

The Brave New World of Hedge Fund Indices

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Abstract

That hedge funds have started to gain widespread acceptance while remaining a somewhat mysterious asset class enhances the need for better measurement and benchmarking of their performance. One serious problem is that existing hedge fund indices provide a somewhat confusing picture of the investment universe. In this paper, we present detailed evidence of strong heterogeneity in the information conveyed by competing indices. We also attempt to provide remedies to the problem and suggest various methodologies designed to help build a “pure style index”, or “index of the indices”, for a given style. Finally, we present evidence of the ability of pure indices to improve benchmarking of hedge fund returns. Our results can be extended to traditional investment styles such as growth/value, small cap/large cap.

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That hedge funds have started to gain widespread acceptance while remaining a somewhat mysterious asset class enhances the need for better measurement and benchmarking of their performance.¹ Understanding the risk exposures of hedge funds has actually become a rather important and fertile area of academic research. First and foremost, a better understanding of hedge fund risks is needed for individuals and institutions desiring to make investment decisions involving hedge funds. A detailed analysis of hedge fund risks and returns is also important from the standpoint of asset pricing theory. While it has long been recognized that the payoffs of managed portfolios will show option-like features (see Merton (1981) and Dybvig and Ross (1985)), most long-only active managers still have a dominant passive exposure to their benchmark, and it is actually not until the recent dramatic development of the hedge fund industry that empirical researchers were offered a real opportunity to get their hands on a large set of return time-series resulting from active dynamic trading decisions. Finally, understanding the risk exposure of hedge funds is also key to the design of optimal risk-sharing contracts between hedge fund managers and investors. While the common practice in the hedge fund industry consists in using the risk-free rate as a benchmark for claiming incentive fees, this is appropriate only if these hedge funds carry no systematic risks, and this can only be appreciated within the context of an appropriate asset pricing model.²

The issues regarding the nature of risks associated with different hedge fund strategies are actually challenging because of the complex nature of the strategies and limited disclosure requirements faced by hedge funds. In particular, since hedge fund returns exhibit non-linear option-like exposures to traditional asset classes (Fung and Hsieh (1997, 2000)), standard asset pricing models offer limited help in evaluating the performance of hedge funds. The importance of taking into account such option-like features has been underlined by recent research. In particular, Fung and Hsieh (2002) and Mitchell and Pulvino (2001) stress the importance of taking into account option-like features while analyzing the performance of “trend-following” and “risk-arbitrage” strategies, respectively. More recently, Agarwal and Naik (2003) build on these insights and extend our understanding of hedge fund risks to a wide range of equity-oriented hedge fund strategies. They characterize the risk exposures of hedge funds using buy-and-hold and option-based strategies, and show that a large number of equity-oriented hedge fund strategies exhibit payoffs resembling a short position in a put option on the market index.³ There are actually two possible ways to try and adapt standard asset pricing models to analyze returns on portfolios that exhibit a non-linear dependency to standard asset classes.

¹In 2001, total mutual fund inflows were smaller than total hedge fund inflows (Morgan Stanley, Equity Strategy, 30 April 2002). The hedge fund industry is now a more than \$ 700 billion industry, with more than 7,000 funds worldwide (see Henessee group research report (2002)).

²See for example Agarwal and Naik (2003) for evidence that standard linear models significantly underestimate the systematic risk exposure of hedge funds.

³See also Schneeweis and Spurgin (2000) and Fung and Hsieh (2001) for related papers.

The first approach consists in using a nonlinear APT model (see in particular Bansal and Viswanathan (1993) or Bansal, Hsieh and Viswanathan (1993)). The other method, which has been used by Glosten and Jagannathan (1994), as well as in the aforementioned papers on hedge fund benchmarking, is to include new regressors with non-linear exposure to standard asset classes, e.g., returns on option positions, to proxy for dynamic trading strategies in a linear regression.

Apart from portfolios of options, there actually exists another set of natural candidates for portfolios exhibiting non linear exposure to traditional asset classes. Such natural candidates are hedge fund indices, which are already very commonly used by funds of hedge fund managers to benchmark individual hedge fund returns (see for example Lhabitant (2001) for an example of style and VaR analysis based on hedge fund indices). While using the return on hedge fund indices to explain hedge fund returns involves an obvious self-referencing problem, there are actually two added advantage of using hedge fund indices with respect to option portfolios when it comes to analyzing *individual* fund returns. Firstly, they allow one to capture both passive and active components of hedge fund returns (capture both normal and abnormal returns on actively managed portfolios). Secondly, they allow for relative performance evaluation (compare the performance of a fund to that of other funds in a relevant peer group).

A detailed analysis of hedge fund index returns may also be relevant from a general asset pricing standpoint. It can actually be argued that hedge fund index returns can be used as proxies for unobservable factors. We understand that the world of financial securities is a multi-factor world consisting of different risk-factors, each associated with its own factor-risk-premium. Since long-only investment vehicles cannot span the entire “risk-factor space”, hedge funds offer a unique opportunity for investors to earn, and researchers to study, risk premia associated with different risk-factors. Just as growth and value indices provide us with useful proxies for unobserved underlying risk factors (e.g., a “distress” or “recession” factor, according to Fama and French (1992)), well-chosen hedge fund index returns can potentially be used as proxies for a volatility or liquidity factor, for example.⁴

One concern, however, with using hedge fund indices as non linear factors in a linear asset pricing framework, is that these indices, promoted by various commercial providers, all suffer from a number of shortcomings. There are actually two main shortcomings hedge fund indices suffer from, the presence of which makes practitioners and researchers reluctant to use them to benchmark individual hedge fund returns. One first problem, already well-documented in academic literature, is the presence of measurement biases that hedge fund indices inherit from

⁴It can indeed be argued that some hedge funds collect a liquidity premium from holding distressed securities that the market does not want to hold . This is for example the case for distressed arbitrage managers, and some of the fixed-income arbitrage managers.

hedge fund databases they are built from.⁵ There are at least three main sources of difference between the performance of hedge funds in the database and the performance of hedge funds in the population, namely a *survivorship* bias, a *selection* bias and an *instant history* bias (see in particular Fung and Hsieh (2002) for a detailed analysis of such biases).⁶

Another serious problem, which is the main focus of the present paper, is that existing hedge fund style indices provide a somewhat confusing picture of the investment universe. There are actually at least a dozen competing hedge fund index providers (see table 1) which differ in terms of selection criteria (length of track record, assets under management, restrictions on new investment, etc.), style classification (manager's self-proclaimed styles versus objective statistical-based classification), weighting scheme (equally-weighted versus value-weighted) and rebalancing scheme (e.g., monthly versus annually). As a result of such differences in construction methods, competing index providers offer a very contrasted picture of hedge fund returns, and differences in monthly returns can be greater than 20%! For example, Zürich reports a 20.48% return on *long/short* strategies in February 2000, while EACM reports a -1.56% return in the same month! (See section 2 for more details.) Such disturbing evidence of heterogeneity in competing index returns poses serious problems, not only for portfolio analysis involving hedge funds, but also for empirical tests of asset pricing theory. If hedge fund returns are used as proxies for unobservable risk factors, and if there is very little robustness with respect to the choice of the proxy (index) used in empirical tests, then the relevance of these factors in asset pricing theory may never be empirically testable.⁷

Our contribution to this emerging literature on advanced techniques for hedge fund benchmarking is to show that at least some of the shortcomings inherent to the use of hedge fund indices in modern portfolio analysis and empirical tests of asset pricing theory can be overcome. In what follows, after documenting how heterogeneous existing hedge fund indices are, we attempt to provide remedies to the problem through the construction of so-called *pure style indices*.⁸ We define a *pure style index* as being the true unobserved fully representative and unbiased index that would provide a fair representation of the return on a portfolio encompassing for a given strategy all hedge funds following that strategy and no other. We first explore a statistical approach to the problem of construction of pure style indices, using Kalman filter techniques which are well-suited for the estimation of an unobservable factor from competing

⁵It is believed that these biases account for a total approaching at least 4.5% annually (see Agarwal and Naik (2000b), Liang (1999), Park, Brown and Goetzmann (1999) and Fung and Hsieh (2000a)).

⁶Fung and Hsieh (2001a) suggest using returns on funds of funds, which provide a cleaner estimate of the investment experience of hedge fund investors. Specialized fund of funds, however, are not available for all hedge fund strategies. This makes impossible a complete benchmarking of the entire universe by fund of funds.

⁷This is somewhat reminiscent of Roll's critique (1977) of CAPM.

⁸Related papers are Brittain (2001), Brooks and Kat (2001), Fung and Hsieh (2002), and Schneeweis et al. (2001), who also document measurement and interpretation problems with existing hedge fund indices.

index return observations. Because, it is desirable that a pure index can be regarded as a portfolio of existing indices, we also suggest a portfolio approach to the problem of construction of pure style indices. In particular, we suggest using principal component analysis to extract the *best possible one-dimensional summary* of a set of competing indices, and using minimum variance analysis to extract the *least biased index* from a set of competing indices. We also provide evidence of the ability of the pure style indices to improve current techniques for factor analysis and benchmarking of hedge fund returns.

Our paper complements existing literature on hedge fund indices in the following way. While Fung and Hsieh (2002) focus on correcting for biases (survivorship, selection and instant history biases) that are strongly correlated across hedge fund indices and therefore cannot be diversified away in a portfolio of indices, we instead focus on *diversifiable* biases originating from the fact that an index for a given strategy never encompasses all existing hedge funds following the strategy, while it may encompass hedge funds deviating significantly from the given strategy. Intuitively, the our message is that it is possible to mitigate such biases by mixing indices into an index of indices.⁹

The rest of the paper is organized as follows. In section 1, we review the main providers of hedge fund indices and discuss the database. In section 2, we provide strong evidence that competing indices offer a very contrasted view of hedge fund performance for a given style. In section 3, we offer three possible remedies and discuss the derivation of “pure style indices” from a set of competing indices. Section 4 is devoted to testing the performance of these pure style indices. In section 5, we present our conclusions and suggestions for further research. Detailed information on competing hedge fund indices are delegated to the Appendix.

1 The World of Hedge Fund Indices

We have listed almost a dozen hedge fund index providers.¹⁰ We report some key information about them in table 1, while more details on each of these index providers can be found in Appendix A.¹¹

These indices have been set up to provide the rigorous data and analytics that both man-

⁹The resulting “pure index”, however, still suffer from undiversifiable biases (survivorship, selection and instant history biases), the impact of which can and should be measured and accounted for as described in the literature.

