The Brave New World of Hedge Fund Indexes

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Abstract

In the last decade, the investment community has witnessed the emergence of style investing, not only in the traditional long-only universe but also in the alternative investment universe. 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. The fact that hedge funds have started to gain wide acceptance while remaining a somewhat mysterious asset class enhances the need for better measurement and benchmarking of their performance. One serious problem is that the collection of existing hedge fund indexes consitutes a somewhat confusing partition of the alternative investment universe since the dozen existing competing hedge fund index providers provide a very contrasted picture of hedge fund returns. Our contribution is two-fold. First, we provide detailed evidence of strong heterogeneity in the information conveyed by competing indexes. 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 indexes" for a given style. In particular, we suggest using principal component analysis to extract the best possible one-dimensional summary of a set of competing indexes. We also provide evidence of the ability of the pure style indexes to improve current techniques for factor analysis and benchmarking of hedge fund returns. In particular, we find that our pure style indexes explain on average a significantly larger proportion of hedge fund returns than competing indexes. Our results can easily be extended to traditional investment styles such as growth/value, small cap/large cap.

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1 Introduction

Today, the notion of equity style management is widely accepted in the investment community, and the concept of equity styles permeates the way most investors think about the stock markets and investment managers. Some managers, for example, hold themselves out as "value fund managers" who look for companies with low absolute or relative P/E ratios or price/sales ratios, and/or above market yields or book to market ratios that, in the managers opinion, are temporarily out of favor with other managers, causing their stock price to be depressed. Other managers see themselves as "growth fund managers" who look for companies which are growing rapidly and which are expected to show continued strong growth in earnings and revenue. Within these two broad styles, equity fund managers can further specialize by focusing only on companies of a certain size, the two most common market capitalization styles being small and large. Current interest in style management strategies extends to both passive strategies (replication of a given style benchmark) and active strategies (picking and timing strategies aimed at outperforming a given style benchmark).

Inarguably, current interest in *passive* equity style management is largely due to empirical anomalies which suggest that equity performance benchmarks are not well described by standard capital market equilibrium models such as Sharpe's (1964) CAPM. Many studies have found several distinct dimensions of style. For example, Fama and French (1992) document that both the market capitalization (size factor) and the ratio of book-to-market equity (book to market factor) explain a significant fraction of the cross-sectional difference in expected returns. In one of the most thorough studies on the subject, Roll (1997), using both a single-factor CAPM (S&P500 used as a proxy for risk) and multi-factor APT (with 5 implicit factors), concludes that passive value investing yields significant risk-adjusted returns over the decade 1984 to 1994, while small-cap investing is associated with no significant difference in returns over the period. The best portfolio (low size, high E/P ratio, high B/M ratio) outperformed the worst portfolio (low size, low E/P ratio, low B/M ratio), by more than 15% annually. This strongly suggests that style return differentials are true investment opportunities; not only are they statistically significant and reflect real differences in expected returns, but they also occur above and beyond any measurable risk.

Active equity style management strategies have also gained in popularity. There is actually some academic evidence that style specialization pays in terms of stock picking ability. Coggin, Fabozzi and Rahman (1993), for example, test the risk-adjusted performance of 71 US equity pension managers from January 1983 to December 1990 using various benchmarks. They find negative selectivity skill (poor stock picking performance) when using a broad-based benchmark (S&P500, Russell 3000), but positive selectivity skill (good stock picking performance) when using specific style benchmarks (S&P500, Russell 3000). Hence, it appears that some managers seem to be able to outperform a given style benchmark, even though they fail to outperform the market as a whole. This can be considered as evidence that managerial specialization pays. Also related is a paper by Chan, Chen and Lakonoshok (1999) who study funds in the Morningstar data set, and find that funds that have performed poorly in the past are prone to subsequent shifts in style. Not only *stock pickers* tend to specialize by style; style investing also permeates the way *market timers* think about their investment process. It has indeed become more and more common to see strategic and tactical asset allocation decisions spelled out in terms of investment styles, as opposed to standard stock/bond asset class allocation. Evidence abounds that style allocation rivals standard stock/bond tactical asset allocation.[1] For example, Amenc, El Bied and Martellini (2001) report that a perfectly timed yearly shift among the five S&P/BARRA equity styles (S&P 500 Growth, S&P 500 Value, S&P 500, S&P 400 Mid-Cap and S&P 600 Small-Cap) generates a 27.1% annualized return over 1995-2000 with 7.51% volatility. As a comparison, perfectly timed shifting between the S&P 500 and the Lehman Brothers Global Bond Index generates an annualized 20.88% return with 10.66% volatility over the same period.[2]

Resulting from the emergence of passive and active equity style management strategies, the need to measure the performance of equity investment styles such as growth or value, small-cap or large-cap, has preoccupied many plan sponsors and consultants. The acceptance of equity style investing may also be gauged from the proliferation of style indexes published by several vendors. In the traditional US equity investment universe, there are indeed many families of style indexes to choose from, including Russell (3 sets of large-cap - Russell 1000, Russell 3000, and Russell Top 200, mid-cap and small-cap), Wilshire Associate (large-, mid- and small-cap), BARRA and S&P (large-cap growth and value indexes based on the S&P500, mid-cap 400 and small-cap 600), Prudential Securities International (large-, mid- and small-cap), among many others.[3] From an international perspective, the competition is also fierce. Providers of international equity indexes include MSCI, Boston International Advisors, and Parametric Portfolio Associates, among others. As a result, a manager can no longer hope to be judged on his ability to beat a broad benchmark; portfolio managers are currently held accountable for their excess performance with respect to an appropriate style proxy. From the standpoint of asset pricing theory, such an evolution makes a lot of sense. If we assume that there are factors other than the return on the market index that affect securities returns,

[1] See also Amenc and Martellini (2001) for optimal *strategic* style allocation decisions.

[2] See also Amenc, El Bied and Martellini (2001) for results on the performance of style timing models mixing alternative and traditional investment styles.

[3] Futures and options contracts based on some of these style indexes have also been introduced. For example, on November 6, 1995, the Chicago Mercantile Exchange (CME) and Chicago Board Options Exchange (CBOE) began trading futures, futures options, and index options based on the S&P 500/BARRA Value and Growth indexes.

then seemingly superior risk-adjusted performance can easily be achieved by a manager just through higher exposure to a rewarded source of risk. For example, a manager holding a portfolio that is under- or over-invested in small-cap or large-cap stocks is likely to receive an equilibrium premium as compensation. If the manager's performance is solely measured in terms of his portfolio's beta with respect to broad-based market risk, then it can easily be under or over-stated. Multi-factor models, justified through equilibrium (see Merton's CCAPM (1973)) or arbitrage (see Ross' Arbitrage Pricing Theory (1976)) arguments have the potential to account for differentials in style returns. As a result, it is current practice to adjust performance measures of fund returns by controlling for various factors, in particular Fama and French size and book-to-market factors.[4]

One serious problem, however, is that style indexes 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 methods result in some dramatic heterogeneity in the returns. For example, at the beginning of 1997 technology accounted for 30.8% of the Prudential Securities International (PSI) large growth index, while it represented only 14.5% of the S&P/BARRA Growth Index (see Brown and Mott (1997)). On the same date, General Electric was the biggest company in the PSI index, while Exxon dominated the Russell and S&P indexes, and IBM the Wilshire large value index. Such differences in composition translate of course into potentially dramatic differences in returns that are even noticeable at the level of broad-based equity indexes. For example, in 1998, the Russell 2000 index gained 1.1% while the Wilshire 5000 index rose 23.8%! The same also applies, but to a lesser extent, in the context of bond indexes. Reilly, Kao and Wright (1992) find that the approximate correlation of annual returns between the three main providers of broad-based bond indexes (Lehman Brothers, Merrill Lynch and Salomon Brothers) is a comforting 98%. The authors found, however, sizable return differences at the monthly level, as well as for the specialized sectors covered by the three dealer firms.

