactions occurring at low premia, that is, those less than or equal to the median each month, are positive indicators of future performance for three out of the five measures (though neither of the information ratios are positively forecasted by $LOPREM$). This is consistent with these transactions being driven by rational anticipation of future performance. Taken together, these results suggest either that there is some market segmentation amongst different investor groups in the secondary market for hedge funds, with overbidding by some groups of investors coexisting with the rational anticipation of future performance; or that there may be another common determinant of bidding and future performance (such as the availability of credit) that drives the behaviour of both simultaneously .

6. Conclusion

The secondary market for hedge funds offers an interesting glimpse at the behaviour of hedge fund investors, an area about which little is currently known. The premia and discounts to NAV at which funds are bought and sold on this market are analogous to closed-end mu-

tual fund premia and discounts, which have been extensively studied. Rational theories of closed-end mutual funds that emphasize performance, liquidity and fees as determinants of premia are strongly supported when estimated using closed-hedge fund premia. Premia are negatively associated with withdrawal restrictions in the form of redemption notice periods and the periodicity at which redemptions are permitted by funds. This supports the theory of Cherkes, Sagi and Stanton (2008), and suggests that the secondary market helps attenuate the impact of liquidity shocks which force hedge investors to withdraw capital at times when redemption notice periods in hedge funds are binding. Transactions premia are also negatively associated with high management fees in funds, and positively and nonlinearly associated with past hedge fund performance, offering strong support for theories that highlight the trade off for investors between expectations of high performance and future fees, such as Berk and Stanton (2007). These results are robust to correction for the probability that only certain types of funds are selected for trading on Hedgebay.

The association between future performance and transactions premia is more nuanced. There is some evidence that premia positively forecast future hedge fund performance, however once performance persistence is accounted for, while moderate transactions premia continue to forecast future performance, higher transactions premia are negatively associated with future performance. This suggests the presence of heterogeneously informed investors in the secondary market for hedge funds. This potential market segmentation in the market for hedge fund investments has been suggested as a factor governing the behaviour of hedge fund flows in Fung, Hsieh, Naik and Ramadorai (2008).

Finally, a surprising finding of this paper is that the time-series behaviour of the hedge fund premium is closely related to that of the closed-end fund premium over the ten year premium in the sample considered in this paper, in both levels and differences. This intriguing finding suggests that there may be some deeper structure underlying different markets for managed investments, a possibility that warrants further investigation.

Appendix 1

Matching Hedgebay Data to the Consolidated Hedge Fund Database

The hedge fund and fund of funds data span four different sources: TASS, HFR, MSCI and CISDM. There are a total of 20,823 funds represented in the consolidated data, 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, returns and AUM information is not available for $4,181$ of these $14,927$ funds, which results in a set of $10,746$ funds from the consolidated database.

The 220 funds traded on Hedgebay are then compared to this set of $10,746$ funds. Using the key name and management company information, in consultation with Hedgebay in case of slight differences in names, 91 of the 220 funds are matched to the consolidated database.

For the remaining $220 - 91 = 129$ funds, the consolidated database occasionally has administrative information, but never has return information over the periods surrounding the time at which they are traded on Hedgebay. For 44 of these remaining 129 funds, return data (net of all fees and costs) and administrative information are obtained from Hedgebay (only 33 of these funds have non-disaster transactions on Hedgebay). A cross-check was then conducted to make sure that the two sets of administrative information (from the consolidated database and directly sourced) are congruent with each other. The information was virtually identical. In cases in which there were discrepancies (there are only 11 such cases) the information sourced from Hedgebay was preferred to that contained in the databases. This results in an expansion of the universe of funds to $10,790 = 10,746 + 44$.

This gives the final sample employed in this paper: $91+44 = 135$ funds for which we have administrative information (of which 124 have non-disaster transactions); 95 funds for which we have both administrative information and return information available for 12 months

prior to their non-disaster transactions on Hedgebay; and 80 funds for which we have both administrative information and return information available for 24 months surrounding the transaction on Hedgebay.

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 HFR, TASS, CISDM, MSCI 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	Macro
Fund of Funds	Funds of Funds
Global Macro	Macro
HFRI	Other
Index	Other
Long Bias	Directional Traders

Table A.1. (Continued)

Strategy in Consolidated HFR, TASS, CISDM, MSCI Database	Mapped Strategy
Long/Short Equity Hedge	Security Selection
Long-Short Credit	Fixed Income
Macro	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

Appendix 2
The Closed-End Fund Premium and the Risk-Free Rate, 1965-2007

This figure plots the the value-weighted premium (ln(Price)-ln(NAV)) across all U.S. closed-end mutual funds in CRSP each month (CEFPREM), and the 3 month US Treasury Bill Rate (RF3M). For ease of plotting, the data are standardized for both series by subtracting the in-sample mean and dividing by the in-sample standard deviation. The correlation between RF3M and CEFPREM is -27% over the period between 1965:07 and 2007:03.

