Factor-based replication of hedge funds using a state-space model

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Abstract

It has been suggested that the Kalman filter technique may be used to improve the quality of hedge fund replication, compared to existing replication techniques. This study uses the Kalman filter technique, along with three variations of the rolling-window regression technique, to create clones which attempt to replicate the returns of various categories of hedge fund indices. These clones are created over several scenarios and are used to compare the ability of the Kalman filter and rolling-window regression techniques. The clones are constructed using South African specific asset class and investment style factors. This study finds that the Kalman filter does not provide the expected improvement in replication ability over the rolling-window regression, for the hedge fund indices analysed. The competing techniques appear to each be better suited to replicating different hedge fund index strategies and may, therefore, be used in combination. While some of the hedge fund clones offer desirable risk characteristics, they offer lower mean returns and underperform their indices in most periods. As such, the hedge fund clones constructed in this study require further refinement and are not yet equipped for use in practice.

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Contents

1. Introduction

Vast amounts of academic research have suggested that it may be possible to replicate the returns of hedge funds and their various strategies by using hedge fund replication models (see Hasanhodzic & Lo, 2007; Wei, 2010; Amenc, Martellini, Meyfredi & Ziemann, 2010). Several types of hedge fund replication models exist, including rule-based, distributional, and factor-based replication methods. Factor-based replication has followed a natural progression where attempts have been made to improve its accuracy and, therefore, usefulness by allowing its factor exposures to vary over time. The method has progressed from using standard linear regressions to rolling-window regressions, and more recently to incorporate conditional models such as the Kalman filter and Markov regime-switching methods.

The aim of this study is to implement factor-based hedge fund replication in a South African context using the Kalman filter and rolling-window regression techniques. The models are assessed over different scenarios of data availability and are compared against each other to determine whether there is substantial improvement in replication quality (if any) when using the Kalman filter approach. These models are assessed along different measures of performance, including information ratio, return to risk and tracking error. The author is not aware of any other studies examining hedge fund replication on South African hedge fund indices, and factors, using the Kalman filter technique.

This study will begin with Sections 2, 3 and 4 providing the necessary background theory required to perform such replication strategies. Existing literature and evidence available on the topic are surveyed in Section 5. Thereafter, the data is presented and assessed in Section 6, before the methodology implemented in this study is explained in Section 7. The results are presented and analysed in Section 8, before potential limitations and biases of this study are discussed in Section 9. The paper ends by stating its conclusions in Section 10.

2. Background Theory

In this section the concept of hedge fund replication is introduced, three broad approaches are explained and the benefits of replication are assessed.

2.1 Hedge Fund Replication

There are several reasons why investors may want to invest in hedge funds, but these do not always come without their drawbacks. Often seen as active management in one of its purest forms, hedge funds have the ability to provide higher returns than other types of investment pools. This can be a result of their lack of regulation, allowing them to use high degrees of leverage and take on short positions and, therefore, use the information which they have obtained more efficiently. Though, this lack of regulation to restrict their activities could also mean little protection for investors in hedge funds. Part of the returns of hedge funds may come from investments in illiquid instruments, requiring hedge funds to implement lock-up periods and redemption notices, resulting in investments being less liquid. Hedge funds are free to invest as they please compared to other funds, such as mutual funds, allowing managers to use their skill to generate higher returns for clients, or more stable returns over bear and bull markets, or at least higher risk-adjusted returns. Contrarily, this could be perceived negatively if a fund manager does not actually possess much skill and could result in decreased returns. Investment in hedge funds is typically restricted to high net worth individuals and institutions, making investments in them largely unobtainable by the average investor. Hedge funds are generally less transparent, allowing them to keep their successful strategies to themselves. However, this may come at a cost to the investor, who may not know what the hedge fund is investing in and what exposures it is taking on. Higher fees are also generally associated with the hedge fund industry and an issue of contention is whether the average manager can justify the higher fees they charge based on the returns they provide investors, and if they really outperform on an after-fee basis. Another benefit of investments in hedge funds is that they may provide low correlation to traditional assets, therefore allowing for diversification in an investor's portfolio.

Hedge fund replication has been a topic of much interest in academic literature over the past decade by academics and practitioners alike. Hedge fund replication is the replicating of the performance and risk exposures of hedge funds, via a variety of methods, including using factors, and synthetic trades. Hedge fund replication ideally involves using more passive strategies to try and generate returns similar to those achieved by (the average) hedge funds, or at least provide some proportion of hedge fund returns. There are several approaches for replication, all of which share the common aim of attempting to retain some of the benefits of investments in hedge funds mentioned above, while eliminating or reducing several of the drawbacks associated with hedge funds (Tancar & Viebig, 2008). Due to the fact that hedge fund replication strategies attempt to mimic hedge fund returns and risk exposures, such strategies have been given various names, including hedge fund “clones” and “copycats”. These names may be misleading, as hedge fund replicators, such as factor-based models, attempt to replicate the beta exposures of hedge funds and therefore should any manager skill exist, performance of a clone is likely to be inferior to that of the hedge fund itself (Kat, 2007). In addition, this study will focus on replicating hedge fund indices, which could be viewed as the average hedge fund for a given strategy and, as such, the intention is not to match the full performance of a top-performing hedge fund.

A large part of hedge fund replication is based on the notion that we can separate hedge fund returns into alpha, which is due to the skill of the manager, and beta components, which are returns due to exposure to the market or other factors. The traditional view of beta is that it represents exposure to the market; usually an equity market. A distinct form of beta for hedge funds, known as alternative beta or hedge fund beta, can be a result of dynamic trading strategies on various assets, including traditional assets, and can result from non-traditional risk exposures. If a large part of hedge fund returns come from beta type exposures rather than alpha, then there is a strong case for hedge fund replication. More complex than traditional beta, alternative beta may require methods such as leverage, short selling and derivatives in order to obtain it. Sources of alternative beta can include equity style factors such as value versus growth stocks, small versus large cap stocks and the momentum effect, and can also come from sources such as volatility exposure and spread positions (Jaeger & Pease, 2008:4-5). The presence of alternative beta has consequences for hedge funds as to how much of their returns are actually due to alpha, this may be less than what investors have thought it to be in the past. There may also be implications for the fees that hedge funds charge. If in fact a large part of hedge fund returns are due to beta exposures (traditional and alternative), it may be more difficult for the average hedge fund manager to justify their fee structures. Benchmarks could be constructed using the alternative beta exposures discovered in asset class factor models, and could provide a more accurate way of measuring and evaluating manager performance.

If hedge funds can be replicated, this would provide additional means for investors to gain access to hedge fund type risk exposures. Investors could gain this exposure by investing either directly in hedge fund replication strategies which they implement themselves or through replication products developed by financial institutions. Institutions could use various hedge fund indices, including those for specific hedge fund strategies to develop replication products for hedge funds and their various strategies.

2.2 Methods of hedge fund replication:

• Rule-Based replication

Rule-based replication tries to take on positions in securities which are representative of specific hedge fund strategies in an attempt to achieve comparable returns (Freed, 2013). This type of replication is also called mechanical replication, and is intended to mimic the positions held by hedge funds of the same strategy. A commonly used strategy in rule-based replication is merger arbitrage, which uses public information such as merger or acquisition announcements to take positions in the underlying companies. This could allow for the common returns amongst all merger arbitrage hedge funds to be earned by the replicator fund (Freed, 2013). Additional sets of rules could also be incorporated to determine which mergers should be traded (Bowler, Ebens, Davi, & Amanti, 2006). This would be under the assumption that the cost of implementing the additional rules would be outweighed by an increase in return. A rule-based approach could be used to try replicate other event-driven hedge fund strategies, such as other corporate events or special events.

• Distributional replication

Distributional replication focuses on replicating the distributional properties of a hedge fund or hedge fund strategy. This approach aims to develop strategies that produce returns which have statistical moments (namely mean, standard deviation, skewness and kurtosis) that are similar to that of the hedge fund (Kat & Palaro, 2005). In addition, the replicator should have a correlation with traditional assets, or the investor's portfolio, comparable to that of the hedge fund. The rationale for distributional replication funds is that investors invest in specific hedge funds due to the statistical properties of their returns and not necessarily due to their returns each month (Tancar & Viebig, 2008). Such strategies may be implemented by trading futures contracts.

• Factor-based replication

This has been the most commonly researched form of hedge fund replication and is what the rest of this study will focus on. Factor-based replication uses various market risk factors, which can explain some of a hedge fund's or hedge fund strategy's return. This is done by selecting several risk factors and calculating the sensitivity of a hedge fund strategy's returns to each factor. The risk factors should be liquid and tradable instruments and indices, with the underlying including instruments such as equities, bonds, cash, commodities and currency (Bowler et al., 2006). The factors may be selected in numerous ways, including by means of economic reasoning, factor analysis or principal component analysis (Tancar & Viebig, 2008). Regardless of how the factors are chosen, the economic explanation behind them should be sound. This method has the added benefit that it is not necessary to have a complete grasp of the inner workings of the underlying hedge fund strategy, provided that the factors track the underlying fund or index relatively well (Tancar & Viebig, 2008).

A replicator fund can be constructed by taking long or short positions in the selected risk factors to the extent of the exposure that the hedge fund may have to each factor. The positions in the risk factors should be selected in such a way that the tracking error of the replication fund to the actual hedge fund or index is minimised, given the set of factors (Amenc, Géhin, Martellini & Meyfredi, 2007). The exposures are used to determine the weights of each factor in the replicator fund. These exposures are determined during a sample period of historical hedge fund returns (in-sample) and are then implemented in an out-of-sample period, going forward, to determine the weights of each factor that the replicator fund should hold. This can be compared to pure style analysis where the focus is generally not on predicting out-of-sample exposures but rather explaining the sources of return in-sample. In theory, if the replicator has similar exposures to the underlying hedge fund strategy it should be able to reproduce some of its returns. It should be noted that this form of replication is generally not intended to replicate the top-performing hedge funds but rather to produce returns similar to that of the average hedge fund of a certain strategy (Bowler et al., 2006). The aim is to replicate the portion of hedge fund returns which can be explained by traditional and alternative beta exposures.

2.3 Benefits of Replication

Benefits of factor-based replication include lower costs and fees (and avoidance of performance fees) compared to the average hedge fund, this is due to the potential of the replicator to invest largely in more passive investment products and not having to pay the high active management fees that investments in hedge funds typically require. There is less risk associated with the fund manager, as there is no single fund manager making all the decisions and, if many of the underlying factors are passive products, there may be less risk regarding manager skill. These replicators can display greater transparency than most hedge funds, as they can set an open mandate stating what funds or instruments they invest in to stand proxy for the various factors and just allow the exposures to vary over time.

A large benefit of factor-based replication funds is also improved liquidity, which is obtained as a result of the underlying investments in the liquid instruments which represent each factor, therefore, replication strategies are easily scalable. These instruments are also often listed on exchanges and are, therefore, easily tradable. Replicator funds may also be more accessible to the average investor as smaller amounts are able to be invested relative to those required by hedge funds. This would provide a larger universe of investors with the chance to access hedge fund type risk exposures, and at least some portion of their returns (Bowler et al., 2006). Hedge fund replicators may also be able to scale up their capacity, of total investment amount, to a larger amount. This is due to the liquidity of financial products that the fund invests in. The greater liquidity of hedge fund replicators could result in them having lower market impact costs than comparable hedge funds of a similar size and strategy, especially if the hedge fund attains some of its return from investing in illiquid assets.

3. Asset-Based Style Analysis

This section introduces style analysis and its foundational use in factor-based hedge fund replication.

3.1 Style Analysis

Style analysis is the calculation of the exposures of a fund to the returns of a set of predetermined asset classes and investment styles. The asset classes, or combination thereof, can represent the different styles that may be present in a fund's returns. An early paper on style analysis is that of Sharpe (1992), where an asset class factor model is developed to assess the allocation of funds and investor portfolios among various asset classes. Under this method, monthly fund returns are regressed against the monthly returns of several chosen asset classes using multiple regression analysis. The exposures of a fund's returns to the various asset classes could be obtained by observing their slope coefficients, for each factor, which were determined in the regression analysis. Quadratic programming is used to constrain the coefficients to lie between 0 and 100 (representing percentage weighting) for a long-only fund, and the sum of the coefficients should add up to 100 (i.e. 100% invested).

There are two main types of style analysis, a returns-based approach and a holdings-based approach. The returns-based approach requires just the returns of the fund in question and the underlying asset class or investment style factors. A holdings-based approach assesses and classifies the underlying investments or security holdings of a fund (Morningstar, 2007). A holdings-based approach has the advantage that it assesses the actual holdings of the fund at a point in time and therefore can accurately determine the proportion invested in each category of holdings. The returns-based approach uses historical return data of the fund and related indices or products. This is a simpler approach, however, it uses historical data and may lag behind a fund's actual holdings. The data for a holdings-based approach is not as easily available for hedge funds and hedge fund indices, as such this study focuses on the returns-based approach.

This method of determining a fund's or strategy's exposures may be preferred to a more in-depth analysis of the instruments and positions actually held by a fund, as the only information which is required is the historical return data of the funds and factors. This return data is more readily available compared to the data which may be required for an in-depth analysis that might have to be sourced from information held closely by a fund itself.

Style analysis may be used to decompose the returns of a fund into a portion attributable to style and a portion attributable to selection. Style refers to the portion of a fund's return that is due to its exposures to certain asset class factors, and selection refers the portion of return which is not explained by the model (Sharpe, 1992). Sources of the selection return include return from rotation of asset classes and security selection. Return due to selection is therefore equal to the difference between a funds realised return and the return resulting from exposure to the asset classes and styles.

The proportion of the weightings that a fund has to the various asset classes and investment styles will depend on the type of strategy that the fund adheres to. In the case of hedge funds there are many different strategies used in practice; these can be categorised into four main strategies, namely: event-driven, relative value, macro, and equity hedge strategies (CFA Institute, 2013). Event-driven strategies attempt to profit from corporate events, often involving corporate restructuring. These strategies often revolve around mergers and acquisitions, distressed companies, and shareholder activism; they may use long or short positions. Relative value strategies take advantage of short-term discrepancies in the prices of securities, often by taking on long and short positions in different securities which have some relation to each other. This is done under the assumption that any mispricing is temporary and will correct itself in future, resulting in gains for the fund. Funds may implement this strategy using fixed income instruments, instruments with embedded options, volatility-related instruments, or may take a multi-strategy approach and adapt depending on where opportunities present themselves (CFA Institute, 2013). Macro strategies attempt to profit from economic trends globally, funds take-on long or short positions in various securities based on their expectations of the movements in those securities. This is usually done at a market level using a top down approach, such as taking a position in equities in a certain region by going long or short an equity market. Equity hedge strategies use a bottom up approach to take long and short positions in equities and equity-related instruments. The traditional hedge fund strategies generally fall into this category, and funds implementing such strategies generally operate in listed equity markets. Many different variations of equity hedge funds exist, including: market neutral funds which have very low market risk, growth funds, value funds, and quantitative funds implementing directional bets.

3.2 Applied to Hedge Funds

In order for style analysis, using asset class factors, to be applied to hedge funds, several adjustments would need to be made. This is due to the underlying differences between mutual funds and hedge funds. Mutual funds are more regulated and have to implement their strategies within the constraints enforced by regulation. Hedge funds are more at liberty to invest however they desire and wherever they believe they can add value. Specifically, hedge funds have the ability to use dynamic strategies, taking on short positions, using derivatives and making use of leverage.

The asset class factor model developed by Sharpe (1992) was adapted by Fung and Hsieh (1997) and applied to hedge funds and commodity trading advisors (CTAs), grouped together as hedge funds. Sharpe's (1992) model, which was developed for use with mutual funds, is adjusted to allow for the usage of short selling and leverage to improve its effectiveness in explaining the underlying exposures of hedge funds. Fung and Hsieh (1997) distinguish between two elements of style for hedge funds, one being "location choice" and the other "trading strategy", both of which determine actual returns. In contrast, traditional managers are concerned primarily with location choice, which refers to the exposure of an investment to a specific asset class. Trading strategy refers to the direction, long or short, and quantity, the use of leverage, of an investment. Trading strategy (i.e. direction and quantity) affects the magnitude and sign of the factor exposures. Fung and Hsieh (1997) relax the constraints of Sharpe (1992) for use on hedge funds, allowing regression coefficients to be negative or positive (long and short positions) and greater than positive one and negative one (leverage).

Due to the dynamic nature of hedge funds, there is a need for time-varying factor exposures. This is where a standard regression approach with static exposures may become unrealistic in the space of hedge funds. A standard regression would provide an indication of the average exposures of the fund to the factors over the sample period, clearly overlooking any shorter-term dynamic exposures. Several methods have been suggested and applied in academic research to attempt to allow for factor exposures to vary over time and, therefore, allow factor models to track hedge funds more closely. These methods include rolling-window regressions, particle filters, Bayesians filters, Kalman filters and Markov regime-switching methods.

Rolling regressions have been used to try and capture time-varying factor exposures in attempts to improve the quality of replicated hedge fund returns. Though these have largely failed to provide the desired improvement in performance of hedge fund replicators (see Hasanhodzic & Lo, 2007). In addition, they suffer from several drawbacks, such as the ad hoc selection of the window length, more regular rebalancing, and possibly increased estimation error if smaller sample periods are used. Rolling regressions using a 24-month period provide an estimation of the average exposure of hedge fund returns to asset factors over the preceding two years, and overlooks any shorter-term (and more recent) changes in exposures during the period (Takahashi & Yamamoto, 2008). This could make rolling-window regression factor models slow to respond to changes in exposures. Shorter time periods may be used to overcome this to an extent, however, this could also increase estimation error as well as the turnover of the fund. An increase in turnover could result in higher transaction costs, and increase the cost of the strategy. Regression methods can also be very sensitive to any outliers that exist in the sample period.

More recent studies have suggested using methods such as the Kalman filter to capture time-varying exposures more efficiently than, and overcoming several drawbacks of, rolling-window regressions. The Kalman filter is able to capture the dynamic factor exposures of hedge funds and has provided improved results compared to regressing using rolling windows (Roncalli & Teiletche, 2008). The Kalman filter was initially developed by Kalman (1960), and is used widely in the various fields such as control systems engineering, to control the movement in aircraft, spacecraft and robotics, and in signal processing. The Kalman filter operates in a recursive manner to calculate the optimal estimate of the hidden system state. It is usually described in a two-step process consisting of a prediction stage, during which estimates of the hidden state are calculated *a priori*, and an update stage, during which the estimated value is updated with the latest observation to provide an *a posteriori* estimate of the state (Javaheri, Lautier and Galli, 2002). A transition equation is used to link unobservable states and a measurement equation is used to relate observed data to the unobserved state.

The Kalman filter is a more efficient technique than the standard rolling-window regression and has the ability to adapt quickly when conditions change (Roncalli & Teiletche, 2008). This may enable the Kalman filter to provide more accurate time-varying exposures than rolling-window regressions and therefore explain more of a hedge fund's returns. The Kalman filter is a conditional model and as such there is no need for a rolling-window period, rather new information is added to the model as it occurs (Amenc, Martellini, Meyfredi & Ziemann, 2010). This allows the Kalman filter to adjust for shifts or changes in factor exposures over time, over which the sample size will increase and estimation risk should be reduced as a result. Estimation risk is the risk regarding the uncertainty of parameters that have been estimated in the model. This justifies the appropriateness of using such a method for capturing time-varying factor exposures.

4. Style Factors

In this section style factors are explained and style factor evidence is provided in a South African context.

4.1 Theory

Anomalies are patterns of price behaviour that do not comply with existing theory on efficient markets, rationality and asset pricing theory (Brav & Heaton, 2002). Examples of anomalies include, amongst others, the size effect, post-earnings-announcement drift, the momentum effect, the value effect, reversals and the day-of-the-week effect.

Hedge funds may exploit these anomalies, in addition to other exposures, in order to generate the returns that their investors require from them. The ability of hedge funds to use leverage and take on short positions, in addition to long positions, provides more opportunity for them to take advantage of such anomalies compared to mutual funds and other long-only funds which face heavy regulation. If hedge fund replicators can gain exposure to the anomalies which contribute to hedge fund returns they may be able to generate the performance, at least in part, that relates to these factor exposures.

The size effect refers to the relationship between the market capitalisation value of a stock and the return it generates. Empirical evidence of this effect was initially provided by Banz (1981) who discovered that, on average, smaller cap stocks tended to provide higher returns than larger caps stocks on the New York Stock Exchange, on a risk-adjusted basis. This anomaly may be exploited by taking long positions in smaller cap stocks and short positions in larger cap stocks.

The momentum effect refers to the situation where stocks which have performed well in previous months may continue to perform well in future, and stocks which have performed poorly in preceding months will continue to do so in the future. Jegadeesh and Titman (1993) are the first to document their findings on the presence of the momentum effect on the New York Stock Exchange and the American Stock Exchange. Trading strategies based on this anomaly consist of going long past “winners” and going short past “losers”.

The value effect occurs when value stocks tend to outperform other stocks in the long run. Value stocks are often determined by using accounting ratios which provide a measure of value. Initial evidence of this effect was provided by Basu (1977), where it was discovered that stocks with low price-earnings ratios tended to outperform stocks with high price-earnings ratios, in industrial firms on the New York Stock Exchange.

4.2 South African Evidence

Various studies have also been conducted on this topic in a South African context. In a paper looking at style-based risk on the JSE, van Rensburg (2001) tested 23 style factors against the monthly returns of industrial shares during the period February 1983 to March 1999. This was done using a portfolio approach, by ranking shares on various style factors and forming three portfolios. The portfolio containing the top third of shares is given a long position and the bottom portfolio a short position, with the resultant portfolio of the representing the spread for a certain style. The style factors fall into one of three categories, namely "measures of value", "measures of future earnings growth" and "measures of irrationality and neglect", which encompasses price momentum measures. The findings show that three style factors significantly represent style-based risk in JSE industrial shares. These include a momentum factor (twelve month past positive returns), a value factor (earnings-to-price), and a factor relating to the size or quality of a firm (market capitalisation value).

Continuing in the same area of research van Rensburg and Robertson (2003), use a characteristic-based approach at an individual share level. Cross-sectional regressions are used to regress the returns of all shares listed on the JSE against 24 different style factors, over the period July 1990 to June 2000. The style characteristics, although differing slightly, are grouped into the same three categories as van Rensburg (2001), namely "measures of value", "measures of future earnings growth" and "measures of irrationality and neglect". The results of this paper confirm the findings of van Rensburg (2001), providing strong evidence for the existence of a value effect (price-to-earnings) as well as a small firm effect. However, no significant evidence was found to support the existence of a momentum effect, such as the effect previously found in JSE industrial shares.

A more recent study conducted by Strugnell, Gilbert and Kruger (2011), assesses the presence of value and size effects on the JSE, in addition to other topics, for the period January 1994 to October 2007. The interaction between value and size effects, and their independence, are evaluated. The study provides evidence of the size effect and value effect on JSE listed shares. A two-way analysis of size and value, allowing one factor to vary while keeping the other constant and vice versa, shows a small positive relationship between the two effects but not strong enough to allow either to stand proxy for the other. This justifies the use of both size and value factors in explaining returns on the JSE. There is also an indication that the size effect may be diminishing over time, however no strong evidence is provided in this regard.

Hodnett, Hsieh and van Rensburg (2012) examine 32 firm-specific characteristics for 159 shares included in the JSE All Share Index over the period January 1997 to December 2007. The characteristics are tested using cross-sectional regressions over two sub-periods as well as the full sample period. These characteristics fall into one of five categories, “fundamental values relative to share price”, “solvency and liquidity”, “fundamental growth”, “size and return momentum” and “consensus analyst forecast”. The paper found further evidence supporting the existence of a value effect, size effect and a short-term momentum effect in listed equities in South Africa.

4.3 Selecting the Asset Class Factors

There are several characteristics that are desirable for asset class factors and improve the usefulness of the models using them. These characteristics are: factors should ideally be exhaustive of all possible asset classes, factors that are mutually exclusive where there is no or minimal overlap between the instruments in each factor, and the returns of factors should differ (Sharpe, 1992). Although these characteristics are preferred, they are not strictly necessary and may not be realistically achievable in practice. It is also desirable that there are low correlations between the different factors, or, if correlations are not low, then the factors have differing standard deviations. An addition to this, as stated earlier, in the context of hedge funds would be that the factors can be invested in and are liquid. These two characteristics are necessary in order to be able to implement the replication strategies.

After assessing a selection of existing literature on style factors that are present in South African equities, it is apparent that the inclusion of size, value and momentum factors in a factor-based hedge fund replication model is justified. Hedge funds may also have directional investments in South African equities and, as such, a market (domestic) factor should be included. As hedge funds are largely unregulated, they are free to invest internationally gaining exposure to foreign equities. Thus, a factor representing world (non-South African) equities is appropriate. Hedge funds may also have a portion of assets invested in cash, as part of their strategy, or temporarily while waiting for other investment opportunities to present themselves. Thus, a factor representing exposure to cash should also be included in the model. Hedge funds, especially fixed income funds, may also trade in bonds and as such a bond factor should be included in the model.

5. Empirical Evidence

This section provides a brief assessment of academic literature covering style analysis, and surveys evidence of hedge fund replication.

5.1 Style Analysis

Using the asset class factor model developed in his paper, Sharpe (1992) conducted a style analysis of 395 different mutual funds over the period January 1985 to 1989. The mutual funds were divided into seven groups, representing different types of mutual fund styles. The factors used were bills, intermediate-term and long-term government bonds, corporate bonds, mortgage-related securities, large-cap value stocks and growth stocks, mid-cap stocks, small cap stocks, non-U.S. bonds, European stocks and Japanese stocks. It is then assessed what the average exposure of each fund type was to the 12 different asset class and style factors. In order to determine the extent to which the factors could explain the returns of the average fund, the R-squared statistics were analysed. The resulting R-squared statistics ranged from 59.3%, for utility funds, to 90.9%, for growth and income equity funds, with the majority of fund types having close to 90% of their variance explained by the various factors. The returns of several mutual funds could be explained to a large extent by the asset class factor model. This displayed the potential that style analysis could have for constructing benchmarks for the purpose of performance measurement, and the possibility of replicating a large portion of fund returns by investing in the various factors to which the fund is exposed.

