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CAN HEDGE-FUND RETURNS BE REPLICATED?: THE LINEAR CASE*

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In contrast to traditional investments such as stocks and bonds, hedge-fund returns have more complex risk exposures that yield additional and complementary sources of risk premia. This raises the possibility of creating passive replicating portfolios or "clones" using liquid exchange-traded instruments that provide similar risk exposures at lower cost and with greater transparency. By using monthly returns data for 1610 hedge funds in the TASS database from 1986 to 2005, we estimate linear factor models for individual hedge funds using six common factors, and measure the proportion of the funds' expected returns and volatility that are attributable to such factors. For certain hedge-fund style categories, we find that a significant fraction of both can be captured by common factors corresponding to liquid exchange-traded instruments. While the performance of linear clones is often inferior to their hedge-fund counterparts, they perform well enough to warrant serious consideration as passive, transparent, scalable, and lower-cost alternatives to hedge funds.

1 Introduction

As institutional investors take a more active interest in alternative investments, a significant gap has emerged between the culture and expectations of those investors and hedge-fund managers. Pension plan sponsors typically require transparency from their managers and impose a number of restrictions in their investment mandates because of regulatory requirements such as ERISA rules; hedge-fund managers rarely provide position-level transparency

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and bristle at any restrictions on their investment process because restrictions often hurt performance. Plan sponsors require a certain degree of liquidity in their assets to meet their pension obligations, and also desire significant capacity because of their limited resources in managing large pools of assets; hedge-fund managers routinely impose lock-ups of 1–3 years, and the most successful managers have the least capacity to offer, in many cases returning investors' capital once they make their personal fortunes. And as fiduciaries, plan sponsors are hypersensitive to the outsize fees that hedge funds charge, and are concerned about misaligned incentives induced by performance fees; hedge-fund managers argue that their fees are fair compensation for their unique investment acumen, and at least for now, the market seems to agree.

This cultural gap raises the natural question of whether it is possible to obtain hedge-fund-like returns without investing in hedge funds. In short, can hedge-fund returns be "cloned"?

In this paper, we provide one answer to this challenge by constructing "linear clones" of individual hedge funds in the TASS Hedge Fund Database. These are passive portfolios of common risk factors like the S&P 500 and the US Dollar Indexes, with portfolio weights estimated by regressing individual hedge-fund returns on the risk factors. If a hedge fund generates part of its expected return and risk profile from certain common risk factors, then it may be possible to design a low-cost passive portfolio—not an active dynamic trading strategy—that captures some of that fund's risk/reward characteristics by taking on just those risk exposures. For example, if a particular long/short equity hedge fund is 40% long growth stocks, it may be possible to create a passive portfolio that has similar characteristics, for example, a long-only position in a passive growth portfolio coupled with a 60% short position in stock-index futures.

The magnitude of hedge-fund alpha that can be captured by a linear clone depends, of course, on how much of a fund's expected return is driven by common risk factors versus manager-specific alpha. This can be measured empirically. While portable alpha strategies have become fashionable lately among institutions, our research suggests that for certain classes of hedge-fund strategies, portable beta may be an even more important source of untapped expected returns and diversification. In particular, in contrast to previous studies employing more complex factor-based models of hedge-fund returns, we use six factors that correspond to basic sources of risk and, consequently, expected return: the stock market, the bond market, currencies, commodities, credit, and volatility. These factors are also chosen because, with the exception of volatility, each of them is tradable via liquid exchange-traded securities such as futures or forward contracts.

Using standard regression analysis we decompose the expected returns of a sample of 1610 individual hedge funds from the TASS Hedge Fund Live Database into factor-based risk premia and manager-specific alpha, and we find that for certain hedge-fund style categories, a significant fraction of the funds' expected returns is due to risk premia. For example, in the category of Convertible Arbitrage funds, the average percentage contribution of the US Dollar Index risk premium, averaged across all funds in this category, is 67%. While estimates of manager-specific alpha are also quite significant in most cases, these results suggest that at least a portion of a hedge fund's expected return can be obtained by bearing factor risks.

To explore this possibility, we construct linear clones using five of the six factors (we omit volatility because the market for volatility swaps and futures is still developing), and compare their performance to the original funds. For certain categories such as Equity Market Neutral, Global Macro, Long/Short

Equity Hedge, Managed Futures, Multi-Strategy, and Fund of Funds, linear clones have comparable performance to their fund counterparts, but for other categories such as Event Driven and Emerging Markets, clones do not perform nearly as well. However, in all cases, linear clones are more liquid (as measured by their serial correlation coefficients), more transparent and scalable (by construction), and with correlations to a broad array of market indexes that are similar to those of the hedge funds on which they are based. For these reasons, we conclude that hedge-fund replication, at least for certain types of funds, is both possible and, in some cases, worthy of serious consideration.

We begin in Section 2 with a brief review of the literature on hedge-fund replication, and provide two examples that motivate this endeavor. In Section 3, we present a linear regression analysis of hedge-fund returns from the TASS Hedge Fund Live Database, with which we decompose the funds' expected returns into risk premia and manager-specific alpha. These results suggest that for certain hedge-fund styles, linear clones may yield reasonably compelling investment performance, and we explore this possibility directly in Section 4. We conclude in Section 5.

2 Motivation

In a series of recent papers, Kat and Palaro (2005, 2006a,b) argued that sophisticated dynamic trading strategies involving liquid futures contracts can replicate many of the statistical properties of hedge-fund returns. More generally, Bertsimas *et al.* (2001) have shown that securities with very general payoff functions (like hedge funds, or complex derivatives) can be synthetically replicated to an arbitrary degree of accuracy by dynamic trading strategies—called "epsilon-arbitrage" strategies—involving more liquid instruments. While these results are encouraging for the hedge-fund replication problem, the replicating strategies are quite involved and not easily implemented by the typical institutional investor. Indeed, some of the derivatives-based replication strategies may be more complex than the hedge-fund strategies they intend to replicate, defeating the very purpose of replication.[1]

The motivation for our study comes, instead, from Sharpe's (1992) asset-class factor models in which he proposes to decompose a mutual fund's return into two distinct components: asset-class factors such as large-cap stocks, growth stocks, and intermediate government bonds, which he interprets as "style," and an uncorrelated residual that he interprets as "selection." This approach was applied by Fung and Hsieh (1997a) to hedge funds, but there the factors were derived statistically from a principal components analysis of the covariance matrix of their sample of 409 hedge funds and CTAs. While such factors may yield high in-sample R^2s, they suffer from significant over-fitting bias and also lack economic interpretation, which is one of the primary motivations for Sharpe's (1992) decomposition. Several authors have estimated factor models for hedge funds using more easily interpretable factors such as fund characteristics and indexes (Schneeweis and Spurgin, 1998; Liang, 1999; Edwards and Caglayan, 2001; Capocci and Hubner, 2004; Hill, *et al.*, 2004), and the returns to certain options-based strategies and other basic portfolios (Fung and Hsieh, 2001, 2004; Agarwal and Naik 2000a,b, 2004).

However, the most direct application of Sharpe's (1992) analysis to hedge funds is found in Ennis and Sebastian (2003). They provide a thorough style analysis of the HFR Fund of Funds index, and conclude that funds of funds are not market neutral and although they do exhibit some market-timing abilities, "..., the performance of hedge funds has not been good enough to warrant their inclusion in balanced portfolios. The high cost of investing in funds of funds contributes to this result" (Ennis and Sebastian, 2003, p. 111). This conclusion is the starting point for our study of linear clones.

Before turning to our empirical analysis of individual hedge-fund returns, we provide two concrete examples that span the extremes of the hedge-fund replication problem. For one hedge-fund strategy, we show that replication can be accomplished easily, and for another strategy, we find replication to be almost impossible using linear models.

2.1 Capital Decimation Partners

The first example is a hypothetical strategy proposed by Lo (2001) called "Capital Decimation Partners" (CDP), which yields an enviable track record that many investors would associate with a successful hedge fund: a 43.1% annualized mean return and 20% annualized volatility, implying a Sharpe ratio of 2.15,[2] and with only 6 negative months over the 96-month simulation period from January 1992 to December 1999 (see Table 1). A closer inspection of this strategy's monthly returns in Table 2 yields few surprises for the seasoned hedge-fund investor—the most challenging period for CDP was the summer of 1998 during the LTCM crisis, when the strategy suffered losses of −18.3% and −16.2% in August and September, respectively. But those investors courageous enough to have maintained their CDP investment during this period were rewarded with returns of 27.0% in October and 22.8% in November. Overall, 1998 was the second-best year for CDP, with an annual return of 87.3%.

Table 1 Performance summary of simulated short-put-option strategy consisting of short-selling out-of-the-money S&P 500 put options with strikes approximately 7% out of the money and with maturities less than or equal to 3 months, from January 1992 to December 1999.

Statistic	S&P500	CDP
Monthly mean	1.4%	3.6%
Monthly SD	3.6%	5.8%
Minimum month	−8.9%	−18.3%
Maximum month	14.0%	27.0%
Annual Sharpe ratio	1.39	2.15
# Negative months	36	6
Correlation to S&P 500	100%	61%
Return Since Inception	367%	2560%

So what is CDP's secret? The investment strategy summarized in Tables 1 and 2 involves shorting out-of-the-money S&P 500 (SPX) put options on each monthly expiration date for maturities less than or equal to 3 months, and with strikes approximately 7% out of the money. According to Lo (2001), the number of contracts sold each month is determined by the combination of: (1) CBOE margin requirements[3]; (2) an assumption that we are required to post 66% of the margin as collateral[4]; and (3) \$10M of initial risk capital. The essence of this strategy is the provision of insurance. CDP investors receive option premia for each option contract sold short, and as long as the option contracts expire out of the money, no payments are necessary. Therefore, the only time CDP experiences losses is when its put options are in the money, that is, when the S&P 500 declines by more than 7% during the life of a given option. From this perspective, the handsome returns to CDP investors seem more justifiable—in exchange for providing downside protection, CDP investors are paid a risk premium in the same way that insurance companies receive regular payments for providing earthquake or hurricane insurance. Given the relatively infrequent nature of 7% losses, CDP's risk/reward profile can seem very attractive in comparison to more traditional investments, but there is nothing unusual or unique about CDP. Investors willing to take on "tail risk"—the risk of rare but severe events—will be paid well for this service (consider how much individuals are willing to pay each month for

Table 2 Monthly returns of simulated short-put-option strategy consisting of shortselling out-of-the-money S&P 500 put options with strikes approximately 7% out of the money and with maturities less than or equal to 3 months, from January 1992 to December 1999.

	1992		1993		1994		1995		1996		1997		1998		1999	
Month	SPX	CDP	SPX	CDP	SPX	CDP	SPX	CDP	SPX	CDP	SPX	CDP	SPX	CDP	SPX	CDP
Jan	8.2	8.1	−1.2	1.8	1.8	2.3	1.3	3.7	−0.7	1.0	3.6	4.4	1.6	15.3	5.5	10.1
Feb	−1.8	4.8	−0.4	1.0	−1.5	0.7	3.9	0.7	5.9	1.2	3.3	6.0	7.6	11.7	−0.3	16.6
Mar	0.0	2.3	3.7	3.6	0.7	2.2	2.7	1.9	−1.0	0.6	−2.2	3.0	6.3	6.7	4.8	10.0
Apr	1.2	3.4	−0.3	1.6	−5.3	−0.1	2.6	2.4	0.6	3.0	−2.3	2.8	2.1	3.5	1.5	7.2
May	−1.4	1.4	−0.7	1.3	2.0	5.5	2.1	1.6	3.7	4.0	8.3	5.7	−1.2	5.8	0.9	7.2
Jun	−1.6	0.6	−0.5	1.7	0.8	1.5	5.0	1.8	−0.3	2.0	8.3	4.9	−0.7	3.9	0.9	8.6
Jul	3.0	2.0	0.5	1.9	−0.9	0.4	1.5	1.6	−4.2	0.3	1.8	5.5	7.8	7.5	5.7	6.1
Aug	−0.2	1.8	2.3	1.4	2.1	2.9	1.0	1.2	4.1	3.2	−1.6	2.6	−8.9	−18.3	−5.8	−3.1
Sep	1.9	2.1	0.6	0.8	1.6	0.8	4.3	1.3	3.3	3.4	5.5	11.5	−5.7	−16.2	−0.1	8.3
Oct	−2.6	−3.0	2.3	3.0	−1.3	0.9	0.3	1.1	3.5	2.2	−0.7	5.6	3.6	27.0	−6.6	−10.7
Nov	3.6	8.5	−1.5	0.6	−0.7	2.7	2.6	1.4	3.8	3.0	2.0	4.6	10.1	22.8	14.0	14.5
Dec	3.4	1.3	0.8	2.9	−0.6	10.0	2.7	1.5	1.5	2.0	−1.7	6.7	1.3	4.3	−0.1	2.4
Year	14.0	38.2	5.7	23.7	−1.6	33.6	34.3	22.1	21.5	28.9	26.4	84.8	24.5	87.3	20.6	105.7

their homeowner's, auto, health, and life insurance policies). CDP involves few proprietary elements, and can be implemented by most investors, hence this is one example of a hedge-fund-like strategy that can easily be cloned.

2.2 Capital Multiplication Partners

Consider now the case of "Capital Multiplication Partners" (CMP), a hypothetical fund based on a dynamic asset-allocation strategy between the S&P 500 and 1-month US Treasury Bills, where the fund manager can correctly forecast which of the two assets will do better in each month and invests the fund's assets in the higher-yielding asset at the start of the month.[5] Therefore, the monthly return of this perfect market-timing strategy is simply the larger of the monthly return of the S&P 500 and T-Bills. The source of this strategy's alpha is clear: Merton (1981) observes that perfect market-timing is equivalent to a long-only investment in the S&P 500 plus a put option on the S&P 500 with a strike price equal to the T-Bill return. Therefore, the economic value of perfect market-timing is equal to the sum of monthly put-option premia over the life of the strategy. And there is little doubt that such a strategy contains significant alpha: a $1 investment in CMP in January 1926 grows to $23,143,205,448 by December 2004! Table 3 provides a more detailed performance summary of CMP which confirms its remarkable characteristics—CMP's Sharpe ratio of 2.50 exceeds that of Warren Buffett's Berkshire Hathaway, arguably the most successful pooled investment vehicle of all time![6]

It should be obvious to even the most naive investor that CMP is a fantasy because no one can time the market perfectly. Therefore, attempting to replicate such a strategy with exchange-traded instruments seems hopeless. But suppose we try to replicate it anyway—how close can we come? In particular, suppose we attempt to relate CMP's monthly returns to the monthly returns of the S&P 500 by fitting a simple linear regression (see Figure 1). The option-like nature of CMP's perfect market-timing strategy is apparent in Figure 1's scatter of points, and visually, it is obvious that the linear regression does not capture the essence of this inherently nonlinear strategy. However, the formal measure of how well the linear regression fits the data, the "$\overline{R}^2$," is 70.3% in this case, which suggests a very strong linear relationship indeed. But when the estimated linear regression is used to construct a fixed portfolio of the S&P 500 and 1-month T-Bills, the results are not nearly as attractive as CMP's returns, as Table 3 shows.

Table 3 Performance summary of simulated monthly perfect market-timing strategy between the S&P 500 and 1-month US Treasury bills, and a passive linear clone, from January 1926 to December 2004.

Statistic	S&P 500	T-Bills	CMP	Clone
Monthly mean	1.0%	0.3%	2.6%	0.7%
Monthly SD	5.5%	0.3%	3.6%	3.0%
Minimum month	−29.7%	−0.1%	−0.1%	−16.3%
Maximum month	42.6%	1.4%	42.6%	23.4%
Annual Sharpe ratio	0.63	4.12	2.50	0.79
# Negative months	360	12	10	340
Correlation to S&P 500	100%	−2%	84%	100%
Growth of $1 since inception	$3,098	$18	$2.3 × 10^{10}	$429

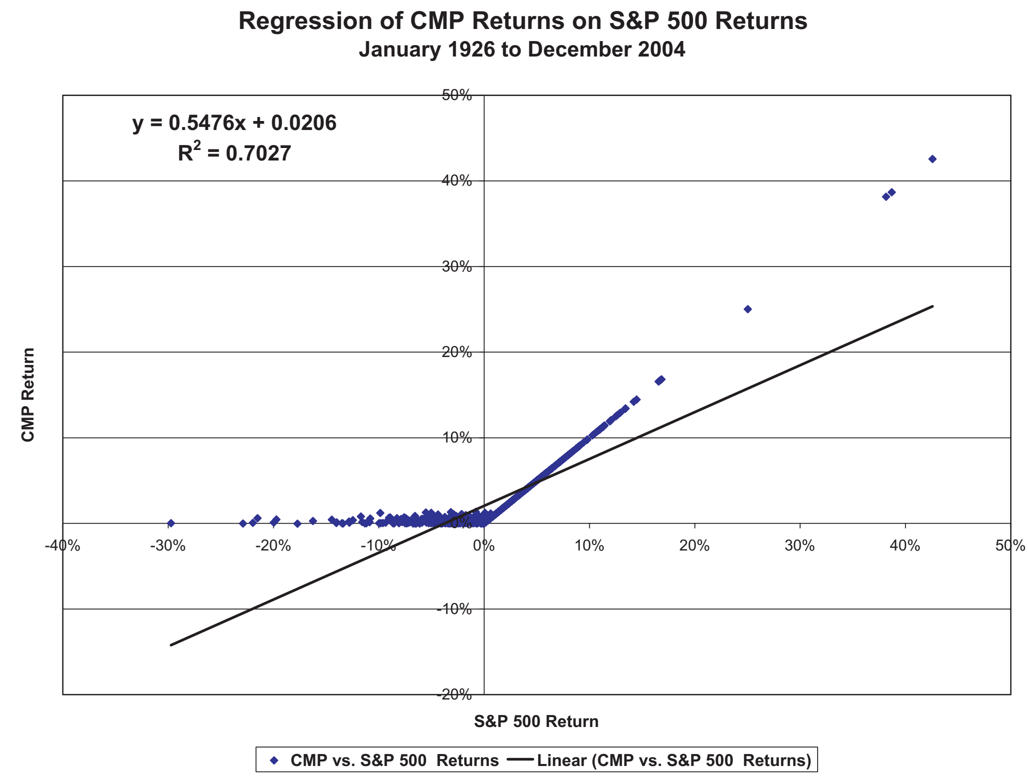


Figure 1 Scatter plot of simulated monthly returns of a perfect market-timing strategy between the S&P 500 and 1-month US Treasury bills, against monthly returns of the S&P 500, from January 1926 to December 2004.