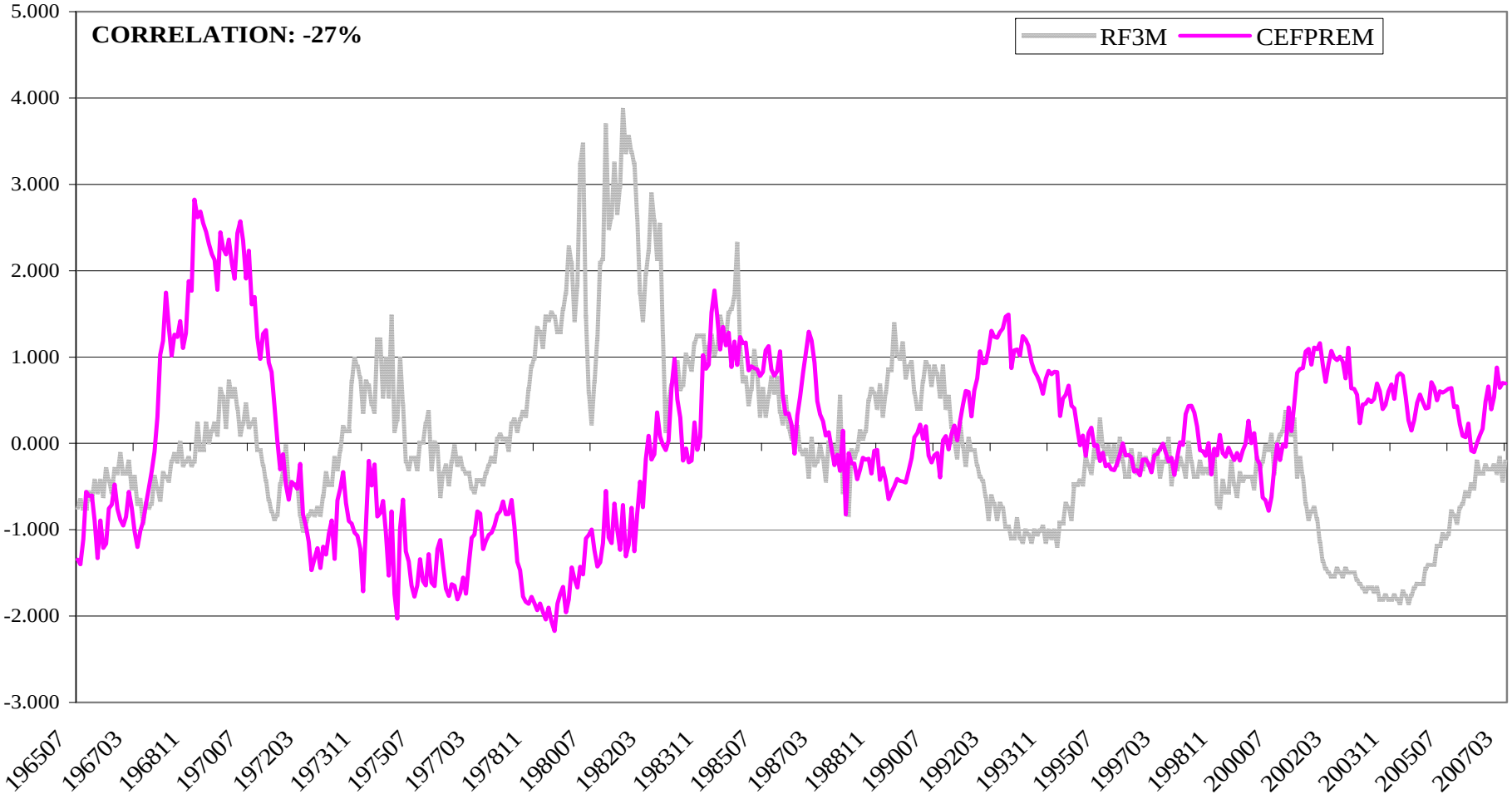

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Table I
Summary Statistics: Full Sample

Table I presents descriptive statistics for all transactions conducted on Hedgebay between August 1998 and March 2007. Panel A presents these statistics for non-disaster transactions, for which there was no severely adverse news such as a fraud or a collapse of the hedge fund in the month in which the transaction occurred. Panel B presents the same statistics for the disaster transactions. The rows show statistics in each year of the sample period, followed by statistics for all transactions (Overall). The columns in order show the number of transactions; the number of funds in which these transactions took place; the mean transaction amount as a percentage of the AUM of the fund (AMT), weighted by the size of the fund across all funds in which transactions took place during each year; the mean percentage premium in excess of NAV paid by the buyer of the fund on Hedgebay (PREM); the mean total percentage in excess of NAV paid by the buyer of the fund on Hedgebay (HFPREM = PREM+COMM, when PREM ≥ 0, where COMM is commission); and the standard deviation of HFPREM across all transactions conducted in each year.

Panel A: Non-Disaster Transactions

Years	Transactions Number	Funds Number	AMT Wtd Avg % of AUM	PREM Mean %	HFPREM Mean %	HFPREM S.D. %
1998	12	6	0.042	0.000	0.528	0.430
1999	51	14	0.299	0.000	0.408	0.874
2000	92	30	0.589	-0.060	0.382	1.480
2001	120	47	0.435	1.318	1.886	3.432
2002	86	29	0.309	1.937	2.603	2.436
2003	124	49	0.601	1.716	2.328	2.283
2004	109	48	0.783	1.353	1.989	2.166
2005	120	61	0.752	0.578	1.173	1.388
2006	104	54	0.948	-0.450	0.006	2.589
2007	51	31	1.452	0.086	0.478	1.281
Overall	869	202	0.640	0.813	1.362	2.399

Panel B: Disaster Transactions

Years	Transactions Number	Funds Number	AMT Wtd Avg % of AUM	PREM Mean %	HFPREM Mean %	HFPREM S.D. %
1998	0	0	0	0	0	0
1999	0	0	0	0	0	0
2000	0	0	0	0	0	0
2001	0	0	0	0	0	0
2002	1	1	2.188	-50.000	-50.000	0.000
2003	5	3	0.830	-65.000	-65.000	28.062
2004	8	4	0.629	-67.072	-67.072	31.279
2005	12	8	1.316	-49.485	-49.485	34.078
2006	19	8	1.497	-31.075	-31.075	23.532
2007	21	14	1.612	-56.167	-56.167	29.468
Overall	66	23	1.416	-49.626	-49.626	30.675

Table II
Summary Statistics: Matched Sample

Table II, Panel A presents descriptive statistics for all non-disaster transactions conducted on Hedgebay between August 1998 and March 2007, which can be matched to information on returns and fund characteristics. The columns in order show the number of transactions, the number of funds in which these transactions took place, the mean transaction amount as a percentage of the AUM of the fund (AMT), weighted by the size of the fund across all funds in which transactions took place during each year, the mean percentage premium in excess of NAV paid by buyers of the fund on Hedgebay (PREM), the mean total percentage in excess of NAV paid by the buyer of the fund on Hedgebay (HFPREM = PREM+COMM, when PREM ≥ 0, where COMM is commission), the percentage of funds with lockup restrictions (LOCK), the average minimum investment required in millions of US dollars (MININV), the average redemption notice period in months (REDEMP), and finally, the average frequency in days at which redemptions are allowed from funds (REDFREQ). The rows show these statistics in each year of the sample period, followed by statistics for all transactions (Overall). Panel B shows how these characteristics differ on average from the universe of hedge funds and funds-of-funds in the consolidated HFR, TASS, CISDM and MSCI database.

