Original Article

Can typical households earn hedge fund returns? An analysis of the Eta® replication approach

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ABSTRACT **In this study, we present an extension to the literature on passive hedge fund replication and its applications by introducing the Eta model, and applying it to hedged mutual funds (HMFs) in an attempt to clone their cumulative returns and assessing the skills of fund managers. Although our replication methodology performed reasonably well for HMFs of certain trading strategies, the clones tend to outperform their respective HMFs, which suggest significant managerial influence that compromises fund performance. Finally, with the aid of the Eta model, we constructed a minimum economic risk portfolio, a long-only portfolio comprising exchange traded funds, with quarterly rebalancing, which nevertheless registered higher cumulative returns than funds with access to long/short strategies, leverage and derivatives. This augurs well for a typical household in that it is possible for them to earn hedge fund returns without hedge fund experience or expertise.**

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INTRODUCTION

This article presents an extension to the literature on passive hedge fund replication and its applications. At present, the replication methods are the Factor Approach (Fung and Hsieh, 1997), the Payoff Distribution Approach (Amin and Kat, 2003; Kat and Palaro, 2005) and the Mechanical Trading Rule Approach (Mitchell and Pulvino, 2001). For a detailed discussion of the various replication approaches, see Kat (2007). We introduce a factor model – the Eta model – whereby the factors of interest relate to the economy, which in turn influences all asset values. This is in contrast to style factors that are appropriate only for particular hedge fund strategies.

Thus far, much has been covered in academia on hedge funds, which hardly pertains to a typical individual investor, who does not have access to these funds meant for the wealthy and 'sophisticated'. Instead, our study delves into investment alternatives that are accessible to a typical individual. The past few years have witnessed innovation in financial markets, resulting in a variety of investment products open to a typical household. Two products come to mind – hedged mutual funds (HMFs) and hedge fund replication products (Kalwarski, 2009, 2010; Laise, 2009; *The Economist*, 2010). We will apply the Eta model to HMFs, attempting to clone their cumulative returns while at the same time assessing the skills of HMF managers. Lastly, with the aid of the Eta model, we will construct a minimum economic risk portfolio and compare it to the performance of HMFs and hedge fund replication products.

In anticipation of the results, we find that the Eta model is successful in cloning the economic factors of HMFs and effective in replicating the cumulative returns of HMFs of certain trading strategies. However, over time, clones of some strategies demonstrate divergence. Investing in the replicating portfolio may result in excess returns over those of HMFs, suggesting the lack of HMF manager skill. The excess returns could be further enhanced with a minimum economic risk portfolio.

The article is structured as follows. We begin by providing a brief overview of HMFs, followed by a detailed discussion of the Eta model. Next, we review the various applications of the Eta model – replication, assessment of fund manager skill and construction of a minimum economic risk portfolio – and present some results for the Eta model in relation to HMFs and hedge fund replication products. Finally, we end with our conclusions.

HMF DATA

It is fairly recent that we witness the emergence of mutual funds that use hedge fund strategies to capitalize on both the long and short side, enhanced with leverage and derivatives. These mutual funds are referred to as HMFs or absolute return mutual funds. Unlike the hedge fund industry, HMFs are regulated by the Securities and Exchange Commission (Agarwal *et al*, 2009).

Any analysis that deals with hedge fund index data will encounter the following problems and the biases that result from them: survivorship, back-filling, return figures that are provided by the hedge fund managers, monthly data and the lack of transparency (Jaeger and Wagner, 2005). HMF data, on the other hand, do not experience such limitations.

The daily closing prices for the various HMFs are obtained from Yahoo Finance, for the period 1 January 2005 to 31 December 2009, a span of 5 years, comprising 1260 data points. As the median net worth of a family in 2007 is US$120 300 (Board of Governors of the Federal Reserve System, 2009), we consider HMFs with a minimum initial investment of $25 000 or less. We further filter with the Morningstar Mutual Fund Screener, under the long/short category, for HMFs with 4 or 5 Morningstar Star Rating. Morey and Gottesman (2006) find supporting evidence that the Morningstar Star Rating

Table 1: Shortlisted hedged mutual funds

Ticker	*Hedged mutual fund name*	*Morningstar Star Rating (long/short)*	*Minimum initial investment (in \$)*
JMNAX	JP Morgan Market Neutral A	4	1000
MLSAX	Aberdeen Equity Long-Short A	4	2000
MERFX	Merger	4	2000
CVSIX	Calamos Market Neutral Income A	4	2500
DIAMX	Diamond Hill Long-Short A	4	2500
TFSMX	TFS Market Neutral	5	5000
COAGX	Caldwell & Orkin Market Opportunity	4	25 000

system predicted future performance, with higher rated funds performing significantly better than lower rated funds. The shortlisted HMFs are listed in Table 1.

Of the seven shortlisted HMFs, three (JMNAX, CVSIX, TFSMX) are market neutral funds, two are of the long/short variety (MLSAX, DIAMX), and one is a merger arbitrage fund (MERFX). On the other hand, it is difficult to classify COAGX as it has a rather vague investment strategy.

METHODOLOGY AND RESULTS

The replication methodology we are introducing, though different from other factor-based approaches, is in the same spirit. Instead of asset returns, economic drivers would serve as factors and asset values as the replication target. As asset values are driven by the economy, the fundamental drivers of a factor-based approach ought to be economic variables. Rather than develop a new set of factors, we utilize the Eta factors developed by the Center for Computationally Advanced Statistical Techniques (c4cast.com, Inc.) using its MacroRisk Analytics platform. This method applies cointegration and advanced computational methodology to relate asset prices to a common set of 18 economic factors. These factor loadings (called an 'Eta profile') are publicly available at www.economicinvestor.com for most US traded stocks, mutual funds and exchange traded funds (ETFs).

Although the particular process for obtaining the Eta profile and the general 'emulation process' are patented,[1] the particular approach we are discussing in this article is a unique extension of the c4cast patented approach. This article extends the c4cast approach to the widely studied application of portfolio cloning and thereby offers a portfolio replication approach that is more cost effective with better performance than methods usually studied in the academic literature.

The Eta equations underlying this have an in-sample R^2 in excess of 0.9 for over 90 per cent of the nearly 21 000 assets analyzed by the c4cast system. It is our hypothesis that assets with similar Eta profiles will generally track each other in the marketplace. For example, Figure 1 compares the Eta profile of the S&P 500 Index (SPX) and the Vanguard 500 Index Investor mutual fund (VFINX), a common index fund benchmarked on the SPX. In contrast, Figure 2 compares the Eta profile of the SPX and the ProShares Short S&P500 ETF (SH), which generally has an opposite-looking Eta profile. Figure 3, for reference, shows the recent performance of VFINX, SH and the index. The two with similar Eta profiles track each other closely whereas the one with the opposite Eta profile was essentially a mirror image in performance.

Our Eta replication approach is to select assets from a buy list so that the Eta profile of the resulting portfolio is as close a match as possible to the replication target. It is our hypothesis that such a portfolio will capture the systematic, economically driven, component of the replication target. It is our further hypothesis that replication targets that themselves have lower R^2 statistics for their own Eta equations will be less accurately replicated than those with higher R^2 statistics because of the relative contribution of the economic factors compared to idiosyncratic firm or manager-related factors to the asset performance.

