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‘ΑΝΑΠΑΡΑΓΩΓΗ ΤΩΝ ΑΠΟΔΟΣΕΩΝ ΤΩΝ HEDGE FUNDS’

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Επιθυμώ να εκφράσω την ευγνωμοσύνη μου στον επιβλέποντα καθηγητή Δημήτρη Μαλλιαρόπουλο για την καθοδήγηση και υποστήριξη που μου παρείχε κατά την διάρκεια της μελέτης και συγγραφής της παρούσας διπλωματικής εργασίας. Επιθυμώ ακόμη να ευχαριστήσω τους υποψήφιους διδάκτορες Αντώνη Αντύπα και Θοδωρή Σταματίου για την πολύτιμη βοήθειά τους.
Η ευθύνη για οποιαδήποτε λάθη παραμένει δική μου.

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1. Introduction

Hedge funds constitute a growing industry that attracts the interest of both academics and investors. Academics are intrigued by the unconventional performance characteristics of hedge funds. While hedge funds initially targeted private wealth, during the last decade institutional investors take a more active interest in alternative investments in order to benefit from their option-like returns and their low correlation with different asset classes. According to their operational framework, institutional investors have to take positions in transparent and liquid investments. They require significant capacity and they often face restrictions in managing their funds. On the other hand, hedge funds operations are rather opaque and illiquid. Hedge funds managers often impose long lock-up periods, the most successful among them have the least capacity to offer and they charge high fees as a fair compensation for their ability to produce returns irrespective of the market conditions.

Consequently, there is a gap between the expectations of institutional investors and hedge funds managers. During the last decade, many researchers have addressed this cultural gap by investigating the sources of hedge funds returns in order to construct portfolios which can replicate hedge funds returns. These replicating portfolios aim at producing similar returns at a lower cost, while offering the transparency, liquidity and capacity needed by the institutional investors. Moreover, replication may contribute to the benchmarking of hedge funds and the determination of a fair reward for their managers. Managers who can produce alpha may be sufficiently compensated for their skills, while hedge funds whose managers follow mainstream beta driven strategies will regress to index-like alternatives at lower fees. From a regulatory standpoint, the success of low-cost replicating products may lead to an improvement in the risk/return quality of the hedge fund industry. The knowledge of the hedge funds risk exposures may allow regulators to detect herding while the liquidity and transparency of the replicating portfolios may alleviate instability concerns. In this context, replication may be conceived as a healthy evolution towards maturity of the hedge funds industry.

A very popular and intuitive approach to replicate hedge funds is based on a multi-factor linear model which draws on Sharpe's (1992) attempt to explain the returns of mutual funds. In essence, the model tries to capture the main systematic risk exposures of the hedge funds. This will hopefully allow distinguishing between beta driven returns and alpha produced by skillful managers. Extensive literature has provided evidence that hedge funds are exposed to several risk factors and a large portion of their returns should be considered as reward for holding systematic risk. As short selling, derivatives trading and complex strategies are employed by hedge funds, many of these risk factors are alternative rather than traditional in nature (see for example Jaeger and Wagner (2005)). Moreover, option-based factors, like those documented by Fung and Hsieh (2001) and Agarwal and Naik (2004), exhibit considerable ability in capturing the non-linear character of hedge funds returns.

In this thesis, we use a broad set of 21 traditional and option-like risk factors, significantly larger than the sets used in previous papers, in an attempt to capture as much systematic risk as possible. Our full sample analysis of HFR indices over the period from January 1995 to September 2007 yields similar systematic exposure and alphas as those reported in previous papers. In a further step, we use a rolling window version of the linear model in order to account for the flexible trading environment of hedge funds by allowing the beta coefficients to change. Motivated by the higher R^2 values and the Sharpe ratios we get, we compare the cumulative performance of the replicating portfolios to that of the corresponding hedge funds indices. The comparison extends to a ten year long period, which is much longer than that used in previous works. This allows us to examine whether replication is persistently successful. With the exception of the Short Bias strategy, we find that the replicating portfolios considerably underperform the original hedge funds indices. This is in contrast to Jaegner and Wagner (2005), who use a much shorter (two and a half year long) period and report encouraging results as regards to the ability of the replicating portfolios to provide similar cumulative returns to those of the corresponding indices.

We next consider a dynamic rolling window version of the multi-factor model, which allows for changes of the risk factors from one window to another. This version attempts to address the fact that managers may follow trends which change in the course of time. Despite the higher R^2 values and the higher Sharpe ratios that this approach yields, the replicating portfolios considerably underperform the corresponding hedge funds indices, the only exception being the Short Bias strategy.

Motivated by previous work on the importance of conditioning in the measurement of mutual and hedge funds performance (Ferson W. E., Schadt R., D., (1996) and Kat H., M., Miffre J., (2002)), we propose a conditional version of the dynamic rolling window approach, where betas are conditioned on a set of information instruments thus incorporating the information available to the market into the performance measurement model. We once again find that original hedge funds indices outperform the replicating portfolios, providing support to the conclusion that alphas possess strong economic significance. We finally use a portfolio intersection argument to illustrate the benefits of adding original hedge funds to a replicating portfolio

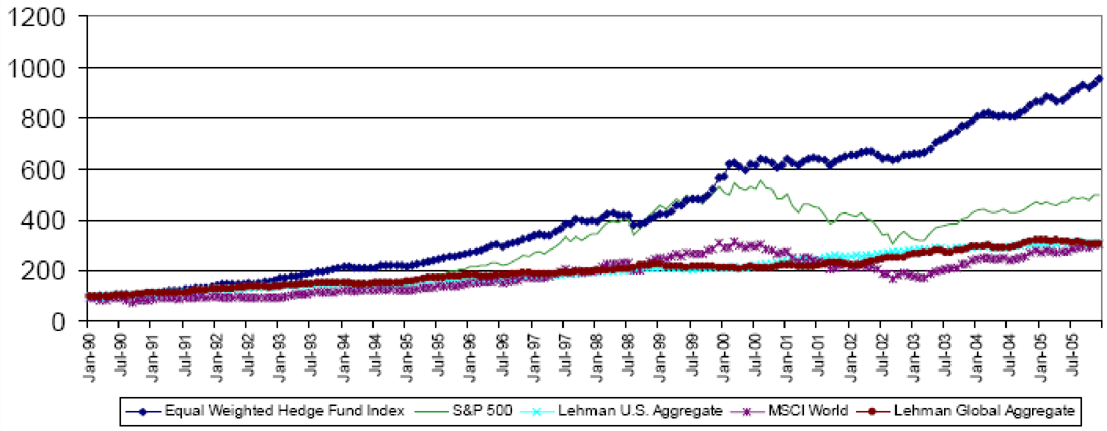
The rest of this thesis is organized as follows. Section 2 presents some basic characteristics of hedge funds. In section 3 we further analyze the separation of hedge funds returns into alpha and beta-driven and comment on the non-linear character of hedge funds returns. Section 4 illustrates the benefits of hedge funds replication and explains the framework in which it is relevant. Section 5 presents the multi-factor linear model in more detail. A literature review is provided in section 6 while section 7 provides a description of the data used as well as a discussion on the biases of hedge funds indices. Section 8 presents the empirical results and section 9 concludes.

2. Getting started with hedge funds

Hedge funds are described as investment vehicles which follow dynamic and highly sophisticated investment strategies. They have great trading flexibility and they are lightly regulated due to their targeting private capital of wealthy individuals. As the industry of hedge funds claims, their returns stem from and depend largely on the ability and experience of their managers, who promise returns independent of the market conditions. This property renders hedge funds particularly attractive to investors. It is this feature which has also attracted the academic interest during the last decade. Hedge funds make investments which usually outperform more conventional investment vehicles, such as mutual funds (Ackermann, McEnally and Ravenscraft, (1999)). **Figure 1** depicts the growth of $100 invested in various assets types. Over the period 1990-2005, the CISDM Equal Weighted Hedge Fund Index had superior return performance relative to other traditional asset classes.

The first hedge fund was established in 1949 by Alfred Winslow Jones and its operations were similar to the modern equity long/short hedge funds. In the course of time the number of hedge funds and the assets under management increased considerably. The number of hedge funds (not including Funds of Funds) has increased from an estimated 530 in 1990 to over 6,700 at year 2005. In the same period, assets under management have grown from less than $30 billion to over $1.2 trillion. And because hedge funds use substantial leverage, they play a far more important role in global securities markets than what the size of their assets suggests. While the assets under management represent a small percentage of world assets (about 1% according to J.P. Morgan), hedge funds are responsible for a considerable percentage of the global daily trading volume.

Figure 1
Growth of $100 invested in 1990 until 2005 in various assets types. The hedge fund index outperforms traditional asset classes.



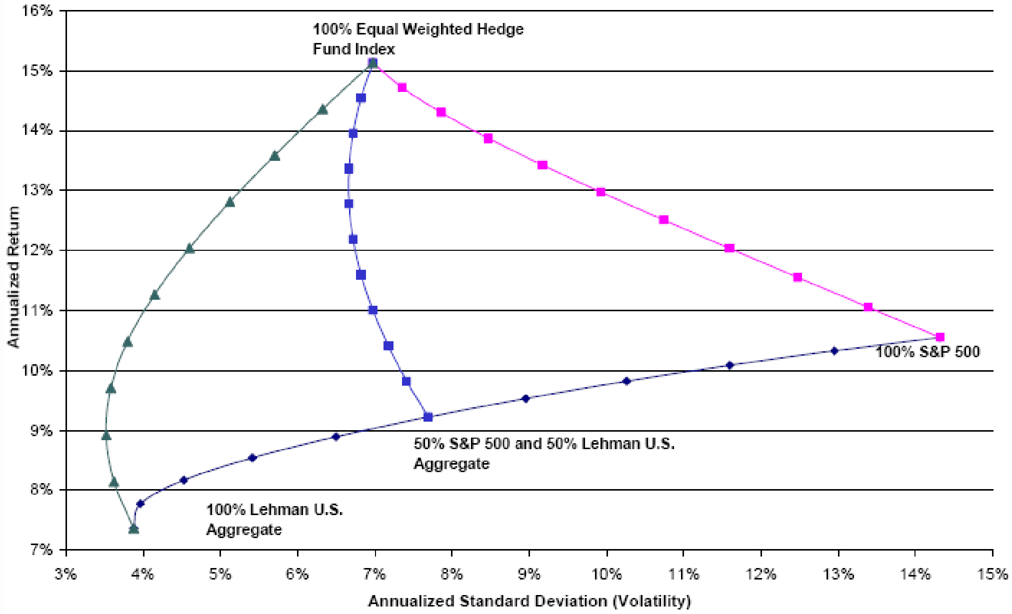
Source: CISDM, "The benefits of hedge funds: 2006 update".

Growth in investor demand for hedge fund products indicates investor appreciation of the potential benefits of active trading in traditional as well as in derivatives markets. The benefit of including hedge funds in diversified portfolios is illustrated in **figure 2**. Over the period form 1990 to 2005, when a portfolio of hedge funds is added to U.S. stocks, Treasury Bonds, or a portfolio of U.S. stocks and bonds, the risk/return profile improves.

Due to the variety of strategies that hedge funds implement in order to exploit market inefficiencies, there does not exist a universally accepted norm to classify them into different strategy classes. Fung and Hsieh (1997) categorize hedge funds according to the asset class they invest in, such as stocks, currency and fixed income assets. Some hedge funds invest in American assets only, while others focus in emerging markets. Multi-strategy hedge funds employ a wide variety of strategies, thus providing greater diversification.

Figure 2

Risk/return performance of combinations of stocks, bonds and hedge funds (1990-2005). When a portfolio of hedge funds is added to U.S. stocks, Treasury Bonds, or a portfolio of U.S. stocks and bonds, the risk/return profile improves.



Source: CISDM, “The benefits of hedge funds: 2006 update”.

Furthermore, hedge funds are often characterized as directional, such as short selling and equity non-hedge, and as non-directional, such as long/short and relative value. Directional hedge funds have open positions and achieve profit when the market moves according to the manager’s expectations. Non–directional hedge funds maintain open positions at a much smaller degree and their returns stem mainly from the exploitation of asset mispricing. As profit opportunities switch from one financial field to another, managers may switch between investment strategies.

3. Hedge funds returns

3.1. Sources of hedge funds returns

One of the most crucial issues about hedge funds is where the returns of hedge funds stem from. This is a difficult question to answer because of the opaqueness of hedge funds operations, the lack of performance reporting standards and the fact that the relatively short history of hedge funds returns makes the assessment of their long term performance difficult.

As mentioned earlier, hedge funds advertise themselves as investment vehicles realizing profit from the exploitation of market inefficiencies, regardless of the market conditions, while they are hedged against systematic risk exposures. The discovery and exploitation of inefficiencies which offer arbitrage opportunities is based on the manager's expertise, experience and personal information. This part of the return which depends on the manager's ability is referred to as alpha. Hedge funds managers charge high fees for providing investors with alpha. Typical level for the so called management fee and incentive fee is 2% and 20% of the profits, respectively. It's common that managers invest their own capital in the fund they manage, which leads to investors facing less agency cost. The importance of incentive fees is investigated by Liang (1999), who documents positive correlation between the height of the manager's reward and the hedge fund's returns.

However, experience has shown that hedge funds may suffer considerable losses in downmarket periods. LTCM is a famous example. This hedge fund was severely affected by the Russian debt crisis in 1998, which caused profound credit crunch. Such incidents can hurt the claim that hedge funds produce positive returns, regardless of the market movements. According to past experience, hedge funds seem to be positively correlated to the market in periods of recession, that is in periods when investors desire correlation the least. Fung and Hsieh (1997) point out that trend follower's returns are positively correlated with the stock market in bullish markets and negatively correlated in bear markets. Billio, Getmansky and Pelizzon (2006) provide extensive literature documenting the presence of conditional correlations between hedge fund indexes and market factors. For these reasons, both investors and academic researchers have started looking into the black box of hedge funds to find out where returns come from.

Voluminous literature has been accumulated during the last decade providing evidence that hedge funds are exposed to various systematic risk factors, according to the strategy that each one follows. Thus, a great portion of their returns stems from risk premia which compensate the investor for holding systematic risk. This part of the total return of hedge funds is referred to as beta.

These betas are actually more complex than traditional betas, such as those of conventional investment vehicles, like mutual funds. The latter usually follow passive strategies (buy-and-hold) on standard asset classes and their risk exposures are static. On the contrary, hedge funds follow active strategies such as investing in derivatives, using leverage and short-selling assets. Facing limited investment restrictions, hedge funds managers can change quickly their risk exposures, according to the market conditions and their expectations in order to time the market. Moreover, hedge funds are exposed to risk factors that are not met in traditional investments. For example, equity market neutral and long/short hedge funds are exposed to style factors such as small cap-large cap spread and value-growth spread. Merger arbitrage funds are exposed to deal risk, whereas distressed securities are exposed to liquidity risk. The beta coefficients of these unconventional risk factors are called alternative betas.

Equation (1) describes mathematically the decomposition of hedge funds returns into the two parts analyzed above. Alpha arises from the fund's idiosyncratic character, as this is formed by the manager's actions. The second part is the investor's reward for being exposed to systematic risk factors. Alpha is directly observable. It can only be indirectly measured as what is left after all systematic risks, those accounted for by the model and those that the model has not taken into account, have been separated out from the total return. Hedge funds outperformance is attributed not only to the manager's alpha, but also to alternative beta exposures.

$$\text{Hedge fund return} = \text{manager's alpha} + \sum \beta_i * \text{factor}_{i,\ \text{modeled}} + \sum \beta_i * \text{factor}_{i,\ \text{not modeled}} \quad (1)$$

The research on the sources of hedge funds returns is important for several reasons. The uncovering of the systematic risks that hedge funds are exposed to is important to the setting of performance benchmarks. Investors willing to invest in hedge funds should wonder whether a manager is capable of adding alpha and also whether this alpha is destroyed by manager's fees. Based on these benchmarks investors can determine the extent to which a hedge fund has outperformed the market as well as define a rational reward for the fund's manager. Investors can also determine more accurately how the addition of hedge funds in their portfolio improves its efficiency and diversification and thus design better portfolios. They can also detect inconsistent bets by managers and reduce disclosure risk. From a regulatory standpoint, the knowledge of hedge funds' systematic risks is important in order to assess the financial turbulence they may provoke and the impact they may have on the economy, especially on emerging markets. For example, a better understanding of hedge funds operations would help to the assessment of whether and to what extent their speculative bets should be blamed for the recent food crisis in many developing countries.

3.2. The non linear character of hedge funds returns.

The exposure of hedge funds to alternative risk factors gives rise to the non-linear character of hedge funds returns. Merton (1981) notes that portfolios managed in a superior information framework, like hedge funds, exhibit non-linear option like payoffs. Agarwal and Naik (2000) claim that there are several reasons why hedge funds returns are non-linear. First, manager's reward depends on the profits, which, from the investor's perspective is similar to writing a call option. As a consequence, even if gross returns are linear, net of fees returns become non linear. The second reason is the opportunistic nature of hedge funds, in other words the fact that hedge funds take positions whose returns depend on market conditions. Merger arbitrage funds are a typical example. These funds take positions in merger deals, which usually go through in upmarket periods. However, the returns may be much lower than the losses that merger arbitrage funds may suffer, if market conditions deteriorate and the deals are called off. Thus, the payoff function of merger arbitrage funds may exhibit non-linear characteristics.

