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

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Abstract

Rational theories of the closed-end fund premium puzzle highlight fund share and asset illiquidity, managerial ability and compensation, and fees as important determinants of the premium. Several of these attributes are difficult to measure for mutual funds, and easier to measure for hedge funds. This paper employs new data from a secondary market for hedge funds, discovers a closed hedge fund premium which is highly correlated over time with the closed-end mutual fund premium, and shows that the closed hedge fund premium is well-explained by variables suggested by the rational theories. Sentiment-based explanations do not find support in the data.

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The closed-end fund premium puzzle is one of the best known in financial economics: Although the secondary market price of a closed-end mutual fund and its net asset value (NAV) are both claims to exactly the same set of underlying cash-flows, their levels are very different, and this difference – the premium – fluctuates greatly over time. Recently, two promising solutions to this puzzle have been advanced. Berk and Stanton (2007), in the tradition of models by Boudreaux (1973), Gemmill and Thomas (2002) and Ross (2002), conjecture that the closed-end fund premium is driven by the trade-off between expectations about fund managers' ability to generate performance, and the fees paid to managers. Cherkes, Sagi and Stanton (2009) point out that investments in closed-end funds grant investors indirect access to illiquid underlying assets with high expected returns. In their model, as investors dynamically weigh the benefits of this access against the illiquidity of the fund's own shares and the fees paid to fund managers, the premium fluctuates.

These recent theories move us towards a resolution of the puzzle. However, while they may be correct, testing their predictions on mutual fund data is difficult for at least three reasons. First, measures of mutual fund share and asset liquidity are inferred with measurement error. Second, researchers have been hard-pressed to find evidence of positive risk-adjusted performance in mutual funds. This makes empirical inference about how ability is related to premiums virtually impossible.[1] Third, Berk and Stanton acknowledge the paucity of evidence in mutual funds for a crucial ingredient of their model, namely, pay for performance.[2] These three difficulties combine to create yet another: It is unclear how the liquidity-based explanation and the ability-based explanation interact, as they have yet to be tested simultaneously. If fund liquidity, asset liquidity and fund performance are correlated with each other, omitting any of these determinants could result in incorrect inferences about the true drivers of the premium.[3]

This paper adopts a new approach to resolve this conundrum, testing the rational theories in a setting which seems better suited to evaluating their predictions. Closed-end structures exist in hedge funds, close relatives of actively managed mutual funds. Hedge funds often close to new investments to avoid the negative impact of capacity constraints, and simultaneously impose lockup and redemption notice periods, effectively closing funds for the period when these constraints bind.[4] There is extensive evidence that the risk-adjusted performance of hedge funds is significantly different from zero, and that it varies both in the cross-section of funds and over time (see Kosowski, Naik and Teo (2007), Fung, Hsieh, Naik and Ramadorai (2008), and Jagannathan, Malakhov and Novikov

(2010)). Share illiquidity in hedge funds is very easy to measure – detailed data on fund-imposed restrictions on the timing and amount of capital inflows and withdrawals are readily available from hedge fund databases. Finally, unlike in mutual funds, hedge fund manager pay is explicitly linked to performance. Hedge funds employ incentive fees, hurdle rate and high-water mark provisions that combine to create option-like compensation for their managers. The 'delta' of these options, and the manager's ownership fraction in the fund have recently been computed and found to predict future hedge fund returns (see Agarwal, Daniel and Naik (2009)).

To measure closed hedge fund premiums, this paper analyzes all completed transactions from Hedgebay, the longest running secondary market for hedge funds.[5] Transactions on this market occur in funds that restrict inflows and outflows, and existing investors of the funds trade stakes with one another at premiums and discounts to the end-of-month NAV reported by funds. These premiums and discounts are conceptually similar to those on closed-end mutual funds. However, they also differ in several respects. Closed-end mutual funds and the shares held in their portfolios are both traded on public 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 exchange. Moreover, when hedge funds are traded on Hedgebay, they are closed to new investments and withdrawals – but for a shorter duration than closed-end mutual funds, which only rarely accept additional capital after their initial establishment by means of rights issues (see Khorana, Wahal and Zenner (2002)), and do not normally (apart from distributions or liquidations) repatriate capital to investors over their lifetimes.[6] Finally, the investors in hedge funds that transact on Hedgebay are primarily institutional investors such as funds-of-funds, pension funds, endowments, family offices and banks, or wealthy individuals, rather than the small investors identified as the primary clientele for closed-end mutual funds (Lee, Shleifer and Thaler (1991)). This creates the presumption that sentiment, a frequently-cited explanation for the behavior of the closed-end fund premium, is less likely to drive the closed hedge fund premium.

While these differences are important, they don't appear to invalidate the testing on hedge fund data of theories first formulated to explain closed-end mutual fund premiums. Indeed, despite these differences, the closed-end mutual fund premium and the closed hedge fund premium strongly co-move. The correlation between the closed hedge fund premium and the closed-end mutual fund premium is around 40% in monthly data between 1998 and 2008. This relationship is in part driven by the tendency for both series to co-move with the short-term interest rate.[7] Perhaps surprisingly, however, over the sample period, neither the closed-end mutual fund premium nor the closed hedge fund premium are related to commonly employed proxies for investor sentiment (the University of Michigan index and Baker and Wurgler's (2007) index).

In the cross-section of closed hedge fund premiums, both the Cherkes et al. model and the Berk and Stanton model receive strong support. Premiums are negatively related to the share illiquidity of hedge funds. Premiums are also significantly related to measures of the ability of hedge funds such as past performance, fund size, and fund age. These findings are particularly important since the evidence from mutual funds on the relationship between closed-end fund premiums and performance is mixed at best. Premiums also help to predict future hedge fund performance. The sign of this predictive relationship depends on the level of the premium, and on whether past performance is included as a conditioning variable.[8]

Measures of the alignment of incentives between hedge fund managers and their outside investors are also important for explaining the closed hedge fund premium. High levels of managerial investment in the fund, and in some specifications, the presence of a hurdle rate or a high water mark in a fund, are positively associated with higher premiums. There is also weak evidence that the square of managerial investment is negatively related to the closed hedge fund premium in some specifications. This suggests that moderate levels of managerial ownership are interpreted positively by investors, whereas they seem to value very high levels of managerial ownership somewhat less, justifying the Berk and Stanton assumption that managers are entrenched. Finally, ceterus paribus, premiums are consistently lower for funds with high management fees. Both Cherkes et al. and Berk and Stanton emphasize fees as an important driver of premiums, as do Gemmill and Thomas (2002) and Ross (2002). All 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 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.

Taken together, the results represent significant evidence in support of the rational theoretical models advanced to explain closed-end fund premiums. The use of hedge fund data to evaluate these theories constitutes an out of sample test, which is useful in light of concerns about datasnooping biases that arise from the extensive empirical literature on closed-end mutual funds. It is worth reiterating that until quite recently, explanations for the closed-end fund puzzle have relied heavily on investor sentiment.[9] Older rational theories of the puzzle have also emphasized taxes (Malkiel (1977), Brickley, Manaster and Schallheim (1991), fund holdings of restricted stock (Lee, Shleifer, and Thaler (1991)) and private benefits of managerial control (Barclay, Holderness and Pontiff (1993)).

The organization of the paper is as follows. Section I describes the data. Section II presents facts about the behavior of the closed hedge fund premium in time-series, and describes the measurement of variables predicted by the theories. Section III discusses estimation and the correction for selection bias. Section IV describes the results from estimation, and Section V concludes.

I. Data

A. Secondary Market Transactions

The secondary market data come from Hedgebay, the longest-running trading venue for hedge funds. The investors transacting via Hedgebay are primarily institutional investors, domiciled in over 40 countries, with investment pools sourced mainly from the US and Europe. Over the sample period, transactions almost exclusively occurred in closed share classes of 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 throughout the month, they are settled during the last few days of the month, immediately following the report of the fund's NAV at the end of each month. Thus, these are technically short-dated forward contracts entered into during the month, which are legally binding between counterparties once approval of the fund manager has been obtained. More details on the trading process can be found in Appendix A.

A.1. The Closed-Hedge Fund Premium

I denote by $PREM$ the percentage premium in excess of NAV agreed on between the buyer and the seller of a fund in a given transaction. $PREM$ excludes trading costs on Hedgebay, and $TOTPREM$ includes these trading costs measured as a percentage of NAV.[10] The specifications estimated in the paper explain both $TOTPREM$ and $PREM$, to ensure that the results are not just driven by changes in trading costs.

The data comprise 1,005 transactions in a total of 225 funds, between August 1998 and August 2008.[11] There has been considerable growth in the market – in 1999, the value of the average transaction was around 600,000 U.S. dollars, and by 2008, this number was up to 4.6 million dollars per transaction. Table I 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 1.2% of AUM in 2008. These percentages are AUM-weighted across all funds each year, so the observed growth is not being driven by trades in small funds.

[TABLE I HERE]

The premiums demonstrate interesting time-series variation: In the period up until 2005, the average premium is positive for all but one year, and the fraction of transactions occurring at a discount is less than a third. (The fact that almost every one of these early transactions occurs between pre-existing investors in the fund partly assuages concerns that asymmetric information should generate discounts to compensate buyers against adverse selection risk.) In 2007 and 2008, in contrast, the average transactions premium is large and negative, and by 2008, over half of the transactions occur at discounts. Two factors appear to drive this time variation: First, both the premium and the cross-sectional standard deviation of premiums appear to reflect conditions in the broader economy. Second, transaction numbers and the amounts transacted in funds experiencing liquidations, frauds, or the sudden imposition of gates (bans on withdrawals) 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.

B. Matching to Hedge Fund Data

The funds with transactions on Hedgebay are matched to a combined database of 9,305 live and dead hedge funds and funds-of-funds from HFR, CISDM, TASS and MSCI. The matching procedure results in a final sample of 522 transactions in 126 funds.[12] (Internet Appendix Table II presents some descriptive statistics at the fund level for the 126 matched funds).

[TABLE II HERE]

Table II shows summary statistics for the matched transactions. While the percentage of these transactions for which the premium is negative has roughly the same time pattern as in Table I (rising through the sample period, largest in 2008), the transactions with the largest negative premiums are clearly absent from the matched sample. This confirms the findings of prior research on hedge funds (Fung and Hsieh (2000), Liang (2000)), that the non-response bias documented in much hedge fund research is likely greatest in funds that generate low performance. Collectively, the difficulties in matching transactions to the databases add to the possibility that selection bias affects the results of this study, a possibility for which I attempt to correct later in the analysis.

II. Explaining the Hedge Fund Premium

A. Stylized Facts in the Time Series

Closed-end mutual fund premiums have been found to vary over the business cycle, and to co-move with aggregate stock and bond returns. For example, Brickley, Manaster and Schallheim (1991) find that premiums on 17 closed-end funds over the 1969 to 1978 period are pro-cyclical, and attribute this cyclicality to the tax-timing option value of closed-end funds. Lee, Shleifer and Thaler (1991) document that premiums are positively correlated with contemporaneous stock returns, and interpret this as evidence of sentiment driving both equity returns and closed-end fund premiums; and Cherkes, Sagi and Stanton (2009) document that premiums are negatively correlated with the short-term risk-free rate, interpreting this as evidence of the leverage service provided by closed-end funds to their investors. These prior findings suggest that the aggregate variation in the closed hedge fund premium may be related to movements in stock returns, bond returns, aggregate illiquidity and sentiment.

As a first step, therefore, I compute the average value-weighted closed hedge fund premium $VWTOTPREM_t$ across all funds (i) in each month (t):

$$VWTOTPREM_t = \sum_{\tau=1}^{N_t} w_{i,t-1} TOTPREM_{i,t}, \tag{1}$$

where $w_{i,t-1} = \frac{AUM_{i,t-1}}{\sum_{i=1}^{I_t} AUM_{i,t-1}}$ and I_t is the number of funds in which transactions occur in month t.[13] I then estimate the correlation coefficients of $VWTOTPREM$ with a number of monthly variables motivated by theory and prior empirical evidence. As many of these aggregate variables are persistent, I conduct an augmented Dickey-Fuller (ADF) test of the residuals from the regression used to compute the correlation estimate in each case, to check that the correlations are not spurious (see Engle and Granger (1987)). I then estimate the correlations of the first differences of $TOTPREM$ with the first differences of each of the monthly variables; and the correlations after de-trending each variable using the Hodrick-Prescott filter (neither of these is estimated for the S&P500 returns). Newey-West (1987) standard errors, robust to heteroskedasticity and autocorrelation, are computed for all estimated correlations.

[TABLE III HERE]

Table III shows the results of this exercise. First, the correlations of $VWTOTPREM$ with the sentiment measures are statistically insignificant.[14] This is similar to the results of Lemmon and Portniaguina (2006), Qiu and Welch (2006) and Cherkes, Sagi and Stanton (2009). Indirect evidence of the lack of explanatory power of sentiment is also offered by the correlation of de-trended $VWTOTPREM$ with de-trended VIX, which is a statistically significant 8%. The sentiment-based theories would predict that VIX, the market's 'fear gauge' (Whaley (2000)) has a negative relationship with the premium (the higher the fear, the lower the premium), while microstructure based theory and empirical evidence suggest that volatility should be positively associated with higher spreads in asset markets (see Cherkes et al. (2009)), and thus that $VWTOTPREM$ will be positively correlated with VIX (assuming secondary market illiquidity is less responsive to volatility than the illiquidity of underlying hedge fund assets).

[FIGURE 1 HERE]

The relationship between $VWTOTPREM$ and the risk-free rate is strongly negative over the period. Figure 1 plots the one-month risk-free rate, $VWTOTPREM$ and the Hodrick-Prescott trend of $VWTOTPREM$ over the 1998 to 2008 period. While the risk-free rate is highly persistent, the residual from the regression of $VWTOTPREM$ on the rate is stationary, suggesting that the relationship is not spurious (the ADF t-statistic is -8.4, rejecting the null of a unit root at the 1% level of confidence). This adds support to the Cherkes et al. hypothesis on the liquidity-service-amplifying impacts of leverage.[15]

[FIGURE 2 HERE]

The closed hedge fund premium is also highly correlated with the closed-end mutual fund premium over time. The correlation coefficient between the two series in levels is 39%, and 14% between the de-trended components of the two series.[16] Figure 2 plots both series over the sample period. One plausible interpretation of this relationship, given that both premiums co-move with the risk-free rate, is that the cost of leverage drives their common variation. Another possible interpretation has to do with the cyclicality of the two premiums – the T-bill rate is a state variable that has often been linked to variation in the business cycle (see Ferson and Harvey (1991) and Hodrick and Prescott (1997)). Extrapolating from the Berk and Stanton model, if investors expect that active managers have better investment opportunities in booms than in recessions, then we would see lower premiums on both hedge funds and mutual funds when the T-bill rate is high and vice versa.

B. The Cross-Section of Hedge Fund Premiums

This subsection presents empirical measures of the variables employed in the theoretical models that explain the premium, and discusses the predictions of these models for the signs of the regressors employed in the cross-sectional specifications.

