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Hedge funds for retail investors?

An examination of hedged mutual funds

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Abstract

Recently there has been a rapid growth in the assets managed by "hedged mutual funds" – mutual funds mimicking hedge funds strategies. In this paper, we examine the performance of these funds relative to hedge funds and traditional mutual funds. We find that despite their use of similar trading strategies, hedged mutual funds underperform hedge funds. We attribute this evidence to lighter regulation and better incentives faced by hedge funds. In contrast, hedged mutual funds outperform traditional mutual funds. Most interesting, this superior performance is largely driven by managers with experience in implementing hedge fund strategies. Our findings have important implication for investors seeking hedge-fund-like payoffs at a lower cost and within the comfort of a regulated environment.

JEL Classifications: G11, G12
Keywords: Hedge funds, mutual funds, hedged mutual funds, hybrid mutual funds

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Hedge funds for retail investors?
An examination of hedged mutual funds

Fairly recently, a number of mutual fund companies have begun offering funds that use hedge-fund-like trading strategies designed to benefit from potential mispricing on the long as well as the short side. Recognizing that these funds are unique, Morningstar and Lipper have created the new style categories of "Long/Short Equity" and "Market Neutral" to classify these funds. Despite their use of hedge fund strategies, these "hedged" mutual funds are regulated by the Securities and Exchange Commission (SEC) in exactly the same way as "traditional" mutual funds. They are available to retail investors, with an average required minimum investment of just $5,000, while hedge funds are only available to accredited and/or qualified investors with a minimum investment of roughly $1 million.[1]

We believe that hedged mutual funds will play an increasingly important role in the field of investment management as they provide access to hedge-fund-like strategies with the fee structure, liquidity, and regulatory requirements of mutual funds.[2] This paper conducts an in-depth analysis of this new class of managed portfolios by comparing them with hedge funds (HFs) on one hand and traditional mutual funds (TMFs) on the other. Although HFs and hedged mutual funds (HMFs) employ similar trading strategies, HFs are subject to lighter regulation and have better incentives. Regarding regulation, HMFs must comply with restrictions that include, among others, covering short positions, limiting borrowing to only one-third of total assets, and

[1] Accredited investors are those with a net worth of $1 million or more or two consecutive years of income of $200,000 (or $300,000 of household income) while qualified investors are those with net worth of $5 million. Recently, the SEC proposed changing the standard to require investable assets of $2.5 million for accredited investors (Anderson, 2006).

[2] A recent study by Cerulli Associates found that over half of the Registered Investment Advisers who do not currently use hedge funds for their clients would add hedged mutual funds to their portfolios (see O'Hara, Neil, "Funds of Funds," http://www.onwallstreet.com/article.cfm?articleid=3217, 2/1/2006). These funds are also attractive to retirement plan administrators. For example, Lake Partners, Inc., a Greenwich, Connecticut, investment adviser offers a fund of hedged mutual funds, called LASSO, which is only available to entities with 401(k) or 403(b) plans (see Wiles, Russ, "Hedged Mutual Funds Offer Defensive Strategy," http://www.findarticles.com/p/articles/mi_qn4155/is_20050214/ai_n9728927, 2/14/2005).

restricting investment in illiquid securities to 15% of total assets. They must also provide daily liquidity and audited semi-annual reports. In contrast, hedge funds do not face such constraints, as they are largely unregulated.[3] In addition to lighter regulation, hedge funds have better incentives as they usually charge performance-based incentive fees, while hedged mutual funds usually do not.[4] Differences in both regulation and incentives imply that HMFs are likely to underperform HFs (our *Regulation and Incentives Hypothesis*). We find evidence supporting this hypothesis. Controlling for risk and fund characteristics, HMFs underperform HFs by about 3.3% per year on a net-of-fee basis.

Further, although both HMFs and TMFs are subject to the same regulations, HMFs have greater flexibility in terms of trading strategies. For example, HMFs can sell short and use derivatives to exploit investment opportunities that TMF managers often disallow in their prospectuses. Thus, HMFs are able to capture alpha on both the long and the short side, which should help them to outperform TMFs (our *Strategy Hypothesis*). Of course, this relaxation in constraints could also lead to increase in agency costs. However, we find strong support for the Strategy Hypothesis suggesting that the benefits of loosening constraints exceed the costs associated with greater agency risk.[5] Despite higher fees and turnover, HMFs outperform TMFs by as much as 4.8% per year on a net-of-fee basis, when controlling for differences in risks, fund characteristics, and past performance.

Although HMFs as a group outperform TMFs, our sample of HMFs exhibits an interesting dimension of heterogeneity. About half the HMFs have managers with HF

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[3] This mandatory disclosure by mutual funds can result in leakage of funds' private information to outsiders, who can trade on it and move security prices against them (see, e.g., Wermers (2001), Frank et al (2004)).
[4] If a mutual fund wishes to charge a performance-based incentive fee, the fee must be symmetrical such that the fee will increase with good performance and decrease with poor performance. Not surprisingly, this type of fee (also called a "fulcrum" fee), is unpopular among mutual funds. In a study of incentive fees, Elton, Gruber, and Blake (2003) document that only 108 of their sample of over 6,000 mutual funds use fulcrum fees. Of our sample of 52 hedged mutual funds, only 2 use fulcrum fees.
[5] We further discuss this issue in Section 2.2.

experience, while the rest have managers without such experience. These "experienced" HF managers concurrently manage hedge funds and hedged mutual funds, and in all cases, the hedge fund experience was gained either concurrent with or prior to the manager's starting a hedged mutual fund. This heterogeneity enables us to investigate whether an individual HMF's superior performance is related to its manager's experience in implementing HF-like strategies (our *Skill Hypothesis*). Arguably, HMF managers with HF experience should be more adept at implementing HF strategies, and therefore should outperform those without such experience.[6] We find support for the Skill Hypothesis. HMF managers with HF experience outperform those without. The difference in risk-adjusted performance is as much as 4.1% per year net-of-fees while controlling for fund characteristics and past performance. This result implies that most of the superior performance of HMFs relative to TMFs is largely driven by these "skilled" fund managers.

Given this result, a natural question arises. Why would a HF manager start a HMF, given the tighter constraints, stricter regulation, and lower incentives in the mutual fund industry? One possibility is that the hedge funds offered by these managers are underperforming other hedge funds. We test this possibility by comparing the performance of these two groups and find no significant difference. Hence, it does not appear that the managers of poorly-performing hedge funds choose to offer hedged mutual funds. We conjecture that the reason for offering both HMFs and HFs is that these managers are trying to raise additional capital, given that it can be extremely difficult for smaller HFs to raise assets. This idea is corroborated by a recent study showing that 70% of new capital flows go to the top 100 HFs by size, leaving only 30% for the

[6] It is also conceivable that HMFs with HF managers will benefit from positive externalities such as a reduction in transaction costs due to economies of scale in the trading process. We are implicitly grouping such externalities together as "skill" in our hypothesis.

8,000-plus remaining HFs.[7] Finally, HMFs might also be attractive to HF managers since mutual fund investors tend to be slow to withdraw assets from poorly-performing funds but quick to invest in well-performing funds (see Sirri and Tufano (1998)). Thus, having both HMFs and HFs in their product range provides "client diversification" benefits to the manager.[8]

All our findings supporting the three hypotheses (Regulation and Incentives, Strategy, and Skill) hold for different risk models and on a pre-fee basis. In addition, our results are robust to conducting our analyses at the monthly and annual levels, and to the use of alternate econometric methodologies including random-effects, a matched sample analysis, and the Fama-MacBeth (1973) approach.

While ours is the first paper to examine the relative performance of HMFs vis-à-vis both HFs and TMFs, three other studies have examined the rationale behind allowing mutual fund managers flexibility in implementing investment strategies (Koski and Pontiff (1999), Deli and Varma (2002), and Almazan, Brown, Carlson, and Chapman (2004)). This flexibility typically enables the manager to use derivative contracts, invest in restricted securities, sell securities short, and/or borrow money to create leverage. In general, these studies find evidence that providing flexibility to managers does *not* improve fund performance, but rather, enables managers to control expenses, manage cash flows, and manage risk more efficiently. Additionally, the existence of investment constraints (i.e., reduced investment flexibility) is consistent with optimal contracting in the mutual fund industry — empirically, these studies show that funds with a greater need for monitoring face more investment restrictions.

We build on this literature by focusing on the performance of a specific group of mutual funds that use HF-like trading strategies. Our research provides three important contributions to

[7] See "Hedge Fund Market Trends 1Q 2007," published by Hedge Fund Research (www.hedgefundresearch.com).
[8] We examine these issues in more detail in Section 6.

the existing literature. First, the superior performance of HMFs over TMFs is driven by managers with HF experience. This finding implies that simply allowing managers flexibility will not necessarily result in better performance (as confirmed by prior studies). Second, we demonstrate that these HMFs have significantly higher turnover and expenses than TMFs suggesting that they are not using flexibility for cost reduction, but rather, to implement HF-like strategies. Finally, focusing on funds that use HF-like trading strategies allows us to compare their performance with those of HFs, thereby shedding light on the role of regulation and incentives. We find that despite using similar trading strategies, HMFs underperform HFs as the latter are lightly regulated and face stronger performance-related incentives.

The paper is structured as follows. Section 2 discusses related literature and outlines the three hypotheses. Section 3 describes the data. Section 4 investigates the *Regulation and Incentives Hypothesis.* Section 5 examines the *Strategy Hypothesis.* Section 6 tests the *Skill Hypothesis* and performs a battery of robustness tests, and Section 7 concludes.

2. Related literature and testable hypotheses

2.1. Related literature

As noted in the Introduction, our paper is related to literature that examines the motivation for controlling a mutual fund's investment flexibility. One reason for restricting a fund's flexibility is to minimize agency costs by preventing the manager from strategically altering the fund's risk to increase his own compensation (Almazan et al. (2004)).[9] Another reason for allowing a fund flexibility is to reduce transaction costs, liquidity costs, and

[9] For example, the tournaments literature (e.g., Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997)) documents that mutual funds strategically change their risk in the latter half of the year to be "winners" and thereby attract greater capital flows, which results in higher compensation for the manager. By contrast, results for hedge funds imply that managers do not increase risk in the latter half of the year to attempt to be winners – providing evidence that career concerns and reputational effects outweigh the agency costs for hedge fund managers (see Brown, Goetzmann, and Park (2001)).

opportunity costs of holding cash (rather than to enhance performance) (Koski and Pontiff (1999), Deli and Varma (2002)). We contribute to this strand of literature by demonstrating that a certain type of investment flexibility, by which managers use hedge fund trading strategies per their prospectuses, can actually enhance fund performance.

To further clarify the differences between our paper and prior work, we calculate the constraint score for our sample as in Almazan et al. (2004). This score is computed using SEC filings that report whether funds are permitted to use derivatives, leverage, short selling, and restricted securities. A score of 0 means the fund is completely unrestricted, while a score of 1 means the fund is completely restricted. The average score for the universe of mutual funds in their sample is 0.36, while the average score for our sample is 0.23, indicating that on the whole, our funds are less restricted than the entire sample of mutual funds.

More important however, are our constraint score results for short sales, the investment technique most commonly associated with the hedge fund strategies of the funds in our sample. Within our sample, 78% of funds are permitted to use short sales, as compared with 31% of all mutual funds as reported by Almazan et al. (2004). Further, only about 10% of this 31% of funds actually short-sell, which is 3.1% of the total universe of mutual funds. By contrast, of our 78% of funds that are permitted to short sell, 78% actually do, which constitutes a full 61% of our sample. Finally, short sales as a percentage of assets under management for the funds in our sample averages about 19%, indicating that short-selling is indeed a crucial component of our funds' investment strategies.[10] Clearly, our sample is substantially different from that of Almazan et al (2004).

In addition, two recent working papers examine potential conflicts of interest in side-by-side management of mutual funds and hedge funds. Cici, Gibson, and Moussawi (2006) and

[10] Almazan et al. (2004) do not report this statistic for the funds in their sample.

Nohel, Wang, and Zheng (2006) study this relationship from the perspective of the management company and individual manager respectively. These papers focus on mutual funds that are managed side-by-side with hedge funds. Since the mutual fund universe predominantly consists of TMFs, their research sheds light on the differences between HFs and TMFs offered by the same agent (manager/management company). By contrast, we compare the performance of HMFs with HFs on one hand, and TMFs on the other. In order to isolate the effect of skill, we divide the HMFs into those that have HF managers and those that do not. While prior papers examine the issue of conflicts of interest in side-by-side management, we focus on the effect of skill gained in the hedge fund industry on the performance of HMFs. Thus, our paper complements this recently burgeoning literature.