¹⁰Standard & Poor’s and MSCI have recently announced plans to create hedge fund indices (see Appendix A for more details).

¹¹Magnum publishes the performance of funds of funds (since January 1997), as opposed to non-investible indices. Because they are well-established in the industry, we have chosen to include them in our analysis. This is consistent with Fung and Hsieh (2001a) who suggest using returns on funds of funds as proxies for hedge fund indices.

Providers	# of Indices	Launch Date	# of Funds	Website
EACM	13	1996	100	eacmalternative.com
HFR	33	1994	1,300	hfr.com
CSFB/Tremont	9	2000	383	hedgeindex.com
Zürich Capital	5	2001	60	zcmgroup.com
Van Hedge	15	1995	750	vanhedge.com
Hennessee Group	23	1992	500	hedgefund.com
Hedgefund.net	33	1998	1,800	hedgefund.net
LJH Global Investments	16	1992	800	ljh.com
MAR	19	1994	1,500	marhedge.com
Altvest	14	2000	2,000	altvest.com
Magnum	16	1994	NA	magnum.com

Table 1: Competing Indices in Hedge Fund Universe. This table provides a listing of competing hedge fund index providers, with information on the number of strategies, launch date, number of selected funds and web site.

agers and investors increasingly demand for measuring performance and risk in this rapidly growing asset class. As argued in the introduction, one serious problem is that existing hedge fund style indices provide a somewhat confusing view of the alternative investment universe, because the collection of such indices is neither collectively exhaustive, nor mutually exclusive.

More specifically, hedge fund indices are built from databases of individual fund returns, and therefore inherit their shortcomings in terms of scope and quality of data, which vary a lot among various data vendors. There are three main competing databases (TASS, MAR, HFR) that are used by providers of hedge fund indices. While all three data bases are marred to some extent by the presence of the usual biases (survivorship, selection and instant history biases), they are far from being homogeneous in terms of population. For instance, HFR excludes managed futures from its databases while TASS and MAR take them into account. The majority of funds are present in one but not the other: of the 1,162 HFR funds and the 1,627 TASS funds, only 465 are common to both databases. 59% of the funds that are still in activity and 68% of the funds that no longer report to HFR are not part of the TASS database. Out of the 465 funds in common between the HFR and TASS databases, only 154 (or 33.1%) have been included in both databases at the same time (cf. Liang (2001)).

As a result of the incompleteness and heterogeneity of hedge fund data, existing hedge fund indices, which are built from that data, potentially suffer from the following two major shortcomings (see figure 1).¹²

¹²Such shortcomings obviously also apply to traditional equity style indices and also, albeit to a lesser extent, to bond indices (see Reilly, Kao and Wright (1992)). In the case of hedge fund indices, the problem

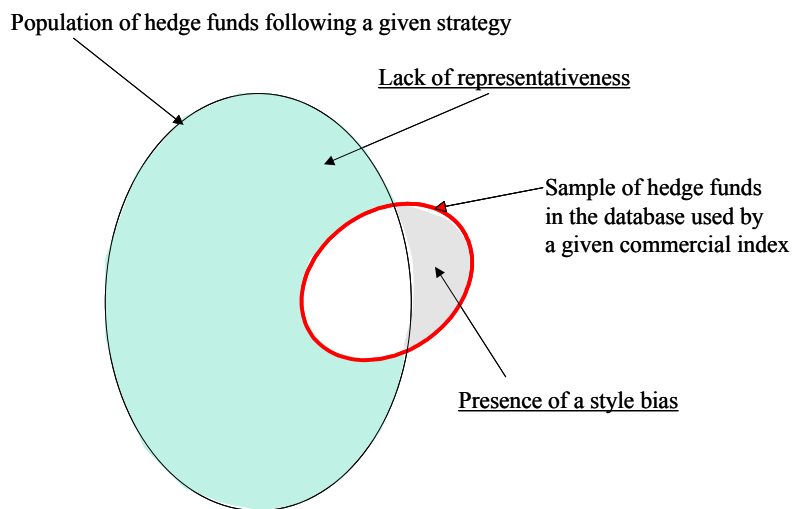


Figure 1: Problems with Style Indices.

First, *existing indices are not fully representative* (i.e., some funds that should be part of an index are not included in the index). In the one-factor CAPM world of the sixties and seventies, the notion of a good index was one that was representative of the value-weighted portfolio of all traded assets, and the real challenge was to provide investors with the closest approximation of the true market portfolio (see Roll (1977)). The market cap logic, however, does not easily extend to the alternative investment universe. First, hedge funds are not submitted to reporting requirements so that information on the asset under management is very hard to gather with some degree of accuracy. This is the reason why all existing hedge fund indices, to the notable exception of CSFB/Tremont, use an equally-weighted, as opposed to value-weighted, scheme. Beside, because of the lack of regulation on hedge fund performance disclosure, existing data bases only cover a relatively small fraction of the hedge fund population. Probably only a little more than half of existing hedge funds choose to self-report their performance to one of the major hedge fund databases - see Appendix A for more details. As simple evidence of the fact that existing indices are not fully representative of the universe, it perhaps suffices to note that one of the most popular hedge fund indices, the EACM 100, does not account for more than a tiny percentage of all existing hedge funds (100 among more than 7,000 funds).

Second, *existing indices are biased* (i.e., some funds that should not be part of an index are included in the index). Most hedge fund indices (actually all indices, except the Zürich indices - see Appendix A) are based upon managers' self-proclaimed styles. Given that hedge fund managers jealously protect the secret of their investment strategies (the so-called black-box problem), relying on managers' self-proclaimed style is actually almost a necessity. The is dramatically amplified due to the complex nature of the strategies involved, and the absence of regulation concerning performance disclosure.

problem is that this procedure only makes sense under the following two conditions: (1) a manager follows a unique investment style;¹³ (2) a manager's self-proclaimed style matches the manager's actual trading strategies. Of course, none of these assumptions can be taken for granted. In particular, it is well documented (see for example Lhabitant (2001)) that some significant *style drift* occurs; as opportunities eventually disappear in their original strategies, it is common practice for some hedge fund managers to start looking at other markets (e.g., managers who start pursuing fixed income arbitrage strategies and end up investing in emerging markets as arbitrage opportunities tend to disappear in liquid US markets). As a result, all competing indices for a given style are likely to encompass funds that should not be included.

2 Hedge Fund Indices are not Created Equal

Hedge fund indices come in very different shapes and forms. The existence of a profound heterogeneity in the set of assets under consideration, as well as some heterogeneity in the index construction method, result in some dramatic heterogeneity in the returns, which we document now.

2.1 The Data

There are some serious challenges one has to face when attempting to provide a detailed picture of the universe of hedge fund indices. We first had to compile what we believe is an exhaustive database of all existing hedge fund indices. The data collection work involved was rather formidable as there is not, to the best of our knowledge, a single integrator of all these sources.¹⁴ Fortunately, a significant number of index providers offer the possibility to download the data from their web site at no cost for registered users. When possible, we have set up an account with these data vendors, and collected data on every single hedge fund index they would carry. In other instances, we had to purchase the database from the vendor.¹⁵ Finally, we have also used some proprietary data obtained from specific contacts

¹³Similarly, building a growth index on the basis of growth stocks relies on the assumption that each stock can be labelled either 100% growth or 100% value. This, of course, is a somewhat heroic assumption. Some have proposed probabilistic classification techniques for style: 95% growth, 5% value (e.g., Russell, Salomon Brothers) (see Borger (1997)).

¹⁴PerTrac, a vendor of systems for asset management, offers integrated access to a series of databases including Hedgefund.net, Hedge Fund Research (HFR), Altvest, TASS, and MAR. PerTrac provides three types of manager search selections: information search, statistics search and style search. However, specific contracts are required with each of these prime data providers.

¹⁵Van Hedge in particular do not post the historical performance of their indices on the web, but such data can be purchased from them with a discount price charged when the data is used for academic purposes.

we have developed in the hedge fund industry.¹⁶ As a result of that somewhat painful data collection process, we have been able to obtain a database consisting of indices maintained by the dozen aforementioned hedge fund index providers.

A second step involves sorting index return data by strategy, i.e., listing all competing indices for a given strategy. One problem we had to face is that the terminology of hedge fund strategies is not entirely stabilized, as we are dealing with a relatively new industry.¹⁷ Therefore, the same strategy can be referred to under different names. For example, some hedge fund index providers use the name *convertible hedge*, while others use the name *convertible arbitrage*. In the same vein, EACM and HF Net use the label *risk arbitrage* to denote strategies that are otherwise referred to as *merger arbitrage* by Altvest, HFR, Zürich or Hennessee. We have used our knowledge of the hedge fund industry to try to generate the most consistent classification possible. While it is almost impossible to ascertain that a given classification does not pair together inconsistent strategies, or leave similar strategies apart, we feel confident that our classification scheme includes in a consistent way most of the available information. At the end of this process, we have finally listed as many as 25 different hedge fund strategies for which there are at least two competing index providers.

In the interest of brevity, we do not report the results for all 25 strategies in this paper, but only focus on the most popular ones. To that end, we have performed a selection based on the following rules: (1) we eliminate strategies for which not more than 3 competitors are available, (2) we eliminate strategies with narrow focus (e.g., *sectors - health care*). As a result of that selection, we are left with the following list of 12 styles, including the composite *fund of funds* style (see table 2), with 4 to 8 index providers for each style.

The strategies left aside are listed in Appendix B (see table 10). To that list should also be added composite global across-strategies indices.¹⁸ We do not imply of course that these strategies do not represent an important part of hedge fund investing. The results for these strategies are available from the authors upon request.

We have collected and merged monthly return data from competing indices for each strategy. As a result, we had to use the starting date of the database with the shortest history as the starting date for our study. The starting date turned out to be January 1998 for each sub-universe where Zürich has created an index, for example, as the starting date for Zürich

¹⁶In particular, we would like to thank Francisco Portillero from Zürich Capital Markets in London for providing us with access to Zürich index performance data.

¹⁷One of the authors is currently involved in a large-scale project, undertaken under the umbrella of the Association for Investment Management and Research (AIMR), aiming at a standardization of the terminology and style definition in the hedge fund industry.

