Can Hedge Fund Returns be Replicated?

— A Factor Replication of Nordic Hedge Fund Returns

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ABSTRACT

Research on the topic of replicating hedge fund returns has been around for more than a decade and has shown that a substantial portion of hedge fund returns can be attributed to a collection of risk premia of market returns, rather than any superior management skills of hedge fund managers. Focusing on Nordic hedge fund returns, we create replicating portfolios, or clones, to explore the low-cost, transparent, liquid and scalable world of replication. Using monthly returns data for 102 Nordic hedge funds in the Hedgenordic (NHX) Index from 2005 and to 2010, we attempt to replicate the returns using two linear factor models. We find that the performance of the linear clones captures a significant portion of the hedge fund returns and risk characteristics, in line with previous research. This point to the conclusion that hedge fund returns can to a large extent be replicated with a simple linear factor model, with performance of the clones in line with that of the underlying funds.

Keywords: Hedge Funds, Factor Replication, Hedge Fund Replication, Clones

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1 INTRODUCTION

Over the last decade, numerous articles have been published about hedge fund replication. So what then justifies yet another article to be written and read about the topic? The main reason behind the topic's continued appeal is that the real sources of hedge fund returns are still far from understood. Empirical evidence is limited and the models that exist are inadequate. Which are the risk factors that give rise to hedge fund returns and how can we model reality when we do not know which factors to model? Lately, the hedge fund industry has realized that a substantial portion of its returns derives from risk premia instead of market inefficiencies, in other words, "beta" instead of "alpha". But the key question is not whether we should define it as alpha, beta or even as will be discussed later, "alternative beta". The key question is which risk factors are the ones that give rise to hedge fund returns? Does alpha even exist or can hedge fund returns be fully attributed to a selection of known/unknown risk factors?

We do not expect to answer all of these questions in this paper. What we strive to accomplish, however, is to shed some light on the topic of factor replication. Hedge fund replication is still a relatively new concept that can actively be invested in, but it is one that rapidly has been gaining interest. The origin of this interest is partly driven by the increased sums of money being allocated to hedge funds by institutional investors with a strong demand for transparency and liquidity. Several large investment banks such as Deutsche Bank, Goldman Sachs and JP Morgan have introduced replication funds with names such as Absolute Return Beta Index, Absolute Return Tracking Index and Alternative Beta Index, respectively (EDHEC–RISK, 2008). Research on the topic has been around for more than a decade and has shown that a substantial portion of hedge fund returns can be attributed to a collection of risk premia of market returns such as equities, credit, bond market duration and market volatility; rather than any superior management skills of hedge fund portfolio managers (Fieldhouse, 2008).

Three main approaches of replication, which we will go through in this essay, are *Factor Replication* (which we also will employ), *Distribution Replication* and *Mechanical Replication*. An article by Hasanhodzic and Lo (2006) regarding factor replication caught our interest early on, and we will use this article as a base to perform a similar replication, but on a sample of Nordic hedge funds. Our thesis aims to sort out various replication issues while performing a test using a factor-based strategy to clarify the mechanics of hedge fund replication. Our main objective is therefore to attempt to replicate Nordic hedge fund returns using two linear factor models.

But why replicate hedge fund returns at all? Unquestionably the biggest advantage with replication is that you avoid the high management and performance fees, as well as the time consuming hedge fund manager selection. Not to be neglected is the clones' offering of a highly liquid and transparent form of investing with hedge fund like returns. Investors implementing a replication strategy know at all times the precise composition of the portfolio, allowing for increased risk control. Finally, replicating hedge funds in liquid markets will never lead to any capacity constrains (Kamel, 2007).

There are undoubtedly disadvantages with hedge fund replication as well. Some major flaws are the lack of reactivity of hedge fund replication and its inability to capture tactical allocations. Further, replication strategies struggle with apprehending the characteristic non-linear positions of the underlying hedge fund industry and higher moments of hedge fund returns. Finally, but perhaps most importantly, is the lack of access to alpha of hedge funds (Roncalli and Weisang, 2008).

The strategy that we will employ in this essay is a factor-based strategy, which in essence is a strategy that tracks historical hedge fund returns using liquid assets. A statistical model then finds the optimal weights to emulate the returns of the tracked strategies and these weights are then updated dynamically as time passes and new information is made available to the database (Fieldhouse 2008).

1.1 CONTRIBUTION

The contribution of our thesis is threefold. The primary contribution of this paper is that it expands the paper of Hasanhodzic and Lo (2007). We apply their factor replication of US hedge funds on a sample of Nordic hedge funds. This study also modifies the model used by Hasanhodzic and Lo with two new beta factors, representing European equities and small cap, in order to customize the model to our Nordic sample. Finally we hope that our thesis will further enhance the knowledge on the extent of hedge fund returns being attributable to systematic risk factors.

1.2 OUTLINE OF THE PAPER

This paper is organised as follows. The first part reviews previous findings within hedge fund replication research and provides a framework for our paper. In the second part, we present our hypotheses, which are followed by the third part containing a presentation of the data that we have used. The methodology that has been used is discussed in the fourth part, which ends with a description of how we construct the replicated portfolios. Finally, we conclude our paper by discussing our results, summing up our findings and reflect over their implications for future research.

2 THEORETICAL FRAMEWORK AND PREVIOUS FINDINGS

2.1 ALPHA, ALTERNATIVE BETA AND TRADITIONAL BETA

During the last decade, one of the most heated debates within the hedge fund industry has focused on the sources of hedge fund returns. Some regard hedge fund returns as a product mainly of exposure to systematic risks, in other words, beta. Others argue that hedge fund returns depend mainly of the specific skill set of the hedge fund managers, i.e. alpha. Extensive analysis of hedge fund data and increasing empirical evidence point to hedge fund returns being a mixture of both systematic risk exposure and specific management skill sets. However, the question remains to what degree returns are attributable to beta versus alpha.

There is yet today no consensus on the definition of alpha, and so, there is neither any consensus model within the hedge fund industry separating out alpha. We have defined alpha as the part of return that cannot be attributed to any known systematic risk factor, and is thus part of the return that originate from the specific skill sets of the hedge fund managers. One way to approach this problem is to focus on modelling the systematic risk exposure instead, i.e. beta, of which there is more consensus.

A few decades ago, beta was considered well understood and defined as a portfolio's exposure to the stock market, in line with the classic model of CAPM. If the stock market increases with 1%, then the portfolio is expected to increase by 1% if its beta is 1.0 and 2% if its beta is 2.0. Alpha was at this time a manager's expected return above or below that attributable to their beta and that attributable to the risk free rate. If the generated return was above that corresponding to the beta it possessed, this meant that a positive alpha had been generated by the manager. Repeatedly, this simple way of looking at reality has failed to fully capture expected return, and the concept of beta has been expanded and generalized to include exposures to also other risk factors. One of the most famous generalizations is Fama and French's (1993, 1996) three-factor model, in which they use three different betas. 1) systematic exposure to the stock market (old beta), 2) exposure to excess performance of value stocks over growth stocks (high-minus-low beta), and 3) exposure to excess performance of stocks with small capitalization over stocks with large capitalization (small-minus-big beta).

When it comes to hedge fund returns; it is not only problematic to separate out alpha and beta, there are even difficulties distinguishing between the two. Jaeger (2005) argues that a main reason behind this confusion is the lack of understanding of how to measure the diverse risk factors that hedge funds are exposed to. Focus must be on understanding the underlying systematic risk factors affecting hedge fund returns.

In the midst of the difficulties with distinguishing alpha from beta, we are beginning to realize that hedge fund beta is in fact different from traditional beta. While they are both a result of the exposure to systematic risk factors, alternative beta is in essence more complex than traditional beta. Already in 2004, Asness suggested a simple way to separate the different forms in theory. If the return in question is limited to only a few investors and there is no simple systematic process readily available to extract it, it is most likely true alpha. If the return on the other hand can be specified in a systematic way, but using non-conventional techniques such as leverage, short-selling or derivatives, it could still be labelled as beta, though possibly in an alternative form. Asness (2004) refers to this form of beta as "alternative beta". Alternative beta is often defined as alpha by the hedge fund industry but there is increased criticism against this definition by investors and academics. Finally, if the return does not require any special techniques but rather long-only investing in systematic risk factors, it is traditional beta.

Another way of thinking about alternative beta versus traditional beta is what we want to credit managers with high skill. As we will go through under Mechanical replication in more detail, a strategy such as merger arbitrage would previously seem to justify great credit, and its attractiveness great skill. But today, this would be more commonly seen as beta, albeit alternative beta. In general, a technique that initially is innovative and deserving of being defined as alpha can with time, as it become more recognised and implemented, become more appropriately defined as beta.

2.2 FACTOR REPLICATION

2.2.1 Initial Findings and Origin of the Model

One of the first methods of replicating hedge fund returns is *Factor Replication*, which was introduced through a risk management perspective by Fung and Hsieh already in 1997 and based on Sharpe's (1991) style regression analysis. They applied techniques similar to what Sharpe had used for mutual funds, but introduced instruments used by hedge funds, such as leverage and short selling. The equation below accounts for all hedge fund variation that comes from the risk exposure of the various asset classes:

$$Hedge\ fund\ excess\ return\ = alpha + \sum (beta_i \times Factor_i) + random\ fluctuations$$

Instead of the portfolio return being a weighted average of a large number of asset returns, it is now a weighted average of a small number of asset classes. Fung and Hsieh (1997) grouped assets into the eight classes of US equities, non-US equities, emerging market equities, US government bonds, US non-government bonds, one-month eurodollar deposits, gold, and the trade weighted value of the US dollar. Using five self-described strategies of hedge funds, referred to as "style factors" they also identified two trend following strategies, one global/macro, one value, and one distressed securities. They stressed that any investment fund's return is a function of where it trades, how it trades and how much it trades, or in other words; asset class exposure, strategy applied and amount of leverage. The typical mutual fund employs long-only strategies that are relatively static without much use of leverage. Because of this, indices of standard asset classes are suitable benchmarks for mutual funds, as Sharpe (1992) exhibited. But for hedge funds, the reality is more complex and returns generated are often non-linear that require customized benchmarks. Later they also introduced the idea of incorporating assets with contingent payout profiles such as options.

As the equation above shows, alpha is extracted by estimating and subtracting the betas times the beta factors. Alpha can therefore never be directly observed, but is to be seen in relation to beta. By separating out everything else out, the remainder is then classified as alpha. This does not mean that no additional risk factors exist, simply that we do not yet know how to model them. If we leave out an important risk factor, alpha will be artificially inflated. Because of this, when we measure alpha in some models, what we are really measuring could be beta, or an alternative form of beta.

2.2.2 The Factor Model Takes Shape

Linear regression analysis of hedge fund returns was then proposed among others by Jaeger and Wagner (2005) and Hasanhodzic and Lo (2007). As Fung and Hsieh (1997), Hasanhodzic and Lo's (2007) model also has its origin in Sharpe's asset class factor model. Fung and Hsieh statistically derived the factors from a principal components analysis of the covariance matrix. Hasanhodzic and Lo (2007) state that while these factors may yield high in-sample R^{2}'s, they suffer from over-fitting bias and also lack economic interpretation, which is one of Sharpe's primary motivations for decomposition. A simple linear factor model used for hedge fund replication was thus postulated by Hasanhodzic and Lo in 2007. This was in line with previous research on factor replication and built on the same assumption that part of hedge fund returns derives from simple, passive exposure to certain asset classes, as opposed to superior management performance. Hasanhodzic and Lo (2007) uses six factors that correspond to some of the basic sources of risk: the stock market, the bond market, currencies, commodities, credit and volatility. The amount of exposure to these factors, i.e. the portfolio weights, is then determined by regressing the fund's return on the chosen risk factors, in an attempt to "clone" the hedge fund return.