Finally, our paper contributes to the large literature on hedge funds that examines risk and return characteristics, performance, and compensation structures.[11] However, there is relatively scant literature that compares hedge funds and mutual funds directly. One reason is that significant differences in regulation, incentives, and trading strategies between hedge funds and mutual funds make it difficult to conduct a direct comparison. Our study overcomes these limitations to some extent. Since HMFs and hedge funds use similar trading strategies, it allows us to attribute the differences in performance to differences in regulation and incentives rather than to differences in trading strategies. In the process, our paper also contributes to the vast

[11] See, for example, Ackermann, McEnally, and Ravenscraft (1999), Agarwal and Naik (2000, 2004), Asness, Krail, and Liew (1999), Baquero, ter Horst, and Verbeek (2004), Boyson (2005), Brown, Goetzmann, and Ibbotson (1999), Brown, Goetzmann, and Liang (2004), Brown, Goetzmann, and Park (2001), Das and Sundaram (2002), Fung and Hsieh (1997, 2000, 2001, 2004), Getmansky, Lo, and Makarov (2004), Goetzmann, Ingersoll, and Ross (2003), Jagannathan, Malakhov, and Novikov (2006), Kosowski, Naik, and Teo (2007), Liang (1999, 2000), and Mitchell and Pulvino (2001).

literature on mutual funds.[12] It is closest in spirit to studies of individual mutual fund asset classes such as money market funds, equity mutual funds, and bond funds.[13]

2.2. Development of hypotheses

This paper tests three hypotheses. First, the *Regulation and Incentives Hypothesis* posits that due to lighter regulation and better incentives, HMFs should underperform HFs. Mutual funds are regulated by the SEC through four federal laws: the Securities Act of 1933, the Securities Exchange Act of 1934, the Investment Company Act of 1940, and the Investment Advisers Act. These Acts impose several constraints on mutual funds. The Investment Company Act of 1940 restricts the ability to use leverage or borrow against the value of securities in the portfolio. The SEC requires that funds engaging in certain investment techniques, including the use of options, futures, forwards, and short selling, to cover their positions. With respect to pricing and liquidity, mutual funds are required to provide daily net asset values (NAVs) and allow shareholders to redeem their shares at any time. By contrast, HFs are largely unregulated with respect to investment options, disclosure, and incentives. Finally, HF managers are compensated through performance-based incentive fees, providing better incentives to deliver superior performance. As a result, we expect HMFs to underperform hedge funds.[14]

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[12] See, for example, Brown and Goetzmann (1995), Carhart (1997), Chevalier and Ellison (1999), Daniel, Grinblatt, Titman and Wermers (1997), Elton, Gruber, and Blake (1996a&b), Jegadeesh and Titman (1993), Jensen (1968), and Wermers (2000).

[13] For example, see Comer (2005), Elton, Gruber, and Blake (1995), Ferson (2005), and Tiwari and Vijh (2004).

[14] Under the Investment Advisers Act, the SEC recently proposed that HF advisers be subject to some of the same requirements as mutual fund advisers, including registration with the SEC, designation of a Chief Compliance Officer, implementation of policies to prevent misuse of nonpublic customer information and to ensure that client securities are voted in the best interest of the client, and implementation of a code of ethics. Since February 2006, HF advisers have been asked to comply with these requirements, which are still much less onerous than for mutual fund managers. However, a federal appeals court decision recently invalidated the SEC rule regulating HFs, so the future of this regulation is uncertain.

Second, the *Strategy Hypothesis* posits that since HMFs follow trading strategies routinely used by HFs, HMFs should outperform TMFs that do not use these trading strategies. The ability of HMFs to outperform arises from their greater flexibility. For example, a long-short fund can potentially benefit from taking long positions in undervalued securities and short positions in overvalued securities. Importantly, implementation of most of the zero-cost investment strategies proposed in the asset pricing literature such as the size, value, and momentum strategies requires the funds to take both long and short positions at the same time. The relaxation of constraints can also potentially lead to an increase in agency costs. Hence, our Strategy Hypothesis implicitly examines whether the benefits of loosening constraints outweigh the costs associated with greater agency risk.

Finally, the *Skill Hypothesis* predicts that HMF managers with experience in implementing hedge fund strategies should outperform HMF managers without these skills, and by extension of the *Strategy Hypothesis*, should outperform TMFs as well. As a measure of skill, we use a manager's experience in the hedge fund industry. Specifically, if the HMF manager *concurrently* manages a hedge fund along with a HMF, the manager is considered to be skilled or experienced. Hence, we require that managers have HF experience that is either concurrent with or precedes their experience in HMFs.[15]

3. Data and variable construction

3.1 Hedged mutual funds

We utilize a rigorous process to select the sample of HMFs. For brevity, we summarize the process here and describe it in greater detail in Appendix A. For our primary analysis, we use the CRSP Survivorship-Bias Free mutual fund database. We begin the HMF sample

[15] Since managers at hedged mutual funds sometimes change, a hedged mutual fund can be categorized as having a hedge fund manager during some years but not others.

selection by including all HMFs that appear in the Morningstar and Lipper databases, which began classifying funds as hedged mutual funds in March 2006. This step results in 26 unique funds. Since these lists are new, they do not include defunct funds. In addition, they do not include mutual funds that follow hedge fund investment strategies other than Long/Short Equity and Equity Market Neutral. To overcome these limitations, we search the CRSP and Morningstar mutual fund databases for fund names, and search internet news archives for articles regarding hedged mutual funds. As detailed in Appendix A, our search includes the terms “long/short”, “short”, “option”, “market neutral”, “arbitrage”, “hybrid”, “hedged”, “merger”, “distressed”, “arbitrage”, and “alternative.” We believe that our search of news articles has a very strong chance of identifying HMFs. Since this is a relatively new fund category that could bring additional assets to a fund family, particularly given the media attention paid to hedge funds, it is logical that fund families will want to advertise the existence of these funds. However, recognizing that this search might not identify all possible funds, we perform an additional “completeness” test, detailed below.

This initial search yields a list of 90 funds from which we eliminate those that do not use equity-based strategies or that use passive (index-based) investment strategies, based on their descriptions at www.Morningstar.com. We then review the annual reports and prospectuses of the remaining funds from 1994 to the present to determine whether they are, in fact, following “real” hedge fund strategies. We identify 22 additional funds through this process providing us a final sample of 49 funds, 13 of which are “dead” at the end of the sample period, 1994-2004. Our choice of this sample period is driven by two reasons: first, there were very few HMFs (less than 10) in operation prior to 1994, and second, to match with reliable HF data, which begins in 1994.

We perform a final "completeness" step to ensure that we are including all hedged mutual funds. Since it is possible that certain hedged mutual funds, particularly defunct funds, may not be mentioned in news stories or may have names that do not sound like hedge fund strategies, we use a statistical approach to identify additional funds. First, we calculate the average market beta from a four-factor model for the already-identified 49 hedged mutual funds as 0.36. We then calculate the four-factor market betas for all other mutual funds. Finally, we review the prospectuses and annual reports for all funds besides the 49 already identified that have market betas of less than 0.40 (rounding up the average of 0.36) for at least two years of their existence. Of this list of more than 500 funds, we identify 3 additional funds that should be classified as HMFs, one of which is defunct. Of the remaining funds with low market betas, none fit the criterion of a hedged mutual fund. Their low betas are typically due to their being sector funds, balanced funds, "asset allocation" funds, very small funds on the verge of closing, or having their assets mostly invested in cash. This final step yields us with our final sample of 52 HMFs of which 14 are defunct.

We also divide the sample of HMF managers into those with hedge fund experience ("skilled") and those without. To qualify as a manager with hedge fund experience, the manager must concurrently manage both a hedge fund and a mutual fund, or have obtained hedge fund experience prior to becoming a mutual fund manager. Of the 52 HMF managers, 27 have hedge fund experience and 25 do not. Section 6 describes in further detail the methodology used to identify "skilled" managers. Finally, we combine duplicate share classes and take asset-weighted averages of the expenses, turnover, loads, and fees following Kacperczyk, Sialm, and Zheng (2006).

3.2. Traditional mutual funds

For the sample of traditional mutual funds, we include all equity mutual funds from the CRSP Survivorship Bias Free mutual fund database. As with the sample of HMFs, we combine duplicate share classes and take asset-weighted averages of the expenses, turnover, loads, and fees. We identify a total of 3,679 TMFs during our sample period.

3.3. Hedge funds

We use HF data from the TASS database, which includes monthly net-of-fee returns, as well as management and incentive fees, size, terms (such as notice and redemption periods), and investment style of the HFs. It has been well-documented that HF databases suffer from several biases including survivorship bias and instant history or backfilling bias.[16] We control for survivorship bias by including defunct funds until they disappear from the database and mitigate the backfilling bias by excluding the fund's "incubation period" from the time-series of returns.[17] Since we need to compare the HMFs with HFs for our analysis, we restrict ourselves to those HF investment styles that closely match those used by HMFs. This provides us with the final sample of 2,179 HFs following Long/Short Equity, Equity Market Neutral, and Event Driven strategies.[18]

3.4. Key variables

Since mutual funds and hedge funds are exposed to a number of risk factors, we use risk-adjusted performance measures (alphas) for all the analyses. Alphas are defined as the intercepts from two separate regression models. The first is the Carhart (1997) four-factor model widely used in mutual fund studies. The four factors include the CRSP value-weighted market return,

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[16] For example, see Ackermann, McEnally, and Ravenscraft (1999), Fung and Hsieh (2000), Liang (2000), and Brown, Goetzmann, and Park (2001).

[17] To mitigate the incubation bias, we use data from the "Performance Start Date" instead of the "Inception Date" from the TASS database.

[18] See www.hedgeindex.com for description of investment styles.

the two Fama and French (1993) factors: size (SMB) and book-to-market (HML), and the Jegadeesh and Titman (1993) UMD (momentum) factor.

The second model is the Fung and Hsieh (2004) seven-factor model, which includes an equity market factor, a size-spread factor, a bond market factor, a credit spread factor, and three option-based factors for bonds, currencies, and commodities.[19] For both models, we estimate alphas individually for each fund using the prior 24 months of gross-of-fee and net-of-fee returns for our gross and net performance measures.[20]

Finally, we estimate two other models for robustness. These include Carhart's (1997) 4-factor model augmented with (a) Pastor and Stambaugh's (2003) liquidity factor, or (b) Agarwal and Naik's (2004) out-of-the-money put and call option factors. The results (not tabulated) from these models are similar to those from the four and seven factor models.

Table 1 reports summary statistics for HMFs, TMFs, and HFs. HMFs are further subdivided into those that have HF managers and those that do not. Panels A and B report the number and size of funds by year. All types of funds have increased in both number of funds and size. HMFs have grown 24-fold since 1994, from $743 million to over $18 billion (see column 4 of Panel B). HFs also grew rapidly during this period, increasing 20-fold from $19 billion to over $400 billion, while TMFs increased 3-fold from $541 billion to over $2 trillion (see last two columns of Panel B).[21]

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[19] We thank Kenneth French and David Hsieh for making the returns data on the four and seven factors, respectively, available on their websites.

[20] Since some funds are missing return data for some months, we require that a fund have at least 12 of the prior 24 months' returns to be included in the sample. For the analysis in Section 4, we calculate the gross performance measures for hedge funds accounting for the option-like incentive-fee contract as in Agarwal, Daniel, and Naik (2006). To compute gross-of-fee returns for mutual funds, we follow Gaspar, Massa, and Matos (2006) and others, and add to each month's net-of-fee returns, the fund's annual expense ratio divided by 12 and the total load divided by 7, as most loads expire after 7 years.

[21] The growth figures reported here are only for HFs and TMFs selected by us for this study. In particular, the selected HF funds follow investment styles corresponding those of HMFs and the TMFs are only equity-based mutual funds.

Panel C reports fund characteristics. We first compare HFs to HMFs. HFs are younger and have lower fixed expenses (measured as a percent of assets).[22] HFs also have incentive fees, but since HMFs and TMFs do not, we do not report these fees here. However, in our analysis of gross performance, these fees are considered (see footnote 20 for more detail). HFs and HMFs have similar flows and size. Since turnover and load data is not available for HFs, we do not report these statistics. Comparing HMFs to TMFs, HMFs are smaller and have lower total loads but have higher expenses, flows, and turnover. Finally, comparing HMFs with hedge fund managers to those without, their expenses are lower but turnover is higher.

Panel D reports the results of a univariate analysis of performance using both net-of-fee and gross-of-fee risk-adjusted returns. First, comparing HFs to HMFs, HFs outperform HMFs based on 4-factor and 7-factor gross and net alphas.[23] Second, comparing HMFs to TMFs, HMFs outperform TMFs based on 4-factor and 7-factor gross and net alphas. Ours is the first study to examine the performance of hedged mutual funds and document their superior performance relative to traditional mutual funds. Finally, comparing HMFs with hedge fund managers to those without, the univariate performance differences are not statistically significant at traditional levels.

Panels E and F report betas from different multifactor models. Comparing HMFs to HFs, betas for most of the factors in both the 4-factor and 7-factor models are very similar, with the

[22] At first, it seems a bit surprising that HFs are so much younger than HMFs. Upon closer investigation, we find that this result is largely driven by a few HMFs that started many years ago. If we exclude the 10 oldest HMFs which have an average age of 40 years, the remaining HMFs in the sample have an average age of 9 years, which is much closer to that of HFs. Also, "Fixed expense" is typically referred to as the "management fee" for HFs. To use a common term for both HFs and mutual funds, we refer to it as "expense" in this paper.

[23] Our finding that hedge funds have positive risk-adjusted performance is consistent with prior literature. Specifically, the magnitude of 7-factor alphas of about 6.4% per annum using net-of-fee returns is similar to that reported in Kosowski, Naik, and Teo (2007), who document alphas of about 5.4% per year during 1994-2002 period. Some other papers report positive Jensen's alphas for hedge funds. Using data from 1988-1995, Ackerman, McEnally, and Ravenscraft (1999) find annual alphas in the 6-8% range while Brown, Goetzmann, and Ibbotson (1999) report annual alphas of about 5.7% per year for offshore hedge funds.

sole exception that HFs load more heavily on the small-cap factor in both models. The similarities in market betas for the 4 and 7 factor models, and the fact that both are well below the beta on the market of 1, indicate that HMFs are following similar investment strategies to HFs, notably, strategies that are not "long-only" in nature. Comparing HMFs and TMFs, the market beta on both models is significantly higher for TMFs than for HMFs, again, indicating that TMFs tend to be mostly "long-only" in their investment styles (with market beta very close to 1), relative to HMFs. Finally, comparing HMFs with HF managers to those without, those with HF managers tend to load more heavily on the small-cap factors.