Panel A: Descriptive Statistics

Years	Transactions Number	Funds Number	AMT Wtd Avg % of AUM	PREM Mean %	HFPREM Mean %	LOCK %	MININV Mean $MM	REDEMP Mean Months	REDFREQ Mean Months
1998	10	4	0.035	0.000	0.500	50.000	2.250	1.500	3.750
1999	24	6	0.270	0.167	0.748	33.333	2.033	1.250	2.667
2000	50	19	0.361	0.070	0.528	36.842	1.626	1.167	2.421
2001	85	34	0.338	0.740	1.309	26.471	1.371	1.152	2.235
2002	55	18	0.195	1.003	1.659	27.778	1.224	1.157	1.889
2003	74	30	0.417	1.061	1.662	36.667	1.711	1.289	2.683
2004	45	25	0.410	0.758	1.266	40.000	2.129	1.467	2.320
2005	64	35	0.495	0.746	1.402	40.000	2.064	1.591	2.543
2006	57	32	0.787	-0.186	0.299	25.000	2.006	1.858	2.820
2007	31	18	1.363	0.001	0.343	50.000	2.258	2.213	2.778
Overall	495	124	0.436	0.556	1.109	31.710	1.747	1.583	2.756

Panel B: Comparison With Universe of Hedge Funds

	SAMPLE	UNIVERSE	[2.5%,97.5%]
NUMBER	124	10666	
MININV ($MM)	1.747	3.476	[1.414,5.498]
LOCK (%)	31.710	31.110	[30.239,31.986]
REDEMP (Months)	1.583	1.159	[1.146,1.182]
REDFREQ (Months)	2.756	2.408	[2.357,2.466]
MGMTFEE (%)	1.540	1.434	[1.422,1.448]
INCFEE (%)	19.839	16.993	[16.896,17.154]
OFFSHORE (%)	83.704	57.610	[56.676,58.542]

Table III
The Time Series Behaviour of the Hedge Fund Premium

Table III relates *HFPREM* (where $HFPREM_t = \sum_{\tau=1}^{N_t}\left(PREM_{i,t,\tau} + COMM_{i,t,\tau}\right)$), the mean total percentage in excess of NAV paid by buyers of the fund on Hedgebay in each month *t* across all transactions occurring in that month (N_t) to a number of covariates: the value-weighted closed-end fund premium across all US general equity closed-end mutual funds found in the CRSP database (CEFPREM); Baker and Wurgler's (2007) sentiment index (SENT$^{\perp}$, orthogonalized to a set of macroeconomic variables); the University of Michigan's consumer sentiment index (MICHSENT); the level of equity market illiquidity (PSLIQLEVEL) obtained from WRDS, and computed as in Pastor and Stambaugh (2003); the 3-month US Treasury Bill rate (RF3M), obtained from Kenneth French's website; the level of the credit spread (the Moody's average BAA yield less the yield on a 10-year constant maturity Treasury bond); the ratio of the S&P 500 Price Level to a ten-year moving average of earnings (PE10Y) obtained from Robert Shiller's website; and the return on the CRSP value-weighted market portfolio (Rm). The first row of statistics shows the correlations between HFPREM and the levels of each of these variables. The second block of statistics shows the persistence of HFPREM as measured by the sample autocorrelation coefficient; the persistence of the covariate; and the t-statistic from an Augmented Dickey-Fuller test of the residual from the regression (the 5% critical value for rejecting the null hypothesis of a unit root is -2.915). The final block of statistics shows correlations between the first difference of HFPREM and the first differences of each of these variables (except for Rm, which is not differenced in this regression). The final row shows the number of observations in each case (this differs across covariates because of data availability). The longest sample period (in levels) extends from August 1998 to March 2007. Newey-West (1983) autocorrelation and heteroskedasticity-robust standard errors are reported below coefficient estimates in *italics*, and coefficients significant at the 5% (10%) level are in **underlined bold** (underlined).

	Correlations with HFPREM(t)							
Covariate →	**CEFPREM(t)**	**SENT^(t)**	**MICHSENT(t)**	**PSLIQLEVEL(t)**	**RF3M(t)**	**BAAMTSY(t)**	**PE10Y(t)**	**Rm(t)**
Correlation in Levels	**0.542**	**-0.477**	**-0.360**	-0.045	**-0.698**	-0.167	**-0.485**	-0.007
	0.102	*0.084*	*0.140*	*0.115*	*0.084*	*0.123*	*0.102*	*0.092*
Persistence of HFPREM	*0.594*	*0.586*	*0.594*	*0.617*	*0.594*	*0.594*	*0.594*	*0.594*
Persistence of Covariate	*0.899*	*0.860*	*0.877*	*0.004*	*0.966*	*0.361*	*0.986*	*0.032*
ADF T-Statistic of Error	*-10.269*	*-10.351*	*-10.026*	*-8.607*	*-12.973*	*-8.747*	*-10.289*	*-8.942*
Correlation in First Differences	0.169	0.141	0.134	0.132	0.028	**-0.196**	0.052	0.009
	0.101	*0.119*	*0.092*	*0.106*	*0.094*	*0.084*	*0.107*	*0.098*
N(Observations)	104	89	104	101	104	104	104	104

Table IV
Liquidity and the Hedge Fund Premium

The columns in order show regressions for the percentage premium in excess of NAV paid by buyers of the fund on Hedgebay (PREM), and the total percentage in excess of NAV paid by the buyer of the fund on Hedgebay (HFPREM = PREM+COMM, when PREM ≥ 0, where COMM is commission), for all non-disaster transactions in the data that can be matched to information on returns and fund characteristics. These variables are regressed on LOCK, a dummy variable which takes the value of 1 if the fund imposes a lockup period on its investors; REDEMP, the length of the redemption notice period in months; REDFREQ, the frequency in months at which redemptions are allowed from the fund; AMT, the size of the transaction, in percent of the AUM of the fund in the month of the trade; GLMTHETA0, a measure of underlying asset illiquidity computed from the moving average model of Getmansky, Lo and Makarov (2004); and RF3M, the contemporaneous 3-month US Treasury Bill rate. The point estimates are produced with pooled OLS and the standard errors (in parentheses) are Rogers (1983, 1993) robust standard errors, which account for cross-sectional and serial correlation of the errors. All pooled regressions are estimated with strategy-specific fixed effects. Coefficients significant at the 5% (10%) level are in **underlined bold** (underlined). The Adjusted R-squared is reported below coefficient estimates. The sample period extends from August 1998 to March 2007. Each of the regressions is estimated on 380 transactions from a total of 95 funds.