Fung and Hsieh (1997) apply Sharpe's (1992) asset class factor model to 3237 U.S. mutual funds and 409 hedge funds. For mutual funds 92% of funds have 50% or more of their returns explained by the model, with the model explaining over 75% of the mutual funds returns for 47% of the funds studied. Using this same model on hedge funds, 48% of hedge funds had R-squareds below 25%. For this asset class factor model 8 factors are used, including three equity factors (domestic, foreign and emerging), two bond factors (U.S. government and non-U.S. government), a cash factor, a commodity factor, and a currency factor. This result shows that the returns generated by hedge funds are different to those from mutual funds, and adjustments would need to be made to the model to better explain hedge fund returns. Fung and Hsieh (1997) find that unlike mutual funds, hedge funds have low correlations to returns generated by standard asset classes, and performance of hedge funds tend to differ more between hedge funds than is the case with mutual funds.

5.2 Hedge Fund Replication

Hasanhodzic and Lo (2007) apply linear factor models to the subject of hedge fund replication, and attempt to create passive hedge fund clones that gain exposure to some hedge fund type risks at a lower cost and improved transparency. The factor model is applied to 1610 individual hedge funds, grouped into different categories by strategy, over the period from 1986 to 2005, by regressing their returns against six asset class factors. The six factors used provided exposure to the stock market, credit, the bond market, commodities, currencies and volatility. The paper assesses and compares two differing approaches to obtaining the factor exposures, namely an approach using fixed-weight regression and an approach using regressions with rolling-window periods. The results using fixed weights and rolling-windows were largely consistent, however, replicators using rolling-windows generally had lower returns. Differences in the performance of the two methods were attributable largely to look-ahead bias present in the fixed-weight methodology and larger estimation errors present in the rolling-window replicators. The look-ahead bias present when using fixed-weights brings their possibility of success out-of-sample into question. For several categories of hedge funds, including long/short equity and global macro, the study found that the performance of clones was comparable to the hedge funds themselves. However, for other hedge fund categories, including event driven, the replicators fall short in their performance.

Extending on the work of Hasanhodzic and Lo (2007), a study conducted by Amenc, Martellini, Meyfredi and Ziemann (2010) incorporates non-linear and conditional models into the topic of hedge fund replication. The study uses two conditional methods, namely a Markov regime-switching method and the Kalman filter, in addition to, a 24-month linear rolling-window regression and a non-linear option-based factor model. The study uses certain factors for different strategies, rather than using the same factors for all strategies as done by Hasanhodzic and Lo (2007). Monthly returns for the period January 1997 until December 1998 to calibrate the models, and an out-of-sample period, from January 1999 to December 2006, is used to assess the clones. Over the full sample period, 1998 to 2006, and using the same factors as Hasanhodzic and Lo (2007), all four methods are tested. According to their adjusted R-squared values, the option-based factor model improves the fit of the rolling-window regression. The Markov regime-switching model also provides a better fit, with R-squared values ranging from 0.16 to 0.61, though the Kalman filter is able to explain the returns substantially better than the other methods, with R-squared values ranging from 0.51 to 0.82. It is noted that, regardless of the method used, the models generally have greater explanatory power for directional strategies, such as long/short equity and dedicated short bias, as opposed to strategies such as equity market neutral. In the out-of-sample analysis, the quality of performance of the replication methods does not differ substantially, as measured by root mean squared error and correlation coefficients. The Kalman filter does not provide significantly improved replication as may be expected given the in-sample analysis. The excess returns of the replication methods, over their indices, are also assessed and although almost all excess returns are negative for almost all hedge fund strategies, the Kalman filter provides superior returns than the other methods. The Sharpe ratios of the hedge funds and their clones indicate that, regardless of the replication method, their lower performance is not compensated with lower volatility. Amenc, Martellini, Meyfredi and Ziemann (2010) then add five additional factors, and specify certain factors for each hedge fund strategy, removing factors for some. The majority of strategies experience a decrease in adjusted R-squared for the in-sample period. For the out-of-sample period, where replication is being attempted, the majority of strategies experience a decrease in root mean squared error and therefore better replication performance. The Kalman filter and the Markov regime-switching model, both experience a substantially greater reduction in mean squared root error than the other two methods. Overall, Amenc, Martellini, Meyfredi and Ziemann (2010) find that the option-based and conditional models do not necessarily provide an improvement in the quality of replication. However, the Kalman filter is able to better replicate the returns of several hedge fund strategies compared to the other techniques.

Roncalli and Teiletche (2008) look at replacing rolling-window regressions with the Kalman filter for factor-based hedge fund replication. The factor models are developed for the period 1994 to 2007 using six factors, and for three hedge fund indices separately, namely Composite HFR index, the CSFB-Tremont total index and the HFR Funds-of-Funds index. The paper notes that, in general, hedge funds appeared to have long exposures to the equity market (S&P 500). The factor exposures of the hedge fund indices are calculated using 12-month, 24-month and 36-month rolling-window regressions as well as the Kalman filter. The Kalman filter appeared to have identified changes in some exposures earlier than the rolling-window regressions, and tended to exhibit less variability in exposures over time. Although the results show that on occasion the rolling-window regression provided higher excess return than the Kalman filter, the Kalman filter generally provided better risk-adjusted returns. Notably, the Kalman filter tended to provide a higher proportion of positive monthly returns, smaller maximum drawdowns and higher correlations with the hedge fund indices, compared to the rolling-window regressions.

In the same manner as the above study, Wei (2010) assesses both rolling-window regressions and the Kalman filter for modelling the returns of hedge funds. Ten factors are used in the models, including factors representing value, size, bonds, commodities, currency and momentum. These factors are used to explain the monthly returns for HFR indices covering five hedge fund strategies, over the period January 1990 to December 2009. The index returns, for eight strategies, are first regressed against the style factors to assess the exposures and relevant factors. The results suggest that hedge funds typically select small cap and value stocks, with several funds exhibiting significant exposure to the momentum factor. For most strategies, the bond and commodity factors have little significance. On comparing the two techniques, it is found that the Kalman filter reacts quicker to changes in the factor exposures than do rolling-window regressions. The hedge fund replicators constructed using the Kalman filters produced higher returns than the rolling-window regression for all but one of the hedge fund strategies. In addition, the Kalman filter clones generally exhibited higher correlations with the indices. Comparing the returns of the Kalman filter clones and index returns for each strategy, the difference between the two appeared to decrease over time. This could be due to a more competition in the hedge fund industry and, perhaps, a decrease in exploitable arbitrage opportunities over time (Wei, 2010). As a result, hedge funds may have had to increase their reliance on returns due to factor exposures, i.e. an increased reliance on alternative beta as a source of return rather than alpha.

Amenc, Géhin, Martellini and Meyfredi (2008) examine existing literature on factor-based hedge fund replication techniques as well as replication using a payoff distribution. The authors empirically test these two approaches and assess their benefits and restrictions. After reviewing a selection of studies using factor-based replication they conclude that, in general, the accuracy of results is not satisfactory and therefore these replicators could not be seen as an alternative to hedge funds. The study then attempts to replicate that of Hasanhodzic and Lo (2007) applying fixed-weight and 24-month rolling-window regression clones to the EDHEC monthly hedge fund indices for the period January 1997 to December 2006. The 24-month rolling-window regression clones all, except short selling index, had lower mean returns than the hedge fund indices they were replicating. The difference in mean returns of clones to the index was often substantial. The study also applies the payoff distribution approach of Amin and Kat (2003), the aim of this approach is to replicate the return distribution of the underlying hedge fund index. It is pointed out that this technique is “less ambitious” than factor-based replication, as the return distribution can be replicated without returns being equal. Whereas factor-based models attempt to replicate the returns of hedge fund indices, and, therefore, are attempting to have the same return distribution as well. The study implements the payoff distribution strategy using S&P 500 index and Eurodollar futures contracts. While the clone mean returns were, in general, significantly different from the indices’ returns, their volatilities were relatively similar to in most cases. Skewness and kurtosis were also close to that of the indices, in all but one case.

Amenc, Géhin, Martellini and Meyfredi (2008) note that, while the payoff distribution strategy produced superior results than the factor-based clone, this was over a long out-of-sample period. When the out-of-sample test period was reduced to 4 years (from 8 years), performance deteriorated significantly. Therefore, this payoff distribution strategy is more suited to long-term investors and may rule these clones out for many investors.

6. Data and Univariate Statistics

In this section the data used in the analysis is introduced and described, univariate statistics and correlations are presented on the full data set and factor selection is explained.

6.1 Data

The full sample period used in this study is January 2007 to April 2015. This period was chosen due to the availability of return data for hedge fund indices, which was more restrictive than the availability of factor return data. The hedge fund indices used in this study are the Hedge News Africa indices, which provide monthly return data for 5 categories of hedge funds. These five categories are as follows: composite, fixed income, long/short equity, multi strategy, and neutral and quantitative (hereafter referred to as quantitative). Monthly return data for the hedge fund indices was obtained from INET BFA for this sample period.

The asset class and style factors selected for use in this study are those that could proxy for some of the common exposures of hedge funds and are easily accessible to South African investors. The objective of using South African-specific data is that investors in this geography may have access to different factors or different proxies for the factors. Hedge funds operating in this country may also have unique characteristics compared to those operating in other countries. It is important that these factors can be invested in and are liquid so that they can be used to replicate the performance of the hedge fund index, by investors directly or indirectly through institutional products. The risk factors used in this study include a momentum factor, a value factor, a South African equity market factor, a world (non-South African) equity market factor, a cash factor and a bond factor. The asset class and investment style factors and their underlying investment products or indices are presented in *Table 6.1* below.

Monthly asset class and investment style factor returns were obtained for this period from the Salient Quantitative Investment Management Portfolio Toolkit®. The Hedge News Africa hedge fund indices and factors will be used to construct the factor models. A size factor cannot be included in the factor model as there are no investment products available to invest in and gain exposure to size as a factor in South Africa. Including a size factor would, therefore, defeat the purpose of the replication model, as the model would not be able to be implemented in practice.

Table 6. 1 – Asset Class Factors

Factor	Index/Investment
Cash	Short Term Fixed Interest Index (STeFI)
Momentum	Salient Momentum Index Fund
Value	Salient Value Index Fund
Market (Domestic Equity)	JSE Top 40
World Equity	MSCI World
Bonds	ALBI

The Salient Momentum Index Fund and Salient Value Index Fund are both managed by Salient Quantitative Investment Management. The momentum fund tracks the Salient Momentum Index and the value fund tracks the Salient Value Index. Both of these funds use rule-based strategies and both invest in 25 to 30 stocks each, chosen from the 60 largest and most liquid stocks on the JSE. The momentum fund weights stocks on their recent performance, while the value fund weights stocks based on their cheapness as determined by several value metrics (Salient Quantitative Investment Management, 2015; Salient Quantitative Investment Management, 2016).

When developing a means to explain or replicate hedge fund returns out-of-sample, it is important to ensure that the data used is data that would actually be available to an investor at the time and not data from a future period.

The weightings for clones constructed using the Kalman filter technique were determined using the Eviews 8 statistical software package. Weightings for the various rolling-window regression clones were determined using the Fund X-Ray tool available on the Salient Investment Management Portfolio Toolkit.

6.2 Univariate statistics

This section presents the univariate statistics and correlations of the asset and investment style factor returns, as well as hedge fund index returns for the full data set.

6.2.1 Asset class and style factors

All univariate statistics and correlations presented in this section are for the full sample period acquired, January 2007 to April 2015. It should be noted that this sample period contains the financial crisis of 2007 and 2008, therefore, summary statistics may be influenced by this period of extreme volatility and uncertainty. Volatility of factors may be higher than would be experienced in a non-crisis period. The correlations between different asset classes also tends to increase during periods of crisis (Manda, 2010). This is probably due to panic by investors worldwide, and the selling out of risky positions. Portfolios may also be liquidated in part to hold some capital in cash, which is safer and escapes the market volatility.

Table 6.2

Univariate statistics of asset class and style factor returns* 2007.01 - 2015.04

	ALBI	ALSI40	MOMENTUM	MSCIWORLD	STEFI	VALUE
Mean	0.0071	0.0111	0.0146	0.0088	0.0059	0.0118
Median	0.0057	0.0147	0.0181	0.0118	0.0051	0.0120
Maximum	0.0851	0.1303	0.1872	0.1091	0.0098	0.0963
Minimum	(0.0464)	(0.1427)	(0.2041)	(0.1252)	0.0039	(0.1238)
Std. Dev.	0.0212	0.0489	0.0541	0.0369	0.0018	0.0414
Skewness	0.7242	(0.2250)	(0.7675)	(0.2819)	0.8757	(0.4417)
Kurtosis	4.7559	3.9046	6.1622	4.7127	2.3908	3.5104
Jarque-Bera	21.5876	4.2534	51.4823	13.5465	14.3282	4.3368
Probability	0.0000	0.1192	0.0000	0.0011	0.0008	0.1144
Sum	0.7121	1.1144	1.4593	0.8761	0.5921	1.1805
Sum Sq. Dev.	0.0443	0.2363	0.2901	0.1349	0.0003	0.1695
Observations	100	100	100	100	100	100

* returns shown in decimal form

Table 6.2 presents the univariate statistics of the asset class and style factors for the period January 2007 to April 2015. These statistics are somewhat as may be expected. The equity factors have the highest monthly mean returns amongst the factors, especially the ALSI Top 40, momentum and value.

The returns of these three factors are also the most volatile, having the highest standard deviations. The cash and bond factors have the lowest but most stable returns, determined by low volatility, as would be expected. All equity factors exhibit a negative skewness for the sample period, while the bond and cash factors have positive skewness. Moderately strong positive skewness is present in the ALBI and STEFI factors, while momentum has a moderately strong negative skewness for the sample period. The remaining factors display only a weak skewness. All factors, except ALSI Top 40 and Value, have Jarque-Bera statistics which reject the null hypothesis of normality at a 5% and 1% level.

6.2.2 Hedge fund indices

Table 6.3

Univariate statistics of hedge fund index returns* 2007.01 - 2015.04

	Composite	Fixed income	Long/short equity	Multi strategy	Quantitative
Mean	0.0090	0.0091	0.0097	0.0077	0.0074
Median	0.0089	0.0087	0.0117	0.0073	0.0068
Maximum	0.0244	0.0246	0.0399	0.0280	0.0203
Minimum	(0.0042)	(0.0107)	(0.0465)	(0.0333)	(0.0010)
Std. Dev.	0.0050	0.0061	0.0157	0.0094	0.0045
Skewness	0.2982	(0.5409)	(0.8167)	(1.0711)	0.6484
Kurtosis	3.3887	4.7834	4.5378	6.1498	3.1494
Jarque-Bera	2.0904	17.9481	20.7615	59.8554	7.0291
Probability	0.3516	0.0001	0.0000	0.0000	0.0298
Sum	0.8922	0.9049	0.9647	0.7631	0.7282
Sum Sq. Dev.	0.0024	0.0037	0.0241	0.0087	0.0019
Observations	100	100	100	100	100

* returns shown in decimal form

The univariate statistics of the hedge fund indices' returns are presented in table 6.3. Long/short equity has the highest mean return, as well as the highest standard deviation of returns. The hedge fund indices have lower standard deviations than the asset class and style factors, except STEFI, with which the hedge funds may have exposure to. This is intuitive as the hedge funds are generally invested in a diverse selection of assets, hence there are some diversification effects resulting in lower volatility. The hedge fund indices also had lower mean returns than most of the equity-related factors. Long/short equity and multi strategy both exhibit moderately strong negative skewness. All indices, except composite, have Jarque-Bera statistics which reject the null hypothesis of normality at a 5% significance level.

6.2.3 Correlation

Table 6.4

Correlation between factor returns						2007.01 - 2015.04
	ALBI	ALSI40	MOMENTUM	MSCIWORLD	STEFI	VALUE
ALBI	1	0.03	0.10	(0.24)	0.03	0.40
ALSI40	0.03	1	0.83	0.57	(0.18)	0.68
MOMENTUM	0.10	0.83	1	0.45	(0.19)	0.65
MSCIWORLD	(0.24)	0.57	0.45	1	(0.36)	0.29
STEFI	0.03	(0.18)	(0.19)	(0.36)	1	(0.15)
VALUE	0.40	0.68	0.65	0.29	(0.15)	1

The correlations between hedge fund indices and the various factors could provide an indication as to which factors may be able to account for a significant amount of return of a specific hedge fund index. It is also useful to look at the correlations between the different factors to decide which should be included in the factor model. If factors are too similar, multicollinearity may arise and one of the factors could be left out of the model. It is only worthwhile including a factor in the model if it explains a unique portion of a hedge fund index's return. The correlations between the various asset class factors, investment style factors and hedge fund indices are presented in Tables 6.4 and 6.5, for the full sample period, January 2007 to April 2015.

Assessing correlations between the various asset class and style factors, the ALSI Top 40 has a significant positive correlation with the momentum and value factors, and a moderate correlation with the MSCI world factor. Its largest correlation is with momentum, 0.83, and, as such, a large portion of movements in one variable might be able to be explained by the other. The ALBI and STEFI factors do not correlate strongly with any of the equity factors or each other. The highest correlations being 0.40 between ALBI and value, and -0.36 between STEFI and MSCI world. The STEFI returns are negatively correlated with the returns of all other factors, excluding ALBI which had returns that were essentially uncorrelated. The negative relationship between the returns of STEFI and the other factors may be due to the manner in which their underlying asset classes respond to different economic events, such as interest rate changes. When interest rates increase, the returns on money market instruments would increase and, over time, stock prices may tend decrease as credit becomes more expensive for consumers and corporations, hitting the growth and the bottom-line of companies. Investors may also move large portions of their portfolios out of equities and into cash during times of high uncertainty, resulting in negative correlations between these asset classes.

Table 6.5

Correlation between factors and Indice returns						2007.01 - 2015.04
	ALBI	ALSI40	MOMENTUM	MSCIWORLD	STEFI	VALUE
Composite	0.03	0.61	0.62	0.40	(0.02)	0.60
Fixed income	0.13	0.22	0.31	(0.03)	0.04	0.11
Long/short equity	0.10	0.71	0.78	0.47	(0.33)	0.67
Multi strategy	0.03	0.57	0.60	0.37	(0.30)	0.53
Quantitative	(0.18)	0.30	0.29	0.19	0.24	0.32

In table 6.5, several of the hedge fund indices have significant positive correlations with the equity-related factors; the ALSI top 40, value and momentum factors. As may be expected, the long/short equity index has the strongest correlation with these factors, with correlations of 0.71 with ALSI top 40, and 0.78 and 0.67 with the momentum and value style factors respectively. The composite and multi strategy indices also have moderate correlations with these three equity factors. The fixed income index is not strongly correlated with any of the factors, with its strongest correlation being with the momentum factor of 0.31, and, perhaps counterintuitively, having lower correlations with ALBI and STEFI compared to the equity-related factors. The quantitative index doesn't have strong correlations with any of the factors. Seeing as the quantitative index includes neutral funds, such as market neutral, it may be expected that this index would have low correlations to the equity factors.

The returns of the composite, long/short equity, and multi strategy indices exhibit strong positive correlations with each other, ranging from 0.75 between multi strategy and composite indices, 0.76 between multi strategy and long/short equity, and 0.78 between long/short equity and composite indices. The fixed income index does not correlate strongly with any of the other hedge fund indices, the factors which explain large portions of this index's return may differ from the factors which explain the equity-related hedge fund indices' returns.

6.3 Factor Selection

Initially all asset class and style factors were included in the factor model. However, it may not be the case that all six factors are suited to each of the hedge fund index categories and they may not all provide exposures that contribute significantly to the index return. Including too many factors than are required, to significantly contribute to return, for a specific index may cause other more important, or relevant, factors to be less significant in the model.

The ALSI top 40 factor was removed from the model due to a high correlation with the momentum, 0.83, and value, 0.68, factors, as shown in section 6.2.3. The reason for its removal was that of possible multicollinearity, where a large portion of the ALSI top 40 return could be explained by the momentum, and possibly value, factors. This is intuitive as the momentum and value factors are constructed, by Salient Investment Management, using the 60 largest and most liquid shares on the JSE. As such, these factors could have significant exposures to the top 40 shares, and may therefore justify the ALSI top 40's exclusion from the model. After this asset class factor was removed, all clones had an improvement in the significance of their coefficients (factor weightings), as well as improvements in their Akaike information criterion (AIC) scores.

Different indices may be more reliant on some factors and less reliant on others. Rather than applying the same "blanket" of factors to each hedge fund index, factors were selected for each index based on how significant their coefficients were and the impact of their removal on the Akaike information criterion scores (AIC). Factors with very large p-values, i.e. non-significant coefficients, were removed from the model. In each case, after the variables with large p-values were removed the coefficients of the remaining variables improved in significance and the AIC scores of each model as a whole improved. This implied that there was an improvement in model quality after specific variables were removed. Although the AIC cannot explain the actual quality of fit of the clones/models, it can be used to compare the quality of one model relative to another. This criterion was applied when excluding factors from each model, and the removal of factors was only justified if the significance of coefficients improved and the AIC score improved.

Table 6.6 presents the asset class and style factors applied to each hedge fund index after removing non-essential variables from the models, using the above measures. These factors are used in both the Kalman filter and rolling-window regression models to allow for comparability.

Table 6.6

Factors applied per hedge fund index category

Composite	Fixed Income	Long/short equity	Multi strategy	Quantitative
MOMENTUM	ALBI	MOMENTUM	MOMENTUM	ALBI
MSCIWORLD	MOMENTUM	MSCIWORLD	MSCIWORLD	MSCIWORLD
STEFI	STEFI	STEFI	STEFI	STEFI
VALUE	VALUE	VALUE	VALUE	VALUE

7. Methodology

In this section the methodology used in this study is described for the various rolling-window regressions and the Kalman filter state-space model. It is then explained how the hedge fund clone portfolios were constructed and implemented.

7.1 Style analysis

A typical style analysis decomposition, apportions a fund's returns to several different sources, such as asset class or investment style factors. Described below, equation 7.1, is the classic linear factor model used in style analysis.

$$R_t = \sum_{i=1}^{m} w_{i,t} F_{i,t} + \varepsilon_i \qquad t = 1, \dots, T \qquad (7.1)$$

Where for period t:

R_t *is the total return of the fund*

$w_{i,t}$ *is the exposure of the fund to factor i*

$F_{i,t}$ *is the returns of the factor i*

m is the number of factors

Alpha is set to zero, as done by previous style analysis and factor-based replication studies (see Sharpe, 1992; Takahashi & Yamamoto, 2008). A justification for this could be that the aim in style analysis is to explain systematic exposures and hedge fund clones aim to replicate the performance of hedge funds via these exposures. The hedge fund clones in this study are intended to replicate beta and alternative betas. In addition, the expected value of alpha is also generally assumed to be zero, as not all hedge fund managers have skill. This is also logical for this study as an attempt is made to replicate a hedge fund index and not an individual hedge fund. The index contains many different hedge funds and those with managers that do generate substantial alpha may be cancelled out by those that don't. Therefore, on average we may expect the value of alpha to be zero.

7.2.1 Rolling-window Regression

The rolling-window regression has been a widely used technique to allow for the beta values of factors to vary over time. In this study, rolling-window regressions were conducted on the data using 12-month, 24-month and 36-month window lengths. The monthly hedge fund indices' returns are run against the monthly returns of the asset class and investment style factors. The coefficients for the factors determined in the regression analysis are used as the weightings for those factors in the respective hedge fund index. Below, equation 7.2 shows the rolling-window regression used to calculate the time-varying factor exposures, β_i, of the m factors. Factor returns, F_i, are regressed on hedge fund index returns, R, from time $t-r$ to $t-1$ to calculate the beta at time t.

$$R_{t-j} = \sum_{i=1}^{m} \beta_{i,t}\, F_{i,t-j} + u_{t-j} \qquad j = 1, \dots, r \qquad (7.2)$$

$Where$:

$t\ is\ time\ in\ months$

$r\ is\ the\ window\ length$

$R\ is\ return\ of\ hedge\ fund\ index$

$\beta\ is\ the\ exposure\ of\ the\ hedge\ fund\ to\ factor\ i$

m is the number of factors

The above rolling-window regression is subject to the constraint that the absolute sum of the weights is less than 200% invested, i.e.

$\sum_{i=1}^{m} \beta_{i,t} \leq |2|$

7.2.2 State-Space Model

Exposures can be allowed to vary over time using a state-space model. A state-space model consists of two main sets of equations, the measurement equation and the state equations. Below the state-space representation is specified.

The measurement equation (signal equation) is defined as:

$$R_t = \boldsymbol{F}_t\,\boldsymbol{\beta}_t + \epsilon_t \qquad (7.3)$$

Where:

R_t *is the hedge fund return*

F_t *is the return of the factors*

β_t *is the unobservable factor exposures*

ϵ_t *is the measurement noise*

F_t is 1 x m matrix (row vector) and β_t is called the state vector and is a *m* x 1 matrix (column vector).

The state equation (transition equation) is defined as:

$$\boldsymbol{\beta}_t = I\boldsymbol{\beta}_{t-1} + \boldsymbol{\eta}_t \qquad (7.4)$$

Where:

β_t *is the unobservable factor exposure*

η_t *is the process noise*

I *is the identity matrix*

β_t is a *m* x 1 matrix (state vector), and η_t is a *m* x 1 matrix, with *m* being the number of asset class factors. In this study, the number of asset class factors is six, however four are used in each model.

