Send in the Clones?
Hedge Fund Replication Using Futures Contracts

Nicolas P.B. Bollen†

Gregg S. Fisher

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Abstract

Replication products strive to offer investors some of the benefits of hedge funds while avoiding their high fees, illiquidity, and opacity. We test whether a replication algorithm can deliver the diversification and high Sharpe ratio that investors seek. Our procedure constructs monthly clone returns out-of-sample using fully collateralized futures positions held for one-month, with position sizes determined using rolling window regressions. Clone returns have high correlation with their hedge fund targets, indicating replication is possible. Clones also have high correlation with a buy-and-hold investment in stocks, however, and neither the targets nor their clones demonstrate successful time variation in factor loadings.

†Bollen is the E. Bronson Ingram Professor of Finance, Owen Graduate School of Management, Vanderbilt University. Email nick.bollen@owen.vanderbilt.edu. Phone (615) 343-5029. Fisher is President and Chief Investment Officer of Gerstein Fisher. Thanks to Spencer Hezzelwood for excellent research assistance. Bob Whaley, Jacob Sagi, and seminar participants at Vanderbilt University provided useful comments.

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1. Introduction

The hedge fund industry recovered quickly from the contraction experienced in the post-financial crisis period, with aggregate assets under management exceeding $2 trillion during Q1 2012.[1] Several issues continue to keep many investors on the sidelines, however, including a spate of insider-trading scandals, opaque holdings, and high fees. In an effort to cater to the demand for an alternative investment that offers some of the benefits of hedge funds while avoiding these problems, a number of financial institutions have developed a new set of products using relatively liquid, transparent, and low-cost strategies. The goal of this article is to determine the performance and appropriate use of these hedge fund clones.

Most hedge fund replication products attempt to mimic the future time series properties of a target fund or fund index by constructing a portfolio of investable factors that matches the target's historical returns as closely as possible.[2] The factors represent investments in asset classes such as equities, fixed income, and commodities. The dynamic nature of the target's actual unobserved trading strategy requires that the composition of the clone portfolio changes over time. To achieve this, hedge fund replication is an iterative process, in which the target's exposures to the factors are re-estimated periodically and the allocation weights of the clone are adjusted accordingly.

To understand what clones can and cannot capture, it is useful to consider the classic decomposition of managerial skill into security selection and market timing. Because the target's actual positions are unknown, it is impossible to try to capture security selection. This limitation is reflected in the generic building blocks of replication products: liquid securities such as futures contracts or ETFs. What factor-based replication can offer, however, is a procedure for attempting to match the factor timing activity of a target. As hedge fund managers trade, the correlation between fund returns and those of the investable factors change. These changes are then translated by the replication procedure into new allocation weights. If managers have timing skill, then the clone will feature higher allocation to a factor during periods of high returns. To

[1] HFR Market Microstructure HF Industry Report – Q1 2012.
[2] See, for example, descriptions of IndexIQ's offerings at www.indexiq.com and a series of exchange traded notes designed by Credit Suisse at https://notes.credit-suisse.com/csfbnoteslogin/etn/csetns.asp.

test the effectiveness of factor-based replication, therefore, we employ several tests of market timing ability.

We choose the Dow Jones Credit Suisse hedge fund indexes as our target investments. These indexes are asset-weighted portfolios of hedge funds selected on the basis of capacity and other operational risk requirements. We choose to replicate hedge fund indexes as opposed to individual funds since University endowments, pension funds, and other institutional investors typically invest in portfolios of funds.[3] To create the clones, we use a parsimonious set of five liquid futures contracts to permit low-cost exposure to major asset classes. The clone procedure is based around a series of rolling window regressions to estimate the time varying exposure of the hedge fund indexes to the asset classes. Each regression yields a set of allocation weights which are then used to construct a clone portfolio that is held for one-month out-of-sample. We vary implementation details, such as the estimation window length, to determine their impact on clone performance.

Our methodology is similar to that of Hasanhodzic and Lo (2007), who estimate linear factor models using returns of individual hedge funds for the purpose of constructing replicating portfolios. We make three contributions. First, the set of factors used by Hasanhodzic and Lo are not all investable, including, for example, the Goldman Sachs Commodity Index and the spread between the Lehman BAA Corporate Bond Index and the Lehman Treasury Index. In contrast, all of our factors are returns on liquid futures contracts. Second, their sample period ends in 2005, prior to the global financial crisis. Our sample extends an additional six years, allowing us to comment on clone performance directly before and after the turmoil that has defined investments ever since. Third, and perhaps most important, we argue that the only way clones can add value is by capturing the factor timing activity of the target, thereby motivating our analysis of the market timing ability of the clones.

The rest of the paper proceeds as follows. Section 2 reviews relevant prior literature on hedge fund replication, factor models, and market timing. Section 3 provides details about the data used in the study and presents some of the empirical methods. The cloning procedure and empirical results are described in Section 4. Section 5 offers a brief summary with concluding remarks.

[3] In addition, Bollen (2012) argues that the ability of factor models to explain individual fund returns is quite limited.

2. Prior Literature

2.1. Competing Replication Procedures

There are two main approaches to replicating hedge funds. Factor-based replication takes positions in liquid instruments to match the target fund's exposures to a number of risk factors. Factor-based clones are typically assessed by their ability to mimic the returns of the target fund out-of-sample. Distribution-based replication uses complex trading strategies to match the historical return distribution of the target fund. Distribution-based clones are typically assessed by their ability to mimic the distribution of the target fund out-of-sample, either the unconditional distribution, as in Amin and Kat (2003), or the bivariate distribution of the target fund return and the return of some other asset such as a stock market index, as in Kat and Palaro (2005).

We focus on factor-based replication for three reasons. First, using a distribution as the basis for replication requires a relatively long time period to establish the target distribution ex-ante using historical returns, estimate the resulting clone's distribution ex-post, and asses its similarity to that of the target. Using the necessarily long time series is problematic since hedge fund return distributions are highly transitory given the freedom with which managers can change investment strategies and leverage ratios. Furthermore, Amenc et al. (2008) show that distribution-based clones achieve out-of-sample success only over long assessment periods of at least six years. It is unlikely that investors would have the patience to wait six years before evaluating investment performance.

Second, the distribution-based clones rely on relatively sophisticated mathematical techniques, which can be traced to Dybvig (1988), to create a high-frequency trading system. For many investors the appeal of clones is their transparency. While the distribution-based clone's trade engine can be explicitly defined and shared with investors, for many it will remain a black box. Third, by construction, distribution-based clones do not attempt to match the month-by-month returns of a target fund, and so have difficulty matching the conditional distribution of target returns. The exception to this is the bivariate distribution target of Kat and Palaro (2005), but in their out-of-sample tests they fail to match target returns during volatile periods.

2.2. Factor Models and Factor-Based Clones

The mechanics of factor-based replication can be attributed to Sharpe (1992), who infers asset allocation choices using a linear factor model to measure the relation between the returns of an investment vehicle and those of standard asset classes. Sharpe then applies the model to a sample of open-end mutual funds and shows how estimates of factor loadings correspond to the expected asset mix of each fund given their stated investment style. As discussed by Fung and Hsieh (2001), the combination of a linear structure and buy-and-hold factors is inappropriate for analysis of hedge funds given the non-linear relation between hedge fund returns and those of standard assets. Non-linearities can be generated by dynamic exposure via relatively high frequency trading and by positions in securities with option-like payoffs such as credit default swaps. Linear factor models can capture dynamic exposure to an underlying asset or strategy if factor loadings are allowed to change over time. This is the approach implicit in our use of rolling estimation windows when establishing clone portfolios, as described below.

Like Hasanhodzic and Lo (2007), Amenc et al. (2008) test the out-of-sample performance of factor-based clones. When comparing one-month out-of-sample clone returns to their target returns they find correlations typically below 0.50 and low regression R-squared. They conclude that linear-based clones do not work well, and argue that a major weakness is the inability of linear factor models to capture the time varying exposure of hedge funds to underlying factors. Amenc et al. conclude that non-linear factor models may be the solution. Amenc et al. (2010) study whether non-linear factor models can improve the performance of factor-based clones by estimating a regime-switching model as well as a model of stochastic exposures using a Kalman filter. Perhaps not surprisingly, the in-sample fit of these models with time varying factor exposures is superior to that of fixed exposures. More importantly, the out-of-sample performance is no better and in many cases is inferior to the simpler model, suggesting a risk of over-fitting.

In this paper, we employ rolling estimation windows to allow for time varying exposures to underlying asset classes. Though somewhat crude, the results in Amenc et al. (2010) illustrate that more sophisticated techniques are plagued by over-fitting and poor out-of-sample performance. In addition, a natural consequence of a rolling window is that factor exposures can evolve smoothly over time, depending on the length of the estimation window, resulting in a relatively low rate of portfolio turnover in the clone.

2.3. Estimating Market Timing Ability in Factor Models

As described in Section 1, an appropriate goal for factor-based replication is to capture the market timing ability of a target. There are two ways to estimate market timing ability in the context of a factor model.

First, one can estimate exposures to factors that are constructed to reflect the returns of active market timing strategies. Fung and Hsieh (2001), for example, develop a family of trend-following factors to capture dynamic exposures of funds to various asset classes including equities, bonds, currencies, and commodities. These factors are constructed from portfolios of options in order to replicate a look-back straddle, which in turn generates payoffs equivalent to a successful market timer. While these factors have been widely adopted in hedge fund research to characterize the risk and return profile of hedge funds, they are problematic in the context of replication because they are not readily investable. We limit the set of factors to futures contracts in order to construct a low-cost, liquid investment vehicle.