Panel G compares risk measures among the three categories. HFs have higher standard deviation, skewness, and excess kurtosis compared to HMFs. Comparing HMFs and TMFs, TMFs have higher standard deviation, more negative skewness, and lower kurtosis than HMFs. Finally, comparing HMFs with HF managers to those without, the only significant difference is that standard deviation is lower for those HMFs with HF managers.

The next section tests our first hypothesis.

4. Testing the *Regulation and Incentives Hypothesis*

We begin our analysis by comparing the performance of HFs and HMFs. We expect that differences in regulation related to trading, leverage, disclosure, liquidity, and transparency between HMFs and HFs, as well as differences in incentive compensation plans will cause HMFs to underperform HFs. Thus, we propose the following hypothesis:

Regulation and Incentives Hypothesis: Given the more stringent regulations and weaker incentives faced by TMFs as compared to HFs, we expect HMFs to underperform HFs.

While Table 1 provides initial evidence that HFs outperform HMFs on a risk-adjusted basis, these univariate statistics do not control for fund characteristics, past performance, and other factors that have been shown to be related to hedge fund and mutual fund returns. Hence, we estimate the following regression using annual data for all three fund types — HMF, TMF, and HF:

$$Perf_{i,t} = \beta_0 + \beta_1 HF + \beta_2 HMF + \beta_3 Perf_{i,t-2} + \beta_4 Size_{i,t-1} + \beta_5 Age_{i,t-1} + \beta_6 Expense_{i,t-1} + \beta_7 Flow_{i,t-1} + \sum_{t=1}^{9} \beta_8 I(Year_t) + \xi_{i,t} \quad \textbf{(1)}$$

where $Perf_{i,t}$ and $Perf_{i,t-2}$ are the performance measures of fund *i* in years *t* and *t-2* respectively, *HF* is an indicator variable that equals 1 if the fund is a HF and 0 otherwise, *HMF* is an indicator variable that equals 1 if fund is a HMF and 0 otherwise, (hence, the missing variable represents *TMF*), $Size_{i,t-1}$ is the size of the fund measured as the natural logarithm of the assets under management for fund *i* during year *t-1*, $Age_{i,t-1}$ is the logarithm of age of fund *i* at the end of year *t-1*, $Expense_{i,t-1}$ is the expense ratio of fund *i* during year *t-1*, $Flow_{i,t-1}$ is the percentage money flow in fund *i* in year *t-1*, and $I(Year_t)$ are year dummies that take a value of 1 during a particular year and 0 otherwise, and $\xi_{i,t}$ is the error term. The total load and turnover variables are not included in regression in equation (1) since they are not available for hedge funds.

Since the regressions use annual data but the dependent variable is measured using 24-month alphas, there is overlap in the dependent variable of one year. This overlap causes misstatement in the standard errors, as noted by Petersen (2006). In addition, as noted by Brav (2000), cross-sectional correlation between fund residuals in the same year can also lead to improperly stated standard errors. To correct for both these potential problems, as well as any unobserved autocorrelation, we use White (1980) standard errors adjusted to account for autocorrelation within two separate "clusters"; clusters include both "fund" and "time".[24] In addition, we lag the performance measures used as independent variables by two periods to ensure the independent and dependent variables also have no overlap.[25] Finally, as hedge fund returns are known to have a non-normal distribution, we adjust for its effect on finite-sample inference by using bootstrapped standard errors using 1,000 replications. Hence, throughout the paper, we report the bootstrapped p-values.[26]

Since the omitted dummy variable in this regression is the *TMF* variable, a positive coefficient on the *HF* dummy variable indicates that HFs outperform *TMFs*. We find this to be the case, and the difference is quite large, ranging from 41.4 bp per month (about 5.0% per year) to 79.0 bp per month (about 9.5% per year). This result is consistent with prior hedge fund literature; for example, see Ackermann, McEnally, and Ravenscraft (1999) and Liang (1999). However, our focus is not on comparing HFs with TMFs, but rather on testing the *Regulation and Incentives Hypothesis*, which compares the performance of HFs to HMFs. A positive and significant difference *(HF-HMF*) indicates support for the *Regulation and Incentives Hypothesis.*

For both four-factor and seven-factor models, using both gross and net alphas, we find strong support for the hypothesis: HFs outperform HMFs in a statistically and economically

[24] This correction is also known as the Rogers (1993) correction, and controls for autocorrelation over the entire time-series of each fund's observations. This adjustment may be contrasted with the Newey-West (1987) correction for autocorrelation, which can be specified up to a particular lag length. As Petersen (2006) notes, the Rogers (1993) correction produces unbiased estimates, while the Newey-West (1987) correction will lead to biased estimates (although the longer the lag length, the smaller the bias). The approach also controls for cross-correlation, to address the issue noted by Brav (2000). Petersen (2006) describes the approach that we follow in this paper, where we cluster on both fund and time to adjust standard errors for both types of potential auto- and cross-correlation. We thank Mitchell Petersen for providing us the STATA code for this analysis.

[25] We acknowledge that this imposes a survival requirement of four years for funds to be included in our sample. This kind of bias is referred to as look-ahead bias (Carpenter and Lynch (1999). In our defense, we offer two explanations for why this should not affect our results. First, since we are interested in relative and not absolute performance of HMFs, such bias should not materially affect our results as it should affect both the TMFs and HMFs. Second, for robustness, we exclude lagged alpha as an independent variable from our regression, which reduces the survival requirement to two years. Our results remain unchanged with this alternative specification.

[26] One could also conduct this analysis (and all analyses in the paper) at the monthly level rather than at the annual level. Later, we test the robustness of our findings using monthly data and find that all our results continue to hold.

significant way (at the 1% level). The differences in net-of-fee performance range from a low of 19.1 bp to 27.9 bp per month (from about 2.3% to 3.3% per year) for the 4-factor and 7-factor models respectively. The corresponding figures for the gross-of-fee alphas are larger ranging from 31.4 bp to 40.7 bp a month (from about 3.8% to 5.0% a year). The difference in the level of outperformance of HFs using net and gross performance measures can be related to the higher fees charged by HFs. We attribute these differences in performance to lighter regulation and better incentives in HFs. Moreover, the statistical significance of these results is even more impressive given the small sample size of HMFs.

To summarize, our results in this section strongly support the regulation and incentives hypothesis. Hedge funds outperform hedged mutual funds, indicating that using strategies similar to hedge funds cannot alone overcome the regulatory and incentive-based constraints of mutual funds. However, while hedge funds outperform hedged mutual funds by a significant margin (2.3% to 5.0% per year), it is not nearly as large as the margin of outperformance of hedge funds over traditional mutual funds (5.0% to 9.5% per year). This implies that HMFs are adding value relative to TMFs. This result leads naturally to our test of the second hypothesis: the *Strategy Hypothesis.*

5. Testing the *Strategy Hypothesis*

The second hypothesis is as follows:

Strategy Hypothesis: HMFs should outperform TMFs due to major differences in strategy.

HMFs use strategies such as "long-short equity" that are not commonly used by mutual funds. The ability to profit from both long and short trades in equity markets with lower systematic risk should enable HMFs to outperform TMFs. We use the regressions presented in

Table 2 to test the *Strategy Hypothesis.* A positive and statistically significant coefficient on the *HMF* indicator variable indicates that HMFs outperform TMFs (the omitted variable).

The results in Table 2 strongly support the *Strategy Hypothesis*. For all four regression specifications, HMFs outperform TMFs at a statistically significant level. The differences in performance range from 21.5 basis points (2.6% per year) for the gross four-factor model to 40.2 basis points (4.9% per year) for the net 7-factor model (see the row for "HMF indicator"). This finding is encouraging. Despite the heavy regulations of the mutual fund industry, the trading strategies employed by HMFs can be successful in improving performance. This result is even more impressive considering the higher expense ratios of HMFs relative to TMFs.

For robustness, we also conduct a matched sample analysis to compare the performance of three categories of funds (HFs, HMFs, and TMFs). For this purpose, each year we match each of the HMFs first with HFs and then with TMFs that follow the same strategy, have similar assets under management, and have been in existence for the same time (i.e., age). We follow a one-to-one matching procedure and report the results from the non-parametric Wilcoxon signed rank tests in Table 3.[27] The results from the matched sample procedure confirm our earlier findings from multivariate regressions in Table 2. In particular, we continue to find that HFs outperform HMFs ranging from 35 to 38 bp per month using gross-of-fee returns, and from 28 to 33 bp per month using net-of-fee returns. This result confirms the support for the *Regulation and Incentives Hypothesis*. In addition, we continue to find that HMFs significantly outperform TMFs by 15 to 34 bp per month on a gross-of-fee basis, and about 29 bp per month on a net-of-fee basis. This result lends support to the *Strategy Hypothesis*.

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[27] Recently, Davies and Kim (2006) show that following these practices increases the statistical power of the tests and provides better test properties.

We also perform a number of other robustness checks for our empirical tests later in Section 6.3. We demonstrate that our results continue to hold using alternative specifications. In the next section, we investigate whether strategy alone appears to be driving these results, or if there might be a further explanation, notably manager skill.

6. Testing the *Skill Hypothesis*

6.1. Regression Analysis

The previous section provides evidence that HMFs outperform TMFs based on strategy. In this section, we investigate whether skill is also driving this outperformance. The dataset of HMFs has a unique feature: about one-half of the HMFs are run by managers that concurrently manage HFs. We hypothesize that experience gained in the HF industry should be advantageous in managing HMFs:

Skill Hypothesis: HMFs managed by HF managers will outperform those that are not.

To test this hypothesis, we subdivide the sample of HMFs into those funds having HF managers and those without. We gather information regarding managers from a variety of sources. The first approach is to match the manager name, management company name, and/or fund name from the CRSP database with the hedge fund database (TASS). We find 9 matches in this way, all of which we verify using the second approach of searching for the mutual fund company's website for manager's information and the additional funds he/she manages. This information is reported in the fund's Statement of Additional Information (SAI) that funds are required to file regularly with the SEC (available from funds' website or www.sec.gov). In addition to searching these venues, we perform a broad internet search looking for interviews with the manager in which he/she specifically discusses his/her management of both a HMF and a hedge fund.

Using this search process, we identify 27 HMFs that are run by HF managers and 25 that are run by TMF managers. Interestingly, 12 of the 14 defunct HMFs belong to this latter category, providing preliminary support for the *Skill Hypothesis*. We create an indicator variable set to 1 for the years when the HMF is run by a HF manager (*HFM-YES*) and zero otherwise. We also create a variable set to 1 if the HMF is not run by HF manager (*HFM-NO*) and zero otherwise. Effectively, we are splitting the *HMF* indicator variable from Table 2 into two separate variables.

To formally test the *Skill Hypothesis*, we first estimate the following multivariate regression:

$$\begin{aligned} Perf_{i,t} &= \beta_0 + \beta_1 HF + \beta_2 HFM-YES + \beta_3 HFM-NO + \beta_4 Perf_{i,t-2} + \beta_5 Size_{i,t-1} \\ &+ \beta_6 Age_{i,t-1} + \beta_7 Expense_{i,t-1} + \beta_8 Flow_{i,t-1} + \sum_{t=1}^{9} \beta_9 I(Year_t) + \psi_{i,t} \end{aligned} \tag{2}$$

where all variables except *HFM-YES* and *HFM-NO* have been defined previously for the regression in equation (1).

HFM-YES is set to 1 if the HMF is managed by a HF manager, and *HFM-NO* is set to 1 if it is not. The missing variable is *TMF*. We perform the same regression analysis as in Table 2, but with the new indicator variables. If the *Skill Hypothesis* holds, then the difference between the *HFM-YES* and *HFM-NO* variables will be positive and statistically significant.

The results in Table 4 generally support the *Skill Hypothesis.* In both of the gross regression specifications, the difference between *HFM-YES* and *HFM-NO* is positive and statistically significant (see last row of Table 4), and the differences range from a low of 22.9 basis points per month (2.8% annually) for the four-factor gross return model, to a high of 35.8 basis points per month (4.4% annually) for the seven-factor gross return model. For net-of-fee returns, although the difference is positive, it is not statistically significant.[28] In addition, the coefficient on the *HFM-YES* variable is always positive and statistically significant while that on the *HFM-NO* variable, although always positive, is only statistically significant for net returns. This suggests that our earlier result of HMFs outperforming TMFs are at least partially driven by those HMFs that are run by HF managers.