These difficulties raise the question of what exactly the concept of a "good" index means. 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 challenge was to provide investors with the closest practical approximation of the true market portfolio (see Roll (1977)). Following the development of multi-factor analysis (Merton (1973), Ross (1976)) and multi-style analysis (Sharpe (1988, 1992), Fama and French (1992)), the focus has shifted, and indexes are no longer meant to be representative of the market, but rather of "factors", or "styles" such as growth or value. The challenge, therefore, is to be able to exhibit styles indexes with 100% correlation with style factors. This has, however, somewhat

[4] Carhart (1997) argues that an adjustment for a momentum factor should also be performed.

of a chicken-and-egg flavor as it is not clear how to identify style factors in the first place, and different index providers use different criteria. For example, Russell growth and value indexes are constructed by sorting the companies in the Russell universe based on both the company's book/price ratio (adjusted to amortize the FAS 106 write-offs) and I/B/E/S long-term growth rate. S&P/BARRA growth and value indexes are constructed by sorting the S&P 500 companies based on their price-to-book ratios. Wilshire growth and value indexes are constructed by using a set of criteria to eliminate names from the Wilshire universe (e.g., companies with high relative P/E, low relative dividend yield, and high relative price-to-book are eliminated from the Value index). For BARRA/S&P and Wilshire, each company is included in either the growth or the value index. In the Russell classification, 30% of the stocks appear in both the growth and value categories.

In this paper, we attempt to emphasize the need for a better understanding of investment style benchmarks where the problems are most visible by focusing on the *alternative investment universe*. Beyond traditional styles such as growth/value, small-cap/large-cap, alternative investment styles such as equity market neutral, event driven, long/short, etc. have recently become popular. Alternative investment strategies actually come in many different shapes and forms (see the Appendix for a classification of hedge fund strategies), and can be regarded as a natural extension of the logic of traditional style investing. Interest in hedge fund investing, in particular, is undoubtedly gathering pace, and the consequences of this potentially significant shift in investment behavior are far reaching, as can be seen from the conclusion of a recent research survey about the future role of hedge funds in institutional asset management (Gollin/Harris Ludgate survey, 2001): "Last year it was evident (...) that hedge funds were on the brink of moving into the mainstream. A year on, it is safe to argue that they have arrived". According to this survey, 64% of European institutions for which data was collected currently invest, or were intending to invest, in hedge funds (this figure is up from 56% in 2000). Interest is also growing in Asia, and of course in the United States, where the hedge fund industry was originated by Alfred Jones back in 1949. As a result, the value of the hedge fund industry is now estimated at more than 500 billion US dollars, with more than 5,000 funds worldwide (Frank Russell - Goldman Sachs survey (1999)), and new hedge funds being launched every day to meet the surging demand.

The fact that alternative investment styles have started to gain widespread acceptance while remaining a somewhat mysterious asset class enhances the need for better measurement and benchmarking of hedge fund performance. One serious problem is that existing hedge fund style indexes convey a somewhat confusing view of the alternative investment universe, because the collection of such indexes is neither collectively exhaustive, nor mutually exclusive (see figure 1 for an illustration).[5]

Insert figure 1 about here

There are at least a dozen competing hedge fund index providers (see table 1) which differ in the construction methods they use, in terms of selection criteria (examples of selection criteria include length of track record, assets under management and restrictions on new investment), 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 the 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, Zurich reports a 20.48% return on Long/Short strategies in February 2000, while EACM reports a -1.56% return in the same month! Also, the mean correlation between competing indexes within a particular style can be as low as .45 or less (see section 2 for more details).

As previously underlined, such shortcomings also apply to the traditional equity investment universe and also, albeit to a lesser extent, to bond indexes. In this paper, we choose to focus on the alternative investment universe where the problem is dramatically amplified due to the complex nature of the strategies involved, and the absence of regulation concerning performance disclosure. In other words, we attempt to emphasize the need for a better understanding of investment style benchmarks where the problems are most visible, but the bulk of our message is more general and certainly extends to traditional equity investment styles. Mostly related to ours are recent papers by Fung and Hsieh (2001a) and Brittain (2001) documenting measurement and interpretation problems with existing hedge fund indexes. Also related is a recent paper by Brooks and Kat (2001) who also report some evidence of significant heterogeneity between indexes that aim to reflect the same type of strategy. Our paper differs from these in that we provide a systematic investigation of how heterogenous existing hedge fund indexes are, while the aforementioned authors report illustrations and examples related to the problem. Also, we attempt to provide remedies to the problem through the construction of so-called "pure style indexes".[6] More specifically, our contribution is two-fold. First, we provide detailed evidence of strong heterogeneity in the information conveyed by competing indexes.

[5] As simple evidence of the lack of collective exhaustivity, it perhaps suffices to say that one of the most frequently used hedge fund indexes, the EACM 100, does not account for more than a small percentage of all existing hedge funds.

[6] Fung and Hsieh (2001a) suggest using returns on funds of funds as proxies for hedge fund indexes. Their motivation is different than ours, however. What they attempt to do is to correct for biases such as self-selection and instant history biases. What we attempt to do is not to correct each index, but rather provide the best one-dimensional summary of competing index providers. As a matter of fact, we do use funds of funds as one source of hedge fund indexes.

We have computed various measures of heterogeneity for each given sub-universe, including maximum difference in monthly returns in the sample period, mean and median correlation between competing indexes in each style universe, as well as a customized heterogeneity index. 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 indexes” for a given style. In particular, we suggest using principal component analysis to extract the “best possible one-dimensional summary” of a set of competing indexes. We argue that this method is a natural generalization of the idea of taking a portfolio of competing indexes. We also provide evidence of the ability of the pure style indexes to improve current techniques for factor analysis and benchmarking of hedge fund returns. In particular, we find that our pure style indexes explain on average a significantly larger proportion of hedge fund asset returns than competing indexes.

The rest of the paper is organized as follows. In section 1, we review the main providers of hedge fund indexes and discuss the database. In section 2, we provide strong evidence that competing indexes offer a very contrasted view of hedge fund performance for a given style. In section 3, we offer a possible remedy and discuss the derivation of “pure style indexes”. Section 4 is devoted to testing the performance of these pure style indexes in terms of style analysis, correlation with passive indexes and exposure to suitable factors. In section 5, we present our conclusions and suggestions for further research, while some information on hedge fund strategies is contained in the Appendix.

2 Hedge Fund Indexes

We have listed a dozen hedge fund index providers. Table 1 summarizes some key information concerning all hedge fund index providers.

Insert table 1 about here

These indexes have been set up to provide the rigorous data and analytics that both managers and investors increasingly demand for measuring performance and risk in this rapidly growing asset class. It should be noted, however, that there are inherent problems in compiling a benchmark for the hedge fund industry, specifically including the presence of various biases in the databases. There are three main sources of difference between the performance of hedge funds in the database and the performance of hedge funds in the population (see Fung and Shieh (2001a)).

- Survivorship bias. This occurs when unsuccessful managers leave the industry, and their successful counterparts remain, leading to successful managers only being counted in the database. The inherent problem is that a database over-estimates the true returns in a strategy, because it only contains the returns of those that were successful, or at least of those that are currently in existence.

- Selection bias. This occurs if the hedge funds in the database are not representative of those in the universe. Information on hedge funds is not easily available. This is because hedge funds are often offered as a means of private placement, and no obligation of disclosure is imposed in the US. As a result, information is collected by database vendors on those hedge fund managers who cooperate only.

- Besides, when a hedge fund enters a vendor database, the fund history is generally backfilled. This gives rise to an instant history bias (Park (1995)). Since we expect hedge funds with good records to report their performance to data vendors, this may result in upwardly-biased estimates of returns for newly introduced funds

The standard procedure for measuring survivorship bias (see Malkiel (1995)) is to take the difference for the period under consideration between the average return on a population and the average return on the surviving funds. Fung and Hsieh (2000), using the TASS database, find that the surviving portfolio had an average return of 13.2 % from 1994 to 1998, while the observable portfolio had an average return of 10.2 % during this time, from which a 3% survivorship bias per year for hedge funds (a similar number is obtained in Park et al. (1999)). The attrition rate, defined as the percentage of dead funds in the total number of funds has been reported by Agarwal and Naik (2000b) as 3.62%, 2.10% and 2.22% using quarterly, half-yearly and yearly returns, which is consistent with an average annual attrition rate of 2.17% in the HFR database reported by Liang (1999) for 1993-97. These attrition rates are much lower than the annual attrition rate of about 14% for offshore hedge funds in 1987-96 reported by Brown, Goetzmann and Ibbotson (1999) and 8.3% in the TASS database in 1994-98 as reported by Liang (1999). Overall, it is probably a safe assumption to consider that these biases account for a total approaching at least 4.5% annually (see Park, Brown and Goetzmann (1999) and Fung and Hsiesh (2000)), as can be seen from table 2.

Insert table 2 about here

We now provide more details on each of these index providers.

2.1 Main indexes

There are three main providers of hedge fund indexes.

2.1.1 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. In principle, EACM seeks investment managers that genuinely represent an appropriate investment style and meet eligibility requirements regarding minimum track record and asset size. Investment manager allocations are rebalanced at the beginning of each calendar year. It was launched in 1996 with data going back to 1990.

