Original Article

Efficient hedge fund style allocations: A rules-based model

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ABSTRACT The hedge fund literature has predominantly focused on the return and risk characteristics as well as the portfolio properties of different hedge fund styles. However, relatively little is known about how hedge fund investors should allocate their capital across various hedge fund styles. The aim of this study is to develop a rules-based framework that can be used by investors to optimize their hedge fund style allocation. We construct four hedge fund style indices using a sample of 6088 hedge funds from the Lipper TASS Hedge Fund Database over the January 1995–September 2010 time period. We also develop technical and fundamental indicators on the basis of the style return drivers from earlier hedge fund studies. We use these indicators to generate trading recommendations through a style allocation model that systematically over- and underweights the four major hedge fund styles. The empirical results indicate that our hedge fund style allocation

model delivers an outperformance of up to 1 per cent per year over an equally weighted portfolio.

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INTRODUCTION

Hedge funds are private investment vehicles that are traditionally organized as limited partnerships with high minimum investments. Their primary targets are family offices or institutional investors. The hedge fund industry experienced its first boom phase between 1967 and 1968, but the popularity of hedge funds really began to expand dramatically during the late 1980s. Since then, the industry has continued to flourish despite setbacks during the Russian debt crisis in 1998 and the current worldwide financial crisis since 2008.

However, as some researchers have noted, the ongoing financial market crisis has impacted hedge funds in a somewhat negative way (Healy and Lo, 2009; Hartmann and Kaiser, 2011; Ben-David *et al*, 2012; Maier *et al*, 2012). In particular, hedge funds seem to have lost some of their pre-eminence since 2008, when they were unable to generate the promised absolute returns. But in spite of these developments, 2010 was a record year for hedge funds. The industry experienced its largest increase in assets under management (+US\$149 billion) during the fourth quarter, reaching a new all-time high of \$1.917 trillion.¹

The academic hedge fund literature so far has focused on exploring the return and risk characteristics of hedge fund styles, and establishing the value-added of these investments in a traditional equity and fixed-income

portfolio context. For example, Fung and Hsieh (1997a, 1998, 2002), Agarwal and Naik (2000, 2004), Schneeweis and Spurgin (1999), Amin and Kat (2002), Titman and Tiu (2011), Bali *et al* (2011), and Patton and Ramadorai (2012) document substantial variations in the risk and return characteristics of hedge funds. They show how hedge funds often exhibit option-like return exposures and little correlation with mutual funds. Based on these hedge fund risk exposures, related studies by Mitchell and Pulvino (2001), Fung and Hsieh (2001, 2002), and Gatev *et al* (2006), among others, develop specific trading rules designed to mimic some of these performance characteristics.

Compared with the extensive literature on hedge fund return and risk analysis, relatively little has been published about the optimal style allocations of hedge fund portfolios. The studies most closely related to our research question, such as Popova *et al* (2006a, b) and Kaiser *et al* (2008), have focused on quantitative models that derive information from the return time series of hedge funds themselves. The idea for our study draws initially from Hartmann and Kaiser (2011). They document that it is possible to combine the informational content of hedge fund data (generally available on only a monthly basis) with data derived from the long-term risk exposures of hedge funds (which are available at a higher frequency) in order to achieve a more

efficient diversification of hedge fund style portfolios.

We use this notion as a starting point and develop a systematic and robust hedge fund style allocation model that captures the relevant hedge fund return drivers. In addition to the well-documented risk exposures of hedge funds, our framework also incorporates other coherences, such as technical and fundamental indicators, which seem important for hedge fund style allocation. Moreover, we propose a simple consolidation mechanism that combines the trading signals from all indicator groups. Ultimately, our aim is to optimize a portfolio consisting of four main style indices such that it delivers a statistically significant outperformance against a benchmark of an equally weighted hedge fund style portfolio.

We use January 1995 through September 2010 as the sample period for our empirical analysis, and we construct four hedge fund style indices on the basis of a refined Lipper TASS database comprised of 6088 funds. To cleanse the data set, we first classify each fund. Next, we construct our own style-specific peer groups for Equity Hedge, Event Driven, Relative Value and Tactical Trading. Based on these aggregated data, the empirical analysis indicates that our hedge fund style allocation model delivers an outperformance of up to 1 per cent per year over an equally weighted portfolio.

The remainder of our study is organized as follows. The next section describes the cleansing process and our data set in more detail. The subsequent section discusses how we construct technical and fundamental indicators which are used to allocate the four hedge fund style indices in a portfolio context. This section also presents a full rules-based mechanism that combines the trading recommendations generated from the

different groups of indicators. The penultimate section explores the performance of different trading strategies, and the last section concludes and discusses implications for the asset management practice.

DATA

Hedge fund managers follow an absolute return approach and enjoy great flexibility with regard to their investment strategies. They are able to use any financial instruments, asset classes or global regions that are not prohibited by their offering memorandums. As a result, the breadth of their potential investment strategies is vast, and the exact distinctions between related strategies can sometimes be obscure. Therefore, various classification procedures have been developed for the hedge fund universe. Two of the most widely used hedge fund data providers, Hedge Fund Research, Inc. (HFR) and Dow Jones Credit Suisse (DJCS), group hedge funds according to their respective investment processes and investment techniques. We take the same approach and categorize hedge funds into four major styles: Equity Hedge (EH), Event Driven (ED), Relative Value (RV) and Tactical Trading (TT).

The hedge fund style indices used in our analysis are calculated from the Lipper TASS Hedge Fund Database, which is, according to Füss *et al* (2009), the most popular database for empirical hedge fund studies. In a first step, we combine the November 2010 versions of the Lipper TASS 'live' and 'graveyard' hedge fund databases. Funds in the 'graveyard' database have ceased to report performance data to Lipper TASS, because they were liquidated, are closed to new investments, or have been restructured or merged with another hedge fund. This results in

a master database with performance information and descriptive variables for 16 191 hedge funds, spanning January 1992 through November 2010.

In a second step, we exclude all funds of funds from the database. Next, to ensure that the database is as representative as possible, we classify each hedge fund into one of our four major hedge fund style groups. Our final step is to cleanse the database as follows:

- If a fund reports different currency classes, we include only the US dollar share class.
- If a fund reports onshore and offshore structures, we consider only the offshore funds.
- We exclude any hedge funds that do not use monthly performance intervals.
- If a hedge fund's performance is stated in a currency other than the US dollar, we convert the performance to a US dollar-hedged equivalent.

After these adjustments, our final database contains 6088 single hedge funds, of which 2166 are from the 'live' database, and 3922 are from the 'graveyard' database. Table 1 shows that the most common hedge fund strategy is Equity Hedge (2841), followed by Tactical Trading (1400), Relative Value (985) and Event Driven (862).

Because the database we use includes all hedge funds that 'died' during the observation period (the 'graveyard' funds), there is no danger of a survivorship bias. Moreover, we account for the backfilling bias by deleting the first 12 months of performance from the data histories, a method suggested by Fung and Hsieh (2000) and Malkiel and Saha (2005). After these adjustments, we calculate the style indices as equally weighted

Table 1: Number of hedge funds in the equally weighted style portfolios

Style portfolio	Number of single hedge funds (SHFs)		
	Live	Dead	Total
Equity hedge	1026	1815	2841
Event driven	300	562	862
Relative value	307	678	985
Tactical trading	533	867	1400
Total	2166	3922	6088

arithmetic averages of the monthly performance of all hedge funds in the respective peer groups.