The 18 economic factors in the Eta model include the FTSE 100 Index, Gold Index, Corporate Bond (BAA) Yield, Consumer Price Index, Short-term Government Bond Yield, Medium-term Government Bond Yield, Long-term Government Bond Yield, Tokyo Stock Exchange Index, the Euro Exchange Rate, Agricultural Exports, Housing Starts, Monetary Base, M2 Money Supply, Corporate Cash Flow, Unemployment Rate, Auto Sales, New Durable Goods Orders, and Energy Prices.

Some traditional factors are not included in this list, including Gross Domestic Product (GDP). However, GDP contributes little information beyond these 18 factors and therefore is a redundant variable. Size factors are

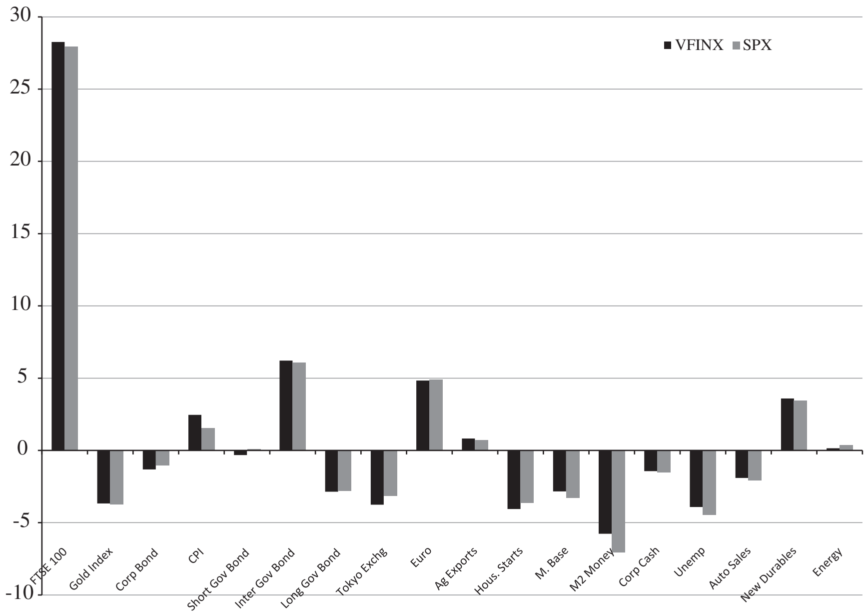

Figure 1: Eta profile of VFINX and SPX on 31 December 2009.

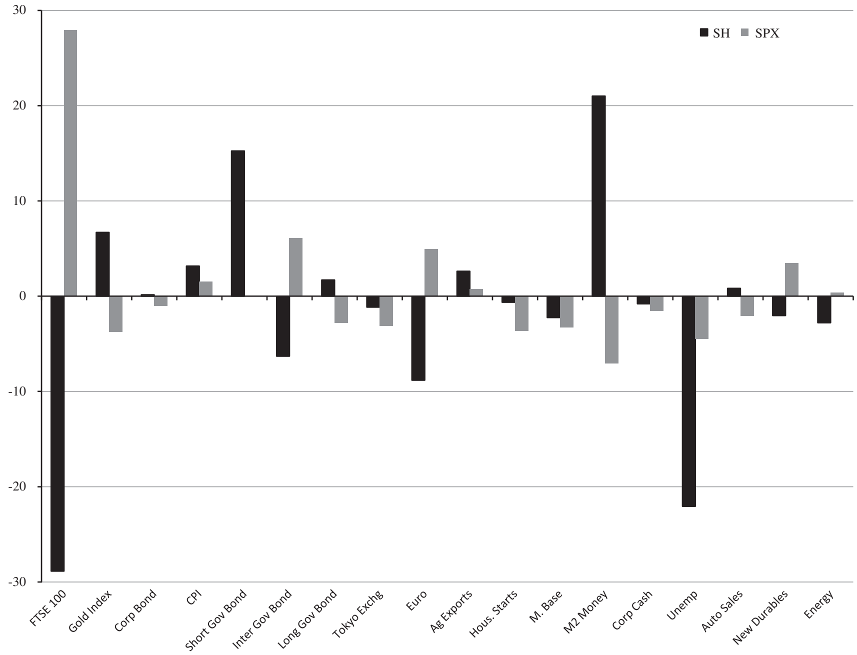

Figure 2: Eta profile of SH and SPX on 31 December 2009.

Figure 3: Cumulative returns of VFINX, SH and SPX, 31 December 2008 – 31 December 2009.

also not included because size is a firm-specific, not systematic, variable. The Eta model only includes systematic variables.

Figure 4 illustrates an investment's Eta profile and the 18 economic factors' influence, with their corresponding *t*-statistics, on 1 January 2005.

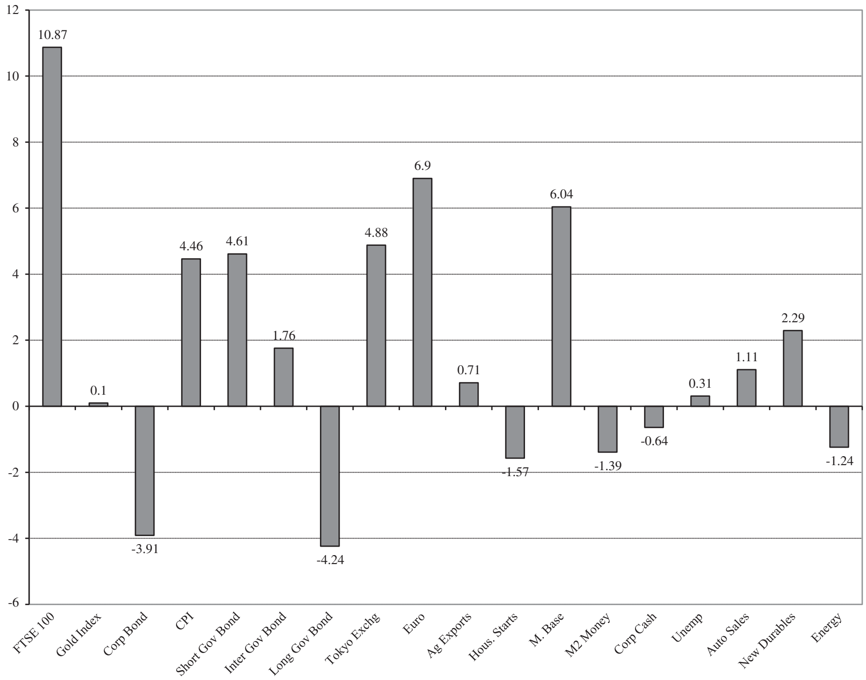

Figure 4: Eta profile with factor loadings.

In addition to illustrating how the economic factors affect an asset's value, the Eta model could also be applied to replicating the economic characteristics of another asset, to assessing a fund manager's investment skills and, lastly, to creating a minimum risk portfolio.

Replication

As with Jaeger and Wagner (2005), Hasanhodzic and Lo (2007), Amenc *et al* (2008) and Amenc *et al* (2010), we assess the out-of-sample replication quality of the Eta model by attempting to clone the time-series characteristics of HMFs.