Another reason for which hedge funds returns are non-linear is that hedge funds invest in derivatives either directly or indirectly through their dynamic strategies. As a result, hedge funds returns cannot be accounted for by conventional buy-and-hold strategies. Fung and Hsieh (2001) analyze trend following hedge funds and find that traditional risk factors, such as those used by Sharpe (1992) for mutual funds, fail to explain the unconventional performance characteristics of hedge funds. Trend following hedge funds exhibit positive returns, both in periods of growth and in periods of recession. This non-linear payoff, which resembles that of a straddle, is interpreted as evidence of dynamic non conventional strategies. The authors use lookback straddles in order to capture this non linearity. **Table 1** presents the adjusted R^2 values for various sets of regressors. It is obvious that the lookback straddles are much more successful than traditional risk factors in explaining hedge funds returns. It's also interesting to note that an investor using standard asset benchmarks would have erroneously concluded that trend followers had no systematic risk.

Table 1

Regression of trend following funds on several sets of regressors. Lookback straddles yield the highest explanatory power

	Sets of risk factors	Adjusted R^2 of regression (%)
1	Eight major asset classes in Fung and Hsieh (1997a) (U.S. equities, non-U.S. equities, U.S. bonds. Non-U.S. bonds, gold, US. Dollar index. Emerging market equities, one-month Eurodollar)	1.0
2	Five major stock lndiccs (S&P 500. FTSE 100, DkX 30. Nikkei 225, Australian All Ordinary)	-2.1
3	Five government bond markets (U.S. 30-year, UK Gilt, German Bund French 10-pear, Australian 10-year)	7.5
4	Six three-month interest rate markets (Eurodollar, 3m Sterling, Euro-DM, Euro-Yen, Australian Bankers Acceptance, Paris Interbank Rate)	1.5
5	Four currency markets (British pound, deutschemask, Japanese yen, Swiss franc)	-1.1
6	Six commodity markets (corn, wheat, soybean, □lued oil, gold, silver)	-3.2
7	Goldman Sachs Commodity Index	-0.7
8	Commodity Research Bureau Index	-0.8
9	Mount Lucas/BARRA Trend-Following Index	7.5
10	Five PTFS portfolios (Stock PTFS, Bond PTFS, Currency PTFS, three-month interest rate PTFS, Commodity PTFS)	47.9

Source: Fung and Hsieh 2001.

4. Hedge funds replication.

The determination of the systematic risks of hedge funds is of crucial importance for the construction of portfolios replicating hedge funds returns, that is portfolios which can deliver returns similar to those of the original hedge funds without the contribution of managerial skills. This implies that replication tries to circumvent managers and consequently, managerial fees.

During the last few years, the issue of replicating hedge funds has become important as, besides wealthy individuals, more and more institutional investors, like pension funds and universities, want to include hedge funds in their portfolios. Institutional investors aim to take advantage of the alternative risk premia that hedge funds provide with as well as to achieve higher degree of portfolio diversification. These investors are subject to a tighter regulatory regime, thus they need transparent and liquid investments. However, hedge funds are rather opaque regarding the strategies they implement. Their investments can be illiquid, levered and the management fees are quite high. Replication can be the answer to all these disadvantages, by constructing synthetic investment vehicles which can deliver returns similar to those of hedge funds while being more liquid and transparent, having lower minimum investment level, costing less than hedge funds and contributing to the diversification of a traditional portfolio. Hence, replication can render hedge funds accessible to a broader range of investors who did not have the possibility to invest in hedge funds or who were afraid of the prevailing black box picture about hedge funds.

These potential new investors and the implied increase in market share in the alternative market can explain why large investment banks have already launched replication programs, which, according to what these banks claim, successfully replicate the returns of original hedge fund indices. For example, Merrill Lynch has launched the Merrill Lynch Factor Index and Goldman Sachs has launched the Goldman Sachs Absolute Return Tracker Index. Competition is fierce since a lot of money can be raised by investment banks via hedge fund replicating products. Almost all synthetic hedge funds are based on the risk factors replication method, which will be described in section 5.

Hedge funds replication becomes relevant as the increase of the number of hedge funds and the increase of the assets under management raises doubt about whether managers can produce enough alpha for all investors. Berk and Green (2004) believe that managers face decreasing returns to scale in deploying their ability, and hence in producing alpha. Smedts K. and Smedts J. (2006) mention that the growth of the hedge funds industry results in arbitrage strategies becoming scarcer as the markets become more efficient through hedge funds' operations. The deepening of derivatives markets contributes to the markets efficiency. Strategies that initially delivered alpha become systematic risk when they are implemented by a large number of hedge funds. Asness C. (2004) indicates that hedge fund risk becomes more and more alternative beta risk and it is more likely to add value through timing the beta exposures than hunting alpha. Moreover, the lucrative fees and lower entry barriers attract managers with a lower skill level, who tend to dilute the average performance and thus the average alpha of the hedge fund industry. Lars Jaeger (2007) analyzes data from January 2000 to March 2007 for the Equity Hedge, Event Driven, Merger Arbitrage and Convertible Arbitrage strategies and reports a decrease in alpha in all strategies. The author concludes that, as hedge funds returns become progressively beta driven, investors, on average, benefit from the alternative betas rather than from the manager's alpha. In this context, hedge fund replication seems to be a healthy evolution for the industry as it could lead to the survival of those funds that are ran by capable managers. On the other, hand, less talented managers who employ common and widespread beta driven strategies might have to give way to replicating products. This development could improve the risk-return ratio of the hedge fund industry. From a regulatory point of view, it could contribute to a safer global financial system.

Motivated by these observations, Fung, Hsieh, Naik and Ramadorai (2006) want to examine whether the average hedge fund delivers net of fees alpha. For this purpose, they employ a comprehensive sample of 1603 funds of hedge funds from the Lipper TASS, HFR and CISDM databases during the period from January 1995 to December 2004. By using bootstrap techniques they find that there are hedge funds which deliver net of fee alpha to investors. The authors name these funds have-alpha funds, in contrast to the rest, i.e., funds that deliver solely on account of systematic risk exposures, which are named beta-only funds. **Table 2** presents the results. For example, during the period 1996-1997 34% out of 259 funds were found to be have-alpha and 66% of them were beta-only. 17% of these have-alpha funds continued to be have-alpha in the next period 1998-1999 while 74% switched to beta-only. 5% of have-alpha funds liquidated and 5% stopped reporting. In contrast, 7% of the 1996-1997 beta-only funds were classified as have-alpha in 1998-1999, 73% were reclassified as beta-only, 13% liquidated and 6% stopped reporting. On average, 22%

of funds of hedge funds were found to be have-alpha and 78% were beta-only. It becomes obvious that have-alpha funds tend to persistently deliver alpha. They also exhibit smaller liquidation rate compared to beta-only funds.

Table 2

Classification of funds of hedge funds into have-alpha and beta-only funds and transition probabilities. Have-alpha funds are those delivering net of fees alpha, while the rest are classified as beta-only. The table reads as follows: For example, during the period 1996-1997 34% out of 259 funds 34% were found to be have-alpha and 66% of them were beta-only. 17% of these have-alpha funds continued to be have-alpha in the next period 1998-1999 while 74% switched to beta-only. 5% of have-alpha funds liquidated and 5% stopped reporting. In contrast, 7% of the 1996-1997 beta-only funds were classified as have-alpha in 1998-1999, 73% were reclassified as beta-only, 13% liquidated and 6% stopped reporting.

Classification Period	Number of Funds	Proportion			P(Two-Year Transition)			
		Have-Alpha	*Beta-Only*	From/To:	*Have-Alpha*	*Beta-Only*	*Liquidated*	*Stopped Reporting*
1995-1996	195	0.21	0.79	*Have-Alpha*	0.24	0.68	0.02	0.05
				Beta-Only	0.04	0.82	0.10	0.04
1996-1997	259	0.34	0.66	*Have-Alpha*	0.17	0.74	0.05	0.05
				Beta-Only	0.07	0.73	0.13	0.06
1997-1998	307	0.10	0.90	*Have-Alpha*	0.81	0.16	0.00	0.03
				Beta-Only	0.26	0.58	0.09	0.07
1998-1999	374	0.17	0.83	*Have-Alpha*	0.27	0.65	0.05	0.03
				Beta-Only	0.18	0.62	0.12	0.09
1999-2000	448	0.42	0.58	*Have-Alpha*	0.24	0.64	0.06	0.06
				Beta-Only	0.09	0.70	0.12	0.09
2000-2001	506	0.22	0.78	*Have-Alpha*	0.30	0.65	0.03	0.02
				Beta-Only	0.10	0.77	0.08	0.04
2001-2002	584	0.17	0.83					
2002-2003	700	0.15	0.85					
Average	3373	0.22	0.78	*Have-Alpha*	0.28	0.65	0.04	0.03
				Beta-Only	0.14	0.69	0.11	0.06

Source: Fung and Hsieh 2006

Table 3 sheds more light on the differences between have-alpha funds and beta-only funds. The authors use a multi risk factor model, called ABS model, in order to measure the exposures of funds of funds to various risk factors. They examine three periods: the first is from January 1995 to September 1998, the second is from October 1998 to March 2000 and the third from April 2000 to December 2004. The events which triggered the break of the full period into the three sub-periods were the Russian crisis in 1998 and the Internet bubble burst in 2000. A regression is ran for each period and the constant is alpha, according to equation (1). It becomes obvious that the have-alpha funds persistently deliver bigger alpha than the beta-only funds. Nevertheless, there has been a statistically significant decline in the magnitude of alpha. The beta-only funds produce negative alpha in periods 1 and 3, although not statistically significant.

Table 3
Intertemporal variation in the alpha of have-alpha and beta-only funds of hedge funds.

	Period 1		**Period 2**		**Period 3**	
	Have-alpha	**Beta-only**	**Have-alpha**	**Beta-only**	**Have-alpha**	**Beta-only**
Constant	0.0047**	-0.0017	0.0160**	0.0066**	0.0018*	-0.0002

Notes: Statistical significance at the 1% and 10% level is denoted by ** and *, respectively.

The discussion about hedge funds replication is quite intense. The success of the clones to persistently deliver returns comparable to those of the original hedge funds is closely related to the research on the sources of the returns and the separation of systematic risk premia from alpha. Some hedge funds outperform due to their managers' undoubted ability and experience. These hedge funds appear to be rather difficult to replicate. The discussion about replication seems to be more relevant when it comes to hedge funds which belong to the average of the industry

5. Risk factors replication model

While exceptional hedge funds may require advanced technology to be replicated, average hedge funds returns may be replicated with a linear multi risk factor model. This is a simple and straightforward method which was first used by Sharpe (1992) for mutual funds. It consists of a linear regression of hedge fund returns on various risk factors. This approach is in line with the view that a considerable part of hedge funds returns arises from exposure to systematic risk factors. It actually implies that hedge funds returns can be achieved without the manager's ability, by implementing a more passive and conventional investment strategy.

The model is mathematically described by equation (2). $R_{hf,t}$ is the realized hedge fund return in period t, f_{it} is the value of the risk factor i at the same period, β_i is the exposure to factor i and ε_t is a random error. The regression of equation (2) provides estimates for the beta coefficients. These beta coefficients are then used to measure the returns R, of the replicating portfolio according to equation (3), in order to assess the goodness of the fit.

$$R_{hf,t} = \alpha + \sum\beta_i{*}f_{it} + \varepsilon_t. \qquad (2)$$

$$R_t = \sum\beta_i{*}f_{it} + \varepsilon_t. \qquad (3)$$

The constant term α of the regression represents that part of the hedge fund return that doesn't stem from any of the regressors included in the sum term of model (2). As already mentioned, this α may be broken into two components. The first component is manager's alpha, the value added by the manager's ability, while the second component represents that part of hedge fund return which arises from exposure to systematic risks not included in the model. The smaller the term α and the bigger the explanatory power R^2 the more successful is the model in capturing the main sources of returns. Thus, the question whether hedge funds can be replicated by the risk factors model is actually transformed to what percentage of hedge funds returns is attributed to the risk factors included in the model. As a consequence, it's crucial to know which factors should be included in the regression in order to get this percentage maximized.

Due to the variety of assets and strategies that hedge funds employ, a single-index model would overestimate alpha. Thus, a multi-factor model like that described by equation (2) seems to be more appropriate to capture the several risks that hedge funds are exposed to. Moreover, it's important to note that the beta coefficients in equation (2) are considered to be constant in time. However, the dynamic nature of hedge funds trading implies that managers may change their exposure to risks according to the economic conditions and their expectations

Another important issue about the estimation of beta coefficients is the sample used. One can perform in sample analysis by regressing hedge funds returns on the respective values of risk factors and calculate the coefficients β_i. However, an out of sample analysis can test the reliability of the in sample analysis findings. Given the values of betas estimated in the stage of in sample analysis, we measure hedge funds returns during a period which was not used in the calculation of betas. Equation (4) describes mathematically the procedure.

$$R_{\text{out of sample}} = \sum \beta_i * f_{it} + \varepsilon_t \qquad (4)$$

We next compare the observed returns to the calculated returns. In this manner, it is possible to assess whether and to what extent the model was successful in capturing the true systematic risk factors or whether the calculated betas were just a statistical artifact which depends strongly on the specific sample used to calculate them. In the latter case, betas are not able to replicate the original hedge funds.

6. Literature review

A great part of hedge funds replication literature is based on the risk factors model. Hasanhodzic and Lo (2007) use six factors which provide a reasonable cross-section of risk exposures for the typical hedge fund. These factors are: the US Dollar Index, the Lehman Corporate AA Intermediate Bond Index, the spread between the Lehman BAA Bond Index and the Lehman Treasury Index, the S&P 500 Index, the Goldman Sachs Commodity Index total return and the first difference of the end of month value of the CBOE Volatility Index (VIX). The authors use these factors because each factor returns can be realized through relatively liquid instruments, such as forward and futures contracts, so that the returns of linear clones may be achievable in practice. The TASS Hedge Fund Live database is used, which contains 1610 individual hedge funds. The sample period is from February 1986 to September 2005. The TASS Hedge Fund Live database classifies hedge funds into the following indices, according to the strategies they follow: convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event driven, fixed income arbitrage, global macro, long/short equity, managed futures, multi strategy and funds of funds.

The authors use two approaches to construct hedge funds clones. The first approach is to consider constant betas and construct fixed-weight portfolios. The entire sample period is used to estimate beta coefficients for each hedge fund style. For this purpose, a modified version of equation (2) is used. In particular, the constant term α is omitted and betas are restricted to sum to 1 so as to be interpreted as portfolio weights. The authors use the estimated betas to calculate the returns of the replicating portfolios.

As discussed above, managers may modify their risk exposures in order to profit form opportunities arising from changing economic conditions. Risk exposures may also change due to managers changing strategies as opportunities roll from one financial market to another. As a result, the fixed weight approach suffers from look-ahead bias because the entire history of funds is used in order to calculate the clone's portfolio weights. The authors address this issue by implementing a rolling window approach. In particular, a 24-month window is used to estimate the beta coefficients, which are then used to calculate the replicating portfolio's return for the month right after the end of the window. The procedure is repeated until the sampling period is covered. Thus, the portfolio weights are rebalanced monthly, capturing to some degree, the dynamic nature of hedge funds strategies arising from the manager's asset timing ability. One should note that the rolling window approach is a form of out of sample analysis.

Each individual hedge fund's returns are regressed on the six factors according to equation (2) and a clone portfolio is constructed for each fund. For each hedge fund strategy the authors construct an equal-weighted portfolio of all fixed-weight clones corresponding to that strategy. They do the same for the rolling–window clones. **Table 4** shows how the equal-weighted replicating portfolios compare to the corresponding equal-weighted portfolios of the original hedge funds. Portfolios of fixed-weight clones underperform portfolios of their respective funds in four strategies, outperform them in four others and display comparable results in three. Portfolios of rolling-window clones underperform portfolios of their respective funds

Table 4
Comparison of equal-weighted fixed-weight and rolling-window replicating portfolios with their corresponding portfolios of original hedge funds. Data are taken from the TASS database from February 1986 to September 2005. Analysis by Hasanhodzic and Lo (2007).