The four constructed hedge fund style indices contain the full breadth of strategies. There is a significant degree of diversity among them regarding where (asset class) and how (trading strategy) managers from each style index trade. Accordingly, the selection of return factors is equally diverse and contains different asset classes and proxy variables for each trading strategy (see the next section). All return time series are USD-based, and are computed on a monthly basis from January 1995 through September 2010.

HEDGE FUND STYLE ALLOCATION MODEL

The idea behind developing a hedge fund style allocation model is to create a framework that will adequately capture a particular set of hedge fund return drivers and offer a robust allocation methodology across different style indices. In addition to analysing trading styles and asset class exposures, we also identify other important coherences for hedge fund style

allocation and incorporate them into a rules-based model.

The allocation model is comprised of three parts, which we describe in more detail next. The first part consists of the technical analysis of financial markets, for example, the construction of technical indicators, the generation of trading signals based on hedge fund exposures and their application to the four hedge fund style indices. The second part consists of fundamental indicators developed from economic theory, prior academic hedge fund research and empirical observations. The fundamental indicators are again used to extract trading signals for the four hedge fund style indices. Finally, the third part includes the merging of the technical and fundamental trading signals into a fully systematic (rules-based) hedge fund style allocation framework.

Technical indicators

Technical analysis is the study of market development for the purpose of forecasting future price trends (Murphy, 1999; Lo *et al*, 2000). There are three general assumptions in this approach. First, the market incorporates all factors (for example, fundamental, political and psychological) that can possibly affect prices. Therefore, it is sufficient to study price developments in order to derive a market view. Second, prices tend to follow trends.

This concept is essential to the technical analysis approach, because most indicators are also trend-following. Third, history repeats itself. Therefore, patterns that were identified and exploited in the past will continue to appear and offer the same profit-making opportunity in the future.

The link between technical analysis and hedge fund style allocation can be derived from the decomposition of hedge fund style returns. Fung and Hsieh (2002) show that ED and EH returns are largely explained by a long equity market exposure. This finding is underscored by the high explanatory power (as measured by *R*-squared) and the statistical significance of the coefficients on the Russell 2000 index in the regressions that involve ED and EH. The synchronous behaviour of the returns of these two styles can be exploited by means of technical market analysis, which provides an opportunity to allocate to and away from these two styles more efficiently. The underlying notion is that the returns of traditional asset classes, contrary to those of hedge funds, can be observed more frequently and at almost no cost. Furthermore, because a performance link between different asset classes has been established, any information gained from the traditional asset classes through technical analysis can be used to optimize hedge fund style allocations.

In our model, we use a simple moving average. Moving averages are versatile, relatively simple to construct, and are thus the most widely used technical indicators in mechanical trend-following systems (Murphy, 1999). The subset of data to be averaged moves forward with each new trading day:

$$SMA_t^{\text{Arithmetic},n} = \frac{\sum_{i=0}^{1 \leq n} X_{t-i}}{n}. \quad (1)$$

where $SMA_t^{\text{Arithmetic},n}$ is the simple moving average at time t ; X_{t-i} is the closing price at time $(t-i)$; and n is the number of days over which the moving average is computed. An upward-trending market is indicated when the shorter moving average rises above the longer

moving average, and vice versa. We investigate both short-term (20- and 5-day) and long-term (200- and 60-day) *SMA*-specifications. We also use more complicated moving averages as technical indicators.²

Fundamental indicators

Incorporating fundamental indicators into a hedge fund style allocation model is generally done to gain information beyond the current direction of a particular market. Most importantly, by investigating macroeconomic variables, some of which possess forward-looking properties, it may be possible to identify structural imbalances at an early stage. Our model uses fundamental indicators derived from hedge fund style correlations, equity market correlations, financial market illiquidity, business cycle analysis and financial market volatility. Table A1 summarizes all indicators used in our analysis together with their implications for each hedge fund style.

Hedge fund style correlations

Depending on the investment style, markets and financial instruments traded by hedge funds usually vary. However, we expect that hedge fund style pairs, which are active in the same markets and trade similar instruments, will display more uniform return patterns than other pairs. Fung and Hsieh (1997a) and Agarwal and Naik (2000, 2004) show that the Russell 2000 index is an important explanatory variable for both the ED and EH styles. Thus, both have parts of their assets in similar trades on similar markets. We would expect them to be highly positively correlated, with the potential to become unstable under plummeting equity market conditions. In contrast, there are several

reasons to assume that the correlation between TT and other hedge fund styles is dynamic and displays distinct patterns:

- TT funds invest in a variety of markets, many of which have historically been uncorrelated with equity and fixed-income markets.
- A large number of TT funds are trend-following in nature (for example, CTAs) (Billingsley and Chance, 1996).³ Furthermore, according to Fung and Hsieh (2001), these funds perform best in highly volatile markets, an environment where ED, EH and RV have historically delivered below-average performance (Fung and Hsieh, 1999; Schneeweis and Spurgin, 1999).
- TT funds tend to enter aggressively into markets when they are trending, which implies that correlations with styles that exhibit directional exposures, such as ED, EH, and to some extent RV, may rise in strong market environments.
- TT funds are mainly invested in liquid futures markets; thus, market downturns are not expected to hurt their performance as badly as funds invested in stocks, bonds and less liquid high-yield or distressed securities (Fung and Hsieh, 1998).

These return characteristics indicate a dynamic correlation between TT and other hedge fund styles, which essentially moves among three corridors depending on the overall market environment. Specifically, its correlation with ED, EH and RV is zero or negative in high volatility markets, becoming more positive as markets expand, and remaining high and positive as the expansion peaks and markets move in a sideways direction.

Overall, we expect relatively stable and high correlations between all hedge fund style pairs, except those involving TT. We assume that, because three out of four styles share common return factors, investors will only reap substantial diversification benefits from TT.⁴ Failing to invest in TT may increase vulnerability to herding behaviour, especially in declining market environments, because ED, EH and RV all share common return sources. However, given that TT's correlation with the other styles is time-varying, the added value from including it into a hedge fund style portfolio may also change depending on the overall market environment.

As an economic expansion reaches its peak, the correlations of TT with ED, EH and RV increase. At this point, a cooling of economic activity, along with a downward correction of the financial markets, is imminent. Cautious investors should shift investments away from styles with directional exposures to the equity market and away from RV (with a short put exposure), and reallocate them to TT. Note that ED, EH and RV funds are often invested in less liquid assets, which increases their vulnerability to buying and/or selling pressure in declining markets and escalates the probability of herding.

Owing to the distinct correlation patterns of TT with the other styles, only the three pairs that contain TT are considered as indicators in our model. We calculate the Bravais-Pearson correlation coefficient for all three style pairs on the basis of our four style indices from the Lipper TASS database. A high correlation environment for a given style pair is signalled when the most recent correlation coefficient is at least 1 standard deviation above the mean historical correlation.⁵ If this is the case for all three style pairs involving

TT, this may indicate that markets are overdue for a correction, and thus increased attention should be paid to herding. In this situation, our rules-based approach suggests that it would be prudent to overweight TT. In contrast, a low correlation environment is signalled when the correlation level drops by more than 1 standard deviation below the mean historical correlation. Such an environment, where markets may still be contracting or an economic recovery may be slowly beginning, is accompanied by a neutral recommendation for TT.