We initiate the economic factor replication process at the beginning of each quarter, starting with 1 January 2005, using a buy list comprising only ETFs. As an illustration, we can see from Figure 5 the Eta profiles of DIAMX and her clone. Of the 18 factors 5 are in the opposite direction whereas the others have lower tracking errors. The magnitude of the tracking errors is represented graphically in Figure 6. Figure 7 graphs the time series for DIAMX and her clone, for the period 1 January 2005 to 31 December 2009.

Up until end-2007, the clone performed reasonably well at replicating the return series of DIAMX, after which the tracking error increased. Going forward from 2008, the clone outperforms DIAMX. 'However, out-performance is not necessarily the goal of replication products, but instead to track hedge fund performance. Hence, out-performance of hedge fund indices is not *per se* a proxy for success of a replication product' (see Wallerstein *et al*, 2010).

Table 2 presents the summary statistics for HMFs and their respective clones. (See Figure 8 for their cumulative returns.[2]) Our replication

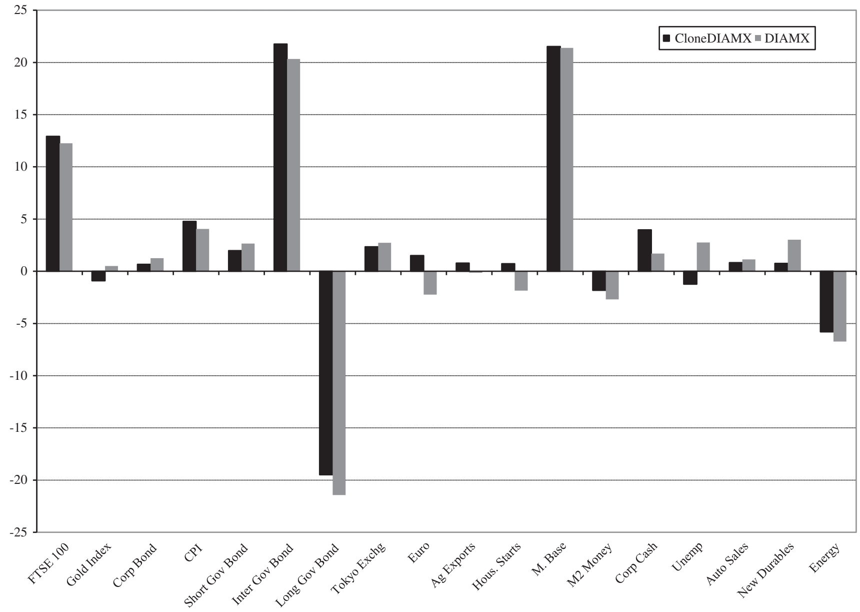

Figure 5: Eta profiles of the clone and DIAMX on 1 January 2005.

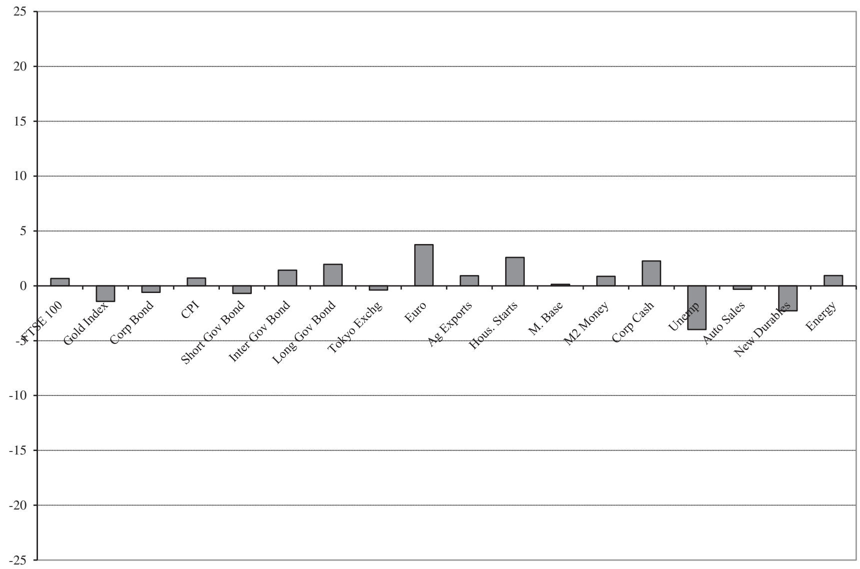

Figure 6: Divergence Eta profile between the clone and DIAMX on 1 January 2005.

methodology lends itself well to certain hedge fund strategies but not to others. This is consistent with findings in existing literature[3] even if previous studies were replicating hedge fund indices (either overall or by hedge fund strategies) as opposed to individual funds (Fung and Hsieh, 2004).[4]

To further improve the efficacy of replication, various studies have explored asset-based style (ABS) factors in an attempt to capture

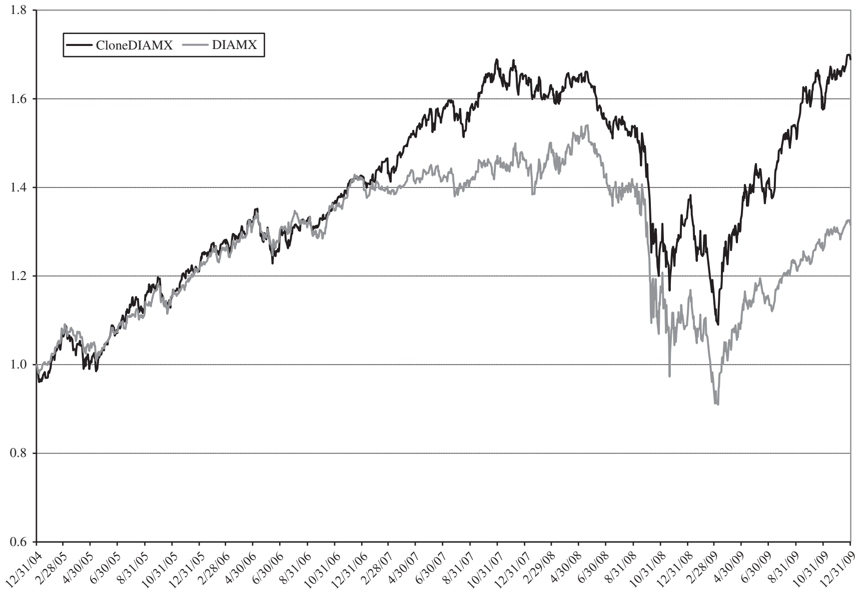

Figure 7: Time series for the clone and DIAMX, 1 January 2005 – 31 December 2009.

