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Hedge Funds for Retail Investors? An Examination of Hedged Mutual Funds

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Abstract

Recently, there has been rapid growth in the assets managed by "hedged mutual funds"—mutual funds mimicking hedge fund strategies. We examine the performance of these funds relative to hedge funds and traditional mutual funds. Despite using similar trading strategies, hedged mutual funds underperform hedge funds. We attribute this finding to hedge funds' lighter regulation and better incentives. Conversely, hedged mutual funds outperform traditional mutual funds. Notably, this superior performance is driven by managers with experience implementing hedge fund strategies. Our findings have implications for investors seeking hedge-fund-like payoffs at a lower cost and within the comfort of a regulated environment.

I. Introduction

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

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"Long/Short Equity" and "Market Neutral" to classify them. Despite their use of hedge fund strategies, "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 covering short positions, limiting borrowing to only one-third of total assets, and restricting investment in illiquid securities to 15% of total assets. They must also provide daily liquidity and audited semiannual reports.[3] In contrast, HFs do not face such constraints, as they are largely unregulated. In addition to lighter regulation, HFs have better incentives, usually charging performance-based incentive fees, whereas HMFs 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 differences in risks, fund characteristics, and past performance, HMFs underperform HFs by approximately 3.3% per year on a net-of-fee basis.

Furthermore, 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

[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 N. O'Hara, "Funds of Funds," http://www.onwallstreet.com, 2/1/2006). These funds are also attractive to retirement plan administrators. For example, Lake Partners, Inc., a Greenwich, CT, investment adviser, offers a fund of hedged mutual funds, called LASSO, which is available to 401(k)-style programs.

[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, Poterba, Shackelford, and Shoven (2004)).

[4]If a mutual fund wishes to charge a performance-based incentive fee, the fee must be symmetrical, such that it 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 in their sample of over 6,000 mutual funds use fulcrum fees. In our sample of 52 HMFs, only two use fulcrum fees.

constraints could also lead to an 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 experience, while the rest have managers without such experience. These "experienced" HF managers concurrently manage HFs and HMFs, and, in all cases, the HF experience was gained either concurrent with or prior to the manager's starting an HMF. 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 an HF manager start an HMF, given the tighter constraints, stricter regulation, and weaker incentives in the mutual fund industry? One possibility is that the HFs offered by these managers are underperforming other HFs. 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 HFs choose to offer HMFs. Instead, we conjecture that the reason for offering both HMFs and HFs is that these managers wish to raise additional capital, given that this task can be extremely difficult for smaller HFs. 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 8,000+ 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 managers.[8]

All our findings supporting the three hypotheses (Regulation and Incentives, Strategy, and Skill) hold for different risk models and on a prefee, as well as a postfee, basis. In addition, our results are robust to conducting our analyses at both the monthly and yearly levels, and to the use of alternate econometric

[5]We further discuss this issue in Section II.A.

[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.

[7]See "Hedge Fund Market Trends 1Q 2007," published by Hedge Fund Research (http://www.hedgefundresearch.com).

[8]We examine these issues in more detail in Section VI.

methodologies including random effects, a matched sample analysis, and the Fama and 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 makes three important contributions to the existing literature. First, we show that 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 do TMFs, suggesting that they are not using flexibility for cost reduction but, rather, to implement HF-like strategies. Finally, by focusing on funds that use HF-like trading strategies and comparing their performance with those of HFs, we shed light on the role of regulation and incentives. We show that despite using similar trading strategies, HMFs underperform HFs, which face lighter regulation and stronger performance-related incentives.

The paper is structured as follows. Section II discusses related literature and outlines the three hypotheses. Section III describes the data. Section IV investigates the Regulation and Incentives Hypothesis. Section V examines the Strategy Hypothesis. Section VI tests the Skill Hypothesis and performs a battery of robustness tests, and Section VII concludes.

II. Related Literature and Testable Hypotheses

A. Related Literature

As noted in the Introduction, our paper is related to literature that examines the motivation for controlling a fund's investment flexibility. One reason to restrict 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 to allow a fund flexibility is to reduce the transaction

[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

costs, liquidity costs, and opportunity costs of holding cash (Koski and Pontiff (1999), Deli and Varma (2002)). We contribute to this literature by showing that a special type of investment flexibility, by which managers intentionally use HF trading strategies, can actually enhance fund performance.

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 Nohel, Wang, and Zheng (2008) study this relationship from the perspective of the management company and individual manager, respectively. 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 both HFs and TMFs. To isolate the effect of skill, we divide the HMFs into those that have HF managers and those that do not. Hence, we focus on the effect of skill gained in the HF industry on the performance of HMFs, as opposed to examining conflicts of interest in side-by-side management. Thus, our paper complements this recently burgeoning literature.

Finally, we contribute to the literature on HFs that examines risk and return characteristics, performance, and compensation structures (e.g., Ackermann, McEnally, and Ravenscraft (1999), Agarwal and Naik (2000), (2004), Asness, Krail, and Liew (2001), Baquero, ter Horst, and Verbeek (2005), Boyson (2008), Brown, Goetzmann, and Ibbotson (1999), Brown, Goetzmann, and Liang (2004), Brown et al. (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)). However, relatively scant literature compares hedge funds and mutual funds directly. One reason is that significant differences in regulation, incentives, and trading strategies make it difficult to conduct a direct comparison. Our study overcomes these limitations to some extent. Since HMFs and HFs use similar trading strategies, we may attribute the differences in performance to differences in regulation and incentives, rather than to differences in trading strategies. We also contribute to the vast literature on mutual funds (e.g., Brown and Goetzmann (1995), Carhart (1997), Chevalier and Ellison (1999), Daniel, Grinblatt, Titman, and Wermers (1997), Elton et al. (1996a), (1996b), Jegadeesh and Titman (1993), Jensen (1968), and Wermers (2000)). Our paper is closest in spirit to studies of individual mutual fund asset classes, such as money market funds, equity mutual funds, and bond funds (e.g., Comer (2005), Elton et al. (1995), Chen, Ferson, and Peters (2005), and Tiwari and Vijh (2004)).