Strategies	Fixed-weight clones Return/ volatility/ skewness/ kurtosis	Rolling-window clones Return/ volatility/ skewness/ kurtosis
Convertible Arbitrage	= / = / = / -	- / = / +p / -
Dedicated Short Bias	-/+/=/-	+/+/+p/=
Emerging Markets	-/+/=/-	-/+/+n/+
Equity Market Neutral	+/+/=/-	+/+/+p/-
Event Driven	- / + / = /-	- / + / -n / -
Fixed Income Arbitrage	- / + / -n / -	- / = / -n /
Global Macro	+ / + / -p / -	+ / + / = / -
Long/Short Equity	= / + / -n / -	- / + / +n / +
Managed Futures	+ / = / -p / -	= / + / -p / -
Multi-Strategy	= / + / -p / -	- / + / = / =
Funds of Funds	+ / = / -p / -	+ / + / -p / -

Key: Return:+when clones outperform funds; - when they underperform; = when performance is similar. Volatility: + when clones display higher volatility; - for lower volatility; = when volatility is similar. Skewness: +p when clones display higher positive skewness; -p when they display lower positive skewness; +n when they display higher negative skewness; -n when they display lower negative skewness. Kurtosis: + when clones display higher kurtosis; - for lower kurtosis; = when kurtosis is similar.
Source: Amenc et al (2007).

in six strategies, outperform them in four others and display comparable results in one. Focusing on volatility, equal-weighted portfolios of fixed-weight clones generate higher volatility than equal-weighted portfolios of their respective funds in eight strategies, and similar volatility in three. Equal-weighted portfolios of rolling window clones display higher volatility than equal-weighted portfolios of their respective funds in nine strategies, and similar volatility in two. It also happens that for the third moment of the return distribution five fixed-weight clones show skewness similar to that of their respective funds, two fixed-weight clones show lower negative skewness compared to their respective funds, and four fixed-weight clones show lower positive skewness. Two rolling-window clones show skewness similar to that of their respective funds, two rolling-window clones show lower negative skewness than their respective funds, two rolling-window clones show lower positive skewness, three rolling-window clones show higher positive skewness, and two rolling window clones show higher negative skewness. Finally, concerning kurtosis, all funds from the 11 strategies exhibit fatter tails than fixed weight clones. Using a rolling-window approach, this remains the case for seven strategies, while the opposite result holds for two other strategies, and similar kurtosis is found for the remaining two.

Jaeger and Wagner (2005) attempt to replicate several hedge funds strategies extracted from the Hedge Fund Research (HFR) database. The returns of the non investable HFR indices (HFRI) are regressed on a set of risk factors, different for each strategy, from January 2004 to December 2004 (in sample period). The explanatory power R^2 ranges from 34.3% (managed futures) to 88.5% (long/short equity). In a further step, the authors perform out of sample analysis by using a 60-month rolling window. The risk factors used are the same as in the in sample analysis. The cumulated returns of the replicating portfolios are compared to the cumulated performance of the corresponding HFRI indices and the corresponding investable indices (HFRX). The cumulated returns data are from March 2003 to August 2005. **Table 5** summarizes the results. Clones underperform the non investable indices in eight of the nine strategies and outperform them in one. However, clones outperform the investable indices in all strategies with the exception of short selling.

Table 5

Comparison of the cumulated returns of the replicating portfolios to those of the corresponding non-investable (HFRI) and investable (HFRX) indices. The adjusted R^2 values of the in sample analysis are also presented. Analysis by Jaeger and Wagner (2005)

	Out of sample results			**In sample results**
Strategy	**Clone**	**HFRX**	**HFRI**	**Adj-R^2**
Equity Hedge	27.8%	16.0	32.8%	88.5%
Market Neutral	6.2%	-3.9	10.9%	35.3%
Short Selling	-28.2%	N/A	-23.0%	81.2%
Event Driven	29.8%	24.1	40.0%	79.3%
Distressed	20.1%	23.3	44.8%	68.4%
Merger Arbitrage	13.0%	10.9	15.3%	52.9%
Fixed Income	7.8%	N/A	16.3%	40.5%
Convertible Arbitrage	7.6%	-5.3	2.4%	54%
Global Macro	16.7%	10.1	24.6%	49.7%
Managed Futures	9.2%	N/A	N/A	34.3%

Schneeweis, Kazemi and Karavas (2003) attempt to replicate European based hedge funds returns form the Schneeweis Partners LLC database. The period used is from January 1998 to March 2003. The model is specified on the basis of two different approaches, a multi-factor model and a style-based analysis. The factors selected in the multi-factor analysis are European market factors that include equity market risk, interest rate risk, credit risk and volatility risk. The factors selected in the style-based analysis are a set of various futures and option contracts. The authors argue that clones consisting of options and futures contracts offer several advantages due to derivatives exhibiting high liquidity and transparency, small transaction costs and requiring small investments. The in-sample period is a rolling 24 month window, and the out-of-sample period is the month immediately following the sample window.

Table 6

Results of a factor replication approach by Schneeweis, Kazemi Karavas (2003), where both a multi-factor model and a style based analysis are used.

Strategies	**In sample results R^2**	**Out of sample results Mean strategy/clone// std dev strategy/clone// correlation**
	Multi-factor analysis	
Funds of Funds	54.3%	4.19/-2.05 // 2.01/3.90 // 20%
Long/Short Equity	67.7%	-0.98/-9.99 // 3.83/7.13 // 46%
Event Driven	85.8%	-2.67/-6.34 // 4.79/6.97 // 90%
Convertible Arbitrage	31.9%	8.28/1.88 // 1.82/1.54 // 17%
Fixed Income Arbitrage	29.2%	7.87/2.89 // 2.96/2.58 // 16%
	Style-based analysis	
Long/Short Equity	46.7%	-0.98/-6.82 // 3.83/8.26 // 69%
Event Driven	81.8%	-2.67/-6.83 // 4.79/6.10 // 91%
Convertible Arbitrage	33.4%	8.28/0.61 // 1.82/1.86 // 12%
Fixed Income Arbitrage	30.2%	7.87/3.53 // 2.96/2.00 // 47%

Source: Amenc et al (2007).

With the multi factor approach, the explanatory power of the in sample analysis ranges from 29% (Fixed Income Arbitrage) to 86% (Event Driven), while for the out of sample analysis the correlation between clones and original hedge fund indices ranges from 16% (Fixed Income Arbitrage) to 90% (Event Driven). With the style based approach, the authors obtain R^2 from 30% (Fixed Income Arbitrage) to 82% (Event Driven) for the in sample analysis, while for the out of sample analysis the correlation between clones and original hedge fund indices ranges from 12% (Convertible Arbitrage) to 91% (Event Driven). **Table 6** presents the results for the hedge fund indices used. It's important to note that even if the correlation between clones and original hedge funds is high, the returns and their standard deviation may differ dramatically.

Hedge funds investors tend to invest in diversified portfolios including several hedge funds strategies. Thus, it's important to know how much of the risk of such an investment can be identified by systematic risk factors. Fung and Hsieh (2004) use a seven factor linear model to replicate the returns of diversified hedge funds portfolios. The model was specified as follows. By using principal components analysis, return-based style factors were extracted from hedge funds returns. These factors were then linked to observable market risk factors, which are called asset-based style (ABS) factors. The authors consider seven ABS factors, based on previous research on Trend Following funds (Fung and Hsieh (2001)), Merger Arbitrage funds, (Mitchell and Pulvino (2001)), Fixed Income funds (Fung and Hsieh (2002)), and Equity Long/Short funds (Fung and Hsieh (2004)). Market risk and the spread between small cap and large cap stocks are the equity ABS factors and they are found in Equity Long/Short funds. The change in 10-year treasury yields and the change in the yield spread between 10-year treasury and Moody's Baa bonds are significant return drivers in Fixed Income funds and they are called Fixed-Income ABS factors. The portfolios of lookback straddles on bonds, currencies, and commodities are the remaining three factors and they are referred to as Trend-Following ABS factors.

The authors use the Hedge Fund Research Fund of Funds Index (HFRFOF) as a proxy for a diversified portfolio of hedge funds. They perform in sample analysis for the period January 1994 to December 2002 and they find that the Equity and Fixed Income ABS factors are statistically significant. Two of the three Trend-Following ABS factors are significant, namely the bond and the commodity factors. The alpha turns out to be statistically significant and the explanatory power of the regression is 55%.

Table 7
Regression of the HFRFOF Index on seven risk factors. Analysis by Fung and Hsieh (2004).

	Jan 94-Sep 98	**Apr 00-Dec 02**	**Jan 94-Dec 02**
Constant	0.00192	0.00212	0.00477
	(0.00176)	(0.00133)	(0.00128)**
S&P	0.32426	0.17300	0.21533
	(0.04539)**	(0.02938)**	(0.02873)**
SC-LC	0.17794	0.14972	0.22561
	(0.06628)**	(0.03633)**	(0.03629)**
10Y	-1.11718	-2.70801	-1.56445
	(0.94950)	(0.63269)**	(0.65403)**
Cred Spr	-6.66498	-2.13051	-2.96390
	(2.24776)**	(0.98164)*	(1.19194)**
Bd Opt	-0.01057	-0.00682	-0.01529
	(0.01064)	(0.00601)	(0.00731)*
FX Opt	0.00655	0.00313	0.00703
	(0.00741)	(0.00692)	(0.00670)
Com Opt	0.02719	0.03563	0.01903
	(0.01382)*	(0.01280)**	(0.01042)*
Adj-R^2	0.69%	0.80%	0.55%

Notes: S&P: Standard & Poors 500 stock return. SC-LC: Wilshire 1750 Small Cap – Wilshire 750 Large Cap return. 10Y: month end-to-month end change in the Federal Reserve's ten year constant maturity yield. Cred spr: month end-to-month end change in the difference between Moody's Baa yield and the Federal Reserve's ten year constant maturity yield. Bd Opt: return of a portfolio of lookback straddles on bond futures. FX Opt: return of a portfolio of lookback straddles on currency futures. Com Opt: return of a portfolio of lookback straddles on commodity futures Single asterisk denotes 5% significance level. Double asterisk denotes 1% significance level. Standard errors are shown in parentheses.

To test the stability of the ABS factor loadings, the authors used a modified test of cumulative recursive residuals which led them to identify September 1998 and March 2000 as sample breaking points. The triggering events behind these points are the LTCM debacle and the Internet bubble burst, respectively. Accordingly, the full sample period is divided into two subperiods: the first from January 1994 to Sept 1998 and the second from April 2000 to December 2002. **Table 7** reports the results of the time variation analysis. The R^2 increased from 55% to 69% (period 1) and 80% (period 2), illustrating the fact that regression results depend strongly on the sample used. In the period 2000-2001, the exposure to the market is almost half of what it was in the earlier period and the beta of the 10year T-bond factor remains negative and it gets smaller. These findings are consistent with the bearish market conditions that prevailed after the Internet bubble burst. In a further step, the authors apply the seven factor model to fund of funds indices of several databases. The results provide evidence that the construction method of the database used affects the regression results.

Agarwal and Naik (2004) use a multi-factor model where the risk factors are buy-and-hold and option-based. Their work draws from Glosten και Jagannathan (1994), where they suggest using benchmark-style indices that have embedded option like features in order to characterize the risk of managed portfolios. The buy-and-hold risk factors are equities, bonds, currencies, and commodities. The authors add the Fama-French "size" and "book-to-market" factors, Carhart's "momentum" factor, and a credit risk factor. The option-based risk factors are at-the-money (ATM) and out-of-the- money (OTM) European call and put options on the S&P 500. Monthly hedge fund returns form the HFR database are used during the period from January 1990 to June 2000.

First, a stepwise regression is conducted to identify the significant factors, for eight HFR indices. The authors obtain in sample adjusted R^2 ranging from 40.5% to 91.63%. The option based factors are statistically significant for six hedge funds strategies. **Table 8** shows that the event driven, restructuring and event arbitrage strategies have significant exposure to the factor corresponding to writing an OTM put option, consistent with the view that these strategies suffer losses when markets decline. Moreover, short selling shows significant factor loading to the factor corresponding to writing an OTM call option, which is justified by the fact that this strategy performs poorly when markets are up.

In a second step, the authors examine whether the replicating portfolios based on the identified factor loadings do a good job of mimicking the out-of-sample performance of hedge funds indices. Standard t-tests and Wilcoxon sign-tests indicate that the difference in return (mean and median) between HFR indices and their respective replicating portfolios are statistically insignificant during the out-of-sample period from July 2000 to December 2001. According to the authors, the figure plotting the returns displayed by clones and their respective HFR indices during the out-of-sample period shows that the former closely track the hedge fund returns during the out-of-sample period. The analysis is repeated using the CSFB/Tremont database, in order to check the robustness of the results in terms of the database used. The authors find similar risk exposures that are consistent with the types of trading strategies the hedge funds claim to follow.

Table 8

Results of a factor replication approach by Agarwal and Naik (2004) where both buy-and-hold and option-based factors are used. The hedge funds indices are from the HFR database from January 1990 to June 2000 (in-sample period). The third column shows the significant option-based factors in each strategy and the sign (in parentheses) of their beta coefficients.

Strategies	Adj-R^2	Significant option-based factors
Convertible Arbitrage	40.50%	SPP_a (-)
Equity Hedge	72.50%	-
Equity non-Hedge	91.63%	-
Event Driven	73.40%	SPP_o (-)
Relative Value	52.20%	SPP_o (-)
Restructuring	65.60%	SPP_o (-)
Event Arbitrage	44%	SPP_o (-)
Short Selling	82%	SPC_o (-)

Notes: SPC_a(SPP_a) denotes at-the-money call(put) options and SPP_o(SPP_o) denotes out-of-the-money call(put) options. All options are on the S&P 500 composite index.

7. Data

7.1. Description of risk factors and hedge funds data.

Our multi-factor linear model is specified by a set of risk factors representing a broad spectrum of financial markets. In an attempt to capture as many potential explanatory variables as possible, we use a set of 21 traditional, alternative and option-like risk factors, which is larger than the sets used in previous papers. The option-like factors may account for the non-linearity of hedge funds returns discussed earlier. The risk factors representing equities consist of the S&P 500 Composite Index, the S&P 600 Small Cap Index and the Morgan Stanley Capital International (MSCI) Emerging Markets Index. The factors representing the bond markets are the Lehman U.S. Corporate AA Intermediate Bond Index, the Lehman Highyield B Bond Index, the

Table 9
Descriptive statistics of the risk factors returns during the period from January 1995 to September 2007.

Risk factor	Mean	St. Dev	Median	Kurtosis	Skewness	Min Value	Max Value
SP500	0.47%	0.32%	0.94%	53.66%	-47.00%	-11.61%	11.67%
SP600	0.67%	0.41%	1.22%	250.04%	-93.41%	-21.92%	12.08%
Emerg	0.16%	0.54%	0.53%	333.50%	-106.18%	-32.32%	16.16%
AA	-0.29%	0.09%	-0.24%	111.16%	-31.86%	-4.21%	2.75%
Highyield	-0.26%	0.17%	-0.21%	404.73%	-27.20%	-7.94%	7.86%
World	0.24%	0.19%	0.16%	50.79%	28.77%	-5.80%	7.92%
Conv	0.22%	0.27%	0.43%	306.31%	-73.60%	-13.56%	11.99%
Commod	0.37%	0.46%	0.31%	5.21%	-11.46%	-17.69%	14.96%
Vix	-0.11%	1.30%	-0.66%	69.28%	51.20%	-38.09%	57.57%
SMB	-0.15%	0.33%	-0.50%	693.61%	82.52%	-17.15%	21.76%
HML	0.08%	0.29%	0.09%	268.75%	0.19%	-13.22%	13.43%
Mom	0.47%	0.42%	0.35%	526.43%	-66.15%	-25.54%	17.98%
Carrytrade	-0.33%	0.07%	-0.29%	336.67%	-95.68%	-3.84%	1.56%
Crspread	-0.30%	0.08%	-0.28%	545.89%	-63.84%	-4.66%	4.05%
Termspread	0.25%	0.14%	0.26%	87.46%	-30.70%	-5.98%	4.72%
BXM	0.52%	0.23%	0.87%	519.9%	-144%	-12.98%	7.02%
PTFSBD	-1.67%	1.15%	-4.72%	416.26%	157.45%	-25.36%	68.86%
PTFSFX	0.42%	1.52%	-2.93%	315.60%	140.01%	-30.00%	90.27%
PTFSCOM	0.04%	1.10%	-2.49%	332.79%	134.13%	-23.04%	64.75%
PTFSIR	0.75%	2.07%	-4.48%	3844.06%	511.71%	-30.21%	221.92%
PTFSSTK	-4.87%	1.05%	-6.45%	212.75%	98.37%	-30.19%	46.15%

Notes: SP500: the S&P 500 Composite Index, SP600: the S&P 600 Small Cap Index, Emerg: the MSCI Emerging Markets Index, AA: the Lehman U.S. Corporate AA Intermediate Bond Index, Highyield: the Lehman Highyield B Bond Index, World: the Citigroup World Government 7-10y Bond Index, Conv: the Merrill Lynch All Convertibles Bond Index, Commod: the Goldman Sachs Commodity Index, Vix: the CBOE VIX Index, SMB: the Fama and French 'size' factor, HML: the Fama and French 'book-to-market' factor, Mom: the Carhart's 'momentum' factor, Carrytrade: the carrytrade strategy factor, Crspread: the credit spread, Termspread: the termspread, BXM: the CBOE BXM Index, PTFSBD: the lookback straddles portfolio on bonds, PTFSFX: the lookback straddles portfolio on currencies, PTFSCOM: the lookback straddles portfolioon commodities, PTFSIR: the lookback straddles portfolio on interest rates, PTFSSTK: the lookback straddles portfolio on stocks

Citigroup World Government 7-10y Bond Index and the Merrill Lynch All Convertibles Bond Index. The Goldman Sachs Commodity Index represents the commodities market. We also use the CBOE VIX Index which represents the volatility of the S&P 500 and the CBOE BXM factor which represents the returns of a covered call strategy, i.e., a strategy where the investor buys a stock and writes a call on it. According to put-call parity, the covered call is equivalent to selling a put. For all these indices we calculate monthly returns in excess of the 1-month U.S. T-Bill. All the above data are taken from Datastream.