This example underscores the difficulty in replicating certain strategies with genuine alpha using linear clones, and cautions against using the $\overline{R}^2$ as the only metric of success. Despite the high $\overline{R}^2$ achieved by the linear regression of CMP's returns on the market index, the actual performance of the linear clone falls far short of the strategy because a linear model will never be able to capture the option-like payoff structure of the perfect market-timer.

3 Linear regression analysis

To explore the full range of possibilities for replicating hedge-fund returns illustrated by the two extremes of CDP and CMP, we investigated the characteristics of a sample of individual hedge funds drawn from the TASS Hedge Fund Database. The database is divided into two parts: "Live" and "Graveyard" funds. Hedge funds that are in the "Live" database are considered to be active as of the end of our sample period, September 2005.[7] We confine our attention to funds in the Live database since we wish to focus on the most current set of risk exposures in the hedge-fund industry, and we acknowledge that the Live database suffers from survivorship bias.[8]

However, the importance of such a bias for our application is tempered by two considerations. First, many successful funds leave the sample as well as the poor performers, reducing the upward bias in expected returns. In particular, Fung and Hsieh (2000) estimated the magnitude of survivorship bias to be 3.00% per year, and Liang's (2000) estimate is 2.24% per year. Second, the focus of our study is on the *relative* performance of hedge funds versus relatively passive portfolios of liquid securities, and as long as our cloning process is not selectively applied to a peculiar subset of funds in the TASS database, any survivorship bias should impact both funds and clones identically, leaving their relative performance unaffected.

Of course, other biases plague the TASS database such as backfill bias (including funds with return histories that start before the date of inclusion),[9] selection bias (inclusion in the database is voluntary, hence only funds seeking new investors are included),[10] and other potential biases imparted by the process by which TASS decides which funds to include and which to omit (part of this process is qualitative). As with survivorship bias, the hope is that the impact of these additional biases will be similar for clones and funds, leaving relative comparisons unaffected. Unfortunately, there is little to be done about such biases other than to acknowledge their existence, and to interpret the outcome of our empirical analysis with an extra measure of caution.

Although the TASS Hedge Fund Live database starts in February 1977, we limit our analysis to the sample period from February 1986 to September 2005 because this is the timespan for which we have complete data for all of our risk factors. Of these funds, we drop those that: (i) do not report net-of-fee returns[11]; (ii) report returns in currencies other than the US dollar; (iii) report returns less frequently than monthly; (iv) do not provide assets under management or only provide estimates; and (v) have fewer than 36 monthly returns. These filters yield a final sample of 1610 funds.

3.1 Summary statistics

TASS classifies funds into one of the 11 different investment styles, listed in Table 4 and described in Appendix A, of which 10 correspond exactly to the CSFB/Tremont sub-index definitions.[12] Table 4 also reports the number of funds in each category for our sample, as well as summary statistics for the individual funds and for the equal-weighted portfolio of funds in each of the categories. The category counts show that the funds are not evenly distributed across investment styles, but are concentrated among five categories: Long/Short Equity Hedge (520), Fund of Funds (355), Event Driven (169), Managed Futures (114), and Emerging Markets (102). Together, these five categories account for 78% of the 1610 funds in our sample. The performance summary statistics in Table 4 underscore the reason for the growing interest in hedge funds in recent years—double-digit cross-sectional average returns for most categories with average volatility lower than that of the S&P 500, implying average annualized Sharpe ratios ranging from a low of 0.25 for Dedicated Short Bias funds to a high of 2.70 for Convertible Arbitrage funds.

Another feature of the data highlighted by Table 4 is the large positive average return-autocorrelations for funds in Convertible Arbitrage (42.2%), Emerging Markets (18.0%), Event Driven (22.2%), Fixed Income Arbitrage (22.1%), Multi-Strategy (21.0%), and Fund of Funds (23.2%) categories. Lo (2001) and Getmansky *et al.* (2004) have shown that such high serial correlation in hedge-fund returns is likely to be an indication of illiquidity exposure. There is, of course, nothing inappropriate about hedge funds taking on liquidity risk—indeed, this is a legitimate and often lucrative source of expected return—as long as investors are aware of such risks, and not misled by the siren call of attractive Sharpe ratios.[13] But illiquidity exposure is typically accompanied by capacity limits, and we shall return to this issue when we compare the properties of hedge funds to more liquid alternatives such as linear clones.

Table 4 Summary statistics for TASS Live hedge funds included in our sample from February 1986 to September 2005.

Category	Sample size	Annualized mean (%)		Annualized SD (%)		Annualized Sharpe ratio		ρ_1 (%)		Ljung-Box p-value (%)		Annualized performance of equal-weighted portfolio of funds		
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean (%)	SD (%)	Sharpe
Convertible arbitrage	82	8.41	5.11	6.20	5.28	2.70	5.84	42.2	17.3	11.0	22.2	11.07	5.36	2.07
Dedicated short bias	10	5.98	4.77	28.27	10.05	0.25	0.24	5.5	12.6	24.2	20.3	6.40	23.23	0.28
Emerging markets	102	20.41	13.01	22.92	15.16	1.42	2.11	18.0	12.4	36.3	30.2	22.34	17.71	1.26
Equity market neutral	83	8.09	4.77	7.78	5.84	1.44	1.20	9.1	23.0	32.6	29.7	12.83	6.23	2.06
Event driven	169	13.03	8.65	8.40	8.09	1.99	1.37	22.2	17.6	27.0	29.3	13.47	4.37	3.08
Fixed income arbitrage	62	9.50	4.54	6.56	4.41	2.05	1.48	22.1	17.6	35.9	35.2	10.48	3.58	2.93
Global macro	54	11.38	6.16	11.93	6.10	1.07	0.58	5.8	12.2	43.1	32.5	14.91	8.64	1.73
Long/Short equity hedge	520	14.59	8.14	15.96	9.06	1.06	0.58	12.8	14.9	36.0	30.5	16.35	11.84	1.38
Managed futures	114	13.64	9.35	21.46	12.07	0.67	0.39	2.5	10.2	40.1	31.5	15.96	19.24	0.83
Multi-strategy	59	10.79	5.22	8.72	9.70	1.86	1.03	21.0	20.1	28.2	30.1	14.59	5.78	2.52
Fund of funds	355	8.25	3.73	6.36	4.47	1.66	0.86	23.2	15.0	27.1	26.3	11.93	7.48	1.59

3.2 Factor model specification

To determine the explanatory power of common risk factors for hedge funds, we perform a time-series regression for each of the 1610 hedge funds in our sample, regressing the hedge fund's monthly returns on the following six factors: (1) USD: the US Dollar Index return; (2) BOND: the return on the Lehman Corporate AA Intermediate Bond Index; (3) CREDIT: the spread between the Lehman BAA Corporate Bond Index and the Lehman Treasury Index; (4) SP500: the S&P 500 total return; (5) CMDTY: the Goldman Sachs Commodity Index (GSCI) total return; and (6) DVIX: the first-difference of the end-of-month value of the CBOE Volatility Index (VIX). These six factors are selected for two reasons: They provide a reasonably broad cross-section of risk exposures for the typical hedge fund (stocks, bonds, currencies, commodities, credit, and volatility), and each of the factor returns can be realized through relatively liquid instruments so that the returns of linear clones may be achievable in practice. In particular, there are forward contracts for each of the component currencies of the US Dollar index, and futures contracts for the stock and bond indexes and for the components of the commodity index. Futures contracts on the VIX index were introduced by the CBOE in March 2004 and are not as liquid as the other index futures, but the OTC market for variance and volatility swaps is growing rapidly.

The linear regression model provides a simple but useful decomposition of a hedge fund's return R_{it} into several components:

$$R_{it} = \alpha_i + \beta_{i1}\mathrm{RiskFactor}_{1t} + \cdots + \beta_{iK}\mathrm{RiskFactor}_{Kt} + \epsilon_{it} \qquad (1)$$

From this decomposition, we have the following characterization of the fund's expected return and variance:

$$\mathrm{E}[R_{it}] = \alpha_i + \beta_{i1}\mathrm{E}[\mathrm{RiskFactor}_{1t}] + \cdots + \beta_{iK}\mathrm{E}[\mathrm{RiskFactor}_{Kt}] \qquad (2)$$

$$\mathrm{Var}[R_{it}] = \beta_{i1}^2\mathrm{Var}[\mathrm{RiskFactor}_{1t}] + \cdots + \beta_{iK}^2\mathrm{Var}[\mathrm{RiskFactor}_{Kt}] + \mathrm{Covariances} + \mathrm{Var}[\epsilon_{it}] \qquad (3)$$

where "Covariances" is the sum of all pairwise covariances between $\mathrm{RiskFactor}_{pt}$ and $\mathrm{RiskFactor}_{qt}$ weighted by the product of their respective beta coefficients $\beta_{ip}\beta_{iq}$.

This characterization implies that there are two distinct sources of a hedge fund's expected return: beta exposures β_{ik} multiplied by the risk premia associated with those exposures $\mathrm{E}[\mathrm{RiskFactor}_{kt}]$, and manager-specific alpha α_i. By "manager-specific," we do not mean to imply that a hedge fund's unique source of alpha is without risk—we are simply distinguishing this source of expected return from those that have clearly identifiable risk factors associated with them. In particular, it may well be the case that α_i arises from risk factors other than the six we have proposed, and a more refined version of Eq. (1)—one that reflects the particular investment style of the manager—may yield a better-performing linear clone.

From Eq. (3), we see that a hedge fund's variance has three distinct sources: the variances of the risk factors multiplied by the squared beta coefficients, the variance of the residual ϵ_{it} (which may be related to the specific economic sources of α_i), and the weighted covariances among the factors. This decomposition highlights the fact that a hedge fund can have several sources of risk, each of which should yield some risk premium, that is, risk-based alpha, otherwise investors would not be willing to bear such risk. By taking on exposure to multiple risk factors, a hedge fund can generate attractive expected returns from the investor's perspective (see, e.g. Capital Decimation Partners in Section 2.1).[14]

3.3 Factor exposures

Table 5 presents summary statistics for the beta coefficients or factor exposures in Eq. (1) estimated for each of the 1610 hedge funds by ordinary least squares and grouped by category. In particular, for each category we report the minimum, median, mean, and maximum beta coefficient for each of the six factors and the intercept, across all regressions in that category. For example, the upper left block of entries with the title "Intercept" presents summary statistics for the intercepts from the individual hedge-fund regressions within each category, and the "Mean" column shows that the average manager-specific alpha is positive for all categories, ranging from 0.42% per month for Managed Futures funds to 1.41% per month for Emerging Markets funds. This suggests that managers in our sample are, on average, indeed contributing value above and beyond the risk premia associated with the six factors we have chosen in Eq. (1). We shall return to this important issue in Section 3.4.

The panel in Table 5 with the heading R_{sp500} provides summary statistics for the beta coefficients corresponding to the S&P 500 return factor, and the entries in the "Mean" column are broadly consistent with each of the category definitions. For example, funds in the Dedicated Short Bias category have an average S&P 500 beta of -0.88, which is consistent with their shortselling mandate. On the other hand, Equity Market Neutral funds have an average S&P 500 beta of 0.05, confirming their market neutral status. And Long/Short Equity Hedge funds, which are mandated to provide partially hedged equity-market exposure, have an average S&P 500 beta of 0.38.

The remaining panels in Table 5 show that risk exposures do vary considerably across categories. This is more easily seen in Figure 2 which plots the mean beta coefficients for all six factors, category by category. From Figure 2, we see that Convertible Arbitrage funds have three main exposures (long credit, long bonds, and long volatility), whereas Emerging Markets funds have four somewhat different exposures (long stocks, short USD, long credit, and long commodities). The category with the smallest overall risk exposures is Equity Market Neutral, and not surprisingly, this category exhibits the second lowest average mean return, 8.09%.

The lower right panel of Table 5 contains a summary of the explanatory power of (1) as measured by the $\overline{R}^2$ statistic of the regression (1). The mean $\overline{R}^2$s range from a low of 10.4% for Equity Market Neutral (as expected, given this category's small average factor exposures to all six factors) to a high of 40.4% for Dedicated Short Bias (which is also expected given this category's large negative exposure to the S&P 500).

To provide further intuition for the relation between $\overline{R}^2$ and fund characteristics, we regress $\overline{R}^2$ on several fund characteristics, and find that lower $\overline{R}^2$ funds are those with higher Sharpe ratios, higher management fees, and higher incentive fees. This accords well with the intuition that funds providing greater diversification benefits, that is, lower $\overline{R}^2$'s, command higher fees in equilibrium. See Hasanhodzic and Lo (2006b) for further details.

3.4 Expected-return decomposition

Using the parameter estimates of (1) for the individual hedge funds in our sample, we can now reformulate the question of whether or not a hedge-fund strategy can be cloned as a question about how much of a hedge fund's expected return is due

Table 5 Summary statistics for multivariate linear regressions of monthly returns of hedge funds in the TASS Live database from February 1986 to September 2005 on six factors: the S&P 500 total return, the Lehman Corporate AA Intermediate Bond Index return, the US Dollar Index return, the spread between the Lehman US Aggregate Long Credit BAA Bond Index and the Lehman Treasury Long Index, the first-difference of the CBOE Volatility Index (VIX), and the Goldman Sachs Commodity Index (GSCI) total return.

	Sample		Intercept					R_{sp500}					R_{lb}					R_{usd}				
Category	size	Statistic	Min	Med	Mean	Max	SD	Min	Med	Mean	Max	SD	Min	Med	Mean	Max	SD	Min	Med	Mean	Max	SD
Convertible arbitrage	82	**beta**	−0.52	0.41	0.43	1.57	0.37	−0.63	−0.01	−0.02	0.45	0.15	−0.08	0.26	0.30	1.73	0.29	−0.98	0.01	−0.02	0.68	0.28
		t-stat	−1.56	2.12	4.55	83.10	11.35	−2.58	−0.14	0.06	7.65	1.53	−0.52	1.60	1.60	4.50	1.12	−2.23	0.15	0.12	2.91	1.22
Dedicated short bias	10	**beta**	−0.04	0.77	0.67	1.13	0.38	−1.78	−1.01	−0.88	−0.11	0.50	−0.60	0.18	0.25	0.96	0.48	−0.08	0.73	0.67	1.25	0.51
		t-stat	−0.12	0.73	0.91	1.83	0.66	−10.95	−3.29	−3.88	−0.48	2.72	−1.37	0.24	0.17	1.05	0.70	−0.19	1.26	1.07	1.99	0.77
Emerging markets	102	**beta**	−0.75	1.19	1.41	6.50	1.08	−0.41	0.31	0.43	3.30	0.52	−4.53	0.02	0.01	2.33	0.77	−4.66	−0.39	−0.42	2.18	0.79
		t-stat	−1.03	1.83	2.74	44.67	4.57	−1.77	1.69	1.65	5.46	1.61	−2.17	0.09	0.22	3.71	1.09	−3.74	−1.03	−0.97	2.53	1.20
Equity market neutral	83	**beta**	−0.61	0.59	0.59	2.42	0.41	−1.22	0.05	0.05	0.90	0.27	−1.16	0.05	0.02	0.82	0.33	−2.83	0.02	−0.04	1.24	0.44
		t-stat	−1.40	2.02	2.88	13.89	3.00	−4.86	0.75	0.65	4.16	1.98	−3.74	0.30	0.27	2.67	1.09	−4.17	0.08	0.16	3.65	1.39
Event driven	169	**beta**	−0.12	0.78	0.93	6.18	0.78	−0.35	0.08	0.13	1.17	0.22	−4.23	0.08	0.04	1.31	0.46	−6.38	−0.05	−0.13	1.46	0.60
		t-stat	−0.69	3.38	3.88	21.54	2.89	−2.80	1.26	1.34	10.87	1.88	−2.31	0.40	0.42	3.21	1.08	−2.86	−0.31	−0.14	3.40	1.35
Fixed income arbitrage	62	**beta**	0.00	0.52	0.58	2.03	0.42	−0.39	0.03	0.02	0.23	0.10	−0.55	0.20	0.27	1.86	0.40	−0.66	0.05	0.07	0.77	0.35
		t-stat	0.00	2.85	3.85	24.30	3.91	−2.42	0.55	0.44	3.23	1.25	−2.63	1.00	1.26	11.02	1.99	−3.48	0.38	0.66	4.62	1.68
Global macro	54	**beta**	−0.79	0.63	0.59	1.75	0.54	−0.49	0.01	0.10	1.14	0.30	−0.74	0.21	0.34	2.03	0.56	−2.00	−0.23	−0.23	1.35	0.67
		t-stat	−1.56	1.53	1.71	7.66	1.62	−2.97	0.19	0.59	6.16	1.84	−1.93	0.71	0.92	6.05	1.51	−6.51	−0.83	−0.73	4.52	1.95
Long/Short equity hedge	520	**beta**	−1.53	0.84	0.89	7.60	0.75	−1.37	0.33	0.38	3.13	0.44	−3.04	−0.01	0.03	3.49	0.59	−2.57	−0.03	−0.09	2.45	0.60
		t-stat	−1.80	1.84	1.86	10.47	1.38	−3.72	2.06	2.27	20.07	2.50	−3.47	−0.01	0.06	3.33	1.06	−4.60	−0.10	−0.19	3.41	1.18
Managed futures	114	**beta**	−1.84	0.48	0.42	3.69	0.73	−0.81	−0.01	0.03	2.30	0.37	−0.44	0.88	0.89	2.62	0.67	−2.65	−0.37	−0.39	1.14	0.63
		t-stat	−2.36	0.72	0.65	4.98	1.08	−2.94	−0.05	0.20	7.88	1.43	−1.70	1.46	1.60	4.34	1.22	−4.25	−0.83	−0.72	1.99	0.98
Multi-strategy	59	**beta**	−0.41	0.71	0.71	2.68	0.47	−0.31	0.07	0.15	1.34	0.26	−1.81	0.10	0.12	2.40	0.51	−1.84	0.07	0.01	0.78	0.41
		t-stat	−0.43	3.22	3.41	10.51	2.41	−2.22	1.27	1.37	5.98	1.68	−1.49	0.58	0.57	3.49	1.13	−2.78	0.36	0.39	3.19	1.34
Fund of funds	355	**beta**	−0.77	0.42	0.43	1.88	0.34	−0.80	0.09	0.12	0.85	0.15	−0.50	0.12	0.18	2.25	0.29	−1.12	−0.07	−0.10	0.62	0.24
		t-stat	−3.55	2.34	2.67	10.51	2.14	−2.65	1.56	1.84	9.44	1.80	−1.59	0.83	0.95	4.84	1.17	−3.63	−0.53	−0.42	3.32	1.28