This method focuses on replicating month-by-month returns with little regard to other statistical characteristics. It is simpler than Kat and Palaro's model (Refer to *Section 2.3*) both in theory and implementation with its linear, passive characteristic, which prevents it from achieving other objectives such as skewness, kurtosis or volatility. This method might not exactly replicate a particular hedge fund but this is not the objective, rather the question is whether passive replication could work at all. Despite a slight underperformance, the analysis showed that for certain categories of hedge funds, a substantial portion of the return can in fact be replicated by simple, passive investments. Though the majority of hedge fund returns might be explained by a linear relationship to a set of common assets, let us not forget that the main issue of *which* these common assets are remain to be determined.

2.2.3 Criticism against Factor Replication

First and foremost, linear replication suffers from the common issue of *spurious correlation*, which in essence is the question of cause and effect. Despite contingent statistical significance of any factor, this does not imply causality between the factor exposures and hedge fund returns.

As Roncalli (2008) points out, one possible reason behind the lower performance of linear factor models is the presence of non-observable dynamic trading strategies. This creates non-linear return profiles, which struggle to be captured by a linear framework. One proposed solution to this issue is to build synthetic factors corresponding to known trading strategies, such as the writing of options on equity indices. But the extent of nonlinearities in hedge fund has been in question; and factor models using an option factor have been used to assess the extent of the presence of nonlinearities in hedge fund returns. The results are interesting; on a fund by fund basis only approximately 20% of the whole universe of hedge funds reported in the Lipper/TASS database display significant nonlinearity with respect to the market return. Roncalli (2008) further suggests that rather than nonlinear factors, one should focus on models capable of capturing the dynamic allocation of hedge fund managers. While these results do not rule out the occasional necessity to model nonlinearities, they highlight the fact that linear models are in general suitable. Though it has been suggested that the model is best suited to capture aggregate return; we must remember that this could be simply due of the lack of understanding of the risk factors.

2.3 DISTRIBUTION REPLICATION

2.3.1 Introduction to Distribution Replication

"Once we accept that hedge fund return are not superior, but just different, the obvious next question is: is it possible to generate hedge fund-like returns ourselves by mechanically trading stocks and bonds […]" (Kat and Palaro, 2005) – a debatable statement indeed but fit to introduce the theory behind the method of *Distribution Replication*. In a series of papers, Harry Kat and Helder Palaro, show that the statistical properties of hedge fund returns can be synthetically replicated by dynamic trading strategies using liquid futures contracts.

A core assumption behind distribution replication is that any alpha creation of a hedge fund cannot be sustained since hedge funds operate in near efficient markets. This is a disputed fact, but there is considerable empirical evidence showing that alpha *on aggregate* is close to zero. The argument is then, assuming efficient markets, that it is not excess return that is the appeal of hedge fund replication; rather, it is qualities such as mitigated downside risk, positive skewness, low or negative correlation, or decreased volatility, that are hedge funds' real value proposition (Kat and Palaro, 2005).

2.3.2 Details of the Method

Distribution replication provides the investor with the ability to specify the exact distribution desired, but it also means that the monthly return of the clone versus the fund can differ, and that expected return will be set by the return of the underlying asset minus the net cost of downside protection implicitly bought. This methodology thus deemphasizes return, which unfortunately is not in line with most investors' interest. Investors are in general more interested in simple bankable return, as opposed to a fund's particular skewness, kurtosis or correlation, and the majority of hedge funds also market themselves using absolute return goals (Kamel, 2007).

2.3.3 Criticism against Distribution Replication

One important implication of this methodology is that a clone might in fact end up employing a trading strategy far more complex than the fund it aims to replicate. As the trading strategies become more complex, they also become less accessible to the typical institutional investor and the purpose itself with replication disappears. And with Kat and Palaro further clarifying that one should chose an underlying asset with a high expected risk adjusted return since the clone can at best be as good as the underlying asset's, one might wonder why to bother with replicating a particular fund at all. By this logic, one could simply define the ideal statistical properties, and then create it by taking the corresponding positions in exotic options on a diversified portfolio of stocks and bonds (Kamel, 2007).

2.4 MECHANICAL REPLICATION

2.4.1 Mechanical Replication in Essence

This is a bottom-up technique, which also often has been referred to as reverse engineering. Mechanical replication aims to identify broad and fundamental concepts of hedge fund strategies and implement these with automated trading algorithms. The strategies in focus are normally well-known and well-understood, using simple and low-cost trading algorithms. Mechanical replication differs from the other two replication methods in that it does not try to infer statistical patterns from the hedge fund return series, but instead apply the actual hedge fund strategies (Wallerstein et al, 2009).

2.4.2 Example: Merger Arbitrage

Mitchell and Pulvino (2001) analyse merger arbitrage, also called risk arbitrage. This refers to a strategy that attempts to profit from the spread between the target firm's current stock price and the bid price from the acquirer. After the announcement of a merger or acquisition, the target firm's stock normally trades at a discount to the price offered by the acquiring company. Provided that the merger is successful, the spread disappears and the arbitrageur turns a profit. If the merger is unsuccessful, the arbitrageur incurs a loss, which is normally much greater that the profit derived from successful bets. In order to hedge market risk and only earn returns from the contraction of the spread, a long position is taken in target firm's stock and a short position in the acquiring firm's stock. Mitchell and Pulvino (2001) constructed a data set of 4,750 merger deals between 1963 and 1998 to characterise the risk and return in merger arbitrage, and found merger arbitrage returns are positively correlated with market returns in strongly depreciating markets but uncorrelated in flat or appreciating markets. These payoff properties are more similar to those obtained from writing uncovered index put options and in most parts of the world, a small put premium is collected, while it is rarer that a large payment is made. The results suggest that the strategy explains a significant part of the merger arbitrage hedge fund returns, with excess returns of four per cent per year, controlling for transaction costs. The excess return could reflect a premium paid to risk arbitrageurs for providing liquidity, particularly during market downturns.

Despite the practical implementation differing between merger arbitrage and say for example convertible arbitrage[1] or statistical arbitrage[2], or even between two merger arbitrage portfolios, the only real issue is whether it helps us understand hedge fund returns, and represents a real, viable and potentially important investment choice.

Duarte, Longstaff and Yu (2007) also created hedge fund replicators, though replication was not their main focus. Instead, they were used as a means to explore the risk and return characteristics of five fixed income strategies, defined by rules in a similar approaches Mitchell and Pulvino (2001). However, the results still provide us with insight into the world of hedge fund replication. They find that a substantial portion of returns from sophisticated fixed income arbitrage is in fact beta driven; something which supports the beta driven method applied in this paper and is in line with the findings of Lo and Hasanhodizic. However, Duarte, Longstaff and Yu also find that three of these strategies generate significant alpha after adjusting for bond and equity risk, which is a drawback for beta-based replicators since they, by construction, cannot produce alpha. An interesting conclusion of theirs is that the more complicated a hedge fund strategy is, the more difficult it is to replicate with simple beta factors.

2.4.3 Criticism against Mechanical Replication

By replicating the actual strategies that hedge funds employ, one might begin to question what the difference really is between a hedge fund strategy and a hedge fund replication strategy. The concept of identifying broad and fundamental concepts of hedge fund strategies and implementing these with automated trading algorithms might sound easy; but any easily accessible strategy is quickly identified in today's competitive markets and opportunities often appears only temporarily. The strategies

[1] A strategy with a long a convertible security and short in the same issuer's common stock.
[2] Short-term mean-reversion strategies involving large numbers of securities.

employed thus have to become more complex, and as the complexity increases the point of replication diminishes. For why replicate a hedge fund that uses complex strategies with equally complex replication strategies?

3 HYPOTHESES

3.1 HYPOTHESIS NO 1

Can Nordic hedge fund returns be replicated with a simple linear factor model?

3.2 HYPOTHESIS NO 2

Are our results in line with those of Hasanhodzic and Lo in terms of performance, explanatory power, liquidity and leverage?

3.3 HYPOTHESIS NO 3

Can we improve our results by modifying the original factor model with new factors?

4 DATA

4.1 Nordic Hedge Fund Index

To study the prospect of replicating Nordic hedge fund returns we look into the database behind the Hedgenordic (NHX) Index. NHX is an equal-weighted hedge fund index derived from the performance of hedge funds within the Nordic region. The index is managed by the Danish company Hedgenordic who aims to be the single access point to the Nordic hedge fund industry. Both onshore and offshore vehicles are eligible for inclusion as long as the investment manager is located in the Nordic region. To be admitted into NHX full performance history of the hedge fund, reported either as monthly returns net of all fees or monthly NAVs net of all fees, must be provided. The inception date of NHX is January 2005 and the database currently consists of 126 Nordic hedge funds, although a minority of the hedge funds has provided performance histories that stretch further back in time (Hedgenordic, 2011).

The hedge funds are categorized based on strategy and which instruments they trade. Currently the classifications are Equities, Fixed Income, Fund of Funds, Managed Futures & CTAs and Multi Strategy. Equities contain a wide range of strategies involving long and short positions in equities, Fixed Income tries to arbitrage from price anomalies between related interest rate securities and Fund of Funds invest in multiple hedge funds (BSD). Managed Futures & CTAs go long and short in futures such as metals, grains and different indices using a proprietary trading system or discretionary method (Summa). Finally, Multi Strategy allocates capital dynamically using several strategies (HFR).

4.2 Sample

We have picked a sample period between January 2005 and December 2010. It is the longest possible period in the database with performance available from a reasonable share of the included hedge funds. Of the hedge funds available in this period we drop those with less than 36 monthly returns, which leave us with a final sample of 102 hedge funds. The hedge funds are not evenly distributed across the categories. There are 50 hedge funds in Equities, 8 in Fixed Income, 16 in Fund of Funds, 12 in Managed Futures & CTAs and 16 in Multi Strategy.

Although Hedgenordic allows dead hedge funds to be included in the index, the database only consists of live hedge funds during our sample period. Since not all dead funds are included, it is likely that NHX suffers from survivorship bias and will thus be biased upwards (Ackerman et al, 1999). The magnitude of the bias is toned down as the most successful funds sometimes are missing and since a study like this focus on relative performance, i.e. the replicated portfolios will be affected by the same amount of survivorship bias (Hasanhodzic and Lo, 2006). By using the whole database in the replication process we hope to minimize any selection bias, which can arise if we construct the replicated portfolios based on individual hedge funds with significant factor exposures or high explanatory power.