B. Development of Hypotheses

This paper tests three hypotheses. First, the Regulation and Incentives Hypothesis posits that, due to the lighter regulation and better incentives experienced

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to be "winners" and thereby attract greater capital flows, which results in higher compensation for the manager. By contrast, HF 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 HF managers (see Brown, Goetzmann, and Park (2001)).

by HFs, 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 of 1940. These acts impose several constraints on mutual funds. The Investment Company Act of 1940 restricts a fund's ability to use leverage or borrow against the value of securities in its portfolio. The SEC requires that funds engaging in certain investment techniques, including the use of options, futures, forwards, and short selling, cover their positions. 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. Also, HF managers are compensated through performance-based incentive fees, providing better incentives to deliver superior performance. As a result, we expect HMFs to underperform HFs.[10]

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

Finally, the Skill Hypothesis predicts that HMF managers with experience in implementing HF strategies should outperform HMF managers without these skills and, by extension of the Strategy Hypothesis, should outperform TMFs as well. We use a manager's experience in the HF industry as the measure of skill. Specifically, if the HMF manager *concurrently* manages an HF and an HMF, the manager is "skilled." Hence, managers must have HF experience that is either concurrent with or precedes their experience in HMFs.[11]

III. Data and Variable Construction

A. Hedged Mutual Funds

We utilize a rigorous process to select the HMF sample. For brevity, we summarize the process here and describe it in greater detail in Appendix A. Our

[10]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 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 those imposed on mutual fund managers. However, a federal appeals court decision recently invalidated the SEC rule regulating HFs, so the future of this regulation is uncertain.

[11]Since managers at HMFs sometimes change, an HMF may be categorized as having an HF manager during some years but not others.

primary analysis uses the CRSP Survivor-Bias-Free mutual fund database. We begin by including all HMFs that appear in the Morningstar and Lipper databases, which began classifying funds as HMFs 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 HF 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 HMFs. 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 HFs, 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.

The 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 review the annual reports and prospectuses of the remaining funds from 1994 to 2004 to determine whether they are, in fact, following "real" HF strategies. We identify 22 additional funds through this process, generating a 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 factors: first, very few HMFs (fewer than 10) were in operation prior to 1994, and, second, we want to match with reliable HF data, which begins in 1994.

We perform a final "completeness" step to ensure that we include all HMFs. Since it is possible that certain HMFs, particularly defunct funds, might remain unidentified by our original search, we use a statistical approach based on market beta to identify additional funds. First, we calculate the mean four-factor market beta of 0.36 for the already-identified 49 HMFs. We then calculate the four-factor market betas for all other mutual funds. Using this information, we review the prospectuses and annual reports for all mutual funds with market betas of less than 0.40 (rounding up the mean market beta of 0.36) for at least two years of existence. Of this list of more than 500 funds, we identify three additional funds that should be classified as HMFs, one of which is defunct. None of the other funds fit the HMF criterion. Their low betas are due to a few factors: style (primarily sector funds, balanced funds, and "asset allocation" funds), size (very small funds on the verge of closing), or portfolio makeup (their assets are primarily invested in cash). This final step yields the final sample of 52 HMFs, of which 14 became defunct by the end of 2004.[12]

[12]To understand the flexibility available to our HMFs, we compute their constraint score, as in Almazan et al. (2004), 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 mean score for our sample is 0.23. More important, however, are our constraint score results for short sales, the investment technique

We also divide the sample of HMF managers into those with HF experience ("skilled") and those without. To qualify as a "skilled" manager, the manager must concurrently manage both a hedge fund and a mutual fund, or have obtained HF experience prior to becoming a mutual fund manager. Of the 52 HMF managers, 27 have HF experience and 25 do not. Section VI further describes 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 (2008).

B. Traditional Mutual Funds

For the sample of TMFs, we include all equity mutual funds from the CRSP Survivor-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.

C. Hedge Funds

We use HF data from the TASS database, which includes monthly net-of-fee returns, management and incentive fees, size, terms (such as notice and redemption periods), and investment styles of the HFs. It has been well documented that HF databases suffer from several biases, including survivorship bias and instant history or backfilling bias (e.g., Ackermann et al. (1999), Fung and Hsieh (2000), Liang (2000), and Brown et al. (2001)). We control for survivorship bias by including defunct funds until they disappear from the database, and we mitigate backfilling bias by excluding the fund's "incubation period" from the time series of returns.[13] Since our analysis compares HMFs with HFs, we restrict the sample to HFs with 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.[14]

D. 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 are the CRSP value-weighted market return, the two Fama and French (1993) factors (size (SMB) and book-to-market (HML)), and the Jegadeesh and Titman (1993) UMD (momentum) factor.

most commonly associated with the HF strategies of the funds in our sample. Within our sample, 78% of funds are permitted to use short sales, and, of these, 78% actually do. Furthermore, short sales as a percentage of assets under management for the funds in our sample average approximately 19%.

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

[14]See http://www.hedgeindex.com for a description of investment styles.

The second model is the Fung and Hsieh (2004) seven-factor model, made up of 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.[15] 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.[16]

We also estimate two other models for robustness: Carhart's (1997) four-factor model augmented with either i) Pástor and Stambaugh's (2003) liquidity factor, or ii) 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. The HMFs are subdivided into those that have HF managers and those that do not. Panels A and B report the number of funds and their size, respectively, by year. All types of funds have increased in both number and size. In size, HMFs have grown 24-fold since 1994, from $743 million to over $18 billion. HFs also grew rapidly during this period, increasing 20-fold from $19 billion to over $400 billion, while TMFs increased three-fold from $541 billion to over $2 trillion.[17]

Panel C of Table 1 reports fund characteristics. HFs are younger than HMFs and have lower fixed expenses (measured as a percent of assets).[18] 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 16 for detail). HFs and HMFs have similar flows and size. Since turnover and load data are not available for HFs, we do not report these statistics. In comparison to TMFs, HMFs are smaller, with lower loads but higher expenses, flows, and turnover. Finally, in comparison to HMFs without HF managers, those with such managers have lower expenses but turnover is higher.