Table 5 (*Continued*)

Category	Sample size	Statistic	R_{cs} Min	Med	Mean	Max	SD	ΔVIX Min	Med	Mean	Max	SD	R_{gsci} Min	Med	Mean	Max	SD	Statistic	Significance (%) Min	Med	Mean	Max	SD
Convertible arbitrage	82	**beta**	0.00	0.39	0.52	2.87	0.57	−0.25	0.05	0.05	0.32	0.08	−0.07	0.01	0.02	0.16	0.03	**Adj. R^2**	−11.0	16.0	17.3	66.2	15.4
		t-stat	0.19	3.06	2.95	7.72	1.58	−1.41	0.50	0.66	3.56	0.98	−1.15	0.52	0.51	2.17	0.69	**p(F)**	0.0	1.0	11.8	97.1	23.6
Dedicated short bias	10	**beta**	−0.98	−0.26	−0.19	0.93	0.67	−0.26	0.05	0.04	0.44	0.23	−0.38	−0.11	−0.12	0.06	0.13	**Adj. R^2**	−3.5	39.7	40.4	79.5	25.4
		t-stat	−2.67	−0.68	−0.44	2.54	1.64	−1.11	0.24	0.23	2.56	1.10	−2.19	−0.86	−0.95	0.54	0.92	**p(F)**	0.0	0.0	8.3	83.0	26.2
Emerging markets	102	**beta**	−0.56	0.46	0.59	2.89	0.67	−1.41	−0.05	0.01	3.91	0.50	−0.34	0.05	0.06	0.34	0.09	**Adj. R^2**	−4.7	17.4	19.4	54.7	14.3
		t-stat	−1.97	1.32	1.33	4.82	1.36	−3.95	−0.35	−0.28	3.88	1.17	−1.46	0.68	0.60	2.40	0.79	**p(F)**	0.0	0.2	8.4	78.8	17.7
Equity market neutral	83	**beta**	−1.78	−0.03	−0.06	0.72	0.31	−1.19	0.02	0.03	0.80	0.23	−0.12	0.01	0.02	0.38	0.07	**Adj. R^2**	−8.1	7.2	10.4	63.2	13.7
		t-stat	−3.83	−0.27	−0.35	3.34	1.44	−3.10	0.22	0.25	3.95	1.23	−2.05	0.48	0.43	2.80	1.11	**p(F)**	0.0	7.4	19.9	94.1	24.6
Event driven	169	**beta**	−1.96	0.25	0.33	2.01	0.45	−1.81	0.02	0.05	1.19	0.26	−0.27	0.01	0.01	0.27	0.06	**Adj. R^2**	−7.5	15.5	19.5	68.5	16.4
		t-stat	−1.66	1.51	1.81	8.31	1.99	−2.76	0.42	0.36	4.58	1.17	−2.27	0.50	0.60	4.06	1.15	**p(F)**	0.0	0.3	11.1	88.6	20.0
Fixed income arbitrage	62	**beta**	−0.70	0.10	0.19	1.54	0.46	−0.71	0.05	0.07	0.50	0.18	−0.06	0.01	0.02	0.15	0.05	**Adj. R^2**	−8.9	12.8	14.9	78.9	15.9
		t-stat	−3.29	0.80	1.25	11.74	2.56	−3.16	0.85	1.16	5.62	1.93	−1.76	0.57	0.52	2.52	1.10	**p(F)**	0.0	2.1	17.7	94.6	26.3
Global macro	54	**beta**	−0.61	0.13	0.18	1.73	0.42	−0.36	0.03	0.07	0.55	0.19	−0.09	0.02	0.04	0.27	0.08	**Adj. R^2**	−12.6	8.9	14.8	74.0	17.3
		t-stat	−1.60	0.44	0.60	3.96	1.25	−3.08	0.33	0.34	3.61	1.11	−1.22	0.37	0.60	3.92	1.20	**p(F)**	0.0	4.9	16.8	97.0	24.3
Long/Short equity hedge	520	**beta**	−1.37	0.17	0.28	4.55	0.59	−1.67	0.07	0.07	2.76	0.33	−0.33	0.04	0.06	0.88	0.11	**Adj. R^2**	−13.8	18.8	21.6	90.2	19.0
		t-stat	−5.28	0.58	0.69	4.94	1.36	−4.70	0.46	0.38	3.67	1.28	−3.31	0.74	0.77	5.91	1.13	**p(F)**	0.0	0.4	11.8	97.7	22.9
Managed futures	114	**beta**	−5.98	−0.33	−0.35	3.20	0.82	−0.75	0.14	0.15	1.29	0.32	−0.31	0.11	0.13	0.80	0.15	**Adj. R^2**	−6.0	13.3	15.3	70.0	13.3
		t-stat	−2.85	−0.92	−0.73	2.56	1.04	−2.81	0.73	0.74	4.36	1.28	−2.15	1.32	1.36	5.25	1.22	**p(F)**	0.0	0.6	8.2	88.5	17.0
Multi-strategy	59	**beta**	−0.48	0.07	0.17	1.64	0.41	−0.38	0.04	0.09	0.95	0.19	−0.05	0.03	0.04	0.75	0.11	**Adj. R^2**	−13.5	8.9	12.9	51.7	15.7
		t-stat	−2.20	0.72	1.21	6.34	2.12	−1.59	0.68	0.87	3.72	1.31	−1.34	0.87	0.81	2.90	0.97	**p(F)**	0.0	6.7	21.7	97.5	28.9
Fund of funds	355	**beta**	−0.78	0.17	0.17	1.41	0.22	−0.32	0.06	0.07	0.48	0.09	−0.23	0.03	0.05	0.35	0.05	**Adj. R^2**	−7.2	20.4	22.3	72.3	14.9
		t-stat	−3.62	1.38	1.53	6.35	1.55	−2.74	0.98	0.98	4.69	1.12	−3.16	1.38	1.39	4.28	1.01	**p(F)**	0.0	0.2	5.7	84.0	14.3

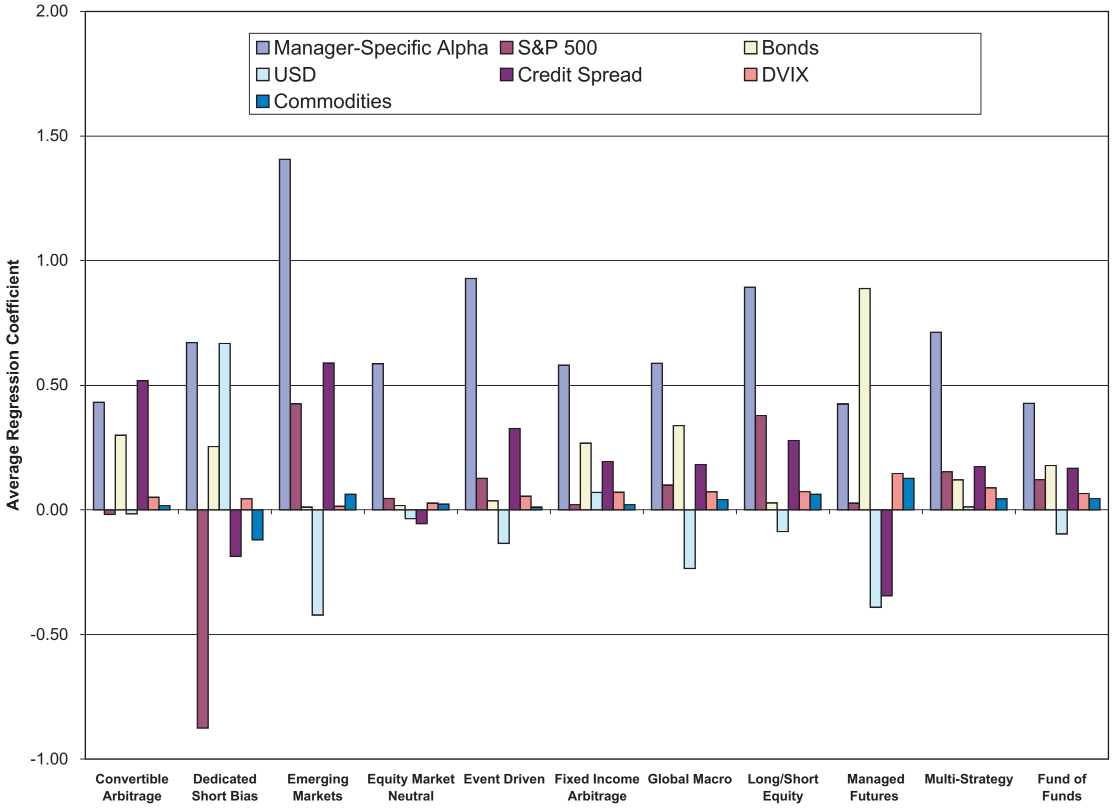


Figure 2 Average regression coefficients for multivariate linear regressions of monthly returns of hedge funds in the TASS Live database from February 1986 to September 2005 on six factors: the S&P 500 total return, the Lehman Corporate AA Intermediate Bond Index return, the US Dollar Index return, the spread between the Lehman US Aggregate Long Credit BAA Bond Index and the Lehman Treasury Long Index, the first-difference of the CBOE Volatility Index (VIX), and the Goldman Sachs Commodity Index (GSCI) total return.

to risk premia from identifiable factors. If it is a significant portion and the relationship is primarily linear, then a passive portfolio with just those risk exposures—created by means of liquid instruments such as index futures, forwards, and other marketable securities—may be a reasonable alternative to a less liquid and opaque investment in the fund.

Table 6 summarizes the results of the expected-return decomposition (2) for our sample of 1610 funds, grouped according to their style categories and for all funds. Each row of Table 6 contains the average total mean return of funds in a given category and averages of the percent contributions of each of the six factors and the manager-specific alpha to that average total mean return.[15] Note that the average percentage contributions add up to 100% when summed across all six factors and the manager-specific alpha because this decomposition sums to 100% for each fund, and when this decomposition is averaged across all funds, the sum is preserved.

The first row's entries indicate that the most significant contributors to the average total mean return of 8.4% for Convertible Arbitrage funds are CREDIT (27.1%), USD (67.1%), BOND (34.9%), and

Table 6 Decomposition of total mean returns of hedge funds in the TASS Live database according to percentage contributions from six factors and manager-specific alpha, for 1610 hedge funds from February 1986 to September 2005.

Category description	Sample size	Avg. $E[R]$	Average of percentage contribution of factors to total expected return (%)						
			CREDIT	USD	SP500	BOND	DVIX	CMDTY	ALPHA
Convertible arbitrage	82	8.4	27.1	67.1	−19.3	34.9	−8.4	31.8	−33.3
Dedicated short bias	10	6.0	12.2	19.4	−108.2	7.0	8.9	−64.9	225.6
Emerging markets	102	20.4	−0.3	−3.2	19.3	0.1	−0.4	6.2	78.3
Equity market neutral	83	8.1	0.2	3.6	4.0	3.9	1.3	6.3	80.8
Event driven	169	13.0	2.1	3.0	4.3	9.4	−0.7	3.1	79.0
Fixed income arbitrage	62	9.5	−1.4	3.3	2.7	18.5	−0.5	4.4	73.1
Global macro	54	11.4	2.0	8.1	9.7	25.0	−3.3	10.0	48.6
Long/Short equity hedge	520	14.6	1.1	1.9	17.8	2.1	−1.8	8.4	70.5
Managed futures	114	13.6	1.9	23.4	−3.4	53.8	−1.5	53.2	−27.5
Multi-strategy	59	10.8	0.5	3.5	5.7	10.1	−1.9	3.2	78.9
Fund of funds	355	8.3	0.5	5.4	9.7	8.8	−2.8	7.3	71.1
All Funds	1,610	11.3	2.3	7.8	8.5	11.3	−1.9	10.9	61.0

CMDTY (31.8%), and the average contribution of manager-specific alpha is −33.3%. This implies that on average, Convertible Arbitrage funds earn more than all of their mean returns from the risk premia associated with the six factor exposures, and that the average contribution of other sources of alpha is negative! Of course, this does not mean that convertible-arbitrage managers are not adding value—Table 6's results are averages across all funds in our sample, hence the positive manager-specific alphas of successful managers will be dampened and, in some cases, outweighed by the negative manager-specific alphas of the unsuccessful ones.

In contrast to the Convertible Arbitrage funds, for the 10 funds in the Dedicated Short Bias category, the manager-specific alpha accounts for 225.6% of the funds' total mean return on average, and the contribution of the SP500 factor is negative. This result is not as anomalous as it seems. The bull market of the 1990s implies a performance drag for any fund with negative exposure to the S&P 500, therefore, Dedicated Short Bias managers that have generated positive performance during this period must have done so through other means. A concrete illustration of this intuition is given by the return decomposition of the annualized average return of the two most successful funds in the Dedicated Short Bias category, funds 33735 and 33736. These two funds posted annualized net-of-fee returns of 15.56% and 10.02%, respectively, but the contribution of the SP500 factor to these annualized returns was negative in both cases (both funds had negative SP500 beta exposures, as they should, and the S&P 500 yielded positive returns over the funds' lifetimes).[16]

Between the two extremes of Convertible Arbitrage and Dedicated Short Bias funds, Table 6 shows considerable variation in the importance of manager-specific alpha for the other categories. Over 80% of the average total return of Equity Market Neutral funds is due to manager-specific alpha, but for Managed Futures, the manager-specific alpha accounts for −27.5%. For the entire sample of 1610 funds, 61% of the average total return is attributable to manager-specific alpha, implying that on average, the remaining 39% is due to the risk premia from our six factors. These results suggest that for certain types of hedge-fund strategies, a multi-factor portfolio may yield some of the same benefits but in a transparent, scalable, and lower-cost vehicle.

4 Linear clones

The multivariate regression results in Section 3 suggest that linear clones may be able to replicate some of the risk exposures of hedge funds, and in this section we investigate this possibility directly by considering two types of clones. The first type consists of "fixed-weight" portfolios, where we use the entire sample of a given fund's returns to estimate a set of portfolio weights for the instruments corresponding to the factors used in the linear regression. These portfolio weights are fixed through time for each fund, hence the term "fixed-weight."[17] But because this approach involves a certain degree of "look-ahead" bias—we use the entire history of a fund's returns to construct the portfolio weights that are applied each period to compute the clone portfolio return—we also construct a second type of linear clone based on rolling-window regressions.