¹⁸CSFB, Altvest, Van Hedge and Hennessee offer a global index; MAR, Zurich, Magnum, HFR and HF Net do not.

Sub-Universe	List of Competing Indices	Date
Convertible Arbitrage	CSFB, HFR, EACM, Zürich, Hennessee, HF Net	01/98
Emerging Markets	CSFB, Altvest, HFR, MAR, Van Hedge, Hennessee, HF Net	01/96
Equity Market Neutral	CSFB, Van Hedge, HFR, MAR, Hennessee, HF Net	01/96
Event Driven	CSFB, Altvest, MAR, EACM, HFR, Hennessee, HF Net, Zürich	01/98
Fixed Income Arbitrage	CSFB, HFR, Van Hedge, Hennessee, HF Net	01/96
Global Macro	CSFB, Altvest, Van Hedge, MAR, HFR, Hennessee, HF Net, Magnum	02/97
Long/Short	CSFB, Altvest, Zürich, EACM, HF Net	01/98
Merger Arbitrage	Altvest, HFR, Zürich, Hennessee, EACM, HF Net	01/98
Relative Value	Altvest, HFR, Van Hedge, EACM, HF Net	01/96
Short Selling	Altvest, HFR, Van Hedge, MAR, EACM	01/96
Distressed Securities	Van Hedge, Altvest, HFR, EACM, Zürich, HF Net, Hennessee	01/98
Fund of Funds	Van Hedge, Altvest, HFR, Zürich	01/98

Table 2: Competing Indices in Hedge Fund Universe. This table provides a listing of competing indices in the hedge fund universe, with details on the competing indices and the starting date. Van Hedge offer two market neutral indices, respectively labelled Arbitrage and Securities hedging. For the purpose of this study, we have combined these two sub-indices into a single one by taking a simple average return on the two strategies. EACM offers two long-short indices, respectively labelled Relative Value and Equity Hedge Fund. For the purpose of this study, we have combined these two sub-indices into a single one by taking a simple average return on the two strategies.

indices was early 1998, and the ending date is December 2000.¹⁹

2.2 Heterogeneity in Competing Hedge Fund Index Returns

We have performed various tests of homogeneity/heterogeneity for each given sub-universe. The first measure is the maximum difference in monthly returns in the sample period (from the starting date to December 2000). The results are reported in table 3.

As can be seen from table 3, differences in monthly returns are spectacular and can be greater than 20%! For example, Zürich reports a 20.48% return on *long/short* strategies in February 2000, while EACM reports a -1.56% return in the same month for the same strategy.

¹⁹We have chosen not to consider a unique sample history for our study because this would imply focusing on the period ranging from January 1998 to December 2000. Given that such a period is relatively short, and does not contain important events such as the LTCM crisis, we have decided to use as much data as possible, and consider the longest possible history for each sub-universe. This comes at the cost of a relative loss in comparability between different styles, which is acceptable for our purposes as we focus on heterogeneity within a given style.

Sub-Universe	Max Difference (with dates and indices)
Convertible Arbitrage	4.75% (Oct 98; CSFB (-4.67) / Hennessee (0.08))
Emerging Markets	19.45% (Aug 98; (MAR -26.65) / Altvest (-7.2))
Equity Market Neutral	5.00% (Dec 99; Hennessee (0.2) / Van Hedge (5.2))
Event Driven	5.06% (Aug 98; CSFB (-11.77) / Altvest (-6.71))
Fixed Income Arbitrage	10.98% (Oct 98; HF Net (-10.78) / Van Hedge (0.2))
Global Macro	17.80% (May 00: Van Hedge (-5.80) / HF Net (12))
Long/Short	22.04% (Feb 00: EACM (-1.56) / Zürich (20.48))
Merger Arbitrage	1.85% (Sep 98: Altvest (-0.11) / HFR (1.74))
Relative Value	10.47% (Sep 98: EACM (-6.07) / Van Hedge (4.40))
Short Selling	21.20% (Feb 00: Van Hedge (-24.3) / EACM (-3.09))
Distressed Securities	7.38% (Aug 98: HF Net (-12.08) / Van Hedge (-4.70))
Fund of Funds	8.01% (Dec 99: MAR-Zürich (2.41) / Altvest (10.42))

Table 3: Measures of Heterogeneity in Hedge Fund Indices (1). This table provides the maximum monthly return difference between competing indices for the same style.

Obviously, replicating or outperforming a *long/short* strategy index was considerably easier that month if the benchmark used was EACM as opposed to Zürich! *Short selling* also posts maximum differences in returns above 20%, while *emerging market* and *global macro* are very close to that number (19.45% and 17.80%, respectively). We also note that the maximum differences tend to be recorded in periods of crisis: for seven strategies, maximum differences are recorded in the period ranging from August to October 1998, which corresponds to the LTCM crisis. This suggests that index returns become less homogeneous in turbulent times. While not surprising, this is bothersome because hedge fund indices fail to agree precisely when reliable information is most needed. Such maximum differences become even more dramatic when computed at a quarterly frequency. For example, we find a maximum difference equal to 30.08% for *long/short* or 16.52% for *relative value*, as opposed to, respectively 22.04% or 10.47%, at the monthly level. This strongly suggests that differences in competing index returns do not smoothen out at lower frequencies.

We also compute the average and lowest correlation between various indices in each given universe. Table 4 summarizes that information.

We find again that there is evidence of strong heterogeneity in the information conveyed by competing indices. For example, the correlation between two competing indices for the same strategy can be as low as .16 (correlation between Hennessee and MAR *equity market neutral* indices). It can even reach a negative -0.1901, as in the case of EACM and Zürich *long/short* indices, thus reflecting a sharp difference in net exposure of these two competing indices. The

Sub-Universe	Average Correlation	Lowest Correlation
Convertible Arbitrage	0.8183	0.6350
Emerging Markets	0.9284	0.8301
Equity Market Neutral	0.4276	0.1258
Event Driven	0.9232	0.8458
Fixed Income Arbitrage	0.5407	0.2254
Global Macro	0.5598	0.2698
Long/Short	0.4575	-0.1901
Merger Arbitrage	0.9193	0.8797
Relative Value	0.6752	0.3042
Short Selling	0.8811	0.7796
Distressed Securities	0.8645	0.7218
Fund of Funds	0.8757	0.7985

Table 4: Measures of Heterogeneity in Hedge Fund Indices (2). This table provides two measures of heterogeneity in the hedge fund index universe (average correlation and lowest correlation).

mean correlation between competing indices within a particular style can also be low, as low as .4. In particular, *equity market neutral* strategies exhibit a low 0.4276 average correlation. Interestingly enough, we find that hedge fund strategies for which mean correlation is the lowest are the ones which are known to come closest to market neutrality, i.e., *equity market neutral*, *long/short*, or to a lesser extent *fixed-income arbitrage*. The intuitive explanation is that these fund managers attempt to follow pure alpha strategies with little, if any, systematic exposure to pervasive risk factors, while more directional strategies maintain a large exposure to standard asset classes in a way that makes them more similar. At the other extreme, we find for example *emerging markets*, *merger arbitrage* or *event driven*, for which there is a fair amount of homogeneity in the information provided by competing indices. For example, in the case of *merger arbitrage*, we find that the maximum difference in monthly returns is a low 1.85% (see table 3) with an average correlation greater than .9 (see table 4). It actually turns out that managers pursuing *merger arbitrage* strategies tend to behave in a consistent manner which explains why competing indices, based on different sets of managers, tend to agree more than for other hedge fund styles. This is consistent with Mitchell and Pulvino (2001) who show that most *risk arbitrage* returns are positively correlated with market returns in severely depreciating markets but uncorrelated with market returns in flat and appreciating markets.

We have also performed a variety of indirect tests of the presence of significant heterogeneity in competing index returns. In particular, one can show that competing indices vary

significantly in the way they correlate with a set of broad-based economic and financial factors. Also, and not surprisingly, optimal allocation to hedge funds generated from minimum variance or minimum Value-at-Risk analysis are found to differ significantly depending on which index is used as a proxy for the return on a given strategy. In the interest of brevity, we do not report the results of these tests in this paper but they can be obtained from the authors upon request.

3 Desperately Seeking Pure Indices

In the presence of many different competing indices, one may be at a loss to decide which one to use for performance benchmarking or asset allocation decisions. The problem is that there is no clear and definitive judgment that one can make in terms of a qualitative assessment of which index provider is doing the best job at representing a given market segment. All existing indices have both advantages and drawbacks. For example, Zürich Capital Markets (ZCM) have tried to design a process to ensure the style-purity of their indices by using an objective statistical cluster-based classification procedure for style classification, as opposed to managers' self-proclaimed styles. On the other hand, ZCM do not use as exhaustive a database as some of their competitors: their hedge fund indices are based upon a data set of 60 hedge funds, while HFR for example uses as many as 1,100 hedge funds (see Fung and Hsieh (2001) for more institutional details). Therefore, while ZCM indices may be less biased than some of their competitors, they fail to properly represent a significant fraction of the entire universe and are therefore less representative than some of their competitors.

In this context, it seems desirable to try and use all available information, as opposed to focus on a single specific index. In what follows, we attempt to provide remedies to both the lack of representativeness and existence of bias problems and suggest various methodologies designed to help extract a “pure style index”, or “index of the indices” from the information conveyed by competing index providers.

3.1 Statistical Approach to the Construction of Pure Style Indices

There is a whole body of the statistical literature that deals with (linear and non linear) factor models with unobservable factors. For example, at the cost of specific assumptions (e.g., assumption that the return on the indices are normally distributed), one may use filtering theory (Kalman filter) to draw inferences on the unobservable variable, based on the observed returns.²⁰

²⁰The assumption that hedge fund returns are normally distributed is at odd with empirical evidence. It can, however, be shown, that, while the Kalman filter forecasts need no longer be optimal for systems that

Many time-series models, including the classical linear regression model and ARIMA models, can be represented in a general form known as the state space form. There are two main benefits to representing a dynamic system in state space form. First, the state space allows unobserved variables (known as the state variables) to be incorporated into, and estimated along with, the observable model. In the present context, the observed variables are the competing indices, and the unobserved variable is the “true” pure index. Second, state space models can be estimated using a powerful recursive algorithm known as the Kalman filter. The Kalman filter is used both to evaluate the likelihood function and to forecast and smooth the unobserved state variables. In this paper, our motivation is to estimate (smooth) the unobserved state variable, based on the observed returns. State space models have been applied in the econometrics literature to model unobserved variables such as (rational) expectations, measurement errors, missing observations, permanent income, unobserved components (cycles and trends), and the natural rate of unemployment. Extensive surveys of applications of state space models in econometrics can be found in Hamilton (1994a, 1994b) and Harvey (1989).