Panel D of Table 1 reports univariate performance statistics using net-of-fee and gross-of-fee risk-adjusted returns. First, HFs outperform HMFs based on four-factor and seven-factor gross and net alphas.[19] Second, HMFs outperform

[15]We thank Kenneth French and David Hsieh for making the returns data on the four and seven factors, respectively, available on their Web sites (http://mba.tuck.dartmouth.edu /pages/faculty/ken .french/data_library.html and http://faculty.fuqua.duke.edu/∼dah7/HFData.htm).

[16]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 IV, we calculate the gross performance measures for HFs accounting for the option-like incentive-fee contract as in Agarwal, Daniel, and Naik (2009). 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.

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

[18]At first, it seems a bit surprising that HFs are so much younger than HMFs. Upon closer investigation, this result is largely driven by a few HMFs that started many years ago. If we exclude the 10 oldest HMFs, with an average age of 40 years, the remaining HMFs in the sample have an average age of 9 years, 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.

[19]Our finding that HFs have positive risk-adjusted performance is consistent with prior literature. Specifically, the magnitude of seven-factor alphas of approximately 6.4% per annum using net-of-fee

TABLE 1

Summary Statistics for Hedged Mutual Funds, Traditional Mutual Funds, and Hedge Funds

Panel A of Table 1 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 (the difference of AUM in year t and 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; Panel C also reports the mean differences and results of a t-test comparing the means. Total load and turnover data are 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

	No. of HMFs				
Year	All HMFs	HFM_YES	HFM_NO	No. of TMFs	No. of HFs
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 (in millions of U.S. dollars)

	HMFs				
Year	All HMFs	HFM_YES	HFM_NO	TMFs	HFs
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

	Mean: HMF					Difference		
Fund Characteristics	All HMFs	HFM_ YES	HFM_ NO	Mean: TMF	Mean: HF	(HMF − HF)	(HMF − TMF)	(HFM_YES − HFM_NO)
AGE (years)	18.23	20.27	18.04	18.06	4.27	13.96***	0.17	2.23*
SIZE (millions of USD)	$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%***
FLOW (% 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%***

(continued on next page)

TABLE 1 (continued)

Summary Statistics for Hedged Mutual Funds, Traditional Mutual Funds, and Hedge Funds

Panel D of Table 1 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- 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 (1997) four-factor model. The four factors are the value-weighted CRSP index less the risk-free rate, which is called the market factor (β_{MKT}); the Fama and French (1993) Small minus Big (SMB) and High minus Low (HML) factors (β_{SMB} and β_{HML}); and Jegadeesh and Titman's (1993) Momentum factor (β_{UMD}). Panel F reports beta coefficient estimates from the Fung and Hsieh (2004) 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 mean 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.

	Mean: HMF					Difference		
	All HMFs	HFM_YES	HFM_NO	Mean: TMF	Mean: HF	(HMF − HF)	(HMF − TMF)	(HFM_YES − HFM_NO)
Panel D. Performance Measures								
Net Return: Annualized								
Four-factor alpha	0.57%	1.04%	−0.27%	−0.76%	6.56%	−5.99%***	1.33%***	1.31%
Seven-factor alpha	−0.32%	0.40%	−1.57%	−4.25%	6.40%	−6.72%***	3.93%***	1.97%
Gross Return: Annualized								
Four-factor alpha	3.39%	3.72%	2.65%	0.90%	8.61%	−5.22%***	2.49%***	1.07%
Seven-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								
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								
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	0.000	−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								
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

TMFs based on four- and seven-factor gross and net alphas. Ours is the first study to examine the performance of HMFs and document their superior performance relative to TMFs. Finally, in comparing HMFs with HF managers to those without, we find that the univariate performance differences are not statistically significant at traditional levels.

Panels E and F of Table 1 report betas from different multifactor models. Comparisons between HMFs and HFs show that betas for most of the factors in both the four- and seven-factor models are very similar, with the sole exception

returns is similar to that reported in Kosowski et al. (2007), who document alphas of roughly 5.4% per year during 1994–2002. Some other papers report positive Jensen's alphas for HFs. Using data from 1988–1995, Ackermann et al. (1999) find annual alphas in the 6%–8% range, while Brown et al. (1999) report annual alphas of approximately 5.7% per year for offshore HFs.

that HFs load more heavily on the small-cap factor in both models. The similarities in market betas for the four- and seven-factor models, and the fact that both are well below the market's beta of 1, indicate that HMFs are following similar investment strategies to HFs, notably, strategies that are not "long-only" in nature. Also, 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, those HMFs with HF managers tend to load more heavily on the small-cap factors than those without.

Panel G of Table 1 compares risk among the three categories. HFs have higher standard deviation, skewness, and excess kurtosis, than HMFs. TMFs have higher standard deviation, more negative skewness, and lower kurtosis than do HMFs. Finally, between HMFs with HF managers and those without, the only significant difference is that the standard deviation is lower for those HMFs with HF managers. Section IV tests our first hypothesis.