Table 2: Summary statistics for HMF and clone returns, 1 January 2005 – 31 December 2009

	Mean return (%)	*SD (%)*	*Skewness*	*Kurtosis*	*Correlation*	*Investment strategy*
CloneJMNAX	0.0251	0.6437	0.0110	5.9186	0.1875	—
JMNAX	0.0181	0.2296	0.3531	4.4667	—	Mkt. Neutral
CloneMLSAX	0.0321	0.8243	0.1905	4.9377	0.6559	—
MLSAX	0.0159	0.4843	−0.2920	5.8858	—	Long/Short
CloneMERFX	0.0278	0.6815	−0.0015	5.1553	0.4452	—
MERFX	0.0168	0.4380	0.7865	31.4097	—	Merger Arb.
CloneCVSIX	0.0294	0.7380	0.1412	5.2834	0.7621	—
CVSIX	0.0089	0.4897	−0.5633	10.1282	—	Mkt. Neutral
CloneDIAMX	0.0459	0.9192	−0.1311	3.3149	0.8213	—
DIAMX	0.0279	1.1012	−0.1588	11.6131	—	Long/Short
CloneTFSMX	0.0331	1.4024	0.1026	2.4565	0.8274	
TFSMX	0.0507	0.7213	−0.3222	2.2066	—	Mkt. Neutral
CloneCOAGX	0.0225	0.8604	0.3157	8.1422	0.2497	—
COAGX	0.0232	0.5399	0.0682	5.0295	—	NA

NA=Not Available.

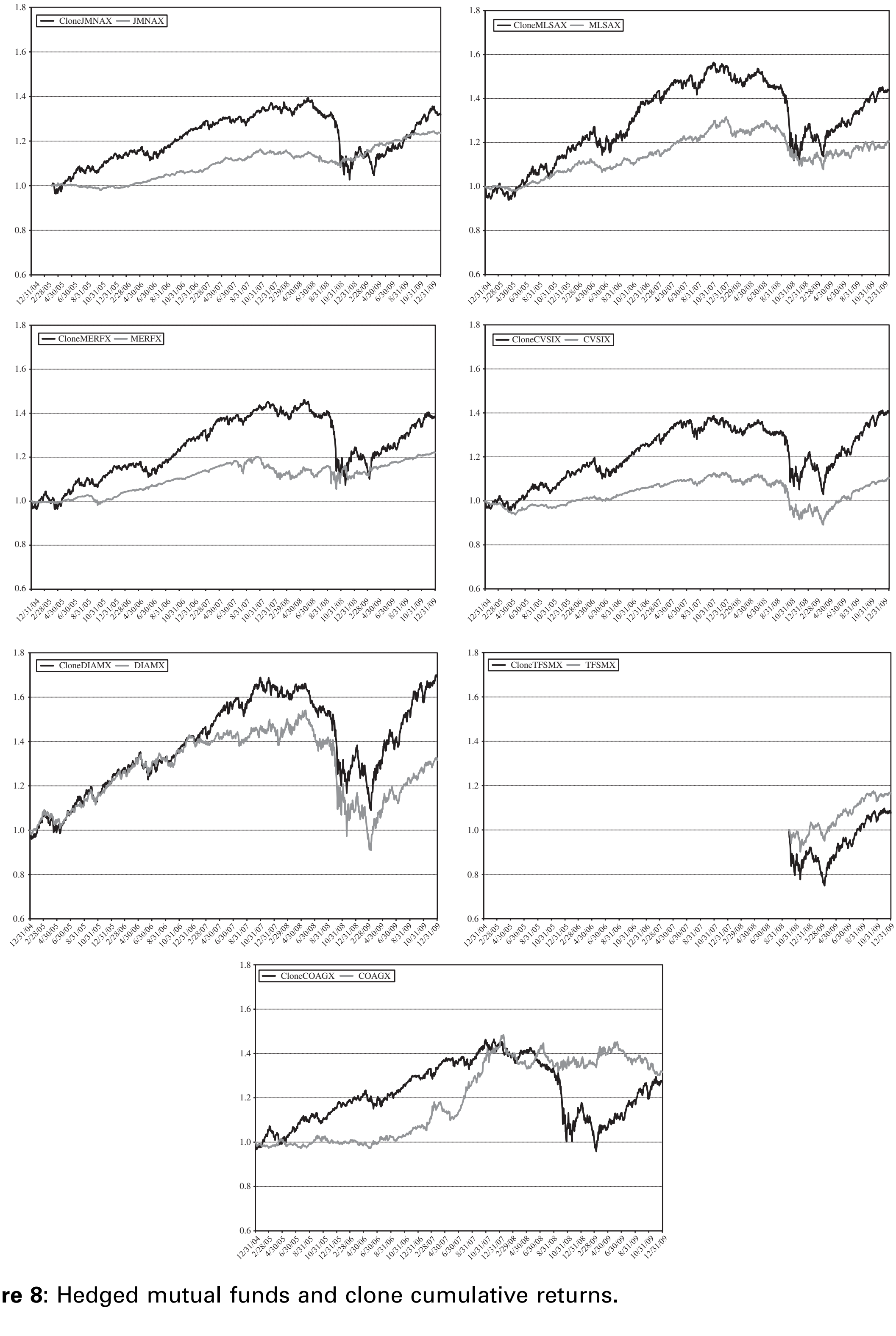

Figure 8: Hedged mutual funds and clone cumulative returns.

a larger percentage of hedge fund returns. Hedge funds are first separated by their investment strategies, after which factors unique to each investment strategy are applied to the replication process. For example, in Jaeger and Wagner (2005), ABS factors for long/short equity were Citigroup convertibles, small-cap spread (Wilshire), CPPI S&P 12M and an AR(1) factor, whereas for merger arbitrage, the replicating factors were S&P 600 Small Cap, Russell 3000 Value, BXM Covered Call Writing Index and the Merger Fund. (For equity market neutral, the factors were Fama-French UMD, S&P 500, Value Spread (MSCI) and Small-Cap Spread (Wilshire).) Amenc *et al* (2008) employed a similar approach and found that it led to substantial improvement in out-of-sample replication quality.[5] Some of these ABS factors are beyond the knowledge of a typical individual investor. Our strategy is simply employing the 18 factors, which will not change irrespective of hedge fund strategies.

As the Eta model is in essence a linear factor model, it possesses similar shortcomings as other linear factor models. An in-depth study of the challenges faced by factor-based replication of hedge fund returns was conducted by Bacmann *et al* (2008) who concluded that 'The cloning process exhibits poor performance if factors are missing or mis-specified or if factor weights change too dramatically' (p. 93). Further, Amenc *et al* (2008) remarked that 'The factor based approach … has mostly failed in thorough empirical tests to produce satisfactory results on an out-of-sample basis' (p. 69) (also see Kat, 2007). An additional limitation unique to the Eta model would be the lag time needed for economic factors to influence asset values. As such, it would be difficult to mimic the time-series properties of an HMF.

Performance evaluation of HMFs

A close cousin of using factors for replication is to use these same factors to assess the skills of fund managers. As fund managers adopt different trading strategies, ABS factors are identified that align themselves to these strategies (Jaeger and Wagner, 2005), in contrast to the same set of factors for all strategies (Hasanhodzic and Lo, 2007). Sharpe (1992) introduced these style factor models to active equity mutual funds, which were subsequently extended by Fung and Hsieh (1997) to hedge funds. Manager's alpha (α), a measure of the skill of the fund manager, can be computed from the following:

$$\text{Hedge fund return} = \alpha + \sum \left(\beta_{\mathrm{i}} \times Factor_{i(modeled)}\right) + \sum \left(\beta_{\mathrm{i}} \times Factor_{i(unmodeled)}\right) + \varepsilon, \quad (1)$$

where ε is the random fluctuation. The Eta model assumes that the 18 economic variables influence all asset values, in which case there is no necessity in identifying ABS factors for different trading strategies.[6] Further, we could invest directly into the replicating portfolio[7] and compare its returns with those of HMFs – it would imply that any underperformance of an HMF relative to the replicating model could be attributed to a lack of manager skill. From Figure 8, we see that the replicating portfolios outperformed all HMFs except COAGX and TFSMX. This is consistent with Jaeger and Wagner (2005) whereby their replicating factor strategies were mostly superior to the returns of hedge fund indices.