Both the process noise, η_t, and the measurement error, ϵ_t, are assumed to be Gaussian with means of zero, i.e. $\epsilon_t \sim N(0, \sigma_\epsilon^2)$ and $\eta_t \sim N(0, \sigma^2)$, and are said to be white noise (Takahashi & Yamamoto, 2008).

The Kalman filter can be used to estimate the state variables (β_t) at each point in time. These state variables are the exposures of a hedge fund index to each of the factors. The Kalman filter has a recursive approach, where estimated betas are predicted and then updated (Wei, 2010).

Let $D_s = (R_1, \dots, R_t; F_1, \dots, F_t)$ be the values of the set of available observations at a point in time, s. These observations are the hedge fund index and factor returns. The conditional expectation of beta provides the beta estimate for time *t* given the information available at the time, *s*. This is presented in the equation below:

$$\beta_{t|s} = E[\beta_t | D_s]$$

In the case where $s = t$ then $\beta_{t|s}$ is filtering, and when $s < t$ then $\beta_{t|s}$ is a prediction, i.e. the predicted value of β for time t given the observation available at time s.

Conditional covariance ($V_{t|s}$) of the state estimate can be described as:

$$V_{t|s} = E[(\beta_t - \beta_{t|s})(\beta_t - \beta_{t|s})^T | D_s]$$

(T is the transpose of the matrix).

$\beta_{t|s}$ and $V_{t|s}$ are obtained by repeating the process of prediction for the following period (one step ahead), and then filtering.

The prediction for the next period is $\beta_{t|t-1}$, that is based on the information at time *t-1*, ($s = t - 1$).

$$\beta_{t|t-1} = \beta_{t-1|t-1}$$

$$V_{t|t-1} = V_{t-1|t-1} + Q$$

Q is the effect of white noise (ε_t).

$$\beta_{t|t} = K_t R_t + (I - K_t F_t^T)\beta_{t|t-1}$$

$$V_{t|t} = V_{t|t-1} - K_t F_t^T V_{t|t-1}$$

Where K is the Kalman gain,

$$K_t = \left(F_t^T V_{t|t-1} F_t + \sigma_\eta^2\right)^{-1} V_{t|t-1} F_t \qquad (7.5)$$

In essence the Kalman gain is used to “weight” the observations, providing a weighted average of the prediction $\beta_{t|t-1}$, and the current observation, R_t, in order to obtain $\beta_{t|t}$ (filtered). The weight applied to the current/new observation is the Kalman gain, and the weight to the prediction is one minus the Kalman gain. $V_{t|t}$ indicates the improvement in accuracy of the state estimation after the addition of the new observation to the model (Takahashi & Yamamoto, 2008).

7.3 Clone Construction

Several clones were constructed for each hedge fund index, using the Kalman filter and 12-month, 24-month, and 36-month rolling-window regression weights. In addition, these models were applied in different scenarios regarding the availability and timeliness of data. Three different clones were constructed per model (Kalman filter, 12-month, 24-month, and 36-month rolling-window regression). The three clone types correspond to different possible scenarios, a clone to provide a base version of the model and to assess its fit, a clone with no inputs lagged and lastly a clone with inputs lagged by one month. All clones are constructed under the assumption that investment was made at the beginning of month t. The clones are constructed for the period February 2010 to April 2015.

7.3.1 Clone to check Model Fit

The Kalman Filter model was first tested for fit using the full sample period, to determine how well it could explain the hedge fund index returns using the various factor returns.

For investment at the beginning of month t, the clone is constructed using the factor weights determined from the hedge fund index and factor returns from the end of month t. These weightings were applied to the factor returns from month t. Weights are determined for investment in month t, with month t's future return data already available and run through the model. The return equation for this "model fit" clone is:

$$R_t = F_t \, \beta_t$$

This clone was constructed only for the purpose of testing model fit as it is using data that would not have been available to an investor at the beginning of the month, when investment was made. Therefore, this clone strategy is not implementable in practice. This clone suffers from look-ahead bias, and, therefore, it is not useful in determining the success of the clone as an investment strategy.

7.3.2 Clone with no lag

For investment at the beginning of month t, the clone was constructed using factor weights determined from hedge fund index and factor returns from the end of month *t-1*. These weightings were applied to the factor returns from month t to calculate the return of this clone.

$$R_t = F_t \, \beta_{t-1}$$

This scenario avoids some look-ahead bias, however, it can't be applied to hedge funds in practice due to a one-month lag in the release or publication of the hedge fund index returns. This method could be applied to unit trusts and other funds where information is released at month-end.

7.3.3 Clone with t-2 hedge fund returns and t-1 factor returns

In an attempt to avoid look-ahead bias, the hedge fund index returns were lagged by an additional month, while still using the most recently available factor returns from the previous month-end, making this clone implementable in practice.

For investment in month *t*, weights are determined from one-month lagged hedge fund index returns and the latest factor returns. These weightings are applied to the factor returns from month *t* to get the clone's performance for period *t*.

$$R_t = F_t \, \beta_a$$

Where β_a was determined using one-month lagged hedge fund index returns and the previous month-end factor returns.

A theoretical issue arises when lagging the hedge fund and factor returns by different periods of time. In such a case, the weights are determined from running the hedge fund index returns from one month against factor returns of another month. However, as the factors returns are from a different month they didn't contribute to the hedge fund returns for that period. For example, equities may have gone up in period t-2 but down in t-1, and hedge funds may have adjusted their asset class or style weightings accordingly in these periods. Therefore, the weights of hedge funds may have been positioned to suit market conditions in period t-2, and, in this clone scenario, they would be run against the returns of factors in period t-1, which may have completely different market conditions.

This model was initially constructed using a Kalman filter approach, however, many of the factors' coefficients were not significant and could not be determined to be significantly different from zero even at a lower significance level. Due to the theoretical dilemma explained above and the insignificance of the results from the model, this clone scenario was not constructed and was, therefore, excluded from the analysis.

7.3.4 Clone with one-month lag

In order to avoid using factor returns which may not have contributed to hedge fund index returns to determine the weights clones, as done in the previous clone scenario (section 7.3.3), the factor and hedge fund returns were both lagged by one-month.

For investment at the beginning of month t, weights determined from both hedge fund index and factor returns from the end of month *t-2* were used in clone construction. These weightings were applied to the factor returns from month t to get performance. The return for this clone in month *t* is described below.

$$R_t = F_t \, \beta_{t-2}$$

In this scenario, the weights are calculated from hedge fund returns and the factor returns which may have contributed to those hedge fund returns (i.e. same month, *t-2*). This may provide more accurate weightings as compared to option in 7.3.3 as one asset class (e.g. equities) may have dropped in *t-2*, and shot up in *t-1*. In option in 7.3.3 the hedge fund index is run against factor returns which may not actually have contributed in the same proportion, therefore, skewing weightings.

7.4 Initialisation period

Approximately the first third of the full data set, 37 months, from January 2007 to January 2010, was used to initialise the models. This period was chosen as the Kalman filter requires several observations in order to stabilise its weightings once enough data has entered the model, and this period was required in order to conduct the 36-month rolling-window regression. The weightings of the Kalman filter tend to be more volatile near the beginning of the full sample period while the model is initialising and would, therefore, have worsened the Kalman filter clones' performance. The no lag and one-month lag clones were also taken into account when determining the initialisation period, this is to ensure that all clones of different lags can be compared over the same period. All performance statistics and analysis, in Section 8, were conducted on the remainder of the full sample, excluding the initialisation period, i.e. the period February 2010 to April 2015, to ensure comparability.

7.5 Tracking error

Tracking error is the standard deviation of the difference between the return of the hedge fund clone and the hedge fund index it is tracking, i.e. its benchmark. The ex-post tracking error can be used to assess how closely a clone tracked its hedge fund index over time and can be used to compare the performance of different clones. The formula for the tracking error of the clones is shown in equation 7.6. This calculates the monthly tracking error of clones in this study, and can, therefore, be annualised for comparison.

$$Tracking\ error = \sqrt{\frac{\sum_{i=1}^{n}(R_{Clone} - R_{Index})^2}{N-1}} \qquad (7.6)$$

7.6 Information ratio

The information ratio can be used to assess how well a clone performs against its benchmark hedge fund index. This takes the excess returns of the clone into account as well as the consistency of those returns, i.e. the tracking error.

$$IR = \frac{ER}{TE} \tag{7.7}$$

Where:

$ER \text{ is the excess return of the clone over its benchmark hedge fund index}$

$TE \text{ is the standard deviation of the excess returns, also referred to as the tracking error}$

It should be noted that the information ratio may become less reliable in its ability to correctly rank portfolios when excess returns are negative (Israelsen, 2005). This is because the information ratio rewards portfolios with negative excess returns for having larger residual risk. In a scenario where two competing portfolios have equal negative excess returns, the one with the higher residual risk would have the highest information ratio and would, therefore, be selected as optimal. However, an investor would prefer the same return, albeit negative, at a lower risk. An adjustment can be made to the information ratio in order to improve its ability to rank portfolios with negative returns. The modified information ratio, suggested by Israelsen (2005), can be calculated using equation 7.8. This adjustment adds an exponent to the denominator, tracking error, of excess return divided by the absolute value of excess return. If the information ratio is positive, it will be equal to the modified ratio. If the excess return is negative, the modified ratio will differ.

$$mIR = \frac{ER}{TE^{\frac{ER}{|ER|}}} \tag{7.8}$$

The modified information ratio, can take on a wide range of values, and as such these values themselves offer little insight. However, the main use of this modified ratio is to more accurately rank different portfolios in the case of negative excess returns. When using the modified information ratio, a portfolio with a higher value, least negative or most positive, is preferred to portfolios with lower values.

8. Results and Analysis

This section presents the results for the Kalman filter clones and thereafter the 12-month, 24-month and 36-month rolling-window regressions. All results, including weightings maps, are shown for the sample period excluding the initialisation period, for the months February 2010 to April 2015.

8.1 Kalman Filter

8.1.1 Tracking error

Table 8.1 Tracking error between clone and hedge fund index returns

Kalman filter 2010.02 2015.04

	Composite	Fixed income	Long/short equity	Multi strategy	Quantitative
Clone - model fit					
Monthly mean difference in return	-0.18%	-0.19%	-0.37%	-0.33%	-0.10%
Monthly tracking error	0.34%	0.58%	0.66%	0.52%	0.37%
Information ratio	(0.5182)	(0.3300)	(0.5641)	(0.6392)	(0.2582)
T-statistic*	**(4.1127)**	**(2.6192)**	**(4.4777)**	**(5.0732)**	**(2.0496)**
Modified information ratio	(0.0604)	(0.1112)	(0.2486)	(0.1741)	(0.0356)
Annualised Tracking error	1.18%	2.01%	2.30%	1.81%	1.29%
Percentage positive**	40%	37%	22%	29%	43%
Percentage negative**	60%	63%	78%	71%	57%
Clone - no lag					
Monthly mean difference in return	-0.19%	-0.20%	-0.39%	-0.35%	-0.10%
Monthly tracking error	0.36%	0.61%	0.70%	0.55%	0.39%
Information ratio	(0.5201)	(0.3282)	(0.5635)	(0.6425)	(0.2591)
T-statistic*	**(4.1285)**	**(2.6049)**	**(4.4723)**	**(5.1001)**	**(2.0563)**
Modified information ratio	(0.0663)	(0.1223)	(0.2767)	(0.1925)	(0.0404)
Annualised Tracking error	1.24%	2.11%	2.43%	1.90%	1.37%
Percentage positive**	40%	37%	22%	29%	43%
Percentage negative**	60%	63%	78%	71%	57%
Clone - one-month lag					
Monthly mean difference in return	-0.19%	-0.20%	-0.40%	-0.35%	-0.11%
Monthly tracking error	0.36%	0.62%	0.70%	0.55%	0.40%
Information ratio	(0.5232)	(0.3272)	(0.5667)	(0.6459)	(0.2656)
T-statistic*	**(4.1525)**	**(2.5974)**	**(4.4977)**	**(5.1271)**	**(2.1080)**
Modified information ratio	(0.0666)	(0.1251)	(0.2792)	(0.1945)	(0.0421)
Annualised Tracking error	1.24%	2.14%	2.43%	1.90%	1.38%
Percentage positive**	40%	37%	22%	29%	41%
Percentage negative**	60%	63%	78%	71%	59%

* T-statistics significant at 5% level in bold

** Proportion of months with positive and negative excess return

Tracking error is the standard deviation of the difference between a clone's return and its respective index's return, i.e. this difference is the excess return the clone has to its index, and can be positive or negative depending on over-performance or underperformance. The lower the amount of tracking error, the closer the clone tracks the index, and the larger the tracking error the more the clone diverges from the index. In the case of replication, a lower tracking error is more favourable. It should be emphasised that the objective of replication performed in this study is to minimise tracking error.

Table 8.1 presents the monthly mean difference in return, tracking error, the proportion of months with positive and negative excess returns, and the information ratios of the Kalman filter clones. The monthly mean difference in return is negative for all clones, across all hedge fund categories and scenarios. This indicates that, although the clones had positive excess returns in some months, they underperformed their respective hedge fund indices on average.

Mean excess return only explains part of the performance of the clones. In order to gain a more complete comparison, the risk of the excess returns needs to be assessed. Long/short equity had the largest tacking error of all clones in each case. The composite and quantitative clones had the lowest tracking error in all cases and, therefore, appear to track their respective indices the most closely. The tracking error of all clones increased, or remained equal, as the clones inputs were lagged by larger periods of time, this is expected as the no lag and one-month lag clones are using older input data than the model fit clone.

The information ratio combines the mean difference in return and tracking error data to provide a single measure with which to compare clones. In all cases, the information ratio is negative, due to the fact that all monthly mean excess returns are negative. As stated in Section 7.6, some complications may arise when using negative information ratios to rank portfolios (see Israelsen, 2005), and, as such, they can be compared using the modified information ratio. In all cases, the quantitative and composite clones had the largest, least negative, modified information ratios and would, therefore, be the preferred portfolios to investors. For all clone categories, the modified information ratios worsened as less recent information was used, i.e. as they moved towards using lagged data. The t-statistics test the null hypothesis that mean excess returns over the benchmark are equal to zero, against the alternative hypothesis that these mean excess returns are significantly different from zero. In all cases the t-statistics are large enough to reject the null hypothesis at a 5% significance level, and it can be concluded that the mean excess returns of all clones is significantly different from zero, in this case to the downside.

Across all clone styles and scenarios, the proportion of months with negative excess returns is larger than the proportion of months with positive excess returns. In general, clones more often than not underperformed their indices, rather than outperforming them. The proportion of positive and negative months remained the same between model fit clones and no lag clones. These proportions remain the same when lagging inputs by one month, except the quantitative clone which had a small deterioration in the number of months with positive excess returns.

8.1.2 Model fit clone

Although the model fit clones are constructed using input data that is not applicable in practice, these could be useful in providing an indication of how well the model can explain the various categories of hedge fund indices, using their respective factors.

Monthly mean return and standard deviation of return data for the hedge fund indices and Kalman filter model fit clones are presented in Table 8.2. Additional univariate statistics for all clones are provided in Appendices A, B and C. In all hedge fund categories analysed, the clones underperformed when compared to their respective indices in terms of mean return. However, in all cases the clones had lower standard deviations of return than the indices. In order to improve comparability of the performance of the clones and indices, their returns were adjusted for the volatility associated with those returns. This can provide a more risk neutral measure, making it easier to compare clone and index returns with varying spreads of returns around the mean. Dividing return by the standard deviation provides a measure of return per unit of risk, allowing for a reasonable comparison. All clones provided a larger return per unit of risk taken on than their respective indices, with the exception of long/short equity and multi strategy. These two clones also underperformed their benchmarks, in terms of mean return, by the largest amount.

Table 8.2 Univariate statistics of clone and hedge fund index returns*

Kalman filter - model fit			2010.02 - 2015.04
	Mean	Std. Dev.	Return/Risk
Hedge fund Indices			
Composite	0.0089	0.0047	1.9014
Fixed income	0.0090	0.0058	1.5618
Long/short equity	0.0118	0.0111	1.0643
Multi strategy	0.0092	0.0065	1.4141
Quantitative	0.0066	0.0041	1.5838
Clones - model fit			
Composite	0.0071	0.0026	2.7154
Fixed income	0.0070	0.0024	2.8489
Long/short equity	0.0081	0.0091	0.8897
Multi strategy	0.0058	0.0045	1.2888
Quantitative	0.0055	0.0019	2.9431

* returns presented in decimal form

Table 8.3 Correlation between clone and hedge fund index returns

Kalman filter - model fit			Period 2010.02 2015.04		
	Composite	Fixed income	Long/short equity	Multi strategy	Quantitative
Clones - model fit					
Composite	**0.72**	0.09	0.80	0.64	0.40
Fixed income	0.31	**0.22**	0.47	0.28	(0.03)
Long/short equity	0.65	0.04	**0.80**	0.59	0.33
Multi strategy	0.65	0.05	0.78	**0.60**	0.33
Quantitative	0.49	(0.21)	0.45	0.45	**0.44**

The correlations between the clones and their respective indices were also evaluated. This was done to assess the manner in which the index and its clone moved in relation to each other, specifically on a linear level. The correlations may provide an indication of how similar the movements in returns are, and, therefore, the degree to which a clone may replicate an index's performance. In table 8.3, the correlations for the Kalman filter model fit clone are presented. The highest correlation, 0.80, exists between the long/short equity clone and its index, with the composite clone having a correlation of 0.72 with its index. The multi strategy clone has a moderate correlation of 0.6 with its index. The lowest correlation, 0.22, of returns was between the fixed income clone and its index. Based on table 8.3 it may be expected that the clones with high correlations would perform better, relative to their indices, than clones with lower correlations with their indices. However, this is not the case as although long/short equity had the highest correlation it had the worst performance relative to its index return and the lowest return to risk measure. This demonstrates the danger of relying on correlation only to determine the quality of clone performance.

Table 8.4 t-test for mean equality between clone and hedge fund indice returns

Kalman filter - model fit		2010.02 - 2015.04
	t-statistic	Probability
Composite	2.5873	0.0108
Fixed income	2.4019	0.0178
Long/short equity	2.0834	0.0393
Multi strategy	3.4955	0.0007
Quantitative	1.6803	0.0954

The returns of all clones were tested for mean equality with their respective hedge fund indices to assess whether or not the differences in their returns were statistically significant. This was done using a t-test under the null hypothesis that the mean returns of the clones and their indices were equal. The t-test results are shown in table 8.4. All clones had large enough t-statistics to reject the null hypothesis of mean return equality at a 5% significance level, except the quantitative clone, which failed to reject the null hypothesis at this significance level. Therefore, at a 5% level it can be concluded that mean return of all clones, except quantitative, are significantly different from the mean return of their indices. This is backed up by the fact that on average the quantitative clone underperformed its index, in terms of mean return, by the smallest amount.

8.1.3 Clone with no lag

The monthly mean returns and standard deviations of the Kalman filter no lag clones are presented in table 8.5. In all cases the clones underperformed the returns of the indices that they were attempting to replicate. Long/short equity and multi strategy underperforming by the largest amount. The quantitative clone had the closest mean return to its respective index. All clones, had lower standard deviations than the indices they were replicating. Compared to the model fit clones, all clones had smaller, or equal, returns and larger, or equal to, standard deviations. This is expected as the input data is less recent and, therefore, less relevant to current investment period. When taking risk into account, the composite, fixed income and quantitative clones provided higher mean returns per unit of risk than their respective indices. The remaining clones had poorer return to risk measures than their indices. Return to risk measures for clones were all smaller than their model fit clone equivalents.

Table 8.5	Univariate statistics of clone and hedge fund index returns		
Kalman filter - no lag			2010.02 - 2015.04
	Mean	Std. Dev.	Return/Risk
Hedge fund Indices			
Composite	0.0089	0.0047	1.9014
Fixed income	0.0090	0.0058	1.5618
Long/short equity	0.0118	0.0111	1.0643
Multi strategy	0.0092	0.0065	1.4141
Quantitative	0.0066	0.0041	1.5838
Clones - no lag			
Composite	0.0070	0.0026	2.6713
Fixed income	0.0069	0.0025	2.7754
Long/short equity	0.0078	0.0092	0.8487
Multi strategy	0.0056	0.0047	1.1938
Quantitative	0.0055	0.0019	2.8148
		* returns presented in decimal form	

Table 8.6	Correlation between clone and hedge fund index returns				
Kalman filter - no lag				Period 2010.02 2015.04	
	Composite	Fixed income	Long/short equity	Multi strategy	Quantitative
Clones - no lag					
Composite	**0.67**	0.09	0.78	0.61	0.35
Fixed income	0.30	**0.10**	0.49	0.26	(0.03)
Long/short equity	0.63	0.06	**0.77**	0.58	0.30
Multi strategy	0.61	0.04	0.76	**0.56**	0.29
Quantitative	0.41	(0.21)	0.41	0.40	**0.33**

Table 8.6 presents the correlations between the returns of the hedge fund indices and the no lag clones. The highest correlations between clones and their respective indices are 0.77, for long/short equity, 0.67 for composite, and 0.56, for multi strategy. The lowest being 0.10 for the fixed income clone, having a very weak correlation with its index. The correlations of all clones with their indices are lower than the correlations for the model fit clones. This may indicate that the clones' returns did not move as similarly with their indices as they did in the model fit scenario. As such, they may not have performed as well when less recent data was used to determine the factor weights. However, as previously noted, the correlations can be misleading as to the actual quality of replication.

Table 8.7 t-test for mean equality between clone and hedge fund indice returns

Kalman filter - no lag		2010.02 - 2015.04
	t-statistic	Probability
Composite	2.7155	0.0076
Fixed income	2.5079	0.0134
Long/short equity	2.1780	0.0313
Multi strategy	3.6238	0.0004
Quantitative	1.7837	0.0769

The t-tests for mean return equality are provided in table 8.7. The t-statistics for the composite, fixed income, long/short equity and multi strategy clones were large enough to reject the null hypothesis of mean equality at a 5% significance level. It can be concluded that these clones' mean returns differ significantly from their indices' mean returns. The quantitative clone failed to reject the null hypothesis at this level, but was able to reject the null hypothesis at a 10% significance level. All clones had higher t-statistics and would be able to reject the null hypotheses at higher significance levels compared to those in the model fit clones.

8.1.4 Clone with one-month lag

The mean returns and standard deviations for the Kalman filter one-month lag clones are presented in table 8.8. All clones underperformed their indices in terms of monthly mean return. Again, the long/short equity and multi strategy clones underperformed by the largest amount on a return basis. As in the previous scenarios, the clones had lower standard deviations than the indices in all cases. Standard deviations of the one-month lag clones, were all larger or equal to the model fit and no lag counterparts. On a risk-adjusted basis, composite, fixed income and quantitative clones had a larger return per unit of risk, the remaining clones had poorer measures than their indices. The mean returns of all clone categories were lower than or equal to the previous two clone constructions, with the majority of mean returns remaining the same between the no lag and one-month lag clones. Return per unit of risk was lower for all clones, compared to the model fit and no lag clones.

Table 8.8 Univariate statistics of clone and hedge fund index returns

Kalman filter - one-month lag			2010.02 - 2015.04
	Mean	Std. Dev.	Return/Risk
Hedge fund Indices			
Composite	0.0089	0.0047	1.9014
Fixed income	0.0090	0.0058	1.5618
Long/short equity	0.0118	0.0111	1.0643
Multi strategy	0.0092	0.0065	1.4141
Quantitative	0.0066	0.0041	1.5838
Clones - one-month lag			
Composite	0.0070	0.0026	2.6560
Fixed income	0.0069	0.0025	2.7354
Long/short equity	0.0078	0.0092	0.8466
Multi strategy	0.0056	0.0047	1.1865
Quantitative	0.0054	0.0020	2.7234

* returns presented in decimal form

Table 8.9 Correlation between clone and hedge fund index returns

Kalman filter - one-month lag				Period 2010.02 2015.04	
	Composite	Fixed income	Long/short equity	Multi strategy	Quantitative
Clones - one-month lag					
Composite	**0.67**	0.09	0.78	0.61	0.35
Fixed income	0.29	**0.07**	0.49	0.26	(0.04)
Long/short equity	0.63	0.06	**0.77**	0.58	0.30
Multi strategy	0.61	0.05	0.75	**0.56**	0.29
Quantitative	0.42	(0.19)	0.42	0.41	**0.32**

Table 8.9 presents the correlations between the one-month lag clones and their respective indices. The highest correlations between a clone and its index are for long/short equity, 0.77, and composite, 0.67. A moderate correlation exists between the multi strategy clone and its index, of 0.56. The weakest correlation is again between the fixed income clone and its index, 0.07, their returns were largely uncorrelated. All correlations were weaker than, or equal to, the model fit and no lag clones.

