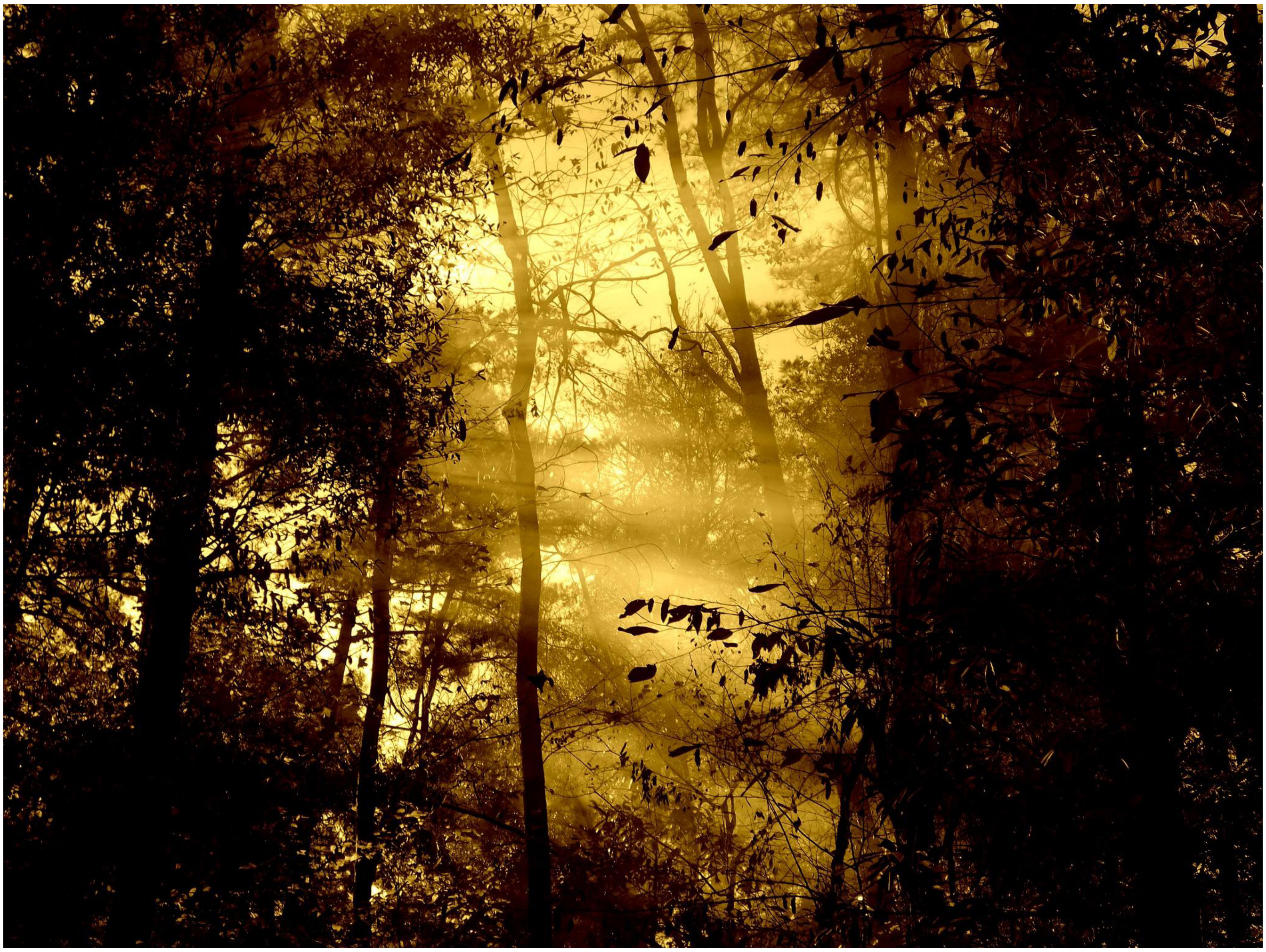

Seeking Fully Investable and Optimized Exposure to Alternative Assets

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Introduction

Historically, some alternative investments have achieved higher returns than their traditional counterparts and have exhibited low(er) correlation with other assets. These characteristics make them attractive investments for most asset managers in search of both alpha and diversification benefits. As a matter of fact, the number of sophisticated investors including endowments that allocate a significant portion of their capital to alternative investments, or follow the alpha/beta separation investment style, is continuously increasing. On average, alternative investments have grown faster than traditional investments over the last six years and have surpassed their 2007 peak levels. For instance, in 2012, the Yale endowment fund allocated more than 60% of its funds in private equity, real estate, and natural resources.[1] However, while hedge fund portfolio optimization has been studied thoroughly, (e.g., Popova, Morton, and Popova, 2003, Switzer and Omelchak, 2009), research on combining hedge funds with private equity and real estate investment strategies has been scarce (see Bird, Liem, and Thorp, 2013). In addition, most academics and professionals appear to be more concerned about including a constrained amount of alternatives in a "traditional" portfolio (equity, debt, and "cash-equivalent" investments).

Professionals and academics tend to agree that standard risk measures are not able to quantify the true risk embedded in modern investments accurately. Due to the non-normal nature of most asset returns, allocation methodologies that only consider the first two moments are inherently flawed, especially when they are applied to alternative investments (Fischer and Lind-Braucher, 2010). In non-Gaussian portfolio optimization, the variance is then replaced by another coherent risk metric that accounts for the higher moments.

For multi-asset allocation, the estimation of the covariance matrix is also a major issue, as it is often estimated with a lot of error when the sample size is reduced. However, shrinkage methods (e.g. Ledoit and Wolf, 2003) are widely used nowadays and provide researchers with a more robust sample covariance matrix.