4.1 Fixed-weight vs. rolling-window clones

To construct a fixed-weight linear clone for fund i, we begin by regressing the fund's returns $\{R_{it}\}$ on five of the six factors we considered in Section 3 (we drop the DVIX factor because its returns are not as easily realized with liquid instruments), where we omit the intercept and constrain the beta coefficients to sum to one:

$$\begin{aligned} R_{it} = {} & \beta_{i1}\mathrm{SP500}_t + \beta_{i2}\mathrm{BOND}_t \\ & + \beta_{i3}\mathrm{USD}_t + \beta_{i4}\mathrm{CREDIT}_t \\ & + \beta_{i5}\mathrm{CMDTY}_t + \epsilon_{it}, \\ & t = 1, \ldots, T \end{aligned} \tag{4a}$$

$$\text{subject to } 1 = \beta_{i1} + \cdots + \beta_{i5} \tag{4b}$$

This is the same technique proposed by Sharpe (1992) for conducting "style analysis," however, our motivation is quite different. We omit the intercept because our objective is to estimate a weighted average of the factors that best replicates the fund's returns, and omitting the constant term forces the least-squares algorithm to use the factor means to fit the mean of the fund, an important feature of replicating hedge-fund expected returns with factor risk premia. And we constrain the beta coefficients to sum to one to yield a portfolio interpretation for the weights. Note that we do not constrain the regression coefficients to be non-negative as Sharpe (1992) does because unlike Sharpe's original application to long-only mutual funds, in our context all five factors correspond to instruments that can be shortsold, and we do expect to be shortselling each of these instruments on occasion to achieve the kind of risk exposures hedge funds typically exhibit. For example, clones of Dedicated Short Bias funds will undoubtedly require shorting the SP500 factor.

The estimated regression coefficients $\{\beta^*_{ik}\}$ are then used as portfolio weights for the five factors, hence the portfolio returns are equivalent to the fitted values R^*_{it} of the regression equation. However, we implement an additional renormalization so that the resulting portfolio return $\widehat{R}_{it}$ has the same sample volatility as the original fund's return series:

$$\begin{aligned} R^*_{it} \equiv {} & \beta^*_{i1}\mathrm{SP500}_t + \beta^*_{i2}\mathrm{BOND}_t + \beta^*_{i3}\mathrm{USD}_t \\ & + \beta^*_{i4}\mathrm{CREDIT}_t + \beta^*_{i5}\mathrm{CMDTY}_t \end{aligned} \tag{5}$$

$$\widehat{R}_{it} \equiv \gamma_i R^*_{it}, \quad \gamma_i \equiv \frac{\sqrt{\sum_{t=1}^{T}(R_{it} - \overline{R}_i)^2/(T-1)}}{\sqrt{\sum_{t=1}^{T}(R^*_{it} - \overline{R}^*_i)^2/(T-1)}} \tag{6}$$

$$\overline{R}_i \equiv \frac{1}{T}\sum_{t=1}^{T} R_{it}, \quad \overline{R}^*_i \equiv \frac{1}{T}\sum_{t=1}^{T} R^*_{it} \tag{7}$$

The motivation for this renormalization is to create a fair comparison between the clone portfolio and the fund by equalizing their volatilities. Renormalizing (5) is equivalent to changing the leverage of the clone portfolio, since the sum of the renormalized betas $\gamma_i \sum_k \beta^*_{ik}$ will equal the renormalization factor γ_i, not one. If γ_i exceeds one, then positive leverage is required, and if less than one, the portfolio is not fully invested in the five factors. A more complete expression of the portfolio weights of clone i may be obtained by introducing an additional asset that represents leverage, that is, borrowing and lending, in which case the portfolio weights of the five factors and this additional asset must sum to one:

$$1 = \gamma_i(\beta^*_{i1} + \cdots + \beta^*_{i5}) + \delta_i \tag{8}$$

The clone return is then given by:

$$\widehat{R}_{it} = \gamma_i(\beta^*_{i1}\,\text{SP500}_t + \cdots + \beta^*_{i5}\,\text{CMDTY}_t) + \delta_i\, R_l \tag{9}$$

where R_l is the borrowing/lending rate. Since this rate depends on many factors such as the credit quality of the respective counterparties, the riskiness of the instruments and portfolio strategy, the size of the transaction, and general market conditions, we do not attempt to assume a particular value for R_l but simply point out its existence.[18]

As discussed above, fixed-weight linear clones are affected by look-ahead bias because the entire histories of fund and factor returns are used to construct the clones' portfolio weights and renormalization factors. To address this issue, we present an alternate method of constructing linear clones using a rolling window for estimating the regression coefficients and renormalization factors. Rolling-window estimators can also address the ubiquitous issue of nonstationarity that affects most financial time-series studies; time-varying means, volatilities, and general market conditions can be captured to some degree by using rolling windows.

To construct a "rolling-window" linear clone, for each month t, we use a 24-month rolling window from months $t-24$ to $t-1$ to estimate the same regression (4) as before[19]:

$$\begin{aligned} R_{it-k} = {} & \beta_{it1}\text{SP500}_{t-k} + \beta_{it2}\text{BOND}_{t-k} \\ & + \beta_{it3}\text{USD}_{t-k} + \beta_{it4}\text{CREDIT}_{t-k} \\ & + \beta_{it5}\text{CMDTY}_{t-k} + \epsilon_{it-k}, \\ & k = 1, \ldots, 24 \end{aligned} \tag{10a}$$

$$\text{subject to } 1 = \beta_{it1} + \cdots + \beta_{it5} \tag{10b}$$

but now the coefficients are indexed by both i and t since we repeat this process each month for every fund i. The parameter estimates are then used in the same manner as in the fixed-weight case to construct clone returns $\widehat{R}_{it}$:

$$\begin{aligned} R^*_{it} \equiv {} & \beta^*_{it1}\text{SP500}_t + \beta^*_{it2}\text{BOND}_t + \beta^*_{it3}\text{USD}_t \\ & + \beta^*_{it4}\text{CREDIT}_t + \beta^*_{it5}\text{CMDTY}_t \end{aligned} \tag{11}$$

$$\widehat{R}_{it} \equiv \gamma_{it}\, R^*_{it}, \quad \gamma_{it} \equiv \frac{\sqrt{\sum_{k=1}^{24} (R_{it-k} - \overline{R}_{it})^2/23}}{\sqrt{\sum_{k=1}^{24} (R^*_{it-k} - \overline{R}^*_{it})^2/23}} \tag{12}$$

$$\overline{R}_{it} \equiv \frac{1}{24}\sum_{k=1}^{24} R_{it-k}, \quad \overline{R}^*_{it} \equiv \frac{1}{24}\sum_{k=1}^{24} R^*_{it-k} \tag{13}$$

where the renormalization factors γ_{it} are now indexed by time t to reflect the fact that they are also computed within the rolling window. This implies that for any given clone i, the volatility of its returns over the entire history will no longer be identical to the volatility of its matching fund because the renormalization process is applied only to rolling windows, not to the entire history of returns. However, as long as volatilities do not shift dramatically over time, the rolling-window renormalization process should yield clones with similar volatilities.

Although rolling-window clones may seem more practically relevant because they avoid the most obvious forms of look-ahead bias, they have drawbacks as well. For example, the rolling-window estimation procedure generates more frequent rebalancing needs for the clone portfolio, which is counter to the passive spirit of the cloning endeavor. Moreover, rolling-window estimators are typically subject to greater estimation error because of the smaller sample size. This implies that at least part of the rebalancing of rolling-window clones is unnecessary. The amount of rebalancing can, of course, be controlled by adjusting the length of the rolling window—a longer window implies more stable weights, but stability implies less flexibility in capturing potential nonstationarities in the data.

Ultimately, the choice between fixed-weight and rolling-window clones depends on the nature of the application, the time-series properties of the strategies being cloned, and the specific goals and constraints of the investor. A passive investor with little expertise in trading and risk management may well prefer the fixed-weight clone, whereas a more active investor with trading capabilities and a desire to implement dynamic asset-allocation policies will prefer the rolling-window clone. For these reasons, we present results for both types of clones in Sections 4.2–4.5.

4.2 Performance results

Table 7 contains a comparison between the performance of fixed-weight and rolling-window linear clones and the original funds from which the clones are derived.[20] The results are striking—for several categories, the average mean return of the clones is only slightly lower than that of their fund counterparts, and in some categories, the clones do better. For example, the average mean return of the Convertible Arbitrage fixed-weight clones is 7.40%, and the corresponding figure for the funds is 8.41%. For Long/Short Equity Hedge funds, the average mean return for fixed-weight clones and funds is 13.12% and 14.59%, respectively. And in the Multi-Strategy category, the average mean return for fixed-weight clones and funds is 10.32% and 10.79%, respectively.

In five cases, the average mean return of the fixed-weight clones is higher than that of the funds: Dedicated Short Bias (6.70% vs. 5.98%), Equity Market Neutral (10.00% vs. 8.09%), Global Macro (15.54% vs. 11.38%), Managed Futures (27.97% vs. 13.64%), and Fund of Funds (9.29% vs. 8.25%). However, these differences are not necessarily statistically significant because of the variability in mean returns of funds and clones within their own categories. Even in the case of Managed Futures, the difference in average mean return between fixed-weight clones and funds—almost 15 percentage points—is not significant because of the large fluctuations in average mean returns of the Managed Futures fixed-weight clones and their corresponding funds (e.g. one standard deviation of the average mean of the Managed Futures fixed-weight clones is 16.32% and one standard deviation of the average mean of the corresponding sample of funds is 9.35%, according to Table 7). Nevertheless, these results suggest that for certain categories, the performance of fixed-weight clones may be comparable to that of their corresponding funds.

On the other hand, at 9.84%, the average performance of the Event-Driven fixed-weight clones is considerably lower than the 13.03% average for the funds. While also not statistically significant, this gap is understandable given the idiosyncratic and opportunistic nature of most event-driven strategies. Moreover, a significant source of the profitability of event-driven strategies is the illiquidity premium that managers earn by providing capital in times of distress. This illiquidity premium will clearly be missing from a clone portfolio of liquid securities, hence we should expect a sizable performance gap in this case. The same can be said for the

Table 7 Performance comparison of fixed-weight and rolling-window linear clones of hedge funds in the TASS Live database and their corresponding funds, from February 1986 to September 2005. The category "Dedicated Short Bias*" excludes Fund 33735.

		Fixed-weight linear clones										24-month rolling-window linear clones									
		Annual mean return (%)		Annual SD (%)		Annual Sharpe		ρ_1(%)		p-value(Q_{12}) (%)		Annual mean return (%)		Annual SD (%)		Annual Sharpe		ρ_1(%)		p-value(Q_6) (%)	
Category description	Sample size	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
								Funds													
Convertible arbitrage	82	8.41	5.11	6.20	5.28	2.70	5.84	42.2	17.3	11.0	22.2	4.04	7.83	5.76	4.55	2.31	8.96	42.3	16.2	12.4	19.4
Dedicated short bias	10	5.98	4.77	28.27	10.05	0.25	0.24	5.5	12.6	24.2	20.3	2.58	7.19	25.91	14.20	0.02	0.42	8.3	5.5	31.9	19.0
Dedicated short bias*	9	4.92	3.58	28.75	10.53	0.20	0.20	3.4	11.3	25.5	21.1	1.42	6.55	26.21	15.03	−0.04	0.39	7.4	4.9	35.2	16.8
Emerging markets	102	20.41	13.01	22.92	15.16	1.42	2.11	18.0	12.4	36.3	30.2	21.12	13.86	19.95	14.06	1.74	2.57	16.0	14.3	39.2	28.1
Equity market neutral	83	8.09	4.77	7.78	5.84	1.44	1.20	9.1	23.0	32.6	29.7	5.71	4.14	6.60	5.91	1.44	1.68	5.3	24.0	40.2	33.9
Event driven	169	13.03	8.65	8.40	8.09	1.99	1.37	22.2	17.6	27.0	29.3	11.65	10.45	7.62	7.68	2.01	1.43	17.2	17.8	31.1	29.8
Fixed income arbitrage	62	9.50	4.54	6.56	4.41	2.05	1.48	22.1	17.6	35.9	35.2	7.80	7.59	5.73	4.52	2.17	1.81	23.3	21.4	30.1	32.4
Global macro	54	11.38	6.16	11.93	6.10	1.07	0.58	5.8	12.2	43.1	32.5	9.01	6.72	11.16	6.50	0.91	0.73	6.6	18.9	44.7	31.2
Long/Short equity hedge	520	14.59	8.14	15.96	9.06	1.06	0.58	12.8	14.9	36.0	30.5	11.90	8.93	13.90	8.69	1.04	0.77	9.8	16.7	42.0	28.5
Managed futures	114	13.64	9.35	21.46	12.07	0.67	0.39	2.5	10.2	40.1	31.5	11.84	8.82	20.19	10.94	0.66	0.52	4.0	14.9	37.0	28.3
Multi-strategy	59	10.79	5.22	8.72	9.70	1.86	1.03	21.0	20.1	28.2	30.1	8.97	6.13	7.65	10.10	1.86	1.25	18.3	22.5	29.1	28.6
Fund of funds	355	8.25	3.73	6.36	4.47	1.66	0.86	23.2	15.0	27.1	26.3	7.34	3.95	5.68	4.29	1.67	0.97	22.6	16.3	24.0	26.5
All except fund of funds	1255	13.29	8.71	13.95	10.76	1.39	1.88	15.7	18.3	33.2	30.9	11.15	9.86	12.38	10.12	1.38	2.64	13.5	19.8	36.6	29.8
								Linear clones													
Convertible arbitrage	82	7.40	3.17	6.20	5.28	1.52	0.62	10.7	10.5	55.6	24.9	2.78	4.95	6.20	6.57	0.71	0.77	6.4	12.7	43.8	29.1
Dedicated short bias	10	6.70	11.59	28.27	10.05	0.32	0.48	2.8	5.9	73.6	17.5	6.83	16.18	29.31	15.61	0.09	0.45	0.4	8.8	36.7	28.7
Dedicated short bias*	9	3.61	6.61	28.75	10.53	0.19	0.29	3.7	5.6	77.3	14.0	9.08	15.41	30.00	16.39	0.17	0.40	−0.7	8.5	36.8	30.4
Emerging markets	102	14.77	11.47	22.92	15.16	0.88	0.58	0.0	9.0	62.7	27.6	5.17	14.70	25.04	17.94	0.47	0.66	7.7	12.4	42.5	27.3
Equity market neutral	83	10.00	7.00	7.78	5.84	1.42	0.58	1.8	9.6	57.0	24.7	4.43	4.90	7.91	6.49	0.64	0.68	4.2	12.7	47.8	27.0
Event driven	169	9.84	6.69	8.40	8.09	1.43	0.52	4.3	11.0	55.8	24.1	6.96	8.33	7.79	7.10	1.05	0.56	3.0	13.3	39.6	27.3
Fixed income arbitrage	62	8.35	5.20	6.56	4.41	1.48	0.59	4.1	8.4	64.4	29.8	4.47	4.63	6.85	5.17	0.84	0.71	4.3	9.9	40.8	30.0
Global macro	54	15.54	8.35	11.93	6.10	1.41	0.55	2.6	8.3	52.2	23.8	12.97	8.90	12.48	7.38	1.08	0.59	4.1	11.1	45.3	28.2
Long/Short equity hedge	520	13.12	8.68	15.96	9.06	0.98	0.57	−0.1	10.0	59.7	26.3	9.08	11.03	15.83	10.64	0.76	0.68	0.3	15.6	42.5	29.1
Managed futures	114	27.97	16.32	21.46	12.07	1.36	0.40	4.7	8.1	61.4	29.0	19.24	13.32	22.96	13.71	0.91	0.57	5.5	10.9	46.5	27.7
Multi-strategy	59	10.32	7.21	8.72	9.70	1.51	0.62	2.3	10.1	59.7	28.8	5.33	7.52	9.16	9.59	0.71	0.60	0.8	13.0	35.9	28.2
Fund of funds	355	9.29	5.62	6.36	4.47	1.59	0.44	−0.1	11.1	50.5	24.7	5.67	4.57	6.22	5.40	1.11	0.54	0.0	13.0	39.8	28.5
All except fund of funds	1255	13.27	10.48	13.95	10.76	1.19	0.61	2.2	10.2	59.2	26.4	8.42	11.06	14.20	12.14	0.79	0.67	2.8	13.9	42.6	28.4

Emerging Markets fixed-weight clones (14.77%) versus their fund counterparts (20.41%).

For Dedicated Short Bias funds, the difference in average mean return between fixed-weight clones and funds—6.70% and 5.98%, respectively—may seem somewhat counterintuitive in the light of the expected-return decomposition in Table 6, where we observed that Dedicated Short Bias funds were responsible for more than 100% of the average total returns of funds in this category. The fact that Dedicated Short Bias clones have better average performance than the corresponding funds is due entirely to the clone of a single fund, 33735, and when this outlier is dropped from the sample, the average mean return of the remaining 9 clones drops to 3.61% (see the "Dedicated Short Bias*" row).[21] The intuition for the underperformance of the fixed-weight clones in this category is clear—given the positive trend in the S&P 500 during the 1980s and 1990s, a passive strategy of shorting the S&P 500 is unlikely to have produced attractive returns when compared to the performance of more nimble discretionary shortsellers.

The results for the rolling-window clones are broadly consistent with those of the fixed-weight clones, though the average performance of rolling-window clones is typically lower than that of their fixed-weight counterparts. For example, the average mean returns of rolling-window clones for all categories except Dedicated Short Bias are lower than their fixed-weight versions, in some cases by a factor of two or three. Part of these differences can be explained by the different sample periods on which rolling-window clones are based—observe that the average mean returns of the underlying funds are lower in the rolling-window sample than in the fixed-weight sample for all categories except Emerging Markets. But the more likely source of the performance difference between rolling-window and fixed-weight clones is the combined effects of look-ahead bias for the fixed-weight clones and the increased estimation errors implicit in the rolling-window clones.