IV. 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 HMFs 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 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):

$$(1) \qquad \begin{aligned} \mathrm{PERF}_{i,t} \;=\; & \beta_0 + \beta_1\mathrm{HF} + \beta_2\mathrm{HMF} + \beta_3\mathrm{PERF}_{i,t-2} + \beta_4\mathrm{SIZE}_{i,t-1} \\ & + \beta_5\mathrm{AGE}_{i,t-1} + \beta_6\mathrm{EXPENSE}_{i,t-1} \\ & + \beta_7\mathrm{FLOW}_{i,t-1} + \sum_{t=1}^{9} \beta_8 I(\mathrm{YEAR}_t) + \xi_{i,t}, \end{aligned}$$

where $\mathrm{PERF}_{i,t}$ and $\mathrm{PERF}_{i,t-2}$ 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 an HF and 0 otherwise; HMF is an indicator variable that equals 1 if fund is an HMF and 0 otherwise (hence, the missing variable represents TMF); $\mathrm{SIZE}_{i,t-1}$ is the size of the fund measured as the natural logarithm of the assets under management (AUM) for fund i during year $t-1$; $\mathrm{AGE}_{i,t-1}$ is the logarithm of age of fund i at the end of year $t-1$; $\mathrm{EXPENSE}_{i,t-1}$ is the expense ratio of fund i during year $t-1$; $\mathrm{FLOW}_{i,t-1}$ is the percentage money flow in fund i in year $t-1$; $I(\mathrm{YEAR}_t)$

is a year dummy that takes a value of 1 during year t and is 0 otherwise; and $\xi_{i,t}$ is the error term. Since the total load and turnover variables are not available for HFs, they are not included in equation (1).

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 (2009). 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 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."[20] In addition, we lag the performance measures used as independent variables by two periods to ensure that the independent and dependent variables also have no overlap.[21] Finally, as HF returns are known to have a nonnormal distribution, we adjust for this effect on finite-sample inference by using bootstrapped standard errors with 1,000 replications. Hence, throughout the paper, we report the bootstrapped p-values.[22]

Since the omitted dummy variable in this regression is the TMF variable, a positive coefficient on the HF dummy variable (which we find) indicates that HFs outperform TMFs. This difference is quite large, ranging from 41.4 basis points (bps) per month (approximately 5.0% per year) to 79.0 bps per month (approximately 9.5% per year), and is consistent with prior HF literature; for example, see Ackermann et al. (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 that of HMFs. Thus, a positive and significant difference (HF − HMF) indicates support for the Regulation and Incentives Hypothesis.

For the four- 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 significant way (at the 1% level). The differences in net-of-fee performance range from 19.1 bps to 27.9 bps per month (roughly 2.3% to 3.3% per year) for the four- and seven-factor models, respectively. The corresponding

[20]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 and West (1987) correction for autocorrelation, which can be specified up to a particular lag length. As Petersen (2009) notes, the Rogers (1993) correction produces unbiased estimates, while the Newey and 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 (2009) 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.

[21]We acknowledge that this imposes a survival requirement of four years for funds to be included in our sample. This type 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 from our regression as an independent variable, which reduces the survival requirement to two years. Our results remain unchanged with this alternative specification.

[22]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.

differences for gross-of-fee alphas range from 31.4 bps to 40.7 bps per month (roughly 3.8% to 5.0% a year). The gross results are larger, since HFs charge higher fees than do HMFs. We attribute these differences in performance to lighter regulation and better incentives in HFs. Moreover, the statistical significance of these results is quite impressive, given the small sample size of HMFs.

To summarize, our results in this section strongly support the Regulation and Incentives Hypothesis. HFs outperform HMFs, indicating that using strategies similar to HFs cannot alone overcome the regulatory and incentive-based constraints of mutual funds. However, while HFs outperform HMFs by a significant margin (2.3% to 5.0% per year), it is not nearly as large as the margin of outperformance of HFs over TMFs (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 Strategy Hypothesis.

V. 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 TMFs. 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 bps (2.6% per year) for the gross four-factor model to 40.2 bps (4.9% per year) for the net seven-factor model. 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 AUM, and have been in existence for the same length of time (i.e., variable AGE). We follow a one-to-one matching procedure and report the results from the nonparametric Wilcoxon signed rank tests in Table 3.[23] 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 with differences ranging from 35 bps to 38 bps per month using gross-of-fee returns, and from 28 bps to 33 bps per month

[23]Davies and Kim (2009) show that following this practice increases the statistical power of the tests and provides better test properties.

TABLE 2

Performance of Hedged Mutual Funds, Traditional Mutual Funds, and Hedge Funds

Table 2 reports the results from the following OLS regression (equation (1)) using annual data for the period 1994 to 2004:

$$\mathrm{PERF}_{i,t} = \beta_0 + \beta_1\mathrm{HF} + \beta_2\mathrm{HMF} + \beta_3\mathrm{PERF}_{i,t-2} + \beta_4\mathrm{SIZE}_{i,t-1} + \beta_5\mathrm{AGE}_{i,t-1} + \beta_6\mathrm{EXPENSE}_{i,t-1} + \beta_7\mathrm{FLOW}_{i,t-1} + \sum_{t=1}^{9}\beta_8 I(\mathrm{YEAR}_t) + \xi_{i,t},$$

where $\mathrm{PERF}_{i,t}$ 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; $\mathrm{PERF}_{i,t-2}$ is the performance measure of fund i during year $t-2$; $\mathrm{SIZE}_{i,t-1}$ and $\mathrm{AGE}_{i,t-1}$ are the logarithms of fund size and age, respectively, of fund i at the end of year $t-1$; $\mathrm{EXPENSE}_{i,t-1}$ and $\mathrm{FLOW}_{i,t-1}$ are the expense ratio and percentage money flows, respectively, in fund i in year $t-1$; $I(\mathrm{YEAR}_t)$ is a year dummy that takes a value of 1 during year t and is 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- and gross-of-fee returns. Since HF and HMF dummy variables are included, the omitted category is TMF. The p-values using bootstrapped (with 1,000 replications) White (1980) standard errors adjusted for autocorrelation within two clusters (also known as the Rogers (1993) 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			
	Four-Factor Alpha		Seven-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 percentage of assets	0.0272**	−0.0667***	0.0180	−0.0821***
	(0.049)	(0.000)	(0.308)	(0.000)
Lagged flow as a percentage 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
No. 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, Traditional Mutual Funds, and Hedge Funds

Table 3 provides the means 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- 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.

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

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 bps to 34 bps per month on a gross-of-fee basis, and by about 29 bps per month on a net-of-fee basis. This result lends support to the Strategy Hypothesis.