B.1. Ability

Berk and Stanton's model predicts that at moderate levels of managerial ability, premiums will be linearly and positively related to demonstrated performance, as investors update their expectations of the manager's ability. As demonstrated performance rises, the inferred ability of the manager rises, and so does the likelihood that the manager will demand a pay increase. This generates a predicted non-linearity in their model, with reductions in premiums at very high levels of performance. In the empirical specifications, the first measure of risk-adjusted hedge fund performance is estimated from factor models of the form:

$$r_{i,t} - r_{f,t} = \alpha_i + \sum_j \beta_{i,j} F_{j,t} + \varepsilon_{i,t} \tag{2}$$

If a transaction occurs for fund i in period h, (2) is estimated using returns r for the fund from $h-12$ (or $h-24$) to $h-1$ to obtain past risk-adjusted performance, and from $h+1$ to $h+12$ (or $h+24$) to obtain future risk-adjusted performance. Three different factor models are employed: A single-factor market model, in which F is the excess return on the CRSP value-weighted portfolio; Carhart's (1997) four factor model, comprising the three Fama-French factors ($Rm-Rf$, SMB and HML), and the momentum portfolio (UMD); and Fung and Hsieh's (2004) seven-factor model.

From (2), $t(\hat{\alpha}_i) = \frac{\hat{\alpha}_i}{se(\hat{\alpha}_i)}$ is computed and used as the performance measure. 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 (2007), and Fung, Hsieh, Naik and Ramadorai (2008). These authors prefer $t(\hat{\alpha})$ to $\hat{\alpha}$, since over short periods in which alphas are estimated with less precision, there is the potential for outliers in $\hat{\alpha}$. By normalizing $\hat{\alpha}$ by its precision, $t(\hat{\alpha})$ provides a correction for these potentially spurious outliers.[17] In the regression context, with the premium on the left-hand side, the Berk and Stanton model predicts a positive sign on $t(\hat{\alpha})$, and a negative sign on $(t(\hat{\alpha}))^2$.

The other two performance measures employed in the paper are the size of the fund and the age of the fund. Both these variables are measured as (time-varying) ranks relative to all other funds in the universe to avoid concerns of non-stationarity, and lagged one month to avoid any mechanical association. Fund size is employed on account of the extensive evidence on capacity constraints in hedge fund strategies, which shows that larger hedge funds, or hedge funds which have experienced high capital flows in the past have lower expected future alphas (see Fung, Hsieh, Naik and Ramadorai (2008), Zhong (2008) and Teo (2009) for hedge funds and Pollet and Wilson (2008) among others for mutual funds). Fund age is also employed as a performance measure. (Berk and Stanton's model predicts that "one place ability ought to show up is in the NAV returns of new managers.") This implies that expected excess NAV returns, and therefore premiums, should be negatively related to the tenure of the manager, proxied by fund age.

B.2. Incentives

The Berk and Stanton model is based on an 'insurance contract' between mutual fund managers and investors – in which pay raises compensate managers for increases in their perceived ability, as inferred by investors by the fund's past performance. For hedge funds, increases in returns automatically generate higher compensation to fund managers, since incentive contracts are commonplace in the hedge fund industry. Incentive compensation to hedge fund managers varies in the cross-section of hedge funds (as incentive fee percentages differ across funds), as well as over time for the same hedge fund (as a function of past returns, fund flows, fund hurdle rates and high water marks). To identify this variation, in an innovative recent paper Agarwal, Daniel and Naik (2009) compute the 'delta' of hedge fund managers' incentive compensation schemes by pricing the implicit call option to the manager granted by incentive-fee-paying investors. They also estimate the manager's investment in the fund, assuming that the incentive fee compensation garnered by the manager in each period is plowed back into the fund. They demonstrate that these measures predict future hedge fund returns.

The hypothesis arising from the work of Agarwal et al. is that the greater the delta or managerial ownership fraction, the higher the expected future performance, and hence, following the logic of Berk and Stanton, the higher the predicted premium. However, excessively high levels of managerial ownership create concerns about managerial entrenchment in the fund (a la Morck, Shleifer, and Vishny (1988) and McConnell and Servaes (1990)), or excessive managerial risk aversion as a large fraction of the manager's wealth is invested in the fund (following Amihud and Lev (1981), Smith and Stulz (1985), Schrand and Unal (1998), and Guay (1999)). To check for the presence of these effects, I also include the square of managerial ownership in the specifications. Finally, I include a dummy for the presence of a high-water mark or a hurdle rate in the fund to capture whether these devices are successfully employed in the fund for the purposes of aligning the incentives of the manager with those of outside investors.

For each transaction, I compute the associated 'option delta' of the hedge fund manager's incentive contract using data on the fund from the event-year prior to the transaction, and the manager's percentage investment in the fund. Details of these computations are in Appendix B. Table II shows that in the sample, managers are on average estimated to own a high percentage – 21.8% – of their funds. This is three times as high as that reported for the average fund in Agarwal et al. (7%). This is not surprising when one considers the difference between the annualized net returns (which are the main time-varying input to option delta calculations) of the hedge funds in the sample in this paper (on average, this is 19% in the year prior to a transaction) and that in Agarwal et al. sample of hedge funds (12.2%).

B.3. Fund Liquidity and Asset Liquidity

Cherkes, Sagi and Stanton (2009) emphasize that the underlying driver of positive premiums is that funds provide access to illiquid assets, with high expected returns. However, if the shares of the fund themselves are illiquid, this drives premiums down. Restrictions on entering funds (in the form of high minimum investment restrictions, and lengthy subscription notice periods) and exiting funds (in the form of long lock-up and redemption notice periods and low redemption frequencies) are contractual terms set between hedge funds and their investors at the point of investment, and widely prevalent in the hedge fund industry. The theory predicts that these restrictions should be associated with lower premiums. Restrictions on entry would generate lower premiums because larger fractions of outside investors' wealth are required to be tied up in the fund (high minimum investment requirements); or there is a delay imposed on investors' ability to access the underlying illiquid assets at a time of their choosing (lengthy subscription notice periods). Restrictions on exit (such as lock-up and redemption notice periods) should also be associated with lower premiums on account of their effect on the ability of investors to withdraw funds if they are hit with a liquidity shock.[18] I sum the lock-up period, redemption notice period and redemption frequency into one variable, which I denote as 'withdrawal restrictions' in the tables. I also sum subscription frequencies and subscription notice periods into one variable denoted as 'subscription restrictions' in the tables, and measure minimum investment levels as ranks relative to other funds in the universe in the month prior to the transaction to avoid concerns of non-stationarity. Finally, the liquidity of hedge fund shares is also improved by the very existence of Hedgebay, which helps to alleviate the restrictions faced by fund investors. Therefore I also include the average trading costs on Hedgebay (lagged one month to avoid mechanical correlation) to capture any variation in premiums arising from changes in secondary market liquidity.

The other side of the coin is the illiquidity of the fund's asset holdings. The hedge fund literature has attempted to measure underlying asset illiquidity as the smoothness of hedge fund returns. Therefore to capture the illiquidity of a fund's underlying investments, I employ two different measures: The first is the simple autocorrelation of a fund's returns over the 12 months prior to the transaction ($t-1$ to $t-12$). The second is Getmansky, Lo and Makarov's (2004) measure of return-smoothing (the tables in the paper employ the simple autocorrelation measure; Internet Appendix

Table VI presents results using the GLM measure, which leave the conclusions unchanged).

Table II shows the variation in the cross-sectional average first order autocorrelation coefficient of funds over time. Autocorrelations are mostly positive, and occasionally negative, as in Bollen and Krepely-Pool (2008).[19] Another recent measure of underlying asset illiquidity is discovered by Liang and Park (2008), who show that lock-up restrictions on offshore funds are more binding once they are imposed, leading to investments in such funds being more illiquid. This suggests that premiums should be positively related to an interaction between a dummy for the presence of lockup restrictions and a dummy representing offshore funds. I also include two aggregate measures under the category of underlying asset illiquidity. The first is Sadka's (2010) measure of hedge fund liquidity risk, constructed as a factor-mimicking portfolio of hedge fund returns,[20] and the second, the one-month risk-free rate.

B.4. Fees

Several theories strongly emphasize that high management fees drive down expected returns and the premium, so I include the level of management fees in all specifications as an explanatory variable. Of course, fees may be endogenous to performance, say, for example, if successful managers raise fees in an attempt to signal high ability. However there are several performance measures included in the specification, and to the extent that these variables successfully capture expected future performance, the marginal impact of management fees over and above these controls is expected to be negative.

A convenient null hypothesis in the estimated specifications is that the theoretically proposed explanatory variables are unrelated to cross-sectional variation in the premiums across funds, and to changes in this cross-sectional variation over time. The next section discusses the specifications employed for estimation, some biases that are likely to arise in estimation, and proposed solutions to overcome these sources of bias.

III. Estimation

I empirically model both $PREM$ and $TOTPREM$ as a function of the variables proposed by theory:

$$TOTPREM_{i,t,\tau} = f(Performance_{i,t-1}, Incentives_{i,t-1}, Fees_i, ... \\ Fund\ Liquidity_{i,t-1}, Asset\ Liquidity_{i,t}, Sentiment_t) + u_{i,t} \quad (3)$$

The function is linear in parameters and non-linear in the variables (as there are several squared variables given the theoretical predictions). The right-hand side consists of pure cross-sectional variables, pure time-series variables (included as a control, given that they explain significant time-series variation in average premiums), and those that vary across both funds and time.[21] Consequently, 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 $TOTPREM$. I also employ strategy-specific fixed effects in estimation, to help assuage concerns of selection (a more extensive discussion follows).

Heteroskedasticity is likely to affect the regressions, and there may be unexplained commonalities in the movement of the residuals in the regressions. Furthermore, the small sample employed, and frequently noted non-normality of hedge fund data (see Kosowski, Naik and Teo (2007) for one recent discussion) raise concerns that asymptotic standard errors may not be appropriate. Therefore, I estimate the standard errors using a non-parametric bootstrap which is robust to heteroskedasticity, contemporaneous correlation, autocorrelation and cross-correlation of the residuals.[22]

Before proceeding to estimation, however, there is an important issue that needs to be considered, namely the issue of selection bias in the sample of funds traded on Hedgebay. The remainder of this section discusses this issue, and presents econometric solutions to this problem.

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

Table IV shows the comparison between the unconditional means of the variables in the sample, and those for the $9,305$ funds in the consolidated database that are not traded on Hedgebay. These sets of means are reported with bootstrap t-statistics of their differences. The comparison shows that there are significant differences in 7 of the 10 variables. The mean monthly return for the funds in the sample is 1.59% per month, 56% higher than the mean in the universe of funds. This confirms a long-held belief that high-performing funds close to new investments. The funds in the sample are also larger in the sample than in the population – on average they are at the 85^{th} percentile across all funds ranked in December of each calendar year. Furthermore, the incentive fees, management fees, withdrawal restrictions and the percentage of funds in the sample that are domiciled in offshore financial centres are all significantly higher in the sample relative to the universe of funds. These preliminary results suggest that there may be bias in the results on account of sample selection issues.

[TABLE IV HERE]

In particular, any coefficients purporting to explain the behavior of premiums on Hedgebay may be contaminated by correlation between the residuals in these explanatory regressions, and the unobserved determinants of the selection of a fund to trade on the market. This necessitates the use of controls to ensure that the results are not biased by this correlation. The first controls that I employ are strategy-specific fixed effects in the panel regressions. These soak up strategy-specific variation in transactions premiums, with the remaining coefficients identified by fund-specific variation in premiums and changes in this fund-specific variation over time. If the unobserved determinants of selection are solely strategy-specific, e.g., if there is a propensity for some strategies to be more frequently traded on the secondary market because they are more prone to being closed to new investments, or disproportionately represented on Hedgebay for other reasons, the use of strategy fixed effects in the estimated specifications will capture this channel, and the remaining coefficient estimates will be unbiased (see Campa and Kedia (2002) for a similar argument employed in a different context). However, this does leave the concern that fund-specific and time-varying reasons exist for funds to be selected to trade on the market. Consequently, the second control is to apply Heckman's (1979) two-stage procedure to correct for possible selection bias. In this procedure, a first-stage probit regression is estimated on the entire universe of hedge funds and funds-of-funds to capture the determinants of selection. The inverse Mills ratio is then computed from this first stage probit, and incorporated into the explanatory regression for the closed hedge fund premium as the selection bias correction. Technical details about estimation are in Appendix D.

B. The Exclusion Restriction

An important identifying assumption when applying the Heckman correction is that there are some variables that explain selection, but not the level of transactions premiums. If there is no such "exclusion restriction," the model is identified only by distributional assumptions about the residuals, which could lead to problems in estimating the parameters of the model (see Sartori (2003)). The exclusion restriction that I employ is $OFFSHORE_i$, a dummy variable that takes the value of 1 if the fund is domiciled in an offshore financial centre. Using the domicile of a fund as the exclusion restriction is justifiable if its domicile status affects the propensity of a fund to be traded on Hedgebay, but does not affect the premium at which the fund changes hands.[23]

There are numerous tax benefits to being located offshore, and the tax implications of a fund's changing hands on Hedgebay are less complicated if the fund is offshore. This is the main reason why, reading from Table IV, 80% of the funds traded on Hedgebay are offshore. This makes the domicile of a fund a useful instrument to explain the propensity of a fund to be traded on Hedgebay. 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. As highlighted in the section on measuring asset illiquidity, these authors document that a useful proxy for the illiquidity of a fund's shares is the interaction between the presence of a lockup restriction and the $OFFSHORE$ dummy. To make sure that the $OFFSHORE$ dummy is not capturing this potential joint determinant of selection and the premium, I also include this interaction term in the selection equation along with the $OFFSHORE$ dummy.

Another line of objection to the possibility of finding exclusion restrictions is that it is difficult to separate determinants of selection from those of the premium, because the very fact of being tradable on Hedgebay increases the current liquidity of the fund's shares, potentially causing higher premiums for the fund through the Cherkes, Sagi and Stanton (2009) channel. I attempt to control for this in two ways. First, I include lagged average trading costs on Hedgebay as a determinant of the premium in the explanatory regressions to capture time-variation in liquidity on Hedgebay. Second, it is important to note that shares trade on Hedgebay only when the fund is closed to new investments, within the tenor of the redemption restrictions, and if the manager approves the transaction. Therefore, 'tradability' is time-varying, and potentially of short duration.[24] To ensure that the selection equation is not merely capturing the current 'tradability' of the fund, which may be more correlated with the determinants of the premium, I lag the dynamic variables (returns, AUM rank and minimum investment rank) in the selection equation, resulting in inverse Mills ratios computed using lagged rather than contemporaneous variables.[25]

To balance concerns of sample size and inclusiveness, I estimate the selection equation as a fund-year panel, with average returns measured over the previous calendar year to December, and the rank variables computed as of December prior to the year in which the trade occurs for the fund on Hedgebay. The final set of variables in the selection equation comprises the strategy dummies; the entire set of static variables subsequently employed in the regressions used to explain the premium; four dynamic variables, namely: Average returns over the previous year, the size of the fund, the minimum investment level of the fund, and the age of the fund, where the last three variables are captured by their rank in the cross-sectional distribution each year; and finally $OFFSHORE$.