Second, one can use a model that allows for exposures to standard asset classes that vary conditional on the magnitude of asset returns. Treynor and Mazuy (1966), for example, specify a quadratic relation between the returns of a fund and those of the market, allowing for a larger exposure during higher market returns. Similarly, Henriksson and Merton (1981) use a piece-wise linear relation between the returns of a fund and those of the market, allowing for different levels of exposure when the market return is above or below a certain level. We use both of these factor models to measure the timing ability of the hedge fund indexes and their clones.

To set expectations, note that prior literature provides limited evidence of market timing ability in hedge funds. Chen (2007) and Chen and Liang (2007) find some evidence of market timing in small subsets of funds. Chen and Liang study the timing ability in a sample of 221 funds that are either explicitly categorized as belonging in a market timing style or describe themselves as such in their prospectus. They find that these funds feature, both individually and collectively, some ability to vary equity market exposure in advance of market moves. Chen finds no evidence of equity market timing ability in a broader sample of funds, but some evidence of the ability to time bond and currency in global macro and managed futures funds. Griffin and Xu (2009) examine timing ability using equity holdings of hedge funds observed from quarterly SEC Form 13F filings. They find no evidence that hedge fund managers can rotate capital among different styles in advance of high returns.

3. Data and Empirical Methods

3.1. Hedge Fund Indexes

Monthly returns of 10 Dow Jones Credit Suisse indexes are used as our targets.[4] The set includes a broad index as well as nine strategy-focused sub-indexes. The indexes are constructed by Credit Suisse Hedge Index LLC using an asset-weighted average return of hedge funds in the Credit Suisse Hedge Fund Database, formerly known as the Credit Suisse/Tremont Hedge Fund Database. To be included in an index, a fund must meet a number of requirements, including assets under management of at least \$50 million, current audited financial statements, and a minimum 12-month track record. To avoid a censoring bias, liquidating funds are kept in an index until the liquidation is complete, thereby generating a more accurate reflection of hedge fund performance.

Summary statistics for the 10 indexes, as well as the total return of the S&P 500 for comparison, are listed in Table 1 using the full sample from January 1994 through December 2011. The broad Hedge Fund Index handily outperforms the S&P 500 over this period, with comparable average return but only half the volatility, resulting in an annualized Sharpe ratio of 0.73 for the Hedge Fund Index versus 0.37 for the S&P 500. Note, however, that the correlation between the two is a relatively high 0.57. The other indexes feature substantial variation in performance, four of which generate lower Sharpe ratios than the S&P 500. Annualized average returns range from –2.0% for the Short Bias Index to 12.0% for the Global Macro Index. Annualized standard deviations range from 5.8% for the Fixed Income Arbitrage Index to 17.0% for the Short Bias Index.

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[4] Data downloaded from www.hedgeindex.com.

Table 2 shows the same statistics computed over three subsets of the data: 1994 – 2003, 2004 – 2007, and 2008 – 2011. Dramatic variation exists across the subsets, as one would expect given the impact of the financial crisis in the most recent period. The Hedge Fund Index, for example, features Sharpe ratios of 0.81, 1.71, and 0.10 over the three periods, respectively. The non-stationarity in index return distributions displayed here illustrates the difficulty in replication procedures that focus on matching the return distribution of a target. Importantly, correlations between the hedge fund indexes and the S&P 500 have general increased over time. The Hedge Fund Index has a correlation of 0.48 in the first period, rising to 0.68 in the second and 0.76 in the most recent period. This result suggests that our ability to match hedge fund returns may improve over time as correlations with systematic risk factors increase.

3.2. Replication Building Blocks

We use positions in five futures contracts to construct clones for each hedge fund index. Futures contract returns are generated from holding the nearby contract and rolling to the next maturity 5 days prior to expiration. The US Dollar Index contract (USDX) is traded on the ICE; the Ten-year T-Note contract (TY) is traded on the CBOT; the Gold contract (GC) is traded on the COMEX; the Crude Oil contract (CL) is trade on the NYMEX; and the S&P 500 contract (SP) is traded on the CME. Summary statistics over the full sample, and three subsets, are listed in Table 3. Over the full sample, Crude Oil has the highest average return and standard deviation, 16.1% and 32.3%, respectively. Gold delivers a slightly higher Sharpe ratio than Crude Oil, 0.56 as compared to 0.50. Correlations between each contract and the S&P 500 are generally low, and in many cases negative. The US Dollar contract, for example, features a correlation of –0.25 over the full sample and –0.63 over the most recent period, as dollar-denominated assets were in high demand during the crisis. Correlations between each pair of contracts are listed in Table 4. The US Dollar and Ten-year T-Note contracts are negatively related to all other assets, with the exception of the Ten-year T-Note and Gold pair. These two assets feature a correlation of 0.41 in the most recent period as investors world-wide fled to safe assets.

One might question our choice of building blocks given the large number of potential candidates and the standard sets of factors used in hedge fund research. The Fung and Hsieh (2004) seven-factor model, for example, is the most widely adopted set of factors used in academic studies of hedge fund risk. We have two concerns which lead us to the five factors described above. First, as mentioned in Section 2, some of the Fung and Hsieh factors are not readily investable. In particular, implementing the trend-following strategies introduced in Fung and Hsieh (2001) would require a great deal of trading in derivative securities. While they may be useful for describing the types of assets and strategies hedge funds use, in the context of this replication study they are not as relevant. Second, though we are using an out-of-sample procedure for assessing the performance of the clones, searching over a potentially large set of factors raises the specter of data-mining. A large enough set almost guarantees we could construct clones that appear to perform well, but then we lose the benefit of an out-of-sample assessment.

Given investor demand for a product that can help diversify holdings of standard asset classes, one might also question our choice of the S&P 500 and Ten-year T-Note contracts. There are two reasons why we include them. First, recall our goal is to replicate the time series of returns of a hedge fund or hedge fund index. If the match between the target and the clone returns is tight, then the clone will inherit the salient features of the target, including its correlation with other assets. Whether the S&P 500 and Ten-year T-Note contracts help match the target is an empirical question which our analysis will answer. Second, our replication procedure allows for negative and time varying factor exposures, so even a clone consisting solely of these two contracts could deliver low correlation with a buy-and-hold investment in stocks and bonds.

3.3. Clone construction

Clones are constructed by estimating coefficients of a linear factor model each month. Coefficients are used as position sizes for the five futures contracts. Positions are entered with a one month delay to realistically reflect the actions of the replication methodology in real time as described below.

To construct the clone return for month t, we use data through month t – 2. So, for example, the clone return for January would be based on a regression using data through the prior November. This represents a one month lag between the end of an index reporting period and establishing the futures positions for replicating the index. The index performance is typically available on the 15th of a given month, so the procedure in effect allows for a two-week period between obtaining the most recent index return and establishing the futures positions. The clone return for January, for example, would be based on index returns through November, which would be available in mid-December. The requisite futures positions would then be entered at the end of December. See Figure 1 for a timeline that illustrates the sequence of events.

A five-factor regression run on date $t - 2$ and using T observations is expressed as:

$$(1) \qquad r_{i,j} = \sum_{k=1}^{5} \beta_{i,k} r_{k,j} + \varepsilon_{i,j} \qquad j = t - T - 1, t - 2$$

where r_i is the excess return of the index and r_k is the return of one of five factors. This regression differs from standard factor models because, following Hasanhodzic and Lo (2007), we have suppressed the intercept, which is typically labeled alpha. Alpha is a primary measure of fund performance, and can be interpreted as the capturing the security selection ability of a manager. Note in our context, however, that it is impossible to replicate alpha; indeed, in the language of regression, the intercept is the averaged unexplained return. By omitting the intercept we are forcing the factors to play a larger role fitting the target's returns. A chief concern of "regression through the origin" is that estimates of β will be biased. We will assess this by focusing on out-of-sample tests of the clone's ability to fit the target return.

We conduct the exercise with four different estimation periods of T = 12, 24, 36, and 48 months. Since this is a regression of excess index returns on the realizable returns of futures positions, the β coefficients can be interpreted as percentage allocation weights of clone capital to notional futures positions. Given the coefficient estimates, computing the clone return r_c for date t begins with the date t fitted value of the regression:

$$(2) \qquad r_{c,t} = \sum_{k=1}^{5} \beta_{i,k} r_{k,t}$$

We assume that the futures positions are "fully collateralized" meaning that for every dollar of notional exposure, positive or negative, a dollar of cash is set aside in an interest bearing account. This assumption makes the β coefficients easy to interpret – a coefficient of 1.0 means 100% of the clone assets are invested in the associated contract. We assume that cash earns the one-month LIBOR rate. In addition, we sum the absolute values of the β from the regressions, where a negative β simply indicates a short position in the futures contract. The sum of the absolute values indicates the percentage of the clone's capital that is deployed as notional futures exposure. If this sum is less than 100%, we assume the remainder of a clone's capital is earning LIBOR. If the sum exceeds 100%, we assume the excess over 100% is borrowed at LIBOR plus 100 basis points.