The Eta model cannot replicate every investment product but if the replication target's R^2 is high enough and there is a big enough universe to choose from for building the replicator, then there is a possibility of increased success. Lower target R^2 means more idiosyncratic factors (in stocks) or managerial factors (in funds or portfolios) present in the historical data. The divergence between the replicator and the target will be greatest when there is significant managerial (or idiosyncratic) influence. In those instances when the replicator outperforms the target, it indicates that managerial influence is not helping the performance (perhaps because of excess generation of fees, emotional buying/selling or other unproductive managerial practices) but when the target outperforms the replicator, that is evidence of managerial factors adding value (perhaps because of better selection of underlying assets, better cost control, more efficient information processing).

The relationship between the clone's ability to replicate can be assessed by the forward correlation between the clone and replication target and the target's R^2 (Figure 9) as well as with a measure that we call 'the Eta Emulation Error' (Figure 10). The Eta Emulation Error, akin to the tracking error standard deviation employed by mutual funds, is represented by

$$\sqrt{\frac{\left(\eta_T^1 - \eta_C^1\right)^2 + \ldots + \left(\eta_T^{18} - \eta_C^{18}\right)^2}{18}}, \qquad (2)$$

where η_j^i is the Eta factor, $i = 1, 2, \ldots, 18$, being the 18 economic factors, and $j = T$ or C, representing the replication target and the clone, respectively. We would expect that as the replication target's R^2 increases, so would the forward correlation between the clone and the target. This is confirmed by the upward sloping trend line in Figure 9. On the other hand, we would expect a downward sloping trend line, as in Figure 10, when we examine the forward

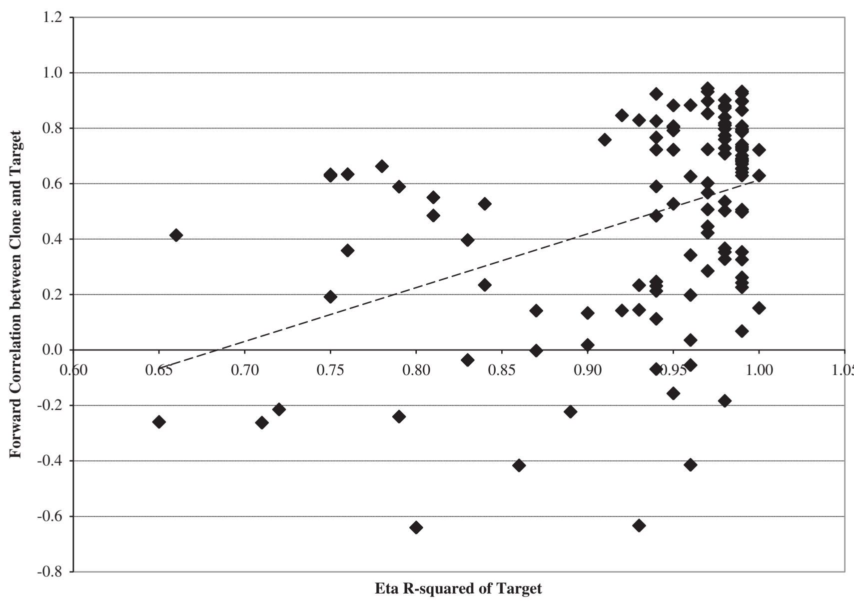

Figure 9: Forward correlation between clone and target versus Eta R^2 of target.

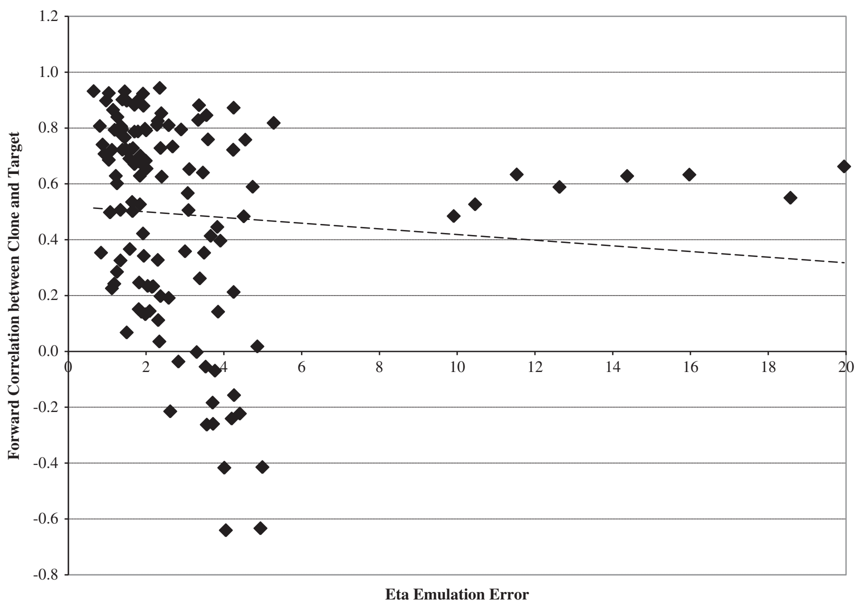

Figure 10: Forward correlation between clone and target versus Eta emulation error.

correlation between the clone and target with the Eta Emulation Error.

Minimum economic risk investment

The hedge fund replication literature basically examines the effectiveness of replication, on the assumption that hedge funds will continue to generate positive returns beyond their betas, hence making it worthwhile to replicate hedge funds at a lower cost (Le Sourd, 2009).[8] However, further exploration of the usefulness of the replication technology is absent. We extend the literature by employing the replication tool that we have developed to test if we can outperform HMFs.

The strategy we undertake is one that is geared toward minimizing economic risk in our long-only portfolio. From our buy list of ETFs, we select those with betas between 0 and 0.7, and construct a portfolio with minimum economic impact – we will refer to this portfolio as the minimum economic risk portfolio (MERP). This process is conducted on a quarterly interval. As the process is initiated at the beginning of each quarter, there is no look-ahead bias.

Unlike HMFs, which take both long and short positions on a daily basis, with leverage, and may include derivatives, MERP is a long-only portfolio of ETFs with quarterly rebalancing. Yet, as evident from Figure 11, throughout the research period, MERP outperformed SPX and most HMFs (with the exception of TFSMX). It contained the downside upon the start of the US recession in December 2007 and participated in the upside upon the recovery of the market in March 2009.