4.3 SUMMARY STATISTICS

Table 1 reports descriptive statistics for all the individual hedge funds and for equal-weighted portfolios of the hedge funds in each category. Overall, the performance of the Nordic hedge funds is below our expectations. The category Equities is the top performer among the different categories with an average annual return of 7.07% and a Sharpe ratio of 0.49 while Managed Futures & CTAs and Multi Strategy performs fairly good, with Sharpe ratios about 0.40. On the other hand, Fund of Funds and Fixed Income do not impress us at all. Most of the indices have high first-order autocorrelation, which is an indication of high illiquidity exposure (Lo, 2001). The exception is Managed Futures and CTAs who has a first-order autocorrelation of 3.43%, maybe due to its investments in liquid exchange-traded futures.

Category	N	Annual Mean		Annual SD		Annual Sharpe		Autocorr (ρ_1)		Equal-Weighted Portfolios		
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Sharpe
All Hedge Funds	102	5.77%	5.41%	10.63%	7.27%	0.42	0.46	12.03%	19.81%	4.81%	4.61%	0.50
Equities	50	7.07%	4.75%	11.65%	7.23%	0.49	0.50	10.71%	19.61%	5.83%	5.83%	0.57
Fixed Income	8	1.60%	12.19%	13.91%	13.18%	0.29	0.61	25.57%	20.12%	3.22%	7.87%	0.09
Fund of Funds	16	3.61%	1.42%	4.97%	1.38%	0.26	0.30	10.26%	17.99%	2.67%	4.03%	0.04
Managed Futures & CTAs	12	7.53%	4.52%	13.24%	4.61%	0.39	0.36	3.43%	19.91%	5.99%	7.19%	0.48
Multi Strategy	16	4.61%	3.69%	9.54%	6.04%	0.41	0.45	17.58%	19.63%	5.72%	3.57%	0.89

Table 1: Descriptive statistics for NHX hedge funds included in our sample from January 2005 to December 2010.

5 METHODOLOGY

5.1 ORIGINAL FACTOR MODEL SPECIFICATION

We use two different factor models in our study. The original model is presented in this section for which we have tried to pick factors similar to those used by Hasanhodzic and Lo in 2006. The second factor model, the modified model, is presented later. To determine the explanatory power of chosen risk factors for the 102 hedge funds in our sample we run individual time-series regressions on them.

Included in the original model are the following six factors: (1) S&P500: Standard & Poor, 500 Composite Index, Total Return; (2) BI: World, Lehman Brothers, Aggregate Bond Index, Total Return; (3) CI: the spread between World, Lehman Brothers, Aggregate Bond Index, Total Return and United States, Merrill Lynch, 3 Month T-Bill Index, Total Return, Close; (4) COI: World, GSCI, Index, Total Return, Close; (5) CUI: United States, Local Indices, G-6 Dollar Weighted Index, Close; and (6) ΔVIX: the first-difference of United States, CBOE, Volatility Index (VIX), Close.

In accordance with Hasanhodzic and Lo we have chosen the six factors listed above for two reasons. Equities, bonds, credits, commodities, currencies and volatility is mainly what hedge funds invest in and should thus represent the risk exposure of the general hedge fund. In addition all of the market factors can be accessed through fairly liquid instruments which make it possible to construct the clones in reality.

We have used the same equations as Hasanhodzic and Lo in 2006. In (1) below the return of each hedge fund R_{it} is decomposed into a number of parts. From the decomposition each fund's expected return is calculated in (2) and variance in (3).

$$R_{it} = \alpha_i + \beta_{i1} RiskFactor_{1t} + \cdots + \beta_{iK} RiskFactor_{Kt} + \epsilon_{it} \quad (1)$$

$$E[R_{it}] = \alpha_i + \beta_{i1} E[RiskFactor_{1t}] + \cdots + \beta_{iK} E[RiskFactor_{Kt}] \quad (2)$$

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

The expected returns in (2) have two sources; beta exposure β_{iK} multiplied with the risk premium connected to the exposure $E[RiskFactor_{Kt}]$ and manager-specific alpha α_i. We probably miss a share of α_i as parts of it may be connected to omitted factors and a more tailor-made approach can likely yield better performing clones.

Category	N	Stat	Intercept					$R_{s\&p500}$					R_{bond}					R_{credit}				
			Min	Median	Mean	Max	SD	Min	Median	Mean	Max	SD	Min	Median	Mean	Max	SD	Stat	Min	Mean	Max	SD
All Hedge Funds	102	beta	-0.03	0.00	0.01	0.03	0.01	-0.56	0.07	0.12	0.74	0.20	-15.66	0.05	-0.55	5.89	2.81	-6.57	0.05	0.54	15.69	2.80
		t-stat	-1.56	1.16	1.12	5.35	1.09	-3.22	1.28	1.28	9.62	1.96	-3.51	0.02	-0.04	2.24	1.10	-2.22	0.03	0.04	3.78	1.13
Equities	50	beta	-0.01	0.01	0.01	0.03	0.01	-0.56	0.11	0.16	0.74	0.25	-15.66	0.11	-0.90	5.89	3.42	-6.57	-0.03	0.80	15.69	3.43
		t-stat	-1.37	1.19	1.28	5.35	1.07	-3.22	1.54	1.63	6.64	2.05	-2.96	0.07	-0.09	2.24	1.18	-2.20	-0.06	0.03	2.89	1.20
Fixed Income	8	beta	-0.03	0.00	0.00	0.02	0.02	-0.06	0.10	0.10	0.29	0.13	-5.38	-1.62	-1.37	4.74	3.34	-4.15	2.16	1.91	5.47	3.32
		t-stat	-1.56	1.08	0.96	4.06	2.00	-0.66	0.75	0.84	2.68	1.24	-3.51	-0.60	-0.76	1.51	1.84	-1.34	0.87	1.09	3.78	1.89
Fund of Funds	16	beta	0.00	0.00	0.00	0.01	0.00	-0.12	0.05	0.04	0.21	0.08	-1.47	0.10	0.12	0.88	0.60	-0.92	-0.12	-0.11	1.21	0.60
		t-stat	-0.11	1.33	1.13	2.40	0.71	-1.56	1.57	0.99	2.14	1.18	-1.59	0.13	0.18	0.96	0.65	-1.06	-0.18	-0.18	1.50	0.67
Managed Futures & CTAs	12	beta	0.00	0.01	0.01	0.02	0.01	-0.06	0.01	0.02	0.17	0.08	-3.87	-0.48	-0.08	3.83	2.27	-3.94	0.72	0.11	3.63	2.24
		t-stat	-1.10	0.93	0.70	1.44	0.82	-1.14	0.04	0.13	2.32	0.88	-0.64	-0.15	0.22	2.12	0.91	-2.22	0.26	-0.20	0.62	0.96
Multi Strategy	16	beta	0.00	0.00	0.00	0.01	0.00	-0.10	0.09	0.12	0.54	0.18	-5.55	-0.14	-0.09	4.05	1.97	-4.03	0.13	0.05	4.81	1.81
		t-stat	-0.49	0.89	1.05	3.15	1.05	-1.65	1.11	1.57	9.62	2.79	-0.86	-0.17	0.03	1.82	0.71	-1.80	0.15	-0.04	0.82	0.69

Category	N	Stat	$R_{commodity}$					$R_{currency}$					ΔVIX					Stat	Significance			
			Min	Median	Mean	Max	SD	Min	Median	Mean	Max	SD	Min	Median	Mean	Max	SD		Min	Mean	Max	SD
All Hedge Funds	102	beta	-0.18	0.02	0.04	0.76	0.12	-0.49	0.04	0.09	1.68	0.31	-0.01	0.00	0.00	0.00	0.00	R^2	0.01	0.30	0.76	0.20
		t-stat	-2.82	0.44	0.56	4.91	1.40	-2.16	0.22	0.45	4.16	1.09	-5.61	-0.86	-1.06	2.29	1.70	F-stat	0.31	5.09	26.48	5.60
Equities	50	beta	-0.18	0.01	0.04	0.50	0.12	-0.49	0.03	0.10	1.23	0.30	-0.01	0.00	0.00	0.00	0.00	R^2	0.05	0.33	0.76	0.19
		t-stat	-2.33	0.38	0.46	4.91	1.40	-1.52	0.18	0.40	4.16	1.12	-5.61	-1.18	-1.23	1.63	1.63	F-stat	0.70	5.96	26.48	6.05
Fixed Income	8	beta	-0.03	0.04	0.14	0.76	0.26	-0.04	0.17	0.41	1.68	0.55	-0.01	0.00	0.00	0.00	0.00	R^2	0.13	0.42	0.68	0.22
		t-stat	-0.62	0.68	0.82	2.38	1.04	-0.21	1.85	1.40	2.02	0.80	-3.40	-1.09	-1.53	0.77	1.46	F-stat	1.45	5.02	12.62	3.38
Fund of Funds	16	beta	0.00	0.04	0.04	0.07	0.02	-0.12	0.07	0.07	0.35	0.11	0.00	0.00	0.00	0.00	0.00	R^2	0.07	0.29	0.60	0.17
		t-stat	-0.06	1.62	1.74	3.97	1.01	-0.81	0.65	0.79	2.30	0.98	-4.41	-1.73	-1.91	0.51	1.63	F-stat	0.76	4.94	18.54	5.41
Managed Futures & CTAs	12	beta	-0.08	0.01	0.02	0.19	0.08	-0.17	0.05	0.09	0.72	0.22	0.00	0.00	0.00	0.00	0.00	R^2	0.01	0.08	0.18	0.05
		t-stat	-1.31	0.08	0.13	2.05	0.96	-0.59	0.14	0.30	1.89	0.69	-1.71	0.05	0.20	2.29	1.23	F-stat	0.31	0.98	2.13	0.59
Multi Strategy	16	beta	-0.15	-0.01	0.00	0.16	0.07	-0.49	-0.01	-0.07	0.19	0.22	0.00	0.00	0.00	0.00	0.00	R^2	0.12	0.32	0.76	0.18
		t-stat	-2.82	-0.24	-0.12	4.17	1.57	-2.16	-0.03	-0.11	1.80	1.15	-4.72	-0.09	-0.42	1.86	1.82	F-stat	0.61	5.65	24.55	6.35

Table 2: Output from multiple regression of NHX hedge funds' monthly returns from January 2005 to December 2010 on the six factors S&P500, BI, CI, COI, CUI and VIX.

5.1.1 Factor Exposures

The output from the multiple regressions of individual hedge funds' monthly returns on the six factors is presented in *Table 2*. The results are grouped by category and for each separate category minimum, median, mean, maximum and standard deviation of the beta factors are reported. In addition t-statistics are reported below betas and explanatory power is reported in the last column of the table. For example, the second upper left column called $R_{s\&p500}$ shows statistics corresponding to the S&P500 factor.

Exposures to the six risk factors vary greatly across the sample, both between categories and between risk factors. Overall there are large exposures towards R_{bond}, R_{credit} and $R_{s\&p500}$ while *Intercept* (alpha) and ΔVIX hardly have any exposure at all. Significance level has minor importance since we do not choose which funds to include based on that as it would create a selection bias. Keep in mind that *Table 2* provides averages of all the funds in any given category. A fund may be significant in one factor and completely insignificant in another. The low t-statistics could also derive from the small sample or the fact that the funds vary a lot. For example Equities contain multiple strategies bunched together in one category. Explanatory power looks satisfactory throughout the sample with a mean of approx. 30%, with the exception of the Managed Futures and CTAs category with a mean of 8%. In all other categories we have funds with R^2 values over 60%, which indicate that the factors can be relevant to some degree.