Given these two effects, the performance of the rolling-window clones is all the more remarkable in categories such as Dedicated Short Bias (6.83% average mean return vs. 2.58% average mean return for the corresponding sample of funds), Equity Market Neutral (4.43% clones vs. 5.71% funds), Global Macro (12.97% clones vs. 9.01% funds), Long/Short Equity Hedge (9.08% clones vs. 11.90% funds), and Managed Futures (19.24% clones vs. 11.84% funds). In the case of Dedicated Short Bias funds, it is not surprising that rolling-window clones are able to outperform both fixed-weight clones and the funds on which they are based—the rolling-window feature provides additional flexibility for capturing time-varying expected returns (such as the bull market of the 1980s and 1990s) that a fixed-weight strategy simply cannot. And in the case of Managed Futures, as with the fixed-weight clones, the rolling-window clones exhibit considerable cross-sectional variation in their mean returns hence the superior performance of clones in this case may not be statistically significant.

Nevertheless, as with fixed-weight clones, rolling-window clones also fall short substantially in the categories of Emerging Markets (5.17% clones vs. 21.12% funds), Event Driven (6.96% clones vs. 11.65% funds), and Fixed Income Arbitrage (4.47% vs. 7.80%). Funds in these categories earn part of their expected return from bearing illiquidity risk, which is clearly absent from the clone portfolios constructed with the five factors we employ. Therefore, we should expect clones to underperform their fund counterparts in these categories.

Another metric of comparison between clones and funds is the average Sharpe ratio, which adjusts for the volatilities of the respective strategies. Of course, given our renormalization process (7), the standard deviations of the fixed-weight clones are identical to their fund counterparts, so a comparison of Sharpe ratios reduces to a comparison of mean returns in this case. However, the average Sharpe ratio of a category is not the same as the ratio of that category's average mean return to its average volatility, so the Sharpe ratio statistics in Table 7 and Figure 3 do provide some incremental information. Moreover, for rolling-window clones, there may be some differences in volatilities depending on the time series properties of the underlying funds, which makes Sharpe ratio comparisons more informative.

The average Sharpe ratio of the fixed-weight sample of Convertible Arbitrage funds is 2.70, which is almost twice the average Sharpe ratio of 1.52 for the fixed-weight clones, a significant risk-adjusted performance gap. Noticeable gaps also exist for Event Driven, Emerging Markets, and Fixed Income Arbitrage clones versus funds (recall that funds in these categories are likely to earn illiquidity risk premia not available to the corresponding clones). However, there is virtually no difference in average Sharpe ratios between fixed-weight clones and funds in the Dedicated Short Bias, Equity Market Neutral, Long/Short Equity Hedge, Multi-Strategy, and Fund of Funds categories. And for Global Macro and Managed Futures, the average Sharpe ratios of the fixed-weight clones are, in fact, higher than those of the funds in these categories.

The gaps between average Sharpe ratios of rolling-window clones and those of the underlying funds tend to be more substantial—for the twin reasons cited above—but with some notable exceptions. On average, rolling-window clones in the Dedicated Short Bias, Global Macro, and Managed Futures categories do better than their fund counterparts on a risk-adjusted basis, with average Sharpe ratios of 0.09, 1.08, and 0.91, respectively, as compared to average Sharpe ratios of 0.02, 0.91, and 0.66, respectively, for the corresponding sample of funds.

4.3 *Liquidity*

Table 7 provides another comparison worth noting: the average first-order autocorrelation coefficients of clones and funds. The first-order autocorrelation ρ_1 is the correlation between a fund's current return and the previous month's return, and Lo (2001, 2002) and Getmansky *et al.* (2004) observe that positive values for ρ_1 in hedge-fund returns is a proxy for illiquidity risk. Table 7 and Figure 4 show that the clones have much lower average autocorrelations than their fund counterparts, with the exception of Managed Futures for which both clones and funds have very low average autocorrelations. For example, the average autocorrelation of Convertible Arbitrage funds in the fixed-weight sample is 42.2%, and the corresponding average value for Convertible Arbitrage fixed-weight and rolling-window clones is only 10.7% and 6.4%, respectively. The average autocorrelation of Fund of Funds is 23.2% in the fixed-weight sample, and the corresponding value for the fixed-weight and rolling-window clones is only −0.1% and 0.0%, respectively.

The last two columns of each of the two subpanels in Table 7 provide a more formal measure of the statistical significance of autocorrelation in the monthly returns of clones and funds, the Ljung–Box Q-statistic, based on the first 12 autocorrelation coefficients in the fixed-weight case and on the first 6 autocorrelation coefficients in the rolling-window case.[22] Smaller p-values indicate more statistically significant autocorrelations, and for every single category, the average p-value of the funds is lower than that of the clones. These results confirm our intuition that, by construction, clones are more liquid than their corresponding funds, highlighting another potential advantage of

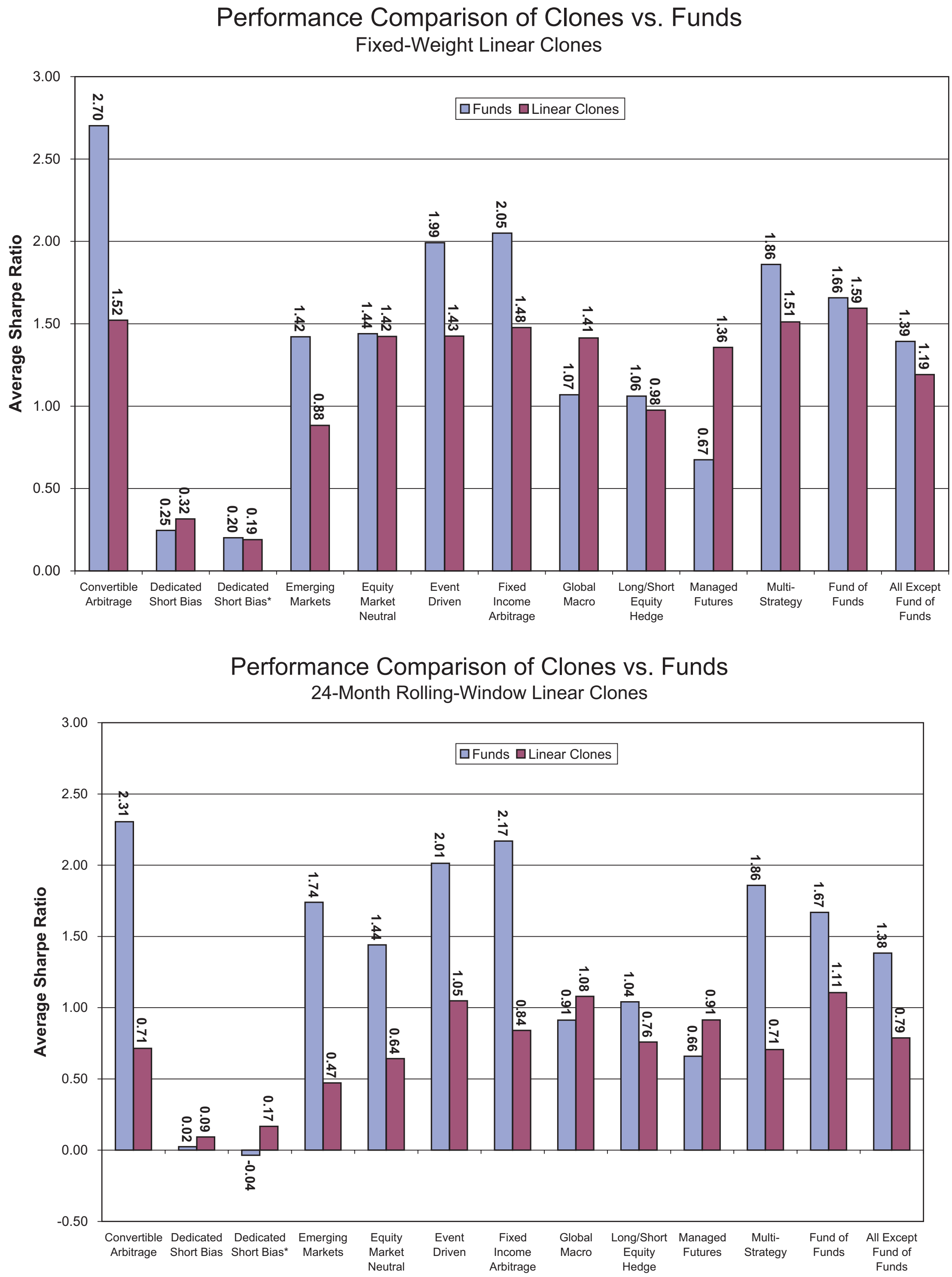


Figure 3 Comparison of average Sharpe ratios of fixed-weight and 24-month rolling-window linear clones and their corresponding funds in the TASS Live database, from February 1986 to September 2005. The category "Dedicated Short Bias*" excludes Fund 33735.

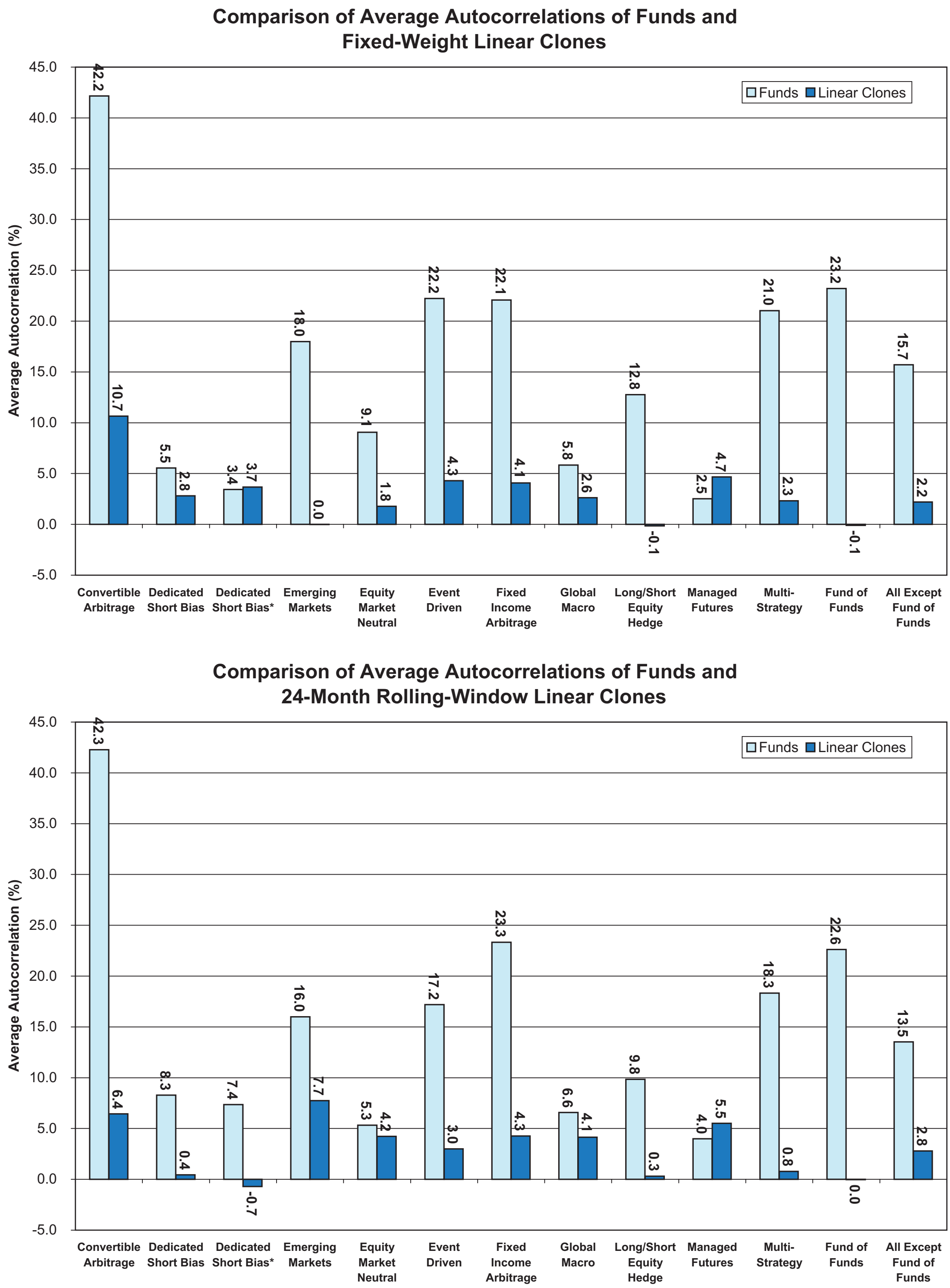


Figure 4 Comparison of average first-order autocorrelation coefficients of fixed-weight and 24-month rolling-window linear clones and their corresponding funds in the TASS Live database, from February 1986 to September 2005. The category "Dedicated Short Bias*" excludes Fund 33735.

clone portfolios over direct investments in hedge funds. However, this advantage comes at a cost; as we saw in Section 4.2, the performance gap between clones and funds is particularly large for those categories with the highest levels of illiquidity exposure.

4.4 *Leverage ratios*

Another consideration in evaluating the practical significance of fixed-weight linear clones is the magnitudes of the renormalization factors γ_i. As discussed in Section 4.1, these factors represent adjustments in the clone portfolios' leverage so as to yield comparable levels of volatility. If the magnitudes are too large, this may render the cloning process impractical for the typical investor, who may not have sufficient credit to support such leverage. The summary statistics in the left panel of Table 8 for the renormalization factors $\{\gamma_i\}$ suggest that this is not likely to be a concern—the average γ_i across all funds in the fixed-weight sample is 2.05, and the median value is 1.81, implying that the typical amount of additional leverage required to yield fixed-weight clones of comparable volatility is 81–105% on average, which is far less than the leverage afforded by standard futures contracts such as the S&P 500.[23] For the individual categories, the average value of γ_i for fixed-weight clones varies from a low of 1.69 for Fund of Funds to a high of 2.76 for Managed Futures. This accords well with our intuition that Fund of Funds is lower in volatility because of its diversified investment profile, and Managed Futures is higher in volatility given the leverage already incorporated into the futures contracts traded by CTAs and CPOs. In fact, outside of the Managed Futures category, even the maximum values for γ_i are relatively mild—ranging from 2.92 for Convertible Arbitrage to 8.85 for Dedicated Short Bias—and the maximum value of 18.35 for Managed Futures is also reasonably conservative for that category.

Developing intuition for the leverage ratios for the rolling-window clones is slightly more challenging because they vary over time for each clone, so the right panel of Table 8 reports the cross-sectional means and standard deviations of the time-series means, standard deviations, first-order autocorrelations, and Q-statistic p-values of each clone i's $\{\gamma_{it}\}$. For example, the value 1.62 is the mean across all rolling-window clones of the time-series-mean leverage ratio of each clone, and the value 0.46 is the cross-sectional standard deviation, across all rolling-window clones, of those time-series means. Table 8 shows that the average time series mean leverage ratios for rolling-window clones are somewhat lower than their fixed-weight counterparts but roughly comparable, ranging from a low of 1.38 for Fund of Funds to a high of 1.97 for Managed Futures, with standard deviations of the time-series means ranging from 0.31 for Fund of Funds to 0.75 for Dedicated Short Bias (recall that Dedicated Short Bias has only 10 funds, and that its short-bias mandate during the bull market is also likely to create more active rebalancings, contributing to more volatile leverage ratios). However, none of these leverage ratios fall outside the realm of practical possibility for the five instruments implicit in the cloning process.

4.5 *Equal-weighted clone portfolios*

The results in Sections 4.2–4.4 suggest that clone portfolios consisting primarily of futures and forward contracts, properly leveraged, can yield comparable volatility levels and some of the same risk exposures as certain types of hedge-fund strategies. But these impressions are based on averages of the 1610 funds in our sample and their corresponding clones, not on specific realizable portfolios. To address this issue, in this section we report the characteristics of equal-weighted portfolios of all fixed-weight and rolling-window clones, and compare them to the characteristics of equal-weighted

Table 8 Summary statistics for renormalization factors γ_i of fixed-weight and 24-month rolling-window clones of hedge funds in the TASS Live database, from February 1986 to September 2005.