We also include Fama and French's (1993) 'size' factor (small cap minus large cap), 'book-to-market' factor (high minus low value) and Carhart's (1997) 'momentum' factor (winners minus losers). These data are taken from Kenneth French's website. A factor representing a carrytrade strategy is included. The investor sells a low interest rate currency basket consisting 100% of Japanese Yen and buys a high interest rate basket consisting 100% of U.S. dollars. The data for the carrytrade factor were taken from Bloomberg. To capture credit risk we use the spread in the returns of the Merrill Lynch U.S. Corporate BBB Index and the Citigroup 7-10y U.S. Treasury Bond Index. A term spread factor is calculated based on the returns of the Citigroup 7-10y U.S. Treasury Bond Index and the Citigroup 3-month U.S. Treasury Bill Index. The data for the credit spread and the term spread are taken from Datastream.

Finally, portfolios of lookback straddles on bonds, currencies, interest rates, stocks and commodities are used. The data are taken from the website http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls. The reader is referred to Fung and Hsieh (2001) for details about the construction of the lookback straddles. **Table 9** provides the descriptive statistics of the risk factors. The sample period is from January 1995 to September 2007, a period that covers both market upturns and downturns (Asian currency crisis, Russian debt default e.t.c.). **Table 10** is the correlation matrix of the risk factors. With the noticeable exception of S&P 600 and Conv factor, the correlations are small, suggesting that multicollinearity should not be a problem.

Hedge funds data were taken from the Hedge Fund Research (HFR) database. The HFR indices are equally weighted. We used monthly excess returns of the non-investable (HFRI) indices. This analysis considers the following hedge funds strategies: Distressed/Restructuring, Merger Arbitrage, Equity Market Neutral, Short Bias, Emerging Markets, Equity Hedge, Event Driven, Convertible Bonds, Fund of Funds Composite, Fund Weighted Composite, Macro, Relative Value, Convertible

Table 10
Correlation matrix of the risk factors during the period from January 1995 to September 2007

	AA	carrytrade	commod	emerg	highyield	hml	mom	conv	crspread	ptfsbd	ptfscom	ptfsfx	ptfsir	ptfsstk	smb	sp500	sp600	termspread	vix	world	bxm
AA	1.00																				
carrytrade	0.00	1.00																			
commod	0.02	-0.02	1.00																		
emerg	-0.11	0.04	0.17	1.00																	
highyield	0.25	0.05	0.02	0.47	1.00																
hml	0.07	0.04	0.01	0.12	0.19	1.00															
mom	-0.05	-0.06	0.11	0.01	0.14	-0.06	1.00														
conv	-0.01	-0.01	-0.03	0.07	0.05	-0.64	-0.05	1.00													
crspread	-0.03	0.06	-0.09	0.27	0.25	-0.19	-0.28	0.56	1.00												
ptfsb	0.10	-0.05	-0.17	-0.08	-0.12	-0.05	-0.05	-0.10	-0.23	1.00											
ptfscom	-0.04	-0.17	-0.09	0.07	0.10	-0.03	0.21	-0.03	-0.07	0.19	1.00										
ptfsfx	0.09	-0.13	0.04	0.07	0.13	0.06	0.10	-0.03	-0.13	0.15	0.25	1.00									
ptfsir	0.09	-0.13	0.04	-0.15	-0.16	-0.04	-0.04	-0.14	-0.24	0.17	0.18	0.13	1.00								
ptfsstk	0.12	-0.09	0.07	0.05	-0.04	0.04	0.09	-0.15	-0.40	0.22	0.11	0.25	0.22	1.00							
smb	-0.04	0.22	0.08	0.18	0.16	-0.48	0.17	0.46	0.34	-0.05	-0.01	0.02	-0.12	-0.13	1.00						
sp500	-0.02	0.02	0.03	0.66	0.39	0.12	-0.12	0.11	0.32	-0.11	0.05	0.07	-0.20	0.03	0.12	1.00					
sp600	-0.01	0.11	-0.05	0.02	0.03	-0.43	-0.10	0.83	0.52	-0.17	-0.08	-0.04	-0.15	-0.24	0.58	0.11	1.00				
termspread	0.09	0.00	-0.03	-0.22	-0.08	0.13	0.17	-0.16	-0.55	0.19	0.07	0.13	0.10	0.25	-0.20	-0.18	-0.23	1.00			
vix	-0.04	-0.02	0.14	0.19	-0.01	0.28	0.14	-0.53	-0.42	0.21	0.00	0.14	0.07	0.51	-0.17	0.11	-0.58	0.19	1.00		
world	0.22	-0.12	0.15	-0.15	0.07	0.03	0.02	0.01	-0.26	0.16	0.11	0.29	0.09	0.27	-0.07	-0.11	-0.06	0.56	0.19	1.00	
bxm	-0.06	0.00	-0.09	-0.11	-0.08	-0.33	-0.31	0.69	0.55	-0.13	-0.14	-0.11	-0.16	-0.42	0.07	0.06	0.69	-0.20	-0.65	-0.07	1.00

Arbitrage and Fixed Income Corporate. A description of the hedge funds categories used is found in **Appendix A**. **Table 11** provides the summary statistics for the hedge funds indices form January 1995 to September 2007.

Table 11
Summary statistics of the HFR indices from January 1995 to September 2007.

	Mean	St. Dev	Median	Kurtosis	Skewness	Min Value	Max Value
Distressed/ Restructuring	0.69%	0.12%	0.81%	957.47%	-169.74%	-8.90%	4.67%
Merger Arbitrage	0.49%	0.08%	0.63%	1051.70%	-217.56%	-6.09%	2.78%
Equity Market Neutral	0.35%	0.07%	0.30%	125.26%	11.19%	-2.07%	3.21%
Short Bias	-0.17%	0.46%	-0.53%	276.98%	25.80%	-21.63%	22.36%
Emerging Markets	0.80%	0.32%	1.37%	577.21%	-113.09%	-21.42%	14.42%
Equity Hedge	0.88%	0.20%	0.97%	200.40%	19.21%	-8.05%	10.50%
Event Driven	0.77%	0.15%	1.05%	554.98%	-131.51%	-9.30%	4.74%
Convertible Bonds	0.52%	0.27%	0.77%	335.79%	-38.98%	-11.91%	13.93%
FoF Composite	0.41%	0.13%	0.52%	463.76%	-44.84%	-7.87%	6.47%
Fund Weighted Comp.	0.67%	0.16%	0.84%	346.36%	-62.57%	-9.10%	7.27%
Macro	0.60%	0.16%	0.45%	50.37%	29.98%	-4.16%	6.44%
Relative Value	0.51%	0.07%	0.58%	2214.21%	-306.20%	-6.20%	2.41%
Convertible Arbitrage	0.49%	0.08%	0.69%	236.80%	-94.09%	-3.59%	3.05%
Fixed Income Corp.	0.30%	0.11%	0.43%	859.56%	-205.82%	-7.56%	2.70%

7.2. Biases of hedge funds indices

Hedge fund databases and the indices constructed thereof are subject to various biases which affect the analysis based on them. Some well know biases are survivorship, backfilling, selection, liquidation and autocorrelation. The survivorship bias stems from the fact that unsuccessful managers stop reporting to the database, thus affecting the representativity of the indices. This creates a positive bias and the alpha calculated by a regression analysis comes out bigger than it really is. The severity of survivorship bias is reduced by the fact that very successful funds that are closed to new investors often stop reporting to databases.

Similar to survivorship bias is backfilling bias which occurs when new hedge funds are included into the index. Given that inclusion to a database is a means of attracting the investor's attention, fund managers usually decide to enter a database after a period of respectable track record. The history prior to the entry date is backfilled based on the recent good performance, thus resulting in an upward bias

As mentioned earlier, hedge funds are private investment vehicles and as such, they are not obliged to disclose information about their operations. It's at the manager's discretion whether to join a database or not. As a result, hedge fund indices suffer from selection bias, which affects their ability to accurately represent the universe of hedge funds. Selection bias accounts for much of the performance deviation among hedge fund indices, as different databases include different individual hedge funds. It's difficult to estimate the selection bias since one cannot observe funds that are not part of a database. Unsuccessful funds may choose not to enter a database but that could also be the case for a successful hedge fund which is closed to new investors. It so becomes obvious that neither the magnitude nor the direction of selection bias is clear.

Another bias hedge funds data suffer from is liquidation bias. This kind of bias stems from the managers practice not to report the liquidation value of the fund they manage. For example, in the event of the Russian crisis in August 1998, those funds which lost all of their money stopped reporting returns in July, thus avoiding to report a -100% return for August. Clearly, liquidation bias imposes an upward bias on hedge fund indices and causes Value at Risk (VaR) models to underestimate the tail risk.

Finally, autocorrelation in hedge fund's returns may result from the funds investing in illiquid assets, which are not accurately priced. It may also be the result of manipulation by managers to smooth their returns in order to achieve a more attractive risk-return ratio. The empirical evidence supports this line of reasoning. The CSFB/Tremont managed futures index, which consists of funds that trade on liquid assets, exhibits not statistically significant first order autocorrelation. On the contrary, the CSFB/Tremont convertible arbitrage index has significant large first order autocorrelation. This result is not surprising given that funds in the convertible arbitrage sector transact primarily in over-the-counter illiquid markets.

Research has not yet reached a consensus about the impact of the biases on the hedge fund indices. Fung and Hsieh (2006) report that survivorship and backfilling bias sum up to roughly 4% per year. Malkiel and Saha (2005) find that the magnitude of these biases is even bigger. It seems that the magnitude of the biases depends on the methodology followed by the database and the period of analysis. Thus, one should keep in mind that the obtained alphas in a regression analysis look bigger than they really are and interpret the results with extra caution.

8. Empirical results

8.1. In sample analysis.

In order to identify the sources of returns of the hedge funds strategies considered, we initially measure hedge fund performance within a context of static model. The monthly excess returns series of each hedge fund strategy is regressed on the various risk factors**.** Despite the non-normality of hedge funds returns, it is assumed that multivariate OLS regression is appropriate. Unlike Hasanhodzic and Lo (2007), we don't restrict the beta coefficients to sum up to one. The reason for this is that since hedge funds can and actually do use excessive leverage, managers make investments whose total value is greater that their initial wealth. For each fund index, the risk factors which appear to be statistically insignificant are removed one at a time, starting with the one which corresponds to the lowest t-statistic value. At the end, only factors statistically significant at the 5% level survive. First order lags that are not statistically significant at the 5% level are also removed. Thus, although we start with a rather large set of regressors, we end up with a parsimonious specification for each fund strategy. **Table 11** reports the results.

The magnitude of the R^2 statistic suggests that hedge funds are significantly exposed to systematic risks, which is in line with the results extensively documented in the literature. The explanatory power of the regressions ranges from 48% (Relative Value) to 88% (Equity Hedge). We notice that we get high R^2 values for directional strategies such as Short Bias and Event Driven, whereas the model explains poorly non-directional strategies such Equity Market Neutral and Relative Value. These results are similar to previous findings in the literature. A possible explanation is that non-directional funds perform more sophisticated techniques in order to hedge the

Table 11
Results of the regression of HFR hedge fund indices on a set of risk factors during the period from January 1995 to September 2007 (in sample). The first column shows the statistically significant factors for each strategy, the second shows the beta coefficients and the third column in italics shows the corresponding t-statistic values.

Distressed			**Merger Arbitrage**			**Equity Market Neutral**			**Short Bias**		
Constant	0.004	*5.65*	Constant	0.004	*6.38*	Constant	0.002	*4.22*	Constant	0.001	*0.70*
SMB	0.080	*4.18*	HML	0.070	*3.08*	COMMOD	-0.019	*-2.25*	HML	0.552	*7.81*
HML	0.059	*2.22*	CONV	0.051	*1.56*	EMERG	-0.031	*-3.21*	CONV	-0.708	*-5.79*
CONV	0.227	*7.18*	SMB	0.069	*3.83*	HML	0.064	*4.33*	SP600	-0.332	*-4.77*
CRSPREAD	0.352	*3.59*	SP500	0.060	*3.83*	MOM	0.101	*10.66*			
TERMSPREAD	0.126	*2.62*	VIX	-0.004	*-0.80*	PTFSSTK	0.011	*3.05*			
PTFSBD	-0.023	*-4.84*	BXM	0.173	*5.08*	SP500	0.043	*2.60*			
AR(1)	0.366	*8.08*				SP600	0.089	*8.14*			
						AR(1)	0.148	*2.54*			
Adjusted R^2	**0.73**		**Adjusted R^2**	**0.52**		**Adjusted R^2**	**0.53**		**Adjusted R^2**	**0.84**	

Emerging Markets			**Equity Hedge**			**Event Driven**			**Convertible Bonds**		
Constant	0.007	*3.23*	Constant	0.005	*5.78*	Constant	0.006	*7.14*	Constant	0.004	*3.31*
EMERG	0.247	*5.69*	MOM	0.047	*3.05*	COMMOD	0.028	*2.41*	MOM	-0.196	*-8.01*
CONV	0.695	*9.25*	CONV	0.529	*13.12*	HML	0.054	*2.04*	CONV	0.920	*14.53*
PTFSIR	-0.018	*-2.08*	CRSPREAD	-0.309	*-3.37*	CONV	0.234	*5.05*	SMB	0.089	*2.35*
SP500	-0.168	*-2.33*	PTFSIR	-0.008	*-2.74*	CRSPREAD	0.272	*3.31*	SP600	-0.100	*-2.12*
VIX	-0.041	*-2.54*	SMB	0.067	*2.91*	SP600	0.148	*6.01*	AR(1)	0.172	*4.90*
			SP600	0.116	*4.01*	AR(1)	0.160	*4.01*			
			AR(1)	0.130	*4.39*						
Adjusted R^2	**0.59**		**Adjusted R^2**	**0.88**		**Adjusted R^2**	**0.80**		**Adjusted R^2**	**0.82**	

Table 11 (continued)

Fund of Funds Composite			Fund Weighted composite			Macro		
Constant	0.002	*3.33*	Constant	0.005	*7.13*	Constant	0.006	*5.16*
MOM	0.053	*3.75*	MOM	0.027	*2.51*	HML	0.109	*2.61*
CONV	0.343	*14.50*	CONV	0.372	*12.39*	CONV	0.394	*9.03*
PTFSFX	0.008	*2.13*	PTFSIR	-0.007	*-2.90*	PTFSCOM	0.022	*2.64*
PTFSIR	-0.009	*-3.09*	PTFSSTK	0.009	*2.01*	PTFSFX	0.021	*3.28*
SMB	0.035	*1.72*	SP600	0.124	*6.07*	PTFSIR	-0.010	*-2.27*
WORLD	-0.067	*-2.03*	AR(1)	0.135	*4.67*	PTFSSTK	0.031	*3.36*
AR(1)	0.214	*4.82*				SMB	0.090	*2.81*
						TERMSPREAD	0.368	*4.65*
						WORLD	-0.202	*-3.41*
Adjusted R^2	**0.72**		**Adjusted R^2**	**0.88**		**Adjusted R^2**	**0.53**	

Relative Value			Convertible Arbitrage			Fixed Income Corporate		
Constant	0.004	*6.38*	Constant	0.004	*5.54*	Constant	0.003	*4.01*
CARRYTRADE	0.157	*2.51*	AA	0.104	*2.05*	CRSPREAD	0.679	*7.34*
HML	0.051	*2.74*	CARRYTRADE	0.168	*2.49*	SP600	0.085	*5.26*
CONV	0.178	*9.08*	CONV	0.095	*4.77*	TERMSPREAD	0.189	*3.81*
PTFSBD	-0.010	*-2.82*	CRSPREAD	0.234	*3.02*	AR(1)	0.334	*6.13*
AR(1)	0.215	*3.57*	TERMSPREAD	0.094	*2.35*			
			AR(1)	0.467	*8.03*			
Adjusted R^2	**0.48**		**Adjusted R^2**	**0.49**		**Adjusted R^2**	**0.58**	

risk, which leads to an idiosyncratic character that cannot be successfully captured by a passive linear multi-factor model. This argument is in line with Agarwal and Naik (2000) who find that a greater proportion of non-directional hedge funds returns is attributed to the trading of derivatives as opposed to their directional counterparts, which show more significant loading to buy-and-hold factors. It's also interesting to note that the model explains quite well the returns of the indices comprising hedge funds of several strategies (i.e. the Fund of Funds Composite and the Fund Weighted Index). This is in line with Kats' (2007) criticism according to which existing replicating programs are successful in tracking indices that contain several hedge fund strategies, just because the idiosyncrasies of these strategies cancel out each other and what is left to replicate is closer to a traditional index-which is more easily replicated by a passive model- rather than an active index.