Category	N	Average Percentage Contribution of Factors to Return						
		S&P500	Bond	Credit	Cmdty	Currency	ΔVix	Alpha
All Hedge Funds	102	14.97%	19.71%	18.18%	9.13%	37.78%	-0.06%	0.28%
Equities	50	19.60%	-13.65%	43.82%	9.66%	40.23%	-0.07%	0.42%
Fixed Income	8	9.63%	-147.54%	192.13%	12.19%	33.67%	-0.29%	0.21%
Fund of Funds	16	8.33%	95.14%	-51.43%	9.75%	38.27%	-0.05%	-0.01%
Managed Futures & CTAs	12	5.95%	69.23%	-23.47%	7.50%	40.35%	0.05%	0.39%
Multi Strategy	16	16.60%	95.06%	-48.07%	6.56%	29.78%	0.00%	0.08%

Table 3: Decomposition of mean returns of NHX hedge funds into percentage contributions from manager-specific alpha and the six factors S&P500, BI, CI, COI, CUI and VIX between January 2005 and December 2010

5.1.2 Expected Return Decomposition

The results of equation (2) is presented in *Table 3* where the mean return of the hedge funds in a given category has been decomposed into average percentage contributions of each of the six factors and manager-specific alpha. All the percentage contributions in each category of hedge funds add up to 100%.

The relative contribution of manager-specific alpha is vital because if a large share of the mean returns comes from alpha it will be hard to clone the hedge funds. On the other hand if a large share of the mean returns comes from identifiable beta factors it might be possible to successfully replicate the hedge funds.

The contributions of alpha are very low across the whole range of categories, especially compared to the estimates of Hasanhodzic and Lo on US hedge funds (Hasanhodzic and Lo, 2006). Since an adequate amount of the hedge fund returns can be attributed to our six risk factors there is a case for replication of Nordic hedge funds.

In the whole sample the most substantial contributors to mean returns are CUI (37.78%), BI (19.71%) and CI (18.18%) while the ΔVIX (-0.06%) and Alpha (0.28%) stand out as the smallest contributors. As the Equities category is much larger than the others the complete sample is of course weighted. ΔVIX hardly seems to contribute to the mean return in any category. All categories shows a large long position in BI and a large short position in CI or vice versa, for example the Fixed Income category with the contributions BI (-147.54%) and CI (192.13%).

5.2 Modified Factor Model Specification

We wanted to create our own model to see if we could improve the original model. Our study's second model is called the modified factor model and in it we add two new equity indices, a European equity index and an index with small cap stocks. In addition to that we have decided to drop ΔVIX and S&P500.

We believe that Nordic hedge funds invest a larger share of their assets in European equities than US hedge funds who invest primarily in US equities and thus we wanted to include a European equity index in our study. We have therefore included STOXXE: STOXX Europe 600, Index, Net Total Return in the modified model.

Our intuition is that hedge funds often invest in small cap stocks, a characteristic not fully captured in neither S&P500 nor STOXXE. In order to capture this feature we have decided to add a second equity index and we have chosen the most widely used small cap index, i.e. RUS2000: Russell 2000, Index, Total Return.

We do not want to include too many factors in the model and has thus decided to drop two of the original factors in connection with the inclusion of the new. With two new equity indices we have an abundance of equity indices and we therefore drop

S&P500. Additionally *Table 3* in the previous section showed that the contributions of ΔVIX were broadly insignificant and thus we drop that factor too.

In summary the modified model consists of the following six factors: (1) STOXXE: STOXX Europe 600, Index, Net Total Return; (2) RUS2000: Russell 2000, Index, Total Return; (3) BI: World, Lehman Brothers, Aggregate Bond Index, Total Return; (4) CI: the spread between World, Lehman Brothers, Aggregate Bond Index, Total Return and United States, Merrill Lynch, 3 Month T-Bill Index, Total Return, Close; (5) COI: World, GSCI, Index, Total Return, Close; and (6) CUI: United States, Local Indices, G-6 Dollar Weighted Index, Close.

The modified model is estimated with the same equations as the original model. In equation (1) the return of each hedge fund R_{it} is decomposed into a number of parts. From the decomposition each fund's expected return is calculated in (2) and variance in (3). Refer to *Section 5.1* for a more detailed specification of the equations.

5.2.1 Factor Exposures

The output from the multiple regressions of individual hedge funds' monthly returns on the six factors is presented in *Table 4*. The results are grouped by category and for each separate category minimum, median, mean, maximum and standard deviation of the beta factors are reported. In addition t-statistics are reported below betas and explanatory power is reported in the last column of the table. *Table 4* for the modified model corresponds to *Table 2* for the original model.

Mean exposures to the six factors still vary to a large extent across the sample, both between categories and between risk factors. In general there are still large exposures to R_{bond}, R_{credit} and now to the new equity index R_{stoxxe} too. The smallest exposure is still towards *Intercept* (alpha). The beta factors are insignificant on average throughout the whole range of categories (Refer to discussion in *Section 5.1.1*). The mean explanatory power has improved from 0.30 in the original model to 0.32 in the modified model and it is superior on average for all categories except Fixed Income. Overall we seem to have improved especially explanatory power in the modified model.

Category	N	Stat	Intercept					R_{stoxxe}					$R_{rus2000}$					R_{bond}				
			Min	Median	Mean	Max	SD	Min	Median	Mean	Max	SD	Min	Median	Mean	Max	SD	Stat	Min	Mean	Max	SD
All Hedge Funds	102	beta	-0.02	0.01	0.01	0.03	0.01	-0.38	0.13	0.19	0.98	0.23	-0.46	-0.03	-0.03	0.32	0.14	-15.40	-0.54	-1.27	4.27	3.11
		t-stat	-0.99	1.25	1.36	7.21	1.16	-2.91	1.85	1.93	9.29	1.97	-5.52	-0.43	-0.45	2.27	1.30	-3.63	-0.37	-0.42	2.04	1.11
Equities	50	beta	-0.01	0.01	0.01	0.03	0.01	-0.38	0.14	0.22	0.98	0.27	-0.46	-0.02	-0.02	0.28	0.13	-14.52	-0.46	-1.63	4.27	3.26
		t-stat	-0.99	1.31	1.53	7.21	1.26	-1.82	2.18	1.96	5.13	1.76	-2.34	-0.27	-0.17	1.56	0.97	-3.17	-0.36	-0.51	2.04	1.15
Fixed Income	8	beta	-0.02	0.00	0.00	0.02	0.01	-0.03	0.16	0.15	0.36	0.13	-0.08	0.00	0.06	0.32	0.13	-15.40	-2.68	-3.93	1.59	5.57
		t-stat	-0.82	1.11	1.17	4.08	1.70	-0.86	1.56	1.21	2.73	1.18	-0.75	0.00	0.03	0.88	0.64	-3.63	-0.85	-1.15	0.90	1.61
Fund of Funds	16	beta	0.00	0.00	0.00	0.01	0.00	0.04	0.12	0.14	0.25	0.07	-0.18	-0.05	-0.05	0.04	0.06	-1.58	-0.73	-0.56	0.79	0.71
		t-stat	0.25	1.61	1.49	2.54	0.78	0.78	2.58	2.83	5.22	1.43	-3.43	-1.33	-1.18	0.82	1.22	-1.92	-0.68	-0.58	0.70	0.74
Managed Futures & CTAs	12	beta	0.00	0.01	0.01	0.02	0.01	-0.19	0.13	0.16	0.51	0.21	-0.31	-0.12	-0.13	0.17	0.15	-5.58	-0.39	-0.56	3.04	2.65
		t-stat	-0.67	1.03	0.87	1.85	0.82	-0.46	1.15	0.98	2.07	0.94	-2.10	-1.18	-0.94	0.56	0.84	-0.96	-0.16	0.08	1.78	0.93
Multi Strategy	16	beta	0.00	0.00	0.00	0.01	0.00	-0.31	0.14	0.18	0.88	0.29	-0.45	-0.01	-0.04	0.15	0.16	-3.27	-0.24	-0.04	3.46	1.87
		t-stat	-0.75	1.33	1.19	3.07	1.06	-2.91	1.49	2.03	9.29	3.26	-5.52	-0.12	-0.49	2.27	2.23	-1.24	-0.21	0.00	1.61	0.89

Category	N	Stat	R_{credit}					$R_{commodity}$					$R_{currency}$					Stat	Significance			
			Min	Median	Mean	Max	SD	Min	Median	Mean	Max	SD	Min	Median	Mean	Max	SD		Min	Mean	Max	SD
All Hedge Funds	102	beta	-4.82	0.58	1.20	17.95	3.16	-0.19	0.02	0.04	0.94	0.13	-0.27	0.13	0.17	1.23	0.27	R^2	0.04	0.32	0.75	0.20
		t-stat	-1.94	0.46	0.40	3.93	1.13	-2.85	0.46	0.53	4.88	1.46	-2.06	0.67	0.80	3.59	1.01	F-stat	0.34	5.19	21.88	5.32
Equities	50	beta	-4.82	0.58	1.47	14.14	3.15	-0.19	0.01	0.05	0.48	0.12	-0.27	0.10	0.19	1.23	0.30	R^2	0.04	0.35	0.72	0.20
		t-stat	-1.94	0.42	0.44	3.18	1.15	-2.43	0.34	0.51	4.88	1.46	-0.89	0.55	0.75	3.59	0.95	F-stat	0.50	5.77	19.21	5.42
Fixed Income	8	beta	-0.70	3.32	4.62	17.95	6.14	-0.03	0.04	0.17	0.94	0.33	0.04	0.20	0.38	1.21	0.39	R^2	0.12	0.35	0.57	0.15
		t-stat	-0.64	1.12	1.49	3.93	1.62	-0.63	0.76	0.82	2.41	1.04	0.18	1.49	1.41	2.39	0.67	F-stat	1.11	3.75	6.03	1.72
Fund of Funds	16	beta	-0.57	0.57	0.51	1.34	0.66	-0.01	0.04	0.04	0.07	0.02	-0.10	0.13	0.12	0.46	0.13	R^2	0.08	0.32	0.54	0.14
		t-stat	-0.64	0.68	0.55	1.71	0.71	-0.21	1.52	1.70	3.49	1.01	-0.68	1.46	1.34	2.84	1.08	F-stat	1.38	5.17	16.43	4.67
Managed Futures & CTAs	12	beta	-3.21	0.52	0.44	4.97	2.53	-0.09	-0.02	0.00	0.20	0.09	-0.15	0.18	0.17	0.65	0.21	R^2	0.04	0.09	0.21	0.05
		t-stat	-1.92	0.22	-0.11	0.91	0.98	-1.52	-0.30	-0.04	2.19	1.05	-0.47	0.63	0.61	1.49	0.62	F-stat	0.34	1.03	2.00	0.51
Multi Strategy	16	beta	-3.35	0.08	-0.09	2.85	1.74	-0.16	-0.01	-0.01	0.19	0.08	-0.18	0.00	0.03	0.29	0.13	R^2	0.17	0.37	0.75	0.22
		t-stat	-1.58	-0.01	-0.06	1.39	0.92	-2.85	-0.20	-0.28	3.44	1.61	-2.06	-0.02	0.23	2.54	1.16	F-stat	0.67	7.22	21.88	7.14

Table 4: Output from multiple regression of NHX hedge funds' monthly returns from January 2005 to December 2010 on the six factors STOXXE, RUS2000, BI, CI, COI, and CUI.