2.1.2 Hedge Fund Research (HFR)

Hedge Fund Research provides indexes 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 indexes 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.

2.1.3 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.[7] The CSFB/Tremont indexes cover nine strategies (convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event

[7] However, for indexes such as the Zurich Capital and EACM indexes, 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.

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.

2.2 Other Hedge Fund indexes

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

2.2.1 Zurich Capital Markets

Zurich Capital Markets hedge fund indexes 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 indexes are based on 60 funds selected from a 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 indexes were launched in 2001 with data going back to 1998. They are equally weighted and are rebalanced quarterly. The Zurich Hedge Fund indexes 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 indexes with monthly liquidity ensured by Zurich Capital Markets. These indexes differ from existing hedge fund indexes 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.

2.2.2 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, indexes will be segregated based on asset class (fixed income, commodities, currencies and stocks) and geographical region. The indexes 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 indexes. 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 indexes.

2.2.3 Van Hedge

Van Hedge fund indexes 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 indexes, 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.

2.2.4 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 indexes were created in 1987 and first published in 1992. Hennessee Group LLC provides research and consulting to hedge fund advisors.

2.2.5 Hedgefund.net

Hedgefund.net's so-called tuna indexes 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.

2.2.6 LJH Global Investments

LJH hedge fund indexes 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 indexes 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.

2.2.7 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-medians"): Zurich Event-Driven Median (Distressed securities and Risk arbitrage sub-medians), Zurich Global Emerging Median, Zurich Global International Median, Zurich Global Established Median (Global Established growth, Global Established small-cap and Global Established value sub-medians), Zurich Global Macro Median, Zurich Market Neutral Median (Market Neutral arbitrage, Market Neutral long/short and Market Neutral mortgage-backed sub-medians), Zurich Sector Median, Zurich Short-Sellers Median, Zurich Fund of Funds Median (Fund of Funds diversified and Fund of Funds niche sub-medians). MAR was recently acquired by Zurich Capital Markets.

2.2.8 Altvest

Altvest hedge fund indexes 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.

2.2.9 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. In contrast to the previous indexes, Magnum publishes the performance of funds of funds (since January 1997), as opposed to non-investible indexes. 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 indexes. The various indexes 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.

3 Hedge Fund Indexes are not Created Equal

Hedge fund indexes 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 carefully document now.

3.1 The Data

There are some serious challenges one has to face when attempting to provide a detailed picture of the universe of hedge fund indexes. In particular, we had to compile what we believe is an exhaustive database of all existing hedge fund indexes. 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.[8] 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.[9] Finally, we have also used some proprietary databases obtained from specific contacts we have

[8] PerTrac, 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.

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

developed in the hedge fund industry.[10] As a result of this somewhat painful process of data collection, we have been able to obtain a database consisting of indexes maintained by the dozen aforementioned hedge fund index providers.

A second step involves sorting the indexes by strategy, i.e., listing all competing indexes 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. 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, Zurich 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 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) eliminate styles for which not more than 3 competitors are available, (2) eliminate styles 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 3), with 4 to 8 index providers for each style.

Insert table 3 about here

The strategies being left aside are listed in table 4. We do not imply of course that these strategies do not represent an important part of hedge fund investing as there is no available evidence on the total assets managed under these strategies. The results for these strategies are available from the authors upon request.

Insert table 4 about here

We have collected and merged monthly return data from competing indexes 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 Zurich has created an index, for example, as the starting date for Zurich indexes was early 1998.[11]

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

[11] It should be noted that the samples vary across sub-universes since the starting dates differ. We have

3.2 The Results

We have computed various measures of homogeneity/heterogeneity for each given sub-universe.

3.2.1 Direct Measures of Heterogeneity

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 5.

Insert table 5 about here

As can be seen from table 5, differences in monthly returns are spectacular and can be greater than 20%! For example, Zurich 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. Obviously, replicating or outperforming a Long/Short strategy index was considerably easier that month if the benchmark used was EACM as opposed to Zurich! 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, they are recorded in the period ranging from August to October 1998, which roughly 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 indexes fail to agree precisely when reliable information is most needed.

We also compute the average and median correlation between various indexes in each given universe. Table 6 summarizes that information for all universes.

Insert table 6 about here

We find again that there is evidence of strong heterogeneity in the information conveyed by competing indexes. For example, the mean correlation between competing indexes within a particular style can be as low as .4 or less. 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

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.

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 indexes. For example, in the case of Merger Arbitrage, we find that the maximum difference in monthly returns is a low 1.85% (see table 5) with an average and median correlation greater than .9 (see table 6). It actually turns out that managers pursuing Merger Arbitrage strategies tend to behave in a consistent manner which explains why competing indexes, 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.[12]

Finally, we have created a customized heterogeneity index aimed at representing the percentage heterogeneity in the sub-universe. For that we simply compute

$$HI = 1 - \frac{\sum_{i,j=1}^{K} \rho_{i,j}}{K}$$

Assume that a universe is made of K perfectly homogeneous indexes. In that case, the correlation matrix is entirely made of 1, and the heterogeneity index is equal to $1 - 1 = 0\%$ heterogeneity. In general, this yields a number between 0 and 1 that can be regarded as a percentage heterogeneity in the sub-universe under consideration. We confirm that existing hedge fund indexes provide a very contrasted view of the return on Equity Market Neutral and Long/Short strategies, as we obtain a heterogeneity index which rises as high as 57.24% and 54.25%, respectively (see table 6).

3.2.2 Indirect Measures of Heterogeneity

It has been reported in the literature that hedge funds are exposed not only to market risks, but also to volatility, credit or liquidity risks (see for example Amenc, Curtis and Martellini (2001)). We now test for the heterogeneity in hedge fund indexes by documenting the differences in their exposure to a set of broad factors. The factors that we use are market risks, including equity risk, proxied by the return on the S&P 500 index, equity volatility risk, proxied by changes in the average of intra-month values of the VIX contract[13], fixed income risks including level

[12] Based on this evidence, they argue that one may passively replicate a significant proportion of the returns generated by hedge funds pursuing Merger Arbitrage types of strategies using portfolios of uncovered index put options.

[13] VIX, introduced by CBOE in 1993, measures the volatility of the U.S. equity market. This index is calculated by taking a weighted average of the implied volatilities of eight OEX calls and puts. The chosen

risk, proxied by the 3-month T-Bill rate, slope risk or term premium risk, proxied by monthly observations of the difference between the yield on 3-month Treasuries and 10-year Treasuries, currency risk, proxied by changes in the level of a volume-weighted exchange index of currencies versus US dollar, commodity risk, proxied by changes in the level of a volume-weighted index of commodity prices, credit risk, proxied by changes in the monthly observations of the difference between the yield on long term Baa bonds and the yield on long term AAA bonds, and liquidity risk, proxied by changes in the monthly market volume on the NYSE.

Table 7 summarizes the information on the correlation of competing indexes with these factors for the fixed income arbitrage universe. (Similar results on other strategies can be obtained from the authors upon request; they are not included in the paper in the interest of brevity.)

Insert table 7 about here

It can be seen from table 7 that competing indices vary significantly in the way they correlate with a set of broad-based factors. For example, the HFR fixed income arbitrage index is negatively correlated with the return on the S&P 500 (-0.16), while the Van Hedge fixed income arbitrage index exhibits a positive correlation greater than .5. Similarly, some fixed income arbitrage strategies are positively correlated with volatility risk (CSFB, HFR, HF Net), while others are negatively correlated with it (Van Hedge, Hennessee).

Because different hedge fund indexes correlate in a very different way with broad-based economic factors, the diversification benefits obtained from including them in a traditional stock and bond portfolio also vary dramatically. As an illustration, we generate efficient frontiers obtained from adding various fixed income arbitrage indexes to an equity and fixed income portfolio, using the S&P 500 and Lehman Brothers Aggregate as proxies for equity and fixed income markets, respectively. This is reported in figure 2, which is based on monthly data for the period extending from January 1996 to October 2001.

Insert figure 2 about here

We first note that the introduction of alternative investment strategies in a fixed income portfolio is likely to generate a dramatic enhancement of the efficient frontier. On the other hand, such improvement varies significantly depending on which index is used as a proxy for the return on fixed income arbitrage strategies.