Category description	Sample size	Fixed-weight linear clone renormalization factor					24-month rolling-window linear clone renormalization factor							
							TS-mean		TS-SD		ρ_1		p-value(Q_6)	
		Min	Med	Mean	Max	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
All funds	1610	0.11	1.81	2.05	18.35	0.96	1.62	0.46	0.36	0.28	80.7	14.6	1.9	9.4
Convertible arbitrage	82	0.11	1.64	1.71	2.92	0.53	1.44	0.40	0.27	0.19	77.1	21.0	3.6	12.6
Dedicated short bias	10	1.13	1.51	2.26	8.85	2.34	1.57	0.75	0.34	0.36	82.4	12.2	0.9	2.8
Emerging markets	102	0.26	1.95	2.13	5.17	0.82	1.68	0.45	0.45	0.38	83.8	10.4	0.5	2.8
Equity market neutral	83	0.39	2.17	2.18	4.25	0.80	1.78	0.54	0.40	0.26	77.6	17.4	5.2	17.3
Event driven	169	0.40	1.60	1.78	4.45	0.62	1.44	0.36	0.28	0.21	81.5	13.1	1.5	8.2
Fixed income arbitrage	62	0.40	1.69	2.07	5.46	1.01	1.47	0.40	0.32	0.21	79.0	14.9	2.9	12.2
Global macro	54	1.13	2.44	2.60	5.67	1.15	1.86	0.45	0.44	0.34	78.2	17.7	2.0	6.3
Long/Short equity hedge	520	1.02	1.92	2.18	6.32	0.89	1.75	0.46	0.38	0.26	79.3	15.1	1.6	8.6
Managed futures	114	1.17	2.41	2.76	18.35	1.76	1.97	0.46	0.56	0.37	82.5	12.4	1.3	8.9
Multi-strategy	59	0.45	1.89	2.04	3.75	0.75	1.57	0.46	0.38	0.30	81.8	11.7	1.6	9.5
Fund of funds	355	0.75	1.58	1.69	7.53	0.65	1.38	0.31	0.27	0.20	82.8	13.3	1.7	8.8

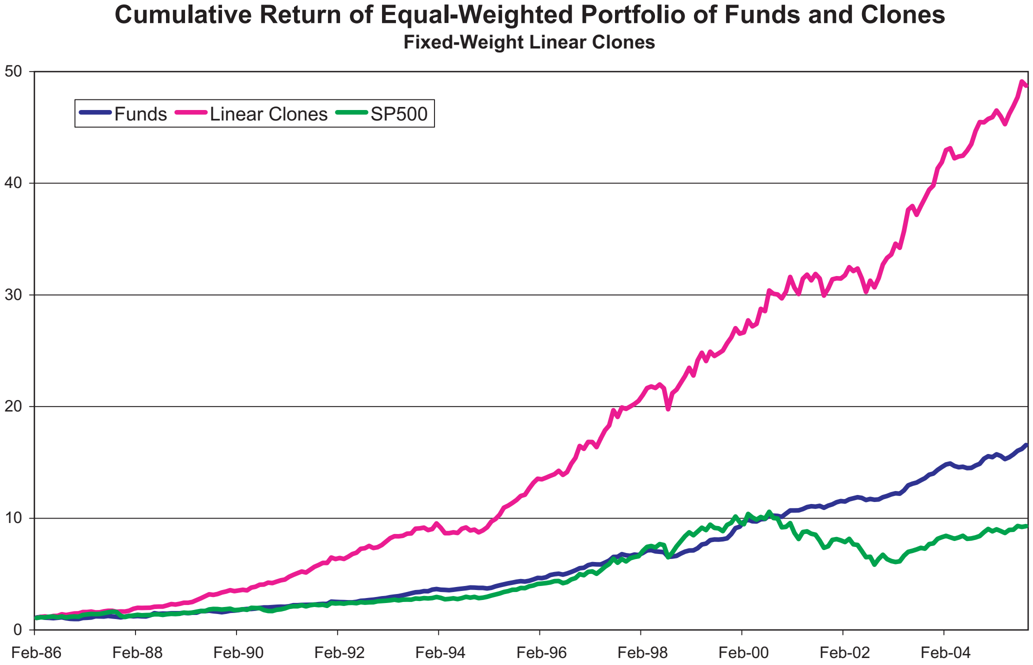
portfolios of the corresponding funds. By including all clones and funds in each of their respective portfolios, we avoid the potential selection biases that can arise from picking a particular subset of clones, for example, those with particularly high $\overline{R}^2$s or statistically significant factor exposures.

Figure 5 plots the cumulative returns of the equal-weighted portfolios of fixed-weight and rolling-window clones, as well as the equal-weighted portfolios of their respective funds and the S&P 500. The top panel shows that the equal-weighted portfolio of all fixed-weight clones outperforms both the equal-weighted portfolio of corresponding funds and the S&P 500 over the sample period. However, the bottom panel shows that the performance of the equal-weighted portfolio of 24-month rolling-window clones is not quite as impressive, underperforming both the funds portfolio and the S&P 500. However, the clones portfolio underperforms the S&P 500 only slightly, and apparently with less volatility as visual inspection suggests.

Tables 9 and 10 and Figure 6 provide a more detailed performance comparison of the portfolios of clones and funds. In particular, Figure 6, which plots the Sharpe ratios of the equal-weighted portfolios of the two types of clones and their corresponding funds, for all funds and category by category, shows that for some categories the fixed-weight clone portfolio underperforms the fund portfolio, for example, Dedicated Short Bias (0.09 for the clone portfolio vs. 0.28 for the fund portfolio), Emerging Markets (0.71 clones vs. 1.26 funds), Event Driven (1.89 clones vs. 3.08 funds), Fixed Income Arbitrage (1.79 clones vs. 2.93 funds), and Multi-Strategy (1.62 clones vs. 2.52 funds). However, in other categories, the fixed-weight clone portfolios have comparable performance and, in some cases, superior performance, for example, Managed Futures, where the fixed-weight clone portfolio exhibits a Sharpe ratio of 1.80 versus 0.83 for the corresponding fund portfolio. When all clones are used to construct an equal-weighted portfolio, Table 9 reports an annualized mean return of 20.44% with an annualized standard deviation of 10.23% over the sample period, implying a Sharpe ratio of 2.00. The annualized mean and standard deviation for an equal-weighted portfolio of all funds are 14.76% and 9.06%, respectively, yielding a Sharpe ratio of 1.63.

The lower panel of Figure 6 provides a comparison of the Sharpe ratios of the rolling-window clone portfolios with their fund counterparts, which exhibits patterns similar to those of the fixed-weight fund and clone portfolios. The rolling-window clone portfolios underperform in some categories but yield comparable performance in others, and superior performance in the categories of Dedicated Short Bias (0.19 clones vs. 0.12 funds), Equity Market Neutral (1.42 clones vs. 1.04 funds), Global Macro (1.48 clones vs. 1.39 funds), and Fund of Funds (1.68 clones vs. 1.61 funds). For the equal-weighted portfolio of all rolling-window clones, the average return is 12.69% with a standard deviation of 10.60%, yielding a Sharpe ratio of 1.20; by comparison, the equal-weighted portfolio of all funds has a 13.71% average return with a standard deviation of 8.51%, yielding a Sharpe ratio of 1.61.

Tables 9 and 10 also report skewness, kurtosis, and autocorrelation coefficients for the two types of clone portfolios, which gives a more detailed characterization of the risks of the return streams. For some of the categories, the differences in these measures between clones and funds are quite striking. For example, according to Table 9, the portfolio of Fixed Income Arbitrage funds in the fixed-weight case exhibits a skewness coefficient of −6, a kurtosis coefficient of 59, and a first-order autocorrelation coefficient of 27%, implying a negatively skewed return distribution with fat tails and significant illiquidity exposure. In contrast, the portfolio of Fixed Income Arbitrage fixed-weight clones has a



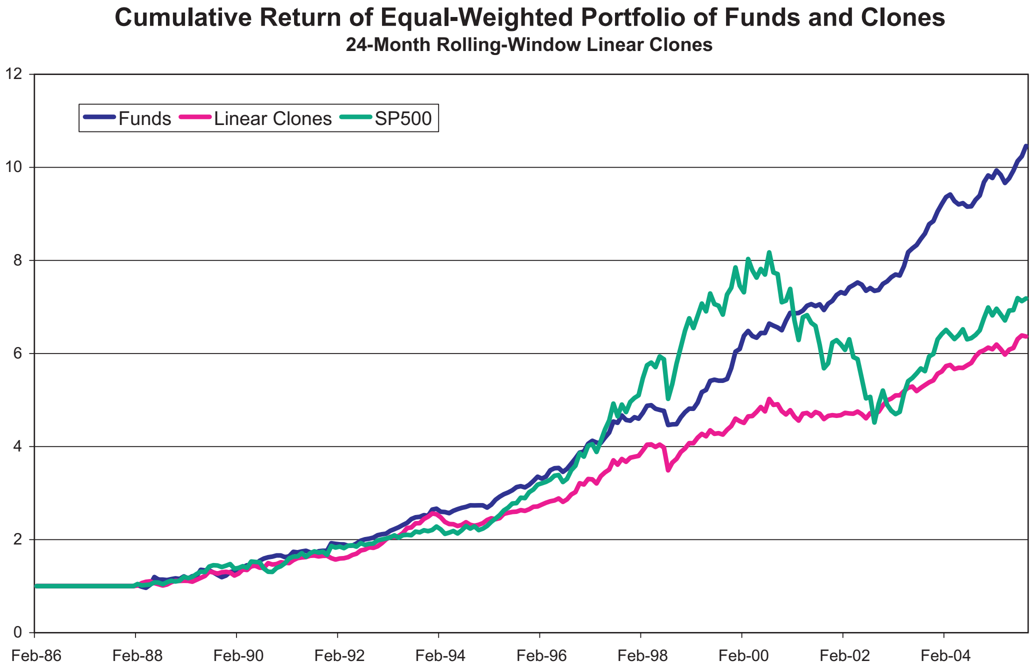


Figure 5 Cumulative returns of equal-weighted portfolios of funds and fixed-weight and 24-month rolling-window linear clones, and the S&P 500 index, from February 1986 to September 2005.

Table 9 Performance comparison of equal-weighted portfolios of all fixed-weight linear clones versus funds in the TASS Live database, from February 1986 to September 2005.

	All funds		Convertible arb		Dedicated short bias		Emerging markets		Equity market neutral		Event driven	
Statistic	Funds	Clones	Funds	Clones	Funds	Clones	Funds	Clones	Funds	Clones	Funds	Clones
Annual compound return	15.34	21.85	11.50	10.17	3.78	−1.01	22.83	12.45	13.40	19.99	14.22	11.95
Annualized mean	14.76	20.44	11.07	9.87	6.40	2.41	22.34	13.69	12.83	18.66	13.47	11.53
Annualized SD	9.06	10.23	5.36	5.45	23.23	26.45	17.71	19.28	6.23	7.73	4.37	6.11
Annualized Sharpe	1.63	2.00	2.07	1.81	0.28	0.09	1.26	0.71	2.06	2.41	3.08	1.89
Skewness	1	0	0	0	0	0	−1	−1	1	1	−1	−1
Kurtosis	5	0	3	2	2	1	5	3	4	1	8	2
ρ_1 (≥ 20% in red)	11	−6	31	9	13	3	36	−3	1	12	32	0
ρ_2 (≥ 20% in red)	−10	5	6	7	−12	−8	7	−3	3	14	10	4
ρ_3 (≥ 20% in red)	−11	0	−4	−2	−6	9	−3	6	21	16	−1	2
Correlations to various market indexes (≥ 50% in red, ≤ −25% in red):												
S&P 500 index	44	69	48	63	−66	−90	47	88	6	37	58	78
MSCI World index	40	59	42	52	−71	−92	51	81	9	23	49	62
Russell 1000 index	44	68	49	63	−70	−90	48	88	6	36	60	78
Russell 2000 index	45	49	52	54	−84	−73	52	73	−1	18	71	64
NASDAQ 100 stock index	38	53	42	48	−78	−74	40	74	3	26	52	66
BBA LIBOR USD 3−month	−13	−37	−29	−35	2	−12	−8	−6	−8	−29	−8	−22
DJ Lehman Bond Comp GLBL	13	57	22	49	2	7	−5	17	15	52	−6	26
US Treasury N/B	−10	−46	−10	−35	−16	−34	12	7	−9	−52	8	−18
Gold (Spot $/oz)	5	−6	−9	−1	−15	−8	0	6	1	1	−5	−7
Oil (Generic 1st 'CL' Future)	−5	16	−20	−9	−14	−9	−9	9	16	29	−1	2
US Dollar spot index	2	−10	6	1	7	21	9	−15	−15	2	18	9
Five risk factors												
CREDIT	3	−9	20	30	−39	−53	38	55	−9	−15	37	37
USD	−15	−13	−2	−1	35	59	−13	−44	−10	14	−2	−1
BOND	13	63	24	58	10	25	−2	9	11	67	3	38
SP500	44	69	48	63	−66	−90	47	88	6	38	58	78
DVIX	−22	−32	−24	−43	50	70	−36	−64	6	−21	−50	−50
CMDTY	5	27	−14	−1	−12	−13	0	16	17	38	5	12
CSFB/Tremont indexes												
All funds	82	56	46	50	−65	−42	55	47	34	48	63	57
Convertible arbitrage	47	26	79	37	−19	−8	34	21	38	24	53	31
Dedicated short bias	−69	−62	−44	−43	84	77	−58	−77	−26	−31	−73	−68
Emerging markets	72	44	42	38	−64	−58	94	55	21	24	60	49
Equity market neutral	50	39	36	25	−29	−39	26	38	51	29	36	36
Event driven	77	57	64	56	−57	−56	69	63	38	35	89	64
Fixed income arbitrage	33	20	39	30	−5	5	24	10	26	22	33	22
Global macro	54	36	26	36	−25	−6	28	17	22	43	31	35
Long/Short equity hedge	82	61	43	47	−79	−58	55	64	36	39	71	60
Managed futures	14	0	−12	−4	10	17	−13	−11	1	9	−17	−7
Multi-strategy	23	13	29	20	−22	−10	0	13	27	8	21	16

Table 9 (*Continued*)

Statistic	Fixed-income arbitrage Funds	Fixed-income arbitrage Clones	Global macro Funds	Global macro Clones	Long/Short equity hedge Funds	Long/Short equity hedge Clones	Managed futures Funds	Managed futures Clones	Multi-strategy Funds	Multi-strategy Clones	Fund of funds Funds	Fund of funds Clones
Annual compound return	10.93	7.91	15.56	24.90	16.79	17.40	15.15	38.37	15.43	15.08	12.30	18.74
Annualized mean	10.48	7.73	14.91	22.87	16.35	17.15	15.96	34.73	14.59	14.51	11.93	17.61
Annualized SD	3.58	4.31	8.64	9.40	11.84	14.01	19.24	19.32	5.78	8.94	7.48	7.97
Annualized Sharpe	2.93	1.79	1.73	2.43	1.38	1.22	0.83	1.80	2.52	1.62	1.59	2.21
Skewness	−6	0	1	0	−2	−1	1	0	2	1	2	0
Kurtosis	59	3	5	0	18	5	2	0	8	7	7	1
ρ_1 ($\geq$ 20% in red)	27	−2	17	17	14	−6	5	9	22	−7	20	5
ρ_2 ($\geq$ 20% in red)	13	5	3	9	−3	−3	−15	−4	15	−2	−8	8
ρ_3 ($\geq$ 20% in red)	1	1	−7	11	−6	2	−13	1	15	12	−10	−1
Correlations to various market indexes ($\geq$ 50% in red, $\leq$ −25% in red):												
S&P 500 index	−5	−4	10	47	77	95	−1	−2	43	71	31	66
MSCI World index	−6	−10	6	38	63	78	−1	−2	44	60	29	49
Russell 1000 index	−4	−4	10	47	79	95	−3	−2	44	71	31	65
Russell 2000 index	2	2	7	30	86	78	−7	−13	45	53	32	49
NASDAQ 100 Stock index	2	−3	3	33	72	78	−7	−9	41	58	28	49
BBA LIBOR USD 3−Month	−4	−25	−13	−35	−5	−12	−13	−40	−15	−19	−9	−35
DJ Lehman Bond Comp GLBL	6	39	13	66	−7	14	27	81	10	40	10	45
US Treasury N/B	−8	−48	−13	−58	8	−7	−28	−85	3	−28	−9	−40
Gold (Spot $/oz)	−1	7	15	6	−10	−11	13	6	3	−4	10	−10
Oil (Generic 1st 'CL' future)	10	20	17	17	−5	7	1	25	9	21	−2	17
US Dollar spot index	11	17	−5	−10	17	8	−14	−27	−6	−6	9	5
Five risk factors												
CREDIT	19	19	2	0	29	28	−24	−60	23	18	2	0
USD	18	32	−4	−7	−7	−12	−11	−11	−8	−10	−9	7
BOND	14	60	17	78	2	21	23	88	6	41	12	60
SP500	−4	−4	10	48	77	95	−1	−1	43	71	31	66
DVIX	27	0	0	−28	−56	−61	13	18	−28	−45	−9	−34
CMDTY	7	24	18	25	3	18	7	34	16	30	8	29
CSFB/Tremont indexes												
All funds	37	29	61	49	72	55	23	17	62	55	91	57
Convertible arbitrage	48	32	26	28	37	21	1	7	46	24	52	28
Dedicated short bias	4	7	−24	−35	−82	−74	13	13	−52	−55	−57	−53
Emerging markets	21	7	24	26	64	52	−9	−11	50	40	70	40
Equity market neutral	−4	−1	36	28	46	41	18	12	47	37	48	35
Event driven	24	18	38	42	74	62	−12	−7	61	51	76	54
Fixed income arbitrage	79	37	18	25	21	12	8	13	25	20	43	25
Global macro	42	36	58	40	37	29	35	25	35	37	68	40
Long/Short equity hedge	12	8	42	42	89	65	4	7	64	58	83	56
Managed futures	−3	9	40	8	−7	−7	84	34	6	2	16	2
Multi-strategy	35	22	31	13	20	11	7	−1	38	13	27	14

Table 10 Performance comparison of equal-weighted portfolios of all 24-month rolling-window linear clones versus funds in the TASS Live database, from February 1986 to September 2005.