Category	N	Average Percentage Contribution of Factors to Return						
		STOXXE	RUS2000	Bond	Credit	Cmdty	Currency	Alpha
All Hedge Funds	102	18.46%	-1.09%	-41.61%	71.22%	8.94%	43.68%	0.40%
Equities	50	21.58%	0.55%	-77.88%	98.74%	9.53%	46.93%	0.56%
Fixed Income	8	15.18%	4.31%	-435.08%	480.64%	13.83%	20.57%	0.55%
Fund of Funds	16	13.80%	-2.75%	39.70%	-2.91%	9.37%	42.68%	0.09%
Managed Futures & CTAs	12	15.42%	-9.74%	49.74%	-14.17%	6.39%	51.93%	0.44%
Multi Strategy	16	17.30%	-0.78%	118.67%	-81.35%	6.13%	39.91%	0.12%

Table 5: Decomposition of mean returns of NHX hedge funds into percentage contributions from manager-specific alpha and the six factors STOXXE, RUS2000,BI, CI, COI and CUI between January 2005 and December 2010.

5.2.2 Expected Return Decomposition

The results of equation (2) is presented in *Table 5* where the mean return of the hedge funds in a given category has been decomposed into average percentage contributions of each of the six factors and manager-specific alpha. All the percentage contributions in each category of hedge funds add up to 100%. *Table 5* for the modified model corresponds to *Table 3* for the original model.

The exposures to alpha are still very low across the whole range of categories, although they have actually improved a bit for every category compared to the original model. The improvement likely comes from the higher explanatory power, but we consider it too small to significantly interfere with our cloning purposes. In other words, we still regard replication by cloning as meaningful to attempt.

Looking at mean for all hedge funds included the largest contributors are CI (71.22%), CUI (43.68%) and BI (-41.61%) while the smallest are Alpha (0.40%) and RUS2000 (-1.09%). Fixed Income stands out with extreme exposures to BI (-435.08%) and CI (480.64%), which seem somewhat problematic so these exposures and the worsened explanatory power should probably be kept in mind going forward. The relationship between BI and CI with a long or short exposure can still be observed.

5.3 LINEAR CLONES

The results from the multiple regressions on the original model and the modified model in the previous sections suggest that it can be possible to replicate an acceptable share of the risk exposures of hedge funds. The most important support for this finding is the adequate explanatory power and low portion of manager-specific alpha on average. We are now going to investigate the possibility directly by construction two different types of clones of the hedge funds, fixed-weight clones and rolling-window clones. The specifications that follow are equivalent to those used by Hasanhodzic and Lo in 2006.

Fixed-weight clones use the whole sample of a given hedge fund's returns to estimate a set of portfolio weights corresponding to the factors used in the linear regression. The calculated portfolio weights are fixed through time for each individual fund. The entire series of a hedge fund's returns are applied each period to compute the clone return, which creates a troublesome look-ahead bias. To overcome the look-ahead bias we also construct a second type of clones, based on rolling-window regressions.

5.3.1 Fixed-Weight Clones

To construct a fixed-weight clone for fund i, we regress the hedge fund's returns R_{it} on the six factors of either the original model (4a) or the modified model (4b), where we omit the intercept and constrain the beta coefficients to sum to one:

$$R_{it} = \beta_{i1} S\&P500_t + \beta_{i2} BI_t + \beta_{i3} CI_t + \beta_{i4} COI_t + \beta_{i5} CUI_t + \beta_{i6} \Delta VIX_t + \epsilon_{it} \tag{4a}$$

$$where\ t = 1, \ldots, T\ and\ subject\ to\ 1 = \beta_{i1} + \cdots + \beta_{i6} = 1$$

$$R_{it} = \beta_{i1} STOXXE_t + \beta_{i2} RUS_t + \beta_{i3} BI_t + \beta_{i4} CI_t + \beta_{i5} COI_t + \beta_{i6} CUI_t + \epsilon_{it} \tag{4b}$$

$$where\ t = 1, \ldots, T\ and\ subject\ to\ 1 = \beta_{i1} + \cdots + \beta_{i6} = 1$$

The estimated beta coefficients B_{ik} are then used as portfolio weights for the six factors and thus the portfolio returns are comparable to the fitted values R_{it}^* of the regression equations. In addition we implement a further renormalization so that the resulting portfolio return $\hat{R}_{it}$ has the same sample volatility as the fund's return series:

$$R_{it}^* = \beta_{i1}^* S\&P500_t + \beta_{i2}^* BI_t + \beta_{i3}^* CI_t + \beta_{i4}^* COI_t + \beta_{i5}^* CUI_t + \beta_{i6}^* \Delta VIX_t \tag{5a}$$

$$R_{it}^* = \beta_{i1}^* STOXXE_t + \beta_{i2}^* RUS_t + \beta_{i3}^* BI_t + \beta_{i4}^* CI_t + \beta_{i5}^* COI_t + \beta_{i6}^* CUI_t \tag{5b}$$

$$\hat{R}_{it} = \gamma_i R_{it}^*, \ \ \gamma_i = \frac{\sqrt{\sum_{t=1}^{T} (R_{it} - \bar{R}_i)^2 / (T-1)}}{\sqrt{\sum_{t=1}^{T} \left(R_{it}^* - \bar{R}_i^*\right)^2 / (T-1)}} \tag{6}$$

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

The renormalization is done in order to create a fair comparison between the hedge fund and the clone portfolio. In other terms renormalization is equal to changing the leverage of the clone portfolio because the sum of the renormalized betas will equal the renormalization factor γ_i and not one. If γ_i is less than one, the portfolio is not fully invested and if it is more than one, leverage is required.

5.3.2 Rolling-Window Clones

To construct a rolling-window clone for fund i, we use an 18-month rolling-window for each month t from months $t - 18$ to $t - 1$ to estimate the regressions below. We still regress on the six factors used in the original model (8a) and the modified model (8b). In addition we still omit the intercept and constrain the beta coefficients to sum to one:

$$R_{it-k} = \beta_{it1} S\&P500_{t-k} + \beta_{it2} BI_{t-k} + \beta_{it3} CI_{t-k} + \beta_{it4} COI_{t-k} + \beta_{it5} CUI_{t-k} + \beta_{it6} \Delta VIX_{t-k} + \epsilon_{it-k} \quad (8a)$$

$$where\ k = 1, \dots, 18\ and\ subject\ to\ 1 = \beta_{it1} + \cdots + \beta_{it6} = 1$$

$$R_{it-k} = \beta_{it1} STOXXE_{t-k} + \beta_{it2} RUS_{t-k} + \beta_{it3} BI_{t-k} + \beta_{it4} CI_{t-k} + \beta_{it5} COI_{t-k} + \beta_{it6} CUI_{t-k} + \epsilon_{it-k} \quad (8b)$$

$$where\ k = 1, \dots, 18\ and\ subject\ to\ 1 = \beta_{it1} + \cdots + \beta_{it6} = 1$$

In contrast to the fixed-weight clones the coefficients are now indexed by both *i* and *t* since the process is repeated each month for every fund *i* due to the rolling-window. The estimated beta coefficients are then used as in the fixed-weight description before to create clone returns $\hat{R}_{it}$:

$$R^*_{it} = \beta^*_{it1} S\&P500_t + \beta^*_{it2} BI_t + \beta^*_{it3} CI_t + \beta^*_{it4} COI_t + \beta^*_{it5} CUI_t + \beta^*_{it6} \Delta VIX_t \quad (9a)$$

$$R^*_{it} = \beta^*_{it1} STOXXE_t + \beta^*_{it2} RUS_t + \beta^*_{it3} BI_t + \beta^*_{it4} CI_t + \beta^*_{it5} COI_t + \beta^*_{it6} CUI_t \quad (9b)$$

$$\hat{R}_{it} = \gamma_{it} R^*_{it}, \ \ \gamma_{it} = \frac{\sqrt{\sum_{k=1}^{18} (R_{it-k} - \bar{R}_{it})^2 / 17}}{\sqrt{\sum_{k=1}^{18} \left(R^*_{it-k} - \bar{R}^*_{it}\right)^2 / 17}} \quad (10)$$

$$\bar{R}_{it} = \frac{1}{18} \sum_{k=1}^{18} R_{it-k}, \ \ \bar{R}^*_{it} = \frac{1}{18} \sum_{k=1}^{18} \bar{R}^*_{it-k} \quad (11)$$

Now we have to index the renormalization factors γ_i by time to take into account that they are calculated each month in the rolling-window too, i.e. we will get a unique renormalization factor γ_i for every window. Therefore the volatility of the returns for each clone *i* will not be equal to the volatility of the corresponding hedge fund's returns. Although if the volatilities do not shift substantially over time the renormalization should still produce clones with similar but not equal volatilities.

The rolling-window clones have weaknesses of their own, even though they prevent the look-ahead bias mentioned earlier. The more active estimation method with rolling-windows creates a need for frequent rebalancing of the clone portfolio and due to the smaller sample size the estimation error is naturally larger. The frequency of rebalancing can be controlled by altering the length of the window, but a longer window implies a decreasing ability to capture varying risk exposures.

Funds	N	Annual Mean		Annual SD		Annual Sharpe		Autocorr (ρ1)	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
All Hedge Funds	102	5.77%	5.41%	10.63%	7.27%	0.42	0.46	12.03%	19.81%
Equities	50	7.07%	4.75%	11.65%	7.23%	0.49	0.50	10.71%	19.61%
Fixed Income	8	1.60%	12.19%	13.91%	13.18%	0.29	0.61	25.57%	20.12%
Fund of Funds	16	3.61%	1.42%	4.97%	1.38%	0.26	0.30	10.26%	17.99%
Managed Futures & CTAs	12	7.53%	4.52%	13.24%	4.61%	0.39	0.36	3.43%	19.91%
Multi Strategy	16	4.61%	3.69%	9.54%	6.04%	0.41	0.45	17.58%	19.63%
Fixed-Weight Clones Original Model	**N**	**Annual Mean**		**Annual SD**		**Annual Sharpe**		**Autocorr (ρ1)**	
		Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
All Hedge Funds	102	8.55%	14.77%	10.63%	7.27%	0.79	0.97	18.84%	16.75%
Equities	50	8.52%	12.24%	11.65%	7.23%	0.71	1.01	20.06%	16.48%
Fixed Income	8	-8.00%	32.42%	13.91%	13.18%	-0.02	0.93	25.04%	21.71%
Fund of Funds	16	5.53%	2.26%	4.97%	1.38%	0.63	0.48	13.71%	16.37%
Managed Futures & CTAs	12	23.54%	10.49%	13.24%	4.61%	1.69	0.82	10.76%	15.98%
Multi Strategy	16	8.68%	8.19%	9.54%	6.04%	0.93	0.88	23.12%	14.22%
Fixed-Weight Clones Modified Model	**N**	**Annual Mean**		**Annual SD**		**Annual Sharpe**		**Autocorr (ρ1)**	
		Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
All Hedge Funds	102	7.82%	13.25%	10.63%	7.27%	0.72	0.86	14.56%	16.62%
Equities	50	8.50%	10.81%	11.65%	7.23%	0.70	0.93	16.23%	14.40%
Fixed Income	8	-8.17%	33.00%	13.91%	13.18%	-0.02	0.93	24.31%	21.05%
Fund of Funds	16	4.97%	2.09%	4.97%	1.39%	0.51	0.46	7.20%	17.34%
Managed Futures & CTAs	12	17.29%	6.96%	13.24%	4.61%	1.27	0.69	4.74%	19.22%
Multi Strategy	16	9.42%	5.58%	9.52%	6.03%	0.93	0.76	19.15%	13.66%

Table 6: Performance comparison of funds from the NHX database and their comparable fixed-weight clones produced using both the original model and the modified model from January 2005 to December 2010.