C. Probit Selection Equation

Table V presents results from estimating the probit model for selection on a total of $44,117$ fund-year observations comprising both hedge funds and funds-of-funds, of which there are 265 fund-years in which trades occurred on Hedgebay. The Chi-squared statistic is 345.01, rejecting the null that none of the variables employed in the probit are useful for explaining selection at the 1% level of significance. The table presents marginal effects of each continuous right-hand side variable, that is, the change in the probability of selection that results from an infinitesimal change in each variable. They reveal that the mean returns of the funds over the year prior to the year of the transaction, the fund size, the management fee, the incentive fee and the redemption restrictions are all positive and significant determinants of selection. These findings confirm the anecdotal evidence that highly successful funds raise their fees and close to new investments. They also accord roughly with the results in Table IV.

[TABLE V HERE]

The interaction between the presence of a lockup restriction and the offshore dummy is not statistically significant, suggesting that concerns about the exclusion restriction $OFFSHORE$ capturing liquidity restrictions may not be warranted. Importantly, however, the exclusion restriction

$OFFSHORE$ is a statistically significant determinant of selection. Next, of the binary variables, four of the strategy dummies, namely those for Security Selection, Global Macro, Multi-Process and Fixed Income, are significant at the 5% level. (The marginal effects of these binary right-hand side variables are differences in the probability of selection when the variable takes the value of 1 rather than 0.) 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, suggesting reasons for their selection.

IV. Results

A. Cross-Sectional Results

Table VI shows results from panel estimation of equation (3), including the inverse Mills ratio computed from the estimates in Table V. The adjusted R-squared of the regression for $PREM$ and $TOTPREM$ is around 36% (including the strategy fixed effects), which is substantial. Taking the variables in groups, it appears that every category of explanations for the premium (with the exception of sentiment) receives support in the data.

[TABLE VI HERE]

The performance variables are all estimated with the signs predicted by theory, and are statistically significant ($t(\hat{\alpha})$ and fund size at the 5% level, the others at the 10% level). This provides direct evidence in support of the Berk and Stanton theory. The economic magnitude of the effect is also large – in a regression in which $\hat{\alpha}$ is employed (Internet Appendix Table VI) instead of $t(\hat{\alpha})$, a 1% increase in $\hat{\alpha}$ (estimated over a 12-month period) is associated with a 60 basis point increase in the premium. This result also adds to the extensive literature on the trend-chasing behavior of hedge fund investors, about which more indirect inferences have been made using measures such as hedge fund flows.[26]

Indirect evidence to support Berk and Stanton's theory also emerges in the set of variables that capture the role of hedge fund managers' incentives. The level of managerial ownership is estimated to have a positive coefficient, which is statistically significant at the 10% level. The variable is measured in units of the pooled standard deviation, so a one-standard deviation increase in the level of managerial ownership is associated with a 75 basis point increase in $TOTPREM$. The coefficient on the squared level of managerial ownership is negative, consistent with the entrenchment hypothesis.[27] The level of management fees that hedge funds charge investors also appears to be a strong driver of transactions premiums. Ceterus paribus, an increase of 1% in a fund's management fees results in an 89 basis point reduction in $TOTPREM$ (the standard deviation of management fees in the cross-section of funds is approximately 60 basis points). This strongly supports the predictions of the Ross (2002), Berk and Stanton (2007) and Cherkes et al. (2009) theories.

The next category of variables contains measures of the illiquidity of hedge fund shares. Three out of four of these measures are negatively signed, and two of the four measures are statistically significant. The magnitude of the coefficient on the minimum investment rank shows that a movement in any month from the 25^{th} to the 75^{th} percentile rank (computed across all hedge funds in the universe alive in that month) moves $TOTPREM$ down by 1%. Subscription and withdrawal restrictions are also important, for example, a one month increase in the total subscription restrictions on a fund is associated with a 35 basis point reduction in the premium paid to acquire it. As discovered in prior research, withdrawal restrictions have a dual role in most hedge funds – while the presence of these restrictions impede fund share liquidity, lock-up and long redemption notice periods have also been found to be associated with high future performance. The former effect seems to marginally dominate in the explanatory power of withdrawal restrictions for the premium.[28]

Turning to the measures of the illiquidity of funds' underlying assets, three of the four proxies are signed as predicted by theory, and two of them are statistically significant, namely the Liang and Park (2008) interaction between lockup and offshore dummies, and the coefficient on the one-month risk-free rate, as detected in the time-series tests above. Measuring hedge fund assets' illiquidity using the smoothness of reported returns is complicated by the possibility that they also capture return-smoothing by managers (see Bollen and Krepely-Pool (2008)). If return smoothness captures asset illiquidity, we would expect a positive association of the measure with the premium, while if it captures managerial return manipulation (likely associated with negative performance-related disclosures in the future), theory would predict a negative association with the premium. The statistical insignificance of the coefficient is possibly a result of the multiple attributes that the variable captures.

Finally, several of the strategy fixed effects are significantly positive. This suggests a number of possible explanations: First, it may be that these strategy dummies capture the average illiquidity of the assets of the funds in the underlying strategies. However, this explanation would be more plausible if, for example, the Fixed Income dummy were strongly statistically significant (it is, but only at the 10% level in the specifications), given Getmansky, Lo and Makarov's (2004) finding that Fixed Income funds demonstrate the highest level of return smoothing. Second, it is possible that the strategy fixed effects capture the presence of high average managerial ability in some strategies relative to others over the sample period. Third, it is possible that these significant results are an indication that determinants of sample selection are strategy-specific rather than fund-specific.

In terms of selection bias captured by the inverse Mills ratio, the coefficient takes the sign of the correlation between the residuals in the regressions that explain selection and the premium (equations (D2) and (D1) in Appendix D). If this sign is estimated to be positive (negative), this suggests that funds that are traded on Hedgebay are more likely (less likely) to exhibit high unexplained transactions premiums. In Table VI, the coefficient on the inverse Mills ratio is negative but not statistically significant. Despite this lack of statistical significance (which could be on account of measurement error), the inclusion of this variable does have important effects on the explanatory regressions – it attenuates the significance of the coefficients on the product of the lockup and offshore dummies, and changes the statistical significance of other regressors in the model (see Internet Appendix Table V for results without the inverse Mills ratio). Overall, these results suggest that performance, managerial incentives, fund share liquidity and asset liquidity all have an important role in explaining premiums on the secondary market for hedge funds.

B. Other Robustness Checks

Internet Appendix Table VII checks the robustness of the results to two additional, important issues – the possibility of backfill bias affecting the results, and the use of the Fung-Hsieh seven-factor model to estimate $t(\alpha)$. All of the regressors in the model (except the statistically insignificant first-order autocorrelation) are signed in the same way as in Table VI, and most are statistically significant. Internet Appendix Table VIII introduces a dummy which takes the value of one for fund-months with negative news stories. When this source of variation is soaked up, the adjusted R-squared rises to around 75%, and the remaining coefficients greatly improve in statistical significance while continuing to be signed consistently with their estimates in Table VI.

C. The Premium and Future Hedge Fund Performance

The positive coefficient discovered for both $PREM$ and $TOTPREM$ on past performance suggests that hedge fund investors engage in performance-chasing behavior, that is, they seem willing to pay high prices for funds exhibiting high past risk-adjusted performance. This is rational if hedge fund performance is persistent, i.e., if premiums in this market chase past performance in rational anticipation that past performance is a reliable indicator of future performance. This suggests that we might be able to use $TOTPREM$ as a forecasting variable for future hedge fund performance.

To forecast future performance, I condition $t(\alpha)$ measured using three different factor models (the single factor market model, the Fama-French (1993) three factor model, augmented using Carhart's (1997) momentum factor and the Fung-Hsieh seven factor model) on $TOTPREM$. In these specifications, I employ a number of different control variables on the right-hand side, following Agarwal, Daniel and Naik (2009), to ensure that any forecasting power detected in $TOTPREM$ is not on account of omitted variable bias. These controls are listed in the header to Table VII.

[TABLE VII HERE]

The table shows that in the first specification, which includes the control variables on the right-hand side, but not the lagged performance measure, the coefficient on $TOTPREM$ is estimated to be positive for two out of three of the performance measures. The next panel of coefficients refines this analysis further, including lagged performance in the set of conditioning information. With this change, while the sign on $TOTPREM$ remains positive, its statistical significance is greatly attenuated, and vanishes for the Fama-French measure. It appears as though on average, the forecasting power possessed by market participants for future performance only pertains to past performance.

The final specification checks whether there is any difference between the predictive ability of premiums that are higher than the cross-sectional median premium in each month and those that are lower than the median. This specification is motivated by the possibility that there may be a "winner's curse" in the secondary market, namely, a situation in which high transactions premiums are a consequence of overbidding for funds, and transactions occurring at lower premiums are from more savvy investors that anticipate future performance more accurately. The results from this final specification are more nuanced. High premium transactions do not hold any forecasting power for future hedge fund returns. In contrast, transactions occurring at low premiums, that is, those less than or equal to the median premium each month, are positive indicators of future performance for all three of the performance measures, even when past performance is in the conditioning information set. This is consistent with these transactions being driven by rational anticipation of future performance. These results suggest either that there is some market segmentation amongst different investor groups in the secondary market for hedge funds, with irrational price-setting by some groups of investors coexisting with the rational anticipation of future performance; or that there is another unobserved determinant of bidding and future performance (such as the availability of credit) that drives the behavior of both simultaneously.[29]

V. Conclusion

The premiums and discounts at which funds are bought and sold on the secondary market for hedge funds are analogous to closed-end mutual fund premiums and discounts, which have been extensively studied in the literature. Recent rational theories of closed-end mutual funds that emphasize performance, liquidity and fees as determinants of premiums are strongly supported when tested using closed hedge fund premiums. Measures of fund share illiquidity are strongly negatively related to premiums, suggesting that the secondary market helps to attenuate the impact of liquidity shocks which force hedge investors to withdraw capital at times when redemption notice periods are binding. Transactions premiums are also negatively associated with high management fees in funds, and positively associated with past hedge fund performance, highlighting investors' trade off between expectations of high performance and future fees.

One perhaps surprising finding of this paper is that the time-series behavior of the hedge fund premium is closely related to that of the closed-end mutual fund premium over the decade between 1998 and 2008, in both levels and differences. This intriguing finding suggests that there are common drivers – such as the cost of leverage and expectations of managerial performance – of investors' decisions to allocate capital to different markets for managed investments. This is a possibility that warrants future investigation.

Appendix A: How Transactions are Conducted on Hedgebay

Indications of interest for buying and selling hedge funds are posted on Hedgebay's website by interested parties, or phoned in to Hedgebay directly. They are matched to countervailing and pre-existing indications of interest in the same fund, or disseminated to prospective buyers or sellers in Hedgebay's client list via telephone. Once an interested party on the other side of the transaction has been identified, bargaining is conducted by both parties engaging in unilateral negotiations with Hedgebay. Strict anonymity is preserved in these transactions about the identities of the counterparties involved. Once agreement has been reached about the terms of the deal (trade amount and discount or premium to end-of-month NAV), the fund manager's approval is required to complete the transaction. (This feature raises concerns about sample selection issues, and I attempt to control for this in the paper.) Almost every completed transaction is conducted between pre-existing investors of the funds. Furthermore, every completed 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 August 2008, according to Hedgebay).

Appendix B: Measuring Managerial Incentives

To compute measures of managerial option delta and managerial investment for the funds in the sample, the Black-Scholes option calculation method outlined in the Appendix of Agarwal, Daniel and Naik (2009) is employed. The calculation is modified by assuming that investors' money flows occur at the end of each year-end working backwards from the month prior to the transaction-month, and that incentive fees are paid according to the same schedule. This is different from Agarwal et al.'s use of December as the end of each calendar year. That is, if the transaction occurred in November of 1996, money flows and incentive fees are assumed to occur in October of each year, the deltas are then calculated as per Agarwal et al.'s method. The modification is to ensure the maximum number of observations of option delta and managerial investment are generated, in order to avoid losing observations in the sample. The correlation between the total deltas computed with this modification and total deltas calculated using the calendar year assumption of Agarwal et al. is 94.83% in the panel of fund-months for which both calculations are possible. Note: As in Agarwal et al., all computed variables are lagged by a month to avoid any mechanical association.

Appendix C: Cross-Sectional Correlation and Autocorrelation Consistent Bootstrap

A non-parametric bootstrap is employed to compute standard errors. Using the parametric bootstrap (drawing residuals) leaves the standard errors virtually unchanged (if anything they are slightly smaller on average). The bootstrap draws are conducted as follows: First, a random number is drawn from the sample $t = 1, ..., T$ (this is a cross-sectional correlation consistent bootstrap, so all cross-sections are automatically drawn for each time period). For the second resample observation, following Politis and Romano (1994), a uniform random variable is drawn from $(0, 1)$. If it is less than a pre-set value Q, then the consecutive observation to the first bootstrap draw is also included (i.e., if $t = 4$ was first drawn, $t = 5$ is also included). If the draw is at the end of the sample, the procedure starts from the beginning again. If the uniform draw is greater than Q, a new observation is drawn (with replacement). Values of $Q = 0, 0.1, 0.5$, are tried, and the paper reports the results for $Q = 0.5$. The other two choices for Q do not materially affect the results. $5,000$ draws are used to compute the final bootstrap standard errors. The presence of a number of dummy variables in the data occasionally results in a null vector in the bootstrap trial X matrix. In such (rare) cases the point estimate of the bootstrap coefficient on the offending variable is set to zero (the null) and the remaining coefficients are estimated using the bootstrap sample.

Appendix D: The Selection Bias Correction

Formally, the determinants of selection are modelled as:

$$\begin{aligned} z_{i,t}^* &= \mathrm{w}_{i,t-1}^{'}\gamma + u_{i,t} \\ z_{i,t} &= 1 \text{ if } z_{i,t}^* > 0 \\ z_{i,t} &= 0 \text{ if } z_{i,t}^* \leq 0. \end{aligned} \tag{D1}$$

Here, $z_{i,t}$ is a 'selection' variable that takes the value of 1 if a trade occurs for fund i in year t on Hedgebay, and 0 otherwise. $z_{i,t}^*$ is an unobserved latent variable, and $\mathrm{w}_{i,t-1}^{'}$ is a set of variables that determine whether a fund is traded in a year. (The $t-1$ time subscript captures the fact that the time-varying variables in the set are lagged – as explained in the discussion in the subsection on the exclusion restriction.) Now consider the regression equation to explain the premium for a fund

i at time t ($TOTPREM_{i,t}$), written with a generic right-hand side vector of determinants of these premiums, $\mathrm{x}_{i,t}$ (which contains many of the same constituents as $\mathrm{w}_{i,t-1}$):

$$TOTPREM_{i,t} = \mathrm{x}_{i,t}^{'}\beta + \varepsilon_{i,t}. \tag{D2}$$

Note that (D2) is observed only if $z_{i,t} = 1$.