	PREM	**HFPREM**
LOCK	0.132	0.207
	0.169	*0.192*
REDEMP	**-0.454**	**-0.515**
	0.161	*0.170*
REDFREQ	-0.145	-0.166
	0.079	*0.087*
AMT	0.008	0.005
	0.007	*0.007*
GLMTHETA0	0.364	0.417
	0.287	*0.301*
RF3M	**-3.556**	**-3.834**
	0.639	*0.714*
Adjusted R-squared	0.158	0.163

Table V
Past Hedge Fund Performance, Fees, and the Hedge Fund Premium

The columns in order show regressions for the mean percentage premium in excess of NAV paid by buyers of the fund on Hedgebay (PREM), and the mean total percentage in excess of NAV paid by the buyer of the fund on Hedgebay (HFPREM = PREM+COMM, when PREM ≥ 0, where COMM is commission), for all non-disaster transactions in the data that can be matched to information on returns and fund characteristics. These variables are regressed on PERF(-12), the mean of fund returns over the 12 months prior to the transaction; the square of PERF(-12); STDPERF(-12), the standard deviation of fund returns over the same interval; RM(-12), the mean return on the CRSP value-weighted stock portfolio over the 12 months prior to the transaction; MGMTFEE and INCFEE, the management fee and incentive fee of the fund; AMT, the size of the transaction, in percent of the AUM of the fund in the month of the trade; AUM in billions of US dollars; and RF3M, the contemporaneous 3-month US Treasury Bill rate. The point estimates are produced with pooled OLS and the standard errors (in parentheses) are Rogers (1983, 1993) robust standard errors, which account for cross-sectional and serial correlation of the errors. All pooled regressions are estimated with strategy-specific fixed effects. Coefficients significant at the 5% (10%) level are in **underlined bold** (underlined). The Adjusted R-squared is reported below coefficient estimates. The sample period extends from August 1998 to March 2007. Each of the regressions is estimated on 380 transactions from a total of 95 funds.

	PREM	**HFPREM**
PERF(-12)	**0.380**	**0.430**
	0.135	*0.150*
PERF^2(-12)	0.042	0.037
	0.031	*0.032*
RM(-12)	**-0.084**	**-0.096**
	0.041	*0.043*
STDPERF(-12))	**-0.244**	**-0.261**
	0.080	*0.088*
MGMTFEE	**-0.968**	**-1.045**
	0.237	*0.254*
INCFEE	-0.019	-0.014
	0.020	*0.022*
AMT	0.008	0.004
	0.008	*0.007*
AUM	**-0.334**	**-0.361**
	0.064	*0.072*
RF3M	**-3.565**	**-3.831**
	0.790	*0.851*
Adjusted R-squared	0.308	0.291

Table VI
Past Alpha, Past Information Ratio, and the Hedge Fund Premium

The columns in order show regressions for the mean percentage premium in excess of NAV paid by buyers of the fund on Hedgebay (PREM), and the mean total percentage in excess of NAV paid by the buyer of the fund on Hedgebay (HFPREM = PREM+COMM, when PREM ≥ 0, where COMM is commission), for all non-disaster transactions in the data that can be matched to information on returns and fund characteristics. In Panel A, these variables are regressed on MKTALPHA(-12) the intercept from a regression of the fund's return on the CRSP VW return over the 12 months prior to the transaction; the square of MKTALPHA(-12); STDPERF(-12), the standard deviation of fund returns over the same interval; MGMTFEE and INCFEE, the management fee and incentive fee of the fund; AMT, the size of the transaction, in percent of the AUM of the fund in the month of the trade; AUM in billions of US dollars; and RF3M, the contemporaneous 3-month US Treasury Bill rate. In Panel B, MKTTALPHA(-12) the t-statistic of MKTALPHA(-12) is used in place of MKTALPHA(-12). The point estimates are produced with pooled OLS and the standard errors (in parentheses) are Rogers (1983, 1993) robust standard errors, which account for cross-sectional and serial correlation of the errors. All pooled regressions are estimated with strategy-specific fixed effects. Coefficients significant at the 5% (10%) level are in **underlined bold** (underlined). The Adjusted R-squared is reported below coefficient estimates. The sample period extends from August 1998 to March 2007. Each of the regressions is estimated on 380 transactions from a total of 95 funds.

Panel A: Alpha

	PREM	HFPREM
MKTALPHA(-12)	**0.482**	**0.559**
	0.216	*0.239*
MKTALPHA^2(-12)	0.002	-0.011
	0.044	*0.048*
STDPERF(-12)	**-0.123**	**-0.133**
	0.056	*0.066*
MGMTFEE	**-1.003**	**-1.087**
	0.239	*0.255*
INCFEE	-0.027	-0.023
	0.022	*0.023*
AMT	0.005	0.001
	0.008	*0.007*
AUM	**-0.336**	**-0.363**
	0.063	*0.071*
RF3M	**-3.525**	**-3.798**
	0.781	*0.831*
Adjusted R-squared	0.283	0.270

Panel B: Information Ratio

	PREM	HFPREM
MKTTALPHA(-12)	**0.157**	**0.173**
	0.044	*0.048*
MKTTALPHA^2(-12)	**-0.001**	**-0.002**
	0.000	*0.000*
STDPERF(-12)	0.052	0.049
	0.062	*0.074*
MGMTFEE	**-1.021**	**-1.106**
	0.266	*0.284*
INCFEE	-0.023	-0.018
	0.022	*0.023*
AMT	0.005	0.002
	0.008	*0.008*
AUM	**-0.291**	**-0.320**
	0.062	*0.069*
RF3M	**-3.343**	**-3.629**
	0.830	*0.881*
Adjusted R-squared	0.250	0.238

Table VII
Past Performance, Liquidity and the Hedge Fund Premium

The columns in order show regressions for the mean percentage premium in excess of NAV paid by buyers of the fund on Hedgebay (PREM), and the mean total percentage in excess of NAV paid by the buyer of the fund on Hedgebay (HFPREM = PREM+COMM, when PREM ≥ 0, where COMM is commission), for all non-disaster transactions in the data that can be matched to information on returns and fund characteristics. These variables are regressed on MKTTALPHA(-12) the t-statistic of intercept from a regression of the fund's return on the CRSP VW return over the 12 months prior to the transaction; the square of MKTTALPHA(-12); STDPERF(-12), the standard deviation of fund returns over the same interval; MGMTFEE and INCFEE, the management fee and incentive fee of the fund; LOCK, a dummy variable which takes the value of 1 if the fund imposes a lockup period on its investors; REDEMP, the length of the redemption notice period in months; MININV, the minimum investment requirement of the fund in millions of US dollars; REDFREQ, the frequency in months at which redemptions are allowed from the fund; AMT, the size of the transaction, in percent of the AUM of the fund in the month of the trade; GLMTHETA0, a measure of underlying asset illiquidity computed from the moving average model of Getmansky, Lo and Makarov [2004]; AUM in billions of US dollars; and RF3M, the contemporaneous 3-month US Treasury Bill rate. The point estimates are produced with pooled OLS and the standard errors (in parentheses) are Rogers (1983, 1993) robust standard errors, which account for cross-sectional and serial correlation of the errors. All pooled regressions are estimated with strategy-specific fixed effects. Coefficients significant at the 5% (10%) level are in **underlined bold** (underlined). The Adjusted R-squared is reported below coefficient estimates. The sample period extends from August 1998 to March 2007. Each of the regressions is estimated on 380 transactions from a total of 95 funds.