Funds	N	Annual Mean		Annual SD		Annual Sharpe		Autocorr (ρ1)	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
All Hedge Funds	102	5.23%	5.99%	10.94%	7.43%	0.37	0.52	12.03%	20.70%
Equities	50	6.04%	5.55%	11.97%	7.44%	0.41	0.56	10.44%	20.01%
Fixed Income	8	2.09%	13.22%	14.73%	13.23%	0.38	0.75	22.38%	25.52%
Fund of Funds	16	3.40%	1.74%	5.23%	1.56%	0.25	0.37	10.63%	19.11%
Managed Futures & CTAs	12	7.64%	5.26%	13.15%	5.02%	0.37	0.38	5.71%	22.98%
Multi Strategy	16	4.33%	4.38%	9.90%	6.09%	0.39	0.53	17.98%	19.57%

Rolling-Window Clones Original Model	N	Annual Mean		Annual SD		Annual Sharpe		Autocorr (ρ1)	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
All Hedge Funds	102	5.93%	9.76%	14.31%	8.51%	0.38	0.71	18.33%	26.38%
Equities	50	7.07%	8.73%	15.48%	9.48%	0.48	0.71	17.13%	21.23%
Fixed Income	8	7.53%	14.90%	15.22%	8.18%	0.36	0.72	16.94%	31.46%
Fund of Funds	16	0.31%	2.77%	8.16%	2.09%	-0.17	0.28	26.15%	24.79%
Managed Futures & CTAs	12	5.01%	13.16%	19.55%	7.73%	0.32	0.68	8.61%	40.97%
Multi Strategy	16	7.85%	10.50%	12.44%	6.58%	0.68	0.78	22.26%	27.25%

Rolling-Window Clones Modified Model	N	Annual Mean		Annual SD		Annual Sharpe		Autocorr (ρ1)	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
All Hedge Funds	102	3.60%	9.30%	13.95%	8.17%	0.19	0.69	7.74%	22.51%
Equities	50	4.78%	8.03%	15.14%	8.94%	0.32	0.70	7.07%	19.37%
Fixed Income	8	7.54%	13.73%	16.15%	8.85%	0.30	0.58	12.50%	27.40%
Fund of Funds	16	-1.10%	2.26%	7.51%	1.98%	-0.39	0.26	5.65%	25.95%
Managed Futures & CTAs	12	-0.13%	13.63%	18.23%	6.91%	0.03	0.65	-0.59%	25.15%
Multi Strategy	16	5.40%	9.57%	12.37%	6.66%	0.42	0.74	15.82%	23.58%

Table 7: Performance comparison of funds from the NHX database and their comparable rolling-window clones produced using both the original model and the modified model from January 2005 to December 2010.

6 RESULTS

6.1 PERFORMANCE

In *Table 6* a comparison between the performance of funds from the NHX database and their comparable fixed-weight clones produced using both the modified and original model is listed. With the *original* model, the average mean return of the fixed-weight clones is in fact higher than that of their corresponding funds for four out of the five categories. For Equities, the average mean return of the clones is 8.52%, compared to 7.07% for the corresponding funds. In the Fund of Funds category, the average mean return for clones and funds is 5.53% and 3.61%, respectively. The highest average mean return is generated by the Managed Futures & CTAs clones with 23.54%, compared to 7.53% for the funds. Finally, in the Multi Strategy category, the average mean return for the clones and funds is 8.68% and 4.61%, respectively. Important to stress, however, is the great variability in mean returns of the funds and their clones within their specific categories. As in previous research (Hasanhodzic, 2006); this variability causes issues with the significance of our results. It is difficult to get around in this case because of the above mentioned reason; but our results suggest, in line with Hasanhodzic (2006), that the clones' performance could be comparable to that of their corresponding funds.

A different image emerges in the Fixed Income category, where the clones' performance is significantly lower, negative in fact, to that of the funds with -8.00% compared to 1.60%. One reason to this underperformance is likely that funds in this category earn part of their return by bearing illiquidity risk. This will clearly be missing from the clone portfolios constructed with common and liquid risk factors.

With the *modified* model, however, the average mean return of the fixed-weight clones is more in line with their corresponding funds. For four categories, the average mean return is higher than that of their corresponding fund: Fund of Funds (4.97% vs. 3.61%), Managed Futures & CTAs (17.29% vs. 7.53%), Multi Strategy (9.42% vs. 4.61%) and Equities (8.50%, vs. 7.07%). The Fixed Income clones underperform as in the original model, with an average mean return of -8.17% compared to 1.60%.

Table 7 contains the performance of funds from the NHX database and their comparable *rolling-window* clones produced again using both the modified and original model. With the original as well as the modified model, the average performance of the rolling-window clones is mostly lower than their fixed-weight counterparts. The average mean returns of the rolling-window clones are in four out of the five categories lower than the fixed-weight clones. The one exception is the Fixed Income rolling-window clones, which outperform both fixed-weight clones and the funds on which they are constructed by. One reason to these differences is the fact that the rolling-window clones are based on a different sample period, since the first 18 months disappear. Also, the funds on which the rolling-window clones are based have lower or similar average mean returns for this sample period. Other reasons to the differences between rolling-window clones and fixed-weight clones is the fact that there is a stronger look-ahead bias for the fixed-weight clones and that the rolling-window clones give rise to increased estimation errors.

Despite a lower average performance by the rolling-window clones compared to the fixed-weight, both of the models still displayed average mean returns in line with the funds. Using the *original* model, the average mean returns are still noteworthy for the rolling-window clones, with three categories still outperforming their funds: Equities (7.07% vs. 6.04%), Fixed Income (7.53% vs. 2.09%), and Multi Strategy (7.85% vs. 4.33%). The differences between the rolling-window clones and their fund counterparts seem to have diminished a bit compared to the fixed-weight clones. For Fund of Funds the performance of the rolling-window clone is somewhat lower with 0.31%, compared to 3.40% for the fund and for Managed Futures & CTAs, the clone underperforms with an average mean return of 5.01% compared to the fund’s 7.64%.

Using the *modified* model, the average mean returns for the rolling-window clones are lower than both the original model and the funds for four categories out of five. The results are still noteworthy when compared to their funds though: Equities (4.78% vs. 6.04%), Fixed Income (7.54% vs. 2.09%), and Multi Strategy (5.40% vs. 4.33%). As with the original model, Fund of Funds underperform with an average mean return of -1.10% compared to the fund’s 3.40%, while the Managed Futures & CTAs has an average mean return of -0.13% compared to 7.64% for the fund. There is considerable cross-variation in their mean returns and so may not be statistically significant.

We have also looked into the Sharpe ratios of the clones versus the funds as a way to measure performance, which takes the volatility into consideration, as can be seen in *Figure 1*. Firstly, the renormalization performed leads to the standard deviations of the fixed-weight clones being identical to that of the funds. However, the average Sharpe ratio of a category is not equal to the ratio of that category’s average mean return to its average volatility, which is why the listed Sharpe ratios in *Table 6* and *Figure 1* still provide valuable information. For the rolling-window clones, there are differences in volatility due to the rolling-window where the volatility may vary between different windows, which make the Sharpe ratio comparisons more informative.

The average Sharpe ratios for the *fixed-weight clones* are both for the original and modified model higher than those of the corresponding funds in four out of five categories. The only category where the clones underperform is Fixed Income, where the funds have an average Sharpe ratio of 0.29 and the clones an average Sharpe ratio of -0.02 both using the original and the modified model. For the Equities funds, which have an average Sharpe ratio of 0.49, both the original and the modified model outperform with 0.71 and 0.70, respectively. The funds within Fund of Funds have an average Sharpe ratio of 0.26, compared to 0.63 for the original model clones and 0.51 for the modified model clones. Managed Futures & CTAs funds have an average Sharpe ratio of 0.39 versus 1.69 for the original model clones and 1.27 for the modified model clones. The Multi Strategy has an average Sharpe ratio of 0.41, being outperformed by the original and modified model both with an average Sharpe ratio of 0.93.

For the *rolling-window clones*, the results are more mixed with Sharpe ratios further in line with those of the underlying funds. Within the Fund of Funds, the average Sharpe ratios are negative for both the original and modified model of -0.17 and -0.39 compared with those of the corresponding funds of 0.25. The Equities funds have an average Sharpe ratio of 0.41, compared to 0.48 for the original model clones and 0.32 for the modified model clones. Fixed income funds have an average Sharpe ratio of 0.38, compared to 0.36 for the original model clones and 0.30 for the modified model clones. The funds within Managed Futures & CTAs funds have an average Sharpe ratio of 0.37 versus 0.32 for the original model clones and 0.03 for the modified model clones. Finally, the Multi Strategy has an average Sharpe ratio of 0.39, being outperformed by the original and modified model both with an average Sharpe ratio of 0.68 and 0.42, respectively.

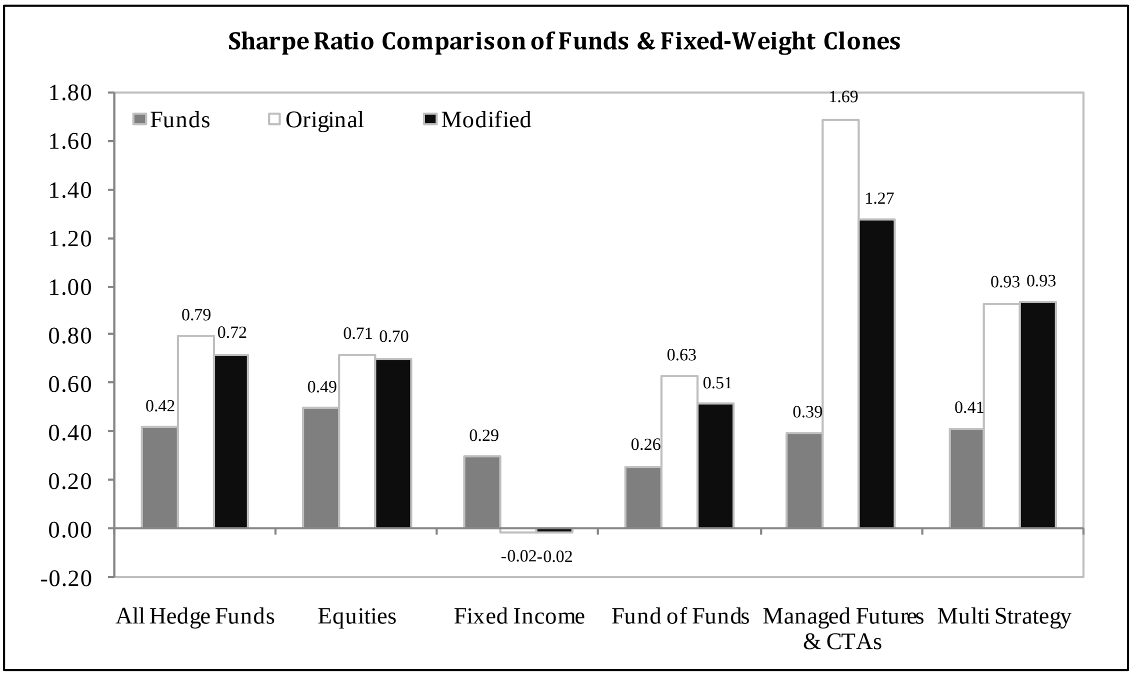

Figure 1: Comparison of average Sharpe ratios of funds from the NHX database and their comparable fixed-weight clones produced using both the original model and the modified model from January 2005 to December 2010.