4 Desperately Seeking Pure Style Indexes

In the presence of many different competing indexes, one may be at a loss to decide which one to use for benchmarking the performance of active or passive managers. There are essentially

options have an average time to maturity of 30 days.

two possible approaches to the problem. One approach involves carefully studying the methods and data used by each index provider, and coming up with a qualitative assessment of which is doing the best job. The problem is that there is no clear and definitive judgement that one can make on the subject. While the existence of universes of managers created according to style characteristics suggests that it is possible to create indexes based on the types of strategies the managers typically follow, one problem is that most hedge fund indexes (actually all indexes, except the Zurich indexes) are based upon managers' self-proclaimed styles. This procedure only makes sense under the following two conditions: (1) a manager follows a unique investment style;[14] (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 highly correlated with emerging market indexes, as arbitrage opportunities tend to disappear in liquid US markets).

All existing indexes have both advantages and drawbacks. For example, Zurich Capital Markets have tried to design a process to ensure the style-purity of their indexes by using an objective statistical cluster-based classification procedure for style classification, as opposed to managers' self-proclaimed styles. On the other hand, Zurich do not use as exhaustive a database as some of their competitors: their hedge fund indexes 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 (2001b) for more institutional details). Therefore, while Zurich indexes may achieve some level of purity, they fail to properly represent a significant fraction of the entire universe.

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 indexes to reach a better understanding of what the common information about a given investment style would be. In other words, what we are after is some notion of "intersection" of competing indexes (see figure 3).

Insert figure 3 about here

One straightforward method for obtaining a composite index based on various competing indexes would involve computing an equally-weighted portfolio of all competing indexes.[15] This would obviously provide investors with a convenient one-dimensional summary of the

[14] Similarly, 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 (is AOL-Time Warner a growth or a value stock?). Some have proposed probabilistic classification techniques for style: 95% growth, 5% value (e.g., Russell, Salomon Brothers) (see Borger (1997)).

[15] Value-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

contrasted information contained in competing indexes. In particular, because competing hedge fund indexes are based on different sets of hedge funds, the resulting portfolio of indexes would be more exhaustive than any of the competing indexes it is extracted from. 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 indexes, and design what can be called "pure style" indexes. Our method is a natural generalization of the idea of taking a portfolio of competing indexes. The refinement involves relaxing the assumption of an equally-weighted portfolio. Namely, we are looking for the portfolio weights that make the combination of competing indexes capture the largest possible fraction of the information contained in the data from the various competing indexes. Technically speaking, this amounts to using the first component of a PCA of competing indexes 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.[16] This is confirmed by the numbers in table 8 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 X as the following matrix

$$X = (X_{tk})_{\substack{1 \leq t \leq T \\ 1 \leq k \leq K}}$$

We have K variables, i.e., monthly returns for K different competing indexes, and T observations of these variables.[17] PCA enables us to decompose X_{tk} as follows[18]

$$X_{tk} = \sum_{i=1}^{K} \sqrt{\lambda_i} U_{ik} V_{ti}$$

where

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

under management with a considerable lag, which implies that such information could not be made available on a timely basis anyway.

[16] We have also tested another method known as orthogonalization which involves computing the residuals of multiple regressions. This method, however, has a number of drawbacks. One initial problem is that, while existence is easy to ensure, uniqueness is not granted. It actually turns out that, in the case of 3 competing indexes, there are 3 different ways of defining the "intersection of X1, X2 and X3" through orthogonalization procedures. Another problem is that the resulting index may not be interpreted as some combination of existing indexes. This undesirable black-box feature would make such indexes unappealing to investors.

[17] The asset returns have first been normalized to have zero mean and unit variance.

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

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

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

Note that these K 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

$$X_{tk} = \sum_{i=1}^{K} s_{ik}F_{ti}$$

where the K 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

$$X_{tk} = \sum_{i=1}^{I} \sqrt{\lambda_i}U_{ik}V_{ti} + \varepsilon_{tk} = \sum_{i=1}^{I} s_{ik}F_{ti} + \varepsilon_{tk}$$

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 $\sum_{i=1}^{I} \lambda_i \big/ \sum_{i=1}^{N} \lambda_i$. By taking $I = 1$, this method can be used to generate "the best one dimensional" summary of a set of competing indexes. Furthermore, a simple normalization

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

allows one to obtain an index which can be regarded as a portfolio of competing indexes, 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 8 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 indexes 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 8 also provides the number of competing indexes for each category in column 2.

Insert table 8 about here

We find that pure style indexes are able to capture a very large fraction of the information. The average (resp. median) percentage of variance explained by the pure style indexes is

81.52% (resp. 84.07%). The percentage of variance explained by the pure index is, of course, all the more significant in that the correlation between competing indexes was high. For example, emerging market style indexes have a percentage of variance explained greater than 90% while it originates from a population of 7 competing indexes. From table 5, we see that the median correlation was 0.95 for emerging markets. In the same vein, Event Driven and Merger Arbitrage pure indexes capture more than 80% of the information originally available in a set of 8 and 4 competing indexes, respectively. The Fund of Funds pure 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 strategies were the ones for which the heterogeneity of information provided by competing index providers was the most extreme (see tables 5 and 6).

5 How Pure is Pure?

In the previous section, we suggested using factor analysis techniques to generate a set of pure indexes that can be thought of as the best possible one-dimensional summaries of information conveyed by competing indexes for a given style, in the sense of the larger fraction of the variance explained. We argue that the procedure makes intuitive sense, and pure hedge fund indexes 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 indexes that implies a lower information loss. It seems, however, desirable to have a more direct assessment of the performance of the pure style indexes. In particular, one would like to know how better off an investor would be by focusing on these pure style indexes, as opposed to any of the competing indexes from which they are extracted. In other words, this section deals with the issue of backtesting the pure style indexes. This 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 indexes!

In this paper, we assess the performance of the pure style indexes in terms of their ability to improve current techniques for style or factor analysis and benchmarking of hedge fund returns.

5.1 Pure Hedge Fund Indexes and Style Analysis

Sharpe ((1988), (1992)) introduced the following model to provide an objective assessment of a manager's effective style mix, as opposed to the manager's declared style mix. This is known as return-based style analysis. The style analysis model reads

$$r_{it} = \sum_{k=1}^{K} w_{ik} I_{kt} + \varepsilon_{it}$$

where r_{it} is the (net of fees) excess return on a given portfolio or fund, I_{kt} is the return on index k for the period t, w_{ik} is the style weight (add up to one), and ε_{it} is an error term.

Technically speaking, style analysis is a specific case of a constrained (multiple) linear regression analysis (statistical terminology) or of a factor model (financial terminology). Such factor models are typically evaluated on the basis of their ability to explain the returns of the assets in question (i.e., the r_{it}). A useful metric is the proportion of variance "explained" by the selected asset classes. Using the traditional definition, for manager i

$$R_i^2 = 1 - \frac{var\left(\varepsilon_i\right)}{var\left(r_i\right)}$$

The right-hand side of this equation equals 1 minus the proportion of variance "unexplained". The resulting R-squared value thus indicates the proportion of the variance of r_i "explained" by the K asset classes/styles. On a technical note, the optimal style weights are actually obtained as the solution to a program of minimization of the variance of the residual term; this is the traditional approach of "least square estimation" (statistical terminology) or "tracking error minimization" (financial terminology). What makes style analysis specific with respect to standard linear regression is that specific portfolio and positivity constraints are imposed on the coefficients so that they can be naturally interpreted as weights.[19]

Since hedge fund returns exhibit non-linear option-like exposures to standard asset classes (Fung and Hsieh (1997, 2000)), traditional linear factor models offer limited help in evaluating the performance of hedge funds. For example, Fung and Hsieh (1997) report that almost half of the hedge funds in their database have R-squared below 30% when standard asset classes are used as regressors. This stands in sharp contrast to the case of traditional investments, where

[19] It should be noted that the presence of these constraints distorts standard regression results. In particular, confidence intervals for coefficients are no longer readily available in closed-form. These may however be numerically estimated (see Lobosco and DiBartolomeo (1997)). Portfolio and positivity constraints may actually sometimes be relaxed, in particular when performing style analysis for hedge funds, because of the ability of hedge fund managers to use leveraged positions and take both long and short positions in traditional asset classes (see Agarwal and Naik (2000)). Style analysis without positivity constraints is sometimes referred to as semi-strong style analysis, while style analysis with no constraints imposed on factor loading is referred to as weak style analysis.

the authors report that 73% of mutual funds in the Morningstar database have R-squared above 80% and 56% above 90%. These results can be seen as a justification of the "alternative" in "alternative investments": *how* hedge funds invest is more important than *where* they invest. This effect has been named the "trading strategy factor".[20] In the literature on hedge fund performance, one remedy has been suggested to try to capture such non-linear dependence: include new regressors with non-linear exposure to standard asset classes to proxy dynamic trading strategies in a linear regression.[21] Natural candidates for new regressors are buy-and-hold positions in derivatives (Schneeweis and Spurgin (2000), Agarwal and Naik (2000) or Fung and Hsieh (2000a)), or hedge fund indexes (Lhabitant (2001)).