We do not account for trading costs hence returns will be slightly upward-biased. Direct transaction costs are minimal in futures markets, typically much less than $1 per contract. The primary cost of constructing the clone will consist of salaries for the traders and risk managers that are required to implement and oversee the plan. Management fees of 100 to 200 basis points are typical in hedge funds – but for a mechanical algorithm like the one used here, a more modest fee is likely more appropriate. By excluding this from our clone return we are providing an upper-bound on the clone's performance.

3.4. Measuring Clone Performance

By construction the clones have no way of capturing alpha, the average unexplained return of the target, and can only hope to deliver performance by matching the dynamic factor exposures of the target. To measure the information content of targets and clones, therefore, we will use two standard market timing tests to determine whether changes in factor loadings occur at the right time, i.e. whether factor loadings increase prior to high factor returns and decrease prior to low factor returns.

In the first test, we use the Henriksson and Merton (1981) timing model which allows for two different levels of factor exposure. The model is estimated using the following regression:

$$r_{i,j} = \alpha + \sum_{k=1}^{5} \beta_{i,k} r_{k,j} + \sum_{k=1}^{5} \gamma_k I_{k,j} r_{k,j} + \varepsilon_{i,j} \tag{3}$$

$$\text{and } I_{k,j} = 1 \text{ when } r_{k,j} > 0 \text{ else } I_{k,j} = 0$$

where γ_k is the incremental loading on factor k during months with a positive factor return. Note we include the intercept here because the objective is to measure the market timing coefficient as accurately as possible. For robustness, we also estimate parameters for the Treynor Mazuy (1967) timing model using the following regression:

$$(4) \qquad r_{i,j} = \alpha + \sum_{k=1}^{5} \beta_{i,k} r_{k,j} + \sum_{k=1}^{5} \gamma_k r_{k,j}^2 + \varepsilon_{i,j}$$

A positive γ_k coefficient in the Treynor Mazuy regression can be interpreted as an exposure that is increasingly positive when factor returns are positive and increasingly negative when factor returns are negative – resulting in a U-shape relation between the returns of the investment vehicle and the returns of the factors.

In the second test, we use a log-odds ratio to determine whether factor loadings are higher during months when factor returns are above their mean. Specifically, the relation between the factor loadings and subsequent returns is measured by whether the factor loading estimated using data through month $t-2$ is above or below its mean and whether the factor return in month t is above or below its mean, allowing for a one-month lag in clone construction. Let HH denote the number of months when the factor loading is High and the subsequent return is High, LL the number of months when both are Low, HL the number of months when the factor loading is High and the subsequent return is Low, and LH the number of months when the factor loading is Low and the subsequent return is High. The normalized Log-Odds ratio equals

$$(5) \qquad \ln\left(HH \times LL / HL \times LH\right) / \sqrt{HH^{-1} + LL^{-1} + HL^{-1} + LH^{-1}}$$

and is distributed standard normal.

4. Replication Performance

4.1. In-sample fit

Before proceeding to the replication analysis, we examine the relation between hedge fund index returns and those of the five futures contracts. For each index, we regress hedge fund index returns in excess of the 1-month LIBOR rate on the raw returns of the five futures contracts. The reason that we regress excess index returns on raw futures returns is that standard cost-of-carry futures pricing models imply that futures returns do not reflect compensation for the time value of money, whereas hedge fund index returns do. For this analysis we include an intercept, as is standard, so that regression coefficients and adjusted R-squared can be interpreted in the usual way as we are interested here in assessing the in-sample fit of the factors.

Table 5 shows results using the full sample of 1994 through 2011. In-sample fit, as measured by the adjusted R-squared of each regression, ranges from 9.9% for the Managed Futures Index to 60.3% for the Short Bias Index, and averages 30.5% across the styles. These low levels of fit are consistent with prior studies. One might be troubled by the low level of in-sample fit for our indexes, since our ultimate goal is to generate a reasonable match out-of-sample. Note, however, that in almost all cases the indexes feature a statistically significant relation to four or five of the factors. More importantly, in-sample fit can be improved by allowing for time varying exposures of the indexes to underlying factors, reflecting the trading strategies of constituent fund managers. To illustrate, we report in Table 6 the adjusted R-squared from regressions using two subsets of the data: 2004 – 2007 and 2008 – 2011. In many cases the increase in adjusted R-squared as compared to the full sample is substantial. The Hedge Fund Index, for example, features a 38.9% adjusted R-squared over the full sample as compared to 68.1% and 69.2%, respectively, for the two latter periods. This result motivates our use of rolling window estimation periods in the out-of-sample analysis.

4.2. Clone details

We present summary statistics of the exposures generated by the cloning algorithm described in Section 3. The average position sizes and typical monthly changes are listed in Table 7. Panels A and B show the average coefficient and the average absolute change in each coefficient from month to month for the 12-month clone. The average positions in Panel A are quite small, typically below 0.25 in absolute value, save for the –0.94 recorded on the S&P 500 factor for the Short Bias Index. The average absolute changes in Panel B, however, are significant, often above 0.10. This means a typical month would involve a trade equal to 10% of assets under management for each factor. Panels C and D show the corresponding statistics for the 48-month estimation window. The average positions are comparable to the results in Panel A, but the changes are much smaller, consistent with the idea that the estimated factor loading each month is actually an average of a dynamic factor loading, hence the average will be more stable the longer is the estimation window.

Table 8 shows the annual percentage turnover each year for each index. The annual turnover equals the sum of the absolute value of the change in exposures each month. Panel A shows the results for the 12-month estimation window. Several features stand out. First, there is substantial variation across time and across indexes. High levels of turnover are observed around the sharp climb and collapse of the dot-com era in 1998 and 2001, respectively. Turnover is also high during the financial crisis years of 2007 – 2009. Turnover is highest for the Managed Futures Index, averaging 1030% per year, and lowest for Fixed Income Arbitrage, at 317% per year. Panel B shows results for the 48-month window. The time series patterns in turnover are similar, but the magnitudes are much smaller. The Managed Futures Index is again the highest, but with an average annual turnover of 186%. The Hedge Fund Index has an average turnover of 410% in Panel A but only 89% in Panel B, which is quite modest, similar to many mutual funds.

These results indicate that the length of the estimation window has a dramatic impact on the size of positions as well as turnover, and is likely the most important variable for implementing a cloning procedure.

4.3. Out-of-sample performance of clones

We measure the ability of clones to fit index returns out of sample by comparing the index returns to the clone returns from February 1998 through December 2011.[5] Table 9 shows results using 12-month estimation windows. Listed are monthly Sharpe ratios, average returns, and standard deviations, as well as *p*-values of tests for a significant difference between the averages and standard deviations of clones and indexes. Panel A lists statistics assuming no lag between the end of the estimation period and the opening of futures positions necessary to replicate the index. As described in Section 3, this is infeasible given that index returns are typically not available until the 15th of a month, but the results show the hypothetical performance in absence of this market friction. For the first seven indexes listed, the clones deliver a higher Sharpe ratio than the index. The Hedge Fund Index delivers a Sharpe ratio of 0.18 compared to 0.20 for the clone, for example. In almost all cases there is no significant difference between the average returns and standard deviations of the clones and the indexes. In

[5] Since we use estimation windows up to 48 months long, data from 1994 through 1997 are used exclusively for measuring exposures. With a one-month lag, the first out-of-sample observation is February 1998.

Panel B, however the clone performance weakens considerably with a one-month lag in portfolio construction. For the Hedge Fund Index, for example, the Sharpe ratio drops to 0.10. This result shows how implementation details are extremely important in determining the actual performance of the replicating positions.

Table 10 shows results using a 48-month estimation period. Without a lag, four of the clones deliver Sharpe ratios above their indexes, whereas three do with a one-month lag. In most cases, however, average returns are not statistically significantly different across the clones and indexes. In four of the clones, there is a significant difference in standard deviations, but in all cases the clones have lower volatility. These results indicate that the clone performance may be considered a reasonable alternative to the indexes.

Interestingly, a naïve strategy of maintaining equal weights on each of the five factors generally outperforms the clones, and even the hedge fund indexes themselves. Over the same time period as the results listed in Tables 9 and 10, a strategy of maintaining futures positions each with notional value equal to 20% of assets under management, fully collateralized with funds earning LIBOR, would have generated a monthly Sharpe ratio of over 0.22. This exceeds all of the clones formed using the one-month lag. Naturally past performance is no guarantee of future success, and events during the sample period were extreme by historical standards. That said, the fact that an equally-weighted portfolio tends to outperform both the clones and the targets suggests that simple alternatives may have merit.

Table 11 provides some more insight regarding the match between the hedge fund indexes and the corresponding clones. Listed are three types of correlations: the correlation between each index and the S&P 500 total return, $\rho_{\text{Index, S\&P 500}}$, the correlation between each clone and the corresponding index, ρ_{Index}, and the correlation between each clone and the S&P 500, $\rho_{\text{S\&P 500}}$. Panel A shows results using the full out-of-sample period February 1998 through December 2011. The first column indicates the correlation between each index and the S&P 500. The Long Short Index has the highest correlation of 0.66. The next two columns involve clones that use a 12-month estimation window. Here the correlations between the clones and the indexes are comparable to correlations between the indexes and the S&P 500. The Hedge Fund Index, for example, features a correlation with the S&P 500 of 0.57, whereas its correlation with the clone is 0.55. Note, however, that the correlation between the clone and the S&P 500 is higher, at 0.68. In most cases, this pattern is repeated. For the 48-month clone in the last two columns, the correlation between the clones and the S&P 500 is generally higher still. This result is unsettling because one of the primary reasons for seeking an alternative investment, or its clone, is to achieve diversification from standard asset classes such as large cap U.S. equities.