Given that we used excess returns for both hedge fund indices and risk factors, the constant term of each regression can be interpreted as Jensen's alpha. Apart from the Short Bias strategy, all constant terms are positive and statistically significant at the 1% level, suggesting that on average managerial skills add value to hedge funds investments. Nevertheless, part of this alpha may be beta in disguise attributed to risk factors not included in the model. The calculated alphas are of the same order of magnitude as those reported by Jaeger and Wagner (2005) and Agarwal and Naik (2004). The first order autoregressive term is significant for eleven out of fifteen strategies, indicating the presence of serial correlation. Serial correlation may be the result of data smoothing by managers. It may also reflect illiquidity risk and valuation risk.

We notice that many fund strategies have significant correlation with Fama and French's size and value factors, indicating that hedge funds profit from betting on the spreads between small cap and large cap stocks as well as between value and growth firms. The term spread and credit spread factors are also significant in many cases. All these bets require small initial investments and managers magnify the returns through leverage. Hence, our results confirm the evidence that hedge funds are extensively exposed to alternative betas. The portfolios of lookback straddles, initially constructed by Fung and Hsieh for trend followers, appear to be significant for almost all fund strategies. The exposure to these factors reflects the non-linearity of hedge funds returns. The option-like character of hedge fund returns is also captured by the Merrill Lynch Convertible Bonds factor, which turns out to be among the statistically significant explanatory variables for several strategies. Finally, many hedge fund indices are exposed to the S&P 600 index instead of the S&P 500, indicating that small cap firms provide more opportunities for higher abnormal returns than what large cap companies do. This stands to reason as small firms are more likely to be mispriced, be in distress, go through a restructuring period or be an M&A target.

8.2. Out of sample analysis.

As already mentioned, due to their opportunistic nature and their trading in a more flexible environment, hedge funds managers rebalance their portfolios frequently in order to exploit investment opportunities. Hence, the next step in our analysis is to perform rolling window regressions in an attempt to increase the explanatory power of the model by capturing that part of the dynamic character of hedge funds returns, which results from the manager's market timing ability. A window of 24 months is used and the returns of the replicating strategies for the succeeding month are calculated based on the betas found in the 24-month period. Only the significant risk factors found in the in-sample analysis for each strategy are used. The length of the window is a trade off of the fact that the window should be large enough to allow for a sufficient number of degrees of freedom ensuring the convergence of the estimated parameters and simultaneously small enough to take into account the non-stationarities of hedge funds data. A comment is in order. Replication techniques including changing betas imply that the clones constructed are less passive in nature than those constructed on the basis of constant betas. This, in its turn, implies that, in practice, one has to depart from purely passive buy-and-hold strategies and possess some degree of expertise in dynamic asset allocation.

As shown in **table 12**, the rolling window analysis provides higher average R^2 values for most of the strategies, suggesting that a dynamic model is more appropriate than its static version to capture the frequent portfolio rebalancing of hedge funds. Graphs (c) in **Figure 3** show how the betas change in time for each strategy. Factor loadings often change signs, illustrating the active nature of the hedge funds operations. These findings support the view that hedge funds managers face limited constraints in changing their exposures to the various asset classes.

Table 12
Adjusted R^2 values obtained by different versions of the multi-factor liner model (2) for hedge funds replication.

	In-sample analysis (95-07)	Rolling window analysis* (97-07)	In-sample analysis (00-07)	Dynamic rolling window* (00-07)	Dyn roll. wind. Conditional* (00-07)
Distressed/Restructuring	0.73	0.67	0.70	0.69	0.76
Merger Arbitrage	0.52	0.63	0.49	0.61	0.75
Equity Market Neutral	0.53	0.59	0.58	0.59	0.76
Short Bias	0.84	0.86	0.83	0.87	0.92
Emerging Markets	0.59	0.55	0.69	0.67	0.70
Equity Hedge	0.88	0.90	0.88	0.90	0.91
Event Driven	0.80	0.82	0.82	0.84	0.88
Convertible Bonds	0.82	0.83	0.83	0.84	0.85
FoF Composite	0.72	0.78	0.76	0.78	0.82
Fund Weighted Comp.	0.88	0.89	0.88	0.91	0.90
Macro	0.53	0.59	0.55	0.62	0.71
Relative Value	0.48	0.55	0.45	0.53	0.64
Convertible Arbitrage	0.49	0.52	0.46	0.48	0.62
Fixed Income Corp.	0.58	0.55	0.55	0.60	0.66

Notes: * denotes average values over the entire set of windows. The sample period of the analysis is shown in parentheses.

Graphs (a) of **Figure 3** show how the monthly returns of the replicating portfolios compare to those of the respective hedge fund indices. By visual inspection we notice that the former closely track the returns of the latter. We perform t-statistic tests for the mean and Wilcoxon tests for the median of each hedge fund style to check the statistical significance of the differences between the returns. The later test seems to be more appropriate since it doesn't require the data to be normally distributed. The null hypotheses that the mean and median values are zero are rejected for all strategies apart from the Short Bias.

To assess the cumulative performance of the replicating portfolios we perform the same exercise as in Jaeger and Wagner (2005) assuming that we invest \$100 in these portfolios and \$100 in the corresponding hedge fund indices. The investment period starts in January 1997 and ends in September 2007. Unlike Jaeger and Wagner, we consider a much longer investment period so as to get a more accurate picture of the relative performance of the indices and the clones. The results are presented in **Figure 3, graphs (b)** for each strategy. It's obvious that the synthetic portfolios significantly underperform the original fund indices they attempt to replicate. This is the case for all strategies with the exception of Short Bias, even for those that the explanatory power of the model is high. The latter result is in line with the findings of Schneeweis et al (2003). Thus, despite the promising results of the in-sample analysis, it seems that the constant term of the regression has strong economic significance and its omission leads to the underperformance of the replicating portfolios. Of course, we should keep in mind that the results may be aggravated by the fact that the constant term is overestimated due to the biases mentioned earlier. The constant term may also include beta driven return in disguise, arising from factors not accounted by the model. **Table 13** provides the Sharpe ratios of the hedge fund indices and the replicating portfolios over the period form January 1997 to September 2007. All replicating portfolios exhibit considerably lower ratios than the fund indices.

Table 13

Sharpe ratios obtained by different versions of the multi-factor liner model (2) for hedge funds replication.

	HFR Indices (97-07)	Rolling Window approach (97-07)	Dynamic Roll.Win. approach (00-07)	Ratio1	Ratio2
Distressed/Restructuring	0.39	-0.04	-0.03	-0.06	-0.28
Merger Arbitrage	0.40	0.07	0.09	0.24	-0.02
Equity Market Neutral	0.32	0.12	0.10	0.34	0.50
Short Bias	0.00	-0.01	0.06	1.00	1.41
Emerging Markets	0.19	0.07	0.01	0.02	-0.02
Equity Hedge	0.30	0.08	-0.01	-0.03	0.18
Event Driven	0.36	0.02	-0.02	-0.07	-0.13
Convertible Bonds	0.12	0.02	-0.01	-0.19	-2.36
FoF Composite	0.22	0.10	-0.04	-0.16	-0.18
Fund Weighted Comp.	0.28	0.05	-0.01	-0.03	-0.09
Macro	0.28	0.08	-0.16	-0.61	-0.27
Relative Value	0.52	0.07	-0.12	-0.16	-0.32
Convertible Arbitrage	0.45	-0.16	-0.18	-0.43	-0.40
Fixed Income Corp.	0.17	-0.22	-0.20	-0.73	-0.99

Notes: Ratio1 is the Sharpe ratio of the dynamic unconditional rolling window approach divided by the Sharpe ratio of the corresponding HFR Index. Ratio2 is the Sharpe ratio of the dynamic conditional rolling window approach divided by the Sharpe ratio of the corresponding HFR Index. The sample period of the analysis is shown in parentheses.

The cumulative returns of the strategies Equity Market Neutral, Emerging Markets, Funds of Funds Composite and Fund Weighted Composite are of particular interest. By visual inspection of the corresponding graphs, we notice that the replicating portfolios do a good job in tracking closely the hedge fund indices in the first few years (approximately until the end of 2001) but then underperform considerably. A possible explanation might be an increase in alpha. However, in accordance to published findings, the average alpha for these strategies is almost twice as large in the period from January 1997 to December 2001 compared to that of the period from January 2002 to September 2007. For the Equity Market Neutral strategy, the FoF and the Fund Weighted Composite Index the replication looks good from 1997 to 2000, that is during the Dotcom bubble where stock prices where skyrocketing. In the case of the Emerging Markets strategy, the replication looks good from 1997 to 2002. This period is characterized by much greater volatility than the following years. These observations illustrate that the success of the replication depends on the period considered and suggest that there might be periods that the market conditions make replication easier.

Up to now, our out-of-sample analysis has been based on a constant set of risk factors used for all rolling windows for a given strategy. These sets have been identified by using the full sample, as described in the in-sample analysis section. However, due to the trading flexibility of hedge funds, besides the risk exposures, the significant risk factors themselves may change from one window to another. Replicating hedge fund returns using factors with weak explanatory power may generate greater estimation error. To address this issue, Darolles and Mero (2007) use recent asymptotic theories developed by Bai and Ng (2006) in order to identify a set of significant risk factors for each window. By analyzing individual hedge funds of the Equity Hedge strategy, they find that a 'dynamic factor selecting' equally weighted replicating portfolio performs better than a 'naive' replicating strategy, which consists of using the same set of regressors for each window. Furthermore, Smedts K. and Smedts J. (2006) point out that using the full sample may hide the exposure of hedge funds to several risk factors, which may be significant only for shorter periods of time. Given that short selling is allowed, long and short positions on risk factors may cancel out, thus hiding the exposure to these factors.

Motivated by the above observations, our next step is to apply the same procedure as in the in-sample analysis to each separate rolling window to identify the corresponding sets of significant risk factors. We start with the full set of 21 regressors and we remove one factor at a time starting with the most insignificant. At the end, we get a set consisting of risk factors significant at the 5% level. As before, we use this sets to calculate the performance of the replicating portfolios for the month following the last month of the window. To allow for sufficient degrees of freedom we extend the window to 60 months. This approach is expected to also capture the manager's selection ability, besides their market timing skills.

The 'dynamic rolling window' model provides higher explanatory power than the 'naïve' model for only two strategies. In all other cases the R^2 values are comparable to those obtained by the 'naïve' approach. The Sharpe ratios are higher for four strategies. The difference between the hedge fund index returns and the replicating portfolio returns is statistically insignificant only for the Short Bias and the Convertible Bonds strategy. **Figure 4** compares the cumulative performance of our 'dynamic factor selecting' (yellow lines) and 'naive' replicating portfolios (blue lines), in the period from January 2000 to September 2007. We find that the former provide a slightly better replication for only four strategies (namely, Equity Market Neutral, Convertible Bonds, Fund Weighted Composite and Convertible arbitrage) and a worse performance for six strategies. Dynamic and naïve portfolios have similar cumulative returns for four strategies. We believe the dynamic rolling window method is more reliable, since it includes only statistically significant factors. Nevertheless, both dynamic and naive portfolios underperform the original hedge funds indices (red lines), with the exception of Short Bias.

8.3. Conditional model

We next try to capture the dynamic nature of hedge funds exposures by considering a conditional version of model (2), where the intertemporal variation of the exposures is driven by the information available to the manager. This approach draws from Ferson and Schadt (1996), who conclude that inferences on the performance of an actively managed portfolio may be significantly altered when one allows for conditional, instead of unconditional moments. Following their work, we assume that beta coefficients depend linearly on a set of information instruments, as shown in equation (5). Z_t is a vector of instruments for the information available at time t and $z_t = Z_t - E(Z)$ is a vector of the deviations of Z_t from the unconditional means. The coefficient β_0 may be interpreted as an average beta. The elements of the vector β' are the response coefficients of the conditional beta with respect to the information variables Z_t. Hence, the conditional version of the initial model (2) may be written as in equation (6). This equation incorporates the change of betas as new information arrives to the market. Note that in (6) β_{0i}, β_i' and z_{it-1} are elements corresponding to the risk factor f_i. The regression (6) may be interpreted as an unconditional multiple factor model which also includes the products of the initial risk factors f_i and the lagged information variables as additional factors. The additional factors may be interpreted as the returns to dynamic strategies.

$$\beta(Z_t) = \beta_0 + \beta'*z_t \qquad (5)$$

$$R_{hf,t} = \alpha + \sum\beta_{0i}*f_{it} + \sum\beta_i'*z_{it-1}*f_{it} + \varepsilon_t \qquad (6)$$

The information variables we use are the 1-month T-Bill returns, the dividend yield of the S&P 500 Index and a term spread between the 7-10y Treasury Bond Index and the 3-month T-Bill. These are the instruments that Keim and Stambaugh (1986) and Fama and French (1989) identify as important in predicting U.S. equity and bond returns. The information variables are demeaned using the data up to the month that performance is measured.

Using the full sample (January 1995-September 2007), the Wald tests can reject the hypothesis that the additional variables including the information instruments do not matter, at the 5% level only for the Emerging Markets and the Relative Value strategy. This suggests that conditioning may be appropriate for measuring the performance of hedge funds.

We then propose a dynamic rolling window approach of the conditional model (6). In particular, for a given strategy we find a set of significant factors for each window and we then add the products of these factors and the information variables. By removing the insignificant terms one at a time, we end up with a new set of statistically significant factors. The window is 60 months long. Such a long window may not be appropriate for capturing abrupt changes of the beta exposures but we assume that this is compensated by the fact that betas now also change due to their dependence on information.

The dynamic rolling window conditional model provides higher R^2 values for most of the strategies than dynamic rolling window unconditional model and the fixed betas model in the period from January 2000 to September 2007 (**Table 12**)**.** This is in line with Kat and Miffre (2000) who present evidence that conditional models provide a more accurate picture of hedge funds than static models. In particular, they examine 77 hedge funds of several strategies from May 1990 to April 2000 using a model similar to that of equation (6), which considers that, apart form betas, alpha is also a linear function of the information variables used. The authors find that allowing for timing dependency in the measures of risk and abnormal performance increases the average fit of the model by 11%, 15% and 16.3% for the three model specifications considered.

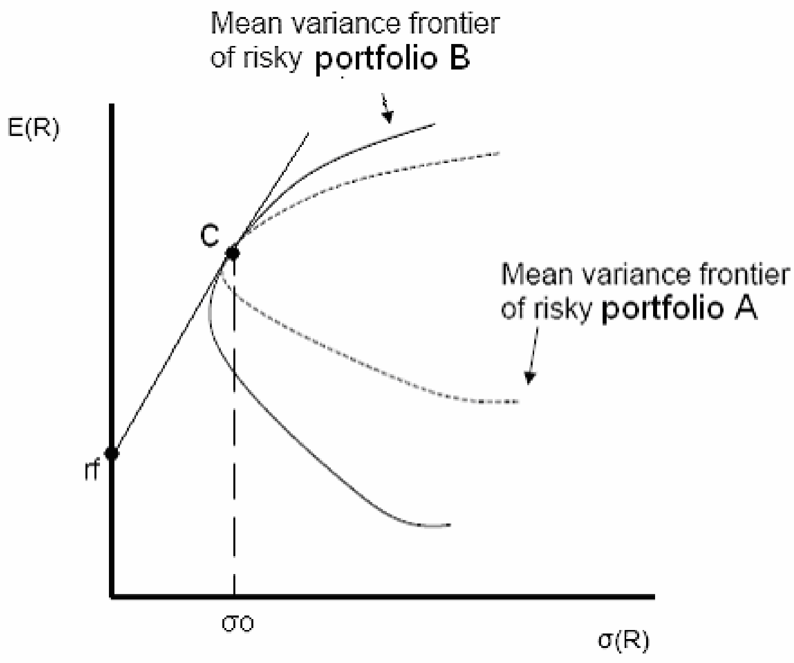
Furthermore, t-statistic tests cannot reject the hypotheses that mean differences between the hedge funds indices and their replicating portfolios are zero for Equity Market Neutral and Short Bias at the 5% level and for Fund Weighted Composite and Relative Value at the 1% level. Wilcoxon tests cannot reject the hypotheses that the median differences are zero for the same strategies at the 5% and for Equity Hedge and Fund Weighted Composite at the 1% level. The same tests in the dynamic rolling window unconditional analysis rejected the hypothesis only for the Short Bias strategy. In a further step, we form the ratio of the Sharpe ratios of the replicating portfolios and the hedge fund indices. We do the same for the dynamic rolling unconditional model. We find that the conditional model yields higher ratios for nine out of the fourteen strategies as compared to the dynamic rolling model. These findings provide evidence that a conditional model may be more appropriate in measuring the performance of active portfolios, such as hedge funds.

However, a comparison of the cumulative performance (**Figure 4**) of the replicating portfolios (black lines) versus the HFR indices (red lines) over the period from January 2000 to September 2007 reveals that the latter considerably outperform the former. An exception is the Short Bias strategy where clones seem to outperform. Thus, once again the alpha possesses strong economic significance. Even those mean and median differences which are not statistically significant turn out to be economically significant.