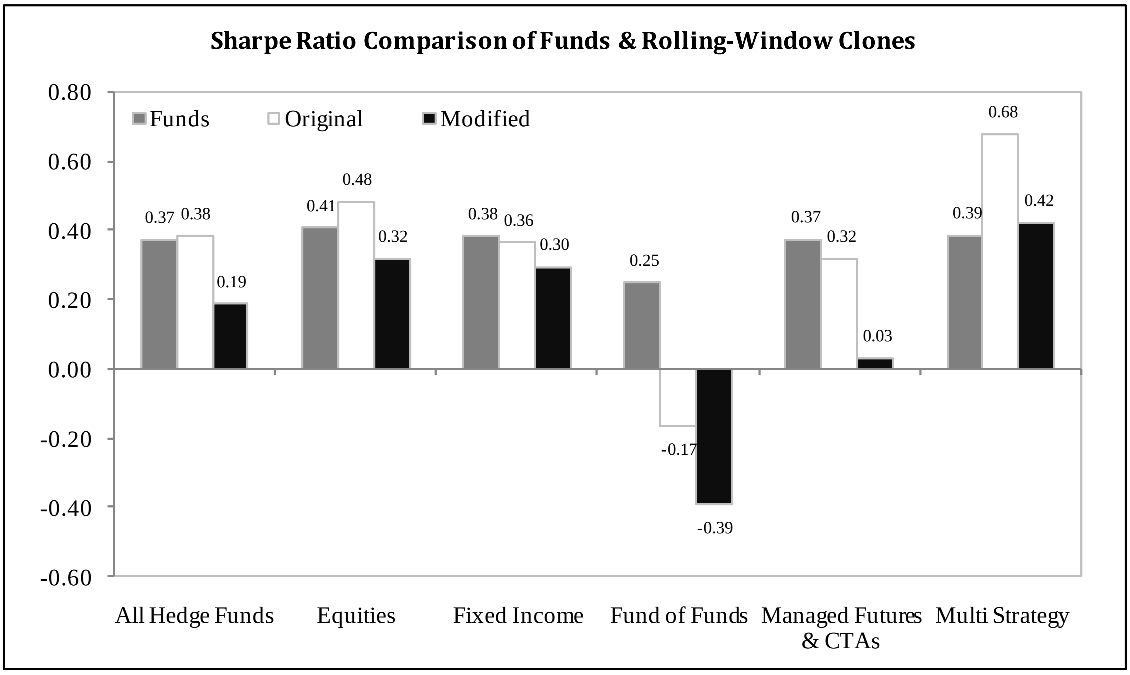

Figure 2: Comparison of average Sharpe ratios of funds from the NHX database and their comparable rolling-window clones produced using both the original model and the modified model from January 2005 to December 2010.

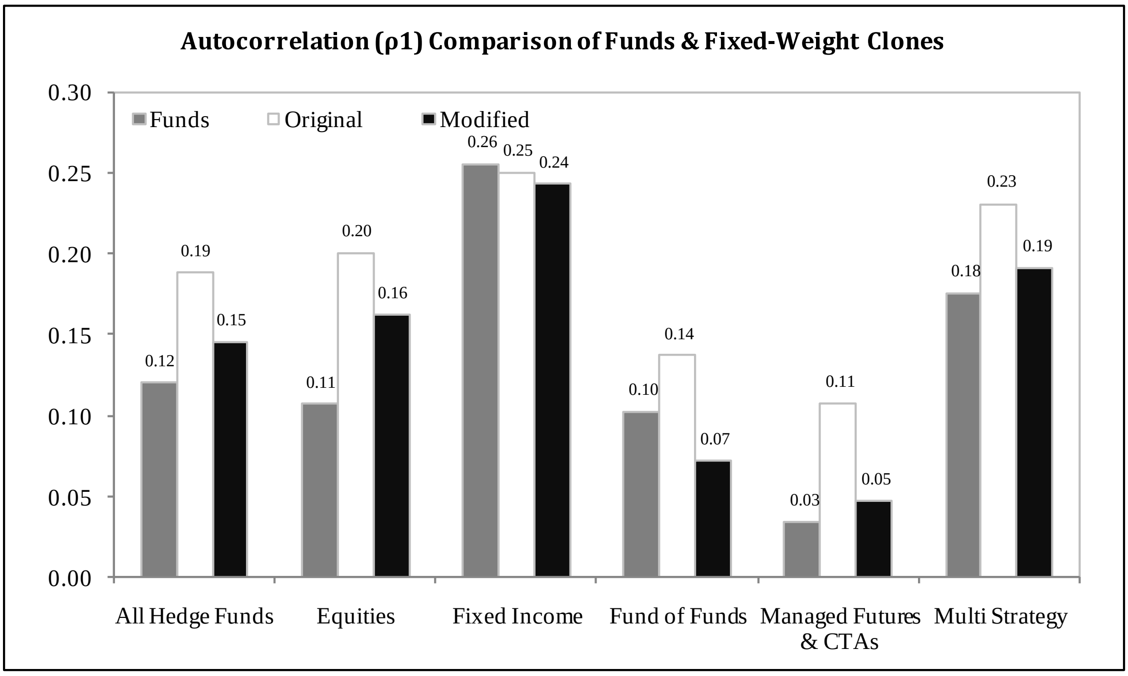

Figure 3: Comparison of average first-order autocorrelations of funds from the NHX database and their comparable fixed-weight clones produced using both the original model and the modified model from January 2005 to December 2010.

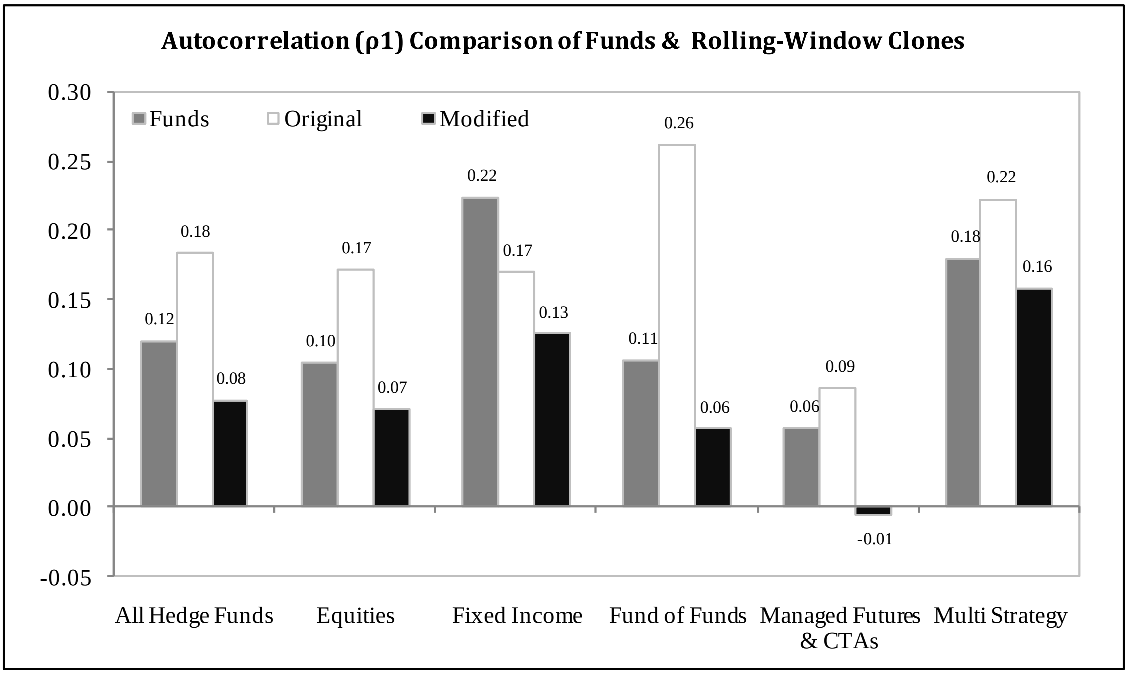

Figure 4: Comparison of average first-order autocorrelations of funds from the NHX database and their comparable rolling-window clones produced using both the original model and the modified model from January 2005 to December 2010.

6.2 LIQUIDITY

Figure 3 and *Figure 4* shows a comparison of the average first-order autocorrelations of funds versus fixed-weight clones and of funds versus rolling-windows clones, respectively. The first-order autocorrelation is the correlation between a fund's current and the previous month's return. As previous research (Hasanhodzic and Lo, 2007 and Lo, 2001) has pointed to, positive autocorrelations is often seen as a proxy for illiquidity risk. Because of this, we would expect to see lower autocorrelation for the clones. However, when comparing the autocorrelations of the funds to those of the fixed-weight clones, *Figure 3* shows that the autocorrelations for the fixed-weight clones are fairly in line with those of the funds. The clones using the original model have higher autocorrelations than the modified model. The rolling-window clones provide similar results, which differ between the original model and the modified model to an increasing extent. The clones using the original model have systematically higher autocorrelations than the corresponding funds, while the clones using the modified model have consistently lower autocorrelation than the corresponding funds. For instance, the average autocorrelation for Equities funds in the rolling-window sample is 10.44%, while it is 17.13% for the original model clones and 7.07% for the modified model. The modified model is more in line with what we would expect to see, and can be interpreted as the clones being more liquid than their corresponding funds.

6.3 LEVERAGE RATIOS

The renormalization factors represent adjustments in the clone portfolio's leverage in order to yield appropriate levels of volatility. If the absolute number is too large, this could create difficulties for the typical investor who may not have the required credit to take these kinds of positions. However, as can be seen in *Table 8*, this should not be an issue. The renormalization factor, or the average leverage ratio for the original and modified fixed-weight clones have a mean of 2.09 and 1.88, respectively. This means that the typical percentage of additional leverage required for fixed-weight clones with corresponding volatility is 109% and 88% on average. For the individual categories using the original model, the renormalization factor varies between 1.56 for the Fund of Funds and 3.92 for Managed Futures and CTAs; in line with results of Hasanhodzic, J and Lo, A (2007). The Fund of Funds has lower volatility due to its diversified profile, and Managed Futures has higher volatility due to the leverage already incorporated into the futures contracts traded by CTAs. Even the maximum leverage ratio required is low given the categories; with 2.44 for Fund of Funds and 6.65 for Managed Futures and CTAs. Using the modified model, the average leverage ratio reduced to 1.44 for the Fund of Funds and 3.15 for Managed Futures and CTAs. Equally, the maximum leverage ratios decrease to 2.25 for Multi Strategy and 5.04 for Equities.