We present here a brief discussion of the specification and estimation of a state space model in the context of pure hedge fund indices. Those desiring greater detail are directed to Hamilton (1994a) and Harvey (1989). The basic intuition is that we want to model the return on these indices as the sum of a true unobservable pure style index I and a white noise capturing the existence of biases and lack of full representativeness. The state space representation of the dynamics of a vector $R_t = (R_{it})_{i=1,\dots,n}$ of the return on competing indices is then given by the following system of equations

$$R_t = \mathbf{1} \cdot I_t + \varepsilon_t \quad (1)$$

$$I_{t+1} = \bar{I} + \nu_{t+1} \quad (2)$$

where $\mathbf{1}$ is a $(n \times 1)$ vector of ones, I_t is the scalar return on the unobservable pure index, \bar{I} the mean of the unobserved pure index, and where ε_t and ν_t are assumed to be independent white noise with $\text{Var}[\varepsilon_{it} | \mathcal{F}_t] = \sigma_\varepsilon^2 = (\sigma_{\varepsilon_i}^2)_{i=1,\dots,n}$, $\text{Var}[\nu_t | \mathcal{F}_t] = \sigma_I^2$ and $\text{Cov}[\varepsilon_{it}, \nu_t | \mathcal{F}_t] = 0$ for all $i = 1, \dots, n$.²¹

Equation (1) is known as the observation (or measurement) equation while equation (2) is known as the state (or transition) equation, which specifies the dynamics of the return on the index. It should be noted that one may consider the more general expression $R_t = A'X + H \cdot I_t + \varepsilon_t$, where A and H are $n \times 1$ vectors of parameters, and X is a $n \times 1$ vector of are not normal, no other forecast based on a linear function of I_t will have a smaller mean squared error (see Hamilton (1994b)). These results parallel the Gauss-Markov theorem for ordinary least squares regression.

²¹Note that because of the presence of biases such as self-selection and instant history biases, the noise term ε may have a positive mean. This unambiguous effect can be accounted for separately from the analysis we present in this section by subtracting an estimate of the impact of the combined biases from the return of competing indices.

observable factors. We have also tested the latter, more general, version of the model.²² We do not report the results here in the interest of brevity; they can be obtained from the authors upon request.

Given observations (R_t) for $t = 1, 2, \dots, T$, our goal is to estimate the parameters σ_ε^2 and σ_I^2 , and make inferences about the state vector I_t . The Kalman filter is a recursive algorithm for sequentially updating the state vector given past information. While we use the more familiar terminology of Kalman *filter*, we actually use in this paper the Kalman *smoother*. The difference between the two is the conditioning information set. The filter is conditional upon information up to time t , and therefore is well-suited for prediction. In the context of prediction, the problem is to provide an optimal forecast of the value of the state vector at date $t+1$ based on information available at date t , denoted $\widehat{I}_{t+1|t}$. In our application, the value of the state vector is of interest in its own right. In such cases it is desirable to use information through the end of the sample (date T) to help improve the inference about the historical value that the state vector took on at any particular date t in the middle of the sample. Such an inference is known as a smoothed estimate, denoted $\widehat{I}_{t|T} = \mathbb{E}[I_t | I_T]$. The mean squared error of this estimate is denoted $P_{t|T} = \mathbb{E}\left[\left(\widehat{I}_{t|T} - I_t\right)^2\right]$.

The smoothed series, which is the best estimate (in terms of mean squared error) of the state series using the full sample T , is obtained as follows. We first compute $\widehat{I}_{t|t}$ and $P_{t|t}$, for $t = 1, 2, \dots, T$, using the recursive Kalman filter procedure, which reads in the general case

$$\begin{aligned}\widehat{I}_{t|t} &= \widehat{I}_{t-1|t-1} + S_{t-1}H (H'S_{t-1}H + \sigma_\varepsilon^2)^{-1} (R_t - A'X - H\widehat{I}_{t-1|t-1}) \\ P_{t|t} &= S_{t-1} - S_{t-1}H (H'S_{t-1}H + \sigma_\varepsilon^2)^{-1} HS_{t-1}\end{aligned}$$

where $S_{t-1} = P_{t|t} + \sigma_I^2$. Note that the recursion for P does not depend on the forecasted state vector $\widehat{I}_{t-1|t-1}$, or on the observed data (R, X) . The smoothed series and its mean squared errors are then computed by the backward recursion

$$\begin{aligned}\widehat{I}_{t|T} &= \widehat{I}_{t|t} + J_t \left(\widehat{I}_{t+1|T} - \widehat{I}_{t+1|t} \right) \\ P_{t|T} &= P_{t|t} + J_t^2 (P_{t+1|T} - P_{t+1|t})\end{aligned}$$

for $t = T - 1, T - 2, \dots, 1$, where $J_t = P_{t|t}P_{t+1|t}^{-1}$.

In table 5, we provide information on the mean, volatility, estimation error, kurtosis, skewness as well as average correlation with competing indices of pure indices generated using the

²²We have actually tested 2 versions of the model, one with $R_t = A + H \cdot I_t + \varepsilon_t$, where A and H are $n \times 1$ vectors of parameters, and another with $R_t = A'X + H \cdot I_t + \varepsilon_t$, where A and H are $n \times 1$ vectors of parameters, and X is a $n \times 1$ vector of observable factors. For the latter formulation of the model, we have used factors that have been found to help explain equity returns (proxies for market, credit and liquidity risks) and subsequently performed Kalman filtering.

Kalman filter smoothing techniques. We also provide (in parenthesis) average values for these parameters for competing indices.

Sub-Universe	Mean	Volatility	Est. Error	Average Correlation
Conv. Arbitrage	0.75% (0.88%)	1.04% (1.35%)	0.01%	0.905
Emerging Markets	0.49% (0.56%)	4.32% (5.08%)	0.01%	0.966
Eq. Market Neutr.	0.71% (0.83%)	0.55% (0.90%)	0.01%	0.707
Event Driven	0.72% (0.82%)	1.70% (2.01%)	0.01%	0.954
Fixed Income Arb.	0.34% (0.41%)	1.09% (1.67%)	0.02%	0.789
Global Macro	0.60% (0.68%)	1.77% (2.44%)	0.01%	0.822
Long/Short	0.84% (1.01%)	2.22% (3.00%)	0.02%	0.704
Merger Arb.	0.71% (0.83%)	1.07% (1.29%)	0.01%	0.969
Relative Value	0.75% (0.88%)	1.39% (1.90%)	0.01%	0.807
Short Selling	0.53% (0.66%)	5.68% (7.42%)	0.02%	0.954
Distressed	0.65% (0.75%)	1.73% (2.14%)	0.01%	0.923
Fund of Funds	0.69% (0.86%)	1.83% (2.40%)	0.02%	0.948

Table 5: Pure Indices from Kalman Filter Analysis. This table provides information (mean, volatility, estimation error as well as average correlation with competing indices) on the monthly returns of pure indexes generated using the Kalman filter smoothing techniques. Numbers in paranthesis are average values for these parameters for competing indices.

As an illustration, we plot in figure 2 the return for the pure index, with the corresponding 95% confidence interval, as well as the return on competing indices for the strategy *convertible arbitrage* on the period 1998-2000.

From table 5 and figure 2, it appears that pure indices generated from Kalman filter analysis have relatively high correlations with corresponding competing indices. On the other hand, they have smoother paths than that of the competing indices, suggesting that noise reduction has actually occurred.

One key problem, however, with this approach is that the estimated pure index can not be expressed as a linear combination of competing indices. As a result, a pure index generated from Kalman smoothing analysis can not be regarded as an index in its own right, since it can not be expressed as a portfolio of individual hedge funds. In what follows, we discuss a portfolio approach to the construction of pure style indices, which allows us to address this black-box problem.

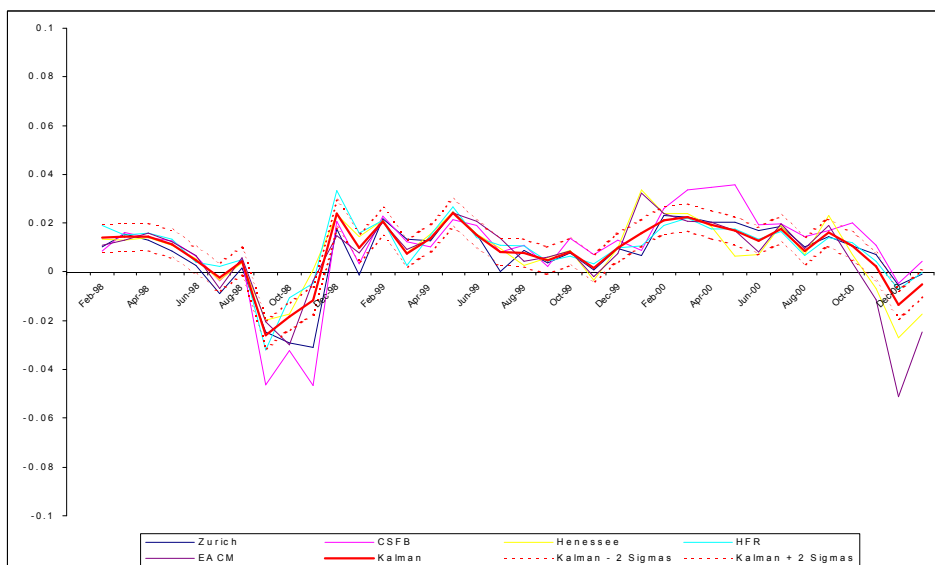


Figure 2: Convertible Arbitrage Pure Index from Kalman Analysis. This figure displays the return for the pure index, with the corresponding 95% confidence interval, as well as the return on competing indexes for the strategy *convertible arbitrage* on the period 1998-2000.

3.2 Portfolio Approach to the Construction of Pure Style Indices

Given that it is impossible to come up with an objective judgement on what is the best existing index, a natural idea consists of using some combination of competing indices to reach a better understanding of what the common information about a given investment style would be.