8.4. Intersection analysis

In a further step we examine the replicating portfolios in the context of intersection of two portfolios. Consider portfolio A, which consists of all replicating portfolios considered in this analysis. This portfolio produces a mean-variance frontier shown in **Figure 5.** Assuming a risk free asset r_f, the tangency point of the efficient frontier with the mean-variance frontier produces the optimal portfolio C. We also consider a portfolio B including portfolio A, and all hedge funds indices. A new mean-variance frontier corresponds to portfolio B. The intersection analysis tests whether both mean-variance frontiers intersect at point C. If this is the case, one can infer that, for a given degree of risk aversion which corresponds to σ_o, investors are indifferent between the two portfolios, as they both produce the same optimal portfolio C. In other words, adding original hedge funds to the replicating portfolios doesn't produce an overall portfolio with different characteristics in terms of risk-return ratio.

Figure 5
Intersection analysis



We now consider the system of k linear regressions (7):

$$hf_t = \alpha + \beta^* rp_t \quad (7)$$

where k is the number of hedge funds indices, rp is a k-column vector of the replicating portfolios returns at time t, hf is a k-column vector of the hedge funds indices returns at time t, α is a k-column vector of the constant terms of the regressions and β is a k x k matrix where each row contains the beta coefficients for each hedge fund strategy. The intersection test described above is equivalent to testing the hypothesis that alphas in the system (7) are jointly zero. Estimating the equations simultaneously this hypothesis is rejected at the 1% significance level. Consequently, we cannot conclude that portfolios A and B intersect at point C. Given that all elements of the vector α are positive and statistically significant, the inclusion of hedge funds in a conventional portfolio provides a portfolio with superior risk-return characteristics.

9. Conclusion

During the last years an increasing volume of capital is directed towards hedge funds as more and more investors seek to benefit from these alternative investment vehicles. However, the opaqueness and illiquidity of hedge funds operations as well as the expensive fees that their managers charge, constitute a barrier for institutional and less wealthy investors. Researchers have been trying to address this issue by examining the sources of hedge funds returns in order to construct transparent and liquid portfolios replicating the hedge funds returns at a lower cost. Given the lack of transparency and the large number of possible market and trading strategy combinations that hedge funds follow, this is a challenging task. The consensus is that hedge funds are widely exposed to systematic risk factors, though not of the traditional buy-and-hold nature. This implies that part of the hedge funds returns may not be attributed to the manager's skills and should not be priced as alpha.

Based on the existing literature, we used a broad set of 21 traditional and option-like factors in an attempt to identify the systematic drivers of the hedge funds returns. We employed several versions of the linear multi-factor replicating model. The first approach was to consider the exposures and the risk factors as being constant throughout the sample period. This analysis has confirmed that systematic factors can explain a substantial part of the variation of the hedge funds returns. Despite this promising finding, a rolling window approach with changing betas and a dynamic rolling window approach with changing betas and risk factors have shown that the replicating portfolios considerably underperform the hedge funds indices providing evidence that the alpha is strongly economically significant. We reach the same conclusions after using a dynamic conditional model where betas are also conditioned on information instruments available to the market. We finally used a portfolio intersection argument to illustrate the benefits of adding original hedge funds to a replicating portfolio.

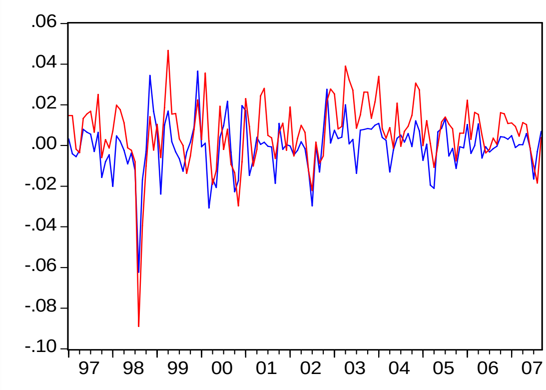
However, one should keep in mind that the alpha may be exaggerated by the biases of the hedge funds indices. Moreover, part of this alpha may be beta in disguise arising by the fact that our model specification misses significant risk factors. The inclusion of more sophisticated factors and the implementation of more advanced technology on interpreting estimated betas into portfolio weights may hopefully lead to a better understanding of hedge funds risks and yield replicating products with higher ability to track the hedge fund return series. After all, there is evidence that the alpha of many strategies is decreasing, which may be attributed to several causes, such as the derivatives markets getting deeper, the assets under hedge funds management increasing, the arbitrage opportunities getting scarcer and the manager's ability to provide alpha exhibiting diminishing returns to scale. In this context, the replication of a hedge fund providing average returns compared to those of the industry may be a feasible goal.

Figure 3

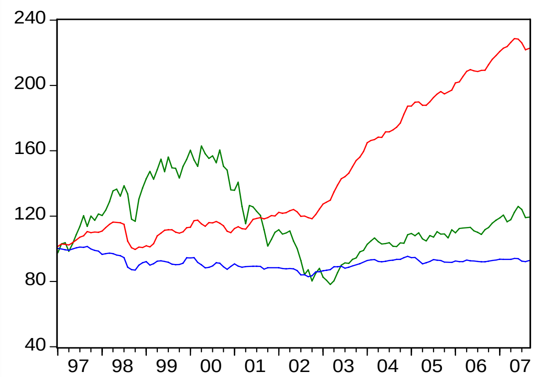
Rolling window replication of several HFR hedge fund indices from Jan. 1997 to Sept. 2007. Graphs (a) and (b) show the monthly returns and the cumulative returns respectively, of the HFR hedge funds indices (red lines) and the replicating portfolios (blue lines). The green line represents the cumulative performance of the market (S&P 500). Graphs (c) show the time variability of the beta coefficients.

Distressed

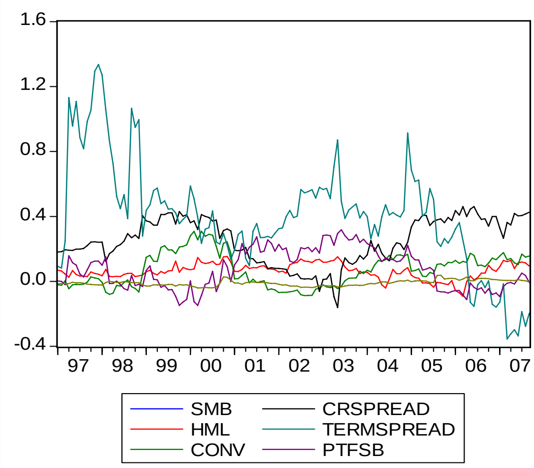
(a)



(b)

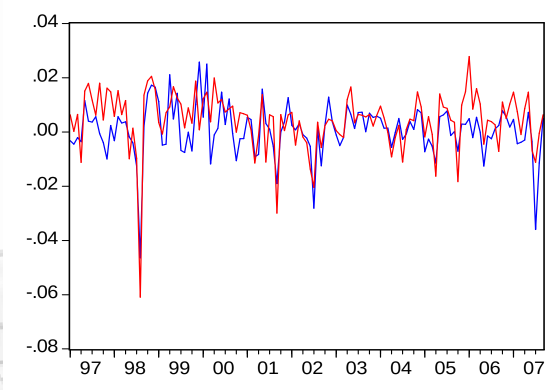


(c)



Merger Arbitrage

(a)



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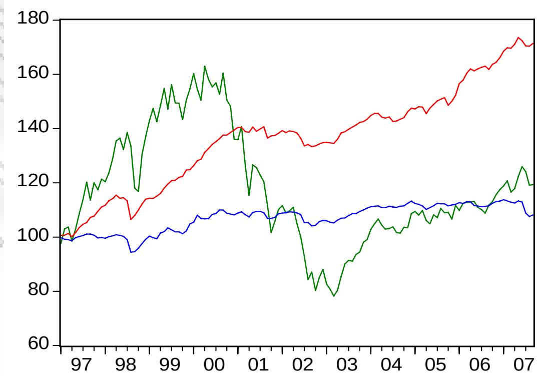

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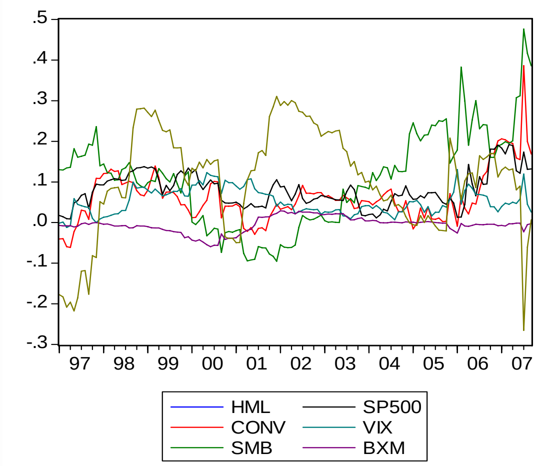
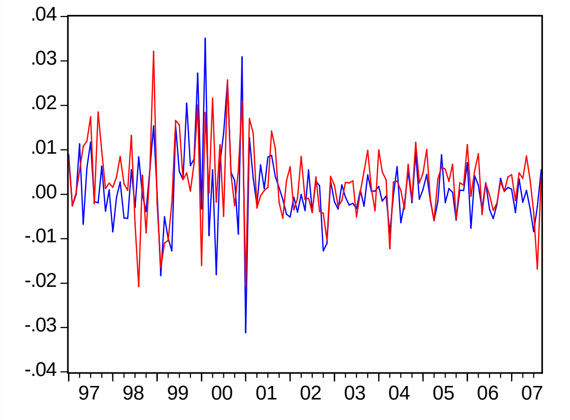


Equity Market Neutral

(a)



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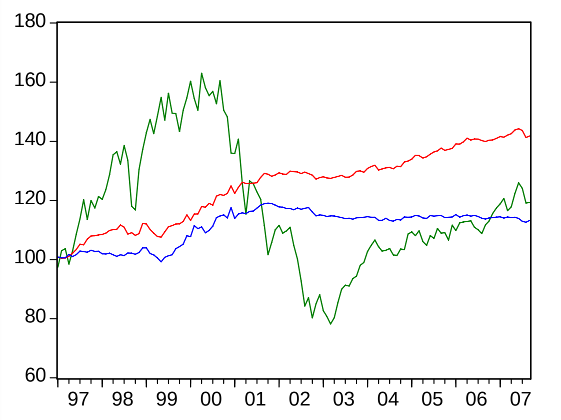

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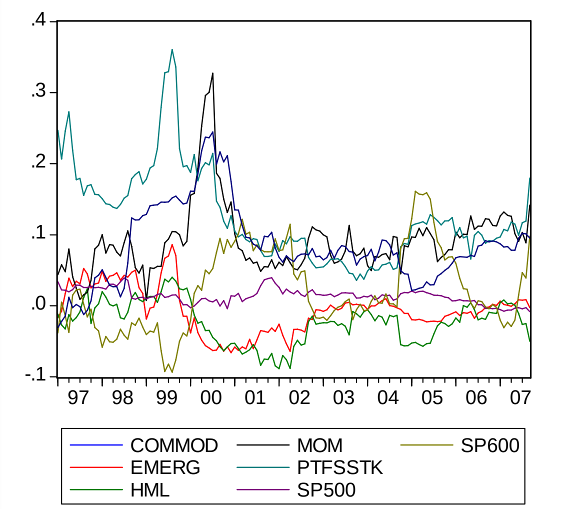
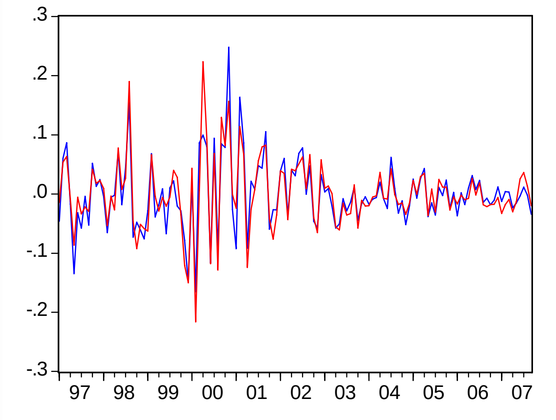


Short Bias

(a)



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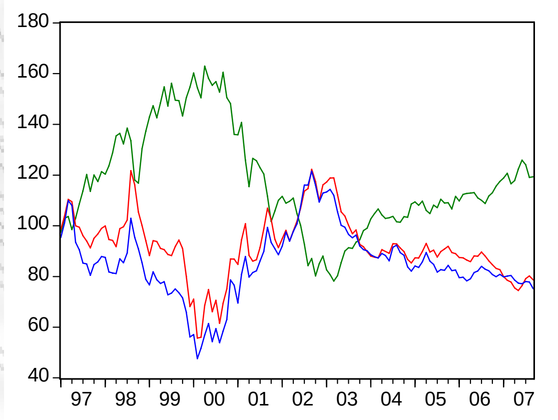

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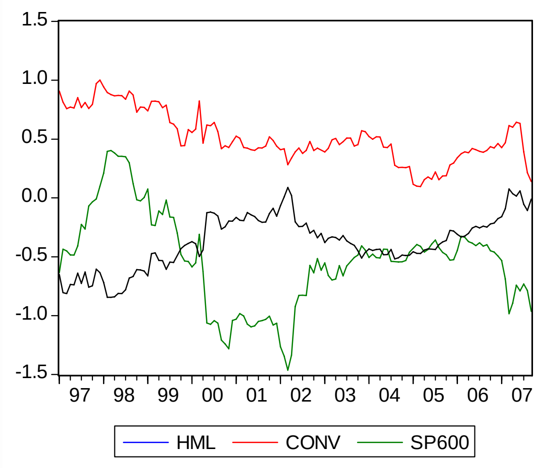
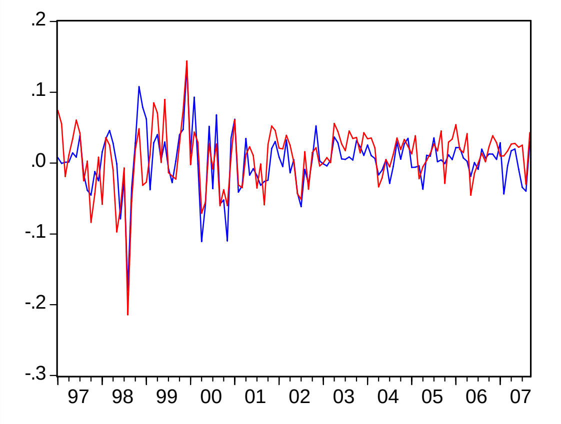


Emerging Markets

(a)



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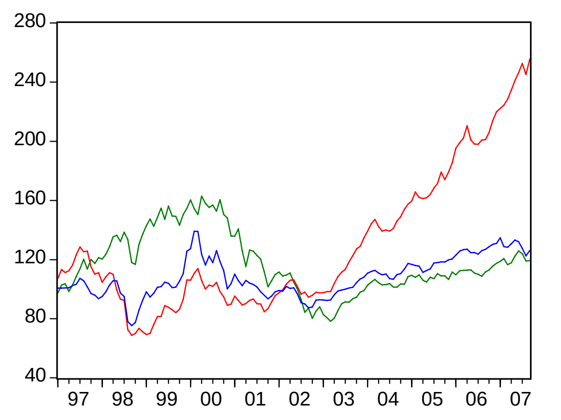

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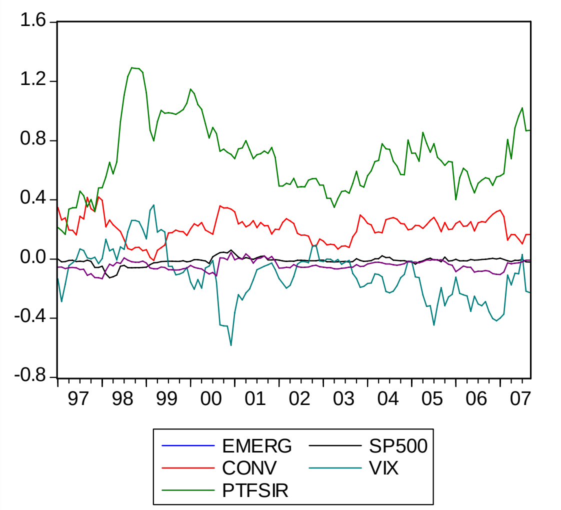
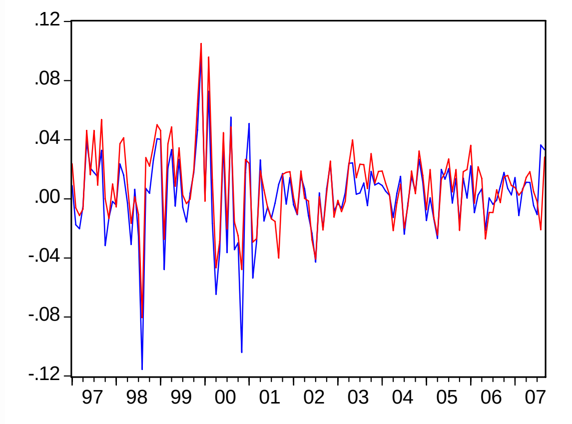


Equity Hedge

(a)