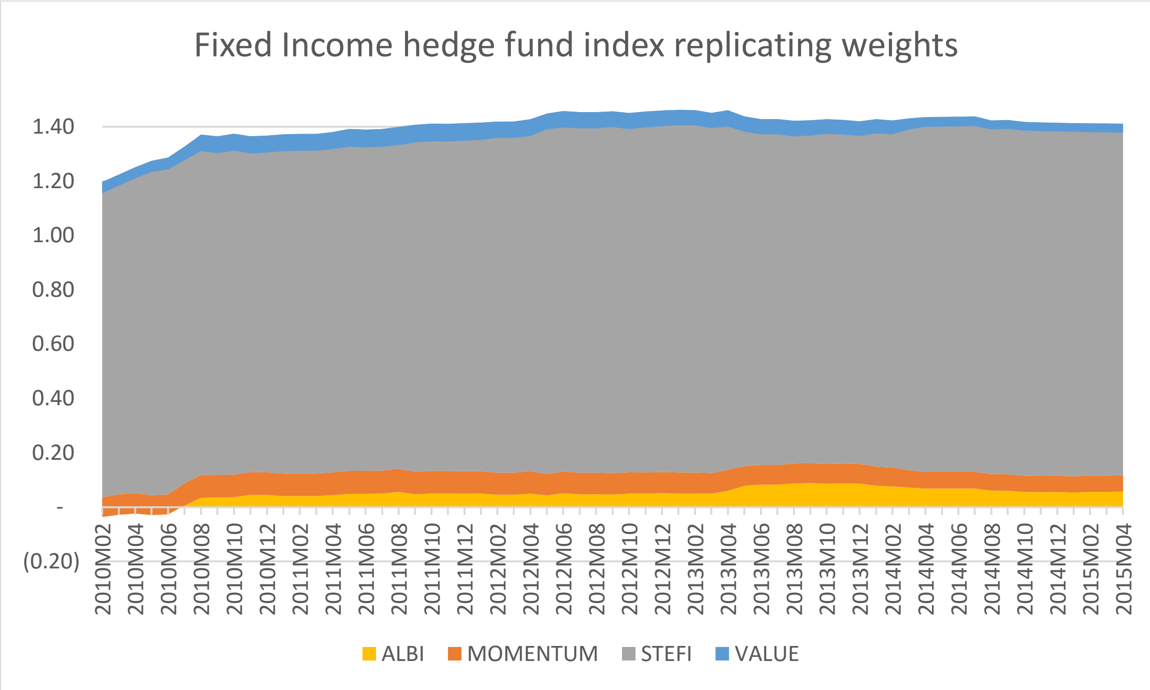
Table 8.10	t-test for mean equality between clone and hedge fund indice returns	
Kalman filter - one-month lag		2010.02 - 2015.04
	t-statistic	Probability
Composite	2.7262	0.0073
Fixed income	2.5283	0.0127
Long/short equity	2.1948	0.0300
Multi strategy	3.6494	0.0004
Quantitative	1.8337	0.0691

The t-statistics for the one-month lag clones, presented in table 8.10, indicate that composite, fixed income, long/short equity and multi strategy all rejected the null hypothesis of equality of mean returns between the Kalman filter one-month lag clones and their indices at a 5% significance level. The quantitative clone fails to reject the null hypothesis at this significance level, and, therefore, it can't be concluded that the clone mean returns are significantly different from their indices. However, it can reject the null hypothesis a t a 10% level.

It is intuitive that some clones, such as long/short equity, performed more poorly once inputs had been lagged, and weights determined using data available at *t-2* (month-end) were used to invest at the beginning of period t. Long/short equity funds are more dependent on the equity factors, which are generally more volatile and can change drastically from one period to another. As such, this reduced performance may be expected. Equities may generate large negative returns in one period and large positive returns in the next, therefore, weights determined using data from one month may not be appropriate for investing in the following month.

8.1.5 Factor weighting maps

Figure 8.1 - Kalman filter fixed income weights



The asset class and style factor weightings for all clones were stacked in order to provide a graphical representation of each clone's holdings and exposures over time. It is important to note that the weightings provided here are not necessarily representative of the holdings of the underlying funds in the index. Firstly, because the index is an amalgamation of all the hedge funds it represents and ,therefore, represents, in kind, an average of all the hedge funds. Secondly, the weightings provided by the Kalman filter are those that are estimated in an attempt to replicate the index return. The exposures may be representative of those required to generate the same return but may differ to those applied in the hedge funds in practice.

Figure 8.1 illustrates the factor and asset class weights of the fixed income clone constructed using the weights determined by the Kalman filter model. These weights were used to attempt to replicate the underlying index's performance. As is evident in the weighting map, this clone is constructed using a large weighting in cash, with a much smaller weighting placed on investment in the ALBI, momentum and value factors. The clone holds a fairly constant exposure to the equity factors, value and momentum, throughout the period while initially holding almost no bond exposure. Bond exposure is increased during the latter half of 2010, and this small exposure is held for the remainder of the sample period.

Figure 8.2 - Kalman filter composite weights

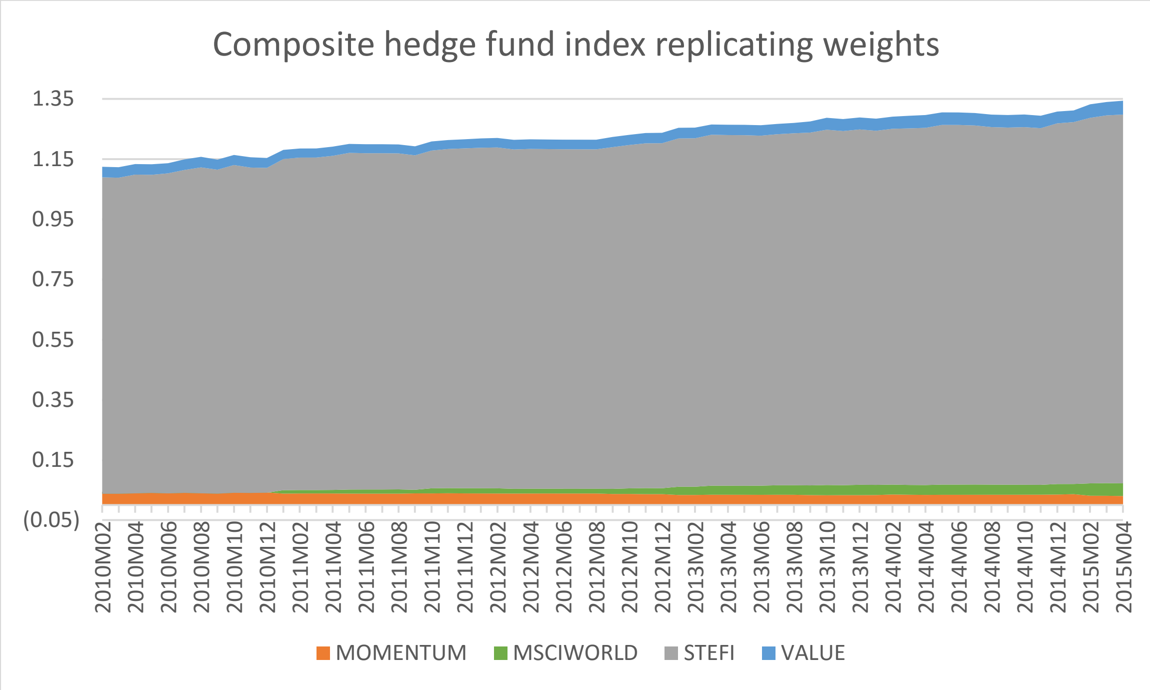
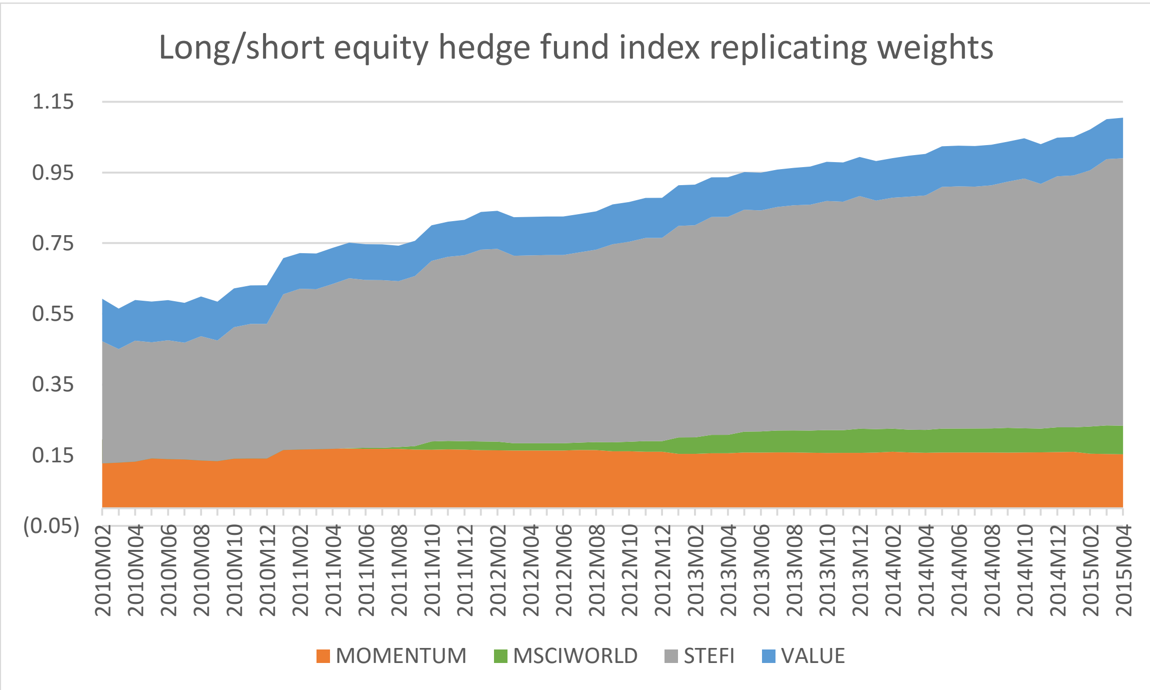


Figure 8.2 illustrates the clone weights for the composite hedge fund index category. This clone has a very large exposure to cash, supplemented by small exposures to international equity (MSCI World), and local momentum and value equity factors.

Figure 8.3 - Kalman filter long/short equity weights



The weights for the long/short equity clone are illustrated in figure 8.3. Over time the overall exposure of the clone increases through the sample period, ending the period with double the exposure it started with. Although there is a large exposure to cash (STEFI), the long/short equity clone also has significant exposure to the local equity factors, value and momentum throughout the sample period. During the sample period the clone takes on a small exposure to international equity, through the MSCI World factor, and gradually increases this exposure over time. The long/short equity hedge fund index has the highest return, of the indices, for the sample period. As such, the long/short equity clone is required to take on larger equity exposures than the other clone categories, as these equity exposures tend to generate higher returns.

Figure 8.4 - Kalman filter multi strategy weights

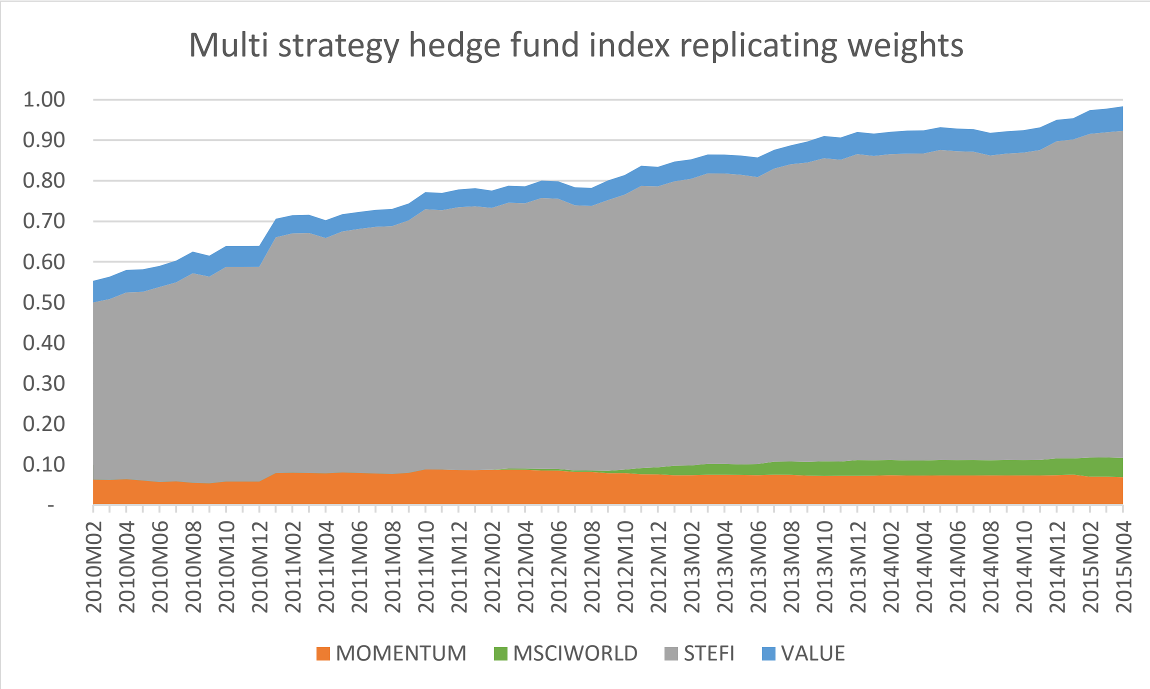
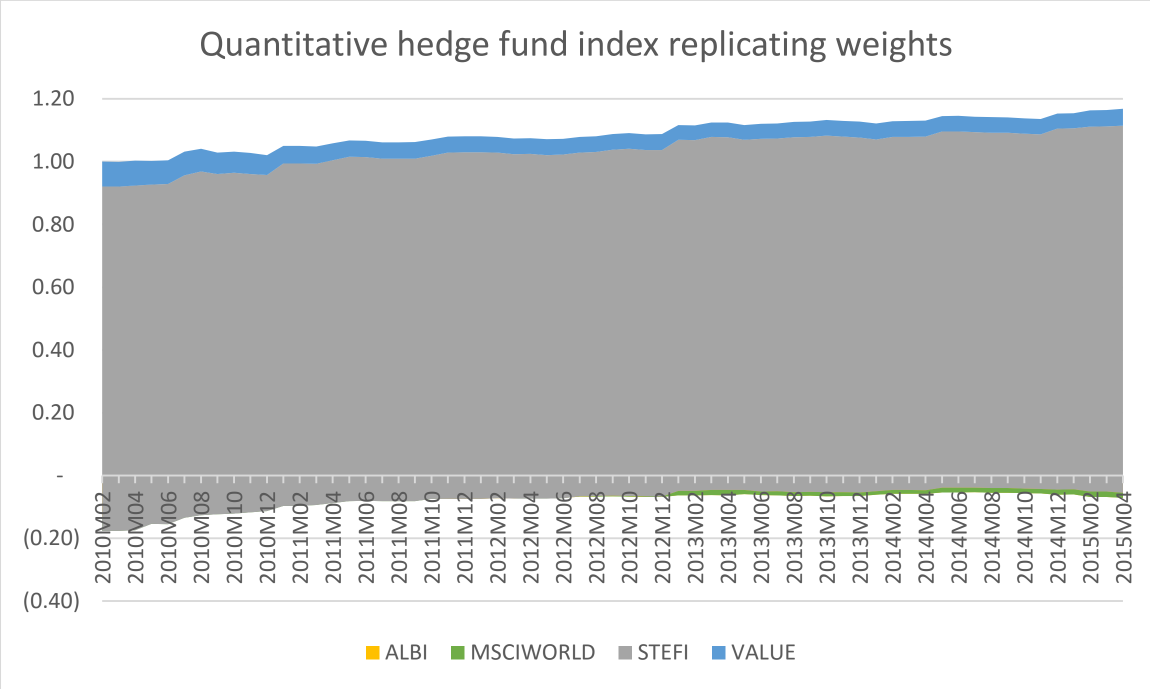


Figure 8.4 illustrates the factor weightings of the multi strategy replicating clone. The clone has a large exposure to the STEFI factor, and exposures to the local equity, momentum and value, factors. During the period a small exposure is taken on international equity, via the MSCI World factor. The overall exposure of the clone also increases during the sample period.

Figure 8.5 - Kalman filter quantitative weights



The factor weightings for the quantitative and market neutral hedge fund clones are illustrated in figure 8.5. The quantitative clone invests mainly in cash, STEFI, and has little exposure to the equity factors. This may be because this hedge fund category includes market neutral funds which have near zero net equity market exposure. Out of all the hedge fund categories, the quantitative index has the lowest mean monthly return and as such has a return that is closest to cash and money market instruments. The quantitative index also has the lowest standard deviation of all the indices. These two characteristics combined may result in cash having a large weighting, as the STEFI has a low return, close to the quantitative returns, as well as a low standard deviation.

Overall, the weights and exposures of the Kalman filter clones are quite stable over time. This is contrary to what may have been expected from this model. However, this is similar to the findings of Roncalli and Teiletche (2008) who noted that the Kalman filter tended to have less variability in exposures over time when compared to the rolling-window regression.

8.1.6 Summary

On average, all Kalman filter clones had negative excess returns and underperformed their benchmark hedge fund indices in terms of mean excess returns. These excess returns were considered statistically significant at a 5% significance level and conclude that all clones significantly underperformed. Long/short equity consistently had the largest tracking error and therefore tracked its index the least closely. The composite and quantitative clones consistently tracked their respective indices the closest and, therefore, had the lowest tracking error. After ranking the clones based on their modified information ratios, the quantitative and composite clones are the preferred clone categories, and, therefore, best suited to the Kalman filter technique. The long/short equity clone is considered the worst investment in all scenarios.

In all clones, for all scenarios of input lags, the standard deviations of the clones were lower than that of their indices. The same applies for the returns of the clones, in all cases. For the Kalman filter technique the composite, fixed income and quantitative clones consistently provided better return per unit of risk compared to that of their respective indices. Across all clones scenarios and categories, except quantitative, the t-test for mean return equality between the clones and their indices rejected the null hypothesis of mean equality at a 5% significance level. Therefore, it can be concluded that all clones, excluding quantitative clones, have significantly different mean monthly returns from their benchmark indices. These clones significantly underperformed their hedge fund indices in terms of mean return.

Comparing the results of the model fit, no lag and one-month lag clones provides reveals how the timeliness of data may affect the performance of the clone and therefore the investment. In general, as the hedge fund indices and factor returns were lagged, each time, the mean returns of the clones either decreased or remained the same. In all hedge fund categories, the standard deviations of the clones either increased or remained the same. It follows that the return per unit of risk decreased for all clones as the lag increased. This highlights the importance of the timeliness of data availability in practice when making investment decisions.

8.2 Rolling-window regression

8.2.1 Tracking error

Table 8.11	Tracking error between clone and hedge fund index returns				
12-month rolling-window regression					2010.02 2015.04
	Composite	Fixed income	Long/short equity	Multi strategy	Quantitative
Clone - model fit					
Monthly mean difference in return	-0.19%	-0.41%	-0.16%	-0.15%	-0.04%
Monthly tracking error	0.25%	0.38%	0.50%	0.42%	0.30%
Information ratio	(0.7538)	(1.0846)	(0.3213)	(0.3690)	(0.1239)
T-statistic*	**(5.9830)**	**(8.6090)**	**(2.5498)**	**(2.9291)**	(0.9836)
Modified information ratio	(0.0458)	(0.1574)	(0.0816)	(0.0637)	(0.0112)
Annualised Tracking error	0.85%	1.32%	1.75%	1.44%	1.04%
Percentage positive**	22%	13%	37%	32%	49%
Percentage negative**	78%	87%	63%	68%	51%
Clone - no lag					
Monthly mean difference in return	-0.19%	-0.41%	-0.13%	-0.16%	-0.06%
Monthly tracking error	0.36%	0.55%	0.77%	0.56%	0.42%
Information ratio	(0.5308)	(0.7333)	(0.1757)	(0.2912)	(0.1390)
T-statistic*	**(4.2131)**	**(5.8202)**	(1.3944)	**(2.3114)**	(1.1031)
Modified information ratio	(0.0677)	(0.2258)	(0.1030)	(0.0911)	(0.0242)
Annualised Tracking error	1.24%	1.92%	2.65%	1.94%	1.45%
Percentage positive**	32%	17%	41%	38%	49%
Percentage negative**	68%	83%	59%	62%	51%
Clone - one-month lag					
Monthly mean difference in return	-0.21%	-0.40%	-0.18%	-0.16%	-0.04%
Monthly tracking error	0.35%	0.60%	0.81%	0.59%	0.43%
Information ratio	(0.5872)	(0.6584)	(0.2218)	(0.2759)	(0.0891)
T-statistic*	**(4.6606)**	**(5.2262)**	(1.7606)	**(2.1899)**	(0.7071)
Modified information ratio	(0.0721)	(0.2388)	(0.1446)	(0.0949)	(0.0162)
Annualised Tracking error	1.21%	2.09%	2.80%	2.03%	1.48%
Percentage positive**	27%	19%	38%	38%	51%
Percentage negative**	73%	81%	62%	62%	49%

* T-statistics significant at 5% level in bold

** Proportion of months with positive and negative excess return

The mean difference in return, tracking error and information ratios for the 12-month rolling-window clones are presented in table 8.11. The monthly mean difference in return is negative for all clones, suggesting that the clones had negative excess returns to their respective benchmarks. The fixed income clone had the lowest excess return in all three clone constructions, underperforming its index by the largest amount, -0.40% for the one-month lag clone. The quantitative clone had the smallest underperformance, having a mean difference in return of -0.04% for the one-month lag clone.

Amongst the model fit, no lag and one-month lag clones, long/short equity exhibited the highest amount of tracking error, while the composite and quantitative clones had the lowest tracking error in all cases. As would be expected, when the inputs were lagged the tracking error of the clones to their indices increased, with the exception of composite which experienced a small reduction in tracking error between the no lag and one-month lag clones. In all 12-month clones, there were a larger proportion of negative excess returns than there were positive excess returns. The tracking error on these clones is, therefore, usually to the downside, this is supported by the negative mean difference in returns.

The t-statistics, calculated from the information ratios, are large enough to reject the null hypothesis in all scenarios for the composite, fixed income and multi strategy clones at a 5% significance level. It can be concluded that for these hedge fund index categories, the 12-month rolling-window regression clones had excess returns which were significantly different from zero. They statistically underperformed their indices. The modified information ratios are the largest for the composite and quantitative clones in all scenarios, suggesting that, of the hedge fund categories being replicated, these would be the most attractive to an investor. This is taking into account the excess returns they offer and the risk associated with these returns, i.e. their consistency. Across all scenarios the fixed income clone was the least preferred investment as it had the lowest modified information ratio. In all categories, the modified information ratios worsened from the model fit to the one-month lag clones, suggesting that an investor would prefer to invest in the model fit clones, if this were possible in practice.

Table 8.12 Tracking error between clone and hedge fund index returns

24-month rolling-window regression					2010.02 2015.04
	Composite	Fixed income	Long/short equity	Multi strategy	Quantitative
Clone - model fit					
Monthly mean difference in return	-0.22%	-0.39%	-0.17%	-0.21%	-0.07%
Monthly tracking error	0.30%	0.47%	0.61%	0.47%	0.35%
Information ratio	(0.7511)	(0.8319)	(0.2843)	(0.4431)	(0.2060)
T-statistic*	**(5.9614)**	**(6.6030)**	**(2.2566)**	**(3.5169)**	(1.6351)
Modified information ratio	(0.0669)	(0.1859)	(0.1047)	(0.0972)	(0.0248)
Annualised Tracking error	1.03%	1.64%	2.10%	1.62%	1.20%
Percentage positive**	21%	16%	32%	30%	43%
Percentage negative**	79%	84%	68%	70%	57%
Clone - no lag					
Monthly mean difference in return	-0.24%	-0.38%	-0.19%	-0.21%	-0.07%
Monthly tracking error	0.34%	0.53%	0.67%	0.51%	0.40%
Information ratio	(0.7000)	(0.7087)	(0.2801)	(0.4012)	(0.1734)
T-statistic*	**(5.5559)**	**(5.6254)**	**(2.2230)**	**(3.1841)**	(1.3766)
Modified information ratio	(0.0815)	(0.2003)	(0.1266)	(0.1057)	(0.0277)
Annualised Tracking error	1.18%	1.84%	2.33%	1.78%	1.39%
Percentage positive**	24%	22%	33%	35%	46%
Percentage negative**	76%	78%	67%	65%	54%
Clone - one-month lag					
Monthly mean difference in return	-0.24%	-0.37%	-0.19%	-0.22%	-0.07%
Monthly tracking error	0.33%	0.55%	0.68%	0.52%	0.40%
Information ratio	(0.7103)	(0.6749)	(0.2789)	(0.4179)	(0.1722)
T-statistic*	**(5.6382)**	**(5.3565)**	**(2.2139)**	**(3.3169)**	(1.3672)
Modified information ratio	(0.0791)	(0.2015)	(0.1290)	(0.1135)	(0.0280)
Annualised Tracking error	1.16%	1.89%	2.36%	1.80%	1.40%
Percentage positive**	22%	22%	30%	35%	49%
Percentage negative**	78%	78%	70%	65%	51%

* T-statistics significant at 5% level in bold

** Proportion of months with positive and negative excess return

The tracking errors for the 24-month rolling-window clones are presented in table 8.12. All clones have negative mean differences in return, underperforming their indices on average. It holds that the long/short equity clones have the largest tracking error and the composite and quantitative clones have the lowest tracking error in all three clone variations. The composite and quantitative clones tend to track their hedge fund indices the most closely, and the long/short equity clone does so the least closely. As the clones' inputs were lagged the amount of tracking error increased in all cases expect for the composite clone which had a slight decrease in tracking error between the no lag and one-month lagged clones. All 24-month rolling-window clones experienced a larger number of months with negative excess returns to their indices, than they did positive excess returns. As such excess returns more often than not negative.

The t-statistics for the composite, fixed income, long/short equity and multi strategy clones were large enough to reject the null hypothesis in all scenarios at a 5% significance level. The quantitative clones failed to reject the null hypothesis at this level. It can be concluded that excess returns of all clone categories, excluding quantitative, are significantly different from zero and that clones significantly underperformed their indices. Using the modified information ratios to rank the clones, the composite and quantitative clones would be preferred by investors in all scenarios, based on their excess return and residual risk characteristics. The clone of least preference to investors was the fixed income clone. In general, an investor would also prefer to invest in the model fit clones, however this is not implementable in practice.