In this section, we follow the latter approach and use the pure style indexes to benchmark hedge fund returns. Given that style analysis is a popular use of broad-based indexes, it is natural to try to test the "superiority" of pure style indexes on the basis of their superior power in the context of style analysis. For this, we perform a style analysis on a proprietary database of 1,500 individual hedge fund managers, the MAR-Zurich database. More specifically, we first select all funds with a history starting early 1998, the earliest starting date of our indexes. We focus on funds of funds given that a style analysis on a specialized fund would not be particularly meaningful.[22] For the same reason, within the category funds of funds, we focus on the "diversified" funds, as opposed to funds of funds of a particular style.

Because the method involves a heavy computational burden, we restrict ourselves to a limited set of competing indexes. Hence, we choose to test our pure style indexes against arguably the most popular provider of style indexes, EACM. We also test the MAR indexes given that the hedge fund data was provided by MAR. More specifically, we perform the following experiment. For each provider of hedge fund indexes (EACM and MAR), we select the set of pure indexes that match the same categories as the ones covered by these index vendors. In the case of EACM, we are left with long/short, convertible hedge, event driven, distressed securities, opportunity and short sellers, while we are left with event driven, emerging markets, international, macro, market neutral and short sellers in the case of MAR indexes. We then run a horse race between each of these two commercial indexes and the corresponding pure style index in term of their respective style analysis power, i.e., we run a style analysis of all diversified funds of funds in the database, and compare the average R_i^2. The intuition

[20] Some "leverage factor" is also involved as hedge fund managers can scale the payoffs of their portfolio due to gearing.

[21] Alternatively, one may allow for a non-linear analysis of standard asset classes. A portfolio interpretation, may, however, no longer be available.

[22] In practice, it is very common for hedge funds to suffer from style biases. For example, a fixed income arbitrage hedge fund might end up pursuing emerging market types of strategies as arbitrage opportunities in developed countries dry up. Therefore, style analysis at the level of the individual fund can be of some relevance.

behind the test is that if pure style indexes contain better and purer information than their competitors, they should be able to explain a larger fraction of hedge fund returns. For the purpose of the analysis, we keep only those funds for which a style analysis regression with either the pure style indexes or their competitor generates sufficient explanation power, the idea being that the explaining power of a set of indexes can only be assessed in a context where there is some explanation power to be expected.[23]

In table 9, we provide a measure of the average R-squared in a style analysis constrained regression of hedge fund returns using pure indexes and competing indexes.

Insert table 9 about here

We find that our pure style indexes explain on average a larger proportion of hedge fund asset returns than competing indexes. In the case of EACM and MAR, the difference is both economically and statistically significant (see t-test value for the null hypothesis of nonsignificant difference in mean R-squared in column 5). Of course, this does not imply that pure style indexes will always outperform all competing indexes, but it still provides some confidence in the fact that the pure indexes tend to allow for better measurement and benchmarking of hedge fund performance.

We now turn to a more direct way of assessing the purity of these indexes.

5.2 Pure Hedge Fund Indexes and Factor Models

Ideally, one would like to test the exposure of an index to a set of factors which best describe a given hedge fund strategy. It is, however, again, a chicken-and-egg type of problem, as it is somewhat difficult to define what the exposure of a pure hedge fund strategy should be with respect to a set of factors without relying on some candidate index to serve as a proxy for the returns generated by following the strategy. Fortunately, there actually is at least one class of strategies, the convertible arbitrage strategies, for which such a decomposition is relatively straightforward.

Convertible arbitrage strategies attempt to exploit anomalies in prices of corporate securities that are convertible into common stocks such as convertible bonds, warrants or convertible preferred stocks. Roughly speaking, if the issuer does well, the convertible bond behaves like a stock, if the issuer does poorly, the convertible bond behaves like distressed debt. Convertible bonds tends to be under-priced because of market segmentation: investors discount securities

[23] In the comparison of EACM indexes to pure style indexes, we have kept only those 104 funds for which a style analysis regression generates at least 50% explanation power using either EACM or the pure style indexes. In the case of MAR, we have kept only those funds for which the style analysis generates at least 40% explanation power, because too few funds would have qualified at the 50% level. This less stringent restriction allows us to keep 66 funds.

that are likely to change types. Convertible arbitrage hedge fund managers typically buy (or sometimes sell) these securities and then hedge part or all of the associated risks by shorting the stock. Delta neutrality is often targeted and over-hedging is sometimes appropriate when there is concern about default, as the excess short position may partially hedge against a reduction in credit quality. Essentially, a convertible bond is a bond plus an option to switch. As a result, it is the combination of a short position in the stock (makes money when stock price goes down), long position in the embedded option (loses money when stock price goes down), and long position in the embedded bond (loses money when credit quality deteriorates). The risks involved relate to changes in the price of the underlying stock (equity market risk), changes in the interest rate level (fixed income market risk), changes in the expected volatility of the stock (volatility risk) and changes in the credit standing of the issuer (credit risk). As a result these strategies will typically make money if expected volatility increases (long vega), make money if the stock price increases rapidly (long gamma), pay time-decay (short theta) and make money if the credit quality of the issuer improves (short the credit differential).

Since we understand the sources of risk and return for these strategies, we can isolate the set of factors that should explain a large fraction of their behavior. Our intuition is that pure style indexes should have a larger R-squared than most competing factors, as competing indexes might include spurious effects emanating from managers following mixed strategies. To test for this, we use the following proxies:

- Return on the S&P 500 as a proxy for equity risk
- T-Bill 3-month rates as a proxy for interest rate risk
- Return on the Lehman Brothers Lehman High Yield Credit Bond Index as a proxy for credit risk
- Changes in value of the VIX index as a proxy for volatility risk

We first identify the set of index providers who maintain a convertible arbitrage index. These are CSFB/Tremont, HFR, EACM, Zurich, Hennessee and HF Net. For each of these indexes, and the corresponding pure style index, we subsequently run a regression of the monthly returns from 1998 to 2000 on the four aforementioned proxies, and we record the R-squared. The results are reported in table 10.

Insert table 10 about here

We find that the factor model does indeed explain a larger fraction of the variance of the returns on the convertible arbitrage pure style index than that of any competing index, except

HFR.[24] The fact that HFR is better explained by the factor model is consistent with evidence reported elsewhere (Fung and Hsieh (2001b)) that one obtains a significantly higher R^2 when regressing the HFR composite index on a set of traditional asset classes index returns. This is because, unlike the CSFB/Tremont indexes for example, the HFR composite index excludes CTAs in the index composition, and CTAs exhibit option-like return payoffs that can not be captured easily by using a linear model of conventional indexes.

There is no obvious way, however, to explicitly isolate the set of factors that are relevant for an analysis of most other hedge fund strategies. That is why we turn next to a more implicit approach to the problem, based on a correlation analysis with *passive indexes* (see more details in next sub-section). We actually show below that in most other cases (4 cases out of 6), the pure indexes are more correlated to passive indexes than the HFR indexes (see table 11). This actually suggests that if an explicit factor type of analysis was easy to conduct on other styles, the percentage of explanation would be greater for the pure style index than for the corresponding HFR index, and that the case of convertible arbitrage strategy is the exception, and not the rule.

5.3 Pure Hedge Fund Indexes and Passive Hedge Fund Indexes

There is ample evidence that hedge funds are typically exposed to a variety of risk sources including volatility risks, credit or default risks, liquidity risks, etc., on top of standard market risks (Schneeweis and Spurgin (1999), Amenc, Curtis and Martellini (2001)).[25] As a result, CAPM-based performance measurement will overestimate the abnormal return of a manager with positive exposure to non-market risk factors, and underestimate the abnormal return of a manager with negative exposure to non-market risk factors. In other words, hedge funds are likely to generate high normal returns through exposure to a variety of rewarded risk factors.

Hossein Kazemi and Thomas Schneeweis at the Center For International Securities and Derivatives Markets (CISDM) at the University of Massachusetts, Amherst, have designed a series of passive indexes aimed at capturing the returns to various hedge fund programs. These indexes are labelled "passive" indexes in that they are aimed at capturing only the normal, or systematic, component of hedge fund performance. This contrasts with traditional "active" indexes (such as the 12 competing indexes listed in this paper), which summarize the total return (both normal and abnormal) on a set of managers actively pursuing hedge alternative investment strategies. Given that these indexes are passive indexes, they are designed to

[24] The fact that HFR is better explained by the factor model is also consistent with the correlation between the CISDM convertible arbitrage passive index and the HFR convertible arbitrage index being higher than that of the passive index and the pure index (0.68 compared to 0.63, from table 11 below).