The trading recommendations for RV are different. These funds often use highly levered arbitrage strategies that, if the spread turns against them, can immediately result in substantial losses (Karavas *et al*, 2005). Owing to their high leverage, these funds are particularly vulnerable to buying and selling herding behaviour in extreme market environments. An underweighting recommendation would thus be issued for this style in a high correlation environment, and a neutral recommendation in a low correlation environment. Because our strategy is fully invested at all times, the trading recommendations for TT and RV will automatically result in dynamic exposures to ED and EH.

Equity market correlation

Between January 1995 and September 2010, the median correlation coefficient between a style index and the S&P 500 index was 0.68 for ED, 0.77 for EH and 0.61 for RV. In contrast, TT was neutral against the equity market, and it exhibited a correlation of virtually zero with the S&P 500. Once stock markets begin trending, TT managers tend to build up

equity exposure, leading to an increased correlation with the equity market.

When stock markets enter into a period of sideways movement or decline, TT managers either enter into short positions or allocate to other markets that display a more favourable performance. Therefore, the correlation of TT with the equity markets will decrease quickly. This behaviour will be reflected in the TT returns in the sense that an increase in correlation with the equity market will signal a period of high-performing stock markets, and vice versa.

Based on this expectation, we can use the information from the correlation between TT and the S&P 500 index to time hedge fund style allocations more efficiently. The allocations to styles with an unequivocal and pronounced equity market exposure should be increased when the correlation between TT and the equity market rises, and vice versa. In contrast, the equity market correlations of all other styles do not provide trading recommendations, and thus they are ignored. Given that ED and EH contain well-established directional exposures to the equity market, the appropriate trading implications are apparent. In contrast, no explicit trading recommendations are generated for RV (and TT itself).

A high correlation between TT and the S&P 500, and thus a favourable equity market environment, is signalled when the mean of the latest 12-month correlation coefficient is more than 1 standard deviation above its historical mean value. In this case, an overweighting recommendation would be issued for both ED and EH. In contrast, an adverse equity market environment is indicated by a prior 12-month mean correlation coefficient below the historical mean value.

In this case, a neutral trading recommendation is implied for ED and EH.

Financial market illiquidity

Market illiquidity reflects the impact of order flows on prices and can be defined as the cost of immediate execution (Amihud and Mendelson, 1986). Investors willing to execute transactions face a trade-off: They can either wait for a favourable price, or insist on an execution at the current bid or ask price. Therefore, the spread between the bid and the ask price represents the sum of the buying premium and the selling concession. In their early study, Amihud and Mendelson (1986) developed the idea that illiquidity affects asset returns. They use the bid-ask spread as a proxy for illiquidity, and they demonstrate that asset returns are an increasing and concave function of this spread.⁶

A market illiquidity measure could be useful in the context of hedge fund style allocation because it constitutes a forward-looking variable and provides information about how investors perceive the future market environment. Boyson *et al* (2010), Sadka (2010), and Kessler and Scherer (2011) all document that shocks to market liquidity are an important determinant of hedge fund performance.⁷ For example, RV contains highly leveraged investment strategies seeking to exploit small spreads within and across different asset classes, and it is thus extremely vulnerable to market illiquidity (Karavas *et al*, 2005; Agarwal *et al*, 2010). Market liquidity also responds asymmetrically to changes in asset market values, which implies that it will decrease much faster during market downturns than it will increase during market upturns (Hameed *et al*, 2010). As a result, the allocations to RV should be conservative when

market liquidity decreases. On a portfolio level, in our model the weights of RV are decreased in illiquid environments, while the weights of TT are increased. In contrast, additional funds are allocated to ED and EH in liquid stock markets.

In line with Amihud (2002), we define illiquidity as the average ratio of the absolute return to the (dollar) trading volume on a given day. This ratio indicates the absolute (percentage) price change per dollar of daily trading volume, or the daily price impact of order flow. Contrary to Amihud (2002), who calculates the illiquidity ratio on a cross-sectional basis for individual stocks traded on the NYSE, we calculate this measure on the basis of the smaller S&P 500 index. We divide the absolute price change per day by the trading volume on that day, and the resulting time series is averaged over each calendar month to yield end-of-month estimates of the daily illiquidity ratio as follows⁸:

$$ILLIQ_{it} = \frac{1}{D_{im}} \sum_{d=1}^{D_{im}} \frac{(|R_{imd}|)}{VOLD_{imd}}. \quad (2)$$

where $ILLIQ_{it}$ denotes the illiquidity ratio; D_{im} is the number of days available for index i in month m ; $|R_{imd}|$ is the absolute return on stock or index i on day d of month m ; and $VOLD_{imd}$ is the trading volume of stock or index i on day d of month m in US\$. On the one hand, a high ratio indicates that the price impact is large relative to the volume of trading, which points to an illiquid market environment. On the other hand, a low illiquidity ratio is the result of a large number of trades with very little price impact, indicating well-functioning or liquid markets with presumably small bid-ask spreads.

An illiquid stock market environment is signalled when the illiquidity ratio in equation (2) is at least 1 standard deviation above its

historical mean value.⁹ In this case, an overweighting recommendation is issued for TT, and an underweighting recommendation for RV. In contrast, a liquid stock market environment, when the illiquidity ratio falls by more than 1 standard deviation below its historical mean, triggers an overweighting recommendation for ED and EH.

Business cycle analysis

We next use a business cycle indicator to analyse alternating sequences of economic expansions and contractions. Cyclical indicators are generally subdivided into coinciding, lagging and leading indicators based on the timing of their movements. Lagging and coinciding indicators of economic activity may be used to identify the development of structural imbalances or to confirm recent movements in the leading indicator. By definition, they are oriented toward the past, and therefore they are not eligible to be incorporated into a forward-looking style allocation model.

The Conference Board leading economic indicator (CB LEI) combines 10 leading indicators into one composite index.¹⁰ The index indicates peaks and troughs over the business cycle by combining the informational content of various leading variables. For example, Levine and Zervos (1996) and Cochrane (2007), among many others, document a connection between economic activity and stock market performance. Roughly speaking, weak economic performance goes along with declining financial markets and above average volatility, while stronger economic performance is accompanied by lower return volatility and upward-trending financial markets.

The CB LEI does not fluctuate in long continuous movements. Expansions are interspersed with occasional months of decline, and recessions can include months of increases. In order to determine whether a short-term change is in fact a signal for an upcoming recession or a recovery, we must consider the duration of the change and its diffusion. Accordingly, in addition to the current level of the CB LEI, its prior six-month development and its prior six-month diffusion are also incorporated into the indicator variable.