Table 8.13 Tracking error between clone and hedge fund index returns

36-month rolling-window regression	Composite	Fixed income	Long/short equity	Multi strategy	Quantitative
				2010.02	2015.04
Clone - model fit					
Monthly mean difference in return	-0.23%	-0.40%	-0.20%	-0.21%	-0.08%
Monthly tracking error	0.31%	0.49%	0.66%	0.48%	0.36%
Information ratio	(0.7505)	(0.8207)	(0.3077)	(0.4312)	(0.2139)
T-statistic*	**(5.9566)**	**(6.5142)**	**(2.4421)**	**(3.4223)**	(1.6980)
Modified information ratio	(0.0724)	(0.1949)	(0.1342)	(0.1004)	(0.0278)
Annualised Tracking error	1.08%	1.69%	2.29%	1.67%	1.25%
Percentage positive**	22%	14%	30%	37%	43%
Percentage negative**	78%	86%	70%	63%	57%
Clone - no lag					
Monthly mean difference in return	-0.25%	-0.39%	-0.24%	-0.24%	-0.09%
Monthly tracking error	0.34%	0.52%	0.70%	0.53%	0.40%
Information ratio	(0.7381)	(0.7512)	(0.3399)	(0.4515)	(0.2204)
T-statistic*	**(5.8587)**	**(5.9625)**	**(2.6979)**	**(3.5838)**	(1.7495)
Modified information ratio	(0.0851)	(0.2046)	(0.1684)	(0.1260)	(0.0344)
Annualised Tracking error	1.18%	1.81%	2.44%	1.83%	1.37%
Percentage positive**	22%	19%	32%	37%	44%
Percentage negative**	78%	81%	68%	63%	56%
Clone - one-month lag					
Monthly mean difference in return	-0.25%	-0.39%	-0.24%	-0.24%	-0.09%
Monthly tracking error	0.34%	0.53%	0.70%	0.54%	0.40%
Information ratio	(0.7421)	(0.7439)	(0.3471)	(0.4470)	(0.2337)
T-statistic*	**(5.8903)**	**(5.9044)**	**(2.7547)**	**(3.5476)**	(1.8546)
Modified information ratio	(0.0872)	(0.2069)	(0.1723)	(0.1285)	(0.0370)
Annualised Tracking error	1.19%	1.83%	2.44%	1.86%	1.38%
Percentage positive**	24%	19%	33%	38%	43%
Percentage negative**	76%	81%	67%	62%	57%

* T-statistics significant at 5% level in bold

** Proportion of months with positive and negative excess return

Table 8.13 presents the mean difference in return, tracking error and information ratios for the 36-month rolling-window regression clones. The mean difference in return is negative in all cases, therefore on average all clones produced negative excess returns to their benchmarks. The quantitative clones underperformed their indices by the smallest amount, while the fixed income clones consistently underperformed their indices by the largest amount. For all clones the percentage of positive excess returns were less than negative excess returns, indicating that in the majority of months the clones underperformed.

The standard deviation of the excess returns, tracking error, was largest for the long/short equity clones in all scenarios. The composite and quantitative clones had the lowest tracking error in all three scenarios. As such, the composite and quantitative clones track their respective indices the most closely, while the long/short equity clone does so the least closely. The tracking errors for each category of hedge fund clone, generally deteriorate as the input data is lagged, i.e. when moving from the model fit clone to the one-month lag clone.

The t-statistics for all hedge fund clone categories, excluding quantitative, are large enough to reject the null hypothesis in all scenarios at a 5% significance level. Therefore, for all hedge fund categories, excluding quantitative, the clones' excess returns over the indices differ from zero. The clones, in general significantly underperform their respective indices. According to the modified information ratio, the clones that would be preferred by investors are the composite and quantitative clones as they have the least negative modified information ratios. These ratios also worsened as the input data was lagged, as such investors would prefer the characteristics of the model fit clones to the one-month lag clones. As was the case with the other rolling-window regressions, the fixed income clone is the least preferred investment.

8.2.2 Model fit clone

Table 8.14	Univariate statistics of clone and hedge fund index returns		
12-month rolling-window regression - model fit			2010.02 - 2015.04
	Mean	Std. Dev.	Return/Risk
Hedge fund Indices			
Composite	0.0089	0.0047	1.9014
Fixed income	0.0090	0.0058	1.5618
Long/short equity	0.0118	0.0111	1.0643
Multi strategy	0.0092	0.0065	1.4141
Quantitative	0.0066	0.0041	1.5838
Clones - model fit			
Composite	0.0070	0.0041	1.6926
Fixed income	0.0049	0.0043	1.1455
Long/short equity	0.0101	0.0102	0.9917
Multi strategy	0.0076	0.0053	1.4223
Quantitative	0.0062	0.0031	1.9968
* returns presented in decimal form			

The univariate statistics of the 12-month rolling-window regression clones for model fit are presented in table 8.14. Additional univariate statistics for all clones are provided in Appendices A, B and C. In all clone categories, mean monthly return was lower than that of their respective indices. The largest difference in mean return was between fixed income and its index, while the smallest difference was between the quantitative clone and its index. All clones had lower standard deviations than their indices, and, therefore, had more stable returns. The mean monthly return per unit of risk of the clones was higher for the multi strategy and quantitative clones, suggesting that these clones offer better return per risk taken on. Therefore, when taking risk into account the multi strategy and quantitative clones are superior to their indices. The remaining clones were inferior to their indices in this regard.

Table 8.15	Univariate statistics of clone and hedge fund index returns		
24-month rolling-window regression - model fit			2010.02 - 2015.04
	Mean	Std. Dev.	Return/Risk
Hedge fund Indices			
Composite	0.0089	0.0047	1.9014
Fixed income	0.0090	0.0058	1.5618
Long/short equity	0.0118	0.0111	1.0643
Multi strategy	0.0092	0.0065	1.4141
Quantitative	0.0066	0.0041	1.5838
Clones - model fit			
Composite	0.0066	0.0031	2.0946
Fixed income	0.0050	0.0039	1.2901
Long/short equity	0.0100	0.0092	1.0922
Multi strategy	0.0070	0.0039	1.7789
Quantitative	0.0058	0.0022	2.6805

* returns presented in decimal form

The 24-month rolling-window clones' univariate statistics are presented in table 8.15. Theses clones have lower mean monthly returns than their indices across all index categories. The largest difference in return exists for the fixed income clone and the smallest difference for the quantitative clone. Standard deviation of return was lower than the indices for all clones, suggesting that the clones had more stable returns compared to their benchmarks. When adjusting for risk, the return per unit of risk was higher for all clone categories, excluding fixed income which produced a poorer mean return to risk measure than its index. Therefore, all clones, except fixed income, provide superior return per unit of risk taken on. Comparing table 8.14 and 8.15, the 24-month rolling-window clones had lower mean returns than their 12-month counterparts in all categories except fixed income. However, the 24-month clones had lower standard deviations in all cases, and higher return to risk characters in all clone categories.

Table 8.16	Univariate statistics of clone and hedge fund index returns		
36-month rolling-window regression - model fit			2010.02 - 2015.04
	Mean	Std. Dev.	Return/Risk
Hedge fund Indices			
Composite	0.0089	0.0047	1.9014
Fixed income	0.0090	0.0058	1.5618
Long/short equity	0.0118	0.0111	1.0643
Multi strategy	0.0092	0.0065	1.4141
Quantitative	0.0066	0.0041	1.5838
Clones - model fit			
Composite	0.0065	0.0030	2.1478
Fixed income	0.0049	0.0035	1.3871
Long/short equity	0.0098	0.0091	1.0708
Multi strategy	0.0070	0.0042	1.6863
Quantitative	0.0057	0.0021	2.7625
	* returns presented in decimal form		

Table 8.16 presents the univariate statistics of the 36-month rolling-window regression clones. The clones provided poorer mean returns across all categories, but had superior risk characteristics, i.e. lower standard deviations. The fixed income clone had the largest reduction in mean return compared to its benchmark, the quantitative clone's return was closest to its benchmark. The return per unit of risk taken on was superior to that of the indices for all clones, except fixed income. Clones with superior risk to return measures may be preferred as less risk needs to be taken on per percentage of return earned.

Table 8.17	Correlation between clone and hedge fund index returns				
12-month rolling-window regression - model fit				Period 2010.02 2015.04	
	Composite	Fixed income	Long/short equity	Multi strategy	Quantitative
Clones - model fit					
Composite	**0.86**	0.05	0.83	0.73	0.58
Fixed income	0.18	**0.75**	0.05	0.20	(0.00)
Long/short equity	0.74	(0.01)	**0.89**	0.62	0.43
Multi strategy	0.76	0.10	0.75	**0.77**	0.48
Quantitative	0.66	(0.01)	0.53	0.52	**0.69**

Table 8.18		Correlation between clone and hedge fund index returns			
24-month rolling-window regression - model fit				Period 2010.02 2015.04	
	Composite	Fixed income	Long/short equity	Multi strategy	Quantitative
Clones - model fit					
Composite	**0.79**	0.04	0.79	0.71	0.50
Fixed income	0.16	**0.58**	0.17	0.16	(0.05)
Long/short equity	0.75	0.02	**0.83**	0.68	0.44
Multi strategy	0.77	0.05	0.75	**0.71**	0.47
Quantitative	0.60	(0.09)	0.57	0.52	**0.54**

Correlations for the model fit 12-month clones are presented in table 8.17. All clone categories had strong correlations between their monthly mean returns and the hedge fund indices' returns. The strongest correlations were for long/short equity, 0.89, and composite, 0.86. The 24-month clones' correlations, in table 8.18, are strongest for long/short equity, 0.83, composite, 0.79, and multi strategy, 0.71. The weakest correlation existed for the quantitative clone. Moderate correlations exist between the remaining clones and their respective indices. The correlations between clones and their index returns were lower for all categories when using 24-month windows in the regression as opposed to 12-months.

Table 8.19		Correlation between clone and hedge fund index returns			
36-month rolling-window regression - model fit				Period 2010.02 2015.04	
	Composite	Fixed income	Long/short equity	Multi strategy	Quantitative
Clones - model fit					
Composite	**0.77**	0.07	0.76	0.69	0.49
Fixed income	0.08	**0.56**	0.14	0.09	(0.16)
Long/short equity	0.72	0.05	**0.80**	0.67	0.41
Multi strategy	0.70	0.12	0.69	**0.67**	0.45
Quantitative	0.57	(0.14)	0.54	0.49	**0.49**

Table 8.19 presents the correlations between the 36-month rolling-window regression clones and their indices. The strongest correlations are for the long/short equity, 0.8, and composite clones, 0.77. The correlations for all categories of 36-month clones were weaker than that of their 24-month and 12-month counterparts. Across all rolling-window variations, the long/short equity and composite clones had the strongest correlations with their benchmark indices.

Table 8.20 t-test for mean equality between clone and hedge fund indice returns

12-month rolling-window regression - model fit		2010.02 - 2015.04
	t-statistic	Probability
Composite	2.3397	0.0209
Fixed income	4.4417	0.0000
Long/short equity	0.8571	0.3931
Multi strategy	1.5804	0.1166
Quantitative	0.5695	0.5700

Table 8.21 t-test for mean equality between clone and hedge fund indice returns

24-month rolling-window regression - model fit		2010.02 - 2015.04
	t-statistic	Probability
Composite	3.1211	0.0022
Fixed income	4.4482	0.0000
Long/short equity	0.9548	0.3415
Multi strategy	2.3186	0.0221
Quantitative	1.2193	0.2250

Table 8.22 t-test for mean equality between clone and hedge fund indice returns

36-month rolling-window regression - model fit		2010.02 - 2015.04
	t-statistic	Probability
Composite	3.2804	0.0013
Fixed income	4.6620	0.0000
Long/short equity	1.1277	0.2616
Multi strategy	2.2876	0.0239
Quantitative	1.3293	0.1862

The mean returns of the 12-month model fit clones were tested for mean equality with their indices using t-tests, presented in table 8.20. The t-statistics for composite and fixed income clones are large enough to reject the null hypothesis of mean equality of returns at a 5% significance level. All other clones failed to reject the null hypothesis at this significance level. The mean returns of the composite and fixed income clones are, therefore, significantly different from their hedge fund indices. The t-statistics for the 24-month clones, table 8.21, are large enough to reject mean equality for the composite, fixed income and multi strategy clones at a 5 % significance level. The remaining clones had t-statistics which failed to reject the null hypothesis at a 5% level. Therefore, the composite, fixed income and multi strategy clones have mean returns which are significantly different from their indices at a 5% significance level. The t-statistics for the 36-month rolling-window clones are presented in table 8.22. Like the 24-month clones, the statistics for the 36-month clones are large enough to reject the null hypothesis at a 5% significance level for the composite, fixed income and multi strategy clones. It is concluded that the returns of these clones differ significantly from their indices.

8.2.3 Clone with no lag

The univariate statistics of the no lag clones constructed from 12-month and 24-month rolling-window regressions are presented in Tables 8.23 and 8.24 respectively. The mean monthly return of all clone styles, across both window lengths, was lower than that of the respective hedge fund indices. The fixed income clones had the largest difference in return to its index, and quantitative clones had the smallest difference in returns, for both window lengths. The standard deviations of all categories of clones were lower than that of the hedge fund indices for both 12-month and 24-month clones, providing the clones with superior risk characteristics. The return per unit of risk measures provided by the 12-month clones were lower than that of the indices for all clones, except for the quantitative clone which had more return per unit of risk.

All of the 24-month clones, except fixed income, offered improved return to risk characteristics compared to their indices. While the 24-month clones had poorer mean returns than the 12-month clones in most cases, the 24-month clones offered improved return to risk than their 12-month counterparts. This is due to a reduction in the standard deviations of returns when using the 24-month window lengths. Table 8.25, presents the univariate statistics for the 36-month clones. As is the case with the 12-month and 24-month clones, the 36-month clones provide lower returns that their indices, but offer superior standard deviations as returns are more stable. In terms of return provided per unit of risk the composite, multi strategy and quantitative are superior to their benchmark hedge fund indices.

Table 8.23	Univariate statistics of clone and hedge fund index returns		
12-month rolling-window regression - no lag		2010.02 - 2015.04	
	Mean	Std. Dev.	Return/Risk
Hedge fund Indices			
Composite	0.0089	0.0047	1.9014
Fixed income	0.0090	0.0058	1.5618
Long/short equity	0.0118	0.0111	1.0643
Multi strategy	0.0092	0.0065	1.4141
Quantitative	0.0066	0.0041	1.5838
Clones - no lag			
Composite	0.0070	0.0039	1.7686
Fixed income	0.0049	0.0054	0.9149
Long/short equity	0.0104	0.0105	0.9904
Multi strategy	0.0075	0.0055	1.3490
Quantitative	0.0060	0.0033	1.8419
		* returns presented in decimal form	

Table 8.24	Univariate statistics of clone and hedge fund index returns		
24-month rolling-window regression - no lag		2010.02 - 2015.04	
	Mean	Std. Dev.	Return/Risk
Hedge fund Indices			
Composite	0.0089	0.0047	1.9014
Fixed income	0.0090	0.0058	1.5618
Long/short equity	0.0118	0.0111	1.0643
Multi strategy	0.0092	0.0065	1.4141
Quantitative	0.0066	0.0041	1.5838
Clones - no lag			
Composite	0.0064	0.0031	2.1055
Fixed income	0.0051	0.0041	1.2572
Long/short equity	0.0099	0.0090	1.0985
Multi strategy	0.0070	0.0039	1.8159
Quantitative	0.0058	0.0022	2.6098
		* returns presented in decimal form	

Table 8.25	Univariate statistics of clone and hedge fund index returns		
36-month rolling-window regression - no lag		2010.02 - 2015.04	
	Mean	Std. Dev.	Return/Risk
Hedge fund Indices			
Composite	0.0089	0.0047	1.9014
Fixed income	0.0090	0.0058	1.5618
Long/short equity	0.0118	0.0111	1.0643
Multi strategy	0.0092	0.0065	1.4141
Quantitative	0.0066	0.0041	1.5838
Clones - no lag			
Composite	0.0063	0.0029	2.1526
Fixed income	0.0050	0.0037	1.3496
Long/short equity	0.0094	0.0095	0.9870
Multi strategy	0.0067	0.0045	1.5027
Quantitative	0.0056	0.0021	2.7244
		* returns presented in decimal form	

The correlations between the 12-month and 24-month clones and their indices are presented in table 8.26 and 8.27. For the 12-month clones, there is strong a correlation between long/short equity and its index, 0.75, and moderate correlations for composite, 0.68, and multi strategy, 0.58, clones. The 24-month clones also have the strongest correlation for long/short equity, 0.79, and have a strong correlation for composite, 0.70, and a moderate correlation for multi strategy, 0.62. The correlations for the 36-month rolling-window clones and their indices are presented in table 8.28. The highest correlations are present for the long/short equity, 0.77, and composite, 0.71, clones. For all window lengths the long/short equity clone had the strongest correlation and the quantitative clone had the weakest correlation. The clones with no lagged inputs have lower correlations than their counterpart model fit clones. This is to be expected as the clones are investing using weights from data which is one month older.

Table 8.26	Correlation between clone and hedge fund index returns				
12-month rolling-window regression - no lag				Period 2010.02 2015.04	
	Composite	Fixed income	Long/short equity	Multi strategy	Quantitative
Clones - no lag					
Composite	**0.68**	0.04	0.77	0.62	0.38
Fixed income	0.15	**0.50**	0.04	0.18	0.02
Long/short equity	0.62	0.01	**0.75**	0.52	0.37
Multi strategy	0.61	0.03	0.68	**0.58**	0.41
Quantitative	0.58	(0.05)	0.53	0.51	**0.38**

Table 8.27	Correlation between clone and hedge fund index returns				
24-month rolling-window regression - no lag				Period 2010.02 2015.04	
	Composite	Fixed income	Long/short equity	Multi strategy	Quantitative
Clones - no lag					
Composite	**0.70**	0.06	0.76	0.66	0.40
Fixed income	0.16	**0.47**	0.21	0.15	(0.05)
Long/short equity	0.72	0.04	**0.79**	0.67	0.43
Multi strategy	0.69	0.05	0.73	**0.62**	0.41
Quantitative	0.49	(0.11)	0.54	0.46	**0.32**

Table 8.28	Correlation between clone and hedge fund index returns				
36-month rolling-window regression - no lag				Period 2010.02 2015.04	
	Composite	Fixed income	Long/short equity	Multi strategy	Quantitative
Clones - no lag					
Composite	**0.71**	0.07	0.74	0.65	0.42
Fixed income	0.12	**0.48**	0.19	0.11	(0.13)
Long/short equity	0.67	0.07	**0.77**	0.65	0.36
Multi strategy	0.62	0.11	0.67	**0.59**	0.38
Quantitative	0.47	(0.14)	0.49	0.43	**0.33**

The t-statistics for the 12-month and 24-month clones are presented in table 8.29 and 8.30 respectively, for the no lag scenario. Composite and fixed income 12-month clones rejected the null hypothesis of mean return equality with their indices at a 5% significance level. The remaining 12-month clones fail to reject the hypothesis at this level. The composite and fixed income clones have returns which differ significantly from their indices. The 24-month clones rejected the null hypothesis for the composite, fixed income, as well as multi strategy at a 5% significance level. Long/short equity and quantitative clones fail to reject the null hypothesis at this level, and it can't be concluded that their returns are statistically different from their indices. Table 8.31 presents the t-tests for the 36-month rolling-window clones. As is the case for the 24-month clones, the 36-month clones reject he null hypothesis of mean equality for the composite, fixed income and multi strategy categories at a 5% significance level. For these categories, the clones have returns which are significantly different to that of their indices.

Table 8.29 t-test for mean equality between clone and hedge fund indice returns

12-month rolling-window regression - no lag	2010.02 - 2015.04	
	t-statistic	Probability
Composite	2.4390	0.0161
Fixed income	4.0302	0.0001
Long/short equity	0.7023	0.4838
Multi strategy	1.6455	0.1024
Quantitative	0.8667	0.3878

Table 8.30 t-test for mean equality between clone and hedge fund indice returns

24-month rolling-window regression - no lag	2010.02 - 2015.04	
	t-statistic	Probability
Composite	3.3526	0.0011
Fixed income	4.2038	0.0000
Long/short equity	1.0509	0.2953
Multi strategy	2.3128	0.0224
Quantitative	1.1766	0.2416

Table 8.31 t-test for mean equality between clone and hedge fund indice returns

36-month rolling-window regression - no lag	2010.02 - 2015.04	
	t-statistic	Probability
Composite	3.5563	0.0005
Fixed income	4.5185	0.0000
Long/short equity	1.3044	0.1945
Multi strategy	2.5449	0.0122
Quantitative	1.5012	0.1358

8.2.4 Clone with one-month lag

Table 8.32	Univariate statistics of clone and hedge fund index returns*		
12-month rolling-window regression - one-month lag		2010.02 - 2015.04	
	Mean	Std. Dev.	Return/Risk
Hedge fund Indices			
Composite	0.0089	0.0047	1.9014
Fixed income	0.0090	0.0058	1.5618
Long/short equity	0.0118	0.0111	1.0643
Multi strategy	0.0092	0.0065	1.4141
Quantitative	0.0066	0.0041	1.5838
Clones - one-month lag			
Composite	0.0068	0.0036	1.8633
Fixed income	0.0051	0.0057	0.8837
Long/short equity	0.0100	0.0098	1.0124
Multi strategy	0.0075	0.0058	1.2890
Quantitative	0.0062	0.0035	1.7928
		* returns presented in decimal form	

Table 8.33	Univariate statistics of clone and hedge fund index returns*		
24-month rolling-window regression - one-month lag		2010.02 - 2015.04	
	Mean	Std. Dev.	Return/Risk
Hedge fund Indices			
Composite	0.0089	0.0047	1.9014
Fixed income	0.0090	0.0058	1.5618
Long/short equity	0.0118	0.0111	1.0643
Multi strategy	0.0092	0.0065	1.4141
Quantitative	0.0066	0.0041	1.5838
Clones - one-month lag			
Composite	0.0065	0.0031	2.0738
Fixed income	0.0052	0.0041	1.2608
Long/short equity	0.0099	0.0090	1.1024
Multi strategy	0.0069	0.0039	1.7870
Quantitative	0.0058	0.0023	2.4970
		* returns presented in decimal form	

Table 8.34	Univariate statistics of clone and hedge fund index returns*		
36-month rolling-window regression - one-month lag		2010.02 - 2015.04	
	Mean	Std. Dev.	Return/Risk
Hedge fund Indices			
Composite	0.0089	0.0047	1.9014
Fixed income	0.0090	0.0058	1.5618
Long/short equity	0.0118	0.0111	1.0643
Multi strategy	0.0092	0.0065	1.4141
Quantitative	0.0066	0.0041	1.5838
Clones - one-month lag			
Composite	0.0063	0.0029	2.1376
Fixed income	0.0050	0.0038	1.3111
Long/short equity	0.0093	0.0095	0.9809
Multi strategy	0.0067	0.0046	1.4701
Quantitative	0.0056	0.0020	2.7350
		* returns presented in decimal form	

The univariate statistics of the one-month lag clones are presented in table 8.32 and 8.33, for the 12-month and 24-month rolling-window clones respectively. The clones constructed using 12-month and 24-month rolling-window regressions all performed more poorly than the hedge fund indices, they all had lower mean monthly returns. All one-month lagged clones, of both window lengths, also displayed lower standard deviations than their respective hedge fund indices. On a return to risk basis, the 12-month clones had lower return per unit of risk in all clones, except quantitative, which offered higher return per unit of risk than its index.

The 24-month clones had higher return to risk measures in all clones, except fixed income. The 36-month rolling-window clones, table 8.34, had poorer monthly mean returns than their indices but offered improved standard deviations. On a risk-adjusted basis, the composite, multi strategy and quantitative 36-month clones offered superior return to risk characteristics than their respective indices. For all three window lengths the fixed income had the largest difference in return to its benchmark, and the quantitative clone had the smallest difference in return.

Table 8.35 Correlation between clone and hedge fund index returns

12-month rolling-window regression - one-month lag				Period 2010.02 2015.04	
	Composite	Fixed income	Long/short equity	Multi strategy	Quantitative
Clones - one-month lag					
Composite	**0.68**	0.05	0.73	0.62	0.41
Fixed income	0.25	**0.44**	0.13	0.24	0.11
Long/short equity	0.60	(0.01)	**0.70**	0.51	0.35
Multi strategy	0.60	0.03	0.65	**0.55**	0.43
Quantitative	0.61	(0.10)	0.54	0.53	**0.37**

Table 8.36 Correlation between clone and hedge fund index returns

24-month rolling-window regression - one-month lag				Period 2010.02 2015.04	
	Composite	Fixed income	Long/short equity	Multi strategy	Quantitative
Clones - one-month lag					
Composite	**0.72**	0.06	0.75	0.67	0.42
Fixed income	0.18	**0.44**	0.23	0.14	(0.05)
Long/short equity	0.73	0.04	**0.79**	0.68	0.43
Multi strategy	0.68	0.03	0.72	**0.60**	0.40
Quantitative	0.51	(0.10)	0.56	0.48	**0.32**

Table 8.37 Correlation between clone and hedge fund index returns

36-month rolling-window regression - one-month lag				Period 2010.02 2015.04	
	Composite	Fixed income	Long/short equity	Multi strategy	Quantitative
Clones - one-month lag					
Composite	**0.70**	0.07	0.74	0.64	0.41
Fixed income	0.13	**0.47**	0.21	0.11	(0.11)
Long/short equity	0.67	0.07	**0.77**	0.65	0.36
Multi strategy	0.62	0.11	0.68	**0.58**	0.36
Quantitative	0.47	(0.13)	0.50	0.44	**0.32**

The correlations between the 12-month rolling-window clones and their indices, shown in table 8.35, are moderate to strong for composite, 0.68, and long/short equity, 0.70. The weakest correlation was between quantitative and its index, 0.37. The 24-month clones, table 8.36, exhibited strong correlations for long/short equity, 0.79, and composite clones, 0.72. A moderate correlation was present for multi strategy clone, 0.6. The correlations for the 24-month clones were stronger than, or equal to, the correlations of the 12-month clones in all categories, except the quantitative clone.