Panel B of Table 11 shows correlations computed over the more recent period of 2008 – 2011. Here the correlations between clones and their indexes are higher than before, but the correlation between clones and the S&P 500 often exceeds 0.80. In some respects this may not be a big surprise. Risky assets in general became more highly correlated in the wake of the financial crisis.

4.4. Market timing ability and dynamic factor loadings

The prior subsection shows that we do have some ability to match time series properties of hedge fund indexes by using backward-looking rolling window regressions to estimate factor loadings, and using these to establish portfolio weights going forward. However, the performance of the clones is inferior to a simple strategy of equally weighting the five futures-based factors. A remaining question is whether the poor performance of the clones is due to the construction methodology, perhaps because the backward-looking estimates always provide stale information, or is due to tracking a target which itself does not contain useful information regarding future returns. As mentioned previously, the performance of the clones is completely attributable to the dynamic nature of factor exposures inferred from the hedge fund indexes, since the clones are constructed directly from the index factor loadings. Thus, to measure the performance of the clones, and the indexes themselves, we assess their market timing performance.

In Table 12, we list Henrikkson Merton timing coefficients for the indexes and the clone with a 24-month estimation window.[6] Listed below each coefficient is a two-sided *p*-value; coefficients significant at the 10% level are in bold. As described in Section 3, positive coefficients indicate that exposures are higher when factor returns are above zero, consistent with timing ability, whereas negative coefficients indicate that exposures are lower when factor

[6] Results for other estimation windows are qualitatively similar and omitted for the sake of brevity.

returns are above zero. Panel A shows the results for the indexes. The vast majority of timing coefficients are statistically insignificant. In 11 cases out of 50, the coefficients are significant but negative, and in only three cases are they positive and significant. These results indicate the indexes themselves do not feature successful time variation in factor loadings. Naturally, since the indexes do not feature timing ability then it hardly seems likely that the clones would either. Panel B confirms this: in six cases the coefficients are positive and significant and in six cases the coefficients are negative and significant.

As discussed in Bollen and Busse (2001), regressions of market timing models tend to lack power when using monthly data and results can be sensitive to the assumed functional form. For this reason we also use a log-odds ratio for robustness. Here we count the number of months in which factor loadings and subsequent returns are simultaneously above or below their mean, and compare it to the number of months when factor loadings are high and returns are low or vice versa. Table 13 shows the resulting log-odds ratios for each index and factor, for both the 12-month clone and the 48-month clone. A positive ratio indicates effective timing. Consistent with the results of our Henrikkson Merton analysis, there is no evidence of market timing. The number of positive and significant coefficients is equal to the number expected under the null hypothesis of no ability, three for the case of the 12-month clone and two for the case of the 48-month clone.

5. Conclusion

Hedge fund replication products constitute a relatively new choice for investors in their pursuit of alternative investments. We analyze the performance of hedge fund clones constructed by taking time varying positions in five liquid futures contracts. The targets we attempt to replicate are the Credit Suisse hedge fund indexes.

Our results are mixed. On the one hand, we are able to construct clones with out-of-sample correlations with their respective targets that exceed 0.50 for seven or eight of the indexes, depending on the estimation window length chosen. The clone of the broad Hedge Fund Index, for example, features a correlation with the index of 0.75 using a 12-month window and 0.81 with a 48-month window. On the other hand, the Sharpe ratios of clones are generally inferior to those of the hedge fund indexes, and annual returns of clones are often below those of the indexes. Our ability to match the time-series properties of hedge fund indexes appears to be largely the result of matching the exposure of the indexes to the equity market, which calls into question the benefit of a supposedly alternative investment. In addition, standard market timing regressions and log-odds ratio tests indicate that neither the clones nor the target indexes feature market timing ability.

Despite the poor performance of the clones relative to the targets, there is still utility in our replication procedure. For example, a portable alpha strategy, in which individual funds are selected based on their potential for alpha generation, requires an algorithm for eliminating systematic risk, as described in Kung and Pohlman (2004). Even market neutral funds can have residual exposure, as shown in Patton (2009), hence the need for this type of hedging to make a pure play on alpha generation. In the context of our study, the rolling window factor model regressions indicate the size of the futures positions one should take to remove systematic risk exposure. Such a strategy can aid risk budgeting for large institutional portfolios such as university endowments and pension plans.

References

Amenc, Noel, Walter Gehin, Lioinel Martellini, and Jean-Christophe Meyfredi. (2008) "Passive Hedge Fund Replication: A Critical Assessment of Existing Techniques" Journal of Alternative Investments, 69-83.

Amenc, Noel, Lioinel Martellini, and Jean-Christophe Meyfredi. (2010) "Passive Hedge Fund Replication – Beyond the Linear Case" European Financial Management 16, 191-210.

Amin, Gaurav, and Harry Kat. (2003) "Hedge Fund Performance 1990-2000: Do the 'Money Machines' Really Add Value?" Journal of Financial and Quantitative Analysis 38, 251-274.

Andrews, Donald W.K., Inpyo Lee, and Werner Ploberger. (1996) "Optimal Changepoint Tests for Normal Linear Regression" Journal of Econometrics 70, 9-38.

Bollen, Nicolas. (2012) "Zero-R^2 Hedge Funds and Market Neutrality" Journal of Financial and Quantitative Analysis, forthcoming.

Bollen, Nicolas, and Jeffrey Busse. (2001) "On the Timing Ability of Mutual Fund Managers" Journal of Finance 56, 1075-1094.

Bollen, Nicolas, and Robert Whaley. (2009) "Hedge Fund Risk Dynamics: Implications for Performance Appraisal" Journal of Finance 59, 711-753.

Chen, Yong. (2007) "Timing Ability in the Focus Market of Hedge Funds" Journal of Investment Management 5, 66-98.

Chen, Yong, and Bing Liang. (2007) "Do Market Timing Hedge Funds Time the Market?" Journal of Financial and Quantitative Analysis 42, 827-856.

Dybvig, Peter (1988). "Distributional Analysis of Portfolio Choice" Journal of Business 61, 369-393.

Fung, William, and David Hsieh. (2001) "The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers" Review of Financial Studies 14, 313-341.

Fung, William, and David Hsieh. (2004) "Hedge Fund Benchmarks: A Risk Based Approach" Financial Analysts Journal 60, 65-80.

Griffin, John, and Jin Xu. (2009) "How Smart are the Smart Guys? A Unique View from Hedge Fund Stock Holdings" Review of Financial Studies 22, 2531-2570.

Hasanhodzic, Jasmina, and Andrew Lo. (2007) "Can Hedge-Fund Returns be Replicated? The Linear Case" Journal of Investment Management 5, 5-45.

Henrikkson, Roy, and Robert Merton. (1981) "On Market Timing and Investment Performance of Managed Portfolios. II. Statistical Procedures for Evaluating Forecasting Skills" Journal of Business 54, 513-533.

Kat, Harry, and Helder Palaro. (2005) "Who Needs Hedge Funds? A Copula-Based Approach to Hedge Fund Return Replication" City University Working Paper.

Kung, Edward, and Larry Pohlman. (2004) "Portable Alpha" Journal of Portfolio Management 30, 78-87.

Patton, Andrew. (2009) “Are Market Neutral Hedge Funds Really Market Neutral?” Review of Financial Studies 22, 2495-2530.

Patton, Andrew and Tarun Ramadorai. (2012) “On the High-Frequency Dynamics of Hedge Fund Risk Exposures” Journal of Finance, forthcoming.

Sharpe, William. (1992) “Asset allocation: Management style and performance measurement” Journal of Portfolio Management, 7-19.

Treynor, Jack, and Kay Mazuy. (1966) “Can Mutual Funds Outguess the Market?” Harvard Business Review 44, 131-136.

Figure 1. Timeline for a 24-Month Estimation Window.

Shown is the sequence of events for a single out-of-sample observation and a 24-month estimation window. Months one through 24 are used for estimating factor exposures. The return for month 24 is not made available until the middle of month 25. We assume positions are entered at the end of month 25 and held until the end of month 26. So for estimation windows ending in month *t*, the out-of-sample observation is the return in month *t* + 2.

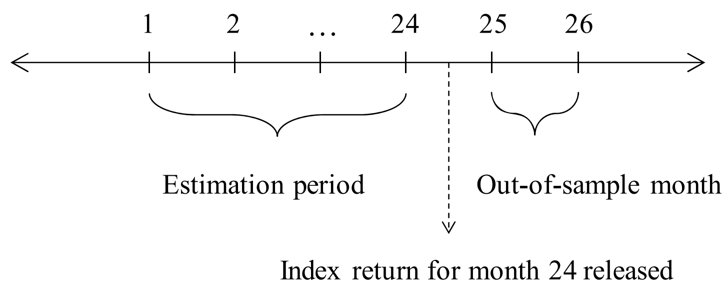

Table 1. Summary Statistics of Hedge Fund Indexes.