Our regression in equation (2) does not control for turnover and total load as information on these variables does not exist for HFs. Therefore, as an additional test of the *Skill Hypothesis*, we use a pooled sample of HMFs and TMFs (i.e., we exclude HFs) and estimate the following regression including turnover and total load as additional control variables:

$$\begin{aligned} Perf_{i,t} &= \beta_0 + \beta_1 HFM - YES + \beta_2 HFM - NO + \beta_3 Perf_{i,t-2} + \beta_4 Size_{i,t-1} + \beta_5 Age_{i,t-1} \\ &+ \beta_6 Expense_{i,t-1} + \beta_7 Flow_{i,t-1} + \beta_8 Turnover_{i,t-1} + \beta_9 TotalLoad_{i,t-1} + \sum_{t=1}^{9} \beta_{10}^{s} I(Year_t) + \psi_{i,t} \end{aligned} \quad \textbf{(3)}$$

The results in Table 5 provide even stronger support for the *Skill Hypothesis.* It appears that including the load and turnover variables is important in this regression. Both of these variables are significant in all but one of the four specifications.[29] In three of the four regression specifications managers with hedge fund experience significantly outperform those without. This outperformance ranges from 27.7 to 46.9 basis points per month (3.3% to 5.6% per year).

Finding support for the *Skill Hypothesis* indicates that retail investors can benefit from the skills of hedge fund managers, within the regulatory environment of mutual funds. A natural question related to this finding is: Why would hedge fund managers choose to enter the mutual

[28] When we repeat our analysis using matched sample procedure (results not reported in the table), we do find the difference based on 4-factor net alphas to be positive and significant (9 basis points per month). Further, the difference based on gross alpha varies from 14 to 21 basis points per month using the two models.
[29] In an earlier version of our paper, we conducted our analysis using a pairwise comparison of HMFs with TMFs, and then of HMFs with HFs. Turnover and load were included as additional variables in the first case (as in Table 4). Since comparing all funds together provides more statistical power as it controls for the differences in the three types of managed portfolios, we now conduct our initial analysis in Section 2 using a pooled sample of HMFs, TMFs, and HFs. Our results from the pairwise comparison are similar to those reported in Section 2.

fund area given its more stringent regulatory restrictions, tighter investment constraints, and lack of performance-based incentives? We explore two possible, though not mutually exclusive, explanations. The first is that perhaps only HF managers who underperform their peers elect to offer HMFs. The second is that these HF managers may be using HMFs to raise assets through alternative means. While it is likely that HF managers prefer the freedom and higher fees associated with HFs, if they are having difficulty attracting assets in their hedge funds, HMFs may provide an attractive means as they can be advertised and can be marketed to a much larger investor base including retail clients. They may also be appealing to institutional investors who prefer greater disclosure and transparency.

To investigate whether only underperforming HF managers offer HMFs, we compare the performance of their hedge funds relative to their peers by estimating the following regression[30]:

$$\begin{aligned} Perf_{i,t} &= \beta_0 + \beta_1 HF-with-HMF + \beta_2 Perf_{i,t-2} + \beta_3 Size_{i,t-1} + \beta_4 Age_{i,t-1} \\ &+ \beta_5 Expense_{i,t-1} + \beta_6 Flow_{i,t-1} + \sum_{t=1}^{9} \beta_7 I(Year_t) + \psi_{i,t} \end{aligned} \quad \textbf{(4)}$$

All variables are as in equation (2) except for the variable *"HF-with-HMF"*, which is an indicator variable set to 1 if the HF manager concurrently manages a HMF and 0 otherwise. A positive coefficient on this variable would indicate that HFs that also have HMFs outperform other HFs. We report our findings in Table 6. The results in Panel A show that the coefficients on the indicator variable are positive, although not statistically significant. This suggests that the performance of HFs offered by managers who also run HMFs is no worse than that of other HFs. As a robustness check, we repeat our analysis using a matched sample procedure as before. The results in Table 6, Panel B corroborate the results in Panel A from the multivariate regression.

[30] It is important to note that this regression is estimated for the pooled sample of only HFs and does not include HMFs and TMFs.

Overall, these results indicate that it is not poor HF performance that drives the managers into offering HMFs.

Next, we investigate the possibility that HFs offer HMFs to gather assets. As argued in the Introduction, it is difficult for smaller HFs to raise assets due to reputational effects and restrictions on advertising. Since it is difficult to test this idea empirically due to the small sample size of HFs with HMFs, we do the following. First, we conduct interviews with two managers who offer both HFs and HMFs – Dennis Bein of Analytical Investors and Lee Schultheis of Alpha Hedged Strategies. Both state that gathering assets under management is a key reason for concurrently managing HFs and HMFs.[31] Second, we cite a number of recent articles supporting the idea that it is difficult for lesser-known HF managers to attract assets, and that the HMF space is a good way for many of them to grow their AUM and establish a stable revenue base. See Appendix B for detailed quotes and citations from these articles. Given this evidence, we conclude that raising assets is a reasonable rationale for why some HF managers also offer HMFs.

To summarize, this subsection's results provide strong evidence in support of the *Skill Hypothesis*. To further investigate the prevalence of manager skill among HF managers with HMFs, the next section examines performance persistence for the two groups of HMFs — those with HF managers and those that without.

6.2. Performance Persistence

[31] Mr. Bein believes that there are additional benefits from offering HMFs concurrently, namely opening up the firm's products to the retail space and having a stable base of assets earning a fixed fee. Mr. Schultheis notes that institutions and fund-of-hedge-funds investing in HFs prefer larger funds. He also makes the point that it is often very difficult for HF managers to gather assets beyond their initial foray into the market. As a result, many of these smaller HFs have to sell portions of their firms to venture capitalists (VC) to achieve critical assets under management (AUM) or to survive in the long term. Offering HMFs concurrently provides them an alternative way to increase AUM, revenues, and long-term sustainability without giving up any equity to VC firms.

Extant literature highlights the importance of using survivorship-bias-free data to study persistence (for example, see Brown, Ibbotson, and Ross (1992) and Brown and Goetzmann (1995)). Our analysis includes both surviving and defunct HMFs – 14 defunct and 38 live funds. Each HMF is ranked relative to all HMFs each year based on the fund's annual return in excess of the risk-free rate. If a fund is in the top (bottom) half of returns for the year, it is called a winner, *W* (loser, *L*). If a fund is a winner (loser) in two consecutive years, we denote it as *WW* (*LL*). If a fund fails after the first period, it is categorized as a loser in the second period. We report the contingency table of winners and losers in Table 7.

We use two statistical tests to measure the significance of the results. The first follows Brown and Goetzmann (1995) and Agarwal and Naik (2000), and uses the cross-product ratio (CPR) of funds that are repeat winners/losers to funds that are not, as well as the associated t-statistic. A positive (negative) and significant t-statistic implies that performance persists (reverses).[32] The second measure of statistical significance is similar, but we calculate it for the winner-winner and loser-loser funds separately to determine which group is driving persistence. For this purpose, we follow Malkiel (1995) to compute the z-statistic as follows:

$$z = \frac{Y - np}{\sqrt{np(1-p)}} \qquad \textbf{(5)}$$

where n is the number of funds, p is the probability that a winner in one period continues to be a winner in the next period, and Y is a random variable for the number of persistently winning funds. When n is reasonably large (n>20), the distribution of z-statistic approaches a standard normal distribution with mean of zero and standard deviation of one.

[32] CPR is given by (WW*LL)/(WL*LW) while the standard error of the logarithm of CPR is $\sigma_{\log(CPR)} = \sqrt{\frac{1}{WW} + \frac{1}{WL} + \frac{1}{LW} + \frac{1}{LL}}$.

The results in Table 7 indicate evidence of persistence in the performance of HMFs. Winners repeat more often than losers (61.3% and 41.7%, respectively, see the fifth column of Table 7, Panel A). We also perform these tests using 4-factor and 7-factor alphas and find that the results are generally consistent (results not reported for brevity).

We next investigate if higher skill is associated with higher persistence. As in the prior section, we divide the sample into HFM-YES and HFM-NO funds. We next calculate the percentage of winner/winner and loser/loser funds based on the total number of funds in each category every year. Panel B reports results.

For the sample period, there are 18 winner-winner HMFs that do not have HF managers and 50 winner-winner HMFs with HF managers. The 18 persistent winner HMFs without HF experience represent 22.5% (18 divided by 80) of the total HMFs without HF experience. The 50 persistent winner HMFs with HF experience represent 37.3% (50 divided by 134) of the total HMFs with HF experience. Hence, in terms of proportion, more of the persistent winner HMFs are those with HF managers. The null hypothesis for no persistence implies that the proportion of funds with repeat performance should be 25% (as opposed to 23% and 37% above). The same interpretation holds for loser-loser funds; in this case, 35% of the HFM-NO funds are repeat losers while only 24% of the HFM-YES funds are repeat losers. Again, it appears that persistence is strongest among HMFs with HF managers.

Overall, the results in Table 7 provide evidence that the repeat winners are more likely to be those HMFs with HF managers, while the repeat losers are likely to be HMFs without HF managers. Despite a modest sample size, this analysis provides further evidence that HMFs with HF managers have skill while their counterparts do not, which can explain the outperformance of HMFs over TMFs.

6.3 Robustness Tests

We perform several robustness tests to check the validity of our results. First, to control for fund-specific and management-company-specific effects, we repeat all our analyses with management-company random effects and fund random effects. We report the robustness checks for all the analyses collectively in Table 8. For the ease of comparison, the first row of this table repeats the findings from the main tables. Panels A, B, and C, of Table 8 corresponding to Tables 2, 4, and 5 indicate that the results for HMFs, HFs, and TMFs are generally robust to the use of alternative econometric specifications.

Second, we repeat all our analyses using monthly data instead of annual data. Although monthly data provides many more observations, it also introduces significant serial correlation in alphas as they are estimated each month using a 24-month rolling window. We conduct this analysis using both pooled and Fama-MacBeth (1973) regressions and report our findings in Table 9, carefully controlling for autocorrelation (clustering on both fund and month) and using bootstrapped standard errors with 1,000 replications to account for the non-normality in the distribution of alphas. Note that the double clustering in pooled regressions adjusts for the correlation of fund's return over time as well as cross-sectional correlation between fund residuals in the same month. For the Fama-MacBeth (1973) regressions, we adjust the standard errors for autocorrelation and heteroskedasticity using the Generalized Method of Moments (GMM, Hansen (1982)) procedure. Our findings continue to provide strong support for our three hypotheses.[33] Hence, the statistical significance of our findings using monthly data is not sensitive to the regression approach used.

[33] We also repeat our entire analysis using the Fama-MacBeth (1973) approach applied to annual data. While the annual results are qualitatively similar the monthly results, the statistical significance is lower due to fewer observations.

Third, we repeat our analysis with alphas estimated from conditional models (e.g., Ferson and Schadt (1996)) instead of unconditional asset pricing models. It is important to note that our use of 24-month rolling windows to estimate "unconditional" alphas does allow for time-variation in alphas and betas.[34] Nevertheless, for robustness, we also conduct our analysis using conditional alphas and report our findings in Table 10. Specifically, we introduce lagged "information variables" to the four and seven factor models. We interact these variables with the market factor (value-weighted CRSP return in the four factor model and S&P 500 return in the seven factor model). We use the same information variables as in Ferson and Schadt (1996): lagged dividend yield on the S&P 500, lagged term spread, lagged credit spread, lagged risk-free rate, and a January dummy. Data for these variables is from CRSP and the U.S. Federal Reserve website.

Conditional models have not been used frequently in the hedge fund literature mainly due to the relatively short time frame for which hedge fund data is available. The few academic studies that have been conducted in this area conclude that using conditional models does not improve the estimation of alphas or betas.[35] In addition, the problem of a short time frame is exacerbated in our sample of HMFs, since many of these funds did not begin until 1998. One reason that we use 24-month alphas in all our analyses is that this time frame is long enough for estimation purposes but short enough that it does not induce too much survivorship bias or lead to exclusion of too many HMFs from our sample. Given these caveats, we perform both

[34] Ferson and Schadt (1996) themselves acknowledge this in footnote 1, page 426 of their paper by stating "Sirri and Tufano (1992) use rolling regressions for Jensen's alpha, an approach that may approximate conditional betas."

[35] A few hedge fund papers that have used conditional models tend to use a much longer time frame to estimate alphas. Some examples include Gupta, Cerrahoglu, and Daglioglu (2003) who find that using conditional models does not improve the estimation of alphas or betas. Kazemi and Schneeweis (2003) come to a similar conclusion using a stochastic discount factor approach.

monthly and annual analyses using the conditional alphas estimated from 24-month rolling windows.

The results of Table 10 from conditional models using both monthly and annual analyses continue to strongly support the regulation and incentives hypothesis as well as the strategy hypothesis. The support for the skill hypothesis is marginally weaker from a statistical standpoint, although the signs on the coefficients are always consistent with the results in Tables 2, 4, 5, and 9.

We also conduct three more robustness checks. For the sake of brevity, we summarize the findings without reporting them in tabular form. First, we repeat our analysis using only the sample period from 1998 to 2004 since there is a large increase in the number of HMFs between 1997 and 1998 (the sample grows from 15 to 27 funds). We believe that this increase is due to the repeal of the "short-short" rule, which constrained mutual funds to receiving less than 30% of their gross income from sale of securities held for less than three months. Violation of this rule resulted in tax penalties on short-term gains. This restricted the funds from investing in derivatives as most options and futures contracts mature within three months and can thereby result in short-term gains.[36] With the repeal of the short-short rule, the number of HMFs grew dramatically. However, regardless of whether we use the sample period 1994-2004 or 1998-2004, our results are qualitatively similar.

Second, we perform robustness tests to determine whether the overlap in the independent variable affects the results, although we specifically control for this bias by adjusting the standard errors for clustering on both time and fund effects. To do so, we split the sample into two sub-samples using odd and even years, still using the double-clustering approach to control

[36] See Yi and Kim (2005) for a good description of the short-short rule and implications of its abolition for mutual funds.

for auto-correlation and cross-sectional correlation. Results for the split sample are very similar to the results for the combined sample.