[25] Non directional strategies such as equity market neutral strategies actually have, in principle, zero exposure to market risk.

capture only the factor, or beta, component, of hedge fund returns. What they leave on the table is the alpha, or active component, i.e., any positive abnormal risk-adjusted performance generated by hedge funds through superior manager skill in adding positive return to the performance of their traditional long-only portfolio.

By modeling a family of hedge-fund strategies, they are able to relate a complex group of trading strategies to observable asset returns without having to specify the detailed workings of the strategies themselves. In other words, this type of approach has the benefit of creating transparency from otherwise opaque investments and overcomes data limitations through the use of observable market prices. Their work is consistent with Gatev, Goetzmann and Rouwenhorst (1999), Fung and Hsieh (2001) and Mitchell and Pulvino (2001) who replicate the Pairs Trading, Trend-Following CTA and Merger Arbitrage strategies, respectively, and also with Agarwal and Naik (2001) who use buy-and-hold strategies in options to replicate a significant fraction of the performance of a variety of hedge fund indexes.

They have benchmarked the following seven categories: convertible arbitrage, distressed securities, equity hedge, equity market neutral, fixed income arbitrage, macro and relative value. The protocol used for index creation is explained in the specific context of equity hedge. They use monthly data from January 1990 to December 2000 to replicate the performance of the HFR Equity Hedge Index using 6 traditional asset classes: Treasury Bill, Russell 1000, Russell 2000, S&P Growth, S&P Value, Lehman Brothers High-Yield Bond Index and Lehman Brothers Intermediate Maturity Treasury Bonds. First, they perform an in-sample optimization using all the data. The goal of this process is to create a portfolio that would have minimum tracking error with the HFR index subject to the constraint that its standard deviation should not exceed the standard deviation of the index. Next, they perform an out-of-sample examination of optimization. Using data for the year 1991, they perform an optimization similar to the previous one. The optimal weights are then used to create a portfolio for the year 1992. Similarly, they use data for the year 1992 to perform the optimization and then the weights are used to create a portfolio for the year 1993. This procedure was repeated for years 1991-2000.

Given that these passive indexes are meant to capture the betas (and not the alphas) of hedge fund returns, they can be regarded as relatively pure indexes, even though the fact that these passive benchmarks are not actual portfolios of hedge funds prevents them from being regarded as active indexes on a footing similar to the dozen competing indexes presented in this paper. Therefore, a measure of correlation of the pure index with respect to the corresponding passive index should be a good indication of purity. Our expectation is therefore that a pure index will be more closely correlated to the corresponding passive index than any of the competing commercial indexes. In table 11, we provide a measure of correlation between the passive index and the pure index for each strategy (column 2), as well as the average correlation between the passive index and competing indexes for the given strategy. We also report the correlation between the passive index and the corresponding HFR index (column 4).[26]

Insert table 11 about here

As can be seen from the comparison between columns 2 and 3, the correlation between a given passive index and the corresponding pure index is always significantly lower than the average correlation between the passive index and corresponding competing indexes. Of course, given that the passive indexes were designed to track the performance of HFR indexes, we expect the correlation between these passive indexes and HFR to be a difficult-to-beat benchmark. It actually turns out that in 4 cases out of 6, pure indexes are more correlated to passive indexes than the HFR indexes they are built to track! (see columns 3 from table 11). We see this as further evidence of the quality of the pure style indexes.

6 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 indexes. 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 indexes” for a given style. In particular, we suggest using principal component analysis techniques to extract the “best possible one-dimensional summary” of a set of competing indexes. We argue that this method is a natural generalization of the idea of taking a portfolio of competing indexes. We also provide evidence of the ability of the pure style indexes to improve current techniques for factor analysis and benchmarking of hedge fund returns. In particular, we find that the pure style indexes explain on average a significantly larger proportion of hedge fund asset returns than competing indexes.

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 (2001b), Cvitanic et al. (2001)). More specifically, recent research (see Amenc and Martellini (2001a) and Amenc, El Bied and Martellini (2001)) has shown that strategic and tactical asset allocation decisions involving alternative investment vehicles are likely to generate superior risk-adjusted returns. It had long been argued that some specific features of hedge fund investing did not facilitate the implementation of active allocation strategies. In particular, the absence of liquidity and the presence of lockup periods typical to investments in hedge funds are likely to prevent investors from implementing any

[26] We thank Hossein Kazemi and Thomas Schneeweis for sharing the data on the return on these passive indexes with us.

kind of dynamic strategy. These limitations, however, may no longer be binding, as market conditions have recently evolved in the alternative investment universe. While in its infancy the world of alternative investment strategies consisted of a disparate set of managers following very specific strategies, significant attempts at structuring the markets have occurred over the last decade. For example, investible portfolios, i.e., replicating portfolios with an approximate 2.5% tracking error, are available for each of the 5 Zurich indexes with monthly liquidity assured by Zurich Capital Markets. In the context of a profound modernization of the hedge fund industry, the need for good and reliable benchmarks of hedge fund performance is obvious.

Because we believe that there is a real value in providing investors with a more objective, or more global, assessment of the performance of alternative investment styles, we have suggested that a database of pure style indexes be maintained at the EDHEC-MISYS Risk and Asset Management Research Center, and posted on a dedicated web site. We have applied the concepts developed in this paper on the production of pure indexes to the following list of 11 styles: Convertible Arbitrage, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro, Long/Short, Merger Arbitrage, Relative Value, Short Selling and Distressed Securities. The index construction methodology we chose for the production of the pure style indexes involves the following 3 steps.

- Step 1: Use the first 3 years of monthly returns to calibrate the model.
- Step 2: Perform a PCA analysis of competing indexes for each strategy on the data used for calibration purposes, obtain the normalized first component, and label it as the "pure style index".
- Step 3: These portfolios are held for 3 months, their monthly returns are recorded, and the same process is repeated.[27]

Our results can easily be extended to traditional investment styles such as growth/value, small-cap/large-cap and we expect to maintain, at the EDHEC-MISYS Risk and Asset Management Research Center, a database of returns on pure indexes constructed on the basis of the S&P/BARRA, Wilshire and Russell equity style indexes.

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[27] Given that the Zurich indexes begin early 1998, and because of the 3-year calibration period, the pure style indexes will be created starting in January 2001.

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8 Appendix: Information on Hedge Fund Strategies

- Convertible Arbitrage. Attempts to exploit anomalies in prices of corporate securities that are convertible into common stocks (convertible bonds, warrants and convertible preferred stocks). Convertible bonds tends to be under-priced because of market segmentation; investors discount securities that are likely to change types: if the issuer does well, the convertible bond behaves like a stock; if the issuer does poorly, the convertible bond behaves like distressed debt. Managers typically buy (or sometimes sell) these securities and then hedge part or all of the associated risks by shorting the stock. Delta neutrality is often targeted. Over-hedging is appropriate when there is concern about default as the excess short position may partially hedge against a reduction in credit quality.

- Dedicated Short Bias. Sells securities short in anticipation of being able to re-buy them at a future date at a lower price due to the manager's assessment of the overvaluation of the securities, or the market, or in anticipation of earnings disappointments often due to accounting irregularities, new competition, change of management, etc. Often used as a hedge to offset long-only portfolios and by those who feel the market is approaching a bearish cycle.

- Emerging Markets. Invests in equity or debt of emerging (less mature) markets that tend to have higher inflation and volatile growth. Short selling is not permitted in many emerging markets, and, therefore, effective hedging is often not available, although Brady debt can be partially hedged via U.S. Treasury futures and currency markets.

- Long/Short Equity. Invests both in long and short equity portfolios generally in the same sectors of the market. Market risk is greatly reduced, but effective stock analysis and stock picking is essential to obtaining meaningful results. Leverage may be used to enhance returns. Usually low or no correlation to the market. Sometimes uses market index futures to hedge out systematic (market) risk. Relative benchmark index is usually T-bills.

- Equity Market Neutral. Hedge strategies that take long and short positions in such a way that the impact of the overall market is minimized. Market neutral can imply dollar neutral, beta neutral or both.

  - Dollar neutral strategy has zero net investment (i.e., equal dollar amounts in long and short positions).

  - Beta neutral strategy targets a zero total portfolio beta (i.e., the beta of the long side equals the beta of the short side). While dollar neutrality has the virtue of simplicity, beta neutrality better defines a strategy uncorrelated with the market return.