	PREM	HFPREM
MKTTALPHA(-12)	**0.183**	**0.202**
	0.043	*0.045*
TALPHA^2(-12)	**-0.002**	**-0.002**
	0.000	*0.000*
STD(-12)	0.085	0.089
	0.052	*0.060*
MGMTFEE	**-0.964**	**-1.038**
	0.254	*0.276*
INCFEE	-0.012	-0.004
	0.020	*0.020*
LOCK	0.010	0.098
	0.214	*0.226*
REDEMP	-0.251	**-0.297**
	0.130	*0.148*
REDFREQ	**-0.184**	**-0.215**
	0.079	*0.087*
AMT	0.008	0.004
	0.009	*0.008*
GLMTHETA0	0.227	0.276
	0.252	*0.271*
AUM	**-0.293**	**-0.321**
	0.074	*0.081*
RF3M	**-3.417**	**-3.739**
	0.831	*0.875*
Adjusted R-squared	0.314	0.310

Table VIII
Probit Selection Equation

This table presents results from a probit selection equation, estimated using maximum likelihood, for the probability of a hedge fund being traded 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 second column reports the White heteroskedasticity robust t-statistic for the associated coefficient estimate of the marginal effect (from the underlying probit equation). The rows list the variables used in the selection equation, namely MININV, the minimum investment requirement of the fund in millions of US dollars; MGMTFEE and INCFEE, the management fee and incentive fee of the fund; REDFREQ, the frequency in months at which redemptions are allowed from the fund; LOCK, a dummy variable which takes the value of 1 if the fund imposes a lockup period on its investors; REDEMP, the length of the redemption notice period in months; eight strategy dummy variables (the ninth, for 'Other' funds is dropped to avoid perfect collinearity); and OFFSHORE, a dummy variable which takes the value of 1 if the fund is domiciled in an offshore financial centre. The last few rows show the observed probability, i.e., the percentage of total funds with non-disaster transactions in the HFR, CISDM, MSCI and TASS databases that are traded on Hedgebay for which we have administrative information; 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	White T-Statistic
MININV	0.000	-1.460
MGMTFEE	0.101	1.340
INCFEE	**0.029**	2.040
REDFREQ	**0.043**	2.590
REDEMP	**0.286**	5.640
LOCK	-0.027	-0.180
STRATEGIES		
Security Selection	**1.260**	2.770
Global Macro	**1.511**	2.590
Relative Value	-0.283	-0.500
Directional Traders	-0.144	-0.400
Funds of Funds	-0.392	-0.650
Multi-Process	**1.130**	2.490
Emerging Markets	0.311	1.300
Fixed Income	0.804	1.940
EXCLUSION RESTRICTION		
Offshore	**0.988**	6.190
N(Funds)	10,790	
Observed Probability	1.149	
Pseudo R-squared	0.114	
Chi2(15)	116.270	
P-value(Chi2)	0.000	

Table IX
Past Performance, Liquidity and the Hedge Fund Premium, Corrected for Selection

The columns in order show regressions for the mean percentage premium in excess of NAV paid by buyers of the fund on Hedgebay (PREM), and the mean total percentage in excess of NAV paid by the buyer of the fund on Hedgebay (HFPREM = PREM+COMM, when PREM ≥ 0, where COMM is commission), for all non-disaster transactions in the data that can be matched to information on returns and fund characteristics. These variables are regressed on MKTTALPHA(-12) the t-statistic of intercept from a regression of the fund's return on the CRSP VW return over the 12 months prior to the transaction; the square of MKTTALPHA(-12); STDPERF(-12), the standard deviation of fund returns over the same interval; MGMTFEE and INCFEE, the management fee and incentive fee of the fund; LOCK, a dummy variable which takes the value of 1 if the fund imposes a lockup period on its investors; REDEMP, the length of the redemption notice period in months; MININV, the minimum investment requirement of the fund in millions of US dollars; REDFREQ, the frequency in months at which redemptions are allowed from the fund; AMT, the size of the transaction, in percent of the AUM of the fund in the month of the trade; GLMTHETA0, a measure of underlying asset illiquidity computed from the moving average model of Getmansky, Lo and Makarov [2004]; IMILLS, the inverse Mills ratio for each fund, computed from the Probit estimation in Table VIII; AUM in billions of US dollars; and RF3M, the contemporaneous 3-month US Treasury Bill rate. The point estimates are produced with pooled OLS and the standard errors (in parentheses) are Rogers (1983, 1993) robust standard errors, which account for cross-sectional and serial correlation of the errors. All pooled regressions are estimated with strategy-specific fixed effects. Coefficients significant at the 5% (10%) level are in **underlined bold** (underlined). The Adjusted R-squared is reported below coefficient estimates. The sample period extends from August 1998 to March 2007. Each of the regressions is estimated on 380 transactions from a total of 95 funds.