One straightforward method for obtaining a composite index based on various competing indices would involve computing an equally-weighted portfolio of all competing indices.²³ This would obviously provide investors with a convenient one-dimensional summary of the contrasted information contained in competing indices. In particular, because competing hedge fund indices are based on different sets of hedge funds, the resulting portfolio of indices would be more exhaustive than any of the competing indices it is extracted from (see theorem 2 section 4.1). In this paper, we wish to push the logic one step further and suggest using factor analysis techniques to extract the *best possible one-dimensional summary* of a set of competing indices, and design what can be called “pure style” indices. Our method is a natural generalization of the idea of taking a portfolio of competing indices. The refinement involves relaxing the assumption of an equally-weighted portfolio.

²³Value-weighting is not a viable alternative, as information on the assets under management is not usually part of the information made available to the public by data vendors. Besides, funds frequently report assets under management with a considerable lag, which implies that such information could not be made available on a timely basis anyway.

3.2.1 Maximization of Representativeness

We first suggest to use factor analysis techniques to generate a set of pure indices that can be thought of as the best possible one-dimensional summaries of information conveyed by competing indices for a given style, in the sense of the larger fraction of the variance explained. Here, we are looking for the portfolio weights that make the combination of competing indices capture the largest possible fraction of the information contained in the data from the various competing indices. Technically speaking, this amounts to using the first component of a PCA of competing indices as a candidate for a pure style index. Note that the first component typically captures a large proportion of cross-sectional variations because competing styles tend to be at least somewhat positively correlated. This is confirmed by the numbers in table 6 below.

The PCA of a time-series involves studying the correlation matrix of successive shocks. Its purpose is to explain the behavior of observed variables using a smaller set of unobserved implied variables. From a mathematical standpoint, it involves transforming a set of K correlated variables into a set of orthogonal variables, or implicit factors, which reproduces the original information present in the correlation structure. Each implicit factor is defined as a linear combination of original variables. Define R as the following matrix

$$R = (R_{tk})_{\substack{1 \leq t \leq T \\ 1 \leq k \leq n}}$$

We have n variables, i.e., monthly returns for n different competing indices, and T observations of these variables.²⁴ PCA enables us to decompose R_{tk} as follows²⁵

$$R_{tk} = \sum_{i=1}^n \sqrt{\lambda_i} U_{ik} V_{ti} \quad (3)$$

where

$(U) = (U_{ik})_{1 \leq i, k \leq n}$ is the matrix of the n eigenvectors of $R'R$.

$(U^\top) = (U_{ki})_{1 \leq k, i \leq n}$ is U transposed.

$(V) = (V_{ti})_{\substack{1 \leq t \leq T \\ 1 \leq i \leq n}}$ is the matrix of the n eigenvectors of RR' .

Note that these n eigenvectors are orthonormal. λ_i is the eigenvalue (ordered by degree of magnitude) corresponding to the eigenvector U_i . Denoting $s_{ik} = \sqrt{\lambda_i} U_{ik}$ the principal component sensitivity of the k^{th} variable to the i^{th} factor, and $V_{ti} = F_{ti}$, one can equivalently write equation (3)

$$R_{tk} = \sum_{i=1}^n s_{ik} F_{ti}$$

²⁴The asset returns have first been normalized to have zero mean and unit variance.

²⁵For an explanation of this decomposition in a financial context, see for example Barber and Copper (1996).

where the n factors F_i are a set of orthogonal variables. One may use the method to describe each variable as a linear function of a reduced number of factors. To that end, one needs to select a number of factors I such that the first I factors capture a large fraction of asset return variance, while the remaining part can be regarded as statistical noise

$$R_{tk} = \sum_{i=1}^I \sqrt{\lambda_i} U_{ik} V_{ti} + \varepsilon_{tk} = \sum_{i=1}^I s_{ik} F_{ti} + \varepsilon_{tk} \quad (4)$$

where some structure is imposed by assuming that the residuals ε_{tk} are uncorrelated one to another. The percentage of variance explained by the first I factors is given by $\sum_{i=1}^I \lambda_i / \sum_{i=1}^N \lambda_i$. By taking $I = 1$ in equation (4) this method can be used to generate “the best one dimensional”

summary of a set of competing indices. Furthermore, a simple normalization

$$R_{tk} = \sum_{i=1}^K \frac{s_{ik}}{\sum_{k'=1}^K s_{ik'}} F_{ti}$$

allows one to obtain an index which can be regarded as a portfolio of competing indices, so that an actual decomposition in terms of actual funds in the index can easily be obtained as long as information is available in each competing index composition.

Table 6 displays the ratio of the eigenvalue associated with the first component to the sum of all eigenvalues. That number can be regarded as the percentage of the information contained in the time-series of competing indices that is captured by the pure index (column 3). An information loss ratio can be computed by simply taking 100% minus the percentage of variance explained by the first factor. Table 6 also provides the number of competing indices for each category in column 2.

We find that pure style indices are able to capture a very large fraction of the information. The average (resp. median) percentage of variance explained by the pure style indices is 79.12% (resp. 81.12%) across all sub-universes. The percentage of variance explained by the pure index is, of course, all the more significant in that the correlation between competing indices was high. For example, *emerging market* style indices have a percentage of variance explained greater than 90% while it originates from a population of 7 competing indices. From table 3, we see that the mean correlation was almost 0.93 for *emerging market* indices. In the same vein, *event driven* and *merger arbitrage* PCA indices capture more than 80% of the information originally available in a set of 8 and 4 competing indices, respectively. The *fund of funds* PCA index also enjoys very low information loss as more than 91% of the information is captured by the one-dimensional summary. On the other hand, the percentage of information loss is higher in the case of *equity market neutral* (41.09% = 100% – 58.91% information loss) and *fixed-income arbitrage* (35% = 100% – 65% information loss). This is because these

Sub-Universe	# of Indices	% of Variance Explained
Convertible Arbitrage	6	84.91
Emerging Markets	7	91.97
Equity Market Neutral	6	58.91
Event Driven	8	85.41
Fixed Income Arbitrage	5	65
Global Macro	8	74.13
Long/Short	6	86.8
Merger Arbitrage	4	83.81
Relative Value	5	71.26
Short Selling	5	78.42
Distressed Securities	7	77.6
Fund of Funds	5	91.19

Table 6: Pure Style Indices. This table provides the ratio of the eigenvalue associated with the first component to the sum of all eigenvalues. That number can be regarded as the percentage of the information contained in the time-series of competing indices that is captured by the pure index (column 3). It also provides the number of competing indices for each category in column 2.

strategies were the ones for which the heterogeneity of information provided by competing index providers was the most extreme (see tables 3 and 4).

Pure hedge fund indices generated as the first component in a factor analysis have an appealing built-in element of optimality, since there is no other linear combination of competing indices that implies a lower information loss. Another approach consists in focusing on minimization of the bias.

3.2.2 Minimization of Bias

In this approach, we still model the return on these indices as the sum of a true unobservable pure style index I and a white noise (the bias)

$$R_{it} = I_t + \varepsilon_{it}$$

We denote as $\mathcal{F}_t = (R_{is})_{s \leq t, i=1, \dots, n}$ the agents' information set. Note that investors do not observe the return on the true index but only the return on the competing indices. The following assumptions will be made for all $i, j = 1, \dots, n$

- Assumption 1: $\mathbb{E}[\varepsilon_{it} | \mathcal{F}_t] = 0$
- Assumption 2: $\text{Var}[\varepsilon_{it} | \mathcal{F}_t] = \sigma_{\varepsilon_i}^2$

- Assumption 3: $\text{Cov}[\varepsilon_{it}, I_t | \mathcal{F}_t] = 0$

Assumption 1 simply states that the bias is not systematic: sometimes the return on the commercial index i exceeds that of the true unobservable index, sometimes it is lower, on average the difference is zero. Assumption 2 is a homoskedasticity assumption which states that the variance of the bias is constant in time (note that $\sigma_{\varepsilon_i}^2$ is a measure of the size of the bias). Assumption 3 is common to linear models; it states the bias is not affected by the level of the true index.

Our goal is to define a portfolio of competing indices that would be as close as possible to the return on the true unobservable factor. We denote as

$$\begin{aligned} R_{pt} &= w' \cdot R_t \\ &= I_t + w' \cdot \varepsilon_t \end{aligned}$$

where w is a n -dimensional vector of weights, and R_t (respectively ε_t) is a n -dimensional vector of index returns (respectively biases). Finally $'$ denotes transpose. We obtain

$$\begin{aligned} \mathbb{E}[R_{pt} | \mathcal{F}_t] &= \mathbb{E}[I_t | \mathcal{F}_t] \\ \text{Var}[R_{pt} | \mathcal{F}_t] &= \sigma_I^2 + w' \cdot \Sigma_\varepsilon \cdot w \end{aligned}$$

where we are using assumption 1 and 3 in the first and second line, respectively, and where σ_I is the volatility of the true unobservable index, and Σ_ε is the variance-covariance matrix of the bias terms.

Our objective is to minimize the bias of the composite index R_p , that is $\text{Min}_w w' \cdot \Sigma_\varepsilon \cdot w$ such that $w' \cdot \mathbf{1} = 1$, where $\mathbf{1}$ is a n -dimensional vector of ones. The solution to this problem is well-known to be (see for example Cochrane (2001))

$$w^* = \frac{\Sigma_\varepsilon^{-1} \cdot \mathbf{1}}{\mathbf{1}' \cdot \Sigma_\varepsilon^{-1} \cdot \mathbf{1}} \quad (5)$$

This is formally similar to a variance minimization problem. Since $\text{Var}[R_{pt} | \mathcal{F}_t] = \sigma_I^2 + w' \cdot \Sigma_\varepsilon \cdot w$, it actually appears that minimization of the bias is equivalent to minimization of $\text{Var}[R_{pt} | \mathcal{F}_t]$. This can be achieved in the usual way, using an efficient estimate of the sample covariance matrix of hedge fund returns (see Amenc and Martellini (2002)). Note also that portfolio constraints may further be imposed to ensure that all the weights are positive. This may actually be a desired property since it is natural that the index of the indices thus obtained be eventually expressed as a portfolio with positive investments in individual funds. In principle, imposing positivity constraints obviously induces a deviation from optimal bias reduction. On the other hand, we find evidence that minimum bias portfolios in the presence of positivity constraints are sometimes more representative than in the absence of such constraint (see table 7 in section 4.2).