As with Fountaine *et al* (2008) we will next ascertain if MERP and HMFs are statistically significant in their cumulative returns via the

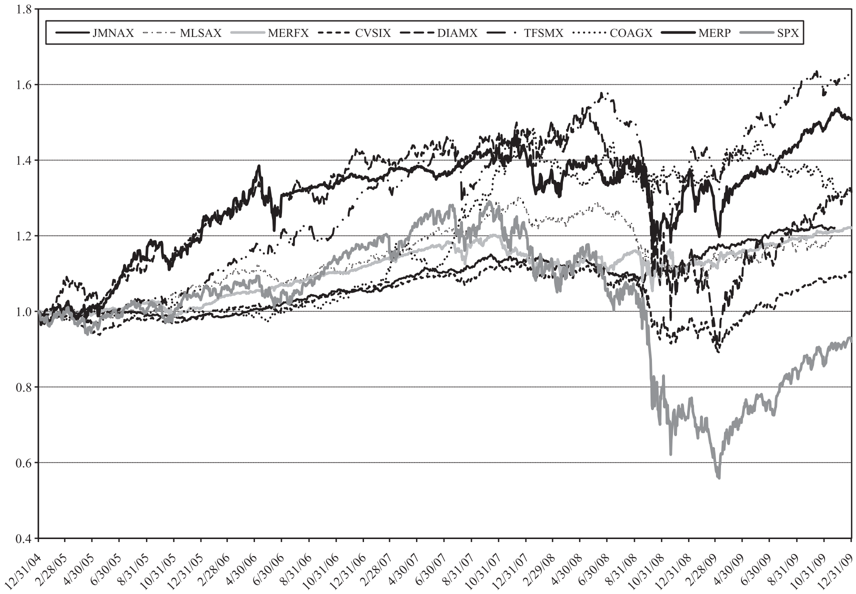

Figure 11: Hedged mutual funds versus minimum economic risk portfolio, 1 January 2005 – 31 December 2009.

portfolio separation test. The null hypothesis is that there is no difference in the cumulative returns between MERP and a particular HMF, that is, there is no portfolio separation. We will test the null hypothesis with the regression

$$MERP = \beta HMF + \varepsilon. \qquad (3)$$

The null hypothesis states that $\beta \leqslant 1$ whereas the alternative hypothesis is $\beta > 1$. The *t*-statistic to test for portfolio separation is computed as $(\beta - 1)/SE$, where SE is the standard error of the regression coefficient. The results are presented in Table 3.

Table 3 reveals that there is indeed portfolio separation in all cases. With the exception of TFSMX, the outperformance of MERP over other HMFs and the SPX is statistically significant at the 1 per cent level. The results suggest that MERP (and the Eta model) contains economically useful information that can be used to separate a higher performing from a lower performing investment.

Table 3: Portfolio separation test results

	β coefficient	*SE*	*t-statistic*
JMNAX	1.1982	0.0022	89.4961*
MLSAX	1.1388	0.0018	75.6078*
MERFX	1.1779	0.0018	98.9524*
CVSIX	1.2628	0.0025	103.8926*
DIAMX	1.0181	0.0026	7.0615*
TFSMX	0.9873	0.0022	−5.8347*
COAGX	1.0763	0.0035	21.7832*
SPX	1.2501	0.0063	39.9803*

*Significant at the 1 per cent level.

In the only other study on HMFs that we are aware of, Agarwal *et al* (2009) showed that the superior performance of HMFs over traditional mutual funds (TMFs) was driven by managers with hedge fund experience, and that HMFs have significantly higher turnover and expenses than do TMFs. With MERP, investors without any investment background could outperform HMFs. Further, with quarterly rebalancing, turnover and expenses are greatly reduced.

Although the Eta model concerns itself with economic risk and not risk associated with returns, we will nevertheless examine returns of MERP via traditional measures. Further inspection of MERP and HMFs are therefore conducted on their conditional volatilities and their conditional correlations with the SPX, which are estimated, respectively, by the GARCH and DCC models.[9]

The GARCH(1, 1) model (Bollerslev, 1986) is by far the most popular model for modeling the conditional variance of asset returns. The asset return (x_t) can be described as

$$x_t = \mu + \varepsilon_t, \qquad \varepsilon_t \sim N(0, h_t), \tag{4}$$

and the conditional variance (h_t) as

$$h_t = \gamma + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}, \tag{5}$$

subject to $\gamma > 0$, α, $\beta \geqslant 0$, $\alpha + \beta < 1$. Examining the relationship between HMFs, MERP and SPX is carried out via the DCC model (Engle, 2002). A conditional covariance matrix therefore requires estimating the GARCH(1, 1) model for each return series and a time-varying correlation matrix (the DCC) and can be expressed as $H_t \equiv D_t R_t D_t$, where D_t is a diagonal matrix of GARCH(1, 1) volatilities. $R_t = Q_t^{*-1} Q_t Q_t^{*-1}$ is the time-varying correlation matrix, with Q_t as described by

$$Q_t = (1 - a - b)\overline{Q} + a\left(\Xi_{t-1}\Xi_{t-1}'\right) + bQ_{t-1}. \tag{6}$$

$\overline{Q}$ is the unconditional covariance of standardized residuals resulting from the first-stage estimation, and Q_t^* is a diagonal matrix composed of the square root of the diagonal elements of Q_t, whereas a and b are scalars. The coefficients of both the GARCH and DCC models are estimated by the maximum likelihood procedure using the BFGS algorithm.

Figure 12 charts the conditional volatilities of selected HMFs, MERP and SPX. With various investment strategies open to HMFs, it should not come as a surprise that they have lower volatilities than the SPX. MERP, on the other hand, exhibits a higher volatility than HMFs but it is still less volatile than the market.

With attaining a low correlation to the market as an investment objective of HMFs, there are periods when their returns are highly correlated with the market; an example would be DIAMX's correlation with the SPX of 0.98 on 3 November 2008 (Figure 13). JMNAX maintains its investment objective throughout the research period, with a correlation of mostly below 0.4. Other than the period mid-2006 to 2007, MERP is highly correlated with SPX.

Amenc *et al* (2010) posed a question 'Is it feasible to deliver hedge fund returns with lower risks?' for which their answer is 'a clear negative'. From our findings, it appears that one could deliver in excess of hedge fund returns while containing economic risk, though not with lower risk when measured by traditional measures.

Dow Jones (DJ) hedge fund sub-indices

As our study covers alternative investments for the typical individual investor, we have

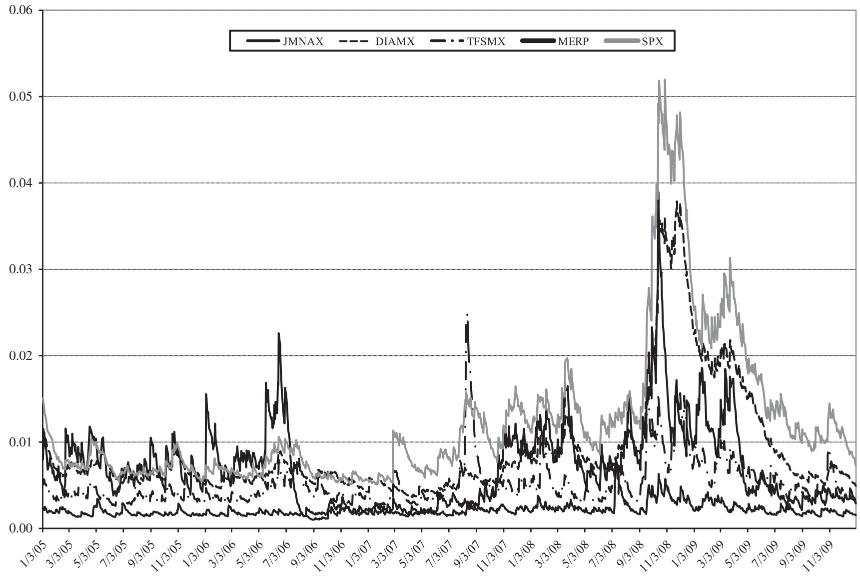

Figure 12: Conditional volatility of selected hedged mutual funds, 1 January 2005 – 31 December 2009.