Table 8.37 presents the correlations between the 36-month rolling-window regressions and their indices. As was the case with the clones of other window lengths, the 36-month clones had the strongest correlations with their indices for the long/short, 0.77, and composite, 0.70, categories. Based on the correlations for one-month lag clones, it may be expected that the long/short equity clones performed the best. This is not the case, however, as these clones had the largest tracking error and were not the preferred clones when ranked by modified information ratio (see tables 8.11 to 8.13).

Table 8.38 t-test for mean equality between clone and hedge fund indice returns

12-month rolling-window regression - one-month lag	2010.02 - 2015.04	
	t-statistic	Probability
Composite	2.7271	0.0073
Fixed income	3.8218	0.0002
Long/short equity	0.9639	0.3369
Multi strategy	1.5994	0.1123
Quantitative	0.5583	0.5776

Table 8.39 t-test for mean equality between clone and hedge fund indice returns

24-month rolling-window regression - one-month lag	2010.02 - 2015.04	
	t-statistic	Probability
Composite	3.3094	0.0012
Fixed income	4.0975	0.0001
Long/short equity	1.0601	0.2911
Multi strategy	2.4377	0.0162
Quantitative	1.1661	0.2458

Table 8.40	t-test for mean equality between clone and hedge fund indice returns	
36-month rolling-window regression - one-month lag	2010.02 - 2015.04	
	t-statistic	Probability
Composite	3.6107	0.0004
Fixed income	4.4858	0.0000
Long/short equity	1.3332	0.1849
Multi strategy	2.5402	0.0123
Quantitative	1.6067	0.1107

The t-statistics for the clones constructed using one-month lagged inputs are presented in table 8.38 and 8.39, for the 12-month and 24-month clones respectively. The 12-month composite and fixed income clones had high enough t-statistics to reject mean equality between the returns of the clones and their indices at a 5% significance level. The remaining clones failed to reject the null hypothesis at this level. For these two categories the 12-month clones generated returns which were significantly different to those of their indices.

Of the 24-month clones, shown in table 8.39, the composite, fixed income and multi strategy were all able to reject the null hypothesis of mean equality at a 5% significance level, concluding that at this level their returns are significantly different from their indices. The t-statistics for the 36-month rolling-window clones, table 8.40, are large enough to reject the null hypothesis of mean equality for the composite, fixed income and multi strategy clones. Therefore, for these three categories the 36-month clones generate returns which are significantly different from those of their indices. The clones which have returns significantly different from their indices all significantly underperform their indices.

8.2.5 Factor weighting maps

Figure 8.6 – 12-month rolling-window regression fixed income weights

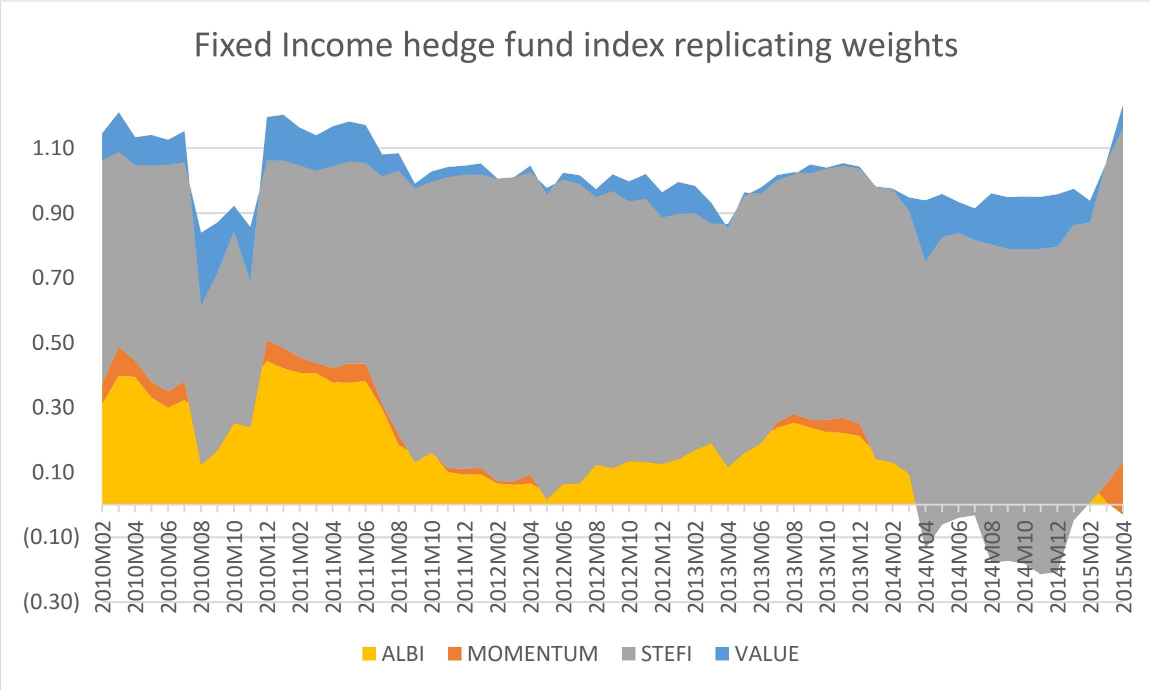


Figure 8.6 illustrates the weightings of the asset class and style factors in the fixed income clone, with factor weights determined using a 12-month rolling-window regression. As was the case with the Kalman filter determined fixed income weights (figure 8.1), this fixed income clone has a large weighting in cash (STEFI), but to a lesser extent than that of the Kalman filter. As may be expected, at certain points in time the fixed income clone has large exposures to bonds, via the ALBI factor. The clone also takes on significant exposure to the value equity factor and a small exposure to the momentum factor over time. Towards the end of the sample period this clone only has a very small exposure to the ALBI factor. Due to the shortness of the window period, 12 months, the weightings are quite volatile and are not very smooth. At certain points, the exposures have large changes from one period to the next. The 12-month clones would, therefore, adjust fastest to large structural changes in the composition of a hedge fund strategies exposures. However, due to its volatility of exposures between periods this clone will require the most frequent rebalancing and could result in higher investment and transaction costs. This means there would be a higher cost of replicating. It is also of interest to note that the weights of the 12-month rolling-window clone are more volatile than the weights of the Kalman filter fixed income clone.

Figure 8.7 – 24-month rolling-window regression fixed income weights

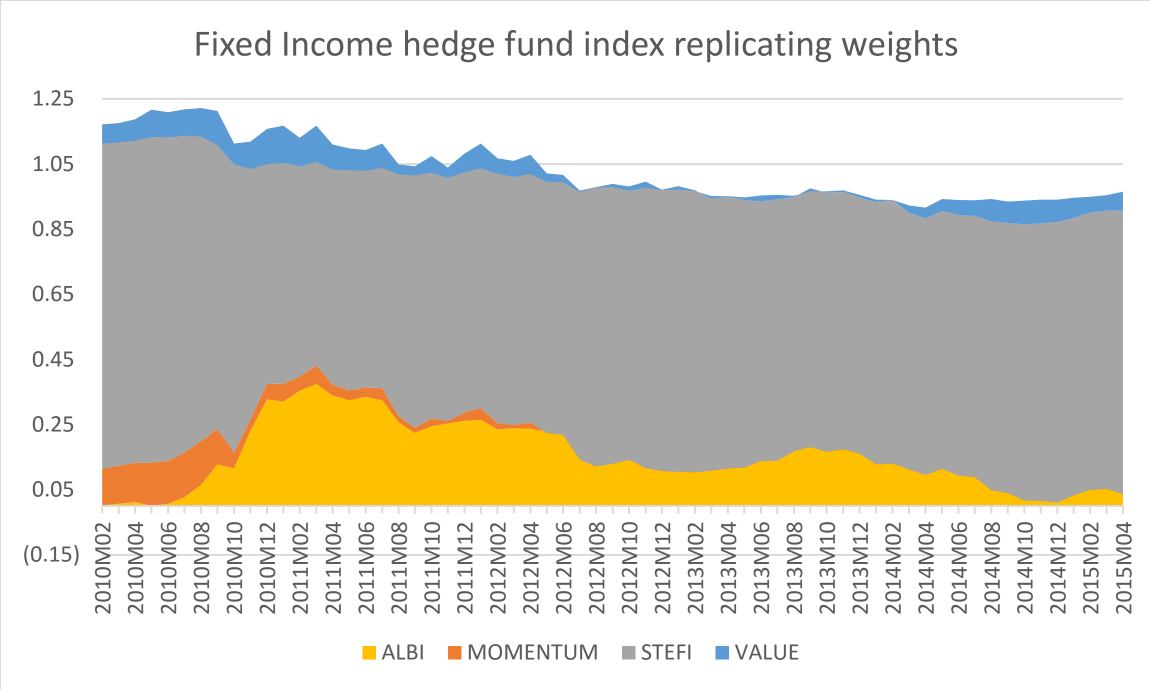


Figure 8.7 illustrates the weightings of the fixed income clone, built using the weights determined by the 24-month rolling-window regression. This fixed income clone has large exposures to cash (STEFI) as was the case with the 12-month rolling-window regression and the Kalman filter clones. The clone has a large exposure to cash at the beginning of the sample period, and during the latter half of 2010 decreases its cash and momentum exposures while taking on a larger weighting of the bond factor, ALBI. A small exposure to the value factor is held throughout the sample period. Towards the end of the sample period, the ALBI weighting has decreased significantly. The weightings in the 24-month rolling-window regression are smoother than those determined by the 12-month rolling-window clone. This is intuitive as the regression is using a larger window period and therefore very short-term fluctuations are smoothed out to an extent.

Figure 8.8 – 36-month rolling-window regression fixed income weights

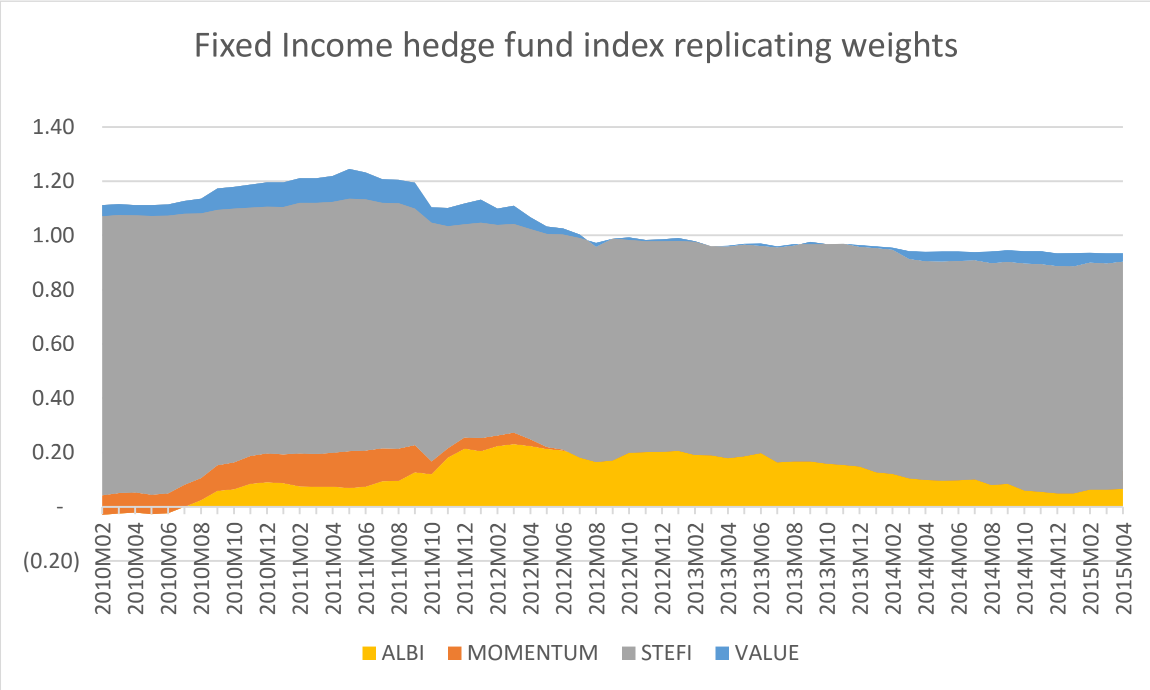


Figure 8.8 illustrates the weightings for the fixed income clone constructed using weights determined by the 36-month rolling-window regression. The clone has a large weighting in cash, as was the case with the previous two window length clones, and has exposures to the value and momentum equity factors, as well as to the bond factor, ALBI. Out of the three window lengths of rolling-window clones, it can be seen graphically that the 36-month clones have the smoothest weightings to the different factors over time. These are the least volatile and generally have the smallest changes in exposures from one period to the next. This is expected as these clones have the largest window length and therefore smoothen out short term changes in exposures, showing a longer-term average exposure. The 36-month clones would take the longest to adjust to structural changes in the exposures of a hedge fund category. As such the weightings are not as volatile and don't change as much from one period to the next, but would require rebalancing infrequently which could result in lower transaction and investment costs compared to the other window lengths.

The factor weighting maps for the remainder of the clones are presented in Appendices D, E and F.

8.1.6 Summary

All clones constructed using the rolling-window regression technique, of all window lengths, had monthly mean differences in return that were negative and therefore underperformed their benchmark hedge fund indices. Although the clones did outperform their indices in certain months, they had a larger proportion of months with negative excess returns. For clones of all window lengths, and in all scenarios, the long/short equity hedge fund category had the largest tracking error from its benchmark. In all cases the composite and quantitative categories of clones had the lowest tracking error to their indices. As such the long/short equity clones performed the worst and tracked their index the least closely, while the composite and quantitative clones performed the best and tracked their indices the closest. Ranking the clones by their modified information ratios resulted in the composite and quantitative clones being the preferred clones for investment in all cases for all window lengths. The fixed income clones were considered the worst investment choice for all window lengths and under all scenarios.

The t-statistics, determined from the information ratio, for composite, fixed income and multi strategy all reject the null hypothesis at a 5% level and it is concluded that the excess returns are significantly different from zero in all window lengths and scenarios. These are, on average, significantly lower than zero. The t-statistics are not large enough to reject the null hypothesis at a 5% significance level for any of the quantitative clones and therefore it can't be concluded that the excess returns are significantly different from zero.

For all rolling-window clones the mean monthly returns and standard deviations were lower than those of their respective indices. While they underperformed on a return basis, they had more desirable risk properties and therefore more stable returns. In all cases the quantitative clones provided superior return to risk measures than their indices. Assessing mean return equality between the clones and their indices, the mean returns of the composite and fixed income clones were significantly different from their indices at a 5% significance level, for all window lengths and scenarios. The multi strategy clone mean returns were significantly different from its index for 24-month and 36-month clones.

8.3 Comparing the two approaches

Table 8.41		Tracking error between clone and hedge fund index returns			
One-month lag clone performance comparison				2010.02 2015.04	
	Composite	Fixed income	Long/short equity	Multi strategy	Quantitative
Kalman Filter					
Monthly mean difference in return	-0.19%	-0.20%	-0.40%	-0.35%	-0.11%
Monthly tracking error	0.36%	0.62%	0.70%	0.55%	0.40%
Information ratio	(0.5232)	(0.3272)	(0.5667)	(0.6459)	(0.2656)
T-statistic*	**(4.1525)**	**(2.5974)**	**(4.4977)**	**(5.1271)**	**(2.1080)**
Modified information ratio	(0.0666)	(0.1251)	(0.2792)	(0.1945)	(0.0421)
Annualised Tracking error	1.24%	2.14%	2.43%	1.90%	1.38%
12-month rolling-window regression					
Monthly mean difference in return	-0.21%	-0.40%	-0.18%	-0.16%	-0.04%
Monthly tracking error	0.35%	0.60%	0.81%	0.59%	0.43%
Information ratio	(0.5872)	(0.6584)	(0.2218)	(0.2759)	(0.0891)
T-statistic*	**(4.6606)**	**(5.2262)**	**(1.7606)**	**(2.1899)**	**(0.7071)**
Modified information ratio	(0.0721)	(0.2388)	(0.1446)	(0.0949)	(0.0162)
Annualised Tracking error	1.21%	2.09%	2.80%	2.03%	1.48%
24-month rolling-window regression					
Monthly mean difference in return	-0.24%	-0.37%	-0.19%	-0.22%	-0.07%
Monthly tracking error	0.33%	0.55%	0.68%	0.52%	0.40%
Information ratio	(0.7103)	(0.6749)	(0.2789)	(0.4179)	(0.1722)
T-statistic*	**(5.6382)**	**(5.3565)**	**(2.2139)**	**(3.3169)**	**(1.3672)**
Modified information ratio	(0.0791)	(0.2015)	(0.1290)	(0.1135)	(0.0280)
Annualised Tracking error	1.16%	1.89%	2.36%	1.80%	1.40%
36-month rolling-window regression					
Monthly mean difference in return	-0.25%	-0.39%	-0.24%	-0.24%	-0.09%
Monthly tracking error	0.34%	0.53%	0.70%	0.54%	0.40%
Information ratio	(0.7421)	(0.7439)	(0.3471)	(0.4470)	(0.2337)
T-statistic*	**(5.8903)**	**(5.9044)**	**(2.7547)**	**(3.5476)**	**(1.8546)**
Modified information ratio	(0.0872)	(0.2069)	(0.1723)	(0.1285)	(0.0370)
Annualised Tracking error	1.19%	1.83%	2.44%	1.86%	1.38%

* T-statistics significant at 5% level in bold

The main scenario for comparison of the Kalman filter and rolling-window regression techniques is the one-month lag scenario, a summary is presented in table 8.41. This is because this scenario is the only one that can be implemented in practice specifically for replicating hedge fund indices. This one-month lag is due to the delay in the availability of hedge fund index return data.

The monthly mean difference in return is negative for all clones across both techniques. This is in agreement with findings of Amenc, Martellini, Meyfredi and Ziemann (2010), where it was found that almost all excess returns were negative for the hedge fund strategies assessed. Between the different techniques, the Kalman filter has the highest, least negative, mean difference in return for the composite and fixed income clones. The 12-month rolling-window regression has the highest return for the remaining categories, long/short equity, multi strategy and quantitative. The 24-month rolling-window clones have the lowest tracking error for the categories of composite, long-short equity and multi strategy. The 36-month rolling-window clone had the lowest tracking error for the fixed income category and the Kalman filter clone had the lowest tracking error for the quantitative category.

The t-statistics, calculated from the information ratios, were large enough to reject the null hypothesis at a 5% significance level for all clones across both the Kalman filter and rolling-window regression techniques. It can be concluded that all clones in the one-month lag scenario have excess returns which are significantly different from zero and, therefore, they all significantly underperformed their respective hedge fund indices.

The clones for both the Kalman filter and rolling-window regression techniques were ranked, within each category, by their modified information ratios. This reveals which clone construction techniques may be best suited to constructing clones for each of the various hedge fund index categories. Out of all techniques, the Kalman filter constructed the clones with the most desirable characteristics for investors for the composite and fixed income categories, but produced the least preferred clones for the long/short, multi strategy and quantitative categories. The 12-month rolling-window technique constructed the preferred clones for the multi-strategy and quantitative hedge fund categories, however the 12-month fixed income clone was the least preferred. The 24-month rolling-window regression was the preferred technique for constructing the long-short equity clones, and was not the least preferred technique for any of the hedge fund clone categories. The 36-month rolling-window regression did not produce clones that were preferred by investors in any of the hedge fund categories, however, it was the least preferred clone for the composite category.

The Kalman filter and the rolling-window regression techniques offer superior return per unit of risk characteristics for quantitative clones when compared to their hedge fund index. This also holds for the composite category for all techniques except the 12-month rolling-window regression. The Kalman filter also offered superior return to risk characteristics for the fixed income category.

Of the techniques analysed in this study, the Kalman filtered technique appears to be the best suited for constructing clones to replicate the composite and fixed income hedge fund index categories. The 12-month rolling-window regression is the preferred technique for constructing clones to replicate the multi strategy and quantitative hedge fund index categories. The 24-month rolling-window regression is the preferred technique for replicating the long/short equity hedge fund category. The Kalman filter would be the least suitable technique for replicating the long/short equity hedge fund index category, whereas the rolling-window regressions would be the least suited for replicating the fixed income category. As such, these results suggest that there may not be one “blanket approach” suitable for replicating all hedge fund indices, rather different techniques may be better suited to different hedge fund categories. Therefore, it may be beneficial to use the techniques in combination when replicating a wide array of hedge fund categories.

9. Limitations and Biases

It should be noted that the Salient value and momentum funds cannot be directly invested in by the average investor. However, financial institutions could construct hedge fund replication products which could be invested in by investors. Exposure to the Salient value and momentum fund can be gained via the Seed Investments Equity Fund, which holds the Salient value and momentum funds in equal proportion. As a result, individual investors would not be able to vary the weights of the value and momentum factors separately. This would limit replication strategies based on these factors to be constructed by institutions and, therefore, could not be implemented directly by individual investors, but rather indirectly through products created by financial institutions.

Choosing factors which represent the different exposures that hedge funds may be exposed to can have a significant impact on the performance of the replication model. It is important that the factors are as exhaustive of the potential exposures as possible and to select factors with minimal overlap, so that different factors are not explaining the same exposures. As such, if the factors used in this study are varied the results may differ. In a South African context, hedge fund replication may be at a disadvantage compared to other countries, such as the United States, as South African investors are more restricted with regards to the universe of factors that they are able to invest in, i.e. in South Africa there are less ETFs and passive investment products to invest in.

It is necessary to allow short positions when conducting hedge fund replication to allow for the dynamic trading strategies of hedge funds. Equally, if not more, important is that the factors used in the asset class factor model can be invested in so that the model can be applied in practice to replicate fund returns. An issue arising as a result of this is that short position could only be allowed on the JSE ALSI top 40 through futures. The remaining factors can't currently be shorted using the products available in South Africa. However, in this study short selling was allowed on all factors to ensure comparison between the Kalman filter and rolling-window regressions. This is due to the model specification of the Kalman filter, which did not allow for restrictions on short exposures. It should be noted that, in general, there was not much short selling activity on the hedge fund clones. In the cases where there were, short positions were of a small magnitude.

Look-ahead bias should not be present in the one-month lag replicators in this study, as it was ensured that the data used in the model was the data that would actually be available to an investor at the time. As such, this one-month lag clone can be implemented in practice, as this study lagged inputs to mimic the real-world scenario. Survivorship bias is often a problem with hedge fund data, and the indices used in this study may not be exempt from this. Only hedge funds that remain in business would be included in the indices, any funds that go bust or close-down would fall out of the indices. Therefore, there may be an upward bias to better performing hedge funds.

The clones constructed in this study are not always invested at 100%, and some clones spend a large portion of the sample period with below 100% invested in the asset class and style factors. This means that there would be a portion of available capital sitting idle without earning any return. In addition, this makes the various clones, rolling-window regressions and Kalman filter, more difficult to compare as two clones which are replicating the same index may have different net exposures. The clone with the lower exposure may earn a lower return and be disadvantaged in the comparison. However, a clone with a lower exposure may also be advantaged in the case of factors having negative returns during that period. These positive and negative effects may cancel out over time. In addition, performance is measured over a period of time, as such, different clones may have different levels of exposure in different periods. The risk incurred in generating returns of the clones was taken into account to allow for fairer comparison

The costs of implementation of these hedge fund clone techniques were not taken into account. Such cost include transaction and investment costs, which will vary with clone rebalancing frequency. Certain clones, such as the 12-month rolling-window regression would incurred higher costs due to rebalancing. These costs would reduce the performance of the clones and may reduce their ability to be used in practice.

10. Conclusion

This study has explained the inner workings of factor-based hedge fund replication, and has stated reasons as to the relevance of this topic for the investment community, who stand to gain from its success. Investment style and asset class factors were assessed and appropriate factors were chosen based on the ability to apply them in practice in a South African context. A review of previous literature on the topic revealed that results in the area of hedge fund replication are mixed, even for a wide variety of techniques.

This study aimed to assess whether using a Kalman filter technique to construct hedge fund replicating clones would provide a significant improvement in quality of replication over the widely-used rolling-window regression technique. The results of this study are to an extent mixed, as the Kalman filter did not outperform the rolling-window regressions in all areas as may have been expected. Overall, the clones did not generate impressive returns compared to the hedge fund indices, however, it should be noted that the clones are only replicating the beta exposures of the hedge funds. While neither of the techniques stood out as the “star performer” across all categories, it appears that the Kalman filter and rolling-window regressions are each stronger at replicating different hedge fund strategies. Ranking the clones by their modified information ratios, it became evident that the different techniques were better suited to replicate different hedge fund categories. In particular, the Kalman filter was preferred for replicating the composite and fixed income categories, but was poorest at replicating long/short equity. The rolling-window regressions were better suited for replicating long/short equity, multi strategy and quantitative categories, between the 12-month and 24-month window lengths. However, the rolling-window regressions were poor at replicating the fixed-income index. Overall, the quantitative and composite clones were the most preferred according to the modified information ratio.

The results of both techniques were underwhelming in terms of mean return, mean excess return and tracking error alone, and may suggest that these hedge fund indices are not easily replicable. Once risk was taken into account, the results became more appealing and many of the clones offered superior return per unit of risk than the hedge fund indices, especially for the composite and quantitative categories. For all hedge fund categories, the risk-adjusted measure of at least one of the cloning techniques offered improved return per unit of risk than their respective indices. Additional research and adjustments need to be made to these hedge fund replication techniques before they can be serious contenders for investors’ capital in practice.