A diffusion index indicates how widespread a particular movement has become over the business cycle.¹¹ For the CB LEI, a diffusion index value of 70, for example, would indicate that seven of its 10 components have risen over the last six months. Unlike the composite index, diffusion indices do not differentiate between small and large variations, but they provide a better picture of the prevalence of a given movement. Therefore, the informational content of diffusion indices is not redundant, although they are calculated from the same data as the original index. In fact, the informational content of the CB LEI can be applied to hedge fund style allocations. A rising CB LEI signals an economic expansion and thus a positive financial market performance. Correspondingly, investors should overweight styles with directional market exposures. In contrast, when the CB LEI signals an economic decline, one expects choppy or declining financial markets with increased volatility. TT funds tend to perform well in this environment, and thus the allocation to this style should be increased.

We define a positive financial market outlook when positive movements of the current month's CB LEI and the six-month CB LEI are accompanied by a six-month diffusion rate

that is higher than 50 per cent (that is, more than 50 per cent of the index components have increased). This scenario implies an overweighting recommendation for ED and EH, and a neutral one for TT. In contrast, when both the one- and six-month changes are negative and less than 50 per cent of the index components have increased (that is, diffusion rate < 50 per cent), an overweighting signal is issued for TT, while ED and EH are kept neutral in this scenario. As a result of its mixed directional and option-like exposure to the financial markets, we do not apply any business cycle signal to RV.

Financial market volatility

Financial market return volatility is most pronounced during economic crises (Schwert, 1989; Campbell *et al*, 2001). This relationship is particularly observable for stock markets, where the contemporaneous correlation between stock market volatility and returns has historically been negative (Pindyck, 1988; Campbell *et al*, 2001). Implied volatility, however, is a forward-looking variable, and prior empirical studies confirm its superior forecasting ability compared with historical standard deviations (Latané and Rendleman, 1976; Chiras and Manaster, 1978; Beckers, 1981; Poon and Granger, 2003; Taylor *et al*, 2010). It may thus be useful for our style allocation model.

The Chicago Board Options Exchange Market Volatility Index (VIX) is the most widely used implied volatility indicator. The VIX estimates the implied market volatility by averaging the implied volatilities of puts and calls over a wide range of strike prices. It is calculated from index options on the S&P 500 index to ensure that the volatility represents a market consensus. Fleming *et al* (1995) as well as Bekaert

and Wu (2000) document an inverse relationship between the VIX and stock market valuations over time, suggesting that it serves as a valid indicator of future stock market performance.¹² In fact, Blair *et al* (2001) and Fleming (1998), among others, show that accurate forecasts of future returns on stock indices are often based on implied volatilities.

In our empirical analysis, the VIX is used to optimize the allocation to hedge fund styles according to the expected stock market volatility. A higher implied volatility predicts increased market turbulence, and thus a weak or negative market performance in the near future. This environment favours TT strategies over other styles that exhibit directional exposures, such as ED and EH (Brealey and Kaplanis, 2001). RV is especially vulnerable in a high-volatility environment, because it generally involves highly leveraged investment strategies that tend to come under pressure from margin calls as asset price volatility rises (Karavas *et al*, 2005). We assume that the VIX signals an increasing stock market volatility when it is more than 1 standard deviation above its historical mean value, implying an overweighting recommendation for TT and an underweighting recommendation for RV; the other two styles remain neutral. In contrast, when the VIX undercuts its historical mean value by more than 1 standard deviation, we expect a low volatility environment with above-average equity market returns. In this case, the two beta strategies ED and EH should be overweighted, while RV and TT are recommended to remain neutral.

Portfolio construction mechanism

Our portfolio construction mechanism brings together the two groups of signals generated on

the basis of technical and fundamental indicators. Given that the applicability of each signal group and each signal to the individual hedge fund styles varies, the pool of signals displays some asymmetry. Accordingly, we initially treat each signal group separately. After the trade signals have been taken into account on a group level, they are aggregated across the two groups and the four styles. This process results in clear and unambiguous trading recommendations for each hedge fund style index.

The trading recommendations from a given technical indicator are classified into overweighting, underweighting and neutral. Trading signals are implemented on the first trading day of a given month, but actually generated five trading days before that date. This lag time is necessary because even the most liquid hedge fund investments require up to a week's time to incorporate rebalancing actions. The impact of a signal extracted from a technical indicator is independent of the indicator itself, and it is consistent across all four style indices (that is, the impact of a signal for a given style index is the same for all four indicators). Note that an overweighting (underweighting) signal leads to an increase (decrease) in the relative (percentage) allocation, while neutral recommendations do not have any implications.

We also divide the signals from our fundamental indicators into overweighting, underweighting and neutral categories, to be executed on the first trading day of each month. Some of the fundamental indicators are calculated from macroeconomic and hedge fund data that may not be readily available. Therefore, some of the fundamental signals will require longer lags than others. The indicators based on financial market data, such as the VIX and the

illiquidity ratio, require no lag. Nevertheless, we provide five trading days for reallocation purposes. For the two indicators calculated from the correlation structure of the hedge fund style indices, we assume at least two weeks until the first month-end performance estimates arrive. Furthermore, the CB LEI for a given month is usually released only two to three weeks after the month-end. For monthly allocation decisions, this translates into a month-long lag for these three indicators, leaving sufficient time for the five-day reallocation period.

The impact of the signals from fundamental indicators is again consistent across all four style indices (regardless of the indicator type). However, unlike the technical indicators, which all serve the same purpose of identifying trending market environments, each fundamental indicator serves a specific function. The consolidation of these trading signals requires a weighting scheme for all the individual signals as well as for their combination into a single trading recommendation.

Only one time series of signals per style is generated for the technical indicators. Within the group of fundamental indicators, however, several signal time series may be applicable to a given style. To resolve this imbalance, we assign an equal gross signal impact X to each group of indicators (defined as the maximum total weighting impact of an indicator group), instead of appointing a specific weight to each individual trading signal. This approach ensures that a technical signal, if applicable to a given style, will always exert the same influence. The impact per signal from fundamental indicators, however, varies depending on how many apply to a given style. Although this approach results in different weightings per signal between technical and fundamental indicators most of the time, the

overall influence of both groups of signals is identical.¹³

After consolidating the signal time series on an indicator or group level, we combine the trading recommendations into a single, unambiguous time series of trading signals, denoted as Z_t . The weighting recommendation generated from each indicator group represents only a preliminary (gross) weight, because the two weights still need to be combined. This linkage is achieved through the use of parameter Y , which determines the relative weight of each of the two groups. Specifically, the relative weight assigned to the technical and the fundamental signal is Y and $(1 - Y)$, respectively. While the base case scenario implies a 50/50 equal weighting scheme, the parameter Y will be altered in our performance analysis. A permanent exception to this equal-weighting base case scenario is allowed for RV and TT. These two style indices do not imply clear and unambiguous market betas that are exploitable through technical analysis (RV), and they do not exhibit any directional exposures (TT). Therefore, technical indicators are not applicable (see section 'Technical indicators'). Given that the technical indicators do not deliver preliminary gross weights, the fundamental indicator group is assigned 100 per cent of the aggregate signal weight for these two styles.

Once the increasing or decreasing weights have been determined for each group and for each aggregate, we can obtain the time series of weighting recommendations for each hedge fund style, labelled Z_t . These incremental weights are then applied to the initial style allocation, which mandates a 25 per cent share of total capital for each style

index. Depending on the mix of signals, the total allocation may significantly exceed or fall short of 100 per cent of the portfolio capital. Thus, in order to be fully invested at all times, the trading recommendations must first be normalized to yield a cumulative allocation of 100 per cent of total capital before any portfolio changes can be implemented.