Listed below are summary statistics of monthly returns of 10 Dow Jones Credit Suisse hedge fund indexes and the total return of the S&P 500 index. Data are from January 1994 through December 2011. The first three statistics are annualized. "Sharpe" is the Sharpe ratio, defined as the average return in excess of the 30-day T-Bill rate divided by standard deviation; "Skew" is skewness; "Kurt" is excess kurtosis; "% Neg" is the percentage of months with a negative return; and "$\rho_{\text{S\&P 500}}$" is the correlation coefficient between an index and the S&P 500.

DJCS Index	Average	Std Dev	Sharpe	Skew	Kurt	% Neg	$\rho_{\text{S\&P 500}}$
Hedge Fund	8.6%	7.6%	0.73	-0.19	2.42	29.6%	0.57
Convertible Arb	7.4%	7.0%	0.62	-2.68	15.96	25.5%	0.37
Short Bias	-2.0%	17.0%	-0.30	0.65	1.44	55.1%	-0.76
Emerging Market	8.3%	15.0%	0.34	-0.76	5.03	38.0%	0.54
Equity Neutral	5.6%	10.4%	0.24	-11.85	161.12	20.4%	0.29
Event Distressed	9.0%	6.4%	0.93	-2.24	10.64	23.2%	0.63
Fixed Income Arb	5.3%	5.8%	0.37	-4.39	30.39	21.8%	0.33
Global Macro	12.0%	9.8%	0.90	0.00	3.78	26.9%	0.24
Long Short	9.4%	10.0%	0.62	0.00	3.25	35.2%	0.66
Managed Futures	6.5%	11.8%	0.29	0.02	-0.03	44.9%	-0.10
S&P 500	8.9%	15.7%	0.37	-0.63	0.90	37.5%	

Table 2. Summary Statistics of Hedge Fund Indexes.

Listed below are summary statistics of monthly returns of 10 Dow Jones Credit Suisse hedge fund indexes and the total return of the S&P 500 index. Statistics are computed over three periods: January 1994 through December 2003 (Panel A), January 2004 through December 2007 (Panel B), and January 2008 through December 2011 (Panel C). The first three statistics are annualized. "Sharpe" is the Sharpe ratio, defined as the average return in excess of the 30-day T-Bill rate divided by standard deviation; "Skew" is skewness; "Kurt" is excess kurtosis; "% Neg" is the percentage of months with a negative return; and "$\rho_{S\&P\ 500}$" is the correlation coefficient between an index and the S&P 500.

Panel A. 1994 - 2003

DJCS Index	Average	Std Dev	Sharpe	Skew	Kurt	% Neg	$\rho_{S\&P\ 500}$
Hedge Fund	10.9%	8.5%	0.81	0.08	1.73	29.2%	0.48
Convertible Arb	10.1%	4.8%	1.26	-1.57	4.06	18.3%	0.12
Short Bias	-1.7%	18.0%	-0.32	0.92	2.15	55.0%	-0.76
Emerging Market	8.5%	17.8%	0.25	-0.58	3.71	40.8%	0.48
Equity Neutral	10.2%	3.1%	1.99	0.21	0.24	15.8%	0.39
Event Distressed	11.0%	6.0%	1.15	-3.46	22.95	20.0%	0.55
Fixed Income Arb	6.7%	3.9%	0.65	-3.25	16.61	18.3%	0.03
Global Macro	14.3%	12.1%	0.84	-0.04	1.98	29.2%	0.23
Long Short	12.1%	11.0%	0.73	0.22	3.35	33.3%	0.59
Managed Futures	7.6%	12.1%	0.29	0.03	0.58	44.2%	-0.23
S&P 500	12.0%	15.8%	0.50	-0.59	0.26	36.7%	

Panel B. 2004 - 2007

DJCS Index	Average	Std Dev	Sharpe	Skew	Kurt	% Neg	$\rho_{S\&P\ 500}$
Hedge Fund	10.4%	4.2%	1.71	-0.17	-0.55	22.9%	0.68
Convertible Arb	4.6%	3.9%	0.30	-0.73	0.92	33.3%	0.41
Short Bias	2.5%	13.4%	-0.06	0.49	0.08	52.1%	-0.81
Emerging Market	16.6%	7.6%	1.76	-0.76	1.05	20.8%	0.48
Equity Neutral	7.9%	2.0%	2.28	0.47	0.12	10.4%	0.15
Event Distressed	12.4%	4.0%	2.28	-0.49	0.85	10.4%	0.62
Fixed Income Arb	4.9%	2.7%	0.55	-0.59	0.73	25.0%	0.27
Global Macro	11.5%	3.7%	2.22	0.57	0.81	16.7%	0.40
Long Short	11.9%	6.0%	1.43	-0.35	-0.78	27.1%	0.75
Managed Futures	5.5%	11.5%	0.18	-0.08	-0.89	43.8%	0.62
S&P 500	9.2%	7.6%	0.78	-0.37	-0.70	31.3%	

Panel C. 2008 - 2011

DJCS Index	Average	Std Dev	Sharpe	Skew	Kurt	% Neg	$\rho_{S\&P\ 500}$
Hedge Fund	1.2%	7.8%	0.10	-1.05	1.49	37.5%	0.76
Convertible Arb	3.8%	12.1%	0.28	-1.94	6.15	35.4%	0.59
Short Bias	-7.6%	17.7%	-0.45	0.08	-0.63	58.3%	-0.82
Emerging Market	-0.7%	12.7%	-0.09	-1.28	3.40	47.9%	0.78
Equity Neutral	-8.0%	21.2%	-0.40	-6.11	40.35	41.7%	0.36
Event Distressed	0.7%	8.4%	0.03	-0.71	0.11	43.8%	0.76
Fixed Income Arb	2.2%	10.2%	0.17	-3.02	11.69	27.1%	0.60
Global Macro	6.5%	7.1%	0.85	-1.12	2.87	31.3%	0.27
Long Short	-0.2%	10.1%	-0.07	-0.59	0.28	47.9%	0.83
Managed Futures	4.9%	11.3%	0.39	0.07	-1.11	47.9%	-0.11
S&P 500	0.6%	20.5%	0.01	-0.44	0.06	45.8%	

Table 3. Summary Statistics of Futures Contracts.

Listed below are summary statistics of monthly returns of five futures contracts used to build clones for hedge fund indexes. Data are from January 1994 through December 2011. Futures contract returns are generated from holding the nearby contract and rolling to the next maturity 5 days prior to expiration. The US Dollar Index contract (USDX) is traded on the ICE; the Ten-year T-Note contract (TY) is traded on the CBOT; the Gold contract (GC) is traded on the COMEX; the Crude Oil contract (CL) is trade on the NYMEX; and the S&P 500 contract (SP) is traded on the CME. The first three statistics are annualized. "Sharpe" is the Sharpe ratio, defined for futures returns as the average return divided by standard deviation; "Skew" is skewness; "Kurt" is excess kurtosis; "% Neg" is the percentage of months with a negative return; and "$\rho_{S\&P\ 500}$" is the correlation coefficient between an index and the S&P 500.

Panel A. 1994 - 2011

Futures Contract	Average	Std Dev	Sharpe	Skew	Kurt	% Neg	$\rho_{S\&P\ 500}$
US Dollar	-0.7%	8.3%	-0.09	0.34	0.74	52.3%	-0.25
10-year T-Note	1.1%	7.0%	0.16	-0.92	6.99	45.8%	-0.15
Gold	9.0%	16.1%	0.56	0.14	1.43	46.3%	0.02
Crude Oil	16.1%	32.3%	0.50	-0.05	1.12	41.7%	0.19
S&P 500	6.7%	15.8%	0.43	-0.64	0.99	38.9%	

Panel B. 1994 - 2003

Futures Contract	Average	Std Dev	Sharpe	Skew	Kurt	% Neg	$\rho_{S\&P\ 500}$
US Dollar	-0.8%	7.7%	-0.11	0.11	-0.08	53.3%	0.03
10-year T-Note	0.2%	7.4%	0.03	-1.73	8.29	46.7%	-0.09
Gold	1.3%	12.3%	0.11	1.00	2.66	50.8%	-0.06
Crude Oil	13.3%	32.0%	0.42	0.26	1.21	43.3%	0.01
S&P 500	10.0%	16.0%	0.62	-0.58	0.36	37.5%	

Panel C. 2004 - 2007

Futures Contract	Average	Std Dev	Sharpe	Skew	Kurt	% Neg	$\rho_{S\&P\ 500}$
US Dollar	-3.0%	6.1%	-0.50	0.04	0.08	50.0%	-0.23
10-year T-Note	0.4%	5.0%	0.07	-0.28	0.71	47.9%	-0.26
Gold	18.7%	15.4%	1.21	0.24	-0.04	43.8%	0.17
Crude Oil	31.1%	27.7%	1.12	-0.04	-0.97	41.7%	-0.17
S&P 500	7.4%	7.7%	0.97	-0.50	-0.50	31.3%	

Panel D. 2008 - 2011

Futures Contract	Average	Std Dev	Sharpe	Skew	Kurt	% Neg	$\rho_{S\&P\ 500}$
US Dollar	1.8%	11.3%	0.16	0.42	0.23	52.1%	-0.63
10-year T-Note	4.0%	7.7%	0.51	0.74	3.11	41.7%	-0.21
Gold	18.4%	23.0%	0.80	-0.57	0.47	37.5%	0.09
Crude Oil	7.8%	37.2%	0.21	-0.45	1.48	37.5%	0.61
S&P 500	-1.9%	20.7%	-0.10	-0.47	0.12	50.0%	

Table 4. Correlations of Futures Contracts.