However, despite all these fixes, a main issue remains: the resulting portfolios are rather concentrated in a few assets. In the search for well-diversified portfolios, a recent strand of the literature brought forth new diversification measures, the most popular methods being the most diversified portfolio of Choueifaty and Coignard (2008), and the maximum diversification technique of Meucci (2009). Meanwhile, another strand of the literature advocates diversification through volatility contribution; notably the so-called equal risk-parity portfolio methodology overweights safer assets such that each has the same contribution to the overall portfolio risk (see Maillard, Roncalli, and Teiletche, 2010).

This article further explores the problem of optimizing and managing a portfolio composed of a wide range of alternative asset classes. We consider only fully investable investment schemes in hedge funds, private equity, real estate, and exotics as some studies found that non-investable indices may overstate the true risk-return characteristics of the asset class (see Boigner and Gadzinski, 2013). We study eight different optimizing methodologies divided into four broad approaches, each based on a different metric: risk-adjusted expected return, predicted risk measure, diversification ratio, and heuristics. Interestingly, the out-of-sample performances of the portfolios are rather contrasting, with substantial differences in allocations over time. We also mix alternatives and traditional assets to build long-only portfolios without imposing an upper bound on the asset weights. Several conclusions are drawn on the importance of alternatives and the relevance of these portfolios for investors.

Data Description

While there is some debate as to what asset classes should fall under "alternatives," it is generally agreed that they include hedge funds, private equity, real estate, commodities, and store-of-value-assets such as fine art. Investors seeking passive exposure to commodities can use futures, swaps, structured notes, and ETFs.

However, managers may also access commodities through specialized hedge funds or funds of funds (within the CTA and Managed Futures hedge fund strategies). While investments into store-of-value assets, such as art are less common, the search for investments that exhibit low correlation with standard portfolios, has brought about the emergence of *exotic* alternatives. These include fine art, rare wines, timber, and carbon trading certificates, among others. Consequently, we construct our portfolios from a set of investable indices or trackers covering a broad universe of alternative assets. The data are all expressed in US dollars.