The portfolio weights are rebalanced monthly, and the trading signals are periodically implemented, beginning with the initial 25 per cent allocation per hedge fund style. This rebalancing does not involve extensive trading (reducing each position to 25 per cent each month), because a new allocation is established at least five days before the first trading day of a given month. Therefore, changes in a given style can be netted out between the old and new allocations. Taken together, we model the consolidation of the

technical and fundamental trade signals for a given style index as follows:

$$Z_t = [TI\{OW, UW, NEUTRAL\}_t \times X] \times Y \times \delta + (1 - Y \times \delta) \times \left[X \times \frac{1}{N} \sum_{i=1}^N FI\{OW, UW, NEUTRAL\}_{i,t} \right]. \quad (3)$$

where Z_t denotes the final weighting recommendation; X is the gross signal impact; Y is the signal weight of the two indicator groups; TI is a technical indicator; FI is a fundamental indicator; N is the number of fundamental indicators for a given style; and δ is a dummy variable that is equal to zero for styles without technical signals (TT and RV). Finally, the overweighting (OW), underweighting (UW) and neutral ($NEUTRAL$) raw signals are replaced by $+1$, -1 and 0 ,

Figure 1: Hedge fund style allocation model.

Table 2: Performance analysis of the hedge fund style allocation model

	<i>Indicator specification</i>	<i>Gross signal impact (%)</i>	<i>Relative weight of technical/ fundamental signals</i>	<i>Total outperformance (%)</i>	<i>Annualized outperformance (%)</i>	<i>Total model vs pure technical signals (%)</i>	<i>Max/min weight</i>	<i>Technical signals only (%)</i>	<i>Fundamental signals only (%)</i>
SMA:	20/5	50	50/50	11.69	0.70***	1.34	42.9/10.8	10.21	7.43
		75	50/50	17.98	1.06***	1.30	53.8/5.1	16.46	10.79
		100	50/50	24.80	1.42***	−0.03	66.7/0	24.84	13.96
		50	75/25	14.22	0.85***	3.64	46.2/10.5	10.21	7.43
		75	75/25	22.91	1.32***	5.53	60.9/4.9	16.46	10.79
		100	75/25	33.62	1.86***	7.04	80/0	24.84	13.96
		50	25/75	9.45	0.57***	−0.69	40/11.1	10.21	7.43
		75	25/75	14.06	0.84***	−2.07	48.3/5.3	16.46	10.79
		100	25/75	18.65	1.09***	−4.96	57.1/0	24.84	13.96
Median outperformance		—	—	17.98	1.06	1.30	53.8/5.1	16.46	10.79
SMA:	200/60	50	50/50	10.07	0.61***	3.34	42.9/10.8	6.52	7.43
		75	50/50	15.53	0.92***	4.86	53.8/5.1	10.17	10.79
		100	50/50	21.49	1.24***	5.87	66.7/0	14.76	13.96
		50	75/25	11.61	0.70***	4.78	46.2/10.5	6.52	7.43
		75	75/25	18.70	1.09***	7.74	60.9/4.9	10.17	10.79
		100	75/25	27.50	1.55**	11.10	80/0	14.76	13.96
		50	25/75	8.69	0.53***	2.04	40/11.1	6.52	7.43
		75	25/75	12.96	0.78***	2.53	48.3/5.3	10.17	10.79
		100	25/75	17.24	1.02***	2.16	57.1/0	14.76	13.96

Table 2 continued

Indicator specification	Gross signal impact (%)	Relative weight of technical/fundamental signals	Total outperformance (%)	Annualized outperformance (%)	Total model vs pure technical signals (%)	Max/min weight	Technical signals only (%)	Fundamental signals only (%)
Median outperformance	—	—	15.53	0.92	4.78	53.8/5.1	10.17	10.79

This table shows a performance analysis by comparing the portfolios generated by the hedge fund style allocation model with the equally weighted style (benchmark) portfolio. The gross signal impact (X) describes the maximum total weighting impact assigned to an indicator group. The relative weight of signals (Y) describes the influence that each indicator group is assigned in the merging process of their gross signals. Total model vs pure technical signals describes the value-added of including the fundamental indicators into the model. max/min weight denotes the resulting maximum and minimum style allocations in the model's portfolios. The technical indicator specification refers to short-term (20- and 5-day) and long-term (200- and 60-day) simple moving averages (SMA). ***/**/* indicate statistical significance of the outperformance at 1/5/10 per cent level, respectively.

respectively. Figure 1 provides a schematic illustration of the implementation of our hedge fund style allocation mechanism.

EMPIRICAL RESULTS

This section provides an overview of the performance of our hedge fund style allocation model.¹⁴ Any outperformance generated by the model depends on (1) the quality of the indicators, that is, the effectiveness of their construction and their economic rationales, and (2) the design of the portfolio allocation mechanism, that is, the gross impact of the trading signals (X) and the relative weight of the two indicator groups (Y). In addition to return outperformance, other strategy parameters, such as the oscillation of the portfolio weights and the maximum and minimum allocations, need to be considered when determining the optimal parameter setting of the model. High portfolio turnover increases transaction costs and can lead to a deterioration in performance. Our empirical analysis investigates the outperformance of the hedge fund style allocation model using *SMAs* calculated with the Russell 2000 index as the technical indicator. We calculate outperformance by comparing the portfolio generated by the style allocation model against an equally weighted style portfolio. Both portfolios are rebalanced on a monthly basis.

Table 2 shows the outperformance of the model for different timing conventions of the technical indicator as well as for specifications of the gross signal impact X and the relative weight of the two indicator groups Y . It also indicates the maximum and minimum allocations per style that result from a given model specification, the stand-alone

performances of both indicators for a given value of X and the value-added from including fundamental indicators into the allocation model.¹⁵

We first investigate both short-term (20- and 5-day) and long-term (200- and 60-day) *SMA*-specifications using the crossover method. As shown in Table 2, the hedge fund style allocation model delivers the highest absolute performance under the short-term *SMA*-specifications.¹⁶ The median outperformance of the short-term *SMA*-specification is 17.98 per cent, 2.45 percentage points higher than the 15.53 per cent median outperformance generated by the long-term specification. Accordingly, if an investor's focus is on excess returns against an equally weighted benchmark portfolio, the short-term *SMA*-specification will be superior.