I assume that the errors in equations (D1) and (D2) have a bivariate normal distribution[30]:

$$(\varepsilon_{i,t}, u_{i,t}) \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_{\varepsilon}^2 & \rho\sigma_{\varepsilon} \\ \rho\sigma_{\varepsilon} & 1 \end{bmatrix}\right), \tag{D3}$$

then, from the moments of the incidentally truncated bivariate normal distribution (see Greene (2003)):

$$E[TOTPREM_{i,t} \mid z_{i,t} = 1, \mathrm{x}_{i,t}, \mathrm{w}_{i,t-1}] = \mathrm{x}_{i,t}^{'}\beta + \delta\lambda(\mathrm{w}_{i,t-1}^{'}\gamma), \tag{D4}$$

where $\delta = \rho\sigma_{\varepsilon}$, which takes the sign of the correlation (ρ) between the residual in the selection equation (D1) and in the explanatory equation (D2), i.e., δ is informative about whether funds that are traded on Hedgebay have higher or lower premiums as a consequence of selection.

$\hat{\lambda}(\mathrm{w}_{i,t-1}^{'}\hat{\gamma})$, the inverse Mills ratio, is computed from the estimated coefficients of equation (D1). To obtain $\hat{\gamma}$, a probit model is estimated using maximum likelihood on the entire universe of hedge funds and funds-of-funds.[31] Then, $\hat{\lambda}(\mathrm{w}_{i,t-1}^{'}\hat{\gamma}) = \frac{\phi(\mathrm{w}_{i,t-1}^{'}\hat{\gamma})}{\Phi(\mathrm{w}_{i,t-1}^{'}\hat{\gamma})}$ (where $\phi(.)$ is the standard normal density function, and $\Phi(.)$ is the standard normal cumulative distribution function) is incorporated into (D2) as a selection bias correction:

$$TOTPREM_{i,t} = \mathrm{x}_{i,t}^{'}\beta + \delta\hat{\lambda}(\mathrm{w}_{i,t-1}^{'}\hat{\gamma}) + \upsilon_{i,t}. \tag{D5}$$

Table I
Summary Statistics: Full Sample

This table presents descriptive statistics for all transactions conducted on Hedgebay between August 1998 and August 2008. 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, 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 percentage of these transactions for which *PREM* was below zero; the mean total percentage in excess of NAV paid by the buyer of the fund on Hedgebay (*TOTPREM*, which also factors in trading costs on Hedgebay); and the standard deviation of *TOTPREM* across all transactions conducted in each year.

Years	**Number of Transactions**	**Number of Funds**	**Transaction Amt. Wtd. % of AUM**	***PREM* Mean %**	***PREM* % Negative**	***TOTPREM* Mean %**	***TOTPREM* Std %**
1998	12	6	0.041	0.000	0.000	0.528	0.412
1999	51	14	0.288	0.000	1.961	0.408	0.865
2000	92	30	0.545	-0.060	3.261	0.382	1.472
2001	120	47	0.356	1.318	4.167	1.886	3.418
2002	87	30	0.313	1.340	1.149	1.998	6.102
2003	127	51	0.430	0.612	6.299	1.210	7.609
2004	109	48	0.673	1.353	9.174	1.989	2.156
2005	124	65	0.669	-0.546	15.323	0.030	6.876
2006	108	53	0.989	-1.899	29.630	-1.460	7.079
2007	99	47	0.669	-5.846	45.455	-5.560	16.894
2008	76	41	1.184	-7.719	51.316	-7.408	17.897
Overall	1005	225	0.602	-0.939	16.219	-0.432	9.213

Table II
Summary Statistics: Matched Sample

This table presents descriptive statistics for all transactions conducted on Hedgebay between August 1998 and August 2008, 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 transaction amount as a percentage of the *AUM* of the fund, weighted by the *AUM* of the fund; the mean *PREM*; the percentage of transactions for which *PREM* is negative; the mean *TOTPREM* (*PREM* and *TOTPREM* are defined in Table I and in the text); the average per-month alpha in the twelve months prior to the trade for all funds estimated as described in the text, with the value-weighted CRSP excess return as the factor; the percentage of the fund owned by the fund manager, computed as in Agarwal, Daniel and Naik (2009); the mean management fee across all unique funds traded in the year; the mean number of months for which there are withdrawal restrictions for each unique fund, i.e., lockup period + redemption notice period + redemption frequency; and the average first order autocorrelation of fund returns in the twelve months prior to the transaction. Overall numbers at the bottom of the fee and withdrawal restrictions columns are taken across the 126 unique funds in the sample, and for the other columns, across all fund-months in the data.

Years	**Number of Transactions**	**Number of Funds**	**Transaction Amt. Wtd. % of AUM**	***PREM* Mean %**	***PREM* % Negative**	***TOTPREM* Mean %**	**Market Model Alpha % Per Month**	**Manager's Investment Mean %**	**Management Fee Mean %**	**Withdrawal Restrictions Mean Months**	**First-Order Autocorrelation Mean %**
1998	9	3	0.031	0.000	0.000	0.444	1.779	13.500	2.667	17.500	-0.167
1999	23	6	0.245	0.174	0.000	0.737	1.153	21.712	2.000	13.917	1.273
2000	41	13	0.306	0.085	0.000	0.574	1.327	19.968	1.712	11.910	12.254
2001	89	32	0.289	1.443	3.371	2.041	0.875	30.556	1.545	9.042	8.044
2002	63	17	0.270	1.995	0.000	2.654	0.701	30.786	1.794	8.902	0.723
2003	84	29	0.329	2.050	3.571	2.653	0.753	22.765	1.569	11.046	3.454
2004	55	24	0.434	1.916	9.091	2.459	0.653	19.220	1.813	9.965	-4.175
2005	59	35	0.358	0.177	6.780	0.777	0.533	13.508	1.786	10.972	9.826
2006	48	28	0.591	-0.353	18.750	-0.001	0.674	16.266	1.686	10.846	9.122
2007	33	20	0.290	-0.386	24.242	-0.179	0.654	18.952	1.813	9.508	9.251
2008	18	11	0.598	0.055	33.333	0.272	1.478	6.182	1.364	8.864	-5.650
Overall	522	126	0.350	0.998	7.280	1.525	0.824	21.805	1.569	9.634	4.930

Table III
The Time Series Behaviour of the Hedge Fund Premium

This table relates the time-series of value-weighted *TOTPREM*, called *VWTOTPREM* to the following covariates: value-weighted closed-end mutual fund premium across all US general equity closed-end mutual funds found in the CRSP database; the level of the University of Michigan's consumer sentiment index; Baker and Wurgler's (2007) sentiment index (orthogonalized to a set of macroeconomic variables); the VIX index of the CBOE; Pastor and Stambaugh's (2003) level of aggregate equity market illiquidity; Sadka's (2010) measure of hedge fund liquidity; the one-month US T-bill rate; and the total return on the S&P 500 index. The first row of statistics shows the correlations between *VWTOTPREM* and the levels of each of these variables. The second block of statistics shows the persistence of *VWTOTPREM* over the sample period as measured by the first-order autocorrelation coefficient; the persistence of each 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 second block of statistics shows correlations between the first difference of *VWTOTPREM* and the first differences of each of these variables (except for the S&P 500 total return which is not differenced in this regression). The final block of statistics shows the correlation between *VWTOTPREM* and the covariate after persistent variables (with autocorrelation greater than 50%) are detrended (using only past data) using a Hodrick-Prescott filter and the monthly smoothing parameter of 14,400. 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 August 2008. Newey-West (1983) standard errors are reported below coefficient estimates in *italics*, and coefficients significant at the 5% (10%) level are in **underlined bold** (underlined).

	Correlations with *VWTOTPREM* (t)							
	Closed-End MF Premium (t)	**Michigan Cons. Sent. (t)**	**Baker-Wurgler Sentiment (t)**	**VIX (t)**	**Pastor-Stambaugh Liquidity (t)**	**Sadka HF Liquidity (t)**	**One-Month Riskfree Rate (t)**	**S&P 500 Total Ret (t)**
Correlation in Levels	**0.388**	0.241	-0.148	0.117	0.032	0.073	**-0.433**	-0.014
	0.127	*0.162*	*0.104*	*0.132*	*0.099*	*0.120*	*0.116*	*0.079*
Persistence of *VWTOTPREM*	*0.576*	*0.576*	*0.576*	*0.576*	*0.576*	*0.576*	*0.576*	*0.576*
Persistence of Covariate	*0.900*	*0.948*	*0.951*	*0.827*	*-0.074*	*0.099*	*0.963*	*0.015*
ADF t-statistic of Error	*-10.308*	*-9.686*	*-9.262*	*-9.426*	*-9.430*	*-9.770*	*-10.890*	*-9.414*
Correlation in Differences	0.153	0.088	0.092	0.068	0.082	-0.067	0.065	
	0.121	*0.101*	*0.092*	*0.077*	*0.104*	*0.096*	*0.084*	
Detrended Correlation	**0.143**	0.019	-0.074	**0.079**	0.043	-0.021	-0.125	
	0.046	*0.017*	*0.157*	*0.023*	*1.373*	*5.426*	*0.966*	
N(Observations)	121	121	113	121	121	121	121	121

Table IV
Preliminary Analysis of Selection

This table compares the averages in the sample of funds traded on Hedgebay and in the entire universe of funds, of each of the variables listed in rows. The rows entitled 'dynamic variables' are variables that are recomputed in each calendar year, for all funds that are in the consolidated dataset in that year. The mean return for each fund-year is computed using any returns reported by the fund in the prior year; the percentile ranks for each variable (values as at December of the previous year) are computed across all funds each year, and the table reports the unconditional average of these ranks. The averages of the remaining (static) variables are computed across all unique funds appearing in the sample and the universe, respectively. The *t*-statistic reported for the difference in means is computed using a cross-correlation and autocorrelation consistent bootstrap estimator for the dynamic variables, and using a non-parametric bootstrap estimator for the static variables. Sample averages that are significantly different from the universe averages at the 5% (10%) level are in <u>**underlined bold**</u> (<u>underlined</u>).

Variable	Sample Average	Universe Average	*t*-statistic of Difference
<u>**Dynamic Variables**</u>			
Mean Monthly Return (previous year)	<u>**1.588**</u>	1.019	2.052
Size (AUM) Rank (percentile)	<u>**85.169**</u>	50.012	4.453
Minimum Investment Rank (percentile)	55.530	50.012	0.251
Age (Years)	61.457	50.012	0.556
<u>**Static Variables**</u>			
Management Fee	<u>1.535</u>	1.424	1.687
Incentive Fee	<u>**19.899**</u>	17.142	4.709
Redemption Restrictions	<u>**9.645**</u>	7.555	2.636
Subscription Restrictions	1.089	1.195	-1.556
Hurdle Rate/High Water Mark Provision	0.716	0.622	1.208
Offshore Dummy	<u>**0.797**</u>	0.560	11.253
Lock Dummy*Offshore Dummy	<u>**0.243**</u>	0.115	5.340

Table V
Probit Model for Selection

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 next column reports the *Z*-statistic for the associated coefficient estimate of the marginal effect (from the underlying probit equation), computed from standard errors that are clustered by calendar year. The rows list the variables used in the selection equation. Note that there are eight strategy dummy variables employed in estimation: the ninth, for 'Other' funds is dropped to avoid perfect collinearity. The last few rows show the observed probability, i.e., the percentage of fund-years in the consolidated database in which there are trades on Hedgebay; the Pseudo R-squared statistic from Probit estimation; the Chi-squared statistic from a Wald test of the null hypothesis that all coefficients are jointly zero, and the p-value at which the null hypothesis is rejected. Coefficients significant at the 5% (10%) level are in **underlined bold** (underlined).

	dF/dX	Clustered *Z*-statistic
Mean Monthly Return (previous year)	**0.009**	5.850
Size (AUM) (percentile rank)	**0.481**	10.890
Minimum Investment (percentile rank)	**-0.048**	-2.280
Fund Age (percentile rank)	0.031	1.370
Management Fee	**0.030**	5.290
Incentive Fee	**0.005**	3.940
Redemption Restrictions (years)	**0.001**	6.820
Subscription Restrictions (years)	**-0.011**	-2.890
Hurdle Rate/High Water Mark Dummy	0.011	0.910
Lock Dummy*Offshore Dummy	-0.013	-0.820
EXCLUSION RESTRICTION		
Offshore Dummy	**0.076**	4.390
STRATEGIES		
Security Selection	**0.165**	3.220
Global Macro	**0.447**	4.490
Relative Value	-0.018	-0.520
Directional Traders	-0.039	-1.310
Funds of Funds	-0.037	-1.120
Multi-Process	**0.128**	2.390
Emerging Markets	0.038	0.810
Fixed Income	**0.162**	2.480
N(Fund-Years)	44,117	
Observed Probability	0.006	
Pseudo R-squared	0.243	
Chi-squared(18)	345.010	
P-value(Chi-squared)	0.000	

Table VI
Explaining the Hedge Fund Premium

The first column of the table shows the theory associated with each group of regressors (Ability, Incentives, Fees, Fund Illiquidity, Asset Illiquidity, Sentiment, Selection Bias); the second the sign predicted by the theory for each coefficient; the third lists the variables; the fourth and fifth (sixth and seventh) show the estimated coefficients and standard errors when *PREM* is the LHS variable (when *TOTPREM* is the LHS variable). All coefficients are estimated using pooled OLS with strategy fixed effects and the standard errors (in parentheses) are estimated using a cross-correlation and autocorrelation consistent bootstrap estimator. Coefficients significant at the 5% (10%) level are in **underlined bold** (underlined). Each regression is estimated on 522 transactions from a total of 126 funds. Panel A shows the estimated coefficients, and Panel B the estimated strategy fixed-effects.

Panel A: Coefficients

Theory	Predicted Sign	Variable	*PREM*		*TOTPREM*	
Ability	+	**Market Model t-Alpha (-12)**	**0.409**	(0.073)	**0.449**	(0.081)
	-	**(Market Model t-Alpha (-12))^2**	-0.009	(0.011)	-0.010	(0.013)
	-	**Fund Age Rank**	-0.015	(0.008)	-0.016	(0.009)
	-	**Size (*AUM*) Rank**	**-0.037**	(0.016)	**-0.041**	(0.017)
Incentives	+	**Manager's Option Delta**	0.145	(0.326)	0.159	(0.347)
	+	**Manager's Investment**	0.615	(0.403)	0.751	(0.422)
	-	**(Manager's Investment)^2**	-0.201	(0.213)	-0.239	(0.233)
	+	**High Water Mark/Hurdle Rate Dummy**	0.501	(0.434)	0.381	(0.463)
Fees	-	**Management Fee**	**-0.832**	(0.263)	**-0.894**	(0.281)
Fund Illiquidity	-	**Minimum Investment Rank**	**-0.019**	(0.009)	**-0.020**	(0.010)
	-	**Subscription Restrictions**	-0.352	(0.202)	-0.352	(0.228)
	-	**Withdrawal Restrictions**	-0.023	(0.014)	-0.028	(0.016)
	-	**lagged Average Commission**	0.129	(0.669)	0.346	(0.713)
Asset Illiquidity	+	**First-Order Autocorrelation**	0.001	(0.005)	-0.001	(0.005)
	+	**Sadka Hedge Fund Liquidity**	-4.135	(4.740)	-4.425	(5.263)
	+	**Lock Dummy*Offshore Dummy**	1.142	(0.714)	1.299	(0.745)
	-	**One-Month US T-Bill Rate**	**-5.476**	(1.106)	**-6.022**	(1.177)
Sentiment	+	**Michigan Consumer Sentiment**	0.002	(0.013)	0.009	(0.015)
Selection Bias	+	**Inverse Mills Ratio**	-0.547	(0.515)	-0.757	(0.577)
		Adjusted R-squared	0.358		0.362	

Panel B: Fixed Effects

Specification	Security Selection	Global Macro	Relative Value	Directional Traders	Funds of Funds	Multi-Process	Emerging Markets	Fixed Income	Other
PREM	**7.777**	**10.198**	**8.237**	**9.137**	**9.212**	**7.256**	6.599	6.345	**9.976**
	(3.076)	(3.211)	(3.572)	(3.492)	(3.505)	(3.363)	(4.640)	(3.407)	(3.754)
TOTPREM	**8.776**	**11.156**	**9.098**	**10.389**	**10.546**	**8.047**	7.560	6.920	**11.046**
	(3.312)	(3.485)	(3.875)	(3.740)	(3.763)	(3.631)	(4.978)	(3.773)	(4.089)

Table VII
Does the Hedge Fund Premium Forecast Future Performance?