	PREM	HFPREM
MKTTALPHA(-12)	**0.185**	**0.203**
	0.044	*0.045*
MKTTALPHA^2(-12)	**-0.002**	**-0.002**
	0.000	*0.000*
STDPERF(-12)	0.083	0.088
	0.053	*0.062*
MGMTFEE	**-0.932**	**-1.023**
	0.260	*0.287*
INCFEE	-0.009	-0.003
	0.023	*0.024*
LOCK	-0.026	0.080
	0.249	*0.259*
REDEMP	-0.221	-0.282
	0.162	*0.185*
REDFREQ	**-0.182**	**-0.214**
	0.081	*0.089*
AMT	0.008	0.004
	0.009	*0.008*
GLMTHETA0	0.220	0.272
	0.259	*0.279*
IMILLS	0.212	0.106
	0.636	*0.684*
AUM	**-0.288**	**-0.319**
	0.078	*0.085*
RF3M	**-3.417**	**-3.739**
	0.828	*0.873*
Adjusted R-squared	0.313	0.309

Table X
The Hedge Fund Premium and Future Hedge Fund Performance

The columns in order show regressions whose left-hand side variables are performance measures for each hedge fund over the 12 months following a month with a transaction on Hedgebay. These performance measures are the average returns of the fund over the 12 months after the month of the transaction; regression intercepts from regressions of hedge fund returns on the CRSP VW return (MKTALPHA) and on the Carhart (1997) four factor (FFALPHA); and the t-statistics of the intercept estimates (MKTTALPHA, FFTALPHA) from each of these models. The RHS variables are: the mean total percentage in excess of NAV paid by the buyer of the fund on Hedgebay (HFPREM = PREM+COMM, when PREM ≥ 0, where COMM is commission) across all transactions in the fund in the month; AMT, the size of the transaction, in percent of the AUM of the fund in the month of the trade; AUM in billions of US dollars; MGMTFEE and INCFEE, the management and incentive fees of the fund in percent; LOCK, a dummy variable which takes the value of 1 if the fund imposes a lockup period on its investors; IMILLS, the inverse Mills ratio from the probit selection equation estimated in Table VIII; and RF3M, the contemporaneous 3-month US Treasury Bill rate. The point estimates are produced with pooled OLS and the standard errors (in parentheses) are Rogers (1983, 1993) robust standard errors, which account for cross-sectional and serial correlation of the errors. All pooled regressions are estimated with strategy-specific fixed effects. Coefficients significant at the 5% (10%) level are in **underlined bold** (underlined). The Adjusted R-squared is reported below coefficient estimates. The sample period extends from August 1998 to March 2007. Each of the regressions is estimated using 267 transaction-months (325 underlying transactions) from a total of 80 funds.

	PERF(+12)	MKTALPHA(+12)	FFALPHA(+12)	MKTTALPHA(+12)	FFTALPHA(+12)
HFPREM	0.045	0.043	0.023	0.354	0.438
	0.034	*0.036*	*0.040*	*0.194*	*0.256*
AMT	-0.006	-0.002	-0.004	-0.033	-0.046
	0.004	*0.004*	*0.007*	*0.018*	*0.024*
AUM	**-0.189**	**-0.125**	-0.029	0.089	0.134
	0.080	*0.063*	*0.065*	*0.146*	*0.196*
MGMTFEE	0.321	**0.340**	**0.423**	**2.751**	**3.578**
	0.171	*0.142*	*0.149*	*0.825*	*1.189*
INCENTFEE	0.006	-0.006	**-0.014**	-0.050	-0.059
	0.006	*0.006*	*0.007*	*0.029*	*0.039*
LOCK	0.070	0.029	-0.072	-0.040	-0.631
	0.090	*0.097*	*0.095*	*0.450*	*0.562*
IMILLS	**0.688**	0.084	0.075	-4.199	-4.406
	0.334	*0.285*	*0.345*	*2.423*	*2.879*
RF3M	0.024	0.437	0.426	0.264	0.403
	0.308	*0.269*	*0.267*	*0.882*	*1.060*
Adjusted R-squared	0.141	0.152	0.159	0.019	0.013

Table XI
The Hedge Fund Premium and Future Hedge Fund Performance, Controlling for Past Performance

The columns in order show regressions whose left-hand side variables are performance measures for each hedge fund over the 12 months following a month with a transaction on Hedgebay. These performance measures are the average returns of the fund over the 12 months after the month of the transaction; regression intercepts from regressions of hedge fund returns on the CRSP VW return (MKTALPHA) and on the Carhart (1997) four factor (FFALPHA); and the t-statistics of the intercept estimates (MKTTALPHA, FFTALPHA) from each of these models. The RHS variables are: the mean total percentage in excess of NAV paid by the buyer of the fund on Hedgebay (HFPREM = PREM+COMM, when PREM ≥ 0, where COMM is commission) across all transactions in the fund in the month; PERFMEAS(-12), the left-hand side variable in each regression, over the 12 months prior to the transaction on Hedgebay; STDPERF(-12), the standard deviation of fund raw returns over the same period; AMT, the size of the transaction, in percent of the AUM of the fund in the month of the trade; AUM in billions of US dollars; MGMTFEE and INCENTFEE, the management and incentive fees of the fund in percent; LOCK, a dummy variable which takes the value of 1 if the fund imposes a lockup period on its investors; IMILLS, the inverse Mills ratio from the probit selection equation estimated in Table VIII; and RF3M, the contemporaneous 3-month US Treasury Bill rate. The point estimates are produced with pooled OLS and the standard errors (in parentheses) are Rogers (1983, 1993) robust standard errors, which account for cross-sectional and serial correlation of the errors. All pooled regressions are estimated with strategy-specific fixed effects. Coefficients significant at the 5% (10%) level are in **underlined bold** (underlined). The Adjusted R-squared is reported below coefficient estimates. The sample period extends from August 1998 to March 2007. Each of the regressions is estimated using 267 transaction-months (325 underlying transactions) from a total of 80 funds.

	PERF(+12)	MKTALPHA(+12)	FFALPHA(+12)	MKTTALPHA(+12)	FFTALPHA(+12)
HFPREM	0.052	0.045	0.012	-0.129	**-0.160**
	0.032	*0.036*	*0.039*	*0.090*	*0.080*
PASTPERF(-12)	-0.145	**-0.181**	-0.077	**0.672**	**0.757**
	0.092	*0.076*	*0.051*	*0.047*	*0.073*
STDPERF(-12)	**-0.155**	**-0.187**	**-0.258**	**-0.227**	-0.151
	0.074	*0.056*	*0.037*	*0.096*	*0.123*
AMT	**-0.006**	-0.002	-0.003	0.011	0.008
	0.003	*0.004*	*0.007*	*0.014*	*0.019*
AUM	**-0.212**	**-0.147**	-0.073	-0.020	0.046
	0.058	*0.039*	*0.044*	*0.172*	*0.161*
MGMTFEE	0.036	0.030	0.070	0.280	0.605
	0.161	*0.138*	*0.134*	*0.338*	*0.404*
INCENTFEE	0.012	0.002	-0.003	0.001	0.036
	0.008	*0.008*	*0.008*	*0.023*	*0.031*
LOCK	0.043	0.018	-0.077	0.016	-0.685
	0.107	*0.112*	*0.113*	*0.374*	*0.387*
IMILLS	0.727	0.103	0.169	-0.149	0.838
	0.371	*0.325*	*0.344*	*1.053*	*1.070*
RF3M	0.589	**1.084**	**1.054**	-0.112	0.123
	0.315	*0.277*	*0.264*	*0.760*	*0.888*
Adjusted R-squared	0.238	0.305	0.329	0.878	0.881