However, when additional strategy parameters, such as portfolio turnover, are included into the decision-making process, we find that the relative performance of the style allocation model based on the short-term *SMA*-specification deteriorates. As shown in Table 3, for identical values of X and Y , the short-term specification comes with substantially higher portfolio turnover and weight oscillation than the long-term one.¹⁷

Under the short-term *SMA*-specification with parameters $X=75$ per cent and $Y=75$ per cent, our style allocation model generates a 143.42 per cent annual portfolio turnover of the total portfolio value (11.95 per cent on a monthly basis), which is substantially higher than the 55.41 per cent (4.62 per cent on a monthly basis) for the corresponding long-term *SMA*-specification. This high turnover is especially hazardous in a hedge fund context, because even allocations

Table 3: Comparison of portfolio turnover for different model specifications

<i>Model specification</i>		<i>Portfolio turnover</i>	
<i>SMA 20/5</i>		<i>Monthly (%)</i>	<i>Annualized (%)</i>
$X=50\%$	$Y=50\%$	5.20	62.34
$X=75\%$	$Y=50\%$	7.56	90.66
$X=50\%$	$Y=75\%$	7.83	94.33
$X=75\%$	$Y=75\%$	11.95	143.42
<i>SMA 200/60</i>			
$X=50\%$	$Y=50\%$	2.33	27.94
$X=75\%$	$Y=50\%$	3.41	40.98
$X=50\%$	$Y=75\%$	3.02	36.18
$X=75\%$	$Y=75\%$	4.62	55.41

This table shows the portfolio turnover under different model specifications. The gross signal impact (X) describes the maximum total weighting impact assigned to an indicator group. The relative weight of signals (Y) describes the influence that each indicator group is assigned in the merging process of their gross signals. The technical indicator specification refers to short-term (20- and 5-day) and long-term (200- and 60-day) simple moving averages (*SMA*).

into the most liquid managed accounts are normally accompanied by subscription notice periods.¹⁸ Redemptions may also be subject to lockup periods, redemption fees and redemption periods. Taken together, high portfolio turnover is extremely costly and may limit the practicality of our model. Accordingly, our discussion focuses on how the style allocation model performs based on the long-term *SMA*-specification.

The outperformance of the style allocation model displays considerable variability even

under the long-term scenario, as shown at the bottom of Table 2. For example, the specification using a gross signal impact $X=50$ per cent and a relative weight $Y=25$ per cent yields an outperformance of 8.69 per cent (0.53 per cent on an annual basis). As a comparison, the model specification with $X=100$ per cent and $Y=75$ per cent results in a 27.50 per cent outperformance (1.55 per cent on an annual basis). This sizeable spread is the result of the performance impact of both model parameters X and Y , where increases in X and Y lead to an increase in the total outperformance of our hedge fund style allocation model. For example, holding $Y=50$ per cent constant, an increase of X from 50 per cent to 75 per cent (that is, increasing the gross signal impact) will lead to a 5.46 per cent increase in outperformance. Holding X constant and increasing Y (that is, increasing the relative weight of the technical indicator) also leads to an increase in outperformance. Similar patterns are also observable under the short-term *SMA*-specification. Our results in Table 2 generally indicate that the performance of the *SMA*-specification is more sensitive to changes in the gross signal impact X than to changes in the relative weighting parameter Y (see Table 2). This behaviour is attributable to the design of our style allocation model. Technical indicators always produce one signal that is assigned the full gross impact. Fundamental signals are aggregated, and only if all the individual indicators are in agreement (that is, if all indicators mutually suggest over- or underweighting) will the same total rebalancing impact be assigned to this group (instead of individually). Because such mutual agreement is rare, however, the fundamental indicator group

exerts less gross signal impact, on average, and it also contributes less to the final trade signal even under the initial $Y=50$ per cent specification.

Furthermore, an increase in Y (that is, increasing the relative weight of the technical signal and decreasing the relative weight of the fundamental signals) also enhances the overall outperformance of our style allocation model. This finding is intuitive for the short-run *SMA*-specification because the stand-alone *SMA* signal outperforms the stand-alone fundamental indicator signal across all specifications (as shown in the last two columns of Table 2), and thus an increase in the weight of the technical signal will result in an even higher outperformance. Furthermore, as the performance of technical indicators deteriorates over longer time horizons, the stand-alone outperformance of both groups will be similar under the long-term *SMA*-specification. In fact, the fundamental indicators deliver superior performance in some of the scenarios. A decrease in Y does not increase the outperformance of the style allocation model because the relative weighting and the strength of the technical signals decrease. The decreasing performance contribution of the technical indicators implies that the value-added from including fundamental indicators into the style allocation model is relatively higher in the long-term *SMA*-specification. In fact, incorporating fundamental indicators results in a median value-added of +4.78 per cent (see bottom line of Table 2) over a model that only incorporates the long-term *SMA* signals.¹⁹

Another important issue relates to the portfolio weights of the different strategies. Even under the long-term *SMA*-specification, the style allocation model delivers portfolio allocations with considerable variations. For example, the model specification with gross

signal impact $X=50$ per cent and relative weight $Y=50$ per cent leads to maximum and minimum portfolio allocations of 42.9 and 10.8 per cent, respectively. When X and Y are increased to 100 and 75 per cent, respectively, the weighting spread increases to 80 and 0 per cent. The latter model specification results in an 'extreme' portfolio, where an investor has 80 per cent of funds invested in one style index and at least one other style with no allocations. For diversification purposes, these extreme weightings should be avoided, and thus we ignore X and Y specifications that lead to situations where more than two-thirds of the total portfolio is invested in only one style.

Across all model specifications, the highest gross signal impact and the highest relative weighting of the technical indicator (that is, $X=100$ per cent and $Y=75$ per cent, respectively) deliver the highest outperformance, with +27.50 per cent (1.55 per cent on an annual basis) under the model's long-term *SMA*-specification. However, this specification also leads to an extreme distribution of portfolio weights that are suboptimal from a diversification standpoint. Simultaneously considering return performance, portfolio turnover and weight distribution, the 'best' possible outperformance is +18.70 per cent (1.09 per cent on an annual basis) for the long-term *SMA*-specification with a gross signal impact of $X=75$ per cent and a relative weight of the technical indicator of $Y=75$ per cent. We consider this parameter constellation to be the 'best-fit' portfolio (or specification). It entails maximum and minimum style allocations of 60.9 and 4.9 per cent, respectively, and only a moderate portfolio turnover (55.41 per cent on an annual basis, see Table 3).

Given the distributional characteristics of hedge fund returns, concentrating only on outperformance is insufficient to establish the superiority of the best-fit specification against an equally weighted style index portfolio. Therefore, we also incorporate higher moments of the return distribution. Table 4 compares the return and risk characteristics of the equally weighted benchmark portfolio and the best-fit portfolio. Regarding the annualized performance numbers, the best-fit portfolio boasts a median return of 13.5 per cent, which is higher than the 11.7 per cent of the equally weighted benchmark; the resulting return difference is statistically significant. In addition, the best-fit portfolio generates a higher maximum and a lower minimum return over the January 1995–September 2010 sample period. Based on the standard deviation, the best-fit portfolio is slightly inferior to the equally weighted portfolio (although the difference between 5.31 and 5.25 per cent per year is not statistically significant).

Most importantly, the return and risk relationship, as indicated by the Sharpe ratio, is still superior for the best-fit portfolio. While the equally weighted returns are negatively skewed and leptokurtic, we can assume the returns of the best-fit portfolio follow a normal distribution, as indicated by the Jarque-Bera test statistic at the bottom of Table 4. Furthermore, the outperformance of the best-fit portfolio is supported by other performance measures, which do not rely on the normal distribution of returns, such as the Sortino ratio. In fact, it is most pronounced for performance measures that can capture the higher moments of the return distribution, such as the Omega measure or the Cornish-Fisher expansion of the value-at-risk.