Finally, we examine if our results are sensitive to general market conditions. For this purpose, we divide the sample period into "up" years (1995-1999 and 2003) and "down" years (1994, 2000-2002, 2004) based on the median return of the S&P 500 index during the sample period. We then re-estimate all our regressions from Tables 2, 4 and 5 for these two sub periods. We find qualitatively similar results. Thus, HMFs outperform TMFs, and HFM-YES funds outperform HFM-NO funds, regardless of the market conditions.

The results of all these robustness tests unequivocally support our three hypotheses and indicate that they are not an artifact of the use of econometric methodologies (pooled versus Fama-MacBeth (1973)), choice of asset pricing models (conditional versus unconditional), and estimation of alphas at different horizons (monthly versus annual).

7. Conclusion

This paper provides the first comprehensive examination of a new category of mutual funds – hedged mutual funds. We define hedged mutual funds as mutual funds that intentionally emulate hedge fund strategies to enhance performance. We test three hypotheses using data on hedged mutual funds, traditional mutual funds, and hedge funds following similar investment styles.

The first hypothesis, the *Regulation and Incentives Hypothesis*, posits that hedged mutual funds will underperform hedge funds, due to significant differences in regulation and incentives between the two industries. This hypothesis holds true. Hedged mutual funds significantly underperform hedge funds, both on a net-of-fee basis (by as much as 4.1% per year) and on a gross-of-fee basis (by about 5.6% per year). Our interpretation is that the tighter regulatory environment in mutual funds, which limits funds' borrowing to one-third of their assets and requires them to provide daily liquidity and pricing in addition to covering their short positions, constrains the ability of hedged mutual funds to implement strategies with the same freedom they have in the hedge fund environment. Further, hedged mutual funds have weaker incentives to deliver superior performance in the absence of performance-based compensation. Thus, it is not surprising that, as a group, hedged mutual funds strongly underperform hedge funds.

Next, the *Strategy Hypothesis* predicts that hedged mutual funds will outperform traditional mutual funds since HMFs possess greater investment flexibility and use strategies that take advantage of good market conditions as well as bad, and profit from both long and short positions in the market. Arguably, greater flexibility is associated with a potential increase in agency costs. However, our finding that hedged mutual funds outperform traditional mutual funds by about 2.6% to 4.8% per year suggests that the benefits of greater flexibility outweigh the increase in agency costs.

Further, the *Skill Hypothesis* provides an additional explanation for the superior performance of hedged mutual funds relative to traditional mutual funds. Specifically, the hypothesis predicts that managers with experience in hedge fund trading strategies will outperform those managers without such experience. Again, we find strong support for this prediction. Managers with hedge fund experience outperform those without by approximately 3.3% to 5.6% per year. In addition, we provide evidence that HMF managers with hedge fund experience are persistent "winners" while those without hedge fund experience are persistent "losers."

Finally, we provide evidence that it is not the poorly performing HF managers that choose to offer HMFs. Anecdotal evidence seems to suggest that this phenomenon is driven by the desire of hedge fund managers to have a diversified clientele base as well as to raise more assets. Taken together, our findings suggest that providing greater flexibility to hedged mutual funds through a wider investment opportunity set helps them to outperform than traditional mutual funds. This is especially true for hedged mutual funds that are run by managers with experience in implementing hedge-fund-like strategies. These findings have important implications for investors seeking hedge-fund-like exposure at a lower cost and within the comfort of a regulated environment.

Table 1: Summary statistics for hedged mutual funds (HMF), traditional mutual funds (TMF), and hedge funds (HF)

Panel A reports the number of hedged mutual funds (HMFs), traditional mutual funds (TMFs), and hedge funds (HF) each year during the sample period, 1994-2004. HMFs are further delineated into those with hedge fund managers (HFM-YES) and those without (HFM-NO). Panel B reports assets under management. Panel C reports the average fund age, size (the beginning-of-the-year assets under management (AUM)), expense ratio (annual expenses stated as a percentage of assets), fund flows (AUM in year *t* minus AUM in year *t-1* less the return between year *t* and *t-1* divided by total assets in year *t-1*), total load, and turnover data, and also reports the mean differences and results of a t-test comparing the means. Total load and turnover data is not available for HFs. The standard errors for the t-test are corrected for auto- and cross-correlation through clustering over fund and time. Differences marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Panel A: Number of funds by type and year

Year	Number of HMFs			Number of TMFs	Number of HFs
	ALL	HFM-YES	HFM-NO		
1994	10	8	2	1,493	352
1995	11	9	2	1,644	469
1996	14	11	3	1,831	616
1997	15	11	4	2,042	760
1998	27	15	12	2,292	897
1999	31	16	15	2,494	1,071
2000	37	20	17	2,788	1,261
2001	42	23	19	2,906	1,420
2002	44	25	19	2,930	1,526
2003	46	26	20	2,933	1,549
2004	46	26	20	2,833	1,512

Panel B: Total assets by type and year

Year	Total assets HMFs ($ millions)			Total assets TMFs ($ millions)	Total assets HFs ($ millions)
	ALL	HFM-YES	HFM-NO		
1994	$743	$578	$165	$541,195	$19,700
1995	$782	$602	$180	$781,188	$26,597
1996	$1,196	$998	$198	$1,037,042	$36,231
1997	$1,321	$1,055	$266	$1,388,759	$52,381
1998	$2,046	$1,447	$599	$1,742,356	$68,262
1999	$3,216	$1,538	$1,678	$2,300,086	$112,874
2000	$4,662	$2,159	$2,503	$2,279,010	$139,531
2001	$5,278	$3,097	$2,181	$1,908,663	$241,176
2002	$5,654	$3,728	$1,926	$1,470,058	$230,799
2003	$10,142	$6,157	$3,985	$1,981,013	$293,901
2004	$18,629	$7,331	$11,298	$2,229,375	$416,782

Panel C: Fund characteristics

Fund Characteristic	Mean: HMF			Mean: TMF	Mean: HF	Difference (HMF – HF)	Difference (HMF – TMF)	Difference (HFM-YES – HFM-NO)
	Mean: ALL	Mean: HFM-YES	Mean: HFM-NO					
Fund age (years)	18.23	20.27	18.04	18.06	4.27	13.96***	0.17	2.23*
Size ($ millions)	$222.32	$185.60	$276.70	$769.90	$191.14	$31.18	–$547.58***	–$91.10
Expenses (% of assets)	1.98%	1.86%	2.16%	1.32%	1.20%	0.78%***	0.66%***	–0.30%***
Annual flows (% of assets)	55.98%	52.79%	61.25%	25.56%	75.89%	–19.91%	30.42%***	–8.46%
Total load (% of assets)	2.56%	2.46%	2.72%	2.89%	NA	NA	–0.33%**	–0.26%
Turnover (% of assets)	346.67%	418.79%	232.54%	99.35%	NA	NA	247.32%***	186.25%***

Table 1 (cont.): Summary statistics for hedged mutual funds (HMF), traditional mutual funds (TMF), and hedge funds (HF)

Panel D provides averages of performance measures including alphas from the Carhart (1997) four-factor model and the Fung and Hsieh (2004) seven-factor model estimated each year using 24 months of net-of-fee and gross-of-fee returns, for HMFs, TMFs, and HFs and differences of means and results of a t-test comparing the means. Panel E reports the averages of the beta coefficient estimates from the Carhart four-factor model. The four factors are the value-weighted CRSP index less the risk-free rate which is called the market factor (B_{MKT}), the Fama-French (1993) Small minus Big (SMB) and High minus Low (HML) factors (B_{SMB} and B_{HML}), and Jegadeesh and Titman's (1993) Momentum factor (B_{UMD}). Panel F reports beta coefficient estimates from the Fung and Hsieh seven-factor model, which includes an equity market factor (SP500), a size spread factor (WSPREAD), a bond market factor (CMTCH), a credit spread factor (BAACMTCH) and three option-based factors for bonds (BLS), currencies (CULS), and commodities (COLS). Panels E and F also report the average adjusted R^2 from the four- and seven-factor models. Panel G reports the average standard deviation, skewness, and kurtosis of monthly returns. For these three panels, differences are reported, and t-tests for the difference in means are performed, with standard errors corrected for auto- and cross-correlation through clustering over fund and time. For Panel D, the standard errors have been bootstrapped with 1,000 replications. Differences marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Panel D: Performance measures

Performance measure	Mean: HMF			Mean: TMF	Mean: HF	Difference (HMF − HF)	Difference (HMF − TMF)	Difference (HFM-YES − HFM-NO)
	Mean: ALL	Mean: HFM-YES	Mean: HFM-NO					
Net return: Annualized								
4-factor alpha	0.57%	1.04%	−0.27%	−0.76%	6.56%	−5.99%***	1.33%***	1.31%
7-factor alpha	−0.32%	0.40%	−1.57%	−4.25%	6.40%	−6.72%***	3.93%***	1.97%
Gross return: Annualized								
4-factor alpha	3.39%	3.72%	2.65%	0.90%	8.61%	−5.22%***	2.49%***	1.07%
7-factor alpha	2.88%	3.50%	1.53%	−2.55%	8.55%	−5.67%***	5.43%***	1.47%

Panel E: Four-factor model beta estimates

Beta estimate	Mean: HMF			Mean: TMF	Mean: HF	Difference (HMF − HF)	Difference (HMF − TMF)	Difference (HFM-YES − HFM-NO)
	Mean: ALL	Mean: HFM-YES	Mean: HFM-NO					
β_{MKT}	0.341	0.349	0.325	0.931	0.346	−0.005	−0.590***	0.024
β_{SMB}	0.127	0.165	0.060	0.108	0.224	−0.097***	0.019	0.105***
β_{HML}	0.075	0.078	0.069	0.018	0.089	−0.014	0.057**	0.009
β_{UMD}	0.017	0.008	0.033	0.007	0.000	0.017	0.010	−0.025
Adjusted R^2	45.27	45.87	44.21	79.59	32.54	NA	NA	NA

Panel F: Seven-factor model beta estimates

Beta estimate	Mean: HMF			Mean: TMF	Mean: HF	Difference (HMF − HF)	Difference (HMF − TMF)	Difference (HFM-YES − HFM-NO)
	Mean: ALL	Mean: HFM-YES	Mean: HFM-NO					
β_{SP500}	0.313	0.323	0.295	0.916	0.354	−0.041	−0.603***	0.028
$\beta_{WSPREAD}$	0.206	0.224	0.176	0.340	0.287	−0.081***	−0.134***	0.048
β_{CMTCH}	−0.126	−0.018	−0.317	0.219	−0.263	0.137	−0.345	0.299
$\beta_{BAACMTCH}$	−0.738	−0.481	−1.192	0.373	−2.646	1.908*	−1.111	0.711
β_{BLS}	0.002	0.001	0.003	0.006	0.002	0	−0.004	−0.002
β_{COLS}	0.003	−0.007	0.019	−0.002	0.004	−0.001	0.005	−0.026***
β_{CULS}	0.005	0.006	0.002	0.004	0.007	−0.002	0.001	0.004
Adjusted R^2	40.42	41.11	39.21	75.39	29.55	NA	NA	NA

Panel G: Risk measures of monthly returns

	Mean: HMF			Mean:TMF	Mean: HF	Difference (HMF-HF)	Difference (HMF - TMF)	Difference (HFM-YES– HFM-NO)
	Mean: ALL	Mean: HFM-YES	Mean: HFM-NO					
Standard Deviation	2.97%	2.77%	3.28%	4.79%	4.16%	−1.19%	−1.82%***	−0.51%*
Skewness	−0.079	−0.087	−0.066	−0.194	0.081	−0.160***	0.115***	−0.021
Kurtosis	0.475	0.536	0.378	0.187	0.718	−0.243**	0.288***	0.158

Table 2: Performance of hedged mutual funds (HMF), traditional mutual funds (TMF), and hedge funds (HF)

This table reports the results from the following OLS regression using annual data for the period 1994 to 2004:

$$Perf_{i,t} = \beta_0 + \beta_1 HF + \beta_2 HMF + \beta_3 Perf_{i,t-2} + \beta_4 Size_{i,t-1} + \beta_5 Age_{i,t-1} + \beta_6 Expense_{i,t-1} + \beta_7 Flow_{i,t-1} + \sum_{t=1}^{9} \beta_8 I(Year_t) + \xi_{i,t}$$

where $Perf_{i,t}$ is the performance measure of fund *i* in year *t*, HF is a dummy that equals 1 if the fund is a hedge fund and 0 otherwise, HMF is a dummy that equals 1 if the fund is a hedged mutual fund and 0 otherwise, $Perf_{i,t-2}$ is the performance measure of fund *i* during year *t-2*, $Size_{i,t-1}$ and $Age_{i,t-1}$ are the log of fund size and log of age of fund *i* at the end of year *t-1*, $Expense_{i,t-1}$ and $Flow_{i,t-1}$ are the expense ratio and % money flows in fund *i* in year *t-1*, $I(Year_t)$ are year dummies that take a value of 1 during a particular year and 0 otherwise, and $\xi_{i,t}$ is the error term. Performance measures are the alphas from the Carhart (1997) four-factor model and the Fung and Hsieh (2004) seven-factor model estimated each year using 24 months of net-of-fee and gross-of-fee returns. Since HF and HMF dummy variables are included, the omitted category is TMF. p-values using bootstrapped (with 1,000 replications) White standard errors adjusted for autocorrelation within two clusters (also known as Rogers standard errors with "clustering" at the fund level and at "time" level) are shown below the coefficients in parentheses. The difference between the coefficients on *HF* and *HMF* is also reported, and F-tests for the significance in this difference are performed. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