Further studies could use different hedge fund indices to compare the rolling-window regression and Kalman filter and may attempt to incorporate additional factors into the various clones. Costs may also be taken into account to create a more accurate comparison between the different techniques, which require different rebalancing frequencies and, therefore, have different costs of replication. Factor weighting tolerances could be implemented, such that rebalancing is only required once the different between the suggested weighting and actual weighting breaches this tolerance.

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12. Appendix A – Univariate statistics – Model Fit Clones

Table A.1

Univariate statistics of hedge fund index returns* 2010.02 - 2015.04

	Composite	Fixed income	Long/Short equity	Multi strategy	Quantitative
Mean	0.008929	0.009018	0.011792	0.009186	0.006557
Median	0.008655	0.00822	0.012885	0.00831	0.005765
Maximum	0.0244	0.02459	0.03563	0.02389	0.0181
Minimum	0.00052	-0.00419	-0.01573	-0.00569	-0.0005
Std. Dev.	0.004696	0.005774	0.01108	0.006496	0.00414
Skewness	0.63584	0.374473	-0.203511	0.19289	0.981826
Kurtosis	3.738315	3.570045	2.535145	2.573419	3.826596
Jarque-Bera	5.585893	2.288503	0.986206	0.854559	11.72625
Probability	0.061241	0.318462	0.610728	0.652281	0.002842
Sum	0.55359	0.55909	0.73111	0.56955	0.40652
Sum Sq. Dev.	0.001345	0.002034	0.007489	0.002574	0.001046
Observations	62	62	62	62	62

* returns presented in decimal form

Table A.2

Univariate statistics of model fit Kalman filter clone returns* 2010.02 - 2015.04

	Composite	Fixed income	Long/Short equity	Multi strategy	Quantitative
Mean	0.007071	0.006977	0.008054	0.00577	0.005539
Median	0.007221	0.006942	0.008482	0.005849	0.005469
Maximum	0.013586	0.013212	0.031293	0.017469	0.011305
Minimum	0.001514	0.002385	-0.013382	-0.005592	0.000711
Std. Dev.	0.002604	0.002449	0.009052	0.004477	0.001882
Skewness	0.143506	0.40841	-0.044087	-0.052949	0.390746
Kurtosis	2.941206	2.841717	3.032716	3.308042	3.942321
Jarque-Bera	0.221733	1.788307	0.02285	0.274103	3.871639
Probability	0.895058	0.408954	0.98864	0.871925	0.144306
Sum	0.438428	0.43255	0.499352	0.357757	0.343448
Sum Sq. Dev.	0.000413	0.000366	0.004998	0.001223	0.000216
Observations	62	62	62	62	62

* returns presented in decimal form

Table A.3

Univariate statistics of model fit 12-month rolling-window clone returns* 2010.02 - 2015.04

	Composite	Fixed income	Long/Short equity	Multi strategy	Quantitative
Mean	0.007004	0.004927	0.010128	0.007592	0.006214
Median	0.007093	0.00472	0.010217	0.007365	0.00575
Maximum	0.019752	0.016862	0.035317	0.020922	0.016821
Minimum	-0.002775	-0.008957	-0.012465	-0.005641	0.000106
Std. Dev.	0.004138	0.004301	0.010213	0.005338	0.003112
Skewness	0.347239	-0.062861	-0.159005	0.116991	1.000254
Kurtosis	3.671756	4.337924	2.756391	2.893857	5.154396
Jarque-Bera	2.411686	4.665107	0.414564	0.170535	22.32892
Probability	0.299439	0.097048	0.81279	0.918267	0.000014
Sum	0.434229	0.305487	0.627925	0.470709	0.385241
Sum Sq. Dev.	0.001044	0.001128	0.006363	0.001738	0.000591
Observations	62	62	62	62	62

* returns presented in decimal form

Table A.4

Univariate statistics of model fit 24-month rolling-window clone returns* 2010.02 - 2015.04

	Composite	Fixed income	Long/Short equity	Multi strategy	Quantitative
Mean	0.006596	0.005008	0.010047	0.007007	0.005814
Median	0.006384	0.004385	0.009635	0.006724	0.005839
Maximum	0.014353	0.015341	0.028807	0.017907	0.011769
Minimum	-0.001291	-0.008056	-0.010803	-0.002425	0.001016
Std. Dev.	0.003149	0.003882	0.009199	0.003939	0.002169
Skewness	0.026795	-0.136475	0.013987	0.121781	0.519733
Kurtosis	2.710765	4.254718	2.314754	3.031526	3.515134
Jarque-Bera	0.223533	4.259448	1.215057	0.155818	3.476782
Probability	0.894253	0.11887	0.544695	0.925049	0.175803
Sum	0.408956	0.310505	0.622883	0.43443	0.360467
Sum Sq. Dev.	0.000605	0.000919	0.005162	0.000946	0.000287
Observations	62	62	62	62	62

* returns presented in decimal form

Table A.5

Univariate statistics of model fit 36-month rolling-window clone returns*					2010.02 - 2015.04
	Composite	Fixed income	Long/Short equity	Multi strategy	Quantitative
Mean	0.00651	0.004888	0.009761	0.007015	0.005735
Median	0.006177	0.004844	0.009043	0.006548	0.005577
Maximum	0.014707	0.01157	0.032071	0.01845	0.013214
Minimum	-0.00019	-0.0088	-0.007514	-0.000847	0.001543
Std. Dev.	0.003031	0.003524	0.009116	0.00416	0.002076
Skewness	0.349252	-0.754198	0.202116	0.869731	0.884157
Kurtosis	2.953327	5.180489	2.640098	3.839509	4.815295
Jarque-Bera	1.266059	18.16029	0.756744	9.637131	16.59077
Probability	0.530981	0.000114	0.684976	0.008078	0.00025
Sum	0.403624	0.303052	0.605161	0.434909	0.355585
Sum Sq. Dev.	0.00056	0.000758	0.005069	0.001055	0.000263
Observations	62	62	62	62	62

* returns presented in decimal form

13. Appendix B – Univariate statistics – No Lag Clones

Table B.1

Univariate statistics of no lag Kalman filter clone returns* 2010.02 - 2015.04

	Composite	Fixed income	Long/Short equity	Multi strategy	Quantitative
Mean	0.00698	0.006883	0.007848	0.005587	0.005472
Median	0.007205	0.006922	0.00806	0.00583	0.005373
Maximum	0.013945	0.013316	0.031856	0.017858	0.01077
Minimum	0.001084	0.002044	-0.018318	-0.009867	0.000746
Std. Dev.	0.002613	0.00248	0.009247	0.00468	0.001944
Skewness	0.075962	0.337339	-0.145646	-0.384799	0.290293
Kurtosis	3.216755	2.816466	3.482554	4.290592	3.562498
Jarque-Bera	0.180998	1.262928	0.82075	5.832932	1.688171
Probability	0.913475	0.531813	0.663401	0.054125	0.42995
Sum	0.432775	0.426759	0.486587	0.346393	0.339249
Sum Sq. Dev.	0.000417	0.000375	0.005216	0.001336	0.000231
Observations	62	62	62	62	62

* returns presented in decimal form

Table B.2

Univariate statistics of no lag 12-month rolling-window clone returns* 2010.02 - 2015.04

	Composite	Fixed income	Long/Short equity	Multi strategy	Quantitative
Mean	0.006956	0.004948	0.010414	0.007483	0.006036
Median	0.00708	0.004854	0.009304	0.007189	0.005851
Maximum	0.018026	0.016918	0.038394	0.022477	0.017047
Minimum	-0.00154	-0.017629	-0.010915	-0.004878	-0.005016
Std. Dev.	0.003933	0.005408	0.010515	0.005547	0.003277
Skewness	0.255503	-0.765846	0.073073	0.233489	-0.053474
Kurtosis	3.272679	7.002015	2.72683	3.274937	6.080929
Jarque-Bera	0.866658	47.43569	0.247951	0.758618	24.55086
Probability	0.648347	0	0.883402	0.684334	0.000005
Sum	0.431243	0.306795	0.645681	0.463918	0.37422
Sum Sq. Dev.	0.000943	0.001784	0.006745	0.001877	0.000655
Observations	62	62	62	62	62

* returns presented in decimal form

Table B.3

Univariate statistics of no lag 24-month rolling-window clone returns*					2010.02 - 2015.04
	Composite	Fixed income	Long/Short equity	Multi strategy	Quantitative
Mean	0.006447	0.005137	0.009891	0.007022	0.005825
Median	0.006312	0.004606	0.009127	0.006579	0.005699
Maximum	0.013794	0.014868	0.02983	0.015759	0.012129
Minimum	-0.001377	-0.00723	-0.011466	-0.001011	0.000249
Std. Dev.	0.003062	0.004086	0.009004	0.003867	0.002232
Skewness	-0.158133	0.0891	0.065115	0.071545	0.440507
Kurtosis	2.650978	3.740355	2.630386	2.55969	3.525544
Jarque-Bera	0.573086	1.498024	0.396733	0.553732	2.718656
Probability	0.750855	0.472833	0.820069	0.758156	0.256833
Sum	0.399737	0.318476	0.613234	0.435394	0.36112
Sum Sq. Dev.	0.000572	0.001018	0.004945	0.000912	0.000304
Observations	62	62	62	62	62
			* returns presented in decimal form		

Table B.4

Univariate statistics of no lag 36-month rolling-window clone returns*					2010.02 - 2015.04
	Composite	Fixed income	Long/Short equity	Multi strategy	Quantitative
Mean	0.006333	0.004961	0.009396	0.006708	0.005634
Median	0.006104	0.005031	0.008932	0.006374	0.005383
Maximum	0.012544	0.012102	0.03227	0.018691	0.011663
Minimum	0.000129	-0.009241	-0.019263	-0.008702	0.000943
Std. Dev.	0.002942	0.003676	0.00952	0.004464	0.002068
Skewness	0.124111	-0.706317	-0.121114	0.029734	0.494564
Kurtosis	2.599212	5.218339	3.432039	4.976599	3.679111
Jarque-Bera	0.574134	17.86779	0.633773	10.10207	3.718875
Probability	0.750461	0.000132	0.728413	0.006403	0.15576
Sum	0.392621	0.307568	0.582521	0.415888	0.349319
Sum Sq. Dev.	0.000528	0.000824	0.005529	0.001216	0.000261
Observations	62	62	62	62	62
			* returns presented in decimal form		

14. Appendix C – Univariate statistics – One-month lag clones

Table C.1

Univariate statistics of one-month lag Kalman filter clone returns* 2010.02 - 2015.04

	Composite	Fixed income	Long/Short equity	Multi strategy	Quantitative
Mean	0.006972	0.006863	0.007821	0.00556	0.005436
Median	0.007219	0.006914	0.008083	0.005843	0.005476
Maximum	0.014001	0.013301	0.031978	0.018008	0.011074
Minimum	0.000996	0.002096	-0.018301	-0.009856	0.000682
Std. Dev.	0.002625	0.002509	0.009238	0.004686	0.001996
Skewness	0.095595	0.338154	-0.130451	-0.355075	0.161967
Kurtosis	3.232919	2.733553	3.495189	4.304275	3.741102
Jarque-Bera	0.23458	1.365001	0.809314	5.697404	1.689929
Probability	0.889327	0.505352	0.667206	0.057919	0.429573
Sum	0.432241	0.425528	0.484886	0.344726	0.337061
Sum Sq. Dev.	0.00042	0.000384	0.005205	0.00134	0.000243
Observations	62	62	62	62	62

* returns presented in decimal form

Table C.2

Univariate statistics of one-month lag 12-month rolling-window clone returns* 2010.02 - 2015.04

	Composite	Fixed income	Long/Short equity	Multi strategy	Quantitative
Mean	0.00679	0.005059	0.009961	0.007511	0.006214
Median	0.007162	0.004956	0.009758	0.006771	0.005591
Maximum	0.014916	0.017537	0.027643	0.027356	0.021838
Minimum	-0.002132	-0.018731	-0.011102	-0.006154	-0.002838
Std. Dev.	0.003644	0.005725	0.009839	0.005827	0.003466
Skewness	-0.153184	-0.87401	-0.260352	0.590514	1.224623
Kurtosis	2.86515	6.870843	2.269184	4.220509	8.870428
Jarque-Bera	0.289451	46.60074	2.080164	7.451543	104.5236
Probability	0.86526	0	0.353426	0.024095	0
Sum	0.421005	0.313649	0.617558	0.465671	0.385247
Sum Sq. Dev.	0.00081	0.001999	0.005905	0.002071	0.000733
Observations	62	62	62	62	62

* returns presented in decimal form

Table C.3

Univariate statistics of one-month lag 24-month rolling-window clone returns*					2010.02 - 2015.04
	Composite	Fixed income	Long/Short equity	Multi strategy	Quantitative
Mean	0.006466	0.005216	0.00988	0.006903	0.005823
Median	0.00645	0.004528	0.009005	0.006722	0.005532
Maximum	0.013829	0.015776	0.03001	0.01564	0.011834
Minimum	-0.00113	-0.007118	-0.011122	-0.000971	0.000757
Std. Dev.	0.003118	0.004137	0.008962	0.003863	0.002332
Skewness	-0.041112	0.073984	0.122808	0.109871	0.422398
Kurtosis	2.613067	3.764473	2.706505	2.534356	3.389313
Jarque-Bera	0.404235	1.566308	0.378373	0.68487	2.235216
Probability	0.816999	0.456963	0.827632	0.710039	0.327061
Sum	0.400923	0.323421	0.612562	0.427964	0.361024
Sum Sq. Dev.	0.000593	0.001044	0.004899	0.00091	0.000332
Observations	62	62	62	62	62
			* returns presented in decimal form		

Table C.4

Univariate statistics of one-month lag 36-month rolling-window clone returns*					2010.02 - 2015.04
	Composite	Fixed income	Long/Short equity	Multi strategy	Quantitative
Mean	0.006293	0.004956	0.009342	0.006695	0.005574
Median	0.006091	0.004995	0.008989	0.006228	0.005408
Maximum	0.012793	0.011968	0.032562	0.019048	0.011419
Minimum	0.0000164	-0.009923	-0.019005	-0.008684	0.000767
Std. Dev.	0.002944	0.00378	0.009524	0.004554	0.002038
Skewness	0.135043	-0.698752	-0.127298	0.071514	0.427576
Kurtosis	2.614241	5.543547	3.41017	4.838385	3.85608
Jarque-Bera	0.57287	21.75851	0.60207	8.783635	3.782407
Probability	0.750936	0.000019	0.740052	0.012378	0.15089
Sum	0.390187	0.307258	0.579208	0.415119	0.345595
Sum Sq. Dev.	0.000529	0.000871	0.005533	0.001265	0.000253
Observations	62	62	62	62	62
			* returns presented in decimal form		

15. Appendix D – 12-Month rolling-window regression clone weights

Figure D.1 – 12-month rolling-window regression composite weights

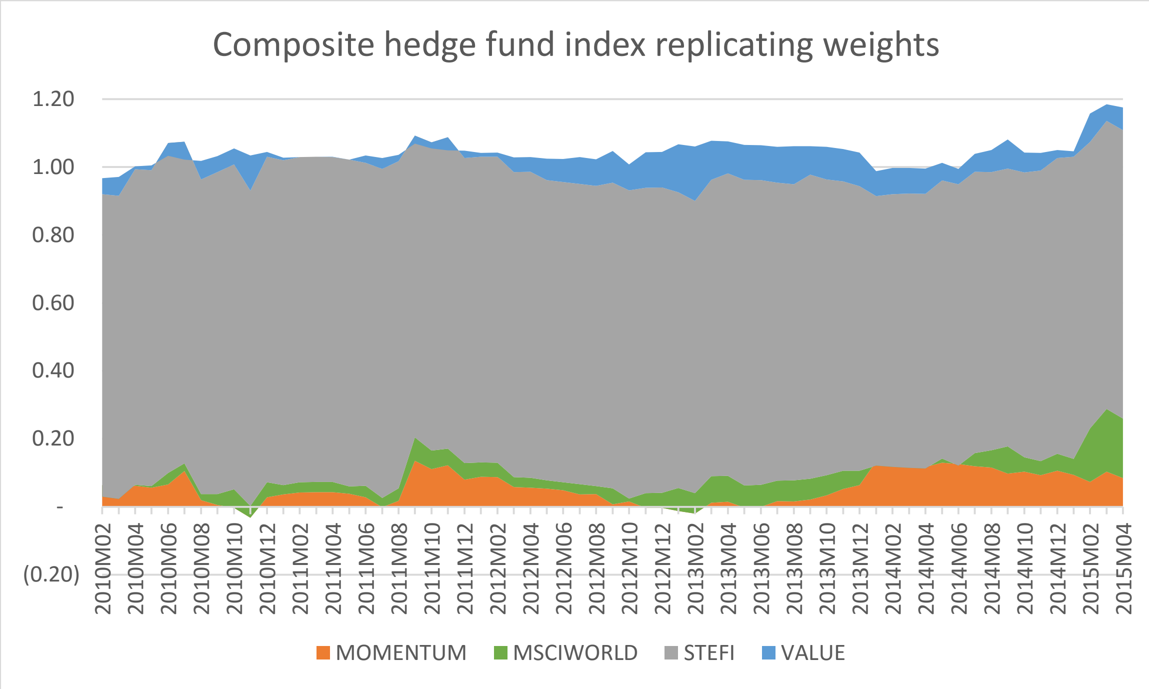


Figure D.2 – 12-month rolling-window regression fixed income weights

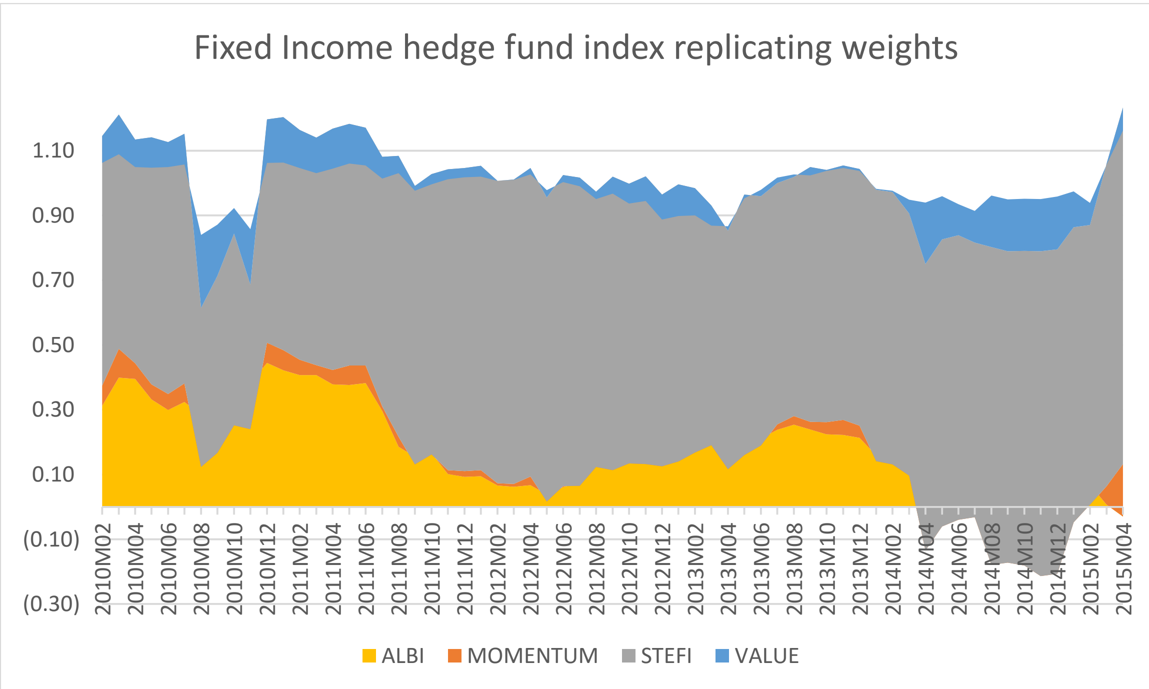


Figure D.3 – 12-month rolling-window regression long/short equity weights

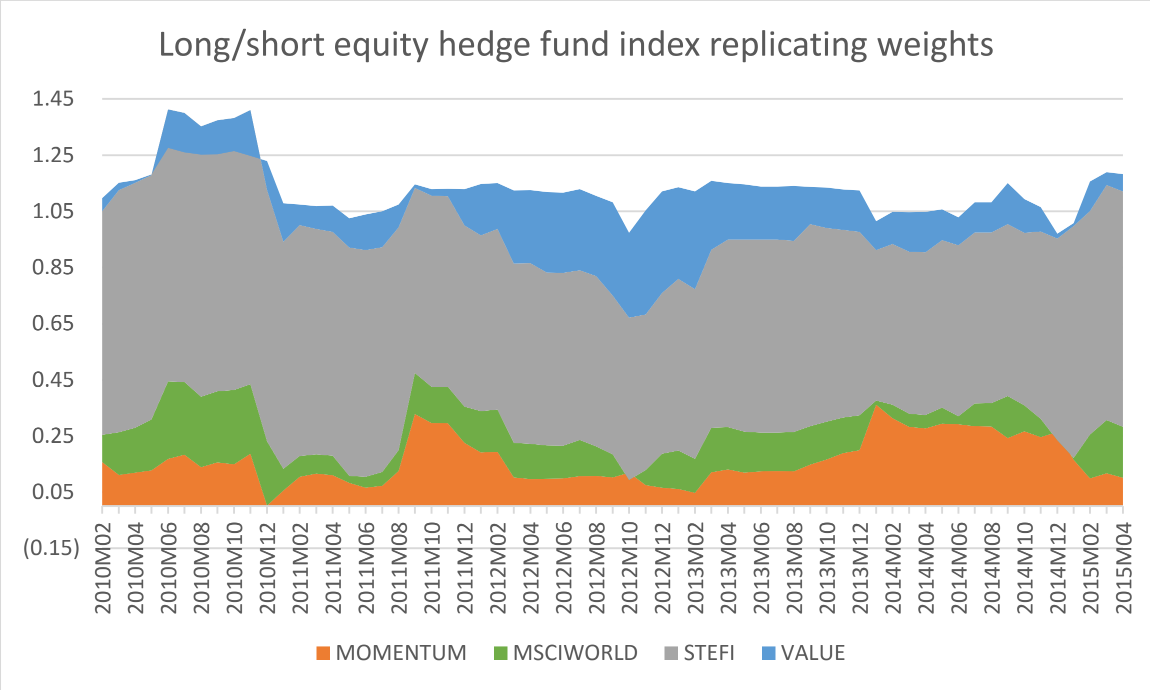


Figure D.4 – 12-month rolling-window regression multi strategy weights

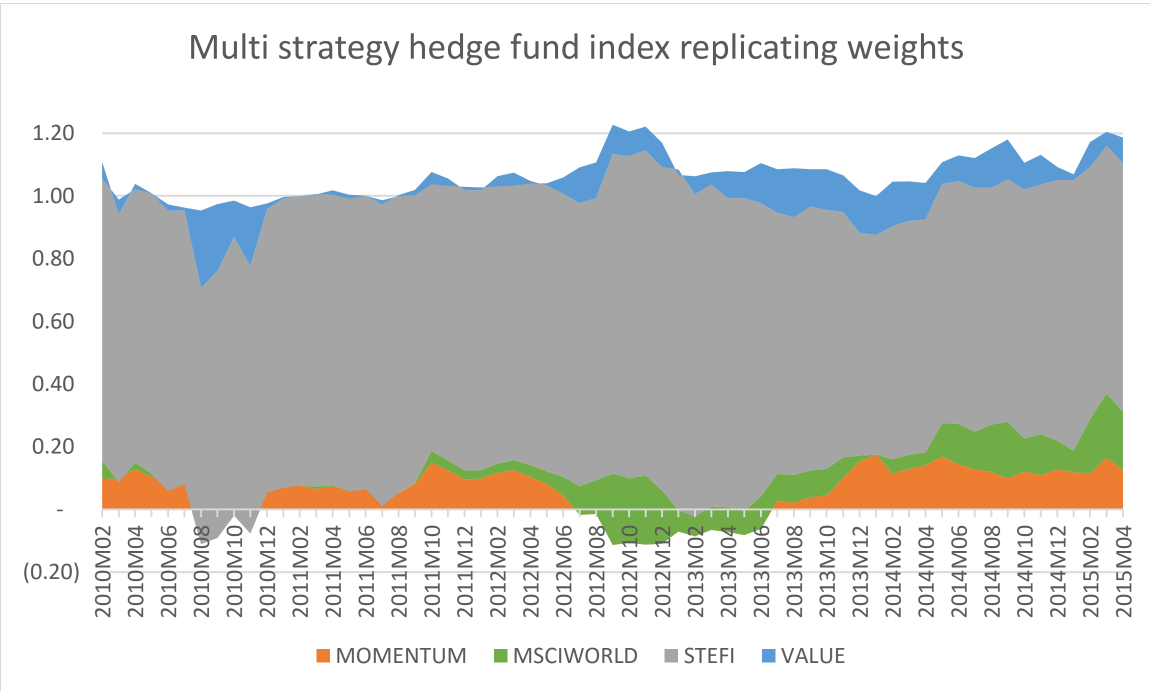
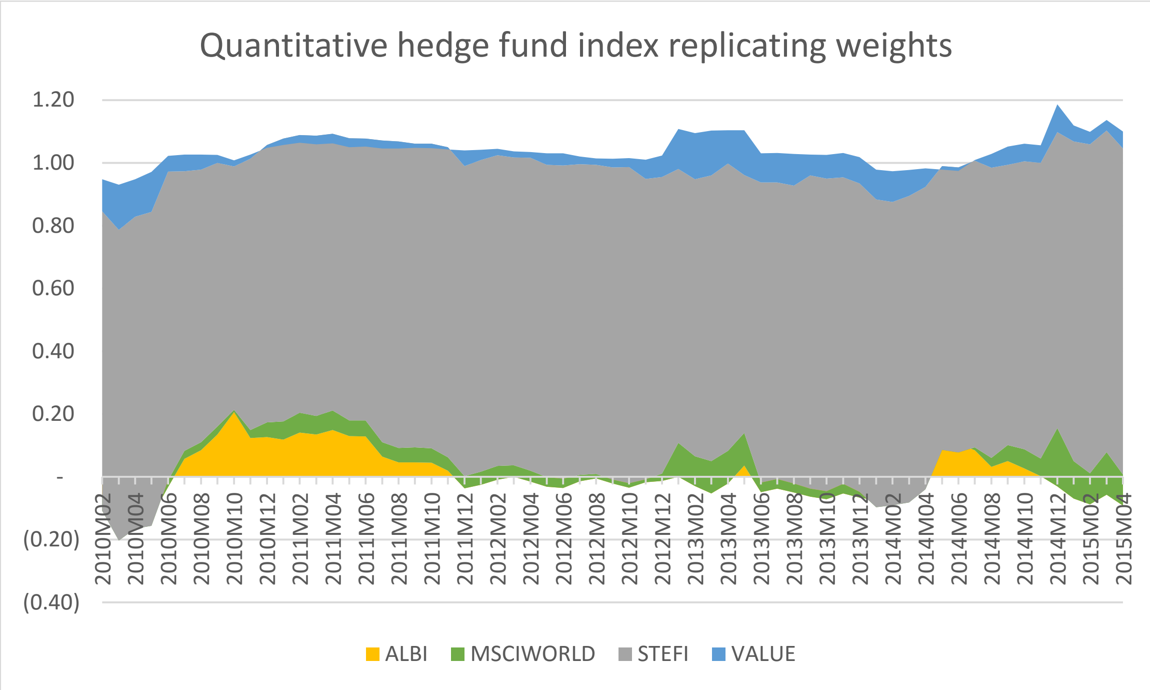