This table presents results from regressions whose left-hand side variables are performance measures for each hedge fund over the 12 or 24 months following a month with a transaction on Hedgebay. The performance measures are listed in the column headers. The first block of coefficients conditions these future performance measures on *TOTPREM*, and a set of control variables (the transaction amount as a percentage of AUM; the fund manager's computed option delta, investment level in the fund and squared investment level in the fund; a dummy which takes the value of one if the fund has a hurdle rate or high water mark provision; the total withdrawal restrictions in the fund; the size (AUM) rank of the fund; the age rank of the fund; the standard deviation of monthly returns of the fund over the twelve months prior to the transaction; the management fee of the fund and the inverse Mills ratio from the probit selection model estimated in Table VI). For brevity, only the coefficient on *TOTPREM* is shown. The second block of coefficients (Specification II) adds the lagged left-hand side variable, estimated over the 12 or 24 month period prior to the transaction to Specification I. Specification III is the same as Specification II, except that separate coefficients are estimated for *TOTPREM* greater than (High) and less than (Low) the median value in the sample. All coefficient point estimates are estimated using pooled OLS and the standard errors (in parentheses) are estimated using a cross-correlation and autocorrelation consistent bootstrap estimator. Coefficients significant at the 5% (10%) level are in **underlined bold** (underlined). Each of the regressions is estimated on 315 transactions from a total of 72 funds.

	Market Model *t*-alpha (+12)	**Fama-French-Carhart Model *t*-alpha (+24)**	**Fung-Hsieh Model *t*-alpha (+24)**
Specification I			
TOTPREM	**0.236**	0.153	0.106
	0.065	*0.083*	*0.073*
Adjusted R-squared	0.133	0.189	0.147
Specification II			
TOTPREM	0.130	0.086	0.024
	0.076	*0.073*	*0.071*
Lagged *t*-alpha	**0.626**	**0.577**	**0.403**
	0.184	*0.104*	*0.096*
Adjusted R-squared	0.666	0.729	0.666
Specification III			
***TOTPREM* (High)**	0.119	0.081	0.014
	0.076	*0.074*	*0.069*
***TOTPREM* (Low)**	**0.826**	0.398	**0.674**
	0.310	*0.243*	*0.245*
Lagged *t*-alpha	**0.632**	**0.578**	**0.406**
	0.183	*0.101*	*0.094*
Adjusted R-squared	0.676	0.730	0.671
Controls	Yes	Yes	Yes

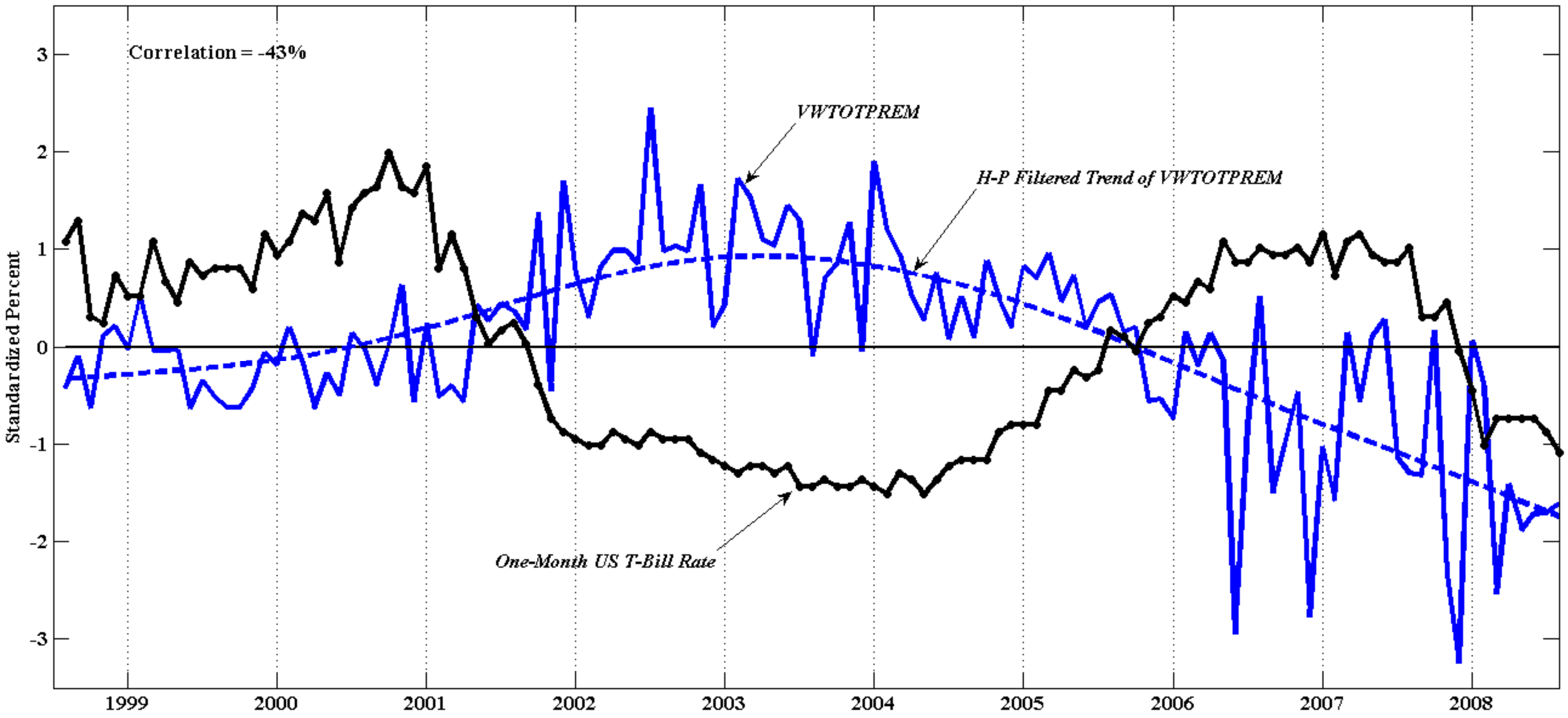

Figure 1: The Hedge Fund Premium and the Risk-Free Rate

This figure plots *VWTOTPREM*, the Hodrick-Prescott filtered trend of *VWTOTPREM* created using the recommended monthly smoothing parameter of 14400, and the one-month US T-bill Rate. 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 *VWTOTPREM* and the T-bill Rate is -43%.

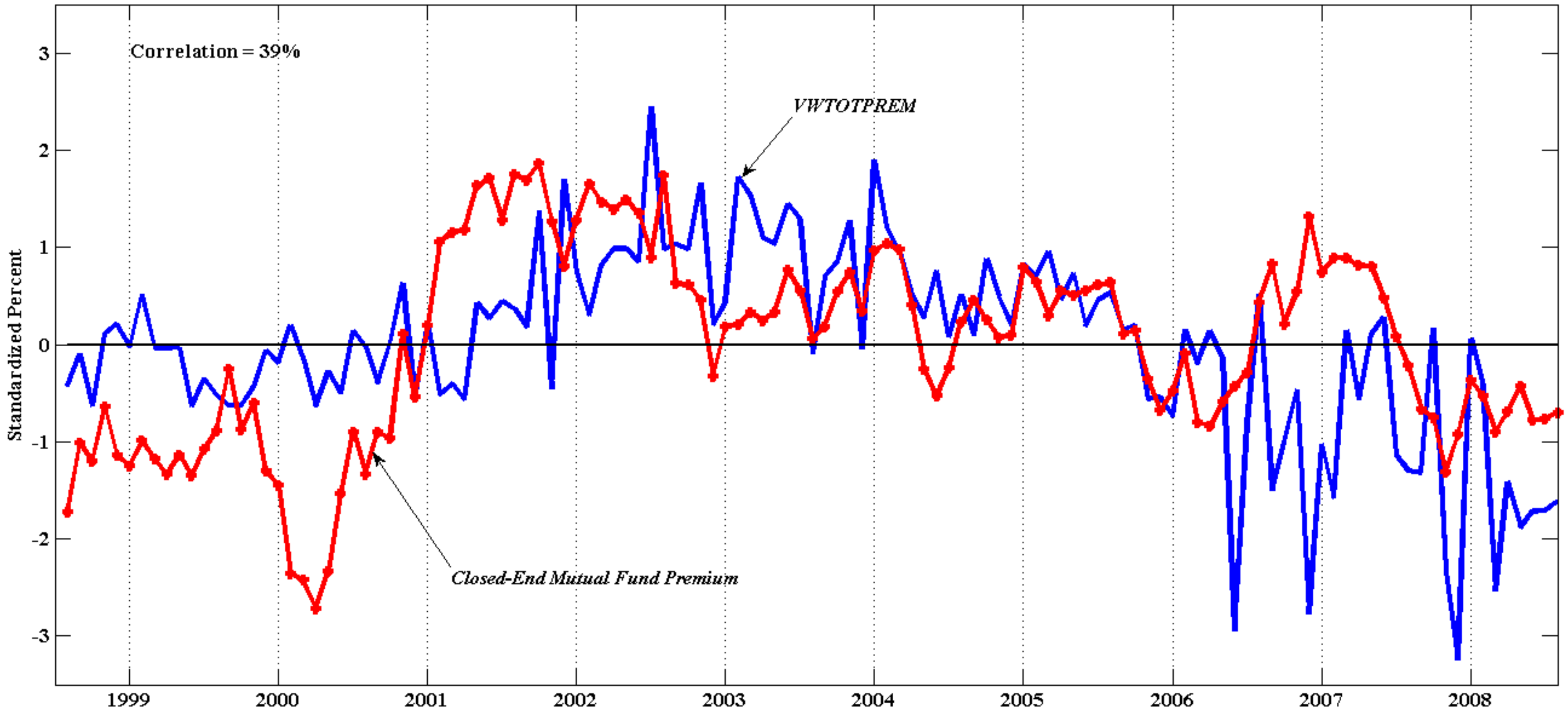

Figure 2: The Hedge Fund Premium and the Closed-End Mutual Fund Premium

This figure plots *VWTOTPREM*, and the value-weighted closed-end mutual fund premium computed using all U.S. closed-end mutual funds in CRSP. 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 39%.

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Notes

[1]Of course, the lack of observable risk-adjusted performance is not inconsistent with the existence of managerial ability in a competitive market for capital provision to mutual funds (see Berk and Green (2004)). Nevertheless, as Berk and Stanton point out, it has empirically "proved so difficult for researchers to find convincing evidence of managerial ability that many, such as Jensen (1968) and Carhart (1997), have concluded that it does not exist."

[2]As performance-linked pay structures are not prevalent in the mutual fund industry, the relationship between pay and performance is often inferred indirectly, e.g., from the flow-performance relationship (see Sirri and Tufano (1998)).

[3]See Edelen (1999), Nanda, Narayanan and Warther (2000) and Chen, Hong, Huang and Kubik (2004) for analysis of these relationships in mutual funds and Aragon (2005) for evidence from hedge funds.

[4]For evidence on hedge fund capacity constraints see Naik, Ramadorai and Stromqvist (2007), Fung, Hsieh, Naik and Ramadorai (2008), Zhong (2008), Teo (2009) and Ramadorai (2009).

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

[6]See Bradley, Brav, Goldstein and Jiang (2010) for evidence that takeovers and liquidations of closed-end funds became more prevalent following important SEC reforms in 1992.

[7]This is not the sole driver of the relationship, however – the correlation between the cylical components of the closed-hedge fund premium and the closed-end mutual fund premium is a statistically significant 14%.

[8]This result is similar to those of Chay and Trzcinka (1999) and Wu and Xia (2001), who find that closed-end mutual fund premiums forecast future NAV returns. One rationale for the relatively strong results for hedge funds is provided by Glode and Green (2009), who point out that performance persistence is more likely in hedge funds than in mutual funds, because hedge funds have incentives to share information rents with investors to prevent them from disclosing information about proprietary strategies to potential new entrants.

[9]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.

[10]The trading costs series includes Hedgebay's trading commission, which over the sample period is charged to buyers on transactions occurring at premiums, and to sellers on transactions occurring at discounts. These costs vary between 30 and 70 basis points on average per annum as can be seen from the difference between $TOTPREM$ and $PREM$ in Table I.

[11]This excludes 54 transactions which are 'junk asset' trades undertaken by limited partners who have not received the proceeds of liquidation in bankrupt funds, pending the completion of the legal process. These are transactions on bankruptcy claims rather than on going concerns, and occur post-liquidation.

[12]The Internet Appendix contains details about the procedures followed to match funds, and discusses the creation

of the combined database. Internet Appendix Table I presents descriptive statistics on the combined database, including on the mapping from funds' detailed strategies to nine strategies from the 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.

[13]When multiple transactions occur for any fund in the same month, these are used as independent observations, and weighted accordingly. Premia are winsorized at the 5 and 95 percentile points of the time-series cross-sectional distribution to mitigate the impact of extreme transactions, only in the time-series analysis in this section and in the figures. Online Appendix Figure 1 plots the equal-weighted premium, and Internet Appendix Table III estimates Table III using the equal-weighted premium.

[14]Internet Appendix Table IV shows the correlation matrix of all the covariates. Online Appendix Figure 2 plots the closed-end mutual fund premium, $VWTOTPREM$ and the Michigan consumer sentiment index.

[15]A low risk-free rate implies that leverage is less costly for closed-end funds (complementing investments in illiquid assets), and consequently a greater liquidity service to outside investors who may be relatively leverage-constrained. This aspect of their theory should apply strongly to hedge funds – which are more reliant on the use of leverage than mutual funds. Internet Appendix Figure 3 shows this relationship between the closed-end mutual fund premium and the one-month T-bill rate over the 1965 to 2008 period.

[16]Also, the first difference of the equal-weighted closed-hedge fund premium is statistically significantly related to the first difference of the closed-hedge fund premium, see Internet Appendix Table III.

[17]$t(\alpha_i)$ is closely related to the "information ratio" of a fund (Treynor and Black (1973)), a commonly used performance measure in the investment management industry. I have also replaced $t(\hat{\alpha})$ with raw returns, alpha measured using other factor models, and the $t(\hat{\alpha})$ measured using other factor models, with very similar results (see Internet Appendix Tables V and VI). Of course, to the extent that there are omitted factors in the model, such as liquidity, the $\hat{\alpha}$ measured in this fashion admits other interpretations. I attempt to control for these other sources of variation in the specifications.