	Performance = 4-factor alpha		Performance = 7-factor alpha	
	Gross	**Net**	**Gross**	**Net**
HF indicator	0.529%***	0.414%***	0.790%***	0.681%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HMF indicator	0.215%***	0.223%***	0.383%***	0.402%***
	(0.001)	*(0.000)*	*(0.000)*	*(0.000)*
Twice-lagged performance measure	0.0063	0.0084	0.0010	–0.0146
	(0.641)	*(0.465)*	*(0.948)*	*(0.224)*
Lagged log of fund size	0.0001**	0.0001***	–0.0001*	–0.00003
	(0.017)	*(0.009)*	*(0.081)*	*(0.485)*
Lagged log of fund age	–0.0005***	–0.0006***	–0.0001	–0.0004***
	(0.000)	*(0.000)*	*(0.297)*	*(0.003)*
Lagged expense as a percent of assets	0.0272**	–0.0667***	0.0180	–0.0821***
	(0.049)	*(0.000)*	*(0.308)*	*(0.000)*
Lagged flow as a percent of assets	0.0008***	0.0004***	0.0007***	0.0003***
	(0.000)	*(0.000)*	*(0.000)*	*(0.006)*
Intercept	0.0005	0.0006	–0.004***	–0.002***
	(0.577)	*(0.399)*	*(0.000)*	*(0.001)*
Adjusted R^2	15.32	13.19	14.36	12.58
Includes time-trend dummies	Yes	Yes	Yes	Yes
Number of fund-years	13,892	16,843	13,023	15,891
Difference between HF and HMF	0.314%***	0.191%***	0.407%***	0.279%***

Table 3: Matched sample results for hedged mutual funds (HMF), traditional mutual funds (TMF), and hedge funds (HF)

This table provides the averages of performance measures including alphas from the Carhart (1997) four-factor model and the Fung and Hsieh (2004) seven-factor model estimated each year using 24 months of net-of-fee and gross-of-fee returns, for matched samples of HMFs, TMFs, and HFs and differences of means and results of a Wilcoxon signed-rank test for the differences. The sample of HMFs is matched with that of TMFs and HFs using size, age, and investment objective each year. Differences marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

Performance measure	Mean: HMF	Mean: TMF	Mean: HF	Difference (HMF − HF)	Difference (HMF − TMF)
		Gross-of-fee			
4-factor alpha	0.33%	0.18%	0.71%	-0.38%***	0.15%*
7-factor alpha	0.29%	-0.05%	0.63%	-0.35%***	0.34%***
		Net-of-fee			
4-factor alpha	0.09%	0.00%	0.37%	-0.28%***	0.09%
7-factor alpha	0.03%	-0.26%	0.36%	-0.33%***	0.29%***

Table 4: Performance of hedged mutual funds with and without hedge fund managers (HFM-YES and HFM-NO), traditional mutual funds (TMF), and hedge funds (HF)

This table reports the results from the following OLS regression using annual data for the period 1994 to 2004:

$$Perf_{i,t} = \beta_0 + \beta_1 HFM-YES + \beta_2 HFM-NO + \beta_3 HF + \beta_4 Perf_{i,t-2} + \beta_5 Size_{i,t-1} + \beta_6 Age_{i,t-1} + \beta_7 Expense_{i,t-1} + \beta_8 Flow_{i,t-1} + \sum_{t=1}^{9} \beta_9 I(Year_t) + \psi_{i,t}$$

where $Perf_{i,t}$ is the performance measure of fund *i* in year *t*, *HFM-YES* (*HFM-NO*) is a dummy variable that equals 1 for a hedged mutual fund that has (does not have) a hedge fund manager and zero otherwise, *HF* is a dummy variable that equals 1 if the fund is a hedge fund and 0 otherwise (hence, the missing dummy variable represents *TMF*s), $Perf_{i,t-2}$ is the performance of fund *i* at year *t-2*, $Size_{i,t-1}$ and $Age_{i,t-1}$ are the log of size and log of age of fund *i* at the end of year *t-1*, $Expense_{i,t-1}$ and $Flow_{i,t-1}$ are the expense ratio and percentage money flows in fund *i* in year *t-1*, $I(Year_t)$ are year dummies that take a value of 1 during a particular year and 0 otherwise, and $\psi_{i,t}$ is the error term. Performance measures are the alphas from the Carhart (1997) four-factor model and the Fung and Hsieh (2004) seven-factor model estimated each year using 24 months of net-of-fee and gross-of-fee returns. p-values using bootstrapped (with 1,000 replications) White standard errors adjusted for autocorrelation within two clusters (also known as Rogers standard errors with "clustering" at the fund level and at "time" level) are shown below the coefficients in parentheses. The differences between the coefficients on *HFM-YES* and *HFM-NO*, as well as between *HF* and *HFM-YES* are also reported, and F-tests for the significance in these differences are performed. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

	Performance = 4-factor alpha		Performance = 7-factor alpha	
	Gross	**Net**	**Gross**	**Net**
HF indicator	0.529%***	0.414%***	0.790%***	0.681%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HFM-YES indicator	0.278%***	0.247%***	0.483%***	0.468%***
	(0.000)	*(0.001)*	*(0.000)*	*(0.000)*
HFM-NO indicator	0.049%	0.173%*	0.125%	0.265%**
	(0.668)	*(0.069)*	*(0.393)*	*(0.016)*
Control Variables				
Twice-lagged performance measure	0.0062	0.0084	0.0009	–0.0147
	(0.648)	*(0.468)*	*(0.958)*	*(0.221)*
Lagged log of fund size	0.0001**	0.0001***	–0.0001*	–0.00003
	(0.016)	*(0.009)*	*(0.083)*	*(0.487)*
Lagged log of fund age	–0.0005**	–0.0006***	–0.0001	–0.0004***
	(0.000)	*(0.000)*	*(0.310)*	*(0.003)*
Lagged expense as a percent of assets	0.0284**	–0.0664***	0.0198	–0.0813***
	(0.040)	*(0.000)*	*(0.266)*	*(0.003)*
Lagged flow as a percent of assets	0.0008***	0.0004***	0.0007***	0.0003***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
Intercept	0.0004	0.0006	–0.0035***	–0.002***
	(0.604)	*(0.403)*	*(0.000)*	*(0.006)*
Adjusted R^2	15.33	13.19	14.39	12.58
Includes time-trend dummies	Yes	Yes	Yes	Yes
Number of fund-years	13,892	16,843	13,023	15,891
Difference between HF and HFM-YES	0.251%***	0.167%**	0.307%***	0.213***
Difference between HFM-YES and HFM-NO	0.229%*	0.074%	0.358%**	0.203%

Table 5: Performance of hedged mutual funds managed with and without hedge fund managers (HFM-YES and HFM-NO) versus the performance of traditional mutual funds (TMF) ONLY

This table reports the results from the following OLS regression using annual data for the period 1994 to 2004:

$$Perf_{i,t} = \beta_0 + \beta_1 HFM-YES + \beta_2 HFM-NO + \beta_3 Perf_{i,t-2} + \beta_4 Size_{i,t-1} + \beta_5 Age_{i,t-1} + \beta_6 Expense_{i,t-1} + \beta_7 Flow_{i,t-1} + \beta_8 Turnover_{i,t-1}$$

$$+\beta_9 TotalLoad_{i,t-1} + \sum_{t=1}^{9} \beta_{10}^{s} I(Year_t) + \psi_{i,t}$$

where $Perf_{i,t}$ is the performance measure of fund *i* in year *t*, *HFM-YES* (*HFM-NO*) is a dummy variable that equals 1 for a hedged mutual fund (HMF) that has (does not have) a hedge fund manager and zero otherwise, (hence, the missing dummy variable represents traditional mutual funds), $Perf_{i,t-2}$ is the performance of fund *i* at year *t-2*, $Size_{i,t-1}$ and $Age_{i,t-1}$ are the log of size and log of age of fund *i* at the end of year *t-1*, $Expense_{i,t-1}$, $Flow_{i,t-1}$, $Turnover_{i,t-1}$, and $TotalLoad_{i,t-1}$ are the expense ratio, percentage money flows, turnover, and total load in fund *i* in year *t-1*, $I(Year_t)$ are year dummies that take a value of 1 during a particular year and 0 otherwise, and $\psi_{i,t}$ is the error term. Performance measures are the alphas from the Carhart (1997) four-factor model and the Fung and Hsieh (2004) seven-factor model estimated each year using 24 months of net-of-fee and gross-of-fee returns. p-values using bootstrapped (with 1,000 replications) White standard errors adjusted for autocorrelation within two clusters (also known as Rogers standard errors with "clustering" at the fund level and at "time" level) are shown below the coefficients in parentheses. The difference between the coefficients on *HFM-YES* and *HFM-NO* is also reported, and an F-tests for the significance in this difference is performed. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

	Performance = 4-factor alpha		Performance = 7-factor alpha	
	Gross	**Net**	**Gross**	**Net**
HFM-YES indicator	0.344%***	0.316%***	0.637%***	0.640%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HFM-NO indicator	0.067%	0.173%*	0.168%	0.301%**
	(0.556)	*(0.098)*	*(0.279)*	*(0.015)*
Control Variables				
Twice-lagged performance measure	–0.0328**	–0.0242**	–0.0432***	–0.0601***
	(0.015)	*(0.038)*	*(0.003)*	*(0.000)*
Lagged log of fund size	0.0001	0.0001***	–0.0001***	–0.0001*
	(0.129)	*(0.001)*	*(0.001)*	*(0.063)*
Lagged log of fund age	–0.0005***	–0.0005***	–0.0001	–0.0001
	(0.000)	*(0.000)*	*(0.553)*	*(0.267)*
Lagged expense as a percent of assets	0.0057	–0.0658***	0.0137	–0.0756***
	(0.741)	*(0.000)*	*(0.513)*	*(0.000)*
Lagged flow as a percent of assets	0.0009***	0.0007***	0.0009***	0.0007***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
Lagged turnover	–0.0002***	–0.0003***	–0.0006***	–0.0007***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
Lagged total load	0.0069***	–0.0059***	0.0035	–0.0085***
	(0.000)	*(0.002)*	*(0.194)*	*(0.001)*
Intercept	0.0018**	0.0016*	–0.0028***	–0.0029***
	(0.033)	*(0.059)*	*(0.002)*	*(0.000)*
Adjusted R^2	10.11	9.61	6.64	6.55
Includes time-trend dummies	Yes	Yes	Yes	Yes
Number of fund-years	11,327	12,926	10,484	12,006
Difference between HFM-YES and HFM-NO	0.277%**	0.143%	0.469%***	0.339%**

Table 6: Performance evaluation of hedge funds (HFs) run along with hedged mutual funds (HMFs)

Panel A of this table reports the results from the following OLS regression using annual data for the period 1994 to 2004:

$$Perf_{i,t} = \beta_0 + \beta_1 HF-with-HMF + \beta_2 Perf_{i,t-2} + \beta_3 Size_{i,t-1} + \beta_4 Age_{i,t-1} + \beta_5 Expense_{i,t-1} + \beta_6 Flow_{i,t-1} + \sum_{t=1}^{9} \beta_7 I(Year_t) + \psi_{i,t}$$

where $Perf_{i,t}$ is the performance measure of fund *i* in year *t*, *HF-with-HMF* is a dummy variable that equals 1 for a hedge fund that is offered along with a hedged mutual fund (HMF) and zero otherwise, $Perf_{i,t-2}$ is the performance of fund *i* at year *t-2*, $Size_{i,t-1}$ and $Age_{i,t-1}$ are the log of size and log of age of fund *i* at the end of year *t-1*, $Expense_{i,t-1}$ and $Flow_{i,t-1}$ are the expense ratio and percentage money flows in fund *i* in year *t-1*, $I(Year_t)$ are year dummies that take a value of 1 during a particular year and 0 otherwise, and $\psi_{i,t}$ is the error term. p-values using bootstrapped (with 1,000 replications) White standard errors adjusted for autocorrelation within two clusters (also known as Rogers standard errors with "clustering" at the fund level and at "time" level) are shown below the coefficients in parentheses. Performance measures are the alphas from the Carhart (1997) four-factor model and the Fung and Hsieh (2004) seven-factor model estimated each year using 24 months of net-of-fee and gross-of-fee returns. Panel B of this table provides the averages of performance measures for matched samples of HFs that are offered along with hedged mutual funds (HMFs) – *HFs with HMFs* versus the others – *HFs without HMFs*. It also provides the differences of means between these two groups and results of a Wilcoxon signed-rank test for the differences. The sample of HFs is matched using size, age, and investment objective each year. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Panel A