Figure D.5 – 12-month rolling-window regression quantitative weights



16. Appendix E – 24-Month rolling-window regression clone weights

Figure E.1 – 24-month rolling-window regression composite weights

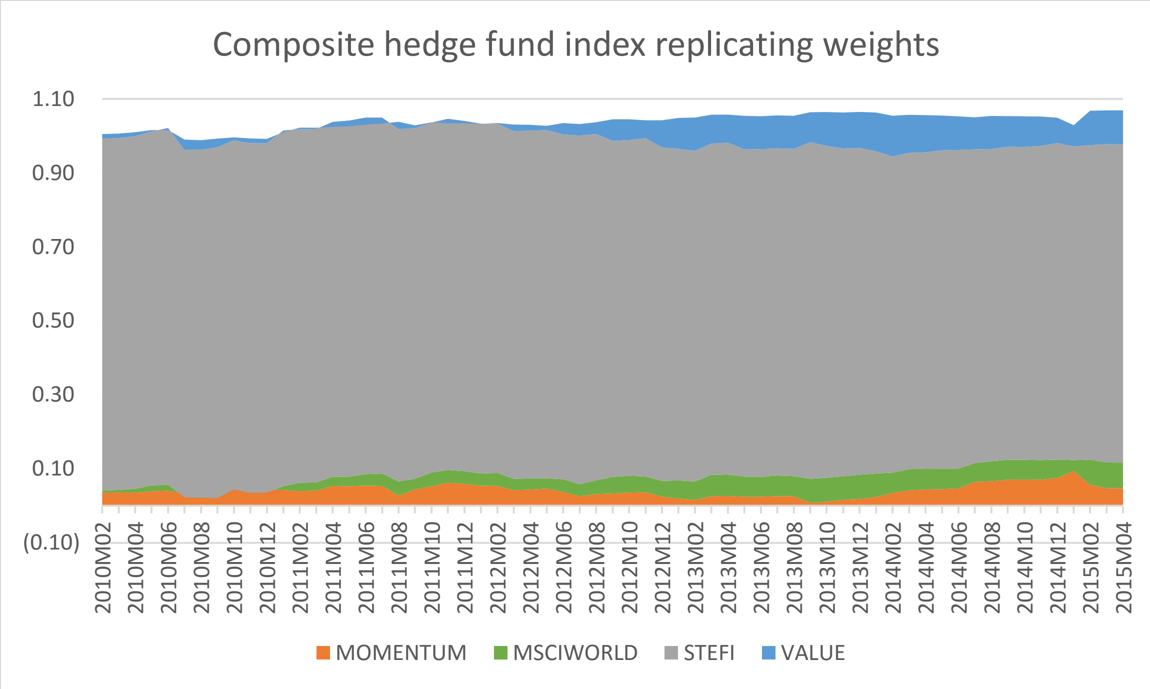


Figure E.2 – 24-month rolling-window regression fixed income weights

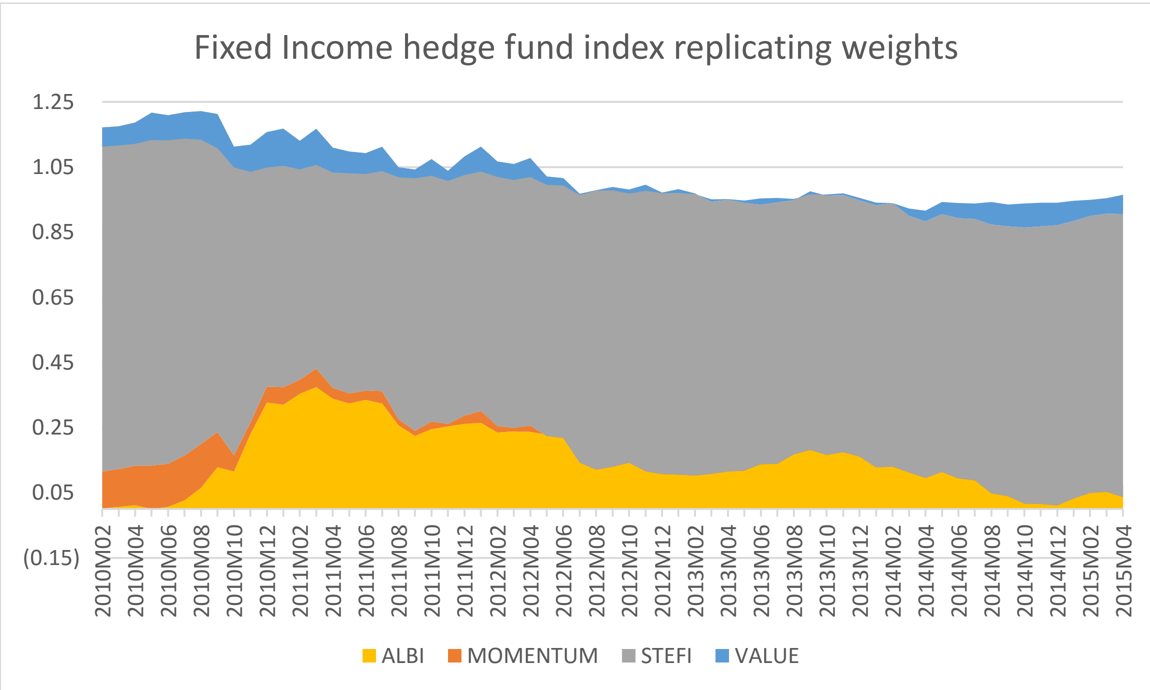


Figure E.3 – 24-month rolling-window regression long/short equity weights

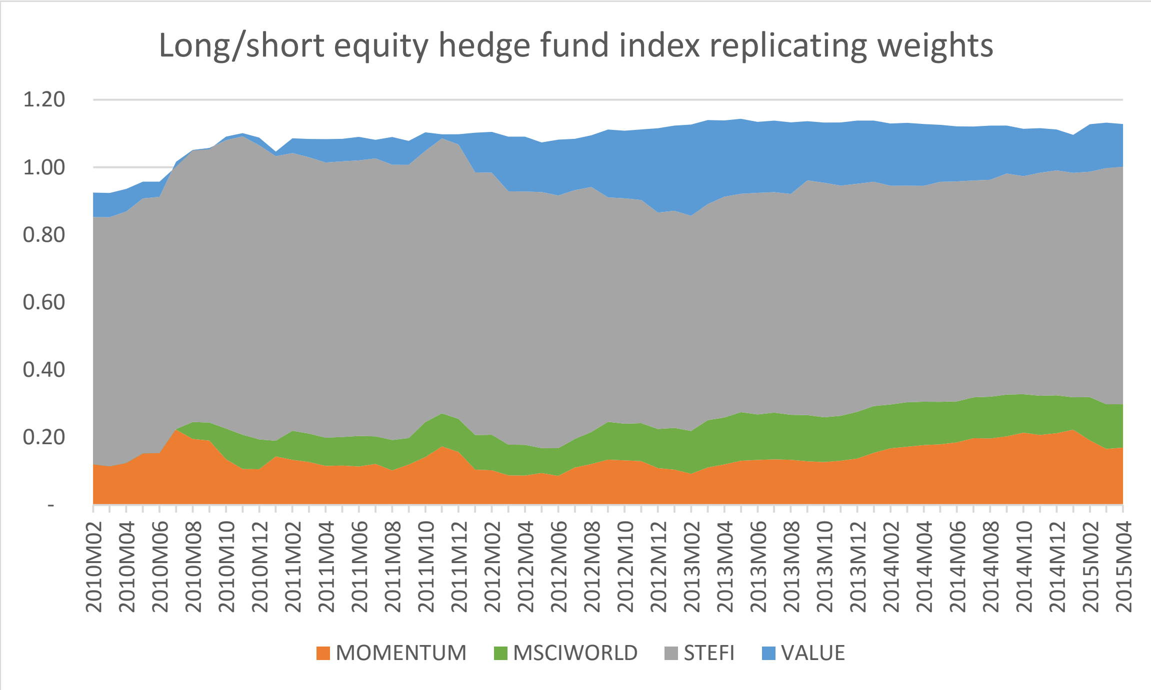


Figure E.4 – 24-month rolling-window regression multi strategy weights

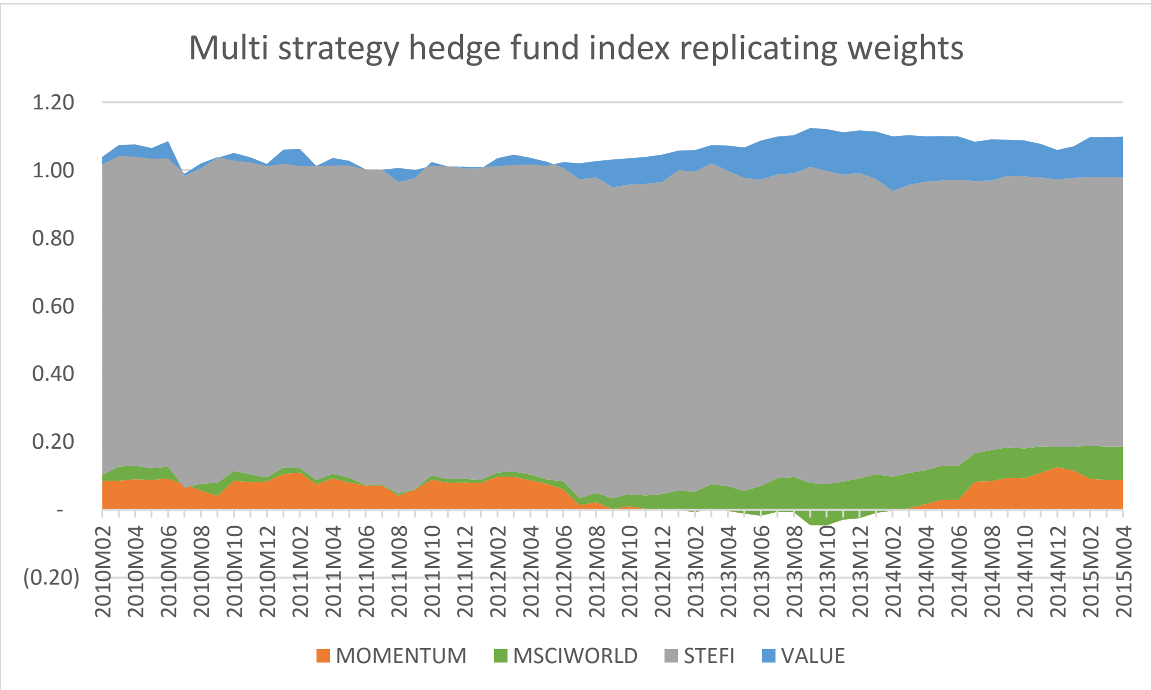
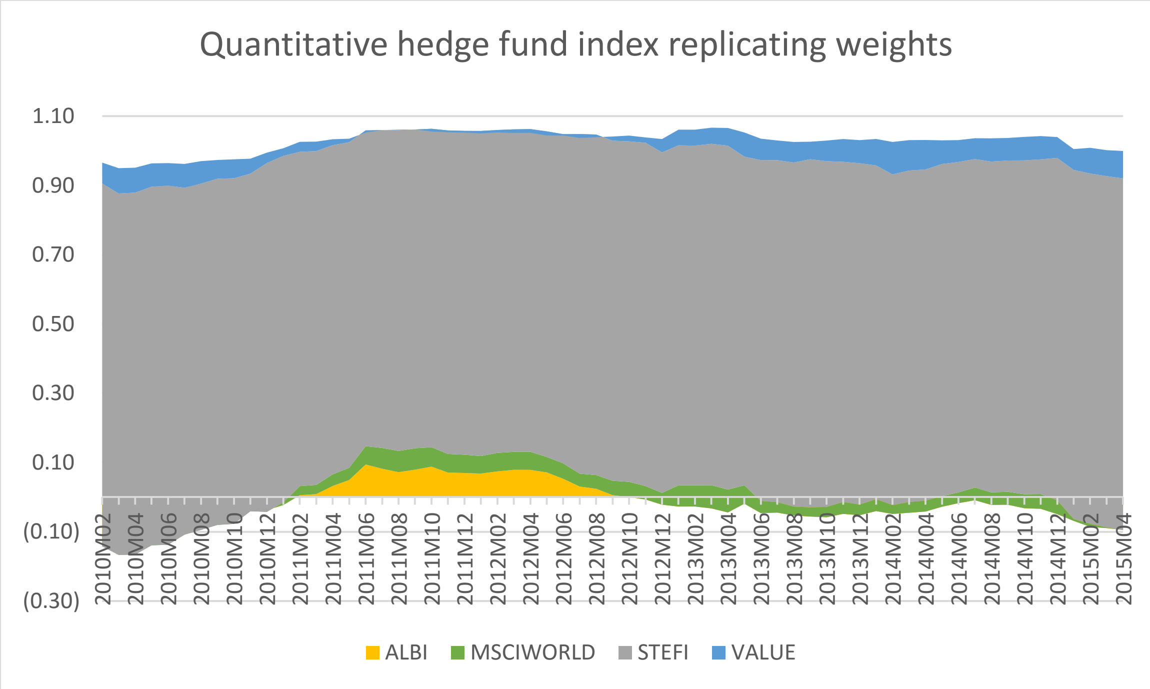


Figure E.5 – 24-month rolling-window regression quantitative weights



17. Appendix F – 36-Month rolling-window regression clone weights

Figure F.1 – 36-month rolling-window regression composite weights

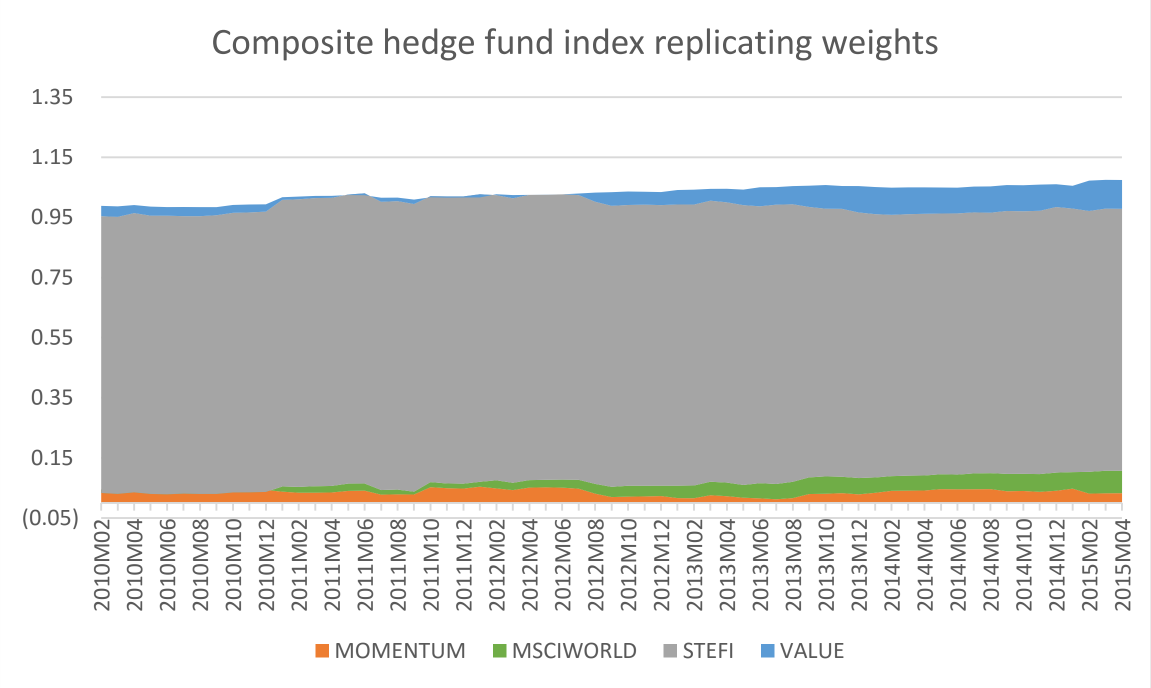


Figure F.2 – 36-month rolling-window regression fixed income weights

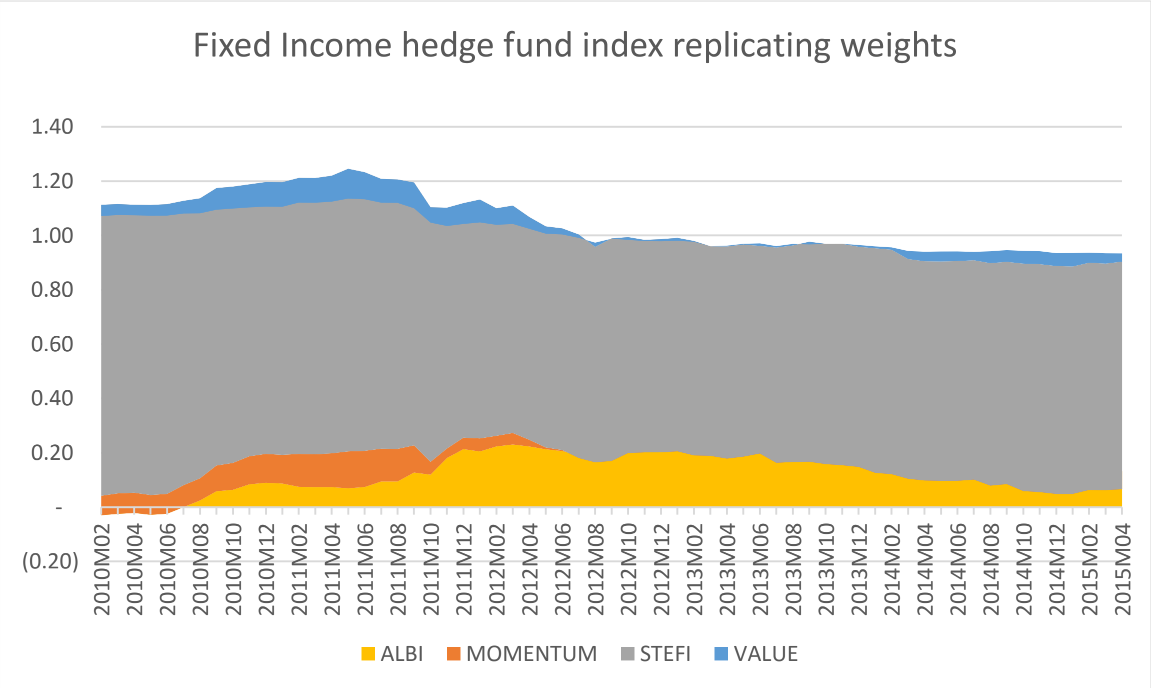


Figure F.3 – 36-month rolling-window regression long/short equity weights

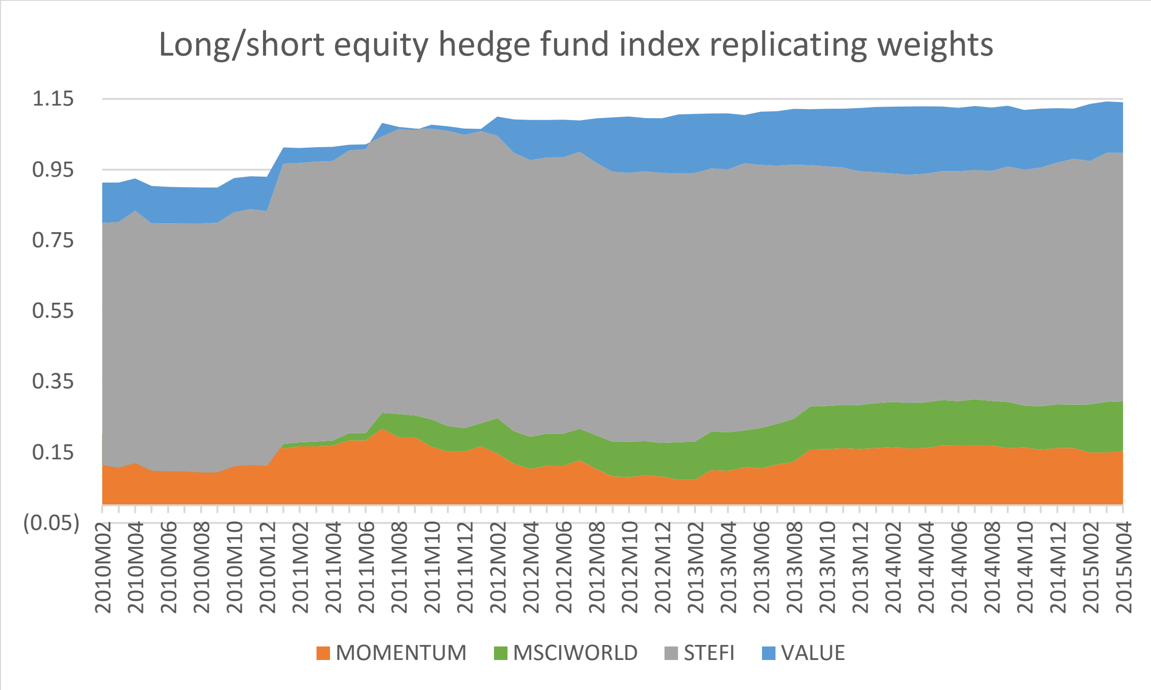


Figure F.4 – 36-month rolling-window regression multi strategy weights

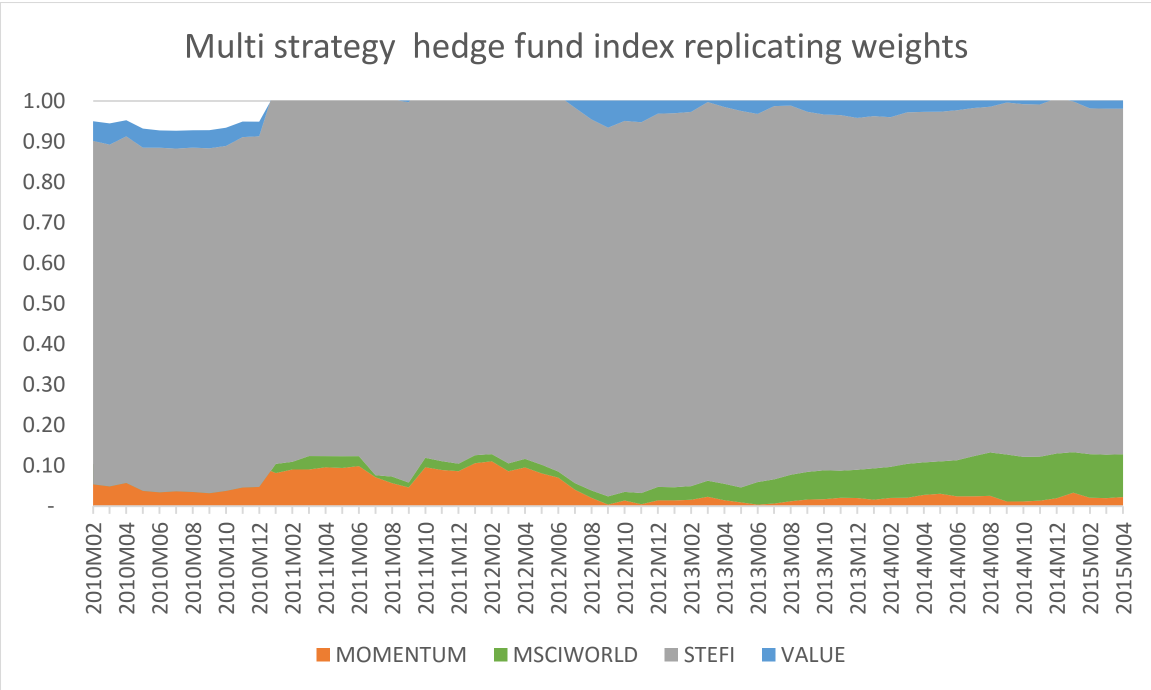


Figure F.5 – 36-month rolling-window regression quantitative weights