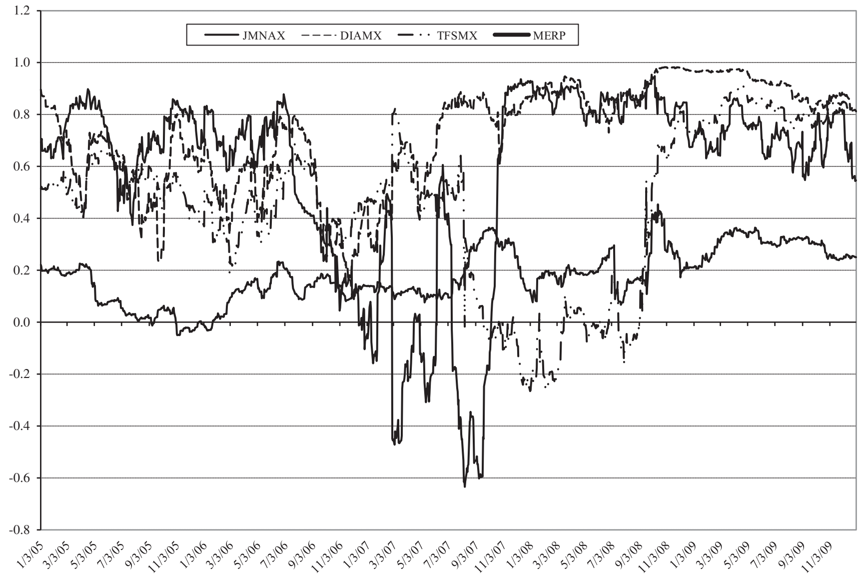

Figure 13: Conditional correlation between selected hedged mutual funds and SPX, 1 January 2005 – 31 December 2009.

deliberately excluded hedge funds from our sample. To align our research somewhat with existing literature, we nevertheless compare MERP with three members of the DJ Hedge Fund Index (Li and Kazemi, 2007)[10] – they are Event Driven, Merger Arbitrage and Equity

Long/Short. We have excluded the overall hedge fund index as well as three other sub-indices (Convertible Arbitrage, Distressed Securities and Equity Market Neutral) owing to missing data.[11] We adopt the DJ Hedge Fund Index as data are provided on a daily basis as opposed to monthly return data from other hedge fund databases (for example, CSFB/Tremont).

As with HMFs, we examine the DJ Hedge Fund Sub-indices by studying their cumulative returns, conditional volatility and correlation. Figures 14–16 are the diagrams of interest. The findings are rather similar to those for HMFs – MERP outperforms the sub-indices with higher return volatility and higher correlation with the market.

Hedge fund replication

Let us now proceed to hedge fund replicators. As with HMFs, we select replicators that a typical household could afford. The daily prices for these replicators can be obtained from Yahoo Finance. As these products are relatively new, the data are from the fund inception rather than from a common date (as with HMFs). It should be noted that currently there is skepticism toward replication products by fund managers. In a survey conducted by Amenc and Schroder (2008), the reasons for such skepticism (pp. 17–20) were poor performance (44 per cent), theoretical impossibility of replicating hedge funds (44 per cent), poor transparency (44 per cent) and flaws in the technologies used by existing products (Gupta *et al*, 2008; Tancar and Viebig, 2008).

Table 4 presents the four hedge fund replicators in our sample whereas Figure 17 compares the cumulative return of MERP with the replicators. Once again, MERP outperforms the replicators.

Figure 14: DJ Hedge Fund Sub-indices versus minimum economic risk portfolio, 1 January 2005 – 31 December 2009.

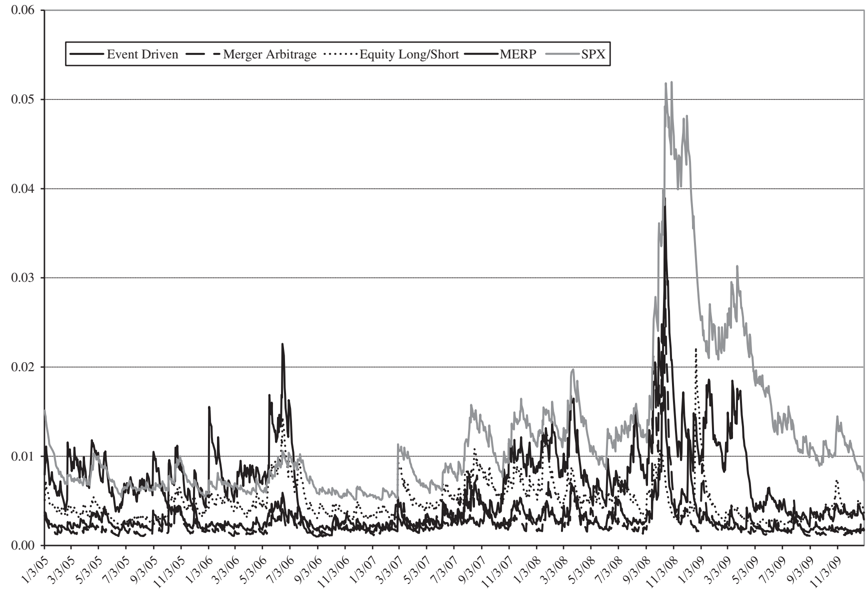

Figure 15: Conditional volatility of DJ Hedge Fund Sub-indices, 1 January 2005 – 31 December 2009.

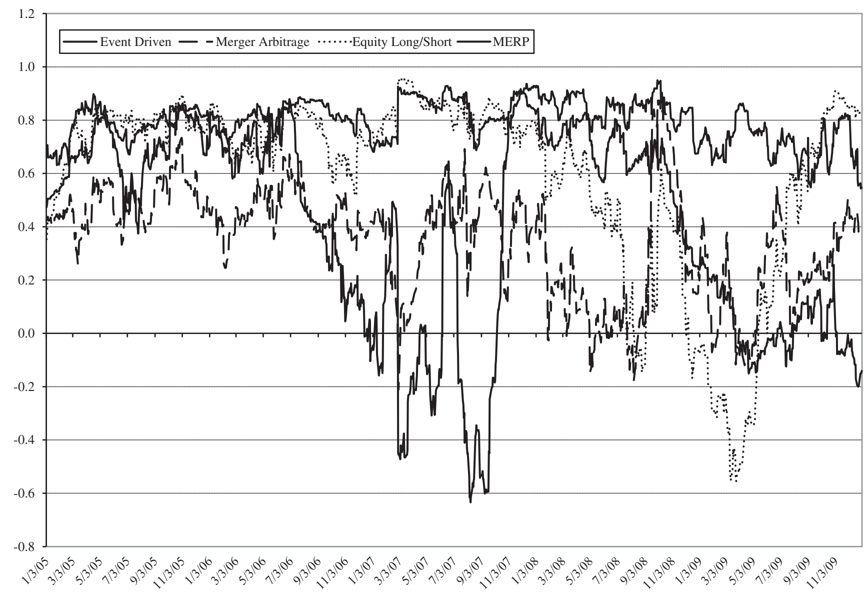

Figure 16: Conditional correlation of DJ Hedge Fund Sub-indices, 1 January 2005 – 31 December 2009.