[18]Another theoretical reason to expect this result (other than the predictions of the Cherkes et al. model), is that these subscription and withdrawal restrictions may be measuring the relative impatience of the seller relative to the buyer, and might therefore be expected to signal lower premiums through lower spreads, as in Vayanos and Wang (2007).

[19]Note that the sample in this paper comprises both live and dead funds. Bollen and Krepely-Pool show that for live funds in the December 2003 CISDM data, autocorrelations are almost always positive, but for dead funds, both positive and negative values are present.

[20]Sadka (2010) identifies that liquidity risk exposure helps to explain the cross-section of hedge fund alphas, and creates a long-short portfolio from the returns of high-liquidity beta funds and low-liquidity-beta funds. The returns on this factor-mimicking portfolio should capture movements in hedge fund liquidity risk. I thank Ronnie Sadka for providing me with this series.

[21]The specification is estimated by stacking all transactions τ in months t for funds i. The results are qualitatively

unaffected by averaging premiums across transactions for each fund-month. Also note that there is no time-series data on fees available, so it is a fund-specific variable. However, Liang (2001) indicates that hedge funds hardly change fees over time, helping to alleviate concerns about the accuracy of this variable.

[22]Appendix C discusses the bootstrap employed in the paper. I also estimated the standard errors using the asymptotic method of Rogers (1983, 1993), which corrects for heteroskedasticity, autcorrelation and cross-correlation; White's (1980) method; and the delete-cross–section jackknife method in the spirit of Shao and Wu (1989) and Shao (1989), with virtually unchanged results. Note that the jackknife estimator is also robust to cross-correlation, heteroskedasticity and non-normality of the errors.

[23]In practice, the MSCI, TASS, HFR and CISDM databases provide onshore-offshore information for most, but not all funds. For the Hedgebay traded funds for which this information is not 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 (Bermuda, Cayman Islands, British Virgin Islands, Bahamas, Bermuda or Jersey). This is done for 4 of the funds in the sample. Note also that the onshore-offshore classifications employed by the vendors are possibly 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.

[24]Following the same line of argument, being located in an offshore financial centre could make it more likely that a fund could someday be traded on Hedgebay due to the tax implications of doing so – and perhaps the premium prices in an increase in the fund's probability of being able to be traded on Hedgebay someday as a consequence of its domicile. However this effect, if it exists, would appear second order, compared to the first-order effect of the main liquidity restrictions associated with the fund, and the large effect of the fund's being offshore on selection, rather than the level of the premium.

[25]I have also estimated the inverse Mills ratios in a specification which makes all the static variables dynamic (measuring their values as ranks in the available universe each year). This change does not alter any of the conclusions.

[26]Flows are indirect signals of investors intentions, as they are constructed from information on fund assets under management (AUM) and returns, and rely on assumptions about the arrival of capital to the fund. For a partial list of papers on hedge fund investor behavior, see Baquero and Verbeek (2005), Aragon (2005), Ding, Liang, Getmansky and Wermers (2007)), Fung, Hsieh, Naik and Ramadorai (2008), Wang and Zheng (2008), and Agarwal, Daniel and Naik (2009).

[27]Although this coefficient is not statistically significant in the regression in Table V, it is estimated to be statistically significant in the specifications in Internet Appendix Table VIII. Another point to note is that the HWM/hurdle rate dummy is statistically significant in some specifications, but the introduction of fund age eliminates this significance. This offers indirect support for the Christoffersen and Musto (2008) result that the importance of HWM provisions as signals of expected returns depend on the level of uncertainty about the fund manager.

[28]The redemption restrictions variable is also statistically significant in the specifications estimated in Internet

Appendix Tables VI and VIII.

[29]In a separate analysis, I checked the forecasting power of high and low absolute values of $TOTPREM$, as well as positive and negative $TOTPREM$. Both negative and low absolute values of $TOTPREM$ have far higher coefficients in the forecasting regressions, although neither is statistically significant on its own. It appears that the forecasting power of low $TOTPREM$ transactions is driven both by 'winner's curse' logic, and a greater ability for market participants to forecast *declines* in hedge fund performance. Thanks to an anonymous referee for suggesting this check.

[30]Equation (D1) is modelled as a probit, normalizing $u_{i,t} \sim N(0,1)$. This is innocuous, since z is 0 or 1 depending on the sign, not the scale of z^*.

[31]When estimating the probit, multiple share classes of funds are treated as separate funds. This is done in order to make the selection bias correction robust to the variations in liquidity restrictions, fee structures and returns that characterize different share classes of the same fund.

Internet Appendix for "The Secondary Market for Hedge Funds and the Closed-Hedge Fund Premium"[1]

[1] Tarun Ramadorai, 2010, Internet Appendix to "The Secondary Market for Hedge Funds and the Closed-Hedge Fund Premium," Journal of Finance, forthcoming, Please note: Wiley-Blackwell is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the authors of the article.

Matching Hedgebay Data to the Consolidated Hedge Fund Database

The final combined database used in the paper comprises 9,305 funds of funds and hedge funds for which comprehensive information on returns and administrative characteristics such as subscription and redemption restrictions and fees are available. The hedge fund and fund of funds data span four different sources: TASS, HFR, MSCI and CISDM (all December 2008 versions). There are 20,823 live and dead funds across all four databases, for which both administrative information (including fund characteristics) and returns information were available. Since an individual fund can appear multiple times from different vendors, there is duplication in the data, and administrative data on the funds are used to remove duplicates. The criteria used for elimination are:

1. Key name: 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 with the same key names occasionally offer shares to investors in multiple 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 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 classification mapping is presented in Online Appendix Table I, Panel B below.

4. Management Company: The names of management companies are standardized in the same way as the creation of key names (1. above).

5. History: 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 return information is available in the database is selected.

This reduces the number of funds-of-funds and hedge funds to 16,659. Next, funds with identical key names, currencies, and beginning-dates are compared based on their reported minimum investment, redemption notice periods and lock-up periods. If all of the three administrative fields are the same for such funds, they are assumed to be duplicates. This procedure eliminates 1,732 names, leaving 14,927 unique funds. Finally, the funds are required to have information available for every one of the fields employed in the selection analysis in Table VI. This eliminates 5,630 funds with missing data, leaving 9,297 funds in the universe. The 225 funds traded on Hedgebay over the sample period are compared to these 9,297 funds. Using key names and management company names, in consultation with Hedgebay in case of slight differences in names, 118 of these funds are matched to the consolidated database. For the remaining 225-118=107 funds, the consolidated database occasionally has (incomplete) administrative information, but never has return information over the periods when the funds are traded on Hedgebay. For 8 of these remaining funds, return data (net of all fees and costs) and a complete set of administrative information were obtained from Hedgebay. A cross-check was then conducted to make sure that the two sets of administrative information (from the consolidated database (incomplete) and directly sourced) are congruent with each other. The information, where it existed in both sets of data, was virtually identical. This results in an expansion of the universe of funds to 9,305=9,297+8, and yields the final sample employed in the paper, namely 118+8=126 funds for which there is return information available for 12 months prior to their transactions on Hedgebay; and 72 funds for which there is return information available for 24 months prior and following the transaction on Hedgebay (employed in Table VIII). The sources of these funds and the percentage that are alive and defunct (either liquidated or closed to new investments) are in Online Appendix Table I, Panel A below. The main reason for the inability to match a higher fraction of funds is that many of the funds traded on Hedgebay either do not report to database vendors at all, or stop reporting prior to their transactions on the secondary market. The main reasons that funds stop reporting to databases are because they close to new investments, or are near liquidation; these are also reasons why they are traded on the secondary market.

Online Appendix Table I

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

Panel A: Data Sources

Source Dataset	Num(Funds)	Alive	Defunct	% Defunct
TASS	3489	1823	1666	47.75
HFR	3770	2288	1482	39.31
MSCI	1823	1113	710	38.95
CISDM	215	196	19	8.837
Proprietary/Hedgebay	8	0	8	100
Total	9305	5420	3885	41.75

Panel B: Vendor Provided Strategies and Mapped Strategies

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

Panel B (Continued)

Strategy in Consolidated Database	**Mapped Strategy**
Foreign Exchange	Global Macro
Fund of Funds	Funds of Funds
Global Macro	Global Macro
HFRI	Other
Index	Other
Long Bias	Directional Traders
Long/Short Equity Hedge	Security Selection
Long-Short Credit	Fixed Income
Macro	Global Macro
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

Online Appendix Table II
Sample Fund Characteristics

Panel A of this table shows the percentiles of the attributes of the 126 funds in the matched sample, and Panel B the number of the 126 funds in each strategy group.

Panel A: Characteristics of Funds in Sample

	Mgmt. Fee	Incent. Fee	Withdrawal Restrictions	Minimum Investment	Subscription Restrictions	HWM/Hurdle Rate Dummy
10th Percentile	1.000	20.000	1.833	100,000.000	0.000	
50th Percentile	1.500	20.000	4.000	1,000,000.000	1.000	
90th Percentile	2.000	25.000	26.500	5,000,000.000	1.500	
Mean	1.569	20.159	9.634	1,742,261.905	1.029	0.746

Panel B: Strategies of Funds in Sample

Strategies	Number of Funds
Security Selection	46
Global Macro	14
Relative Value	2
Directional Traders	7
Funds of Funds	4
Multi-Process	27
Emerging Markets	9
Fixed Income	13
Other	4
Total	126

Online Appendix Table III
The Time Series Behaviour of the Equal-Weighted Hedge Fund Premium

Table III relates the time-series of equal-weighted *TOTPREM*, called *EWTOTPREM* to a number of covariates: the value-weighted closed-end mutual fund premium across all US general equity closed-end mutual funds found in the CRSP database; the level of the University of Michigan's consumer sentiment index; Baker and Wurgler's (2007) sentiment index (orthogonalized to a set of macroeconomic variables); the VIX index of the CBOE; Pastor and Stambaugh's (2003) level of equity market illiquidity; Sadka's (2010) measure of hedge fund liquidity, constructed as the difference between the returns of high and low liquidity beta funds; the one-month US Treasury Bill rate; and the total return on the S&P 500 index. The first row of statistics shows the correlations between *EWTOTPREM* and the levels of each of these variables. The second block of statistics shows the persistence of *EWTOTPREM* over the sample period as measured by the first-order 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 second block of statistics shows correlations between the first difference of *EWTOTPREM* and the first differences of each of these variables (except for the S&P 500 total return which is not differenced in this regression). The final block of statistics shows the correlation between *EWTOTPREM* and the covariate after persistent variables (with autocorrelation greater than 50%) are detrended (using only past data) using a Hodrick-Prescott filter and the monthly smoothing parameter of 14,400. 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 August 2008. 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 *EWTOTPREM* (t)							
	Closed-End MF Premium (t)	**Michigan Cons. Sent. (t)**	**Baker-Wurgler Sentiment (t)**	**VIX (t)**	**Pastor-Stambaugh Liquidity (t)**	**Sadka HF Liquidity (t)**	**One-Month Riskfree Rate (t)**	**S&P 500 Total Ret (t)**
Correlation in Levels	**0.455**	0.231	-0.145	0.128	0.047	0.042	**-0.481**	0.002
	0.129	*0.183*	*0.115*	*0.141*	*0.112*	*0.114*	*0.118*	*0.079*
Persistence of *EWTOTPREM*	*0.746*	*0.746*	*0.767*	*0.746*	*0.746*	*0.746*	*0.746*	*0.746*
Persistence of Covariate	*0.900*	*0.948*	*0.951*	*0.827*	*-0.074*	*0.099*	*0.963*	*0.015*
ADF t-statistic of Error	*-7.699*	*-7.289*	*-6.989*	*-7.152*	*-6.987*	*-7.047*	*-8.376*	*-7.016*
Correlation in Differences	**0.219**	0.038	0.171	-0.008	0.111	0.016	0.021	
	0.107	*0.092*	*0.106*	*0.079*	*0.092*	*0.090*	*0.078*	
Detrended Correlation	**0.208**	-0.041	-0.078	**0.128**	0.074	-0.085	-0.194	
	0.051	*0.021*	*0.190*	*0.027*	*1.711*	*5.693*	*1.076*	
N(Observations)	121	121	113	121	121	121	121	121

Online Appendix Table IV
Correlation Matrix of Aggregate Variables

This table computes the correlations between the aggregate variables in Table III in the paper: *VWTOTPREM*, and its equal-weighted equivalent, *EWTOTPREM*; *CEFPREM*, the value-weighted closed-end mutual fund premium across all US closed-end mutual funds found in the CRSP database; *MICH*, the level of the University of Michigan's consumer sentiment index; *SENT*, Baker and Wurgler's (2007) sentiment index (orthogonalized to a set of macroeconomic variables); *VIX*; *PSLIQ*, Pastor and Stambaugh's (2003) level of equity market illiquidity obtained from WRDS; *SADKA_HFLIQ*, Sadka's (2010) measure of hedge fund liquidity, constructed as the difference between the returns of high and low liquidity beta funds; *RF1M*, the one-month US Treasury Bill rate, from Kenneth French's website; and *SP500RET*, the total return on the S&P 500 index. Each bivariate correlation is computed over the contiguous sample period for which data on the two variables is available.

	***VWTOTPREM*(t)**	***EWTOTPREM*(t)**	***CEFPREM(t)***	***MICH(t)***	***SENT(t)***	***VIX(t)***	***PSLIQ(t)***	***SADKA_HFLIQ(t)***	***RF1M(t)***	***SP500 RET(t)***
VWTOTPREM(t)	1.000	0.892	0.388	0.241	-0.148	0.117	0.032	0.073	-0.433	-0.014
EWTOTPREM(t)	0.892	1.000	0.455	0.231	-0.145	0.128	0.047	0.042	-0.481	0.002
CEFPREM(t)	0.388	0.455	1.000	-0.278	-0.027	-0.153	0.129	-0.065	-0.432	-0.089
MICH(t)	0.241	0.231	-0.278	1.000	0.301	0.078	0.100	0.203	0.412	0.052
SENT(t)	-0.148	-0.145	-0.027	0.301	1.000	0.308	-0.069	-0.059	0.551	-0.242
VIX(t)	0.117	0.128	-0.153	0.078	0.308	1.000	-0.319	-0.068	0.041	-0.318
PSLIQ(t)	0.032	0.047	0.129	0.100	-0.069	-0.319	1.000	0.135	0.022	0.192
SADKA_HFLIQ(t)	0.073	0.042	-0.065	0.203	-0.059	-0.068	0.135	1.000	0.059	0.212
RF1M(t)	-0.433	-0.481	-0.432	0.412	0.551	0.041	0.022	0.059	1.000	0.002
SP500 RET(t)	-0.014	0.002	-0.089	0.052	-0.242	-0.318	0.192	0.212	0.002	1.000

Online Appendix Table V
Explaining the Hedge Fund Premium, No Selection Bias Correction

This table conditions the time-series cross-sectional observations of *PREM* and *TOTPREM* on theoretically motivated regressors. The first column of the table shows the theory associated with each group of regressors (Ability, Incentives, Fees, Fund Illiquidity, Asset Illiquidity and Sentiment); the second the sign predicted by the theory for the coefficient in each case; the third names the variable; the fourth and fifth show the estimated coefficient and standard error when *PREM* is the LHS variable; and the sixth and seventh the coefficients and standard errors when *TOTPREM* is the LHS variable. In all cases, the coefficients are estimated using pooled OLS with strategy fixed effects and the standard errors (in parentheses) are estimated using a cross-correlation and autocorrelation consistent bootstrap estimator. Coefficients significant at the 5% (10%) level are in **underlined bold** (underlined). Each regression is estimated on 522 transactions from a total of 126 funds. Panel A shows the estimated coefficients, and Panel B the estimated strategy fixed-effects.