	All funds		Convertible arb		Dedicated short bias		Emerging markets		Equity market neutral		Event driven	
Statistic	Funds	Clones	Funds	Clones	Funds	Clones	Funds	Clones	Funds	Clones	Funds	Clones
Annual compound return	14.21	12.83	11.07	6.88	−0.64	1.53	16.92	5.34	7.53	12.05	13.64	10.18
Annualized mean	13.71	12.69	10.71	6.84	3.40	5.92	17.43	8.58	7.55	11.77	12.95	9.90
Annualized SD	8.51	10.60	5.79	5.85	27.86	30.63	18.16	24.15	7.23	8.26	4.23	5.80
Annualized Sharpe	1.61	1.20	1.85	1.17	0.12	0.19	0.96	0.36	1.04	1.42	3.06	1.71
Skewness	1	0	0	1	0	1	−1	−2	−2	1	−2	−1
Kurtosis	8	4	5	3	6	6	6	15	7	2	12	6
ρ_1 (≥ 20% in red)	5	2	12	−5	8	−2	30	7	3	14	36	−6
ρ_2 (≥ 20% in red)	−7	−7	13	9	−8	−28	4	−1	9	6	12	8
ρ_3 (≥ 20% in red)	−16	5	4	−2	0	24	−2	2	−18	−8	−4	−2
Correlations to various market indexes (≥ 50% in red, ≤ −25% in red):												
S&P 500 index	41	52	40	61	−57	−78	53	76	12	24	52	65
MSCI World index	28	37	39	50	−63	−79	57	69	11	25	47	50
Russell 1000 index	41	52	42	61	−61	−78	54	77	13	24	54	66
Russell 2000 index	42	37	49	46	−80	−53	55	60	15	12	63	48
NASDAQ 100 stock index	35	41	41	46	−76	−67	44	62	14	15	46	50
BBA LIBOR USD 3-Month	−11	−13	−27	−21	3	−24	−5	−4	−2	−30	−7	−16
DJ Lehman Bond Comp GLBL	6	24	20	31	3	8	−9	1	12	43	−2	16
US Treasury N/B	−8	−17	−6	−20	−14	−34	15	12	−9	−38	9	−13
Gold (Spot $/oz)	3	3	−5	−6	−14	7	6	2	−7	−2	5	−3
Oil (Generic 1st 'CL' Future)	0	15	−8	−2	−17	−16	−1	6	8	18	5	9
US Dollar spot index	13	4	−2	4	8	20	11	3	−10	−5	11	13
Five risk factors												
CREDIT	13	16	23	36	−34	−45	42	50	−11	−3	45	36
USD	−4	−9	−7	−3	30	44	−20	−16	−7	5	−6	4
BOND	14	30	20	37	12	29	−4	4	10	51	4	28
SP500	41	52	40	61	−57	−78	53	76	12	24	52	66
DVIX	−20	−38	−16	−33	46	60	−44	−62	−6	−12	−41	−47
CMDTY	8	21	−2	4	−11	−20	7	6	13	26	9	16
CSFB/Tremont indexes												
All funds	83	56	49	39	−81	−27	58	47	33	37	63	57
Convertible arbitrage	44	31	81	30	−11	−3	34	21	31	20	53	33
Dedicated short bias	−67	−66	−44	−47	79	56	−59	−69	−28	−32	−72	−63
Emerging markets	69	50	40	37	−71	−41	94	53	25	27	60	51
Equity market neutral	48	43	30	19	−12	−30	27	26	52	26	35	31
Event driven	75	61	62	48	−60	−38	70	67	37	36	90	64
Fixed income arbitrage	34	23	45	26	−4	−7	27	20	25	19	33	28
Global macro	58	35	29	26	−39	5	32	21	18	31	30	38
Long/Short equity hedge	80	59	45	38	−83	−31	57	57	38	33	70	57
Managed futures	18	−9	−14	−13	6	24	−15	−27	5	11	−17	−10
Multi-strategy	21	3	35	10	−40	−39	−1	3	21	8	20	9

Table 10 (*Continued*)

Statistic	Fixed-income arbitrage Funds	Fixed-income arbitrage Clones	Global macro Funds	Global macro Clones	Long/Short equity hedge Funds	Long/Short equity hedge Clones	Managed futures Funds	Managed futures Clones	Multi-strategy Funds	Multi-strategy Clones	Fund of funds Funds	Fund of funds Clones
Annual compound return	8.60	4.57	12.74	17.92	17.17	12.79	14.07	14.88	11.31	8.05	10.71	13.84
Annualized mean	8.36	4.56	12.44	17.26	16.42	12.96	14.83	16.04	10.91	8.06	10.43	13.35
Annualized SD	4.11	4.07	8.95	11.66	9.82	13.04	18.19	20.58	5.45	7.74	6.49	7.96
Annualized Sharpe	2.03	1.12	1.39	1.48	1.67	0.99	0.82	0.78	2.00	1.04	1.61	1.68
Skewness	−7	−1	0	0	0	−1	1	0	0	0	1	0
Kurtosis	68	4	3	1	1	4	3	1	2	2	5	3
ρ_1 (≥ 20% in red)	26	−14	8	12	17	−11	2	12	17	−13	5	1
ρ_2 (≥ 20% in red)	2	−19	−10	8	3	1	−14	−11	15	9	1	2
ρ_3 (≥ 20% in red)	−6	4	−3	8	−4	10	−12	2	22	9	−5	13
Correlations to various market indexes (≥ 50% in red, ≤ −25% in red):												
S&P 500 index	−9	3	20	27	74	86	−5	−8	44	61	34	44
MSCI World index	−9	−3	21	20	64	70	−12	−15	48	55	29	32
Russell 1000 index	−8	3	21	27	77	86	−6	−8	45	61	35	45
Russell 2000 index	2	11	20	12	88	65	−9	−9	46	44	36	30
NASDAQ 100 stock index	−1	2	13	15	74	69	−10	−8	44	53	29	35
BBA LIBOR USD 3-Month	−6	−11	−17	−21	−9	−6	−9	−12	−11	−2	−11	−12
DJ Lehman Bond Comp GLBL	5	12	23	27	6	15	19	34	4	17	9	25
US Treasury N/B	−7	−21	−19	−32	2	−4	−28	−42	2	−13	−9	−19
Gold (Spot $/oz)	2	10	14	2	−7	−8	9	10	8	−5	8	1
Oil (Generic 1st 'CL' Future)	10	16	2	13	−12	0	5	17	15	28	7	19
US Dollar spot index	13	15	−10	10	17	8	−3	−3	12	7	11	3
Five Risk Factors												
CREDIT	22	31	2	3	28	29	−22	−28	27	29	14	13
USD	19	14	−12	0	−3	−9	−2	−7	−9	0	−4	−2
BOND	14	31	25	39	10	16	23	41	7	22	15	33
SP500	−9	3	21	27	74	86	−5	−8	43	61	34	45
DVIX	27	−14	−5	−18	−48	−58	17	8	−17	−41	−13	−36
CMDTY	5	14	5	15	0	11	10	21	20	34	13	26
CSFB/Tremont indexes												
All funds	34	21	61	43	73	52	25	14	58	41	90	55
Convertible arbitrage	49	28	25	32	37	24	1	12	44	18	46	32
Dedicated short bias	6	−10	−26	−36	−83	−72	13	1	−43	−52	−56	−59
Emerging markets	15	13	29	33	63	52	−6	−2	51	34	68	46
Equity market neutral	−9	9	33	39	43	40	16	21	34	31	49	41
Event driven	24	27	35	40	74	61	−12	0	58	45	73	59
Fixed income arbitrage	82	20	19	23	23	17	10	7	27	15	39	26
Global macro	42	19	58	37	39	28	37	18	34	26	69	38
Long/Short equity hedge	9	11	44	35	89	59	4	11	58	44	81	53
Managed futures	−6	6	43	12	−8	−14	83	27	7	2	20	−9
Multi-strategy	40	11	28	5	18	7	4	−11	37	17	25	4

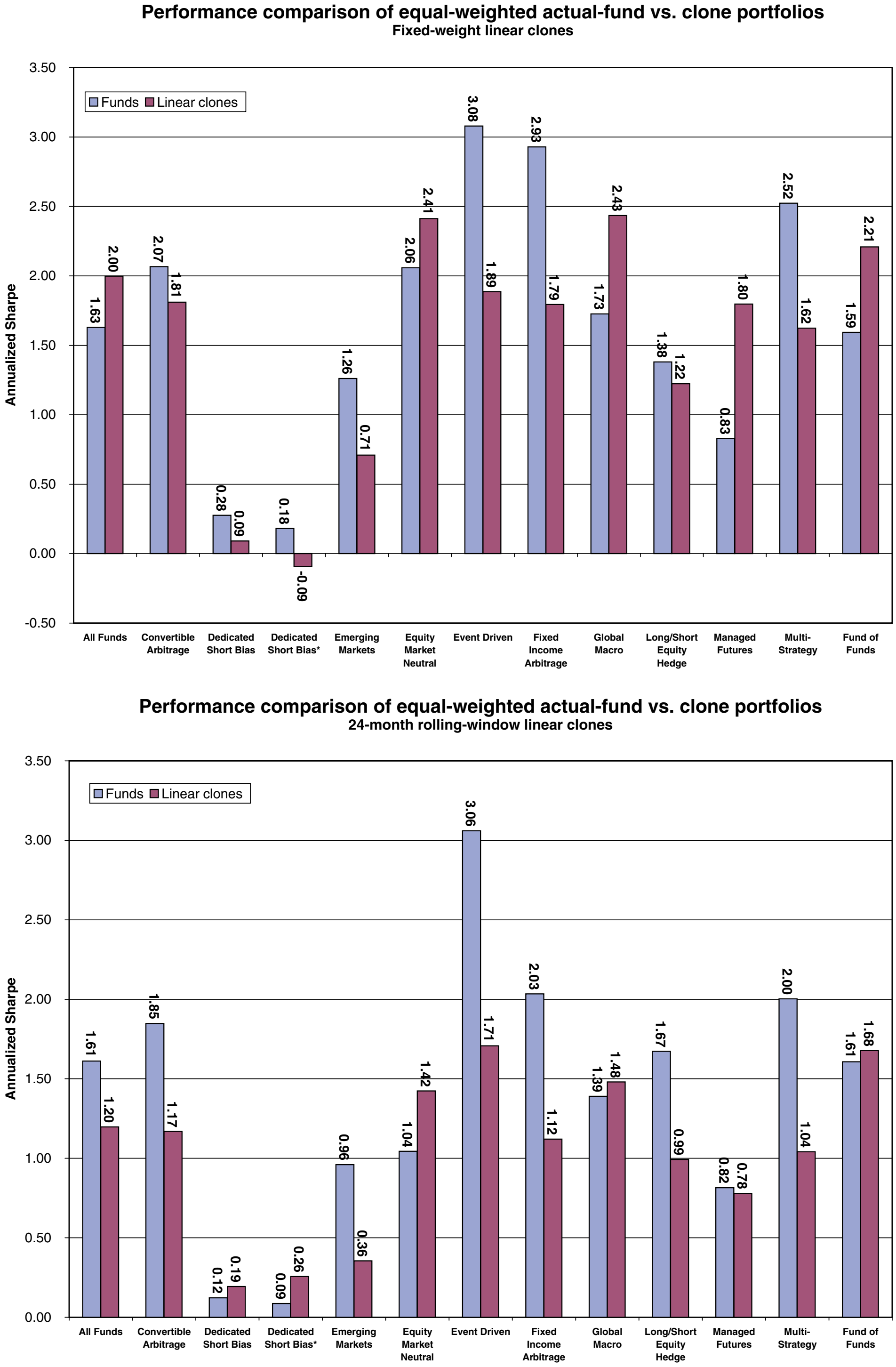


Figure 6 Comparison of Sharpe ratios of equal-weighted portfolios of funds versus fixed-weight and 24-month rolling-window linear clones of hedge funds in the TASS Live database, from February 1986 to September 2005.

skewness of 0, a kurtosis of 3, and a first-order autocorrelation of −2%, and the portfolio of Fixed Income Arbitrage rolling-window clones has similar characteristics, which is consistent with the fact that the clone portfolios are comprised of highly liquid securities. Other examples of this difference in liquidity exposure include the portfolios of funds in Convertible Arbitrage, Emerging Markets, Event Driven, Multi-Strategy, and Fund of Funds categories, all of which exhibit significant positive first-order autocorrelation coefficients (31%, 36%, 32%, 22%, and 20%, respectively) in contrast to their fixed-weight clone counterparts (9%, −3%, 0%, −7%, and 5%, respectively). Similarly, the first-order autocorrelations of the portfolios of funds in these five categories using the rolling-window sample (12%, 30%, 36%, 17%, and 5%, respectively) are all larger than their rolling-window clone counterparts (−5%, 7%, −6%, −13%, and 1%).

While the statistical properties of clone portfolios may seem more attractive, it should be kept in mind that some of these characteristics are related to performance. In particular, one source of negative skewness and positive kurtosis is the kind of option-based strategies associated with Capital Decimation Partners (see Section 2.1), which is a legitimate source of expected return. And liquidity exposure is another source of expected return, as in the case of Fixed Income Arbitrage where one common theme is to purchase illiquid bonds and shortsell more liquid bonds with matching nominal cashflows. By reducing exposures to these risk factors through clones, we should expect a corresponding reduction in expected return. For example, in the case of Fixed Income Arbitrage, Table 9 reports that the portfolio of funds yields an average return of 10.48% with a standard deviation of 3.58% for a Sharpe ratio of 2.93, as compared to the fixed-weight portfolio of clones' average return of 7.73% with a standard deviation of 4.31% for a Sharpe ratio of 1.79.

In addition to its expected return and volatility, a portfolio's correlation with major market indexes is another important characteristic that concerns hedge-fund investors because of the diversification benefits that alternative investments have traditionally provided. Tables 9 and 10 show that the fixed-weight and rolling-window clone portfolios exhibit correlations that are similar to those of their matching portfolios of funds for a variety of stock, bond, currency, commodity, and hedge-fund indexes.[24] For example, the portfolio of Convertible Arbitrage funds in the fixed-weight sample has a 48% correlation to the S&P 500, a −29% correlation to 3-month LIBOR, a 6% correlation to the US Dollar Index, and a 79% correlation to the CSFB/Tremont Convertible Arbitrage Index. In comparison, the portfolio of Convertible Arbitrage fixed-weight clones has a 63% correlation to the S&P 500, a −35% correlation to 3-month LIBOR, a 1% correlation to the US Dollar Index, and a 37% correlation to the CSFB/Tremont Convertible Arbitrage Index.

However, some differences do exist. The equal-weighted portfolios of funds tend to have higher correlation with the corresponding CSFB/Tremont Hedge-Fund Index of the same category than the equal-weighted portfolios of both types of clones. For example, the correlation between the portfolio of funds and the CSFB/Tremont Hedge-Fund Index in the fixed-weight sample is 82%, and the corresponding correlation for the portfolio of fixed-weight clones with the same index is 56%, and the same pair of correlations for the rolling-window case is 83% and 56%, respectively. This pattern is repeated in every single category for both types of clones, and is not unexpected given that the CSFB/Tremont indexes are constructed from the funds themselves. On the other hand, the portfolios of clones are sometimes more highly correlated with certain indexes than their fund counterparts because of how the clones are constructed. For example, the correlation of the portfolio of Equity Market

Table 11 Comparison of signs and absolute differences of correlations of funds and clones to 28 market indexes, where fixed-weight and 24-month rolling-window linear clones are constructed from hedge funds in the TASS Live database, from February 1986 to September 2005.

	Fixed-weight linear clones			Rolling-window linear clones		
Category	% Same sign	Mean $\lvert\rho_f - \rho_c\rvert$	SD $\lvert\rho_f - \rho_c\rvert$	% Same sign	Mean $\lvert\rho_f - \rho_c\rvert$	SD $\lvert\rho_f - \rho_c\rvert$
All funds	86	19	11	93	12	7
Convertible arbitrage	100	12	10	93	12	10
Dedicated short bias	93	13	7	89	19	13
Emerging markets	79	19	12	86	10	9
Equity market neutral	86	19	13	96	12	10
Event driven	89	12	10	86	11	6
Fixed income arbitrage	86	13	13	71	14	13
Global macro	100	20	17	93	10	7
Long/Short equity hedge	89	11	6	96	10	6
Managed futures	96	15	20	96	9	11
Multi-strategy	93	14	10	93	12	6
Fund of funds	89	23	11	96	13	9

Neutral fixed-weight clones with the BOND factor is 67%, whereas the correlation of the portfolio of corresponding Equity Market Neutral funds is only 11%. This difference is likely the result of the fact that the BOND factor is one of the five factors used to construct clone returns, so the correlations of clone portfolios to these factors will typically be larger in absolute value than those of the corresponding fund portfolios.

A summary of the differences in correlation properties between funds and clones is provided by Table 11. The first column in each of the two sub-panels labelled "% Same Sign" contains the percentage of the 28 market-index correlations in Tables 9 and 10, respectively, for which the fund correlation and the clone correlation are of the same sign. The next two columns of each sub-panel contain the mean and standard deviation of the absolute differences in fund- and clone-correlation across the 28 market-index correlations. These results show remarkable agreement in sign for both fixed-weight and rolling-window clones, ranging from 71% to 100%, and mean absolute-differences ranging from 9% to 23%. And even for the largest mean absolute-difference of 23% (fixed-weight clones in the Fund of Funds category), 89% of the correlations exhibit the same sign in this category.

Overall, the results in Tables 9–11 show that the correlations of clone portfolios are generally comparable in sign and magnitude to those of the fund portfolios, implying that portfolios of clones can provide some of the same diversification benefits as their hedge-fund counterparts.