CONCLUSIONS

In this study, we present an extension to the literature on passive hedge fund replication and its applications by introducing a factor model – the Eta model – whereby the factors of interest relate to the economy, which in turn influences

Table 4: Hedge fund replicators

Ticker	*Hedge fund replicator name*	*Morningstar Star Rating (long/short)*	*Minimum initial investment (in \$)*
GARTX	Goldman Sachs Absolute Return Tracker	NA	1000
IABAX	ING Alternative Beta A	NA	1000
GAFAX	Natixis ASG Global Alternatives A	NA	2500
IQHOX	IQ Alpha Hedge Strategy Fund	NA	2500

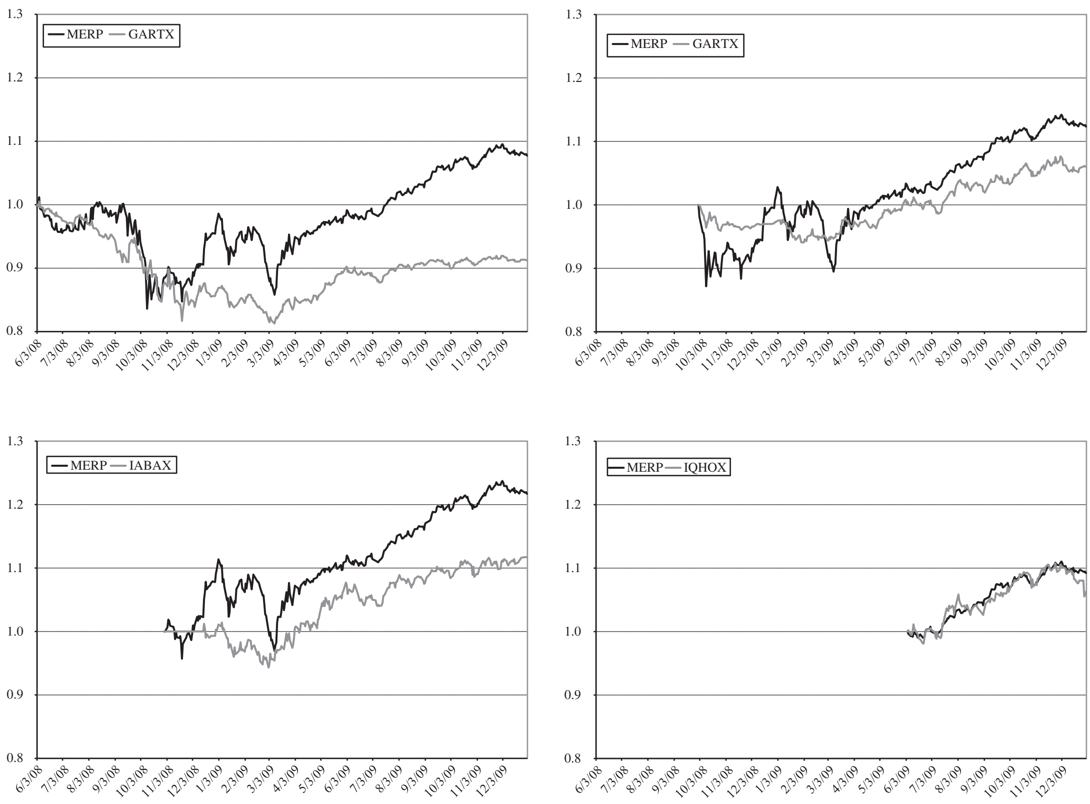

Figure 17: Hedge fund replicators versus minimum economic risk portfolio.

all asset values, rather than style factors that are appropriate only for particular hedge fund strategies.

Although much has been covered in academia on hedge funds, hardly any pertains to a typical household, which does not have access to these funds meant for the wealthy and 'sophisticated'. Instead, our study delves into investment alternatives that are accessible to a typical household. Two products come to mind – HMFs and hedge fund replication products.

We applied the Eta model to HMFs, attempting to clone their cumulative returns while at the same time assessing the skills of HMF managers. In line with current academic findings, our replication methodology performed reasonably well for HMFs of certain trading strategies. We discovered that the clone tend to outperform their respective HMFs, which suggests significant managerial influence that compromises fund performance.

Lastly, with the aid of the Eta model, we constructed MERP and compared it to the performance of HMFs and hedge fund replication products. Although MERP is a long-only portfolio comprising ETFs, with quarterly rebalancing, it nevertheless registered higher cumulative returns than funds with access to long/short strategies, leverage and derivatives. This augurs well for a typical household in that it is possible for them to earn hedge fund returns without hedge fund experience or expertise.

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NOTES

1. A partial list of the patents can be found at www.macrorisk.com.
2. As 3 years of data are needed for the in-sample factor coefficient estimation, we begin the cloning of JMNAX and TFSMX on 1 April 2005 and 1 October 2008 respectively.
3. Gupta *et al* (2008) examined the characteristics and performances of hedge fund replication programs (see also Tancar and Viebig, 2008).
4. 'In general, as one moves away from a well-diversified portfolio of hedge funds to more specific hedge fund styles … one cannot escape the burden of constructing additional risk factors that are specific to the styles' (Fung and Hsieh, 2004).
5. See also Fung and Hsieh (2004) who used 7 ABS factors, to explain up to 80 per cent of monthly return variations for diversified hedge fund portfolios, for example, hedge fund indices and fund of hedge funds.
6. Granted there could be mis-specified or missing factors from the Eta model, but an examination into these issues is beyond the scope of this study.
7. Jaeger and Wagner (2005) refer to such an investment as the Replicating Factor Strategy.
8. Le Sourd (2009) reports that half the hedge fund strategies had cumulative returns above 100 per cent – a compound annual return above 7 per cent – over a 10-year period, even after accounting for the losses suffered by hedge funds in 2008.
9. GARCH and DCC are acronyms for generalized autoregressive conditional heteroskedasticity and dynamic conditional correlation.
10. See Li and Kazemi (2007) for an analysis of the conditional properties of hedge fund returns, using daily data from the DJ Hedge Fund Index, which, unlike other hedge fund indices, does not suffer from back-fill or survivorship biases.
11. Reporting of the Convertible Arbitrage, Distressed Securities and Equity Market

Neutral sub-indices were suspended effective 2 January 2009, 1 May 2009 and 6 November 2009, respectively.

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