	Performance = 4-factor alpha		Performance = 7-factor alpha	
	Gross	**Net**	**Gross**	**Net**
HF-with-HMF indicator	0.090%	0.119%	0.145%	0.174%
	(0.506)	*(0.236)*	*(0.304)*	*(0.110)*
Control Variables				
Twice-lagged performance measure	0.0648***	0.0516***	0.0593**	0.0348*
	(0.008)	*(0.006)*	*(0.030)*	*(0.100)*
Lagged log of fund size	0.0002	0.0002	0.0002	0.0003**
	(0.174)	*(0.182)*	*(0.407)*	*(0.022)*
Lagged log of fund age	–0.0019***	–0.0012***	–0.0013**	–0.0011***
	(0.000)	*(0.000)*	*(0.019)*	*(0.002)*
Lagged expense as a percent of assets	0.1609***	0.0603*	0.1419**	0.0548
	(0.000)	*(0.096)*	*(0.014)*	*(0.178)*
Lagged flow as a percent of assets	0.0004*	0.0001*	0.0005**	0.0001
	(0.067)	*(0.080)*	*(0.039)*	*(0.333)*
Intercept	0.0100***	0.0068***	0.0081***	0.0057***
	(0.000)	*(0.000)*	*(0.003)*	*(0.001)*
Adjusted R^2	12.78	10.31	4.77	4.64
Includes time-trend dummies	Yes	Yes	Yes	Yes
Number of fund-years	2,639	3,979	2,639	3,979

Panel B

Performance measure	**Mean: HFs with HMFs (A)**	**Mean: HFs without HMFs (B)**	**Difference (A-B)**
		Gross-of-fee	
4-factor alpha	0.75%	0.69%	0.06%
7-factor alpha	0.78%	0.60%	0.18%
		Net-of-fee	
4-factor alpha	0.45%	0.51%	-0.06%
7-factor alpha	0.52%	0.40%	0.12%

Table 7: Tests of persistence in fund performance

This table presents two-way tables of ranked total returns over one year intervals for the entire sample period. Panel A reports persistence results for the entire sample of hedged mutual funds (HMFs). Funds are ranked in the first year and held for one year. If a fund's returns are in the top (bottom) half of all returns for the period, we designate it as a "winner", *W* ("loser", *L*). The percent repeat winner/loser column is relative to the number of funds ranked a winner/loser in the prior period. We compute the cross-product-ratio (CPR) as $\frac{(WW * LL)}{(WL * LW)}$ where WW (LL) are the repeat winners (losers) and WL (LW) are winner-loser (loser-winner) over two consecutive periods and the standard error of the logarithm of CPR is given by $\sigma_{\log(CPR)} = \sqrt{\frac{1}{WW} + \frac{1}{WL} + \frac{1}{LW} + \frac{1}{LL}}$. We compute the t-statistic as the log of CPR divided by its standard error. We compute the z-statistic as $\frac{Y - np}{\sqrt{np(1-p)}}$ where *n* is the number of funds, *p* is the probability that a winner (loser) in one period continues to be a winner (loser) in the next period, and *Y* is a random variable for the number of persistently winning (losing) funds. Coefficients with three, two, and one asterisks are significant at the 1%, 5%, and 10% level respectively. The null hypothesis is that 50% of the funds will be repeat winners and 50% of the funds will be repeat losers. Panel B examines persistence by splitting the sample of HMFs into those that have HF managers (HFM-YES) and those that do not (HFM-NO). We report the total number of HMFs in each category, the total number of winner/winner funds, and the total number of loser/loser funds. We also report the percentage of winner/winner and loser/loser funds relative to the total number of HMFs in each category. The null hypothesis is that 25% of HMFs in each category should be repeat winners and 25% of HMFs in each category should be repeat losers.

Panel A: Overall HMF Sample

	Initial year	Next year Winner	Next year Loser	Percent repeat winner or loser	z-test for repeat winner or loser	Cross-product ratio t-test
1994-2004	**Winner**	68	43	61.3%	2.37***	2.84***
	Loser	43	60	41.7%	–2.54***	

Panel B: HFM-NO and HFM-YES Comparison

	Description	Total # of funds by category	# of winner/ winner funds	% winner/winner	# of loser/loser funds	% loser/loser
1994-2004	**HFM-NO**	80	18	22.5%	28	35.0%
	HFM-YES	134	50	37.3%	32	23.9%

Table 8: Robustness tests using random effects

This table presents the results of robustness tests to various econometric techniques for the regressions performed in Tables 2, 4, and 5 above. It presents fund and family-level random effects regressions for each of the above tables. For the sake of comparison, it also reports the results from Tables 2, 4 and 5 in the first row. For brevity, it only reports the coefficients on the HMF and HF variables from Table 2, the HFM-YES, HFM-NO and HF variables from Table 4, and the HFM-YES and HFM-NO variables from Table 5. Panel A reports the results for Table 2: HMF, TMF, and HF with the HMF variable. Panel B reports the results from Table 4: HMF, TMF, and HF, with the HMF indicator variable split into HFM-YES and HFM-NO indicators. Panel C reports the results from Table 5: HMF and TMF, with the HMF indicator variable split into HFM-YES and HFM-NO indicators. p-values using bootstrapped standard errors with 1,000 replications are shown below the coefficients in parentheses.. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Panel A: Coefficients on the HMF and HF variables in HMF, TMF, and HF regressions (Table 2)

Specification	Performance = 4-factor alpha		Performance = 7-factor alpha	
	Gross	**Net**	**Gross**	**Net**
From Table 2				
HF indicator variable	0.529%***	0.414%***	0.790%***	0.681%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HMF indicator variable	0.215%***	0.223%***	0.383%***	0.402%***
	(0.001)	*(0.000)*	*(0.000)*	*(0.000)*
Difference between HF and HMF	0.314%***	0.191%***	0.407%***	0.279%***
1. Family random effects				
HF indicator variable	0.621%***	0.483%***	0.882%***	0.729%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HMF indicator variable	0.150%*	0.153%**	0.299%***	0.298%***
	(0.054)	*(0.021)*	*(0.001)*	*(0.000)*
Difference between HF and HMF	0.471%***	0.330%***	0.583%***	0.431%***
3. Fund random effects				
HF indicator variable	0.608%***	0.468%***	0.907%***	0.775%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HMF indicator variable	0.230%***	0.205%***	0.420%***	0.417%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
Difference between HF and HMF	0.378%***	0.263%***	0.487%***	0.358%***

Table 8, cont.: Robustness tests using random effects, Panel B

Panel B: Coefficients on the HFM-YES, HFM-NO, and HF variables in HMF, TMF, and HF regressions (Table 4)

Specification	Performance = 4-factor alpha		Performance = 7-factor alpha	
	Gross	**Net**	**Gross**	**Net**
From Table 4				
HF indicator variable	0.529%***	0.414%***	0.790%***	0.681%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HFM-YES indicator variable	0.278%***	0.247%***	0.483%***	0.468%***
	(0.000)	*(0.001)*	*(0.000)*	*(0.000)*
HFM-NO indicator variable	0.049%	0.173%*	0.125%	0.265%**
	(0.668)	*(0.069)*	*(0.393)*	*(0.016)*
Difference between HF and HFM-YES	0.251%***	0.167%**	0.307%***	0.213***
Difference between HFM-YES and HFM-NO	0.229%*	0.074%	0.358%**	0.203%
1. Family random effects				
HF indicator variable	0.621%***	0.482%***	0.883%***	0.729%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HFM-YES indicator variable	0.120%	0.092%	0.342%***	0.332%***
	(0.128)	*(0.211)*	*(0.000)*	*(0.000)*
HFM-NO indicator variable	0.206%	0.250%**	0.215%	0.246%*
	(0.189)	*(0.039)*	*(0.290)*	*(0.061)*
Difference between HF and HFM-YES	0.501%***	0.390%***	0.541%***	0.397%***
Difference between HFM-YES and HFM-NO	–0.086%	–0.158%	0.127%	0.086%
2. Fund random effects				
HF indicator variable	0.608%***	0.468%***	0.908%***	0.775%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HFM-YES indicator variable	0.308%***	0.235%***	0.540%***	0.497%***
	(0.000)	*(0.004)*	*(0.000)*	*(0.000)*
HFM-NO indicator variable	0.053%	0.151%**	0.152%	0.280%***
	(0.600)	(*0.026*)	*(0.276)*	*(0.000)*
Difference between HF and HFM-YES	0.300%**	0.233%***	0.368%***	0.278%***
Difference between HFM-YES and HFM-NO	0.255%*	0.084%	0.388%**	0.217%*

Table 8, cont.: Robustness tests using random effects, Panel C

Panel C: Coefficients on the HFM-YES, HFM-NO variables in HMF, and TMF regressions (Table 5)

Specification	Performance = 4-factor alpha		Performance = 7-factor alpha	
	Gross	**Net**	**Gross**	**Net**
From Table 5				
HFM-YES indicator variable	0.344%***	0.316%***	0.637%***	0.640%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HFM-NO indicator variable	0.067%	0.173%*	0.168%	0.301%**
	(0.556)	*(0.098)*	*(0.279)*	*(0.015)*
Difference between HFM-YES and HFM-NO	0.277%**	0.143%	0.469%***	0.339%**
1. Family random effects				
HFM-YES indicator variable	0.286%***	0.215%***	0.516%***	0.475%***
	(0.000)	*(0.003)*	*(0.000)*	*(0.000)*
HFM-NO indicator variable	0.152%	0.251%*	0.220%	0.319%**
	(0.335)	*(0.056)*	*(0.278)*	*(0.034)*
Difference between HFM-YES and HFM-NO	0.134%	–0.036%	0.294%*	0.156%
2. Fund random effects				
HFM-YES indicator variable	0.366%***	0.313%***	0.656%***	0.658%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HFM-NO indicator variable	0.076%	0.176%**	0.200%	0.340%***
	(0.569)	*(0.033)*	*(0.233)*	*(0.000)*
Difference between HFM-YES and HFM-NO	0.290%**	0.137%	0.456%***	0.318%***

Table 9: Robustness using monthly data

This table presents the results of pooled and Fama-MacBeth (1973) regressions performed using monthly data. The regressions are similar to those in Tables 2, 4, and 5 above except that alphas are estimated on a monthly basis using a 24-month window moved forward by a month each time. For brevity, it only reports the coefficients on the HMF and HF variables from Table 2, the HFM-YES, HFM-NO and HF variables from Table 4, and the HFM-YES and HFM-NO variables from Table 5. Panel A reports the results for Table 2: HMF, TMF, and HF with the HMF variable. Panel B reports the results from Table 4: HMF, TMF, and HF, with the HMF indicator variable split into HFM-YES and HFM-NO indicators. Panel C reports the results from Table 5: HMF and TMF, with the HMF indicator variable split into HFM-YES and HFM-NO indicators. For pooled regressions, p-values using bootstrapped (with 1,000 replications) White standard errors adjusted for autocorrelation within two clusters (also known as Rogers standard errors with "clustering" at the fund level and at "time" level) are shown below the coefficients in parentheses. For Fama-MacBeth (1973) regressions, p-values adjusted for autocorrelation and heteroskedasticity using GMM are shown below the coefficients in parentheses. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

Panel A: Coefficients on the HMF and HF variables in HMF, TMF, and HF regressions (Table 2)

Specification	Performance = 4-factor alpha		Performance = 7-factor alpha	
	Gross	**Net**	**Gross**	**Net**
Pooled				
HF indicator variable	0.496%***	0.499%***	0.755%***	0.743%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HMF indicator variable	0.110%***	0.128%***	0.277%**	0.308%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
Difference between HF and HMF	0.386%***	0.371%***	0.478%***	0.435%***
Fama-MacBeth				
HF indicator variable	0.509%***	0.493%***	0.845%***	0.816%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HMF indicator variable	0.166%***	0.182%***	0.404%***	0.430%***
	(0.000)	*(0.001)*	*(0.000)*	*(0.000)*
Difference between HF and HMF	0.343%***	0.311%***	0.441%***	0.386%***

Panel B: Coefficients on the HFM-YES, HFM-NO, and HF variables in HMF, TMF, and HF regressions (Table 4)

Specification	Performance = 4-factor alpha		Performance = 7-factor alpha	
	Gross	**Net**	**Gross**	**Net**
Pooled				
HF indicator variable	0.496%***	0.499%***	0.756%***	0.743%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HFM-YES indicator variable	0.174%***	0.188%***	0.378%***	0.417%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HFM-NO indicator variable	−0.086%	−0.019%	−0.031%	0.042%
	(0.162)	*(0.674)*	*(0.677)*	*(0.456)*
Difference between HF and HFM-YES	0.322%***	0.311%***	0.378%***	0.326***
Difference between HFM-YES and HFM-NO	0.260%***	0.207%***	0.409%**	0.375%***
Fama-MacBeth				
HF indicator variable	0.509%***	0.493%***	0.845%***	0.816%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HFM-YES indicator variable	0.201%***	0.207%**	0.475%***	0.487%***
	(0.001)	*(0.001)*	*(0.000)*	*(0.000)*
HFM-NO indicator variable	0.069%	0.117%**	0.205%**	0.270%***
	(0.230)	*(0.038)*	*(0.045)*	*(0.003)*
Difference between HF and HFM-YES	0.308%***	0.286%***	0.370%***	0.329%***
Difference between HFM-YES and HFM-NO	0.132%	0.090%	0.270%**	0.217%*

Table 9, cont.: Robustness using monthly data, Panel C

Panel C: Coefficients on the HFM-YES, HFM-NO variables in HMF and TMF regressions (Table 5)

Specification	Performance = 4-factor alpha		Performance = 7-factor alpha	
	Gross	**Net**	**Gross**	**Net**
Pooled				
HFM-YES indicator variable	0.228%***	0.239%***	0.228%***	0.514%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HFM-NO indicator variable	–0.089%	–0.018%	–0.088%	0.056%
	(0.139)	*(0.688)*	*(0.139)*	*(0.318)*
Difference between HFM-YES and HFM-NO	0.317%***	0.257%***	0.316%***	0.458%***
Fama-MacBeth				
HFM-YES indicator variable	0.186%***	0.181%***	0.474%***	0.478%***
	(0.002)	*(0.003)*	*(0.000)*	*(0.000)*
HFM-NO indicator variable	0.043%	0.083%**	0.213%**	0.267%***
	(0.323)	*(0.037)*	*(0.022)*	*(0.002)*
Difference between HFM-YES and HFM-NO	0.143%*	0.098%	0.261%***	0.211%**