If we make one additional assumption (assumption 4 below), we can show that the problem of bias minimization actually admits a very simple and elegant closed-form solution (see equation 6).

- Assumption 4: $\mathbb{C}ov[\varepsilon_{it}, \varepsilon_{jt} | \mathcal{F}_t] = 0$ for $i \neq j$

Assumption 4 states that the bias on a given index is independent from that on another competing index, so that Σ_ε is diagonal. Because biases are meant to capture some idiosyncratic component in competing index returns, this can be regarded as a reasonable assumption. On the other hand, that assumption may not be taken for granted, as there might exist some common factors in the biases of various competing index providers for a given style.²⁶ As often the case, a standard trade-off exists between model risk and estimation risk.

Using assumptions 4 and 2, we obtain that Σ_ε is a diagonal matrix with $\sigma_{\varepsilon_i}^2$ terms on the diagonal. Now

$$\sigma_{\varepsilon_i}^2 = \mathbb{V}ar[\varepsilon_{it} | \mathcal{F}_t] = \mathbb{V}ar[I_t - R_{it} | \mathcal{F}_t] = \sigma_I^2 + \sigma_i^2 - 2\mathbb{C}ov[I_t, R_{it} | \mathcal{F}_t]$$

where σ_i^2 is the variance on the return on the i^{th} competing index. Noting that (using assumption 3)

$$\mathbb{C}ov[I_t, R_{it} | \mathcal{F}_t] = \mathbb{C}ov[I_t, I_t + \varepsilon_{it} | \mathcal{F}_t] = \sigma_I^2$$

we finally obtain

$$\sigma_{\varepsilon_i}^2 = \sigma_i^2 - \sigma_I^2$$

From equation (5), we finally get

$$w_i^* = \frac{\frac{1}{\sigma_i^2 - \sigma_I^2}}{\sum_{j=1}^n \frac{1}{\sigma_j^2 - \sigma_I^2}} \quad (6)$$

a very simple and elegant expression.

In practice, the volatility σ_i of the return on the competing index i is replaced by its unbiased estimator $\hat{\sigma}_i$. The problem is that the optimal weight w_i^* is also a function of the volatility of the unobservable true index σ_I . That term can be estimated from the Kalman filter approach described above. Alternatively, one may elect to estimate that term in the following way. Just note that

$$\begin{aligned} \mathbb{C}ov[R_{it}, R_{jt} | \mathcal{F}_t] &= \mathbb{C}ov[I_t + \varepsilon_{it}, I_t + \varepsilon_{jt} | \mathcal{F}_t] \\ &= \sigma_I^2 + \mathbb{C}ov[I_t, \varepsilon_{it} | \mathcal{F}_t] + \mathbb{C}ov[I_t, \varepsilon_{jt} | \mathcal{F}_t] + \mathbb{C}ov[\varepsilon_{it}, \varepsilon_{jt} | \mathcal{F}_t] = \sigma_I^2 \end{aligned}$$

²⁶To check whether assumption 4 is consistent with the data, we have computed the correlation between $R_{it} - I_t$ where the return I_t on the pure index is obtained from Kalman analysis. From that analysis, we find evidence of non trivial correlations between the noise terms for competing indices.

where we use assumptions 3 and 4 in the last line. This suggests that one may use the average covariance between competing indices as an estimator for the variance on the return on the unobservable true factor

$$\hat{\sigma}_I^2 = \frac{1}{n^2} \sum_{i,j=1}^n \hat{\sigma}_{ij}$$

where $\hat{\sigma}_{ij} = \frac{1}{T} \sum_{t=1}^T (R_{it} - \bar{R}_i) (R_{jt} - \bar{R}_j)$ is the estimator of the covariance between the return on index i and index j .

In table 7, we provide information on the mean, volatility, as well as average correlation with competing indices of pure indices generated using equation (6), where the variance of the pure index is estimated from the Kalman filter approach. We also provide (in parenthesis) average values for these parameters for competing indices.

Sub-Universe	Mean	Volatility	Average Correlation
Convertible Arbitrage	1.08% (0.94%)	1.13% (1.34%)	0.90
Emerging Markets	0.80% (0.43%)	3.33% (5.34%)	0.95
Equity Market Neutral	0.85% (0.83%)	0.44% (1.03%)	0.58
Event Driven	0.95% (0.86%)	3.78% (2.09%)	0.87
Fixed Income Arbitrage	0.37% (0.36%)	1.33% (1.70%)	0.78
Global Macro	0.09% (0.69%)	3.73% (2.55%)	0.70
Long/Short	0.78% (1.11%)	0.76% (3.13%)	0.56
Merger Arb.	0.99% (0.89%)	1.15% (1.31%)	0.92
Relative Value	0.82% (0.90%)	1.00% (1.97%)	0.68
Short Selling	0.82% (0.49%)	6.95% (7.70%)	0.47
Distressed	0.46% (0.73%)	2.55% (2.26%)	0.80
Fund of Funds	0.94% (0.91%)	2.45% (2.52%)	0.95

Table 7: Pure Indices from Minimum Bias Analysis. This table provides information (mean, volatility, as well as average correlation with competing indices) on monthly returns of pure indices generated using minimum bias analysis where the variance of the pure index is estimated from the Kalman filter approach. Number in paranthesis are average values for these parameters for competing indices.

From table 7, we see that the volatility of all but one pure indices is lower than the average of competing indices, hence suggesting that a noise reduction has actually occurred. Pure hedge fund indices generated from minimum variance analysis have an appealing built-in element of optimality, since there is no other linear combination of competing indices that implies a lower bias, granted that assumptions 1 to 4 hold (see discussion in section 4).

It should be noted that the sample covariance matrix of historical returns is likely to generate high sampling error when the number of observations is relatively small compared to the number of asset classes.²⁷ Several methods that have been introduced to improve asset return covariance matrix estimation could be applied in the present context.²⁸ Since the focus of the paper is not on estimation of variance-covariance matrices, we use the sample estimate for simplicity. We, however, also try and impose positivity constraints, and we argue in section 5 below that it might help mitigate the estimation error risk.

4 How Pure is Pure?

One may wonder how better off an investor would be by focusing on these pure style indices, as opposed to any of the competing indices from which they are extracted. Backtesting pure style indices is no easy task because of the definite chicken-and-egg flavor associated to it. If we knew what a good style index should be in the first place, we would have all competing index providers agreeing to a larger extent, and we would have no need for composite pure style indices!

In what follows, we first provide two simple results that show the superiority of any portfolio of indices over any single competing index for a given strategy. Obviously, PCA-based and minimum-variance-based pure style indices, which have been specifically designed to address, respectively, the information loss and minimization of the bias problems, should be better than an arbitrarily selected portfolio of competing indices. We also illustrate the performance of the pure style indices in terms of their ability to improve benchmarking of hedge fund returns.

4.1 The two Basic Theorems of Pure Indexing

The mere fact of composing a pure index as an index of the indices, i.e., as a portfolio of existing indices, always leads to a reduction in the size of the bias and an improvement of representativeness, even if the portfolio weights are not optimized. This is the content of the following two straightforward theorems.

Theorem 1 *A portfolio of indices is always less biased than the average of the set of indices it is extracted from.*

²⁷In the present context, the number of assets is not very large, as we deal with portfolio of competing hedge fund indices. The data, however, is scarce, as hedge fund returns are typically available at a monthly frequency only.

²⁸See for example Elton and Gruber (1973), Chan, Karceski and Lakonishok (1999), Jorion (1985, 1986), Ledoit (1999) or Jagannathan and Ma (2000).

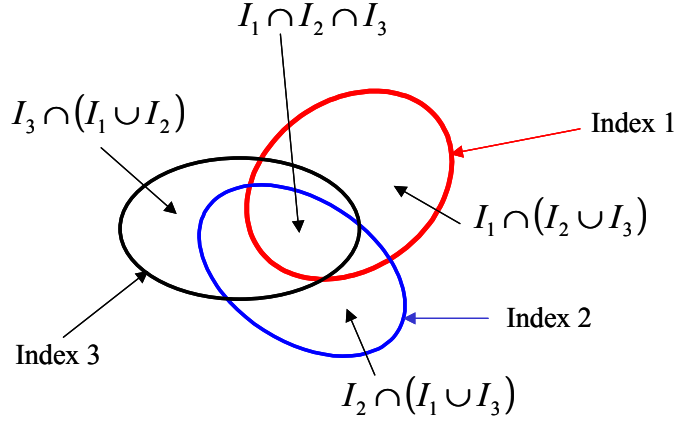


Figure 3: Representativeness of a Portfolio of Competing Indexes. A portfolio of competing indexes encompasses more individual funds than any of the competing indexes.

Proof. Straightforward application of the properties of portfolio diversification. The proof is expressed under the additional assumption 4. Let us consider a portfolio of competing indices $R_{pt} = \sum_{j=1}^n w_j R_{jt}$. Theorem 1 says that the variance of the portfolio bias is always smaller than the average variance of the competing index biases, whatever the portfolio weights, that is

$$\sigma_{\varepsilon_P}^2 \leq \sum_{j=1}^n w_j \sigma_{\varepsilon_j}^2$$

To see why, note that the variance of the portfolio $\sigma_{\varepsilon_P}^2$ is given by

$$\sigma_{\varepsilon_P}^2 = w' \cdot \Sigma_{\varepsilon} \cdot w = \sum_{j=1}^n w_j^2 \sigma_{\varepsilon_j}^2$$

where the portfolio weight vector w is defined as $w = (w_1, \dots, w_n)$. The announced result is obtained from

$$\sum_{j=1}^n w_j^2 \sigma_{\varepsilon_j}^2 \leq \sum_{j=1}^n w_j \sigma_{\varepsilon_j}^2$$

■

Obviously, the noise reduction is the greatest, by construction, for the minimum-biased index. In the same vein, considering a portfolio of hedge fund indices always enhances the representativeness of the index, simply because more funds are accounted for.

Theorem 2 *A portfolio of indices is always more presentative than any competing index.*

Proof. Obvious from figure 3 in the case of 3 indices.