  Many practitioners of market-neutral long/short equity trading balance their longs and shorts in the same sector or industry. By being sector neutral, they avoid the risk of market swings affecting some industries or sectors differently than others.

- Event Driven : corporate transactions and special situations
  - Deal Arbitrage (long/short equity securities of companies involved in corporate transactions)
  - Bankruptcy/Distressed (long undervalued securities of companies usually in financial distress)
  - Multi-strategy (deals in both deal arbitrage and bankruptcy)

- Fixed Income Arbitrage. Attempts to hedge out most interest rate risk by taking offsetting positions. May also use futures to hedge out interest rate risk.

- Global Macro. Aims to profit from changes in global economies, typically brought about by shifts in government policy that impact interest rates, in turn affecting currency, stock, and bond markets. Participates in all major markets – equities, bonds, currencies and commodities – though not always at the same time. Uses leverage and derivatives to accentuate the impact of market moves. Utilizes hedging, but the leveraged directional investments tend to have the largest impact on performance.

- Managed Futures. Opportunistically long and short multiple financial and/or non financial assets. Sub-indexes include Systematic (long or short markets based on trend-following or other quantitative analysis) and Discretionary (long or short markets based on qualitative/fundamental analysis often with technical input).

Providers	# of Indexes	Launch Date	# of Funds	Website
EACM	13	1996	100	eacmalternative.com
HFR	7	1994	1,100	hfr.com
CSFB/Tremont	9	1999	340	hedgeindex.com
Zurich Capital	5	2001	60	zcmgroup.com
MSCI	4	2001	3,000	msci.com
Van Hedge	12	1995	750	vanhedge.com
Hennessee Group	22	1992	450	hedgefnd.com
Hedgefund.net	33	1979	1,800	hedgefund.net
LJH Global Investments	16	1992	800	ljh.com
MAR	15	1990	1,300	marhedge.com
Altvest	13	2000	1,400	altvest.com
Magnum	8	1994	NA	magnum.com

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

Bias	Park, Brown and Goetzmann (1999)	Fung and Hsiesh (2000)
Survivorship	2.6%	3.0%
Selection	1.9%	1.4%
Total	4.5%	4.4%

Table 2: Survivorship and Selection Biases in Hedge Fund Returns. This table provides a measure of survivorship and selection biases in hedge fund returns, from various academic studies on the subject.

Sub-Universe	List of Competing Indexes
Convertible Arbitrage	CSFB, HFR, EACM, Zurich, Hennessee, HF Net
Emerging Markets	CSFB, Altvest, HFR, MAR, Van Hedge, Hennessee, HF Net
Equity Market Neutral	CSFB, Van Hedge, HFR, MAR, Hennessee, HF Net
Event Driven	CSFB, Altvest, MAR, EACM, HFR, Hennessee, HF Net, Zurich
Fixed Income Arbitrage	CSFB, HFR, Van Hedge, Hennessee, HF Net
Global Macro	CSFB, Altvest, Van Hedge, MAR, HFR, Hennessee, HF Net, Magnum
Long/Short	CSFB, Altvest, Zurich, EACM, HF Net
Merger Arbitrage	Altvest, HFR, Zurich, Hennessee, EACM, HF Net
Relative Value	Altvest, HFR, Van Hedge, EACM, HF Net
Short Selling	Altvest, HFR, Van Hedge, MAR, EACM
Distessed Securities	Van Hedge, Altvest, HFR, EACM, Zurich, HF Net, Hennessee
Fund of Funds	Van Hedge, Altvest, HFR, Zurich

Table 3: Competing Indexes in Hedge Fund Universe. This table provides a listing of competing indexes in the hedge fund universe, with details on the competing indexes and the data range. Van Hedge offer two market neutral indexes, respectively labelled ”Arbitrage” and ”Securities hedging”. For the purpose of this study, we have combined these two sub-indexes into a single one by taking a simple average return on the two strategies. EACM offers two long-short indexes, respectively labelled ”Relative Value” and ”Equity Hedge Fund”. For the purpose of this study, we have combined these two sub-indexes into a single one by taking a simple average return on the two strategies. EACM and HF Net use the label "risk arbitrage" for strategies otherwise known as "merger arbitrage".

Sub-Universe	List of Competing indexes
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, Zurich, 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 4: Strategies Not Covered. This table provides a listing of competing indexes 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	Max Difference (with dates and indexes)
Convertible Arbitrage	4.75% (Oct 98; CSFB (-4.67) / Hennessee (0.08))
Emerging Markets	19.45% (Aug 98; (MARH -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) / Zurich (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))
Distessed Securities	7.38% (Aug 98: HF Net (-12.08) / Van Hedge (-4.70))
Fund of Funds	8.01% (Dec 99: MAR-Zurich (2.41) / Altvest (10.42))
Global	18.29% (Dec 99: CSFB (0.09) / Magnum (18.38))

Table 5: Measures of Heterogeneity in Hedge Fund Indexes (1). This table provides the maximum monthly return difference betwen competing indexes for the same style. For "short selling" the numbers reported have been computed after exclusion of Altvest, which features negatively correlated returns with other competing indexes.

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Sub-Universe	Average Correlation	Median Correlation	Heterogeneity Index
Convertible Arbitrage	0.8183	0.8319	0.1817
Emerging Markets	0.9284	0.9502	0.0716
Equity Market Neutral	0.4276	0.4959	0.5724
Event Driven	0.9232	0.9295	0.0767
Fixed Income Arbitrage	0.5407	0.4968	0.4592
Global Macro	0.5598	0.6428	0.4402
Long/Short	0.4575	0.6687	0.5425
Merger Arbitrage	0.9193	0.9269	0.0807
Relative Value	0.6752	0.7498	0.3248
Short Selling	0.8811	0.8662	0.1189
Distessed Securities	0.8645	0.8835	0.1355
Fund of Funds	0.8757	0.8771	0.1243

Table 6: Measures of Heterogeneity in Hedge Fund Indexes (2). This table provides three measures of heterogeneity in the hedge fund index universe (average correlation, median correlation, and a percentage heterogeneity index (1 - average correlation). For the "short selling" and "global" indexes the numbers reported have been computed after exclusion of Altvest, which features negatively correlated returns with other competing indexes. For example, the maximum difference in monthly returns when Altvest is included is 40.74 percent (Jun 00; Altvest -27.76 versus Magnum 12.97).

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Fixed Income Arbitrage	F1	F2	F3	F4	F5	F6	F7	F8
CSFB	0.00	0.12	0.15	0.23	0.42	0.05	-0.38	-0.10
HFR	-0.16	0.14	0.25	0.19	0.57	0.07	-0.24	-0.18
Van Hedge	0.53	-0.47	0.09	0.02	-0.13	0.14	-0.16	-0.05
Hennessee	0.37	-0.37	0.06	0.19	0.26	0.12	-0.22	-0.12
HF Net	-0.10	0.20	0.22	0.20	0.42	0.03	-0.37	-0.01

Table 7: Sensitivity to Broad-Based Factors- The Case of Convertible Arbitrage. This table provides the correlation between competing convertible arbitrage indexes and a set of broad-based factors. F1 stands for the return on the S&P 500 index, F2 stands for changes in VIX, F3 stands for the T-Bill rate, F4 stands for the difference between the yield on 3-month Treasuries and 10-year Treasuries, F5 stands for changes in the volume-weighted index of currencies versus the US dollar, F6 stands for changes in the level of a volume-weighted index of commodity prices, F7 stands for changes in the difference between the yield on long term Baa bonds and the yield on long term AAA bonds and F8 stands for changes in the monthly market volume on the NYSE.

Sub-Universe	# of Indexes	% 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
Distessed Securities	7	77.6
Fund of Funds	5	91.19

Table 8: Pure Style Indexes. 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 indexes that is captured by the pure index (column 3). It also provides the number of competing indexes for each category in column 2. Van Hedge offer two market neutral indexes, respectively labelled "Arbitrage" and "Securities hedging". For the purposes of this study, we have combined these two sub-indexes into a single one by taking a simple average return on the two strategies. EACM offers two long-short indexes, respectively labelled "Relative Value" and "Equity Hedge Fund". For the purpose of this study, we have combined these two sub-indexes into a single one by taking a simple average return on the two strategies. CSFB, Altvest, Van Hedge and Hennessee offer a global index. MAR, Zurich, Magnum, HFR and HF Net do not offer global indexes; we have computed a synthetic global index by taking an equally weighted average of sub-indexes within the universe.