Hedge Funds

Hedge Fund Research (HFR) and Dow Jones Credit Suisse (DJCS) offer investable hedge fund indices construed to represent the hedge fund universe. They contain fewer funds than the corresponding benchmark indices as well as different risk-return characteristics (see Boigner and Gadzinski, 2013, for more details). These investments can be combined in order to build a hedge fund portfolio or an investment into a Fund of Hedge Funds (FoHF), and are available at significantly lower minimum investment sizes.[2]

Private Equity

Due to its risk-return profile, private equity is becoming increasingly attractive to institutional investors (Lahr and Herschke, 2009; Aigner *et al.,* 2012). Private equity consists of investors and funds that purchase stakes in companies that are not publicly traded. Such investments are primarily made by private equity firms with a motivation to nurture expansion, develop new products, or restructure the company's operations, management, and/or ownership. The most common strategies in private equity include (leveraged) buy-outs, venture capital, and mezzanine investments.

Since there is no generally accessible secondary market for private equity, this investment class is considered to be illiquid. However, an increasing number of private equity firms are listed on exchanges, so that private equity can be traded publicly. The so-called Listed Private Equity (LPE) funds are the best available proxies for the general private equity universe, even though they exhibit higher systematic risk than their non-listed counterparts (Lahr and Herschke, 2009). We use the LPX index family published by LPX GmbH, which constructs several indices including the LPX50, containing the 50 largest liquid LPE companies.

Real Estate

Real estate and property investments have long been an important pillar of any diversified institutional portfolio. The benefits of adding real estate into a mix of securities are well discussed in the academic literature (see Hudson-Wilson *et al.*, 2005). Real estate activities are defined as the ownership, trading, and development of income-producing real estate. Real estate is usually sub-divided into several different categories depending on the investment style followed. We use the FTSE EPRA/NAREIT Global Real Estate Index Series, as well as the iShares domestic real estate ETFs, in order to cover general trends in eligible listed real estate stocks worldwide.

Exotic Alternatives

Even though they are not under serious consideration by large segments of the investment community, these exotics should not be completely neglected (Bond, Hwang, and Satchell, 2007). The availability of investable "exotic" alternatives is limited, of course. However, some investment possibilities have been identified. Liv-ex publishes a monthly investable fine wine index. The Liv-ex Fine Wine Investables Index tracks around 200 red wines from 24 top Bordeaux chateaux. The component wines date back to the 1982 vintage and are chosen on the basis of their score from Robert Parker. The Barclays Capital Global Carbon Index (BGCI) is designed to measure the performance of the most liquid carbon-related credit plans. The index currently includes two plans: the European Union Emission Trading Scheme or EU ETS Phase II and the Kyoto Protocol's Clean Development Mechanism. Barclays Capital also makes an investable ETF that tracks the BGCI: the iPath Global Carbon ETN. Guggenheim Funds Investment Advisors, an investment company, provides the Guggenheim Timber ETF, which seeks to track the performance of the Beacon Global Timber Index.

The S&P Global Water Index provides exposure to fifty international companies that are involved in water related activities, such as water utilities and infrastructure, as well as water equipment and materials; the iShares S&P Global Water Index Fund closely tracks this index.

Traditional Assets

Our traditional asset classes comprise the followings: the JPM Global Bond Index, the MSCI World Index, the MSCI Emerging Markets Index, the DJ UBS Commodities Index, and the Barclays US Aggregate Credit Index. These liquid market indexes are all available through futures/ETFs.[3]

The data spans from November 1997 to September 2013.[4] We use the first 60-month rolling window as our initial in-sample period. If the overall dataset comprises 60 indices, however, due to data limitations, we start with three indices at the start of our out-of-sample exercise. We update the universe and weights of our portfolios as more data become available every month and then calculate the out-of-sample monthly portfolios returns.

The following methodologies are used: the Modified Sharpe ratio (MSR), the Bayes-Stein modified Sharpe ratio (BAY), the Conditional Value-at-Risk (CVaR), the Omega measure of Keating and Shadwick (2002), the Most Diversified ratio (MDR) of Choueifaty and Coignard (2008), the maximum diversification technique or Diversified Risk Parity (DRP) of Meucci (2009), the Equal Risk Parity (ERP) and the Equally Weighted scheme (EW). We do not impose any upper bound on the assets weights. The Variance-Covariance Matrix is estimated using the shrinkage method of Ledoit and Wolf (2003). More details are available in the Appendix.