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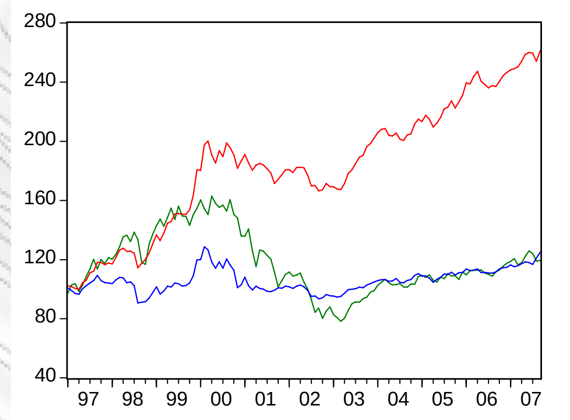

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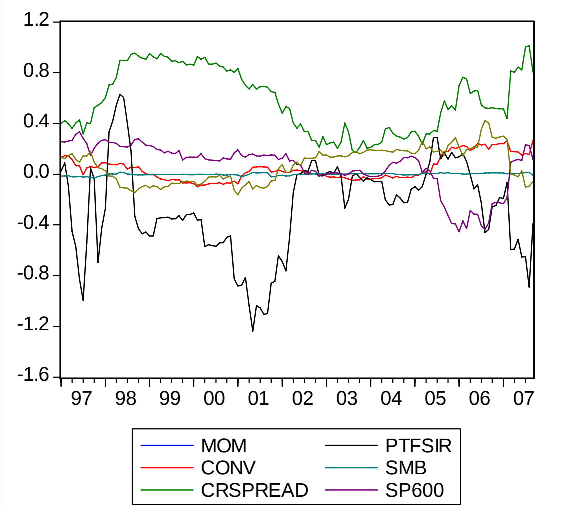
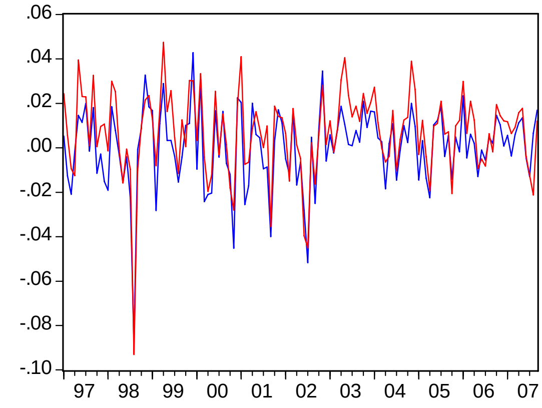


Event Driven

(a)



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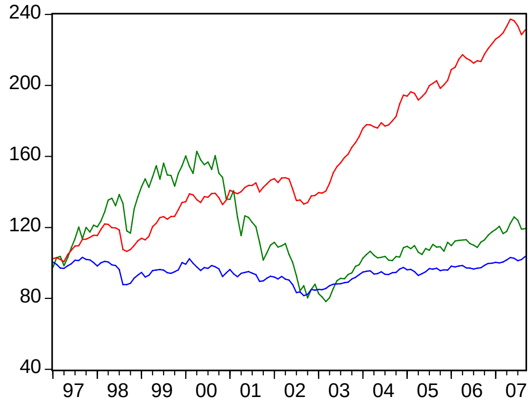

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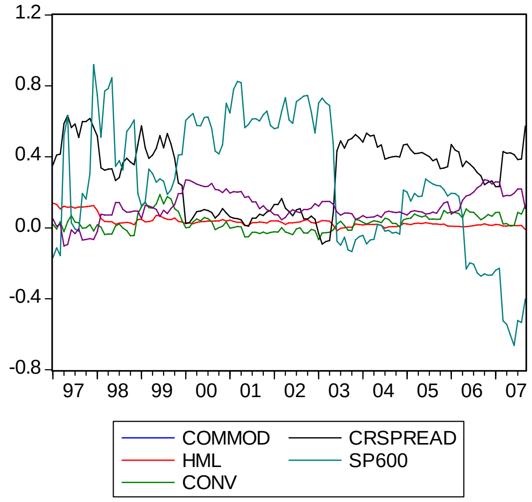
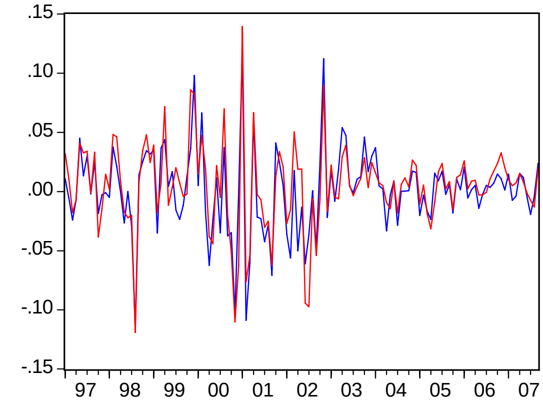


Convertible Bonds

(a)



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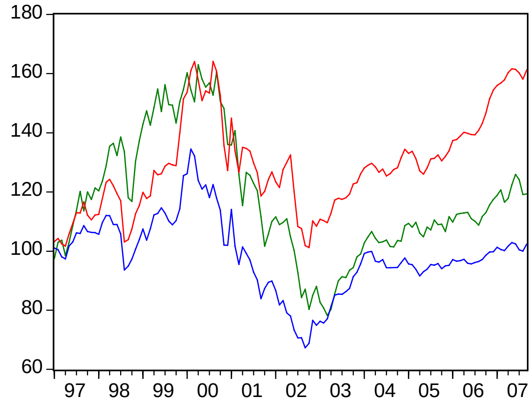

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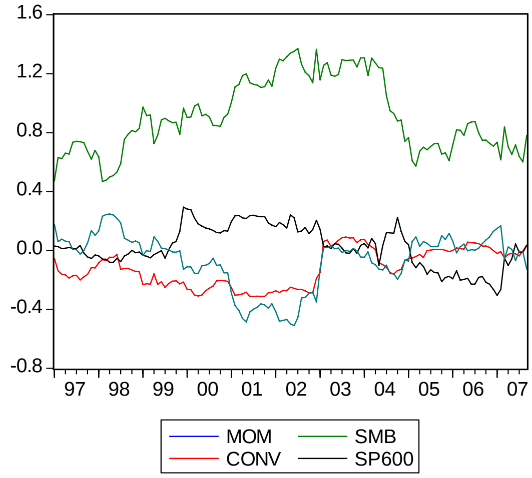
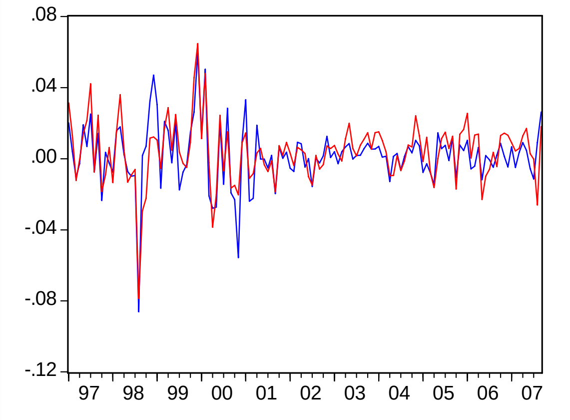


Funds of Funds Composite

(a)



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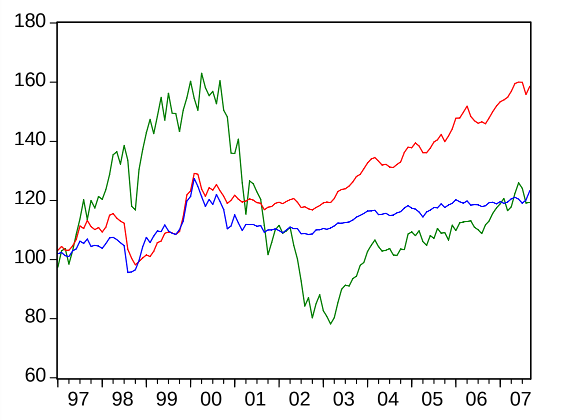

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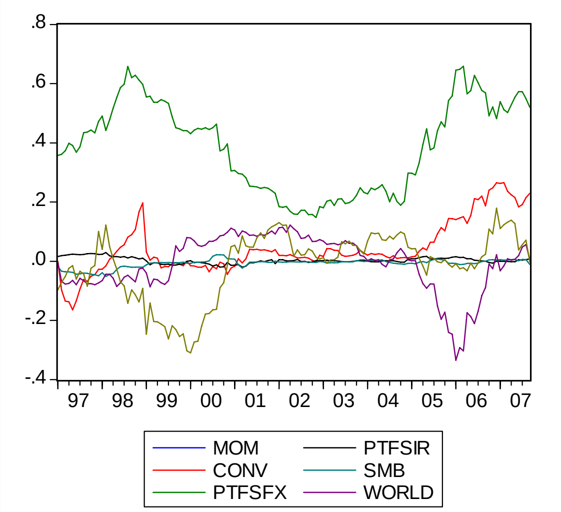
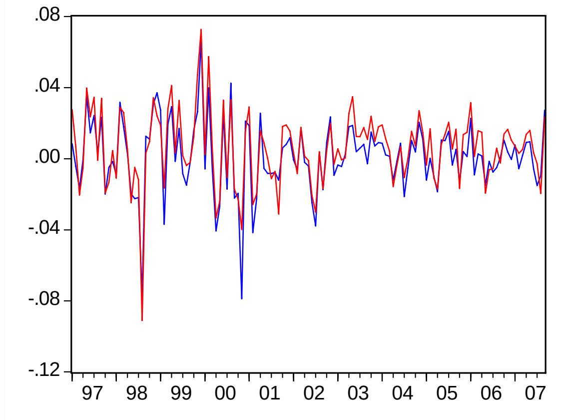


Fund Weighted Composite

(a)



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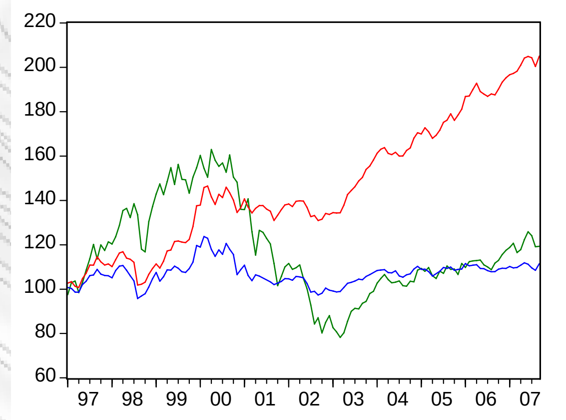
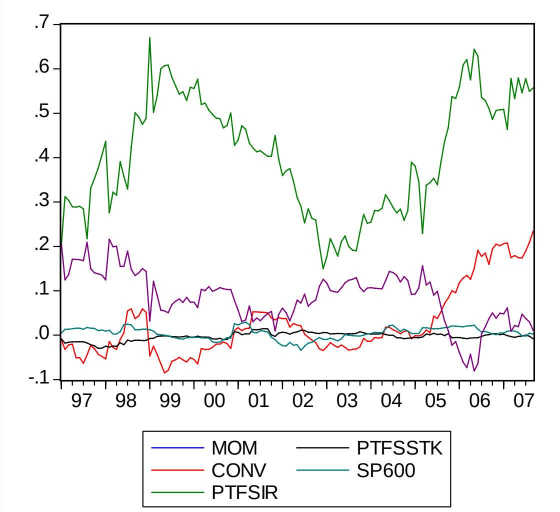
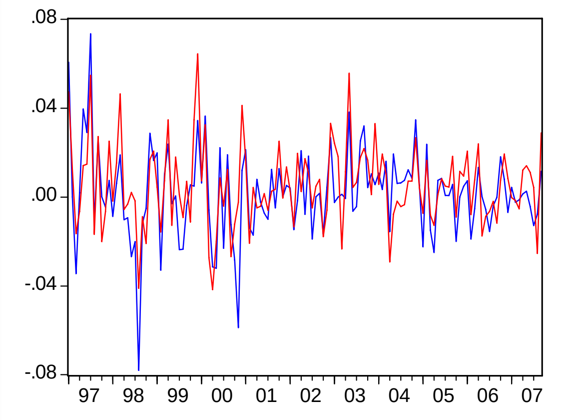


(c)

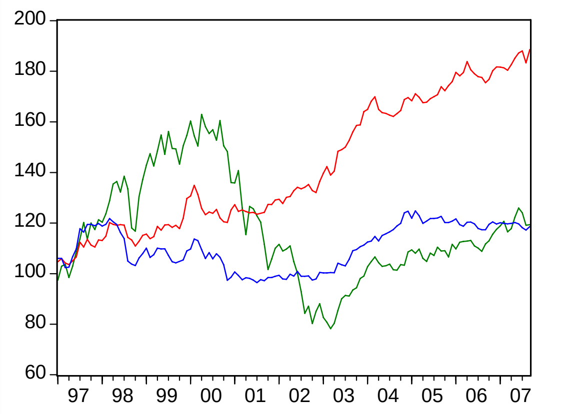


Macro

(a)



(b)



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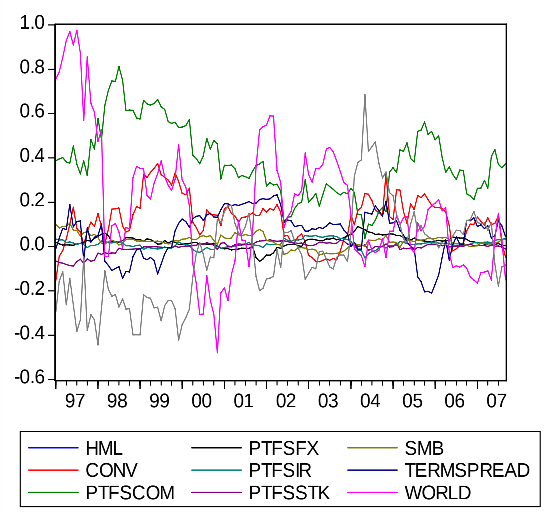
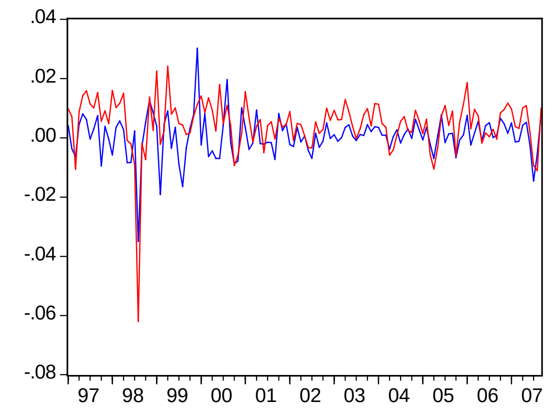


Relative Value

(a)



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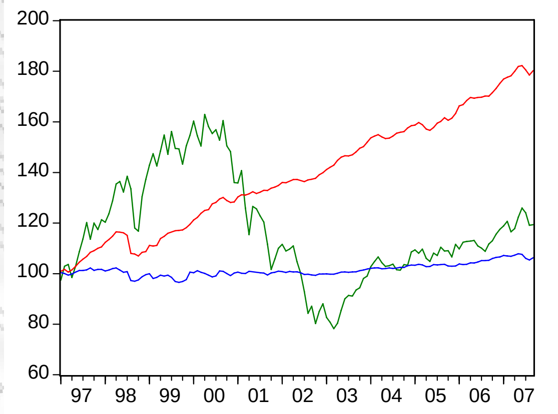

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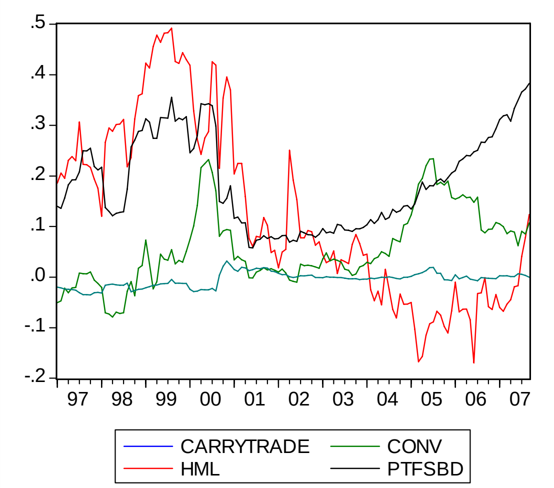
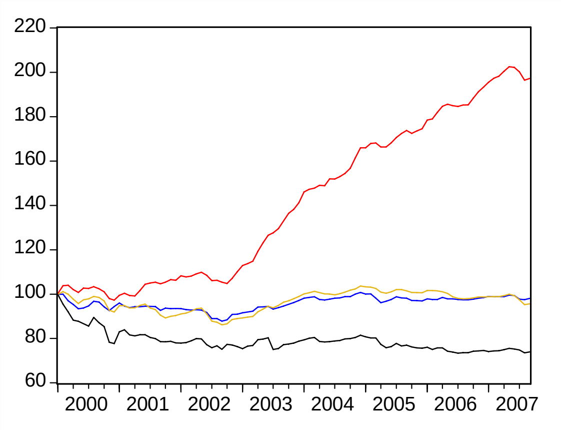