Panel A: Coefficients

Theory	Predicted Sign	Coefficient	*PREM*		*TOTPREM*	
Ability	+	Market Model t-Alpha (-12)	**0.408**	(0.073)	**0.448**	(0.080)
	-	(Market Model t-Alpha (-12))^2	-0.009	(0.010)	-0.010	(0.011)
	-	Fund Age Rank	-0.013	(0.007)	-0.015	(0.008)
	-	Size (*AUM*) Rank	-0.029	(0.015)	-0.030	(0.016)
Incentives	+	Manager's Option Delta	0.217	(0.292)	0.258	(0.298)
	+	Manager's Investment	0.684	(0.419)	0.846	(0.436)
	-	(Manager's Investment)^2	-0.213	(0.221)	-0.257	(0.234)
	+	High Water Mark/Hurdle Rate Dummy	0.548	(0.404)	0.446	(0.434)
Fees	-	Management Fee	**-0.762**	(0.236)	**-0.797**	(0.251)
Fund Illiquidity	-	Minimum Investment Rank	**-0.019**	(0.009)	**-0.020**	(0.010)
	-	Subscription Restrictions	**-0.451**	(0.213)	**-0.489**	(0.233)
	-	Withdrawal Restrictions	-0.018	(0.013)	-0.021	(0.014)
	-	lagged Average Commission	0.123	(0.677)	0.338	(0.706)
Asset Illiquidity	+	First-Order Autocorrelation	0.001	(0.005)	0.000	(0.005)
	+	Sadka Hedge Fund Liquidity	-4.272	(4.719)	-4.615	(5.132)
	+	Lock Dummy*Offshore Dummy	1.233	(0.683)	**1.425**	(0.696)
	-	One-Month US T-Bill Rate	**-5.591**	(1.083)	**-6.180**	(1.145)
Sentiment	+	Michigan Consumer Sentiment	0.001	(0.014)	0.007	(0.015)
		Adjusted R-squared	0.358		0.362	

Panel B: Fixed Effects

Specification	Security Selection	Global Macro	Relative Value	Directional Traders	Funds of Funds	Multi-Process	Emerging Markets	Fixed Income	Other
PREM	**5.665**	**8.173**	**5.841**	**6.655**	**6.725**	**4.980**	4.260	**4.088**	**7.483**
	(1.680)	(1.921)	(1.983)	(1.869)	(1.970)	(1.795)	(3.036)	(1.868)	(2.116)
TOTPREM	**5.853**	**8.353**	**5.781**	**6.954**	**7.104**	**4.896**	4.322	3.795	**7.596**
	(1.816)	(2.066)	(2.148)	(2.031)	(2.229)	(1.921)	(3.198)	(1.967)	(2.257)

Online Appendix Table VI
Explaining the Hedge Fund Premium – Regression with Alpha

This table conditions the time-series cross-sectional observations of *PREM* and *TOTPREM* on theoretically motivated regressors. The first column of the table shows the theory associated with each group of regressors (Ability, Incentives, Fees, Fund Illiquidity, Asset Illiquidity and Sentiment); the second the sign predicted by the theory for the coefficient in each case; the third names the variable; the fourth and fifth show the estimated coefficient and standard error when *PREM* is the LHS variable; and the sixth and seventh the coefficients and standard errors when *TOTPREM* is the LHS variable. In all cases, the coefficients are estimated using pooled OLS with strategy fixed effects and the standard errors (in parentheses) are estimated using a cross-correlation and autocorrelation consistent bootstrap estimator. Coefficients significant at the 5% (10%) level are in **underlined bold** (underlined). Each regression is estimated on 522 transactions from a total of 126 funds. Panel A shows the estimated coefficients, and Panel B the estimated strategy fixed-effects.

Panel A: Coefficients

Theory	Predicted Sign	Coefficient	*PREM*		*TOTPREM*	
Ability	+	Market Model Alpha (-12)	**0.543**	(0.258)	**0.603**	(0.274)
	-	(Market Model Alpha (-12))^2	-0.061	(0.085)	-0.084	(0.093)
	-	Fund Age Rank	-0.013	(0.008)	-0.015	(0.009)
	-	Size (*AUM*) Rank	**-0.033**	(0.016)	**-0.037**	(0.017)
Incentives	+	Manager's Option Delta	0.188	(0.350)	0.202	(0.380)
	+	Manager's Investment	0.608	(0.436)	0.750	(0.450)
	-	(Manager's Investment)^2	-0.232	(0.223)	-0.278	(0.240)
	+	High Water Mark/Hurdle Rate Dummy	0.526	(0.440)	0.392	(0.472)
Fees	-	Management Fee	**-0.687**	(0.280)	**-0.748**	(0.287)
Fund Illiquidity	-	Minimum Investment Rank	-0.017	(0.009)	-0.016	(0.010)
	-	Subscription Restrictions	-0.358	(0.201)	-0.345	(0.235)
	-	Withdrawal Restrictions	-0.027	(0.015)	**-0.033**	(0.016)
	-	lagged Average Commission	-0.184	(0.722)	-0.021	(0.781)
Asset Illiquidity	+	First-Order Autocorrelation	0.002	(0.005)	0.001	(0.005)
	-	Sadka Hedge Fund Liquidity	-7.518	(5.399)	-7.957	(5.897)
	+	Lock Dummy*Offshore Dummy	1.494	(0.775)	**1.674**	(0.818)
	-	One-Month US T-Bill Rate	**-6.058**	(1.143)	**-6.626**	(1.199)
Sentiment	+	Michigan Consumer Sentiment	0.011	(0.015)	0.017	(0.017)
Selection Bias	+	Inverse Mills Ratio	-0.461	(0.549)	-0.676	(0.603)
		Adjusted R-squared	0.328		0.331	

Panel B: Fixed Effects

Specification	Security Selection	Global Macro	Relative Value	Directional Traders	Funds of Funds	Multi-Process	Emerging Markets	Fixed Income	Other
PREM	6.663	**9.091**	6.799	**7.792**	**8.372**	6.350	5.486	5.499	**8.805**
	(3.415)	(3.590)	(3.972)	(3.819)	(3.741)	(3.692)	(4.952)	(3.768)	(4.105)
TOTPREM	**7.700**	**10.110**	7.685	**9.078**	**9.781**	7.221	6.508	6.136	**9.941**
	(3.619)	(3.802)	(4.268)	(4.029)	(3.935)	(3.926)	(5.235)	(4.084)	(4.356)

Robustness to Incubation Bias and the Fung-Hsieh Factor Model

I conduct a few additional checks to check the robustness of the results. First, I eliminate the first twelve months of returns for each fund to control for the possibility of backfill bias (see Fung and Hsieh (2009) for a good summary of the literature on biases in hedge fund data). Second, I re-compute the performance measures (the T-statistic of alpha and its square) using the Fung and Hsieh (2004) factor model over the 24 months prior to each transaction. These seven factors have been shown to have considerable explanatory power for fund-of-fund and hedge fund returns.[2] Third, I recompute the Getmansky, Lo and Makarov (2004) measure of return-smoothness using 24 lagged months of returns for each fund-month and include it in the specification in place of the first autocorrelation of returns. When estimating, k, the number of lags in the moving average model is set to 3 (the results do not differ when k is set to 2), and I winsorize the measure, setting values estimated to be greater than 1 to 1 and those less than zero to zero, as it is difficult to interpret the values as percentages of smoothing otherwise.[3]

Online Appendix Table II shows the results of these changes to the specification in Table VII in the paper. There is a reduction in sample size from 522 to 436 observations in the regression on account of the more stringent requirements. The majority of the results discovered in Table VII continue to be strongly statistically significant. This table helps to assuage concerns that the results discovered in Table VII in the paper are an artefact of backfill bias and/or the use of the market model to estimate alpha.

[2] The set of factors comprises the excess return on the S&P 500 index; a small minus big factor constructed as the difference between the Wilshire small and large capitalization stock indices; the excess returns on portfolios of lookback straddle options on currencies, commodities, and bonds, which are constructed to replicate the maximum possible return to trend-following strategies on their respective underlying assets; the yield spread of the U.S. 10-year Treasury bond over the 3-month T-bill, adjusted for the duration of the 10-year bond; and the change in the credit spread of Moody's Baa bond over the 10-year Treasury bond, also appropriately adjusted for duration.

[3] This is similar to the approach of Aragon (2005). Winsorizing the measure at the 5th and 95th percentile points of the pooled distribution yields virtually identical results.

Online Appendix Table VII
Robustness to Incubation Bias, and the Fung-Hsieh Seven Factor Model

This table makes three changes to the specification estimated in Table VII. First, the first twelve months of each fund's returns is deleted to correct for the possible impact of selection bias. Second, the Fung and Hsieh (2004) factor model is employed (for only those fund-months with at least 24 lagged observations of returns) to compute the T-statistic of alpha performance measure. Third, the GLM measure is employed in place of the first autocorrelation of returns. All coefficients are estimated using pooled OLS with strategy fixed effects and the standard errors (in parentheses) are estimated using a cross-correlation and autocorrelation consistent bootstrap estimator. Coefficients significant at the 5% (10%) level are in **<u>underlined bold</u>** (<u>underlined</u>). Each of the regressions is estimated on 436 transactions from a total of 100 funds. Panel A shows the coefficients of the variables, and Panel B the estimated strategy fixed-effects.

Panel A: Coefficients

Theory	Predicted Sign	Coefficient	*PREM*		*TOTPREM*	
Ability	+	**Fung-Hsieh Model t-Alpha (-24)**	**<u>0.272</u>**	(0.106)	**<u>0.300</u>**	(0.109)
	-	**(Fung-Hsieh Model t-Alpha (-24))^2**	-0.003	(0.007)	-0.003	(0.007)
	-	**Fund Age Rank**	-0.002	(0.011)	-0.003	(0.013)
	-	**Size (*AUM*) Rank**	-0.004	(0.021)	-0.006	(0.021)
Incentives	+	**Manager's Option Delta**	0.684	(0.489)	0.734	(0.505)
	+	**Manager's Investment**	**<u>0.947</u>**	(0.463)	**<u>1.113</u>**	(0.471)
	-	**(Manager's Investment)^2**	-0.200	(0.239)	-0.246	(0.253)
	+	**High Water Mark/Hurdle Rate Dummy**	<u>1.036</u>	(0.562)	0.963	(0.590)
Fees	-	**Management Fee**	<u>-0.614</u>	(0.341)	<u>-0.670</u>	(0.345)
Fund Illiquidity	-	**Minimum Investment Rank**	**<u>-0.025</u>**	(0.013)	<u>-0.026</u>	(0.013)
	-	**Subscription Restrictions**	**<u>-0.025</u>**	(0.010)	**<u>-0.026</u>**	(0.012)
	-	**Withdrawal Restrictions**	-0.014	(0.015)	-0.017	(0.016)
	-	**lagged Average Commission**	0.115	(0.765)	0.289	(0.787)
Asset Illiquidity	+	**Getmansky-Lo-Makarov Illiquidity Measure (-24)**	0.544	(0.814)	0.637	(0.816)
	-	**Sadka Hedge Fund Liquidity**	-3.831	(5.188)	-4.388	(5.233)
	+	**Lock Dummy*Offshore Dummy**	**<u>1.985</u>**	(0.960)	**<u>2.129</u>**	(0.982)
	-	**One-Month US T-Bill Rate**	**<u>-5.790</u>**	(1.354)	**<u>-6.302</u>**	(1.422)
Sentiment	+	**Michigan Consumer Sentiment**	0.007	(0.016)	0.015	(0.017)
Selection Bias	+	**Inverse Mills Ratio**	0.871	(0.851)	0.777	(0.896)
		Adjusted R-squared	0.317		0.324	

Panel B: Fixed Effects

Specification	Security Selection	Global Macro	Relative Value	Directional Traders	Funds of Funds	Multi-Process	Emerging Markets	Fixed Income	Other
PREM	-1.496	0.591	-1.446	-1.078	0.032	-2.193	-3.857	-3.274	-0.741
	(5.233)	(5.391)	(5.464)	(5.854)	(5.414)	(5.711)	(6.976)	(5.749)	(6.521)
TOTPREM	-1.396	0.554	-1.540	-0.797	0.471	-2.332	-3.880	-3.645	-0.678
	(5.379)	(5.555)	(5.703)	(6.035)	(5.490)	(5.921)	(7.198)	(5.961)	(6.750)

Negative News

A news search is conducted on Factiva and Google for each fund-month with large negative discounts (those less than -10%). The search is intended to capture news that could have affected trading in the fund, and is motivated by conversations with the practitioners on Hedgebay about the likely determinants of such discounts, and the ‘normal range’ of discounts and premiums in their experience.

There are several news items uncovered by this search, including the imposition of gates (indefinite suspensions of withdrawals from funds, such as in the case of Absolute Capital); the announcement of a fund's collapse on account of the failure of large trades (such as Amaranth); or reports of a fund's exposure to bankruptcies of counterparties (such as Refco in 2005). The nature of these incidents exacerbates the non-response bias referred to earlier (i.e., funds stop reporting to databases pre-empting negative public announcements) and consequently, in the full sample of transactions, the search uncovered only 2 public news announcements in the same month for funds that I am able to match in the consolidated database.

I include the negative news dummy under the category of fund share illiquidity because the two incidents captured by the variable significantly impeded the ability of investors in the funds to liquidate their investments in the short run. The first news item reported on a fund's outside sources of capital being significantly curtailed on account of regulators' prohibitions on credit unions investing in funds that specialized in subprime assets. This made it very unlikely that the fund would permit redemptions as it had long-term investments coupled with lack of access to short-term funding. The second news story pertained to a fund's assets being frozen on account of them being held with Refco's prime brokerage group, in the month that Refco was indicted for fraud. Consequently, this raised concerns about investors' ability to withdraw money from the fund.

A dummy variable is created which takes the value of 1 representing the above news about the fund in the same month as the occurrence of the transaction on Hedgebay. The inclusion of the dummy variable increased the adjusted R-squared to around 75%, and by soaking up the large negative returns associated with such announcements, causes the statistical significance of many of the other results of the paper to improve dramatically. The point estimate of the coefficient on the negative news dummy is also large, negative, and estimated to be statistically significant. However, I would advise interpretation of this particular result with caution as a consequence of the tiny sample size of news announcements.