We also perform a number of other robustness checks for our empirical tests in Section VI.B. Our results continue to hold. In the next section, we investigate whether strategy alone is driving these results, or if there is a further explanation—notably, manager skill.

VI. Testing the Skill Hypothesis

A. 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 data set of HMFs has a unique feature: roughly one-half of the HMFs have managers that concurrently manage HFs. We hypothesize that this experience should be advantageous when 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 HF database (TASS). We find nine matches in this way, all of which we verify using the second approach of searching on the mutual fund company's Web site for the manager's information and the additional funds he/she manages. This information is reported in the fund's statement of additional information (SAI), which funds are required to file regularly with the SEC (available from funds' Web sites or http://www.sec.gov). We also perform a broad Internet search for interviews with the manager in which he/she specifically discusses his/her management of both an HMF and an HF.

Using this search process, we identify 27 HMFs with HF managers and 25 with TMF managers. Interestingly, 12 of the 14 defunct HMFs belong to the latter category, providing preliminary support for the Skill Hypothesis. We create an indicator variable set to 1 for the years when the HMF has an HF manager (HFM_YES) and 0 otherwise. We also create a variable set to 1 if the HMF has a HF manager (HFM_NO) and 0 otherwise. Effectively, we are splitting the HMF indicator variable from Table 2 into two separate variables.

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

$$\text{(2)} \quad \begin{aligned} \text{PERF}_{i,t} = {} & \beta_0 + \beta_1\text{HF} + \beta_2\text{HFM\_YES} + \beta_3\text{HFM\_NO} \\ & + \beta_4\text{PERF}_{i,t-2} + \beta_5\text{SIZE}_{i,t-1} + \beta_6\text{AGE}_{i,t-1} + \beta_7\text{EXPENSE}_{i,t-1} \end{aligned}$$

$$+ \beta_8 \text{FLOW}_{i,t-1} + \sum_{t=1}^{9} \beta_9 I(\text{YEAR}_t) + \psi_{i,t},$$

with all remaining variables as defined in equation (1); $\psi_{i,t}$ is the error term. Again, 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 support the Skill Hypothesis. In both 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 bps per month (2.8% annually) for the four-factor gross return model to a high of 35.8 bps 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.[24] 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 is 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, since data 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 only (we exclude HFs) and estimate the following regression:

$$\begin{aligned}(3)\quad \text{PERF}_{i,t} = {} & \beta_0 + \beta_1 \text{HFM\_YES} + \beta_2 \text{HFM\_NO} + \beta_3 \text{PERF}_{i,t-2} \\ & + \beta_4 \text{SIZE}_{i,t-1} + \beta_5 \text{AGE}_{i,t-1} + \beta_6 \text{EXPENSE}_{i,t-1} + \beta_7 \text{FLOW}_{i,t-1} \\ & + \beta_8 \text{TURNOVER}_{i,t-1} + \beta_9 \text{TOTAL\_LOAD}_{i,t-1} \\ & + \sum_{t=1}^{9} \beta_{10} I(\text{YEAR}_t) + \psi_{i,t}.\end{aligned}$$

All variables are as in equation (2). TURNOVER is the fund's annual turnover provided by CRSP, and TOTAL_LOAD is the weighted average of load fees. The results, presented in Table 5, provide even stronger support for the Skill Hypothesis. It appears that including the load ($\text{TOTAL\_LOAD}_{i,t-1}$) and turnover ($\text{TURNOVER}_{i,t-1}$) variables is important in this regression. Both of these variables are significant in all but one of the four specifications. In three of the four regression specifications, managers with HF experience significantly outperform those without. This outperformance ranges from 27.7 bps to 46.9 bps per month (3.3% to 5.6% per year).

[24]When we repeat our analysis using the matched sample procedure (results not reported in Table 4), we do find the difference based on four-factor net alphas to be positive and significant (9 bps per month). Furthermore, the difference based on gross alpha varies from 14 bps to 21 bps per month using the two models.

TABLE 4

Performance of Hedged Mutual Funds With and Without Hedge Fund Managers, Traditional Mutual Funds, and Hedge Funds

Table 4 reports the results from the following OLS regression (equation (2)) using annual data for the period 1994 to 2004:

$$\mathrm{PERF}_{i,t} = \beta_0 + \beta_1 \mathrm{HFM\_YES} + \beta_2 \mathrm{HFM\_NO} + \beta_3 \mathrm{HF} + \beta_4 \mathrm{PERF}_{i,t-2} + \beta_5 \mathrm{SIZE}_{i,t-1} + \beta_6 \mathrm{AGE}_{i,t-1} + \beta_7 \mathrm{EXPENSE}_{i,t-1} + \beta_8 \mathrm{FLOW}_{i,t-1} + \sum_{t=1}^{9} \beta_9 I(\mathrm{YEAR}_t) + \psi_{i,t},$$

where 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 0 otherwise; $\psi_{i,t}$ is the error term. Other variables are as defined in Table 2. 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- and gross-of-fee returns. The p-values using bootstrapped (with 1,000 replications) White (1980) standard errors adjusted for autocorrelation within two clusters (also known as the Rogers (1993) 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			
	Four-Factor Alpha		Seven-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 percentage of assets	0.0284**	−0.0664***	0.0198	−0.0813***
	(0.040)	(0.000)	(0.266)	(0.003)
Lagged flow as a percentage 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
No. 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%

Finding support for the Skill Hypothesis indicates that retail investors can benefit from the skills of HF managers within the regulatory environment of mutual funds. A natural question related to this finding is: "Why would HF managers choose to enter the mutual fund area, given its more stringent regulatory restrictions, tighter investment constraints, and lack of performance-based incentives?" We explore two possible, although 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 HFs, HMFs may be attractive, as they can be advertised and marketed to a much larger investor base that includes retail clients. They may also appeal to institutional investors who prefer greater disclosure and transparency.