Table 10: Robustness tests using alphas from conditional models

This table presents the results of robustness tests to using conditional alphas instead of unconditional alphas for the regressions performed in Tables 2, 4, and 5 above. The table reports the results for alphas from the Carhart (1997) four-factor model and the Fung and Hsieh (2004) seven-factor model estimated each year (for annual regressions) and each month (for monthly regressions) using 24 months of net-of-fee and gross-of-fee returns. For brevity, it only reports the coefficients on the HMF and HF variables from Table 2, the HFM-YES, HFM-NO and HF variables from Table 4, and the HFM-YES and HFM-NO variables from Table 5. Panel A reports the results for Table 2: HMF, TMF, and HF with the HMF variable. Panel B reports the results from Table 4: HMF, TMF, and HF, with the HMF indicator variable split into HFM-YES and HFM-NO indicators. Panel C reports the results from Table 5: HMF and TMF, with the HMF indicator variable split into HFM-YES and HFM-NO indicators. p-values using bootstrapped standard errors with 1,000 replications are shown below the coefficients in parentheses. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Panel A: Coefficients on the HMF and HF variables in HMF, TMF, and HF regressions (Table 2)

Specification	Performance = 4-factor conditional alphas		Performance = 7-factor conditional alpha	
	Gross	**Net**	**Gross**	**Net**
Annual regressions				
HF indicator variable	0.417%***	0.418%***	0.635%***	0.649%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HMF indicator variable	0.217%***	0.233%***	0.440%***	0.463%***
	(0.002)	*(0.001)*	*(0.000)*	*(0.000)*
Difference between HF and HMF	0.200%***	0.185%***	0.195%**	0.186%**
Monthly regressions				
HF indicator variable	0.496%***	0.499%***	0.755%***	0.720%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HMF indicator variable	0.107%***	0.105%***	0.292%***	0.342%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
Difference between HF and HMF	0.389%***	0.394%***	0.463%***	0.378%***

Panel B: Coefficients on the HFM-YES, HFM-NO, and HF variables in HMF, TMF, and HF regressions (Table 4)

Specification	Performance = 4-factor conditional alphas		Performance = 7-factor conditional alphas	
	Gross	**Net**	**Gross**	**Net**
Annual regressions				
HF indicator variable	0.417%***	0.418%***	0.635%***	0.649%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HFM-YES indicator variable	0.230%***	0.216%***	0.478%***	0.473%***
	(0.001)	*(0.005)*	*(0.000)*	*(0.000)*
HFM-NO indicator variable	0.184%	0.268%**	0.340%**	0.443%***
	(0.277)	*(0.049)*	*(0.039)*	*(0.000)*
Difference between HF and HFM-YES	0.187%***	0.202%***	0.157%*	0.176%**
Difference between HFM-YES and HFM-NO	0.046%	−0.052%	0.138%	0.030%
Monthly regressions				
HF indicator variable	0.496%***	0.499%***	0.755%***	0.720%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HFM-YES indicator variable	0.125%***	0.129%***	0.334%***	0.392%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HFM-NO indicator variable	0.053%	0.045%	0.161%*	0.219%***
	(0.515)	*(0.446)*	*(0.075)*	*(0.000)*
Difference between HF and HFM-YES	0.371%***	0.370%***	0.421%***	0.328***
Difference between HFM-YES and HFM-NO	0.072%	0.084%	0.173%*	0.173%**

Table 10, cont.: Robustness tests using alphas from conditional models, Panel C

Panel C: Coefficients on the HFM-YES, HFM-NO variables in HMF and TMF regressions (Table 5)

Specification	Performance = 4-factor conditional alphas		Performance = 7-factor conditional alphas	
	Gross	**Net**	**Gross**	**Net**
Annual regressions				
HFM-YES indicator variable	0.284%***	0.251%***	0.645%***	0.632%***
	(0.000)	*(0.001)*	*(0.000)*	*(0.000)*
HFM-NO indicator variable	0.192%	0.254%*	0.385%**	0.479%***
	(0.260)	*(0.095)*	*(0.027)*	*(0.001)*
Difference between HFM-YES and HFM-NO	0.092%	–0.003%	0.260%	0.153%
Monthly regressions				
HFM-YES indicator variable	0.151%***	0.158%***	0.151%***	0.535%***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
HFM-NO indicator variable	0.039%	0.049%	0.039%	0.294%***
	(0.622)	*(0.425)*	*(0.622)*	*(0.000)*
Difference between HFM-YES and HFM-NO	0.112%	0.109%*	0.112%	0.241%***

Appendix A: Hedged Mutual Fund Sample Selection Process

To select the sample of HMFs, we begin with the Morningstar and Lipper lists. Morningstar categorizes HMFs as Long/Short Equity funds, while Lipper divides funds into two categories: Long/Short and Equity Market Neutral. As long as a mutual fund is on either of the lists, we include it in the sample. This process results in 26 unique funds.[1] There are two major issues with using only the Morningstar and Lipper data to compile the sample. First, since these categorizations are quite new (they were implemented in early 2006), defunct funds are not included on either of the lists. Second, a handful of other mutual funds using hedge fund strategies such as merger arbitrage, managed futures, multi-strategy, and event driven are not picked up by Morningstar or Lipper. We address both issues by searching news archives (including Morningstar's website, Lexis/Nexis, and www.google.com) for articles regarding HMFs. In addition, we search the Morningstar and CRSP mutual fund databases, using the following search terms: "long/short", "short", "option", "market neutral", "arbitrage", "hybrid mutual fund", "hedged mutual fund,", "merger", "distressed", "hedged", and "alternative." From this search, we identified 90 additional possibilities for inclusion in the sample.

We next examine these funds to determine if they implement hedge-fund-like strategies. Since the focus of this paper is on equity funds, our first criterion for inclusion is that the fund must have an equity-based trading strategy. Using this criterion, we exclude 5 funds from the sample that follow fixed-income or balanced strategies. Second, we exclude passive funds. This

[1] There are only a small number of funds on Lipper's list of Equity Market Neutral funds, all of which are included on Morningstar's Long/Short list. Hence, we simplify the nomenclature and refer to the funds on these lists "Long/Short Equity." The key theoretical differences in Long/Short Equity and Equity Market Neutral funds are that Equity Market Neutral funds have the specific goal of reducing market risk to a very low level – for example, it is common for Equity Market Neutral funds to have market betas of close to zero. A Long/Short equity fund, by contrast, does not always strive to be market neutral, and typically has a positive, though not too large, market beta.

simple criterion allows us to eliminate over half of the remaining funds.[2] Usually through the use of futures contracts, these funds track the performance of market indices such as the S&P 500. Although these funds have "flexible" trading programs and use derivative securities, they are passively managed in terms of stock-picking. Thus, we exclude these funds. Third, we exclude funds that fall into the category of "short-only" or "bear market". While this is a hedge fund strategy, we identify only 4 mutual funds that appear to follow "active" short-only strategy, which we exclude from our sample.[3] Fourth, of the remaining funds, we first identify those defunct funds that followed long-short equity strategies during their existence. We do not rely solely on the fund names as these might be sometimes misleading (e.g., Cooper, Gulen, and Rau, (2005)). Instead, for each of the defunct funds, we review prospectuses and annual reports from the SEC going back to 1994, the first year for which the SEC has electronic filings. After careful review of all annual reports and prospectuses, we include additional defunct funds in the sample by imposing the same criterion that Morningstar uses in compiling its long/short list, namely that the fund have at least 20% short exposure each year.[4] Using this approach, we identify 13 defunct long/short mutual funds that would have been included on Morningstar's list had they categorized funds in this manner historically. This brings our sample to a total of 39 funds.

After the exclusion of funds from the original list of 90 possibilities, we are down to 17 funds, 2 of which are defunct at the end of the sample period. We carefully review the annual reports and prospectuses of each of these 17 funds. Of these, 7 describe popular hedge fund strategies in their prospectuses. Of the 10 remaining funds, a review of annual reports and prospectuses reveals that they all use hedge fund strategies that would be categorized as

[2] Specifically, we exclude a number of mutual funds offered by Rydex and ProFunds, two fund families that offer a variety of mutual funds in the "enhanced index" category.
[3] However, there are a number of passive short-only funds that attempt to replicate the inverse performance of an index. Many of these are offered by ProFunds and Rydex family.
[4] Per discussion with Dan McNeela of Morningstar on June 7, 2006.

“other/multi-strategy”. For each of these funds, we also identify at least one manager interview where he describes his fund as “using a hedge fund strategy.” Hence, of these 17 funds, we exclude the funds-of-funds and tentatively include the remaining 15 funds in the sample.

We then follow a statistical approach. Since, most long/short hedge funds minimize market exposure, we use a fund’s “market beta” as the final selection criterion by applying the following test: the fund’s average 24-month “market beta” (the coefficient on the market factor in Carhart’s (1997) four-factor model) must be less than the highest market beta from the combined Morningstar/Lipper fund list.[5] Using the highest market beta for the Morningstar/Lipper list of 0.81 as the cut-off criterion removes 5 funds from the list of 15. The 10 remaining funds have market betas ranging from 0.35 to 0.76. Thus, we add these 10 funds, bringing the sample to 49.

Finally, as a last step to ensure that we are including all HMFs, we conduct the “beta test”. It is possible that we have omitted funds from our sample either because they had no news stories, or that their names did not include any of our original search terms. For this test, we calculate the average two-year four-factor market beta for the 49 funds already selected for the sample as 0.36. We then calculate the two-year four-factor market betas for each of the remaining equity funds in CRSP (excluding the 49 funds in our HMF sample). We next review the prospectuses and annual reports for more than 500 funds in the CRSP database that have betas less than 0.36. This helps us identify 3 additional funds that fit our criteria, bringing our final sample to 52 funds, 14 of which are defunct.[6]

[5] We thank Dennis Bein of Analytical Investors for helping us define this general criterion.

[6] We confirm that the low market betas of excluded funds occur for a number of reasons, the most common being that: a) the fund does not follow a primarily equity-based strategy, b) the fund is a sector fund that has low exposure to the market factor, c) the fund is a very small fund, d) the fund is invested primarily in cash, e) the fund is on the verge of closing and is in the process of liquidating its assets.

Appendix B: Rationale for Concurrent Management of Hedge Funds and Hedged Mutual Funds

Below, we provide excerpts from recent press articles that suggest that hedge fund companies may be offering hedged mutual funds concurrently to raise assets and diversify their clientele base. We present our clarifications/comments in italics.

Quote	Publication	Date
What's more, some hedge-fund managers, who historically catered only to the most wealthy, are now offering their services through mutual funds, which are accessible to a wider group of investors.	Denver Post	April 17, 2007
Citigroup reports that hedge fund managers are interested in running [hedged mutual funds] on behalf of long-only houses as a means of obtaining a higher quality earnings stream that will not disappear in times of poor performance.	The Financial Times	April 16, 2007
[Evan Dick] is chief of the billion-dollar mutual fund based on Highbridge Capital Management's new statistical arbitrage model. And chief among his aims has been to bring products that are normally available only to high-net-worth players to ordinary investors. (*This quote relates to the Highbridge Statistical Market Neutral Fund that started in November, 2005 and was advised by Dick. He had 7 years experience at DE Shaw (a hedge fund) and 3 more years' experience at Highbridge before opening the HMF. He continues to manage the HF at Highbridge.)*	The Edge Financial Daily	February 12, 2007
Forward Management...now offers the Forward Long/Short Credit Analysis Fund, run by hedge fund manager Cedar Ridge. The fixed income portfolio is designed for wealthy investors, but with a slimmer price tag and the chance to get money out fast. Forward Management President Alan Reid said. "Offering these types of products is a natural reaction to demand in the marketplace."	Reuters News	January 11, 2007
Some hedge funds are trying to move into traditional portfolio management and beyond their hedge fund clientele. Kurt Borgwardt, portfolio manager of the American Century Long/Short fund, said, "Hedge funds see it as an extension of what they are already doing. Rather than having mutual funds creating an area of expertise, why not try to get as much market shares as they can?" and "It gives hedge funds access to different parts of the asset allocation pools of institutional investors," Kirsten Hill, director at Merrill's Strategic Solutions Group said. "[Hedged mutual fund] products allow them not just to provide investments for the hedge fund bucket but also for the equity bucket. It's a powerful way for them to extend their reach to institutional investors."	HedgeWorld News	December 28, 2006
When the fund started in 2002, it was open only to Schwab's customers. At the time, companies like Banc of America Securities and Oppenheimer Funds were opening hedge funds with smaller minimum investments to lure the middle class. *(This quote is regarding Schwab Hedged Fund, one of the HMFs in our sample)*	International Herald Tribune	February 17, 2006
"I'm bringing a hedged strategy down to the masses," said Mr. Jones, founder and president of All Season Financial Advisors Inc. in Denver. (*This quote relates to a new hedged mutual fund, Integrity All Season Fund, sub-advised by Sam Jones, manager of the All Seasons Fund, a hedge fund.)*	Investment News	May 16, 2005

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