We denote by $N_j = \text{card}(I_j)$ (respectively, $N_p = \text{card}(I_p)$) the number of funds used by index j (respectively, by the portfolio of index $R_{pt} = \sum_{j=1}^n w_j R_{jt}$), i.e., $R_{jt} = \sum_{k=1}^{N_j} p_k^{(j)} R_{kt}$, (respectively, $R_{pt} = \sum_{k=1}^{N_p} p_k^{(p)} R_{kt}$), where R_{kt} is the return at date t on individual fund k and $p_k^{(j)}$ (respectively, $p_k^{(p)}$) the weighting of fund k in the index j (respectively, in the portfolio of indices). In most cases, we have that $p_k^{(j)} = 1/N_j$, since all but one existing hedge fund indices are equally-weighted. We have that

$$I_p = \left(\bigcap_{j=1, \dots, n} I_j \right) \cup \left(\bigcup_{j=1, \dots, n} \left(I_j \cap_{j \neq j'} I_{j'} \right) \right)$$

from which we obtain

$$N_p = \text{card}(I_p) = \text{card} \left(\bigcap_{j=1, \dots, n} I_j \right) + \text{card} \left(\bigcup_{j=1, \dots, n} \left(I_j \cap_{j \neq j'} I_{j'} \right) \right) \geq \max_{j=1, \dots, n} (N_j)$$

Note that $N_p \neq \sum_{j=1}^n N_j$ because funds may report their performance to more than one database (i.e., $I_j \cap I_{j'} \neq \emptyset$). Note also that the index of the indices will not be in general an equally-weighted portfolio of individual funds. ■

In other words, while PCA based portfolios are meant to focus on the representativeness dimension while minimum variance portfolios are meant to focus on the bias dimension, any portfolio of hedge fund indices (e.g., an equally-weighted portfolio of competing indices) should do better than any given index on both dimensions.

4.2 Testing the Representativeness of Pure Hedge Fund Indices

While any improvement of the pure style indexes with respect to existing indexes along the bias dimension is hard to measure, it is somewhat easier to attest their superior representativeness. To that end, we have performed the following test.²⁹ We have first merged the three major databases providing information on individual fund return, MAR, TASS and HFR. We have also added data on funds which do not report to any data base, that had been directly obtained from administrators. As a result of that data collection process, we have gathered monthly returns on a total of 7,422 hedge funds, including 2,317 funds that do not report their returns to the major data bases.³⁰ As a result, our sample represents a very significant fraction of the hedge fund population.³¹ The following table (table 8) provides information on the breakdown of that number into strategies.

²⁹We would like to express our deepest gratitude to Francois-Serge Lhabitant who has provided us with the data needed for this test.

³⁰Dead funds are kept in the sample. This alleviates the survivorship bias problem.

³¹Even though it is impossible to have a precise estimate of that number, we believe that the sample represents approximately 70-80% of the population of hedge funds with more than \$20 million of assets under management.

Sub-Universe	Number of Funds
Convertible Arbitrage	657
Emerging Markets	198
Equity Market Neutral	206
Event Driven	1083
Fixed Income Arbitrage	438
Global Macro	263
Long/Short	2533
Merger Arb.	638
Relative Value	198
Short Selling	302
Distressed	554
Fund of Funds	352
Total	7,422

Table 8: Number of Funds in the Sample. This table provides information on the number of funds in the sample for each strategy.

Then, for each strategy covered in this paper, we have collected all funds with self-proclaimed style matching the strategy under consideration and form equally-weighted portfolios. Because we are following the funds' self-proclaimed style, these equally-weighted portfolios are undoubtedly biased. On the other hand, because they account for the return on all funds for which there is public and some private information, they are as representative as possible.

In table 9, we report for each pure index (PCA, minimum bias with and without positivity constraints, and also Kalman) the correlation with the corresponding equally-weighted portfolio, as well as the mean correlation across competing indices.³²

A number of conclusions can be inferred from these results. First it appears that the PCA-based pure indices are always more correlated with the equally-weighted as-representative-as-possible portfolios than the average competing index. Kalman indices also appear to be more representative than competing indices, except for long/short strategy. Overall, these results strongly suggest that PCA-based indices do achieve the improvement of representativeness they were designed for. On the other hand, indices generated from minimum bias analysis do not always outperform the average competing index in terms of representativeness, at least when no further constraints are imposed on the weights. Under the condition of positive weights,

³²The minimum bias indices without positivity constraints have been generated using equation (6). Minimum bias indices with positivity constraints have been generated from minimum variance analysis based on the sample covariance matrix of competing indices.

Sub-Universe	Mean Value Competing Indices	Kalman	PCA	Min. Bias	Min. Bias Positive Weights
Convertible Arbitrage	0.77	0.84	0.84	0.76	0.78
Emerging Markets	0.95	0.95	0.98	0.95	0.86
Equity Market Neutral	0.35	0.38	0.41	0.38	0.38
Event Driven	0.93	0.95	0.96	0.92	0.92
Fixed Income Arbitrage	0.63	0.93	0.81	0.88	0.76
Global Macro	0.61	0.71	0.77	0.55	0.78
Long/Short	0.67	0.63	0.98	0.41	0.24
Merger Arbitrage	0.83	0.85	0.86	0.86	0.84
Relative Value	0.75	0.88	0.89	0.61	0.88
Short Selling	0.71	0.69	0.73	0.44	0.75
Distressed	0.88	0.95	0.94	0.82	0.91
Fund of Funds	0.88	0.93	0.94	0.93	0.83

Table 9: Testing the Representativeness of Pure Indices. In this table we report for each pure index (Kalman, PCA, minimum bias with and without positivity constraints) the correlation with the corresponding equally-weighted portfolio, as well as the mean correlation across competing indices.

the correlation with the equally-weighted portfolios increases in some cases, suggesting that a better representativeness may then be achieved.

5 Conclusion

In this paper, we attempt to emphasize the need for a better understanding of investment style benchmarks by focusing on the alternative investment universe, where the problems are most visible. Our contribution is two-fold. First, we provide detailed evidence of strong heterogeneity in the information conveyed by competing indices. Second, we attempt to provide remedies to the problem and suggest a methodology designed to help build a “pure style index” or “index of the indices” for a given style. In particular, we explore a statistical approach to the problem of the construction of pure style indices, using Kalman filter techniques for the estimation of an unobservable factor from competing index return observations. Because it is desirable that a pure index can be regarded as a portfolio of existing indices, we also suggest a portfolio approach to the problem. In particular, we suggest using principal component analysis to extract the “best possible one-dimensional summary” of a set of competing indices (addresses the problem of lack of representativeness), and using minimum variance analysis to

extract the “least biased portfolio” from a set of competing indices (addresses the problem of biases).

The relevance of this work is underlined by the recent recognition that asset allocation models and modern portfolio theory can be applied to hedge funds as well as to traditional investment vehicles (Amenc and Martellini (2001, 2002), Amenc, El Bied and Martellini (2002), Cvitanic et al. (2001)). In particular, passive strategies start to emerge in the alternative investment universe, as they have developed in the traditional stock and bond markets over the past 10 years. Very recently, a series of investment products designed to track the performance of hedge-fund indices have actually been launched and various institutions (Credit Swiss First Boston and Zürich Capital Markets, among others) now offer index funds aiming at capturing the average return of a specific hedge fund universe.³³

Our results can easily be extended to traditional investment styles such as growth/value, small-cap/large-cap and a series of returns on pure indices can be constructed on the basis of the S&P/BARRA, MSCI, Dow Jones, Wilshire, Russell, etc., equity style indices. In a companion paper (Amenc and Martellini (2003)), we show that existing indices also provide a somewhat confusing picture of the return on style factors (growth/value, small/large cap), and we also report disturbing evidence that this heterogeneity poses serious problems, not only for modern portfolio analysis, but also for empirical tests of asset pricing theory.³⁴ Some of the techniques introduced in this paper could actually be also used to help design better benchmarks in the traditional investment universe.

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³³See the article “Critics spotlight shortcomings in index funds” in the weekly newsletter “Hedge Fund Alert”, March 6, 2002.

³⁴This is somewhat reminiscent of Roll’s critique (1977) of CAPM: if the true value and size factors are not observable, and if there is very little robustness with respect to the choice of the proxy used in empirical tests, then the relevance of these factors in asset pricing theory may never be empirically testable. In other words, the unobservability of growth/value and size factors adds a joint hypothesis problem to the sample dependence problem to make any inference on the existence, relevance and interpretation of the size and value premium arguable at best.

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A Information on Hedge Fund Indices

A.1 Main indices

There are three main providers of hedge fund indices.

A.1.1 Evaluation Associates Capital Markets (EACM)

Evaluation Associates Capital Markets offer one aggregate index, the EACM 100. This index is an equally-weighted composite of unaudited performance information provided by 100 private investment funds chosen by EACM. There are five broad strategies and 13 underlying sub-strategy styles: Relative Value (long/short equity specialists, convertible hedgers, bond hedgers, multi-strategy), Event Driven (deal arbitrageurs, bankruptcy/distressed debt specialists, multi-strategy managers), Equity Hedge Funds (domestic long biased, domestic opportunistic, global/international), Global Asset Allocators (systematic traders, discretionary managers) and Short Selling. Funds are assigned categories on the basis of how closely they match the strategy definitions. Names in the funds are not disclosed. Investment managers in the index are selected based on guidelines established by EACM. Investment manager allocations are rebalanced at the beginning of each calendar year. It was launched in 1996 with data going back to 1990.

A.1.2 Hedge Fund Research (HFR)

Hedge Fund Research provides indices for seven strategies (convertible arbitrage, equity hedge, event-driven, merger arbitrage, distressed securities), as well as an equally-weighted aggregate index based on 1,100 funds drawn from a database of 1,700 funds. Funds of funds are not included in the composite index. Funds are assigned to categories based on the descriptions in their offering memorandums. One advantage is that the indices eliminate the survivor bias problem by incorporating funds that have ceased to exist. The index was launched in 1994 with data going back to 1990. Hedge Fund Research offers a daily “investible” index to its institutional investors.