Online Appendix Table VIII
Explaining the Hedge Fund Premium – Regression with Negative News Dummy

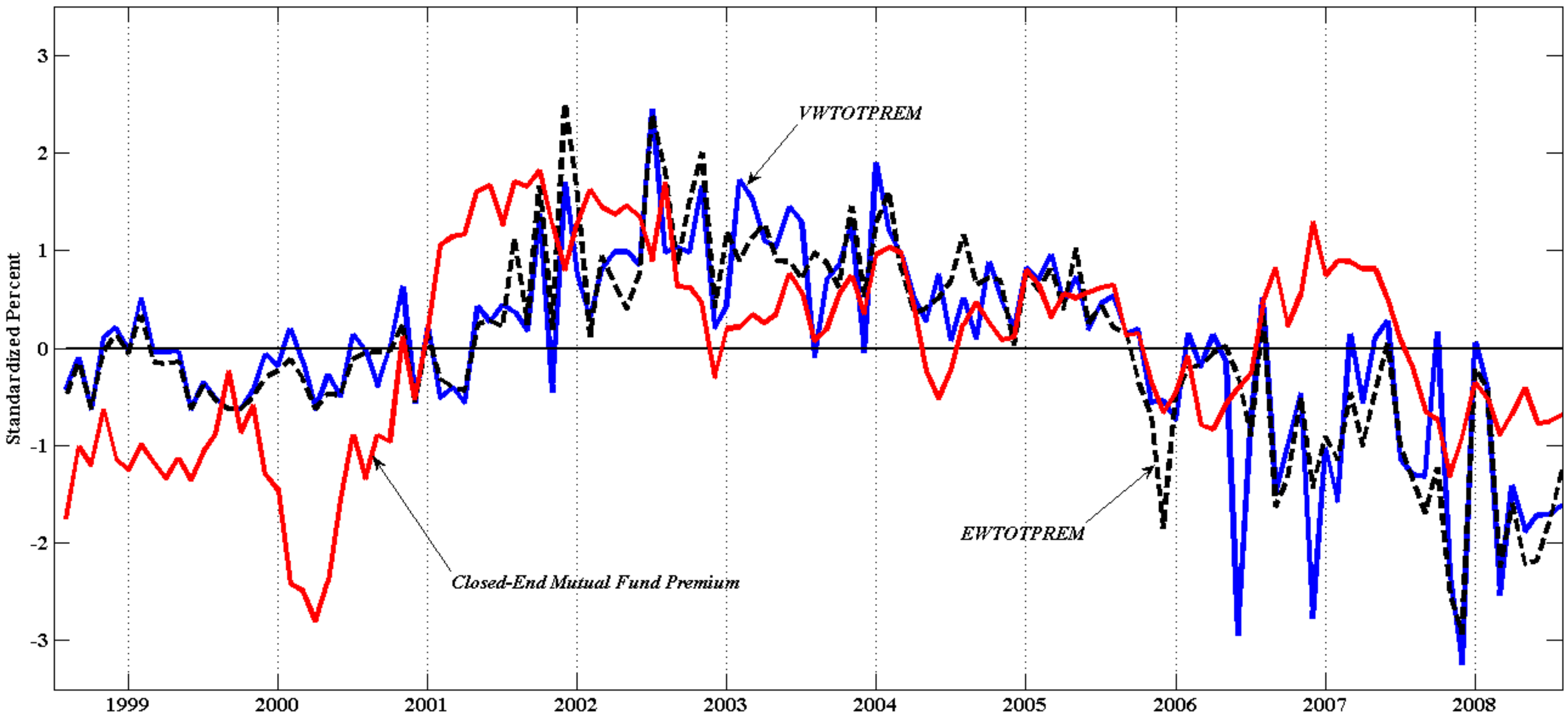
This table modifies the specification in Table VII, by including a dummy for fund-months with a contemporaneous negative news story. In all cases, the coefficients are estimated using pooled OLS with strategy fixed effects and the standard errors (in parentheses) are estimated using a cross-correlation and autocorrelation consistent bootstrap estimator. Coefficients significant at the 5% (10%) level are in **underlined bold** (underlined). Each regression is estimated on 522 transactions from a total of 126 funds. Panel A shows the estimated coefficients, and Panel B the estimated strategy fixed-effects.

Panel A: Coefficients

Theory	Predicted Sign	Coefficient	*PREM*		*TOTPREM*	
Ability	+	**Market Model t-Alpha (-12)**	**0.334**	(0.056)	**0.372**	(0.064)
	-	**(Market Model t-Alpha (-12))^2**	-0.007	(0.014)	-0.008	(0.017)
	-	**Fund Age Rank**	**-0.016**	(0.005)	**-0.018**	(0.006)
	-	**Size (*AUM*) Rank**	**-0.038**	(0.008)	**-0.042**	(0.008)
Incentives	+	**Manager's Option Delta**	-0.227	(0.204)	-0.227	(0.220)
	+	**Manager's Investment**	**0.496**	(0.197)	**0.628**	(0.223)
	-	**(Manager's Investment)^2**	**-0.263**	(0.122)	**-0.304**	(0.139)
	+	**High Water Mark/Hurdle Rate Dummy**	**0.424**	(0.214)	0.301	(0.235)
Fees	-	**Management Fee**	**-1.070**	(0.187)	**-1.140**	(0.205)
Fund Illiquidity	-	**Minimum Investment Rank**	**-0.009**	(0.004)	**-0.009**	(0.004)
	-	**Subscription Restrictions**	**-0.480**	(0.192)	**-0.485**	(0.216)
	-	**Withdrawal Restrictions**	**-0.026**	(0.011)	**-0.031**	(0.012)
	-	**lagged Average Commission**	-0.008	(0.474)	0.203	(0.520)
	-	**Negative News Dummy**	**-32.903**	(10.873)	**-34.054**	(11.688)
Asset Illiquidity	+	**First-Order Autocorrelation**	0.002	(0.003)	0.000	(0.003)
	-	**Sadka Hedge Fund Liquidity**	-0.232	(3.475)	-0.387	(4.214)
	+	**Lock Dummy*Offshore Dummy**	0.237	(0.419)	0.362	(0.454)
	-	**One-Month Riskfree Rate**	**-4.390**	(0.746)	**-4.898**	(0.789)
Sentiment	+	**Michigan Consumer Sentiment**	0.005	(0.013)	0.012	(0.015)
Selection Bias	+	**Inverse Mills Ratio**	**-0.967**	(0.339)	**-1.192**	(0.400)
		Adjusted R-squared	0.765		0.741	

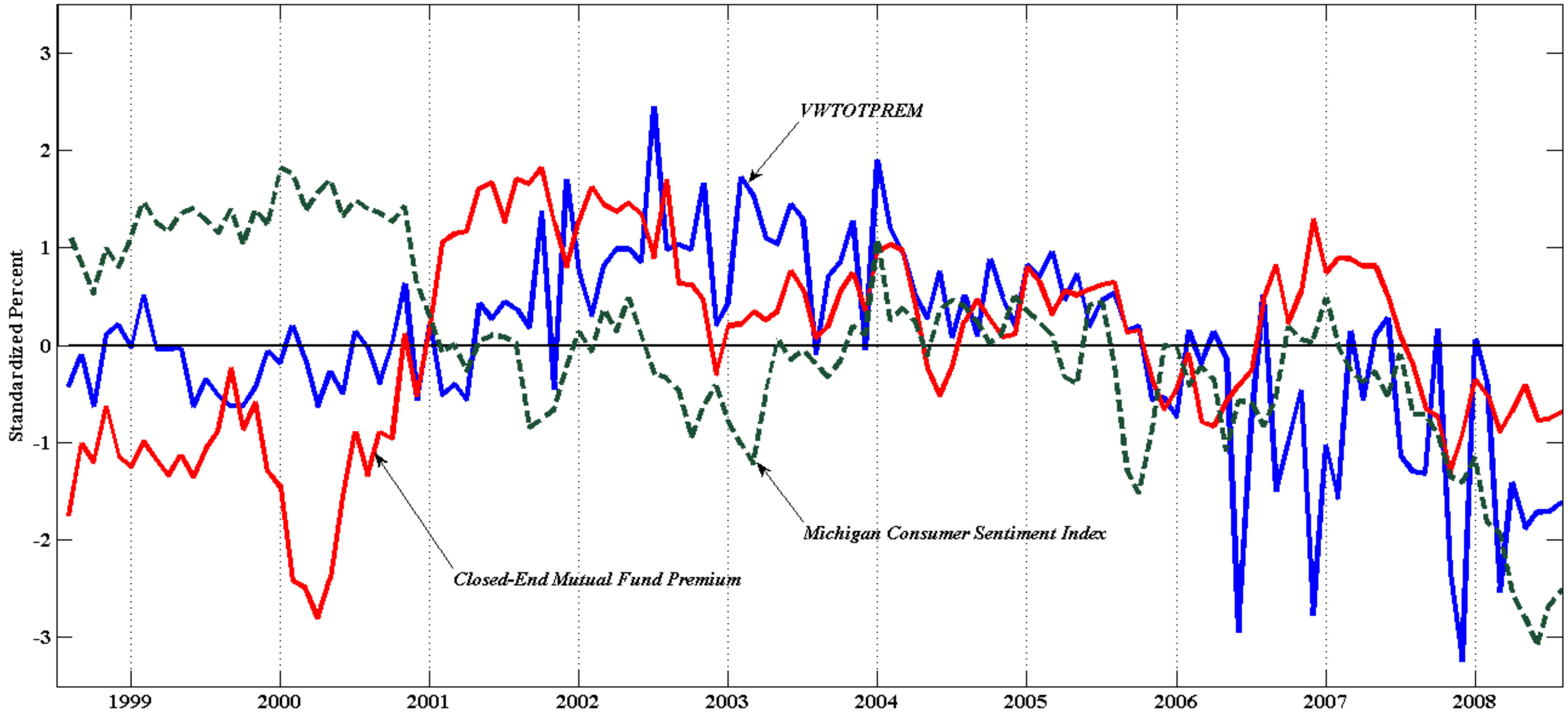
Panel B: Fixed Effects

Specification	Security Selection	Global Macro	Relative Value	Directional Traders	Funds of Funds	Multi-Process	Emerging Markets	Fixed Income	Other
PREM	**9.595**	**12.167**	**10.222**	**11.313**	**11.041**	**9.334**	**10.360**	**9.328**	**12.430**
	(2.037)	(2.231)	(2.297)	(2.229)	(2.181)	(2.305)	(2.329)	(2.292)	(2.526)
TOTPREM	**10.658**	**13.193**	**11.152**	**12.642**	**12.439**	**10.198**	**11.452**	**10.007**	**13.586**
	(2.318)	(2.528)	(2.643)	(2.510)	(2.547)	(2.598)	(2.649)	(2.631)	(2.879)



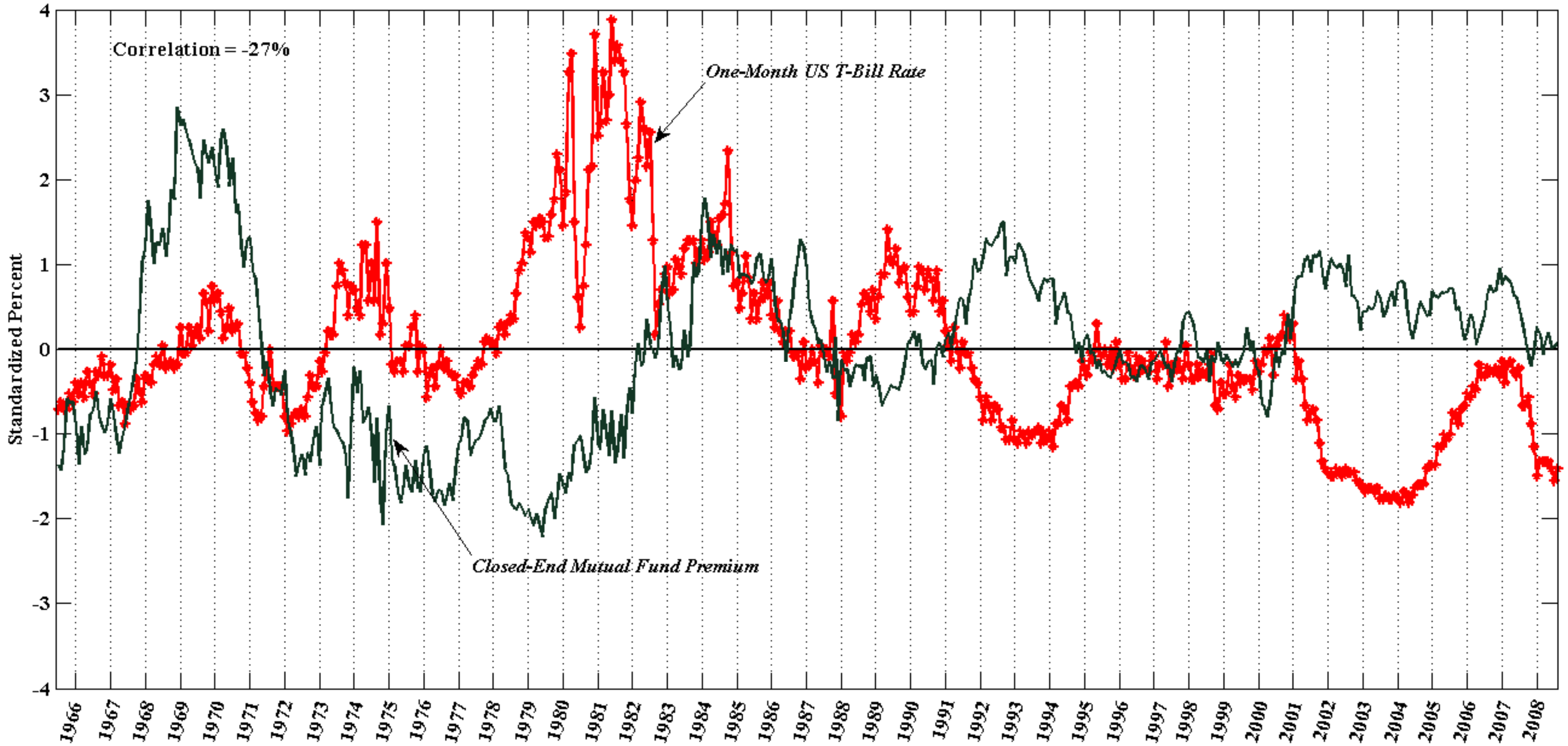
Online Appendix Figure 1
The Equal-Weighted and Value-Weighted Closed-Hedge Fund Premiums

This figure plots the value-weighted premium across all U.S. closed-end mutual funds in CRSP each month, *EWTOTPREM*, the equal-weighted closed-hedge fund premium, and *VWTOTPREM* the value-weighted (by end-of-prior month AUM) closed hedge fund premium. 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.



Online Appendix Figure 2
The Closed-Hedge Fund Premium, Closed-End Fund Premium and Sentiment

This figure plots the value-weighted premium across all U.S. closed-end mutual funds in CRSP each month, *VWTOTPREM*, and the University of Michigan's consumer sentiment index. 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.



Online Appendix Figure 3
The Closed-End Fund Premium and the Risk-Free Rate, 1965-2008

This figure plots the log value-weighted premium across all U.S. closed-end mutual funds obtained from Jeff Wurgler's website, and the One-Month US Treasury Bill Rate. 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 -27% over the period between 1965:07 and 2008:08