It is important to remember for the rolling-window clones in *Table 8* that these leverage ratios vary over time; so the mean of 1.61 is the mean of all rolling-window clones of the time-series mean leverage ratio of each clone, and the standard deviation of 0.38 is the cross-sectional standard deviation across all rolling-window clones of those time-series mean. The average time-series mean leverage ratios for rolling-window clones are lower using the original model with 1.41 for Fund of Funds and 2.06 for Managed Futures and CTAs, with standard deviations of the time-series means of 0.23 for Fund of Funds and 0.35 for Multi Strategy. The average time-series mean leverage ratios for rolling-window clones are still lower using the modified model with 1.29 for Fund of Funds and 1.76 for Managed Futures and CTAs, with standard deviations of the time-series means of 0.20 for Fixed Income and 0.30 for Multi Strategy. In conclusion, these results should not cause any impossible practical implications with leverage ratios in line with expectations.

Category	N	Original Fixed-Weight Leverage Ratios				Modified Fixed-Weight Leverage Ratios				Original Rolling-Window Leverage Ratios				Modified Rolling-Window Leverage Ratios			
										TS-Mean		TS-SD		TS-Mean		TS-SD	
		Min	Mean	Max	SD	Min	Mean	Max	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
All Hedge Funds	102	0.78	2.09	6.65	0.99	0.75	1.88	5.04	0.75	1.61	0.38	0.45	0.24	1.44	0.31	0.35	0.21
Equities	50	0.78	1.94	4.87	0.76	0.75	1.81	5.04	0.71	1.59	0.37	0.42	0.25	1.43	0.31	0.32	0.19
Fixed Income	8	1.17	1.79	2.44	0.40	1.16	1.76	2.40	0.38	1.48	0.25	0.50	0.23	1.41	0.20	0.45	0.22
Fund of Funds	16	1.00	1.56	2.44	0.38	0.95	1.44	2.32	0.37	1.41	0.23	0.34	0.15	1.29	0.23	0.26	0.13
Managed Futures & CTAs	12	2.33	3.92	6.65	1.22	1.99	3.15	4.09	0.55	2.06	0.33	0.71	0.18	1.76	0.27	0.53	0.24
Multi Strategy	16	0.88	1.84	2.59	0.53	0.89	1.65	2.25	0.44	1.59	0.35	0.45	0.24	1.40	0.30	0.35	0.24

Table 8: Summary statistics for leverage ratios of funds from the NHX database and their comparable fixed-weight and rolling-window clones using both the original model and the modified model from January 2005 to December 2010.

6.4 EQUAL WEIGHTED CLONE PORTFOLIOS

Figure 5 and *Figure 6* show the cumulative returns of the equal-weighted portfolios of fixed weight and rolling-window clones for both the original and the modified model, as well as the equal-weighted portfolios of their respective funds and the S&P500 index. As can be seen in *Figure 5*, the equal-weighted portfolio for the fixed-weight clones outperforms both the equal-weighted portfolio for their corresponding funds as well as the S&P500, with little difference between the original and modified model. For the equal-weighted portfolio for the rolling-window clones, the differences diminish though and while the equal-weighted portfolio for the clones using the original model still outperform, the other portfolios are more closely aligned.

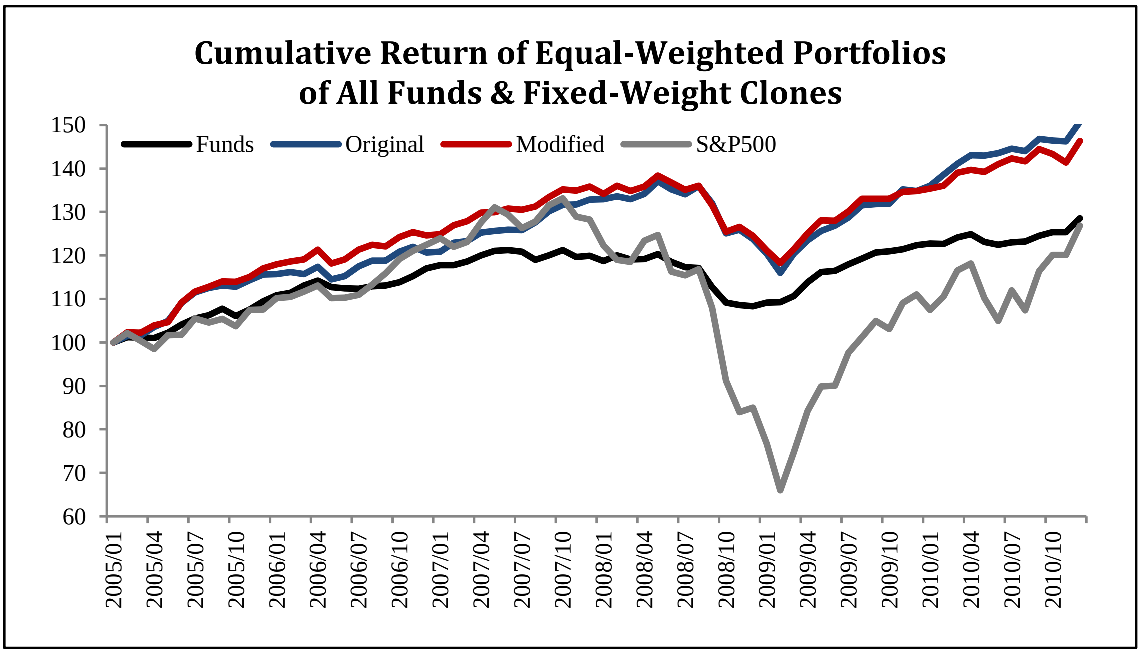

Figure 5: Cumulative Return of equal-weighted portfolios of all NHX funds and their related fixed-weight clones using both the original model and the modified model and from January 2005 to December 2010.

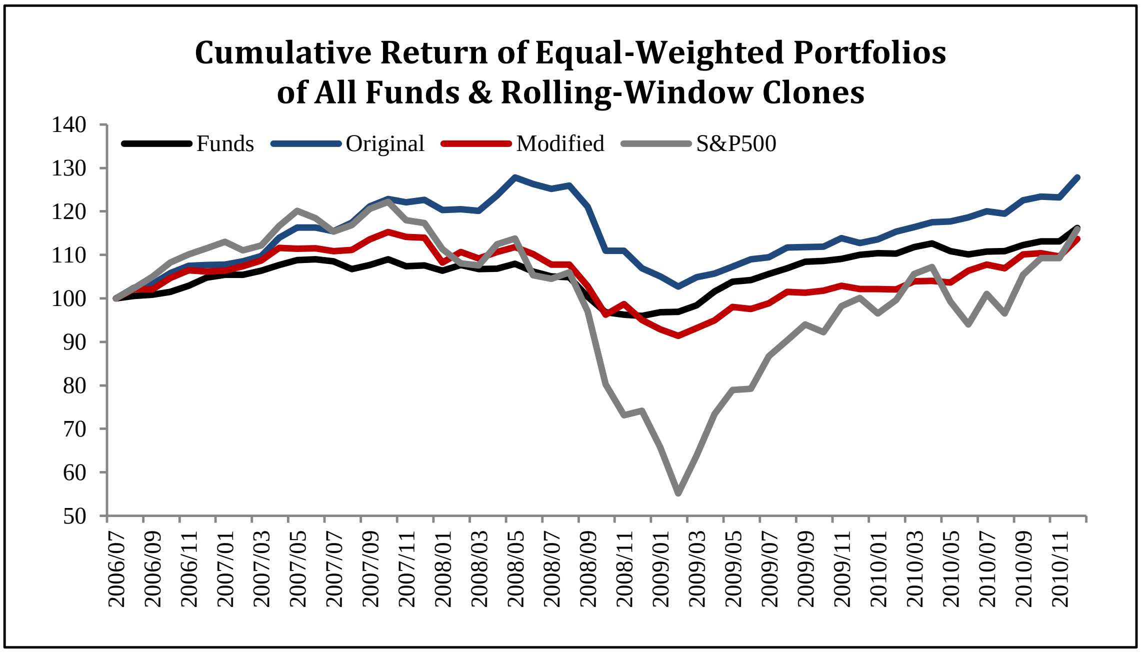

Figure 6: Cumulative Return of equal-weighted portfolios of all NHX funds and their related rolling-window clones using both the original model and the modified model and from January 2005 to December 2010.

7 CONCLUSION

Hypothesis no 1: Can Nordic hedge fund returns be replicated with a simple linear factor model? Our results indicate that performance of the clones is impressive with returns in line with the underlying funds. There is some variability depending on the use of fixed-weight or rolling-window clones, and on the use of the original or modified model. For the fixed-weight clones, the average mean return of the clones is higher than the funds' both using the original model and modified model. For the rolling-window clones, the average mean return is slightly higher using the original model and slightly lower using the modified model. Also, the Sharpe ratios for the clones using the original model are higher than those of the funds; while the Sharpe ratios for the clones using the modified model are somewhat lower than those of the funds. Overall, our results point to the conclusion that hedge fund returns can to a large extent be replicated with a simple linear factor model with performance of the clones in line with that of the funds.

Hypothesis no 2: Are our results in line with those of Hasanhodzic and Lo in terms of performance, explanatory power, liquidity and leverage? As in the paper by Hasanhodzic and Lo (2007), the results are not statistically significant but as previously argued significance is not necessarily the case due to the large variability in mean returns of funds and clones within their own categories, as well as a small sample size. Nonetheless, the results of the clones may be comparable to that of their corresponding funds. The issue surrounding significance is also the reason to why we should not read too much into the fact that our clones using the original model outperformed the funds where the clones of Hasanhodzic and Lo (2007) underperformed; rather we wish to point to the similarities in replicating performance with results in all cases close to those of the funds. Autocorrelation is usually seen as a proxy for illiquidity risk and the autocorrelation characteristics correspond to those of the funds. In line with Hasanhodzic and Lo (2007), lower levels of leverage were required for the clones as compared to that of the funds. Our results therefore support Hasanhodzic and Lo's findings (2007), also for Nordic hedge funds.

Hypothesis no 3: Can we improve our results by modifying the original factor model with new factors? Overall, the average mean return of the clones is higher using the original model than using the modified model, and the fixed-weight clones outperform the rolling-window clones for both models. Whether the additional factors improved our results to the model or not is difficult to determine since the performance of the clones is closely aligned to that of the funds. Using the modified model as compared to the original; the clones have slightly lower average mean returns and lower Sharpe ratios, but they also require less leverage. The issue of determining which factors to use is one of, if not the biggest challenge and since the factors used here have more of a European focus; it would also be interesting to look closer at whether more specific Nordic factors would improve the model.

In conclusion, it is true that hedge funds primarily extract return from risk premia, and only secondly from inefficiencies in imperfect markets. In the same way that mutual funds extracts the equity risk premium, hedge funds also extract various other risk premia awarded for credit risk, interest rate risk or liquidity risk, to name a few. To determine which risk premia lies as grounds for these returns is the primary and still unanswered question and deserves to be in the forefront of future research.

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