5 Conclusion

A portion of every hedge fund's expected return is risk premia—compensation to investors for bearing certain risks. One of the most important benefits of hedge-fund investments is the non-traditional types of risks they encompass, such as tail risk, liquidity risk, and credit risk. Most investors would do well to take on small amounts of such risks if they are not already doing so because these factors usually yield attractive risk premia, and many of these risks are not highly correlated with those of traditional long-only investments. Although talented hedge-fund managers are always likely to outperform passive fixed-weight portfolios, the challenges of manager selection and monitoring, the lack of transparency, the limited capacity of such managers, and the high fees may tip the scales for the institutional investor in favor of clone portfolios. In such circumstances, portable beta may be a reasonable alternative to portable alpha.

Our empirical findings suggest that the possibility of cloning hedge-fund returns is real. For certain hedge-fund categories, the average performance of clones is comparable—on both a raw-return and a risk-adjusted basis—to their hedge-fund counterparts. For other categories like Event Driven and Emerging Markets, the clones are less successful.

The differences in performance of clones across hedge-fund categories raise an important philosophical issue: What is the source of the clones' value-added? One possible interpretation is that the cloning process "reverse-engineers" a hedge fund's proprietary trading strategy, thereby profiting from the fund's intellectual property. Two assumptions underlie this interpretation, both of which are rather unlikely: (1) it is possible to reverse-engineer a hedge fund's strategy using a linear regression of its monthly returns on a small number of market-index returns; and (2) all hedge funds possess intellectual property worth reverse-engineering. Given the active nature and complexity of most hedge-fund strategies, it is hard to imagine reverse-engineering them by regressing their monthly returns on five factors. However, if such strategies have risk factors in common, it is not hard to imagine identifying them by averaging a reasonable cross-section of time-series regressions of monthly returns on those risk factors. As for whether all hedge funds have intellectual property worth reverse-engineering, we have purposely included *all* the TASS hedge funds in our sample—not just the successful ones—and it is unlikely that all of the 1610 funds possess significant manager-specific alpha. In fact, for our purposes, the main attraction of this sample of hedge funds is the funds' beta exposures.

Our interpretation of the clones' value-added is less devious: By analyzing the monthly returns of a large cross-section of hedge funds (some of which have genuine manager-specific alpha, and others which do not), it is possible to identify common risk factors from which those funds earn part, but not necessarily all, of their expected returns. By taking similar risk exposures, it should be possible to earn similar risk premia from those exposures, hence at least part of the hedge funds' expected returns can be attained, but in a lower-cost, transparent, scalable, and liquid manner.

As encouraging as our empirical results may seem, a number of qualifications should be kept in mind. First, we observed a significant performance difference between fixed-weight and rolling-window clones, and this gap must be weighed carefully in any practical implementation of the cloning process. The fixed-weight approach yields better historical performance and lower turnover, but is subject to look-ahead bias so the performance may not be achievable out-of-sample. The rolling-window approach yields less attractive historical performance, but the simulated performance may be more attainable, and the flexibility of rolling-window estimators may be critical for capturing nonstationarities such as time-varying means, volatilities, and regime changes. The costs and benefits of each approach must be evaluated on a case-by-case basis with the specific objectives and constraints of the investor in mind.

Second, despite the promising properties of linear clones in several style categories, it is well-known that certain hedge-fund strategies contain inherent nonlinearities that cannot be captured by linear models (see, e.g., Capital Multiplication Partners). Therefore, more sophisticated nonlinear methods—including nonlinear regression, regime-switching processes, stochastic volatility models, and Kat and Palaro's (2005) copula-based algorithm—may yield significant benefits in terms of performance and goodness-of-fit. However, there is an important trade-off between the goodness-of-fit and complexity of the replication process, and this trade-off varies from one investor to the next. As more sophisticated replication methods are used, the resulting clone becomes less passive, requiring more trading and risk-management expertise, and eventually becoming as dynamic and complex as the hedge-fund strategy itself.

Third, the replicating factors we proposed are only a small subset of the many liquid instruments that are available to the institutional investor. By expanding the universe of factors to include options and other derivative securities, and customizing the set of factors to each hedge-fund category (and perhaps to each fund), it should be possible to achieve additional improvements in performance, including the ability to capture tail risk and other nonlinearities in a fixed-weight portfolio. In fact, Haugh and Lo (2001) show that a judiciously constructed fixed-weight portfolio of simple put and call options can yield an excellent approximation to certain dynamic trading strategies, and this approach can be adopted in our context to create better clones.

Finally, we have not incorporated any transactions costs or other frictions into our performance analysis of the clone portfolios, which will clearly have an impact on performance. The more passive clones will be less costly to implement, but they may not capture as many risk exposures and nonlinearities as the more sophisticated versions. However, by construction, clones will have a significant cost advantage over a traditional fund of funds investment, not only because of the extra layer of fees that funds of funds typically charge, but also because of the clone portfolio's more efficient use of capital due to the cross-netting of margin requirements and incentive fees. For example, consider a fund of funds with equal allocations to two managers, each of which charges a 2% management fee and a 20% incentive fee, and suppose that in a given year, one manager generates a 25% return and the other manager loses 5%. Assuming a 1% management fee and a 10% incentive fee for the fund of funds, and no loss carryforwards for the underlying funds from previous years, this scenario yields a net return of only 4.05% for the fund of funds investors. In this case, the fees paid by the investors amount to a stunning 59.5% of the net profits generated by the underlying hedge funds.

Of course, a number of implementation issues remain to be resolved before hedge-fund clones become a reality, for example, the estimation methods for computing clone portfolio weights, the implications of the implied leverage required by our renormalization process, the optimal rebalancing interval, the types of strategies to be cloned, and the best method for combining clones into a single portfolio. We are cautiously optimistic that the promise of our initial findings will provide sufficient motivation to take on these practical challenges.

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Notes

[1] Nevertheless, derivatives-based replication strategies may serve a different purpose that is not vitiated by complexity: risk attribution, with the ultimate objective of portfolio risk management. Even if an underlying hedge-fund strategy is simpler than its derivatives-based replication strategy, the replication strategy may still be useful in measuring the overall risk exposures of the hedge fund and designing a hedging policy for a portfolio of hedge-fund investments.

[2] As a matter of convention, throughout this paper we define the Sharpe ratio as the ratio of the monthly average return to the monthly standard deviation, then annualize by multiplying by the square root of 12. In the original definition of the Sharpe ratio, the numerator is the *excess* return of the fund, in excess of the risk-free rate. Given the time variation in this rate over our sample period, we use the total return so as to allow readers to select their own benchmarks.

[3] The margin required per contract is assumed to be:

$$100 \times \{15\% \times (\text{current level of the SPX}) - (\text{put premium}) - (\text{amount out of the money})\}$$

where the amount out of the money is equal to the current level of the SPX minus the strike price of the put.

[4] This figure varies from broker to broker, and is meant to be a rather conservative estimate that might apply to a \$10M startup hedge fund with no prior track record.

[5] This example was first proposed by Merton in his 15.415 Finance Theory class at the MIT Sloan School of Management.

[6] During the period from November 1976 to December 2004, the annualized mean and standard deviation of Berkshire Hathaway's Series A shares were 29.0% and 26.1%, respectively, for a Sharpe ratio of 1.12 using 0% for the risk-free benchmark return.

[7] Once a hedge fund decides not to report its performance, is liquidated, is closed to new investment, restructured, or merged with other hedge funds, the fund is transferred into the "Graveyard" database. A hedge fund can only be listed in the "Graveyard" database after being listed in the "Live" database. Because the TASS database fully represents returns and asset information for live and dead funds, the effects of suvivorship bias are minimized. However, the database is subject to *backfill bias*—when a fund decides to be included in the database, TASS adds the fund to the "Live" database and includes all available prior performance of the fund. Hedge funds do not need to meet any specific requirements to be included in the TASS database. Due to reporting delays and time lags in contacting hedge funds, some Graveyard funds can be incorrectly listed in the Live database for a period of time. However, TASS has adopted a policy of transferring funds from the Live to the Graveyard database if they do not report over an 8- to 10-month period.

[8] For studies attempting to quantify the degree and impact of survivorship bias, see Baquero *et al.* (2005), Brown *et al.* (1992), Brown *et al.* (1999), Brown *et al.* (1997), Carpenter and Lynch (1999), Fung and Hsieh (1997b, 2000), Hendricks *et al.* (1997), Horst *et al.* (2001), Liang (2000), and Schneeweis and Spurgin (1996).

[9] See Posthuma and van der Sluis (2003).

[10] We are not aware of any studies focusing on this type of bias, but the impact of selection on statistical inference has been explored in some detail by several authors. See, for example, Leamer (1978) and the citations within.

[11] TASS defines returns as the change in net asset value during the month (assuming the reinvestment of any distributions on the reinvestment date used by the fund) divided by the net asset value at the beginning of the month, net of management fees, incentive fees, and other fund expenses. Therefore, these reported returns should approximate the returns realized by investors.

[12] This is no coincidence—TASS is owned by Tremont Capital Management, which created the CSFB/Tremont indexes in partnership with Credit Suisse First Boston.

[13] It is no coincidence that the categories with the highest degree of average positive serial correlation are also the categories with the highest average Sharpe ratios. Smooth return series will, by definition, have higher Sharpe ratios than more volatile return series with the same mean.

[14] Litterman (2005) calls such risk exposures "exotic betas" and argues that "[t]he adjective 'exotic' distinguishes it from market beta, the only beta which deserves to get paid a risk premium." We disagree—there are several well-established economic models that illustrate the possibility of multiple sources of systematic risk, each of which commands a positive risk premium, for example, Merton

(1973) and Ross (1976). We believe that hedge funds are practical illustrations of these multi-factor models of expected returns.

15 Throughout this paper, all statistics except for those related to the first-order autocorrelation have been annualized to facilitate interpretation and comparison.

16 In fact, a decomposition of the total mean returns of these two funds shows that the six factors account for very little of the two funds' performance, hence the manager-specific alphas are particularly significant for these two managers (see Hasanhodzic and Lo, 2006b, Table 8 for details).

17 In Hasanhodzic and Lo (2006a) and in a previous draft of this paper, we used the term "buy-and-hold" to describe this type of clone. Although this is consistent with the passive nature of the clone portfolio, it is not strictly accurate because a portfolio with fixed weights does require periodic rebalancing to maintain those fixed weights. Moreover, if a clone is to be implemented via futures and forward contracts as we propose, then even in the absence of portfolio rebalancings, some trading will be necessary as maturing contracts are "rolled" into those of the next maturity date. For these reasons, we now refer to clone portfolios with constant portfolio weights over time as "fixed-weight" clones.

18 However, it should be kept in mind that the futures and forward contracts corresponding to the five factors in Eq. (5) have sizable amounts of leverage built into the contracts themselves, so that for reasonable values of γ_i, we can re-write Eq. (9) as:

$$\begin{aligned}\widehat{R}_{it} &= \beta^*_{i1}\ (\gamma_i \mathrm{SP500}_t) + \cdots \\ &\quad + \beta^*_{i5}\ \left(\gamma_i \mathrm{CMDTY}_t\right) + \delta_i\, R_l \qquad (14)\\ &= \beta^*_{i1}\ \mathrm{SP500}^*_t + \cdots + \beta^*_{i5}\ \mathrm{CMDTY}^*_t \qquad (15)\end{aligned}$$

where we have redefined five new instruments in Eq. (15) that can achieve γ_i times the leverage of the original instruments in (9) at no additional cost. Since the coefficients $\{\beta^*_{ik}\}$ sum to one by construction, there is no need for any additional borrowing or lending because each redefined instrument is already leveraged by the factor γ_i, hence $\delta_i \equiv 0$ in Eq. (15).

19 If there are missing observations within this 24-month window, we extend the window backwards in time until we obtain 24 datapoints for our regression. Our choice of 24 months for the rolling window was a compromise between the desire to capture nonstationarities in the data and the need for a sufficient number of observations to estimate the parameters of the clone. We did not try other window lengths because we wished to reduce the impact of "backtest bias" or over-fitting on our empirical results.

20 Note that each type of clone has its own set of matching results for the funds. This is due to the fact that the first 24 months of each fund's history are used to calibrate the initial estimates of the rolling-window clones, hence they are not included in the rolling-window dataset from which fund and clone performance statistics are computed.

21 Specifically, fund 33735 has a small but positive SP500 beta coefficient, hence the clone portfolio for this fund is long the S&P 500 throughout the sample period from April 1997 to March 2005, implying a strong positive contribution for the SP500 factor. Because the SP500 beta coefficient is small and the SP500 factor is the most volatile of the five factors, the un-renormalized volatility of the clone portfolio is considerably smaller than the volatility of the fund, which causes our renormalization process to magnify the positive mean return of the clone substantially.

22 Ljung and Box (1978) propose the following statistic to gauge the significance of the first m autocorrelation coefficients of a time series with T observations:

$$Q = T(T+2)\sum_{k=1}^{m} \hat{\rho}_k^2/(T-k) \qquad (16)$$

which is asymptotically χ^2_m under the null hypothesis of no autocorrelation. By forming the sum of squared autocorrelations, the statistic Q reflects the absolute magnitudes of the $\hat{\rho}_k$s irrespective of their signs, hence funds with large positive or negative autocorrelation coefficients will exhibit large Q-statistics.

23 As of July 28, 2006, the initial margin requirement of the S&P 500 futures contract that trades on the Chicago Mercantile Exchange is \$19,688, with a maintenance margin requirement of \$15,750. Given the contract value of \$250 times the S&P 500 Index and the settlement price of 1284.30 on July 28, 2006 for the September 2006 contract, the initial and maintenance margin requirements are 6.1% and 4.9% of the contract value, respectively, implying leverage ratios of 16.3 and 20.4, respectively (see http://www.cme.com for further details).

24 Except for the SP500 and DVIX factors, the index returns used to compute the correlations in Tables 9 and 10 are derived solely from the indexes themselves in the usual way ($\mathrm{Return}_t \equiv (\mathrm{Index}_t - \mathrm{Index}_{t-1})/\mathrm{Index}_t$), with no accounting for any distributions. The SP500 factor does include dividends, and the DVIX factor is the first difference of the month-end VIX index.

A Appendix

The following is a list of category descriptions, taken directly from TASS documentation, that define the criteria used by TASS in assigning funds in their database to one of 11 possible categories:

Convertible Arbitrage This strategy is identified by hedge investing in the convertible securities of a company. A typical investment is to be long the convertible bond and short the common stock of the same company. Positions are designed to generate profits from the fixed income security as well as the short sale of stock, while protecting principal from market moves.

Dedicated Short Bias Dedicated short sellers were once a robust category of hedge funds before the long bull market rendered the strategy difficult to implement. A new category, short biased, has emerged. The strategy is to maintain net short as opposed to pure short exposure. Short biased managers take short positions in mostly equities and derivatives. The short bias of a manager's portfolio must be constantly greater than zero to be classified in this category.

Emerging Markets This strategy involves equity or fixed income investing in emerging markets around the world. Because many emerging markets do not allow short selling, nor offer viable futures or other derivative products with which to hedge, emerging market investing often employs a long-only strategy.

Equity Market Neutral This investment strategy is designed to exploit equity market inefficiencies and usually involves being simultaneously long and short matched equity portfolios of the same size within a country. Market neutral portfolios are designed to be either beta or currency neutral, or both. Well-designed portfolios typically control for industry, sector, market capitalization, and other exposures. Leverage is often applied to enhance returns.

Event Driven This strategy is defined as "special situations" investing designed to capture price movement generated by a significant pending corporate event such as a merger, corporate restructuring, liquidation, bankruptcy, or reorganization. There are three popular sub-categories in event-driven strategies: risk (merger) arbitrage, distressed/high yield securities, and Regulation D.

Fixed Income Arbitrage The fixed income arbitrageur aims to profit from price anomalies between related interest rate securities. Most managers trade globally with a goal of generating steady returns with low volatility. This category includes interest rate swap arbitrage, US and non-US government bond arbitrage, forward yield curve arbitrage, and mortgage-backed securities arbitrage. The mortgage-backed market is primarily US-based, over-the-counter, and particularly complex.

Global Macro Global macro managers carry long and short positions in any of the world's major capital or derivative markets. These positions reflect their views on overall market direction as influenced by major economic trends and/or events. The portfolios of these funds can include stocks, bonds, currencies, and commodities in the form of cash or derivatives instruments. Most funds invest globally in both developed and emerging markets.

Long/Short Equity Hedge This directional strategy involves equity-oriented investing on both the long and short sides of the market. The objective is not to be market neutral. Managers have the ability to shift from value to growth, from small to medium to large capitalization stocks, and from a net long position to a net short position. Managers may use futures and options to hedge. The focus may be regional, such as long/short US or European equity, or sector specific, such as long and short technology or healthcare stocks. Long/Short equity funds tend to build and hold portfolios that are substantially more concentrated than those of traditional stock funds.

Managed Futures This strategy invests in listed financial and commodity futures markets and currency markets around the world. The managers are usually referred to as Commodity Trading Advisors, or CTAs. Trading disciplines are generally systematic or discretionary. Systematic traders tend to use price and market specific information (often technical) to make trading decisions, while discretionary managers use a judgmental approach.

Multi-Strategy The funds in this category are characterized by their ability to dynamically allocate capital among strategies falling within several traditional hedge-fund disciplines. The use of many strategies, and the ability to reallocate capital between them in response to market opportunities, means that such funds are not easily assigned to any traditional category.

The Multi-Strategy category also includes funds employing unique strategies that do not fall under any of the other descriptions.

Fund of Funds A "Multi Manager" fund will employ the services of two or more trading advisors or Hedge Funds who will be allocated cash by the Trading Manager to trade on behalf of the fund.

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