Table XII
High and Low Premia and Future Hedge Fund Performance

The columns in order show regressions whose left-hand side variables are performance measures for each hedge fund over the 12 months following a month with a transaction on Hedgebay. These performance measures are the average returns of the fund over the 12 months after the transaction; regression intercepts from regressions of hedge fund returns on the CRSP VW return (MKTALPHA) and on the Carhart (1997) four factor model (FFALPHA); and the t-statistics of the intercept estimates (MKTTALPHA, FFTALPHA) from each of these models. The RHS variables are HFPREM, divided into HFPREM greater than (less than) the 50th percentile across all funds in each month, denoted HIPREM (LOPREM); PERFMEAS(-12), the left-hand side variable over the 12 months prior to the transaction on Hedgebay; STDPERF(-12), the standard deviation of fund returns over the same interval; AMT, the size of the transaction, in percent of the AUM of the fund in the month of the trade; AUM in billions of US dollars; MGMTFEE and INCFEE, the management and incentive fees of the fund in percent; LOCK, a dummy variable which takes the value of 1 if the fund imposes a lockup period on its investors; IMILLS, the inverse Mills ratio from the probit selection equation estimated in Table VIII; and RF3M, the contemporaneous 3-month US Treasury Bill rate. The point estimates are produced with pooled OLS and the standard errors (in parentheses) are Rogers (1983, 1993) robust standard errors, which account for cross-sectional and serial correlation of the errors. All pooled regressions are estimated with strategy-specific fixed effects. Coefficients significant at the 5% (10%) level are in **underlined bold** (underlined). The Adjusted R-squared is reported below coefficient estimates. The sample period extends from August 1998 to March 2007. Each of the regressions is estimated using 267 transaction-months (325 underlying transactions) from a total of 80 funds.

	PERF(+12)	MKTALPHA(+12)	FFALPHA(+12)	MKTTALPHA(+12)	FFTALPHA(+12)
HIPREM	0.036	0.023	-0.018	**-0.165**	**-0.224**
	0.036	*0.034*	*0.037*	*0.083*	*0.080*
LOPREM	**0.115**	0.112	**0.124**	0.048	0.127
	0.049	*0.063*	*0.062*	*0.213*	*0.176*
PASTPERF(-12)	-0.141	**-0.172**	-0.070	**0.671**	**0.756**
	0.091	*0.074*	*0.049*	*0.047*	*0.073*
STDPERF(-12)	**-0.152**	**-0.185**	**-0.251**	**-0.216**	-0.134
	0.074	*0.056*	*0.037*	*0.098*	*0.127*
AMT	**-0.006**	-0.002	-0.003	0.010	0.006
	0.002	*0.004*	*0.007*	*0.014*	*0.019*
AUM	**-0.220**	**-0.157**	**-0.085**	-0.034	0.025
	0.057	*0.038*	*0.042*	*0.172*	*0.157*
MGMTFEE	0.017	0.007	0.038	0.246	0.554
	0.158	*0.132*	*0.126*	*0.333*	*0.381*
INCENTFEE	0.011	0.002	-0.003	0.000	0.034
	0.008	*0.008*	*0.008*	*0.024*	*0.031*
LOCK	0.054	0.027	-0.060	0.048	-0.634
	0.104	*0.110*	*0.113*	*0.375*	*0.394*
IMILLS	**0.731**	0.136	0.218	-0.089	0.992
	0.351	*0.318*	*0.332*	*1.062*	*1.098*
RF3M	0.484	**0.965**	**0.921**	-0.234	-0.012
	0.325	*0.277*	*0.266*	*0.827*	*0.945*
Adjusted R-squared	0.230	0.296	0.332	0.878	0.881