A.1.3 Credit Swiss First Boston/Tremont (CSFB/Tremont)

The CSFB/Tremont index is an index that weights component hedge funds according to the relative size of their assets. It is currently the industry’s only asset-weighted hedge fund index. In principle, asset-weighting, as opposed to equal-weighting, provides a more accurate depiction of an investment in the asset class.³⁵ The CSFB/Tremont indices cover nine strategies (convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event driven, fixed income arbitrage, global macro, long-short equity and managed futures), and is based on 340 funds representing \$100 billion in invested capital, selected from a database, the TASS database, which tracks over 2,600 funds. A fund must have US \$10 million in assets to be included. Only funds with audited financials are included. The index is calculated on a monthly basis, and funds are re-selected on a quarterly basis as necessary. Funds are not removed from the index until they are liquidated or fail to meet the financial reporting requirements. The index was launched in 1999 with data going back to 1994.

A.2 Other Hedge Fund indices

There is also a variety of other hedge fund index providers.

A.2.1 Zürich Capital Markets

Zürich Capital Markets hedge fund indices consist of equally weighted portfolios of funds that satisfy a number of qualitative criteria for institutional investment as well as a statistical classification procedure for style classification. The indices are based on 60 funds selected from a

³⁵However, for indices such as the Zurich Capital and EACM indices, which select from a small pool of large, established managers, equal weighting will provide the most efficient estimate of the performance of a particular style. Using equal weights also simplifies independent confirmation of index performance, as funds frequently report assets under management with a considerable lag.

universe of several thousand. Funds within each category must meet asset, years in existence, and statistically-based style purity constraints. Funds that meet these restrictions are asked to participate in the index; however, only those managers who agree to meet reporting constraints are included. Five strategies are available: convertible arbitrage, merger arbitrage, distressed securities, event driven and hedged equity. The indices were launched in 2001 with data going back to 1998. They are equally weighted and are rebalanced quarterly. The Zürich Hedge Fund indices are the only ones to have an independent advisory board. Investible portfolios, i.e., replicating portfolios with an approximate 2.5% tracking error, are available for each of these 5 indices with monthly liquidity ensured by Zürich Capital Markets. These indices differ from existing hedge fund indices by focusing only on those funds/managers that are 1) strategy pure in their style 2) have a two-year minimum performance track record and 3) sufficient assets under management to demonstrate organizational and managerial infrastructure, scalable strategies and the ability to raise funds from sophisticated investors.

A.2.2 Van Hedge

Van Hedge fund indices cover 12 strategies: aggressive growth, distressed securities, emerging markets, fund of funds, income, macro, market timing, market-neutral securities hedging, market-neutral arbitrage, opportunistic, short selling, special situations and value. The company's database, which is used in the construction of the indices, contains detailed information on over 3,400 hedge funds (2,000 U.S. and 1,400 offshore). There are no performance or size criteria and funds are assigned to categories based on their offering memorandums and interviews with the individual managers. Van Hedge Fund Advisors International provides research and advisory services to individual and institutional investors.

A.2.3 Hennessee Group

Twenty-two strategies are available: convertible arbitrage, distressed, event driven, financial equities, fixed income, growth, healthcare and bio tech, high yield, macro, market neutral, merger arbitrage, multiple arbitrage, opportunistic, regulation D, short biased, value, emerging markets, Europe, Pacific rim, Latin America, technology and telecom and media. Results are based on 450 funds including 150 in which Hennessee clients invest, from a database of 3,000 funds. Assets of \$160 billion are represented in the index. The indices were created in 1987 and first published in 1992. Hennessee Group LLC provides research and consulting to hedge fund advisors.

A.2.4 Hedgefund.net

Hedgefund.net's so-called tuna indices are an equally-weighted average of all fund returns. They cover 33 strategies: aggressive growth, convertible arbitrage, country specific, commodity trading advisor, distressed, emerging markets, energy sector, event driven, finance sector, fixed income arbitrage, fixed income, fund of funds, healthcare sector, long only, long/short hedged, macro, market neutral, market timer, opportunistic, options arbitrage, options strategies, other, other relative value, regulation D, risk arbitrage, short bias, short-term trading, small/micro-cap, special situations, statistical arbitrage, technology sector, value and VC/private equity. They are updated from a database of 1,800 hedge funds and funds of funds. The data goes back to 1979 and managers select their own categories. They are among the first to report performance results each month. Hedgefund.net is operated by Links Securities LLC, a NASD registered broker-dealer, and is owned by Links Holding and Capital Z Investments.

A.2.5 LJH Global Investments

LJH hedge fund indices are equally weighted and are calculated as the average performance of all managers for each style. They cover 16 strategies, each composed of 25 to 50 funds: Asian hedge, convertible arbitrage, distressed securities, domestic hedge, emerging markets, emerging markets fixed income, event driven, fixed income arbitrage, European hedge, global hedge, global macro, hedge, market neutral equity, risk arbitrage, short only and technology fund. These indices are rebalanced quarterly or semiannually, depending upon the strategy. Funds must have audited statements and have passed some level of LJH due diligence. Funds are assigned categories by LJH. LJH Global Investments is a consulting and investment advisory firm.

A.2.6 Managed Account Reports (MAR)

The MAR database contains 1,300 funds and managers usually select their own categories. A composite index is not available. There are 9 categories ("medians"), some of which are combined into sub-categories ("sub-mediands"): Zürich Event-Driven Median (Distressed securities and Risk arbitrage sub-mediands), Zürich Global Emerging Median, Zürich Global International Median, Zürich Global Established Median (Global Established growth, Global Established small-cap and Global Established value sub-mediands), Zürich Global Macro Median, Zürich Market Neutral Median (Market Neutral arbitrage, Market Neutral long/short and Market Neutral mortgage-backed sub-mediands), Zürich Sector Median, Zürich Short-Sellers Median, Zürich Fund of Funds Median (Fund of Funds diversified and Fund of Funds niche sub-mediands). MAR was recently acquired by Zürich Capital Markets.

A.2.7 Altvest

Altvest hedge fund indices cover 13 strategies: capital structure arbitrage, currency trading, distressed securities, emerging markets, event driven, fund of funds, health care, long/short equity, macro, merger arbitrage, relative value, short selling and technology. Each fund is assigned to the category in which the largest percentage of its assets is invested. Index results are based on reports from more than 1,400 hedge funds in a database of 1,800 funds. The index was launched in 2000 with data going back to 1993. Altvest is owned by InvestorForce.

A.2.8 Magnum

Founded in April 1994, Magnum focuses on identifying hedge funds likely to generate superior returns and combines them into funds of hedge funds designed to deliver targeted levels of return for given levels of risk. Magnum offers 17 offshore funds of hedge funds, five feeder funds (with lower minimum investment levels) and 2 funds of hedge funds. The various indices they publish are the Magnum Aggressive Growth Fund, Magnum Bull & Bear Fund, Magnum Capital Growth Fund, Magnum e-Com Fund, Magnum Edge Fund, Magnum Europe Equity Fund, Magnum Fund, Magnum Global Equity Fund, Magnum International Equity Fund, Magnum Macro Fund, Magnum Multi Fund, Magnum Opportunity Fund, Magnum Special Situations Fund, Magnum Tech Fund, Magnum Turbo Growth Fund and Magnum U.S. Equity Fund.

A.3 Forthcoming Indices

Two major providers of traditional indices have recently announced their intention to launch hedge fund indices.

A.3.1 S&P

Standard & Poor's has recently announced plans to create the S&P Hedge Fund Index, aimed at providing a transparent benchmark of the hedge fund asset class. The S&P Hedge Fund Index will offer investors an investable benchmark that is broadly representative of the range of major strategies that hedge funds employ. The Index will contain 40 funds divided into three sub-indices: Arbitrage, Event Driven and Tactical, which in turn represent a total of nine specific strategies. These strategies include: Macro, Equity Long/Short, Managed Futures, Special Situations, Merger Arbitrage, Distressed, Fixed Income Arbitrage, Convertible Arbitrage and Equity Market Neutral. The strategies will be equal weighted to ensure well-rounded representation of hedge fund investment approaches and to avoid over-representation

of currently popular strategies. The index is expected to be launched during the third quarter of 2002.

Potential index constituents must pass a series of quantitative screening criteria to ensure that they conform to their stated strategy's return and risk characteristics. After this screening, eligible funds must agree to offer daily transparency so that their valuations can be verified by a third party, in this case Derivatives Portfolio Management (DPM), and so that the index may be computed on a daily basis. Finally, the candidate funds must pass a rigorous due diligence process conducted by Albourne Partners Ltd., a hedge fund consultant to Standard & Poor's, to ensure that they are appropriately managed, adhere to their stated strategy or style, and maintain all necessary risk controls and operational infrastructure. Index values will be posted daily to the www.spglobal.com website.

The index will be maintained by an Index Committee managed by Standard & Poor's that will meet regularly to ensure that inclusion criteria are being met and to implement necessary rebalancing.

A.3.2 Morgan Stanley Capital International (MSCI)

MSCI Hedge Fund Indices are classified according to four basic categories: directional trading, relative value, specialist credit and stock selection. Within each category, indices will be segregated based on asset class (fixed income, commodities, currencies and stocks) and geographical region. The indices will be supported by a platform that allows subscribers to look at the data at a more detailed level (industry focus, fund size, open vs. closed, etc.). Morgan Stanley Capital International, Geneva, has formed a partnership with Financial Risk Management, New York, to produce the hedge fund indices. Financial Risk Management provides a large private hedge fund database that tracks 3,000 funds. This database will serve as the initial core of the indices.

B Strategies not Covered in this Paper

The following table provides a listing of competing indices for hedge strategies that we do not explicitly provide results for in this paper. Results for these strategies can be obtained from the authors upon request

Sub-Universe	List of Competing indices
Market Timing	HFR, Van Hedge
Aggressive Growth	Magnum, Van Hedge, HF Net
International	Magnum, MAR, EACM, Hennessee
Special Situations	Magnum, Van Hedge, HF Net
Opportunity	Magnum, Van Hedge, EACM, HF Net
Emerging Markets - Latin America	HFR, Hennessee
Fixed Income - High Yield	HFR, Hennessee
Regulation D	HFR, HF Net
Sectors - Energy	HFR, HF Net
Sectors - Financial	Van Hedge, Altvest, HFR, EACM, Zürich, HF Net
Sectors - Technology	Altvest, HFR, Magnum, HF Net
Sectors - Health Care	Altvest, HFR, HF Net, Hennessee
Statistical Arbitrage	HFR, HF Net
Capital growth	Magnum, Hennessee

Table 10: Strategies Not Covered. This table provides a listing of competing indices for hedge strategies that we do not explicitly provide results for in this paper. Results for these strategies can be obtained from the authors upon request.