Listed below are correlations of monthly returns of five futures contracts used to build clones for hedge fund indexes. Data are from January 1994 through December 2011. Futures contract returns are generated from holding the nearby contract and rolling to the next maturity 5 days prior to expiration. The US Dollar Index contract (USDX) is traded on the ICE; the Ten-year T-Note contract (TY) is traded on the CBOT; the Gold contract (GC) is traded on the COMEX; the Crude Oil contract (CL) is trade on the NYMEX; and the S&P 500 contract (SP) is traded on the CME.

	1994 - 2011				
	US Dollar	10-year T-Note	Gold	Crude Oil	S&P 500
US Dollar	1.00				
10-year T-Note	-0.11	1.00			
Gold	-0.44	0.19	1.00		
Crude Oil	-0.29	-0.11	0.20	1.00	
S&P 500	-0.25	-0.15	0.02	0.19	1.00

	2004 - 2007				
	US Dollar	10-year T-Note	Gold	Crude Oil	S&P 500
US Dollar	1.00				
10-year T-Note	-0.13	1.00			
Gold	-0.55	0.06	1.00		
Crude Oil	-0.20	-0.03	0.22	1.00	
S&P 500	-0.23	-0.26	0.17	-0.17	1.00

	2008 - 2011				
	US Dollar	10-year T-Note	Gold	Crude Oil	S&P 500
US Dollar	1.00				
10-year T-Note	-0.11	1.00			
Gold	-0.49	0.41	1.00		
Crude Oil	-0.54	-0.38	0.22	1.00	
S&P 500	-0.63	-0.21	0.09	0.61	1.00

Table 5. In-Sample Model Fit

Listed below are results of regressions of monthly excess returns of 10 Dow Jones Credit Suisse hedge fund indexes on the raw returns of five futures contracts. Data are from January 1994 through December 2011. Futures contract returns are generated from holding the nearby contract and rolling to the next maturity 5 days prior to expiration. The US Dollar Index contract (USDX) is traded on the ICE; the Ten-year T-Note contract (TY) is traded on the CBOT; the Gold contract (GC) is traded on the COMEX; the Crude Oil contract (CL) is trade on the NYMEX; and the S&P 500 contract (SP) is traded on the CME. The first column is the regression adjusted R-squared. Subsequent columns list OLS coefficient estimates. "***", "**", and "*" indicate significance at the 1%, 5%, and 10% level, respectively.

	Adj R-squared	Intercept	US Dollar	10-year T-Note	Gold	Crude Oil	S&P 500
Hedge Fund	38.9%	0.0015	0.1582 ***	-0.0424	0.1042 ***	0.0399 ***	0.2746 ***
Convertible Arb	15.9%	0.0016	0.0183	-0.0334	0.0514 *	0.0354 **	0.1470 ***
Short Bias	60.3%	0.0008	-0.2056 **	0.2684 **	-0.1724 ***	0.0063	-0.8240 ***
Emerging Market	35.0%	-0.0008	0.2544 **	-0.3046 **	0.2503 ***	0.0328	0.5045 ***
Equity Neutral	17.6%	0.0014	-0.1859 **	-0.3098 ***	-0.1191 ***	0.0524 **	0.1266 ***
Event Distressed	44.9%	0.0026 ***	0.0341	-0.1380 ***	0.0478 **	0.0332 ***	0.2338 ***
Fixed Income Arb	17.8%	-0.0001	-0.0055	0.0020	0.0391	0.0478 ***	0.0996 ***
Global Macro	13.1%	0.0046 **	0.3131 ***	0.1987 **	0.1476 ***	0.0172	0.1943 ***
Long Short	51.3%	0.0012	0.0148	-0.1411 **	0.1116 ***	0.0539 ***	0.3881 ***
Managed Futures	9.9%	0.0014	-0.2072 *	0.2140 *	0.1163 **	0.0317	-0.0944 *

Table 6. Time Variation of In-Sample Model Fit

Listed below are the adjusted R-squared of regressions of monthly returns of 10 Dow Jones Credit Suisse hedge fund indexes on the returns of five futures contracts. Data are from January 1994 through December 2011. Futures contract returns are generated from holding the nearby contract and rolling to the next maturity 5 days prior to expiration. The US Dollar Index contract (USDX) is traded on the ICE; the Ten-year T-Note contract (TY) is traded on the CBOT; the Gold contract (GC) is traded on the COMEX; the Crude Oil contract (CL) is trade on the NYMEX; and the S&P 500 contract (SP) is traded on the CME.

	Adj R-squared		
DJCS Index	1994 - 2011	2004 - 2007	2008 - 2011
Hedge Fund	38.9%	68.1%	69.2%
Convertible Arb	15.9%	23.8%	39.1%
Short Bias	60.3%	66.1%	70.3%
Emerging Market	35.0%	56.5%	73.8%
Equity Neutral	17.6%	19.1%	32.7%
Event Distressed	44.9%	47.3%	64.3%
Fixed Income Arb	17.8%	34.7%	47.0%
Global Macro	13.1%	50.2%	44.3%
Long Short	51.3%	73.5%	76.4%
Managed Futures	9.9%	41.2%	13.2%

Table 7. Average and Average Change of Futures Positions.

Listed are summary statistics of futures positions by strategy. Panel A shows average position size, measured as percent of assets under management, for clones using a 12-month estimation window. Panel B shows average absolute changes in futures positinos from month-to-month for clones using a 12-month estimation window. Panels C and D show corresponding statistics for clones using a 48-month estimation window.

	Hedge Fund	Convertible Arb	Short Bias	Emerging Market	Equity Neutral	Event Distressed	Fixed Income Arb	Global Macro	Long Short	Managed Futures
Factor	Panel A. 12-Month Estimation Window Average Exposure									
US Dollar	0.07	0.11	-0.11	0.18	-0.17	0.07	0.04	0.14	0.00	-0.34
10-year T-Note	-0.12	-0.10	0.27	-0.34	-0.21	-0.17	-0.07	0.04	-0.12	0.04
Gold	0.07	0.04	-0.19	0.20	-0.03	0.04	0.04	0.06	0.10	0.07
Crude Oil	0.05	0.03	0.01	0.09	0.01	0.04	0.03	0.05	0.06	0.01
S&P 500	0.26	0.13	-0.94	0.48	0.09	0.26	0.08	0.12	0.43	0.04
Factor	Panel B. 12-Month Estimation Window Average Absolute Δ Exposure									
US Dollar	0.11	0.14	0.23	0.19	0.09	0.11	0.08	0.14	0.14	0.26
10-year T-Note	0.12	0.14	0.25	0.22	0.11	0.12	0.09	0.17	0.14	0.28
Gold	0.05	0.06	0.11	0.10	0.04	0.05	0.03	0.07	0.06	0.12
Crude Oil	0.02	0.03	0.05	0.04	0.02	0.02	0.02	0.03	0.03	0.06
S&P 500	0.05	0.07	0.13	0.10	0.05	0.06	0.04	0.07	0.07	0.15
Factor	Panel C. 48-Month Estimation Window Average Exposure									
US Dollar	0.12	0.12	-0.14	0.28	-0.17	0.08	0.05	0.23	-0.04	-0.19
10-year T-Note	-0.12	-0.04	0.31	-0.34	-0.35	-0.16	-0.05	0.06	-0.20	0.21
Gold	0.09	0.05	-0.21	0.22	-0.05	0.06	0.03	0.08	0.11	0.10
Crude Oil	0.04	0.03	0.00	0.06	0.02	0.04	0.04	0.03	0.06	0.03
S&P 500	0.24	0.13	-0.89	0.49	0.07	0.23	0.07	0.12	0.39	0.00
Factor	Panel D. 48-Month Estimation Window Average Absolute Δ Exposure									
US Dollar	0.02	0.02	0.04	0.04	0.02	0.02	0.02	0.04	0.03	0.04
10-year T-Note	0.02	0.02	0.05	0.04	0.02	0.02	0.02	0.03	0.03	0.06
Gold	0.01	0.01	0.02	0.02	0.01	0.01	0.01	0.02	0.01	0.02
Crude Oil	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.01	0.01	0.01
S&P 500	0.01	0.01	0.03	0.02	0.01	0.01	0.01	0.02	0.02	0.03

Table 8. Annual Turnover.

Listed is annual percentage turnover by strategy. Turnover each month is computed by summing the absolute value of the changes in factor exposures from the prior month. Annual turnover is the sum across months. Also listed is the average annual turnover by strategy. Panel A shows results for clones using a 12-month estimation window. Panel B shows results for clones using a 48-month estimation window.