Indexes	Number of Funds	Average R^2	Comparable Pure Index Average R^2	T-Test
EACM	104	69.27	74.93	**-4.56**
MAR	66	50.85	72.35	**-9.54**

Table 9: Comparison of style analysis explanation power between pure indexes and competing indexes (EACM and MAR). This table provides a measure of the average R-squared in a style analysis constrained regression of hedge fund returns using pure indexes and competing indexes. The number of funds is listed in column 2, and a t-test for the null hypothesis of nonsignificant difference in mean R-squared is featured in column 5. Values significant at the 5 percent level appear boldfaced.

Indexes	R^2
Pure Style Index	50.92%
CSFB/Tremont	48.44%
HFR	62.94%
EACM	34.16%
Zurich	46.18%
Hennessee	43.14%
HF Net	48.67%

Table 10: Comparison of explanation power of a factor model for convertible arbitrage strategies between pure indexes and competing indexes (CSFB/Tremont, HFR, EACM, Zurich, Henessee and HF Net). This table provides the R-squared in a regression of convertible arbitrage index monthly returns from 1998 to 2000 onto proxies for equity, volatility, interest rate and credit risks.

	Pure Index	Average Competing Index	HFR Index
Convertible Arbitrage	0.63	0.59	0.68
Distressed Securities	0.86	0.71	0.83
Equity Hedge	0.96	0.88	0.88
Equity Market Neutral	0.65	0.48	0.46
Fixed Income Arbitrage	0.60	0.48	0.52
Macro	0.74	0.65	0.77
Relative Value	0.84	0.71	0.76

Table 11: Comparison of correlation between passive indexes and pure indexes, and correlation between passive indexes and competing indexes. This table provides a measure of correlation between the passive index and the pure index (column 2), and average correlation between the passive index and competing indexes (column 3), as well as correlation between passive indexes and HFR indexes (column 4).

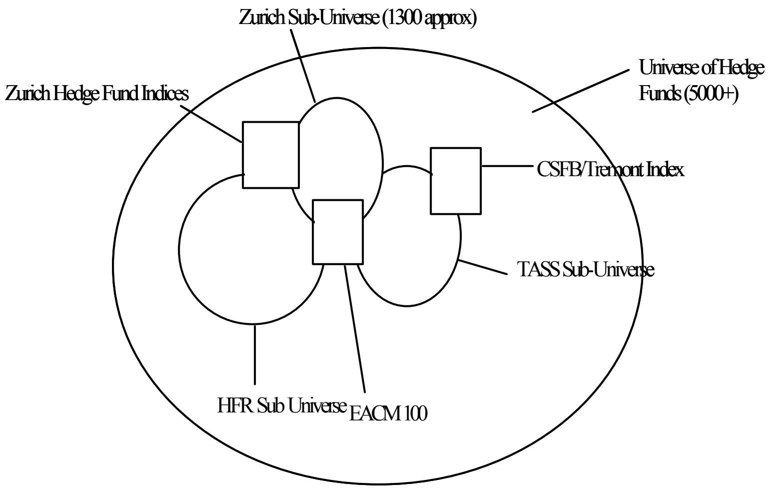

Figure 1: Hedge fund universe. The hedge fund universe is made up of more than 5,000 funds. Several competing indexes exist, none of which fully represents the entire universe.

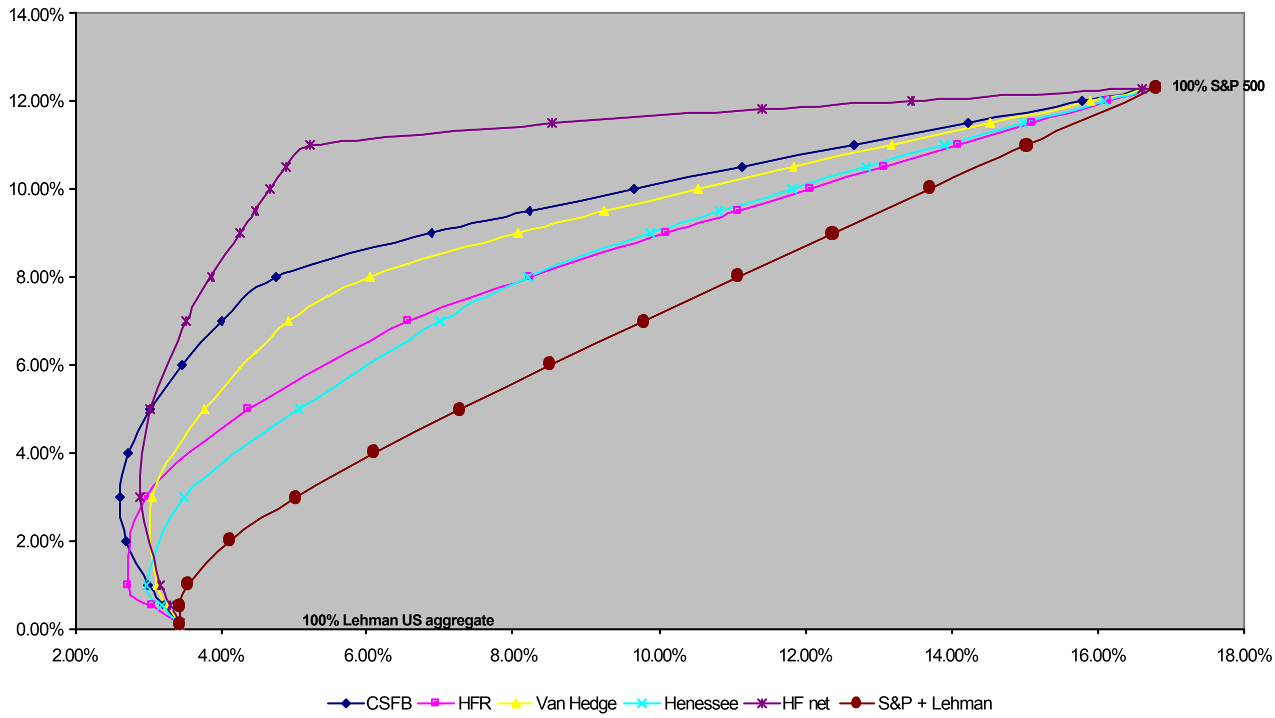

Figure 2: Heterogeneity in Diversification Benefits. In this figure, we generate efficient frontiers obtained from adding various fixed income arbitrage indexes (CSFB, HFR, Van Hedge, Henessee, HF Net) to an equity and fixed income portfolio, using the S&P 500 and the Lehman Brothers Aggregate as proxies for equity and fixed income markets, respectively. This figure is based on monthly data for the period extending from January 1996 to October 2001.

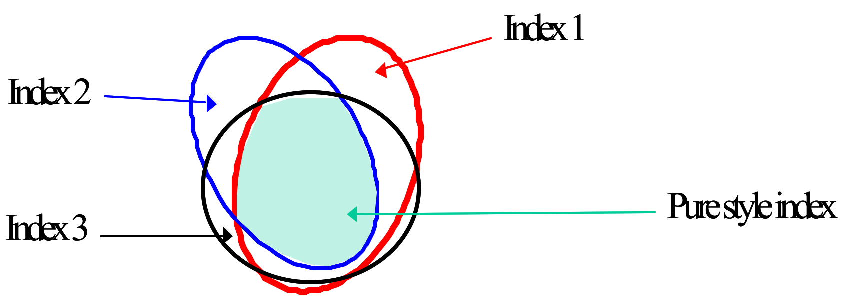

Figure 3: Pure style index. A pure style index is designed to capture the "intersection" of information provided by competing indexes. More precisely, it can be seen as the best one-dimensional summary of a multi-dimensional set of indices.

Hedge fund indexes reflect the returns on hedge funds. Research organizations collect data on hedge fund returns and compile this information into indexes. Since hedge funds are not required by regulation to report their performance, the research firms rely on voluntary cooperation of hedge funds to report returns. Here are some important points to consider when evaluating hedge fund indexes: Constituents determine the index. Poorly performing hedge funds are less likely to report. Returns of hedge fund indexes are likely to be overstated/biased upward due to survivorship bias. Â« Previous Next model â€“ Hedge fund beta is zero â€¢ Hedge fund indexes and sub-indexes are a natural choice for benchmarking hedge fund returns â€¢ Right benchmarking is a fundamental problem in the presence of incentive fees â€¢ Reliable HF indexes are also needed for â€“ Strategic Asset Allocation â€“ Tactical Asset Allocation Â© Edhec 2002 Mesure de la Performance et des Risques de la Gestion Alternative 18/06/02.Â Composite of World Unknown Sub-universe (e.g., MSCI) may or may not represent World Index Competing indexes for the same universe