TABLE 5

Performance of Hedged Mutual Funds Managed With and Without Hedge Fund Managers versus the Performance of Traditional Mutual Funds Only

Table 5 reports the results from the following OLS regression (equation (3)), using annual data for the period 1994 to 2004:

$$\text{PERF}_{i,t} = \beta_0 + \beta_1\text{HFM\_YES} + \beta_2\text{HFM\_NO} + \beta_3\text{PERF}_{i,t-2} + \beta_4\text{SIZE}_{i,t-1} + \beta_5\text{AGE}_{i,t-1} + \beta_6\text{EXPENSE}_{i,t-1}$$

$$+ \beta_7\text{FLOW}_{i,t-1} + \beta_8\text{TURNOVER}_{i,t-1} + \beta_9\text{TOTAL\_LOAD}_{i,t-1} + \sum_{t=1}^{9}\beta_{10}^{s} I(\text{YEAR}_t) + \psi_{i,t},$$

where $\text{TURNOVER}_{i,t-1}$ and $\text{TOTAL\_LOAD}_{i,t-1}$ are the turnover and total load, respectively, in fund i in year $t-1$, and all other variables are as defined in Tables 2 and 4. 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- and gross-of-fee returns. The p-values using bootstrapped (with 1,000 replications) White (1980) standard errors adjusted for autocorrelation within two clusters (also known as the Rogers (1993) 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-test for the significance in this difference is performed. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

	Performance			
	Four-Factor Alpha		Seven-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 percentage of assets	0.0057	−0.0658***	0.0137	−0.0756***
	(0.741)	(0.000)	(0.513)	(0.000)
Lagged flow as a percentage 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
No. 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%**

To investigate whether only underperforming HF managers offer HMFs, we compare the performance of their HFs relative to their peers by estimating the following regression:[25]

[25]We estimate this regression for the pooled sample of HFs only and do not include HMFs and TMFs.

$$\text{(4)} \qquad \mathrm{PERF}_{i,t} = \beta_0 + \beta_1 \mathrm{HF\_with\_HMF} + \beta_2 \mathrm{PERF}_{i,t-2} + \beta_3 \mathrm{SIZE}_{i,t-1} + \beta_4 \mathrm{AGE}_{i,t-1} + \beta_5 \mathrm{EXPENSE}_{i,t-1} + \beta_6 \mathrm{FLOW}_{i,t-1} + \sum_{t=1}^{9} \beta_7 I(\mathrm{YEAR}_t) + \psi_{i,t}.$$

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 an HMF and 0 otherwise. A positive coefficient on this variable indicates that the HFs of HF managers 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 fares 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 Panel B of Table 6 corroborate the results in Panel A from the multivariate regression. Overall, these results indicate that poor HF performance does not drive managers into offering HMFs.

Next, we investigate the possibility that HF managers offer HMFs to gather assets. As argued in Section I, 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 of HF managers who also manage HMFs, we first 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 AUM is a key reason to concurrently manage HFs and HMFs.[26] We then review a number of recent articles supporting the idea that lesser-known HF managers have difficulty attracting assets, and that the HMF space allows them to grow their assets and establish a stable revenue base (see Appendix B for detailed quotes from these articles). Hence, we conclude that raising assets is a reasonable rationale for why some HF managers also offer HMFs. To summarize, this section's results provide strong evidence in support of the Skill Hypothesis.

B. 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 results for all the analyses in Table 7. For ease of comparison, the first row repeats the findings from the main tables. Panels A, B, and C of

[26]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. 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 (VCs) to achieve critical 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.

TABLE 6

Performance of Hedge Funds Run Along With Hedged Mutual Funds

Panel A of Table 6 reports the results from the following OLS regression (equation (4)), using annual data for the period 1994 to 2004:

$$\begin{aligned} \text{PERF}_{i,t} \quad = \quad & \beta_0 + \beta_1 \text{HF\_with\_HMF} + \beta_2 \text{PERF}_{i,t-2} + \beta_3 \text{SIZE}_{i,t-1} + \beta_4 \text{AGE}_{i,t-1} + \beta_5 \text{EXPENSE}_{i,t-1} \\ & + \beta_6 \text{FLOW}_{i,t-1} + \sum_{t=1}^{9} \beta_7 I(\text{YEAR}_t) + \psi_{i,t}, \end{aligned}$$

where 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 0 otherwise, and all other variables are as defined in Tables 2, 4, and 5. The p-values using bootstrapped (with 1,000 replications) White (1980) standard errors adjusted for autocorrelation within two clusters (also known as the Rogers (1993) 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- and gross-of-fee returns. Panel B of Table 6 provides the means of performance measures for matched samples of HFs that are offered along with 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. Results from OLS Regressions

	Performance			
	Four-Factor Alpha		Seven-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 percentage of assets	0.1609***	0.0603*	0.1419**	0.0548
	(0.000)	(0.096)	(0.014)	(0.178)
Lagged flow as a percentage 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
No. of fund-years	2,639	3,979	2,639	3,979

Panel B. Comparison of Average Performance Measures for Matched Samples of Hedge Funds that are Offered Along with Hedged Mutual Funds and Those that are Not Offered Concurrently with Hedged Mutual Funds

Performance Measure	Mean: HFs_with_HMFs (A)	Mean: HFs_without_HMFs (B)	Difference (A − B)
Gross-of-Fee			
Four-factor alpha	0.75%	0.69%	0.06%
Seven-factor alpha	0.78%	0.60%	0.18%
Net-of-Fee			
Four-factor alpha	0.45%	0.51%	−0.06%
Seven-factor alpha	0.52%	0.40%	0.12%

Table 7, respectively, corresponding to Tables 2, 4, and 5, indicate that the results for HMFs, HFs, and TMFs are robust to the use of alternative econometric specifications.