	Hedge Fund	Convertible Arb	Short Bias	Emerging Market	Equity Neutral	Event Distressed	Fixed Income Arb	Global Macro	Long Short	Managed Futures
Year	Panel A. 12-Month Estimation Window									
1998	776	498	1,017	1,434	341	610	444	1,451	814	1,029
1999	801	572	1,225	1,511	234	696	578	1,418	692	882
2000	466	300	944	834	192	183	135	587	804	463
2001	714	588	978	1,256	245	339	175	1,096	1,116	1,243
2002	311	510	715	740	192	401	220	390	381	1,486
2003	247	400	700	548	154	474	251	419	216	848
2004	218	354	675	398	160	320	214	401	233	649
2005	275	636	1,675	609	480	363	233	261	416	1,961
2006	191	377	936	604	190	207	102	273	358	960
2007	639	627	1,693	1,162	379	1,007	396	379	932	1,777
2008	401	687	942	563	596	426	614	654	483	1,043
2009	260	690	566	429	1,249	227	368	340	351	433
2010	211	749	461	346	339	301	450	148	167	718
2011	227	292	415	474	182	433	254	262	220	930
Average	410	520	924	779	352	428	317	577	513	1,030
Year	Panel B. 48-Month Estimation Window									
1998	288	148	345	574	104	178	151	495	190	287
1999	89	59	193	238	41	47	53	154	97	206
2000	149	74	198	161	34	84	43	254	151	197
2001	87	46	96	146	43	55	32	136	118	161
2002	83	61	106	184	34	75	61	136	83	130
2003	53	59	127	113	28	50	32	90	86	105
2004	134	79	157	181	34	47	47	162	212	178
2005	33	61	146	88	28	44	34	59	53	185
2006	39	56	100	75	17	61	45	63	62	196
2007	62	71	139	96	25	75	50	89	63	232
2008	115	183	362	140	317	118	200	175	161	330
2009	53	164	159	90	130	57	116	58	63	136
2010	32	80	90	82	149	49	73	30	41	132
2011	29	57	68	66	91	53	61	41	32	123
Average	89	85	163	160	77	71	71	139	101	186

Table 9. Performance of the 12-Month Clone.

Listed are summary statistics of hedge fund index returns and their out-of-sample clone counterparts. Clone returns for date *t* are fitted values computed out of sample using first-stage regressions with data through *t*-1 (Without Lag) or *t*-2 (With Lag) in which hedge fund index returns are regressed against the returns of five futures contracts. Out-of-sample returns are from February 1998 through December 2011. Panel A shows results using 12 prior months of returns through date *t*-1 in the first-stage regression, whereas Panel B shows results using 12 prior months through date *t*-2. Listed are Sharpe ratios, *S*, means, μ, and standard deviations, σ, as well as *p*-values for tests of a significant difference between means and standard deviations of the index and clone returns.

	12-Month Without Lag							
DJCS Index	S_{hf}	S_{clone}	μ_{hf}	μ_{clone}	*p*-value	σ_{hf}	σ_{clone}	*p*-value
Hedge Fund	0.18	0.20	0.6%	0.6%	0.7995	2.0%	2.1%	0.5204
Convertible Arb	0.16	0.21	0.6%	0.6%	0.8108	2.2%	2.0%	0.1310
Short Bias	-0.09	-0.03	-0.2%	0.0%	0.5992	5.1%	5.0%	0.6944
Emerging Market	0.10	0.13	0.6%	0.8%	0.7157	4.0%	4.2%	0.5432
Equity Neutral	0.05	0.13	0.4%	0.5%	0.7192	3.4%	2.1%	0.0000
Event Distressed	0.21	0.28	0.6%	0.7%	0.5797	2.0%	1.9%	0.4858
Fixed Income Arb	0.08	0.22	0.4%	0.6%	0.2749	1.8%	1.5%	0.0184
Global Macro	0.26	0.15	0.8%	0.6%	0.3662	2.3%	2.5%	0.3098
Long Short	0.17	0.15	0.7%	0.7%	0.8863	3.0%	3.0%	0.8492
Managed Futures	0.10	0.02	0.6%	0.3%	0.4711	3.4%	3.7%	0.3576

	12-Month With Lag							
DJCS Index	S_{hf}	S_{clone}	μ_{hf}	μ_{clone}	*p*-value	σ_{hf}	σ_{clone}	*p*-value
Hedge Fund	0.18	0.10	0.6%	0.5%	0.6184	2.0%	2.4%	0.0523
Convertible Arb	0.16	0.09	0.6%	0.4%	0.6206	2.2%	2.6%	0.0598
Short Bias	-0.09	-0.03	-0.2%	0.1%	0.5790	5.1%	4.7%	0.2896
Emerging Market	0.10	0.09	0.6%	0.6%	0.9928	4.0%	4.3%	0.2823
Equity Neutral	0.05	0.06	0.4%	0.4%	0.9330	3.4%	2.1%	0.0000
Event Distressed	0.21	0.18	0.6%	0.6%	0.9196	2.0%	2.2%	0.2237
Fixed Income Arb	0.08	0.10	0.4%	0.4%	0.8368	1.8%	1.9%	0.7995
Global Macro	0.26	0.06	0.8%	0.4%	0.1188	2.3%	2.7%	0.0373
Long Short	0.17	0.10	0.7%	0.5%	0.5892	3.0%	3.2%	0.3653
Managed Futures	0.10	-0.01	0.6%	0.2%	0.3137	3.4%	3.7%	0.3669

Table 10. Performance of the 48-Month Clone.

Listed are summary statistics of hedge fund index returns and their out-of-sample clone counterparts. Clone returns for date *t* are fitted values computed out of sample using first-stage regressions with data through *t*-1 (Without Lag) or *t*-2 (With Lag) in which hedge fund index returns are regressed against the returns of five futures contracts. Out-of-sample returns are from February 1998 through December 2011. Panel A shows results using 48 prior months of returns through date *t*-1 in the first-stage regression, whereas Panel B shows results using 48 prior months through date *t*-2. Listed are Sharpe ratios, *S*, means, μ, and standard deviations, σ, as well as *p*-values for tests of a significant difference between means and standard deviations of the index and clone returns.

	48-Month Without Lag							
DJCS Index	S_{hf}	S_{clone}	μ_{hf}	μ_{clone}	*p*-value	σ_{hf}	σ_{clone}	*p*-value
Hedge Fund	0.18	0.12	0.6%	0.5%	0.5725	2.0%	1.9%	0.5493
Convertible Arb	0.16	0.17	0.6%	0.5%	0.5674	2.2%	1.5%	0.0000
Short Bias	-0.09	-0.06	-0.2%	-0.1%	0.7493	5.1%	4.9%	0.5760
Emerging Market	0.10	0.12	0.6%	0.7%	0.8231	4.0%	3.9%	0.7543
Equity Neutral	0.05	-0.02	0.4%	0.2%	0.5005	3.4%	2.2%	0.0000
Event Distressed	0.21	0.13	0.6%	0.5%	0.4255	2.0%	1.8%	0.1965
Fixed Income Arb	0.08	0.20	0.4%	0.5%	0.4688	1.8%	1.3%	0.0000
Global Macro	0.26	0.12	0.8%	0.5%	0.1397	2.3%	2.0%	0.0991
Long Short	0.17	0.10	0.7%	0.5%	0.4800	3.0%	2.8%	0.4844
Managed Futures	0.10	-0.01	0.6%	0.2%	0.2258	3.4%	2.3%	0.0000

	48-Month With Lag							
DJCS Index	S_{hf}	S_{clone}	μ_{hf}	μ_{clone}	*p*-value	σ_{hf}	σ_{clone}	*p*-value
Hedge Fund	0.18	0.11	0.6%	0.4%	0.5025	2.0%	2.0%	0.7544
Convertible Arb	0.16	0.13	0.6%	0.4%	0.4770	2.2%	1.6%	0.0001
Short Bias	-0.09	-0.08	-0.2%	-0.1%	0.8467	5.1%	4.6%	0.2157
Emerging Market	0.10	0.13	0.6%	0.7%	0.8142	4.0%	3.9%	0.7450
Equity Neutral	0.05	-0.04	0.4%	0.1%	0.4382	3.4%	2.2%	0.0000
Event Distressed	0.21	0.13	0.6%	0.5%	0.4288	2.0%	1.8%	0.3727
Fixed Income Arb	0.08	0.17	0.4%	0.5%	0.5826	1.8%	1.4%	0.0002
Global Macro	0.26	0.10	0.8%	0.4%	0.0960	2.3%	2.1%	0.1488
Long Short	0.17	0.09	0.7%	0.5%	0.4687	3.0%	2.9%	0.5857
Managed Futures	0.10	-0.02	0.6%	0.2%	0.2150	3.4%	2.3%	0.0000

Table 11. Out-of-sample Correlations.

Listed are correlations between the monthly returns of 10 hedge fund indexes, corresponding clones, and the S&P 500. Clone returns for date *t* are fitted values computed out of sample using first-stage regressions with data through *t*-2 in which hedge fund index returns are regressed against the returns of five futures contracts. Panel A shows results using out-of-sample clone returns from February 1998 through December 2011. Panel B shows results with out-of-sample clone returns from January 2008 through December 2011. The first column shows $\rho_{\text{Index, S\&P 500}}$, the correlation between each hedge fund index and the S&P 500. The second and third columns correspond to clones using 12-month estimation windows, whereas the fourth and fifth column show results using 48-month estimation windows. Listed for each estimation window are ρ_{Index}, the correlation between each clone and the corresponding hedge fund index, and $\rho_{\text{S\&P 500}}$, the correlation between each clone and the S&P 500.