Table 4: Comparison of the performance of the 'best-fit' model with the equally weighted style portfolio

<i>Parameters</i>	<i>'Best-fit' model</i>	<i>Equally weighted benchmark</i>
Mean	0.96%	0.87%
Median	1.06%	0.93%
Maximum	5.28%	4.68%
Minimum	-3.73%	-5.15%
Std. Dev.	1.53%	1.52%
Skewness	0.07	-0.47
Kurtosis	3.16	4.38
Sharpe Ratio*	0.43	0.37
Sortino Ratio*	0.89	0.66
Omega*	2.93	2.56
Value-at-Risk (0.99)	-2.60%	-2.65%
VaR (0.99) Cornish-Fisher	-2.59%	-3.57%
Jarque-Bera	0.33	22.01
Probability	0.85	0.00
Observations	189	189

This table shows a comparison of the performance of the 'best-fit' model with the equally weighted style (benchmark) portfolio. The 'best-fit' model is based on the long-term SMA-specification (200- and 60-day) with a gross signal impact of $X=75$ per cent and a relative weight of the technical indicator of $Y=75$ per cent. All numbers are quoted on a monthly basis.

*For the Sharpe ratio, the Sortino ratio and the Omega ratio the mean USD 1-month LIBOR-rate over sample period (0.3078 per cent) was used as the risk-free rate (or minimum return).

Finally, Figure 2 provides a graphic representation of the outperformance generated by the best-fit portfolio against the equally

weighted benchmark portfolio over time. The performance advantage created by using our style allocation model is remarkably stable. In this best case, our framework delivers an outperformance in 12 of the 15 and three-quarter years under investigation. Its strongest outperformance was in 2008, when it gained 11.25 per cent relative to the equally weighted portfolio. However, on an absolute level, 2008 is the only year in which our model generated a negative performance (-2.61 per cent compared with -12.46 per cent for the equally weighted portfolio).

Figure 2 also shows two periods of negative relative performance for the model. In 2001 and 2002, markets had just emerged from the dotcom bubble and were moving sideways, with a slight downward drift. This environment generally did not favour trend-following indicators, and thus, on a stand-alone basis, the SMAs contributed negative outperformances of -2.27 and -0.97 per cent, respectively, to the total model performance over these two years.²⁰ The two years following the 2008 market crash were also marked by underperformance of our model. In this case, several fundamental indicators, such as the illiquidity measure, the CB LEI and the style correlation indicator, were still at 'depressed levels' because of the rapid market collapse. Accordingly, the model indicated an overweighting recommendation for TT, despite the fact that it underperformed the other styles.²¹ Overall, however, despite these periods of negative relative performance, the best-fit portfolio never falls behind the equally weighted benchmark portfolio in terms of net asset value.

As a robustness check, we analyse the performance of our model using less frequent

Figure 2: Cumulative outperformance of the best-fit portfolio against the equally weighted style portfolio.

rebalancing. Specifically, instead of monthly rebalancing, we test the performance of our model using bi-monthly and quarterly rebalancing. In results not shown, we find that the risk-adjusted performance in terms of Sharpe ratios remains almost unchanged. As expected, however, the portfolio weights become more extreme (with weights for some styles even going below 1 per cent) and the portfolio turnover increases dramatically (to above 100 per cent because the weights deviate more strongly from the initial allocation). Therefore, we conclude that the best model specification is in fact based on monthly rebalancing. Finally, we further look at the performance of less frequent rebalancing in crises years (that is, in the years 2001–2002 and 2008). There are no clear patterns from this analysis, but less frequent rebalancing does not deliver superior performance during crises periods.

CONCLUSION

Over the past two decades, most hedge fund literature has concentrated on analysing the sources of hedge fund returns and establishing the value-added of including hedge funds into traditional equity and fixed-income portfolios. Little research has examined the optimal style allocations of hedge fund portfolios. Our study addresses this neglected issue by developing a style allocation framework that uses hedge fund return drivers from the prior literature to provide a systematic and robust allocation methodology. The intuition behind our framework is to exploit the insights from previous empirical studies that have documented the long-term risk exposures of hedge funds.

The first part of our model is based on hedge fund return analysis. We construct four technical indicators for those styles that exhibit directional asset class exposures. In the second part of our model, a group of fundamental

indicators is incorporated to ensure adequate consideration of other risk factors, such as systematic and macroeconomic risk. This group of fundamental risk factors contains five indicators (hedge fund style correlation, equity market correlation of hedge fund styles, financial market illiquidity, business cycle analysis and financial market volatility) that have been shown to contribute to a statistically significant aggregated outperformance across the four style indices.

We combine both indicator groups by using a rules-based portfolio construction mechanism that contains the two parameters X (gross signal impact) and Y (relative weight of signals). Increases in X and Y enhance the performance of our style allocation model. Nevertheless, an increase in either variable also leads to increasingly extreme portfolio weights, which ultimately endangers the objective of holding a well-diversified portfolio. The performance differences across the different model specifications exhibit consistent patterns across the various indicators and time horizons, indicating the robustness of our model. The model's validity is further reinforced by the fact that it generates a statistically significant outperformance compared with an equally weighted benchmark index.

Overall, our findings suggest the best-fit specification of the model (with $X = 75$ per cent and $Y = 75$ per cent) will generate a total outperformance of $+18.70$ per cent ($+1.09$ per cent on an annual basis) against the benchmark portfolio over the January 1995–September 2010 sample period. In addition, the returns generated by this best-fit portfolio exhibit superior risk–return characteristics and better downside risk protection, as indicated by the Sharpe and

Sortino ratios, the Omega measure and the value-at-risk. The risk advantage of the Cornish–Fisher expansion of the value-at-risk is particularly pronounced because the best-fit portfolio returns follow a normal distribution, while the equally weighted benchmark exhibits negatively skewed and leptokurtic returns.

In addition to the overall performance advantage of the best-fit model, outperformance is realized steadily over the entire sample period. The best-fit model outperforms the equally weighted allocation in 12 of the 15 and three-quarter years under investigation. And although it implies a negative relative performance over four time periods, the net asset value of the best-fit portfolio never falls behind that of the equally weighted model.

Our study contributes to the existing literature by showing that a systematic hedge fund style allocation model can enhance hedge fund portfolio returns by up to $+1.06$ per cent per year (median outperformance). The model achieves this outperformance by incorporating readily observable financial market return factors for hedge funds and by introducing another set of fundamental factors that are based on economic activity, market liquidity and hedge fund style correlations, among others. Therefore, our results highlight the importance and validity of a systematic hedge fund style allocation approach.

Future research should consider testing the framework proposed in this study not only on a style level but on a strategy level as well. This application may promise even more attractive results, because the risk exposures on a strategy level should be more refined than those of broader, less homogenous style groups, thus enabling a clearer and more complete identification of risk factors. The effectiveness

of a systematic framework for hedge fund style allocation could also be tested for higher allocation frequencies. Although the illiquidity of hedge fund investments makes this a difficult undertaking, the attractiveness of such a strategy could be explored using managed accounts, mutual funds that use long-short strategies or investable style/strategy indices, instead of direct offshore hedge fund investments.