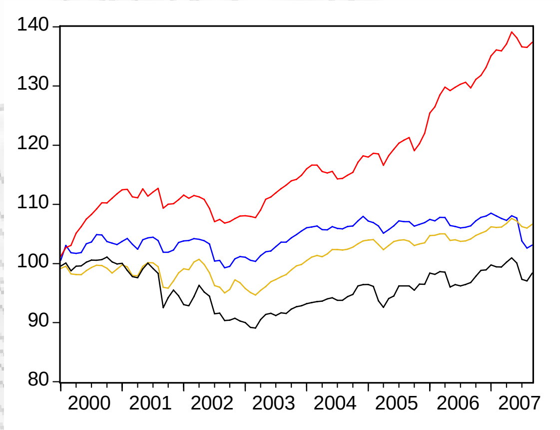
Figure 4

Comparison of the cumulative returns of the HFR hedge funds indices (red lines) with the cumulative performance of the rolling window replicating portfolios (blue lines), the dynamic rolling window replicating portfolios (yellow lines) and the conditional dynamic rolling window replicating portfolios (black lines). The sample period is from January 2000 to September 2007

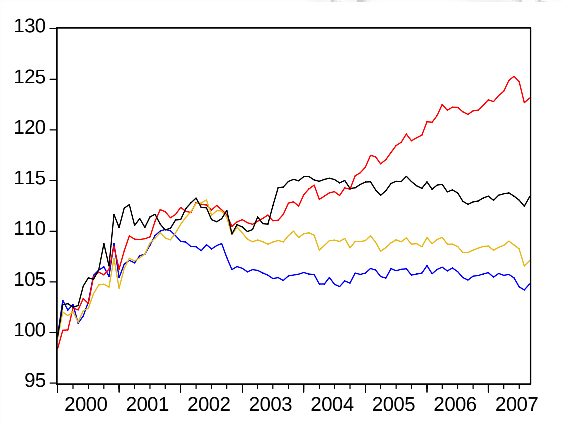
Distressed



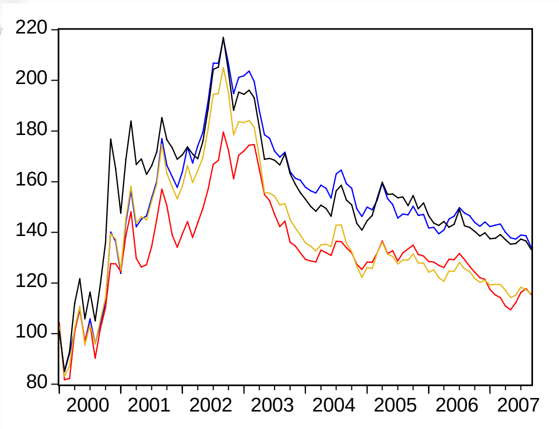
Merger Arbitrage



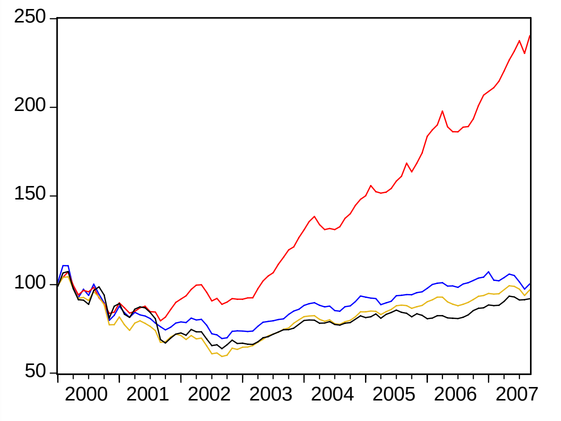
Equity Market Neutral



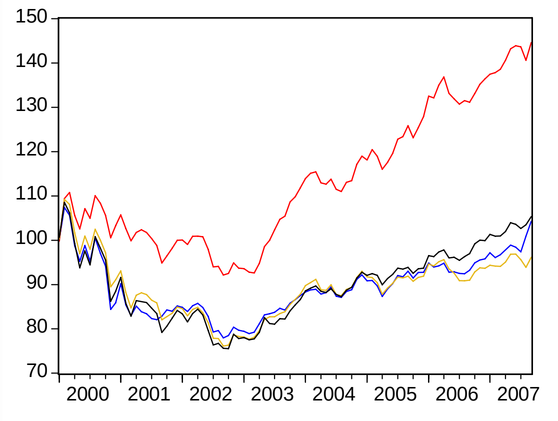
Short Bias



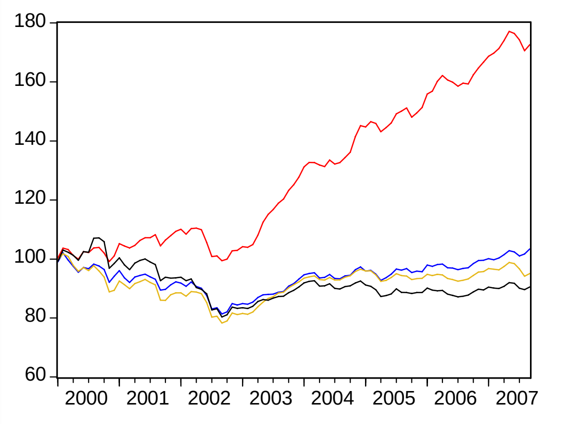
Emerging Markets



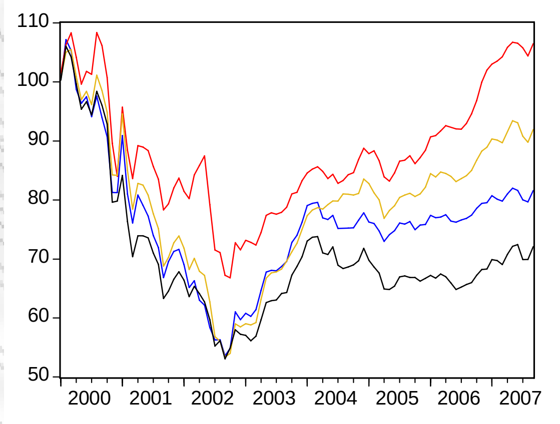
Equity Hedge



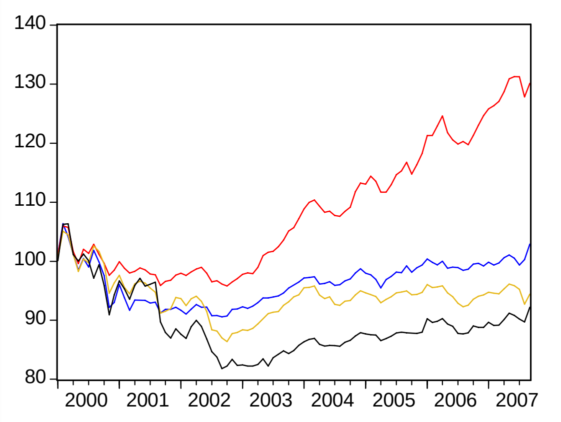
Event Driven



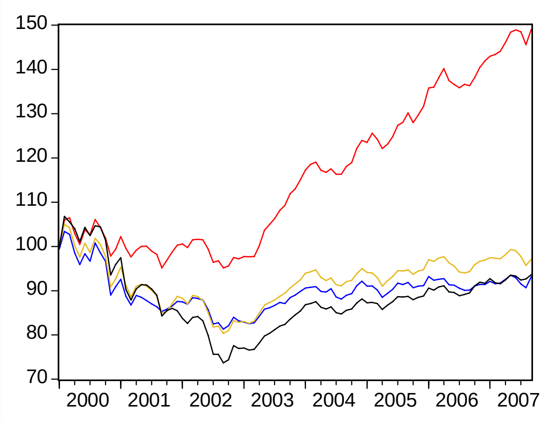
Convertible Bonds



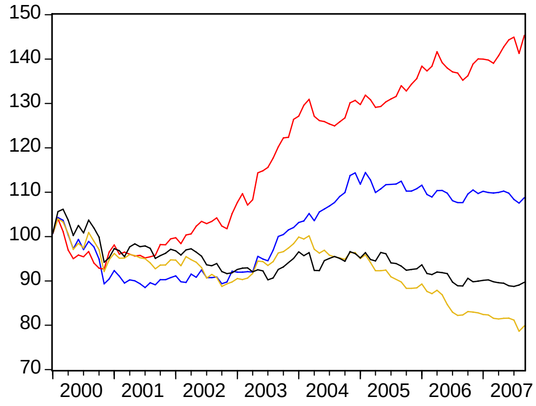
Funds of Funds Composite



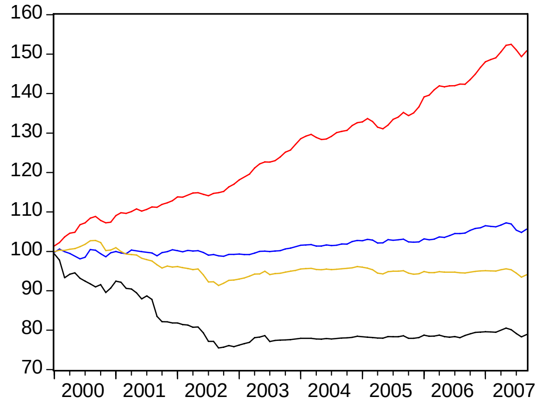
Fund Weighted Composite



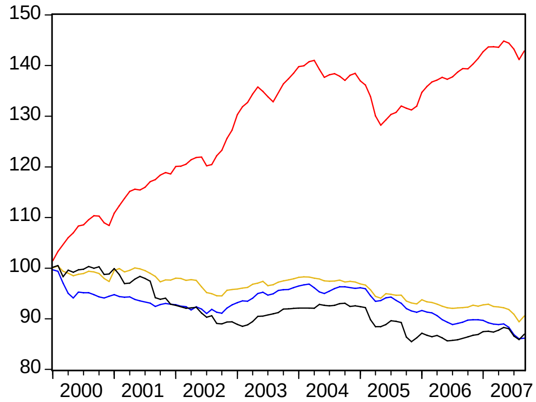
Macro



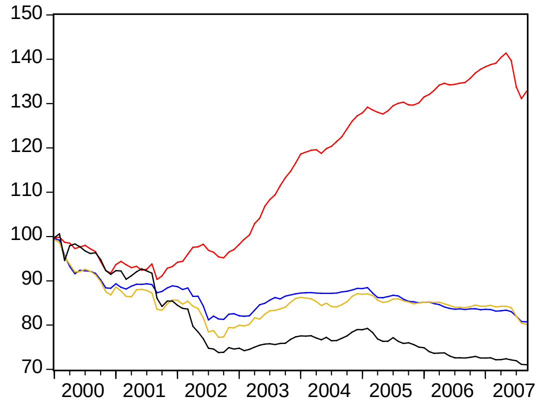
Relative Value



Convertible Arbitrage



Fixed Income Corporate



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Appendix A.

Description of hedge fund strategies.

Equity Hedge: Investment Managers who maintain positions both long and short in primarily equity and equity derivative securities. A wide variety of investment processes can be employed to arrive at an investment decision, including both quantitative and fundamental techniques; strategies can be broadly diversified or narrowly focused on specific sectors and can range broadly in terms of levels of net exposure, leverage employed, holding period, concentrations of market capitalizations and valuation ranges of typical portfolios. EH managers would typically maintain at least 50%, and may in some cases be substantially entirely invested in equities, both long and short.

Event-Driven: Investment Managers who maintain positions in securities of companies currently or prospectively involved in corporate transactions of a wide variety, including but not limited to: mergers, restructurings, financial distress, tender offers, shareholder buybacks, debt exchanges, security issuance or other capital structure adjustments. Security types can range from most senior in the capital structure to most junior or subordinated, and frequently involve additional derivative securities. ED exposure contains a combination of sensitivities to equity markets, credit markets and idiosyncratic, company specific developments. Investment theses are typically predicated on fundamental characteristics (as opposed to quantitative), with the realization of the thesis predicated on a specific development exogenous to the existing capital structure.

Macro: Investment Managers which execute a broad range of strategies in which the investment process is predicated on movements in underlying economic variables and the impact these have on equity, fixed income, currency and commodity markets. Managers employ a variety of techniques, both discretionary and systematic analysis, combinations of top down and bottom up theses, quantitative and fundamental approaches and long and short term holding periods. Although some strategies employ RV techniques, Macro strategies are distinct from RV strategies in that the primary investment thesis is predicated on future movements in the underlying instruments, rather than realization of a valuation discrepancy between securities. In a similar way, while both Macro and equity hedge managers may hold equity securities, the overriding investment thesis is predicated on the impact movements in underlying macroeconomic variables may have on security prices, as opposes to EH, in which the fundamental characteristics on the company are the most significant to investment thesis.

Relative Value: Investment Managers who maintain positions in which the investment thesis is predicated on realization of a valuation discrepancy in the relationship between multiple securities Manager employ a variety of fundamental and quantitative techniques to establish investment theses, and security types range broadly across equity, fixed income, derivative or other security types. RVA position may be involved in corporate transactions also, but as opposed to ED exposures, the investment thesis is predicated on realization of a pricing discrepancy between related securities, as opposed to the outcome of the corporate transaction.

Equity Market Neutral strategies employ sophisticated quantitative techniques of analyzing price data to ascertain information about future price movement and relationships between securities, select securities for purchase and sale. These can include both Factor-based and Statistical Arbitrage/Trading strategies. Factor-based investment strategies include strategies in which the investment thesis is predicated on the systematic analysis of common relationships between securities. In many but not all cases, portfolios are constructed to be neutral to one or multiple variables, such as broader equity markets in dollar or beta terms, and leverage is frequently employed to enhance the return profile of the positions identified. Statistical Arbitrage/Trading strategies consist of strategies in which the investment thesis is predicated on exploiting pricing anomalies which may occur as a function of expected mean reversion inherent in security prices; high frequency techniques may be employed and trading strategies may also be employed on the basis on technical analysis or opportunistically to exploit new information the investment manager believes has not been fully, completely or accurately discounted into current security prices. Equity Market Neutral Strategies typically maintain characteristic net equity market exposure no greater than 10% long or short.

Short-Biased strategies employ analytical techniques in which the investment thesis is predicated on assessment of the valuation characteristics on the underlying companies with the goal of identifying overvalued companies. Short Biased strategies may vary the investment level or the level of short exposure over market cycles, but the primary distinguishing characteristic is that the manager maintains consistent short exposure and expects to outperform traditional equity managers in declining equity markets. Investment theses may be fundamental or technical and nature and manager has a particular focus, above that of a market generalist, on identification of overvalued companies and would expect to maintain a net short equity position over various market cycles.

Merger Arbitrage strategies which employ an investment process primarily focused on opportunities in equity and equity related instruments of companies which are currently engaged in a corporate transaction. Merger Arbitrage involves primarily announced transactions, typically with limited or no exposure to situations which pre-, post-date or situations in which no formal announcement is expected to occur. Opportunities are frequently presented in cross border, collared and international transactions which incorporate multiple geographic regulatory institutions, with typically involve minimal exposure to corporate credits. Merger arbitrage strategies typically have over 75% of positions in announced transactions over a given market cycle.

Distressed/Restructuring strategies which employ an investment process focused on corporate fixed income instruments, primarily on corporate credit instruments of companies trading at significant discounts to their value at issuance or obliged (par value) at maturity as a result of either formal bankruptcy proceeding or financial market perception of near term proceedings. Managers are typically actively involved with the management of these companies, frequently involved on creditors' committees in negotiating the exchange of securities for alternative obligations, either swaps of debt, equity or hybrid securities. Managers employ fundamental credit processes focused on valuation and asset coverage of securities of distressed firms; in most cases portfolio exposures are concentrated in instruments which are publicly traded, in some cases actively and in others under reduced liquidity but in general for which a reasonable public market exists. In contrast to Special Situations, Distressed Strategies employ primarily debt (greater than 60%) but also may maintain related equity exposure.

Fixed Income-Convertible Arbitrage includes strategies in which the investment thesis is predicated on realization of a spread between related instruments in which one or multiple components of the spread is a convertible fixed income instrument.

Strategies employ an investment process designed to isolate attractive opportunities between the price of a convertible security and the price of a nonconvertible security, typically of the same issuer. Convertible arbitrage positions maintain characteristic sensitivities to credit quality the issuer, implied and realized volatility of the underlying instruments, levels of interest rates and the valuation of the issuer's equity, among other more general market and idiosyncratic sensitivities.

Fixed Income-Corporate includes strategies in which the investment thesis is predicated on realization of a spread between related instruments in which one or multiple components of the spread is a corporate fixed income instrument. Strategies employ an investment process designed to isolate attractive opportunities between a variety of fixed income instruments, typically realizing an attractive spread between multiple corporate bonds or between a corporate and risk free government bond. Fixed Income-Corporate strategies differ from Event Driven: Credit Arbitrage in that the former more typically involve more general market hedges which may vary in the degree to which they limit fixed income market exposure, while the latter typically involve arbitrage positions with little or no net credit market exposure, but are predicated on specific, anticipated idiosyncratic developments.