Panel A. February 1998 – December 2011

DJCS Index	$\rho_{\text{Index, S\&P 500}}$	12-Month ρ_{Index}	12-Month $\rho_{\text{S\&P 500}}$	48-Month ρ_{Index}	48-Month $\rho_{\text{S\&P 500}}$
Hedge Fund	0.57	0.55	0.68	0.59	0.79
Convertible Arb	0.38	0.41	0.49	0.41	0.62
Short Bias	-0.79	0.67	-0.78	0.75	-0.91
Emerging Market	0.62	0.62	0.64	0.71	0.77
Equity Neutral	0.28	0.13	0.34	0.18	0.44
Event Distressed	0.63	0.53	0.65	0.62	0.80
Fixed Income Arb	0.32	0.49	0.43	0.41	0.53
Global Macro	0.14	0.19	0.34	0.11	0.43
Long Short	0.66	0.64	0.76	0.71	0.86
Managed Futures	-0.13	0.25	0.00	0.14	0.01

Panel B. January 2008 – December 2011

DJCS Index	$\rho_{\text{Index, S\&P 500}}$	12-Month ρ_{Index}	12-Month $\rho_{\text{S\&P 500}}$	48-Month ρ_{Index}	48-Month $\rho_{\text{S\&P 500}}$
Hedge Fund	0.76	0.75	0.82	0.81	0.88
Convertible Arb	0.59	0.51	0.74	0.49	0.87
Short Bias	-0.82	0.74	-0.82	0.74	-0.92
Emerging Market	0.78	0.80	0.80	0.87	0.87
Equity Neutral	0.35	0.10	0.35	0.13	0.45
Event Distressed	0.76	0.71	0.83	0.76	0.89
Fixed Income Arb	0.60	0.58	0.66	0.50	0.86
Global Macro	0.27	0.55	0.40	0.56	0.49
Long Short	0.83	0.80	0.88	0.84	0.91
Managed Futures	-0.11	0.23	0.15	0.00	0.33

Table 12. Henrikkson Merton Timing Coefficients.

Listed are estimates of market timing coefficients from regressions of hedge fund index and clone excess returns on a set of five futures-based factors. Clone returns for date *t* are fitted values computed out of sample using first-stage regressions with data through *t*-2 in which hedge fund index returns are regressed against the returns of five futures contracts. Excess fitted clone returns and excess hedge fund index returns are then regressed against the five futures-based factors using a Henrikkson Merton (1981) specification in which timing coefficients are estimated when factor loadings are positive. Listed are timing coefficients for the indexes and clones using 24-month estimation windows. Listed below each coefficient estimate is a two-sided *p*-value. Coefficients significant at the 10% level are in bold.

	Panel A. Indexes					Panel B. 24-Month Clones				
	USD	T-Note	Gold	Oil	S&P 500	USD	T-Note	Gold	Oil	S&P 500
Hedge Fund	0.1669	0.0601	-0.0823	-0.0534	**-0.1620**	0.0630	0.0124	**-0.1376**	**0.0625**	-0.0350
	0.3200	0.7199	0.3371	0.2045	0.0530	0.5434	0.9046	0.0101	0.0169	0.4962
Convertible Arb	0.1697	-0.0694	-0.1600	**-0.1601**	-0.0577	**0.2656**	0.1629	-0.0520	-0.0324	0.0397
	0.4402	0.7519	0.1552	0.0041	0.5970	0.0659	0.2575	0.4791	0.3685	0.5778
Short Bias	**-0.7710**	-0.1202	0.0078	-0.0377	-0.0079	0.0316	**-0.8857**	**0.2319**	0.0393	**0.1764**
	0.0238	0.7224	0.9641	0.6562	0.9627	0.8829	0.0001	0.0359	0.4655	0.0994
Emerging Market	0.0288	**0.6604**	-0.1751	0.1123	**-0.5379**	-0.0610	**1.3121**	-0.1195	0.0355	-0.2067
	0.9269	0.0364	0.2751	0.1537	0.0007	0.8283	0.0000	0.4062	0.6140	0.1400
Equity Neutral	**0.6386**	**-1.7128**	**-0.2688**	**-0.1240**	0.0218	0.0848	0.2463	0.1196	0.0239	-0.0023
	0.0315	0.0000	0.0757	0.0942	0.8814	0.7018	0.2666	0.2912	0.6669	0.9829
Event Distressed	0.2340	-0.2182	-0.0963	-0.0265	**-0.2220**	0.1042	**0.4907**	**-0.1784**	0.0115	0.0776
	0.1332	0.1611	0.2260	0.4950	0.0045	0.4010	0.0001	0.0054	0.7105	0.2085
Fixed Income Arb	0.1685	-0.0420	**-0.2143**	**-0.1563**	**-0.1706**	**0.2480**	0.1692	-0.0041	0.0009	-0.0125
	0.3312	0.8084	0.0164	0.0004	0.0485	0.0612	0.2001	0.9513	0.9771	0.8486
Global Macro	0.1188	0.3957	-0.0335	**-0.1606**	-0.1127	-0.0047	-0.2719	**-0.2059**	**0.1355**	-0.0369
	0.6275	0.1071	0.7887	0.0095	0.3542	0.9777	0.1066	0.0174	0.0015	0.6577
Long Short	0.2522	0.2672	-0.1414	0.0776	-0.1590	-0.0483	0.1097	**-0.1094**	0.0370	-0.0098
	0.2659	0.2384	0.2223	0.1721	0.1580	0.6983	0.3792	0.0875	0.2367	0.8746
Managed Futures	0.3615	0.0841	0.2752	-0.1250	**0.3884**	-0.1124	**-1.2461**	-0.0897	-0.0026	0.1039
	0.2946	0.8069	0.1192	0.1485	0.0242	0.6788	0.0000	0.5180	0.9695	0.4406

Table 13. Log-Odds Ratios.

Listed for each hedge fund index are statistics measuring the relation between clone factor loadings and subsequent factor returns. For each month from December 1997 through October 2011 clone factor loadings are determined by regressing hedge fund excess index returns on the returns of five futures-based factors. The relation between the factor loadings and subsequent returns is measured by whether the factor loading estimated in month *t* is above or below its mean and whether the factor return in month *t*+2 is above or below its mean, allowing for a one-month lag in clone construction. Let HH denote the number of months when the factor loading is High and the subsequent return is High, LL the number of months when both are Low, HL the number of months when the factor loading is High and the subsequent return is Low, and LH the number of months when the factor loading is Low and the subsequent return is High. The normalized Log-Odds ratio equals $\ln\left(HH \times LL / HL \times LH\right)/\sqrt{HH^{-1}+LL^{-1}+HL^{-1}+LH^{-1}}$ and is distributed standard normal. Listed are results for 12-month and 48-month estimation windows. Listed below each statistic is a two-sided *p*-value. Statistics significant at a 10% level are in bold.

	12-Month Clone					48-Month Clone				
Index	USD	T-Note	Gold	Oil	S&P 500	USD	T-Note	Gold	Oil	S&P 500
Hedge Fund	1.5865	0.6918	0.8467	**-1.8114**	1.2781	1.6085	**-2.0789**	-0.4943	-0.1131	-1.4577
	0.1126	0.4891	0.3972	0.0701	0.2012	0.1077	0.0376	0.6211	0.9100	0.1449
Convertible Arb	1.0563	0.8477	**-1.9186**	0.4065	0.4354	-0.2450	1.3115	**0.5122**	0.3607	-0.4064
	0.2908	0.3966	0.0550	0.6844	0.6633	0.8065	0.1897	0.6085	0.7183	0.6844
Short Bias	0.1354	-0.3815	0.6660	0.4738	0.1400	0.8954	-0.5360	1.1978	0.7909	1.1645
	0.8923	0.7028	0.5054	0.6356	0.8887	0.3706	0.5920	0.2310	0.4290	0.2442
Emerging Market	0.2510	-0.6079	-1.4523	-0.9627	-1.0054	1.3158	0.5368	-1.6148	0.4085	-1.5878
	0.8018	0.5433	0.1464	0.3357	0.3147	0.1882	0.5914	0.1064	0.6829	0.1123
Equity Neutral	1.1564	0.7027	-0.1420	-1.1442	-0.2050	0.8726	-0.7111	**-1.9045**	-0.8028	-0.8999
	0.2475	0.4822	0.8871	0.2525	0.8376	0.3829	0.4770	0.0568	0.4221	0.3682
Event Distressed	-0.2336	1.2136	0.2450	-0.1952	1.1109	0.3700	0.2198	1.6254	-0.5636	-1.5211
	0.8153	0.2249	0.8065	0.8452	0.2666	0.7114	0.8260	0.1041	0.5730	0.1282
Fixed Income Arb	1.1554	**1.9279**	-0.6660	-0.7023	0.0418	0.8417	-0.8476	-0.0486	0.9254	-0.0983
	0.2479	0.0539	0.5054	0.4825	0.9667	0.4000	0.3967	0.9612	0.3548	0.9217
Global Macro	-0.6570	-0.0690	1.1404	-1.6442	0.4835	**1.7963**	**-1.7829**	1.3315	-1.0957	-0.3138
	0.5112	0.9450	0.2541	0.1001	0.6287	0.0724	0.0746	0.1830	0.2732	0.7537
Long Short	**2.0034**	-0.8695	-0.3606	**-1.7029**	0.7273	0.3801	0.5362	-0.0650	-0.1665	-1.5213
	0.0451	0.3846	0.7184	0.0886	0.4670	0.7039	0.5918	0.9482	0.8678	0.1282
Managed Futures	0.0872	**-3.3075**	0.8645	-0.0019	**1.9437**	0.8521	-1.4687	1.1809	-0.3750	-0.5068
	0.9305	0.0009	0.3873	0.9985	0.0519	0.3942	0.1419	0.2376	0.7077	0.6123