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NOTES

1. See HFR Global Hedge Fund Industry Report Q4 2010, Chicago.
2. Specifically, in addition to the simple moving average (*SMA*), we also use the exponential moving average (*EMA*), a moving average convergence divergence specification (*MACD*), and Kaufman's (1995) adaptive moving average (*KAMA*). The results are not tabulated, but they are available from the authors upon request.
3. For a detailed description of the CTA universe, see Fung and Hsieh (1997b).
4. Billingsley and Chance (1996) and Edwards and Park (1996) show that CTAs, which make up a large proportion of the TT style, can enhance the diversification benefits of stocks and bonds in a mean-variance framework.
5. 'Most recent correlation coefficient' refers to the latest 12-month average of the correlation coefficient. This most recent average is then compared with the average that takes into account all available data points ± 1 historical standard deviation.
6. For a survey of recent literature on liquidity and asset pricing, see Amihud *et al* (2005). As we allocate across different hedge fund styles, our analysis is restricted to market illiquidity. In addition, there is a growing literature that analyses the liquidity of hedge funds (as measured by various forms of share restrictions) and the relationship to returns (Aragon, 2007; Liang and Park, 2007; Khandani and Lo, 2011; Teo, 2011 and Maier *et al*, 2012).
7. Cao *et al* (2012) document that about 20 per cent of their sample hedge funds have significant liquidity-timing ability.
8. The ratio can take values beyond a 10 millionth, and thus it is multiplied by 10^6 .
9. The most recent illiquidity ratio (computed over the latest 12 months) is compared with its historical average ± 1 historical standard deviation. Both parameters include all the available historical data points.
10. The 10 index factors are: (1) average weekly hours, manufacturing (2) average weekly initial claims for unemployment insurance, (3) manufacturers' new orders, consumer goods, and materials, (4) vendor performance, slower deliveries' diffusion index, (5) manufacturers' new orders, non-defense capital goods, (6) building permits, new private housing units, (7) stock prices, S&P 500 common stock, (8) money supply, M2, (9) interest rate spread, 10-year Treasury bond less Federal funds rate, and (10) index of consumer expectations.

11. A diffusion index measures the number of components contained in a given index that have increased over a specific period of time.
12. Fleming *et al* (1995) and Schwert (1989, 1990) further show that the relationship between changes in the VIX and S&P 100 returns displays asymmetry. Negative stock market returns are accompanied by larger absolute changes in expected volatility than positive stock market returns.
13. Both 'indicator groups' are assigned the same rebalancing impact. For a strategy like EH, for which only one technical indicator and four fundamental indicators are applicable, this implies that, for example, a 75 per cent rebalancing impact would be assigned to either group (although the technical indicator is only singular and not really a proper 'group'). This procedure results in equal treatment for both groups. However, because the chance of encountering four overweighting signals among the fundamental indicators is rather small, they will tend to exert the 75 per cent rebalancing impact much less frequently than the technical indicators.
14. We also explore the performance of allocation strategies that are based on technical and fundamental indicators on a stand-alone basis. Detailed results are available from the authors upon request.
15. Our fundamental indicators are constructed for the use in this study, and thus their relevance and efficiency should be explicitly tested. Because the technical indicators generate most of the model's performance, it is imperative to check whether the fundamental indicators – while underperforming the technical indicators as a group – provide true value-added.
16. This result is also true for the model specifications using more complicated technical indicators, such as *EMA*, *KAMA* and *MACD*. Detailed results are available from the authors upon request.
17. In the long-term 200/60 *SMA*-specification, the performance contribution of our fundamental indicators is higher. This reduces the variability of the portfolio weights (which is predominantly induced by the technical indicators).
18. Managed accounts are asset pools that are held by a custodian bank in an investor's name outside a hedge fund's book. The manager preserves the sole right to operate the account, that is, to implement the investment strategy. Managed accounts are usually more liquid than direct hedge fund investments, and they tend to provide protection from operational risks. Therefore, this way of investing into hedge funds has become increasingly popular over the last few years (Giraud, 2005).
19. This compares with a value-added of only +1.30 per cent under the short-term *SMA*-specification (see the upper part of Table 2).
20. The difficulty of the market environment is further documented by the observation that the fundamental indicators also exhibited negative performance for the years 2001 and 2002 (−0.20 and −0.31 per cent, respectively).
21. The TT style received an average portfolio weight of 33.6 per cent from 2009 to 2010, but it only generated a return of 0.31 per cent per month. This compares with returns of 1.29, 1.31 and 0.95 per cent for ED, EH and RV, respectively.

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APPENDIX A

Table A1: Summary of technical and fundamental indicators

Panel A: Technical indicators

- Simple Moving Average (SMA):
- ED (Equity Driven) and EH (Equity Hedge) are overweighted if the shorter moving average rises above the longer moving average, and vice versa.
 - No explicit recommendation for TT (Tactical Trading) and RV (Relative Value).
- Short-term (20- and 5-day) and long-term (200- and 60-day) moving averages

Alternative technical indicators: Exponential Moving Average (EMA), Moving Average Convergence Divergence (MACD) and Kaufman's (1995) Adaptive Moving Average (KAMA)

Panel B: Fundamental indicators

- Style correlation:
- Correlation coefficient of the three style pairs that contain TT
- A high (low) correlation environment is indicated when the most recent correlation coefficient (as measured over the prior 12 months) is at least 1 standard deviation above (below) the mean historical correlation:
- Overweighting (neutral) recommendation for TT in a high (low) correlation environment;
 - Underweighting (neutral) recommendation for RV in a high (low) correlation environment;
 - No explicit recommendation for ED and EH.
- Equity market correlation:
- Correlation coefficient between TT and the S&P 500 index
- A high (low) correlation environment is indicated when the most recent correlation coefficient (as measured over the prior 12 months) is at least 1 standard deviation above (below) the mean historical correlation:
- Overweighting (neutral) recommendation for ED and EH in a high (low) correlation environment.
 - No explicit recommendation for TT and RV.
- Market illiquidity:
- Illiquidity measure based on Amihud (2002), as defined in equation (2)
- An illiquid (liquid) stock market environment is signalled when the illiquidity ratio is at least 1 standard deviation above (below) its historical mean value:
- Overweighting recommendation for TT and underweighting recommendation for RV in an illiquid market environment;
 - Overweighting recommendation for ED and EH in a liquid market environment.

Table A1 *continued*

Business cycle: Conference Board leading economic indicators (CB LEI)	<p>The financial market outlook is positive when positive movements of the current month's CB LEI and the six-month CB LEI are accompanied by a six-month diffusion rate that is higher than 50 per cent. In contrast, the financial market outlook is negative when both the one- and six-month CB LEI changes are negative and the diffusion rate is lower than 50 per cent:</p> <ul style="list-style-type: none"> • A positive outlook implies an overweighting recommendation for ED and EH, and a neutral recommendation for TT; • A negative outlook implies an overweighting recommendation for TT, while ED and EH are kept neutral. • No signal applies for RV.
Financial market volatility: CBOE Volatility Index (VIX)	<p>The VIX signals an increasing (decreasing) stock market volatility when it is more than 1 standard deviation above (below) its historical mean value:</p> <ul style="list-style-type: none"> • An increasing volatility implies an overweighting recommendation for TT and an underweighting recommendation for RV; the other two styles remain neutral. • A decreasing volatility implies an overweighting recommendation for ED and EH; the other two styles remain neutral.

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