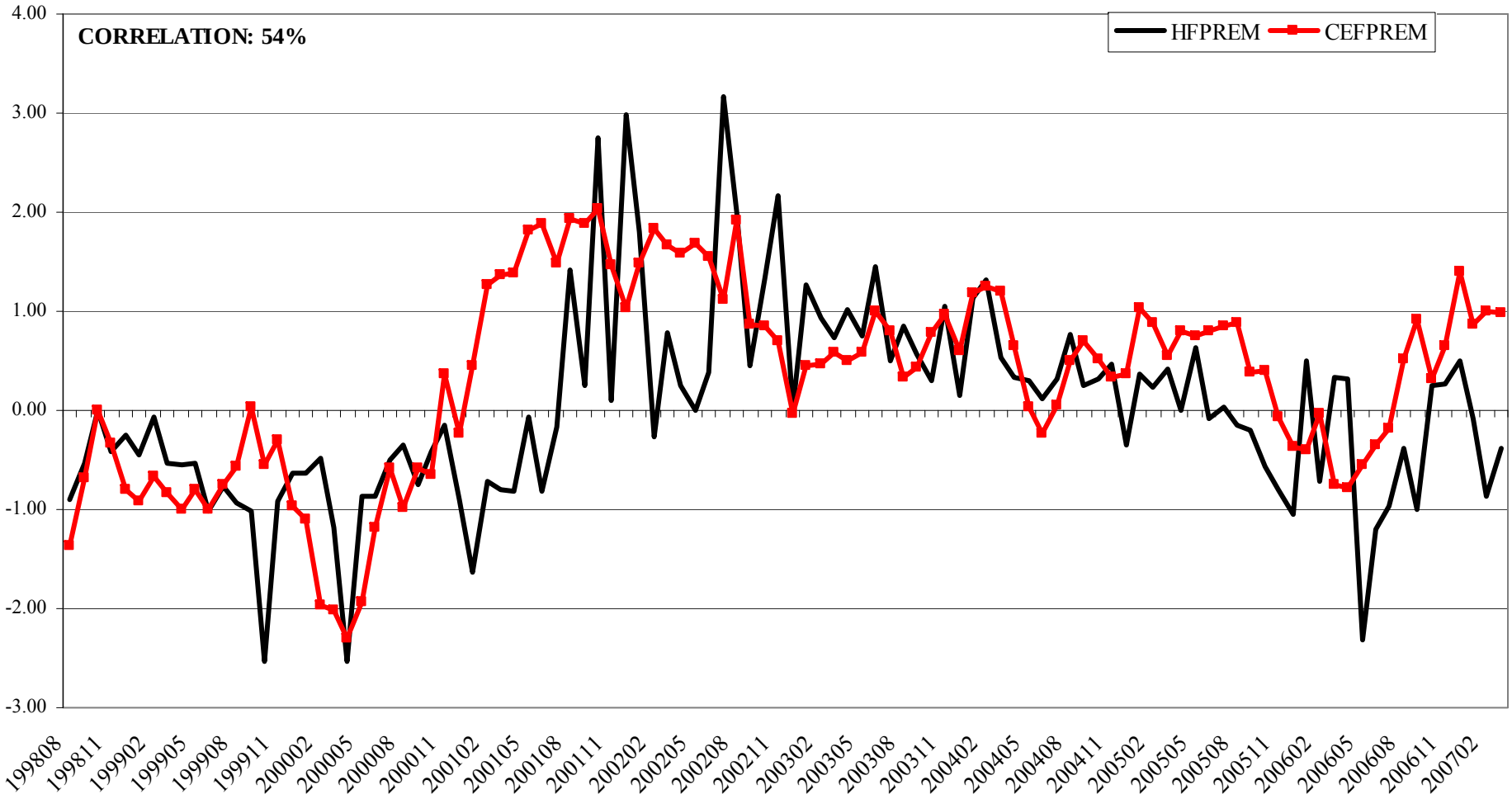

Figure 1: The Hedge Fund Premium and the Closed-End Fund Premium

This figure plots the mean total percentage in excess of NAV paid by the buyer of the fund on Hedgebay (HFPREM), and the value-weighted premium (ln(Price)-ln(NAV)) across all U.S. closed-end mutual funds in CRSP each month (CEFPREM). For ease of plotting, the data are standardized for both series by subtracting the in-sample mean and dividing by the in-sample standard deviation. The correlation between the two series is 54%.

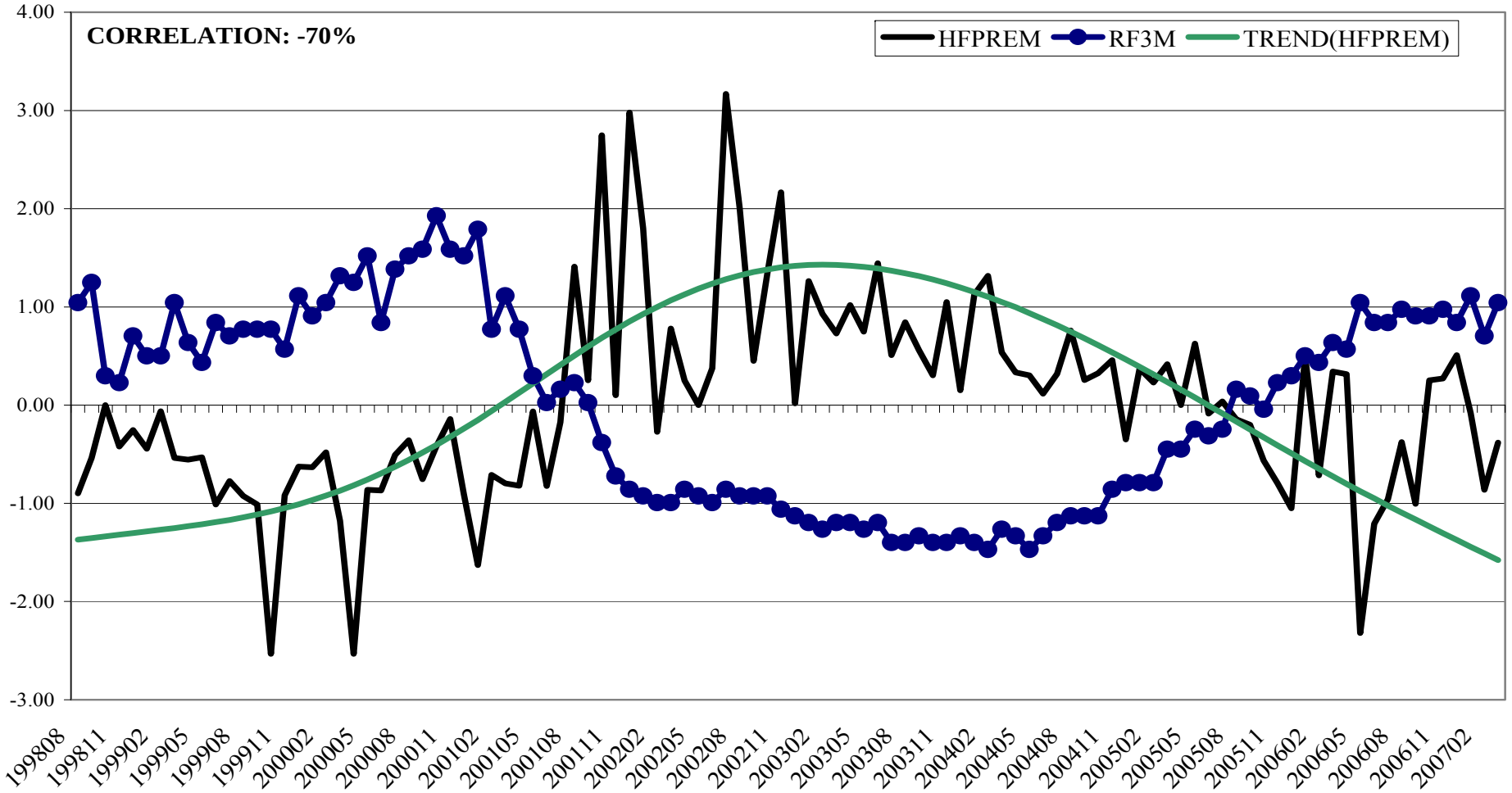

Figure 2: The Hedge Fund Premium and the Risk-Free Rate

This figure plots the mean total percentage in excess of NAV paid by the buyer of the fund on Hedgebay (HFPREM) each month, the Hodrick-Prescott filtered trend of HFPREM using the recommended monthly smoothing parameter of 14400 (TREND(HFPREM)), and the 3 month US Treasury Bill Rate (RF3M). For ease of plotting, the data are standardized for all series by subtracting the in-sample mean and dividing by the in-sample standard deviation. The correlation between RF3M and HFPREM is -70%.