Second, we repeat all our analyses using monthly data instead of annual data. Although monthly data provide many more observations, they also introduce 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 and MacBeth (1973) regressions and report our findings in Table 8,

TABLE 7

Robustness Tests Using Random Effects

Table 7 presents the results of robustness tests to various econometric techniques for the regressions performed in Tables 2, 4, and 5. It presents fund- and family-level random effects regressions for each of the previous 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. The *p*-values using bootstrapped standard errors with 1,000 replications are shown below the coefficients in parentheses. Values 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)

	Performance			
	Four-Factor Alpha		Seven-Factor Alpha	
Specification	Gross	Net	Gross	Net
HF indicator variable	0.529%*** (0.000)	0.414%*** (0.000)	0.790%*** (0.000)	0.681%*** (0.000)
HMF indicator variable	0.215%*** (0.001)	0.223%*** (0.000)	0.383%*** (0.000)	0.402%*** (0.000)
Difference between HF and HMF	0.314%***	0.191%***	0.407%***	0.279%***
1. Family Random Effects				
HF indicator variable	0.621%*** (0.000)	0.483%*** (0.000)	0.882%*** (0.000)	0.729%*** (0.000)
HMF indicator variable	0.150%* (0.054)	0.153%** (0.021)	0.299%*** (0.001)	0.298%*** (0.000)
Difference between HF and HMF	0.471%***	0.330%***	0.583%***	0.431%***
2. Fund Random Effects				
HF indicator variable	0.608%*** (0.000)	0.468%*** (0.000)	0.907%*** (0.000)	0.775%*** (0.000)
HMF indicator variable	0.230%*** (0.000)	0.205%*** (0.000)	0.420%*** (0.000)	0.417%*** (0.000)
Difference between HF and HMF	0.378%***	0.263%***	0.487%***	0.358%***

(continued on next page)

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. The double clustering in pooled regressions adjusts for serial as well as cross-sectional correlation in residuals. For the Fama and MacBeth (1973) regressions, we adjust the standard errors for autocorrelation and heteroskedasticity using the generalized method of moments (Hansen (1982)) procedure. Our findings continue to provide strong support for our three hypotheses.[27]

Third, we repeat our analysis with alphas estimated from conditional models (e.g., Ferson and Schadt (1996)) instead of unconditional 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.[28] Nevertheless, for robustness, we also conduct our analysis using conditional alphas and report our findings in Table 9. Specifically, we introduce lagged "information variables" to

[27]We also repeat our entire analysis using the Fama and 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.

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

TABLE 7 (continued)

Robustness Tests Using Random Effects

Panel B. Coefficients on the HFM_YES, HFM_NO, and HF Variables in HMF, TMF, and HF Regressions (Table 4)

	Performance			
	Four-Factor Alpha		Seven-Factor Alpha	
Specification	Gross	Net	Gross	Net
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%*

Panel C. Coefficients on the HFM_YES and HFM_NO Variables in HMF and TMF Regressions (Table 5)

	Performance			
	Four-Factor Alpha		Seven-Factor Alpha	
Specification	Gross	Net	Gross	Net
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 8

Robustness Tests Using Monthly Data

Table 8 presents the results of pooled and Fama and MacBeth (1973) regressions performed using monthly data. The regressions are similar to those in Tables 2, 4, and 5, except that alphas are estimated on a monthly basis using a 24-month window moved forward by one 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 (1980) standard errors adjusted for autocorrelation within two clusters (also known as the Rogers (1993) standard errors with "clustering" at the fund level and at "time" level) are shown below the coefficients in parentheses. For Fama and MacBeth (1973) regressions, p-values adjusted for autocorrelation and heteroskedasticity using GMM are shown below the coefficients in parentheses. Values 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)

	Performance			
	Four-Factor Alpha		Seven-Factor Alpha	
Specification	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 and 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)

	Performance			
	Four-Factor Alpha		Seven-Factor Alpha	
Specification	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 and 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%*

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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 Ferson and Schadt (1996): lagged dividend yield on the S&P 500, lagged term spread, credit spread, and risk-free rate, along with a January dummy. Data for these variables

TABLE 8 (continued)

Robustness Tests Using Monthly Data

Panel C. Coefficients on the HFM_YES and HFM_NO Variables in HMF and TMF Regressions (Table 5)

	Performance			
	Four-Factor Alpha		Seven-Factor Alpha	
Specification	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 and 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%**

are from CRSP and the U.S. Federal Reserve Web site (http://www.federalreserve.gov/).

Conditional models have not been used frequently in the HF literature, mainly due to the relatively short time frame for which HF data is available. The

TABLE 9

Robustness Tests Using Alphas from Conditional Models

Table 9 presents the results of robustness tests using conditional alphas instead of unconditional alphas for the regressions performed in Tables 2, 4, and 5. This 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- 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. The p-values using bootstrapped standard errors with 1,000 replications are shown below the coefficients in parentheses. Values 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)

	Performance			
	Four-Factor Conditional Alphas		Seven-Factor Conditional Alphas	
Specification	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%***

(continued on next page)

TABLE 9 (continued)

Robustness Tests Using Alphas from Conditional Models

Panel B. Coefficients on the HFM_YES, HFM_NO, and HF Variables in HMF, TMF, and HF Regressions (Table 4)

	Performance			
	Four-Factor Conditional Alphas		Seven-Factor Conditional Alphas	
Specification	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%**

Panel C. Coefficients on the HFM_YES and HFM_NO Variables in HMF and TMF Regressions (Table 5)

	Performance			
	Four-Factor Conditional Alphas		Seven-Factor Conditional Alphas	
Specification	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%***

few academic studies that have been conducted in this area conclude that using conditional models does not improve the estimation of alphas or betas.[29] 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. We use 24-month alphas in all our analyses because, for one thing, this time frame is long enough for estimation purposes but short enough that it does not induce too much survivorship bias or lead to the exclusion of too many HMFs from our sample. We perform

[29]A few HF papers that have used conditional models tend to use a much longer time frame to estimate alphas. Gupta, Cerrahoglu, and Daglioglu (2003), for example, 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.

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

The results from conditional models in Table 9 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 conduct four 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 appears 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 sales of securities held for less than three months. Violation of this rule resulted in tax penalties on short-term gains, restricting funds from investing in derivatives, as most options and futures contracts mature within three months and can thereby result in short-term gains.[30] With the repeal of the short/short rule, the number of HMFs grew dramatically. Regardless of whether we use the sample period 1994–2004 or 1998–2004, our results remain similar.

Second, we perform a test to determine if the overlap in the independent variable affects the results, although we do control for this bias by adjusting standard errors for clustering on both time and fund effects. We split the sample into two subsamples using odd and even years, still using the double-clustering approach to control for autocorrelation and cross-sectional correlation. The results for the split sample are similar to results for the combined sample.

Third, we examine whether 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, and 2004), based on the median return of the S&P 500 index during the sample period. We then reestimate all regressions from Tables 2, 4, and 5 for these two subperiods. The results do not change: HMFs outperform TMFs, and funds with HFM_YES = 1 outperform those with HFM_NO = 1, regardless of market conditions.

Finally, we perform tests of performance persistence within the subsample of HMFs, to determine whether HMFs with HF managers (HMF_YES = 1) have better performance persistence than those without (HMF_NO = 1). We follow Brown and Goetzmann (1995) and Agarwal and Naik (2000) and rank each HMF relative to all other HMFs during the year as either a "winner" (W) or a "loser" (L). Using the cross-product ratio test as well the z-statistic per Malkiel (1995), we find strong evidence of positive performance persistence among HMF_YES funds and also find some evidence of negative performance persistence among HMF_NO funds. These results on persistence provide additional support for the Skill Hypothesis.

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

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

VII. Conclusion

This paper provides the first comprehensive examination of 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 (HMFs), traditional mutual funds (TMFs), and hedge funds (HFs) following similar investment styles.

The first hypothesis, the Regulation and Incentives Hypothesis, posits that HMFs will underperform HFs, due to differences in regulations and incentives. This hypothesis holds true. HMFs significantly underperform HFs, both on a net-of-fee basis (by as much as 4.1% per year) and on a gross-of-fee basis (by roughly 5.6% per year). We infer that the tighter regulatory environment in TMFs, which limits funds' borrowing to one-third of their assets and requires daily liquidity and pricing and coverage of short positions, constrains the ability of HMFs to implement strategies as effectively as in the HF environment. Also, HMFs have weaker incentives to deliver superior performance in the absence of performance-based compensation. Thus, it is not surprising that, as a group, HMFs strongly underperform HFs.

Next, the Strategy Hypothesis predicts that HMFs will outperform TMFs, since HMFs possess greater investment flexibility, 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 HMFs outperform TMFs by approximately 2.6% to 4.8% per year suggests that the benefits of greater flexibility outweigh the increase in agency costs.

Furthermore, the Skill Hypothesis provides an additional explanation for the superior performance of HMFs relative to TMFs. Specifically, the hypothesis predicts that managers with experience in HF trading strategies will outperform managers without this experience. We find strong support for this prediction. Managers with HF experience outperform those without by approximately 3.3% to 5.6% per year.

Finally, we provide evidence that it is not the poorly performing HF managers who choose to offer HMFs. Anecdotal evidence seems to suggest that this phenomenon is driven by the desire of HF managers to have a diversified client base as well as to raise more assets. Taken together, our findings suggest that providing greater flexibility to HMFs through a wider investment opportunity set helps them to outperform TMFs. This is especially true for HMFs 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.

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.[31] 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 HF 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 Web site, Lexis/Nexis, and http://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 identify 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 five funds from the sample that follow fixed-income or balanced strategies. Second, we exclude passive funds. This simple criterion allows us to eliminate more than half of the remaining funds.[32] Usually through the use of futures contracts, the eliminated 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 an HF strategy, we identify only four mutual funds that appear to follow an "active" short-only strategy, which we exclude from our sample.[33] 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 sometimes be misleading (see Cooper, Gulen, and Rau (2005)). Instead, for each of the defunct funds, we review

[31] 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 as "Long/Short Equity." The key theoretical difference in Long/Short Equity and Equity Market Neutral funds is 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, although not too large, market beta.

[32] 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.

[33] 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 the ProFunds and Rydex families.

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.[34] Using this approach, we identify 13 defunct long/short mutual funds that would have been included on Morningstar's list had it 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, two 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, seven describe popular HF strategies in their prospectuses. Of the 10 remaining funds, a review of annual reports and prospectuses reveals that all use HF strategies that would be categorized as "other/multi-strategy." For each of these funds, we also identify at least one manager interview in which the fund is described 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 HFs 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.[35] Using the highest market beta for the Morningstar/Lipper list of 0.81 as the cut-off criterion removes five 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 their names did not include any of our original search terms. For this test, we calculate the mean 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 three additional funds that fit our criteria, bringing our final sample to 52 funds, 14 of which are defunct.[36]

[34]Per discussion with Dan McNeela of Morningstar on June 7, 2006.

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

[36]We confirm that the low market betas of excluded funds occur for a number of reasons, the most common being that: i) the fund does not follow a primarily equity-based strategy, ii) the fund is a sector fund that has low exposure to the market factor, iii) the fund is a very small fund, iv) the fund is invested primarily in cash, and v) 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

In Table B1, we provide excerpts from recent press articles that suggest that HF companies may be offering HMFs concurrently to raise assets and diversify their client base. We present our clarifications/comments in italics.

TABLE B1

Excerpts from Press Articles Providing Rationale for Concurrent Management of Hedge Funds and Hedged Mutual Funds

Quote	Publication	Date
What's more, some HF 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 HF managers are interested in running [HMFs] 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 seven years' experience at DE Shaw (an HF) and three 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 HF 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 HFs are trying to move into traditional portfolio management and beyond their HF 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. "[HMF] 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 HFs 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, an HF.)*	*Investment News*	May 16, 2005

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