Out-of-Sample Performance

Exhibits 1 and 2 report the out-of-sample geometric average returns, volatility, maximum drawdown, and Sharpe ratio of the optimized rolling long-only portfolios for our universe of alternative assets. It appears that the MSR and BAY methodologies are the best strategies, as they outperform the others in terms of cumulative returns, Sharpe ratio, and maximum drawdown. However, the alternative portfolios based on our heuristics and diversification methodologies perform poorly on all accounts. Exhibit 1 also highlights the sharp differences in performance between the "unconstrained" portfolios and the "constrained" portfolios, such as the equally-weighted and risk parity portfolios, which incorporate, by definition, all of the available assets in the portfolio.

Exhibit 3 displays the rolling weights. The best methodology, namely the Bayes-Stein modified Sharpe ratio, only involves a limited number of assets at one point in time. Consequently, the performance of the portfolios at time *t* is greatly influenced by the performance of a few assets. The total number of assets and the average number of assets included in the portfolio at one point in time are 24 and 3.4 respectively. Rebalancing occurs every month, with sudden changes or sometimes a complete shift in portfolio preferences. The portfolio is invested mostly in private equity and hedge funds strategies from 2002 to 2004, then heavily in real estate from 2004 to 2006, and fine wine from 2005 to 2007, but mostly in hedge fund arbitrage strategies from 2008 onwards.

We now include both traditional and alternatives indices and run our methodologies to find the optimized rolling long-only portfolios, still imposing no upper bound on the assets weights. Exhibit 4 shows that the mix of traditional and alternatives achieves the best performance with the Bayes-Stein modified Sharpe ratio methodology. As noted above, including all assets still leads to poorer results. The equally weighted portfolio is the best of its category, returning 4.3% per year. The BAY portfolio outperforms the other methodologies significantly, with 8.9% per year before fees. It also returns the best Sharpe ratio of all portfolios notably, thanks to a lower volatility than the "best" alternatives-only portfolio.

Interestingly, for all portfolios, the share of alternatives is, on average, well above 50% over the sample. For our best portfolios, the ratio even increases to 80%, with some periods fully invested in alternatives. This last result emphasizes the importance of including selected alternatives to a significant extent in order to achieve outstanding performance.

Conclusions

Alternative assets are promising institutional and private investors high-yielding investments. But how does one construct a portfolio of alternative assets that fulfills the requirements of modern portfolio theory and achieve at least comparative risk-adjusted performance to a traditional investment scheme? We explore this issue using a wide range of alternative assets. Our portfolios are optimized using four different objectives with weights periodically re-allocated based on the time-varying risk and return characteristics of the securities available. Our results highlight the importance of a careful and time-varying selection of alternatives chosen among an exhaustive universe in order to achieve outperformance over the last decade. Moreover, we advise sophisticated investors to combine dynamically traditional and alternatives (mixed portfolios) while putting no constraints on the weights allocated to alternatives. We argue that nowadays such a strategy is possible given the availability of fully investable and liquid indices covering most asset classes.

However, for investors who do not want to (or cannot) allocate a large part of their funds to alternatives, we advise them to adopt a core/satellite approach, where the satellite is dynamically managed following the "best" methodologies implemented in this article.

	Geometric Average Return (% p.a.)	Std Dev (% p.a.)	Max.DD	Sharpe Ratio*	Average Number of Assets
MSR	6.4%	8.0%	18.3%	0.63	3.6
BAY	8.6%	9.3%	18.3%	0.72	3.4
CVaR	5.2%	12.2%	48.7%	0.31	2.4
Omega	2.7%	8.4%	30.4%	0.15	4.2
MDR	-1.0%	6.4%	27.6%	-0.37	7.7
DRP	-0.3%	10.9%	43.3%	-0.15	3.7
ERP	0.6%	7.6%	33.7%	-0.10	17.2
EW	2.8%	13.3%	54.8%	0.11	24.0

**Risk-free rate has been averaged over the whole period.*

Exhibit 1 Performances of the Alternatives Portfolios

Source: Author's calculations

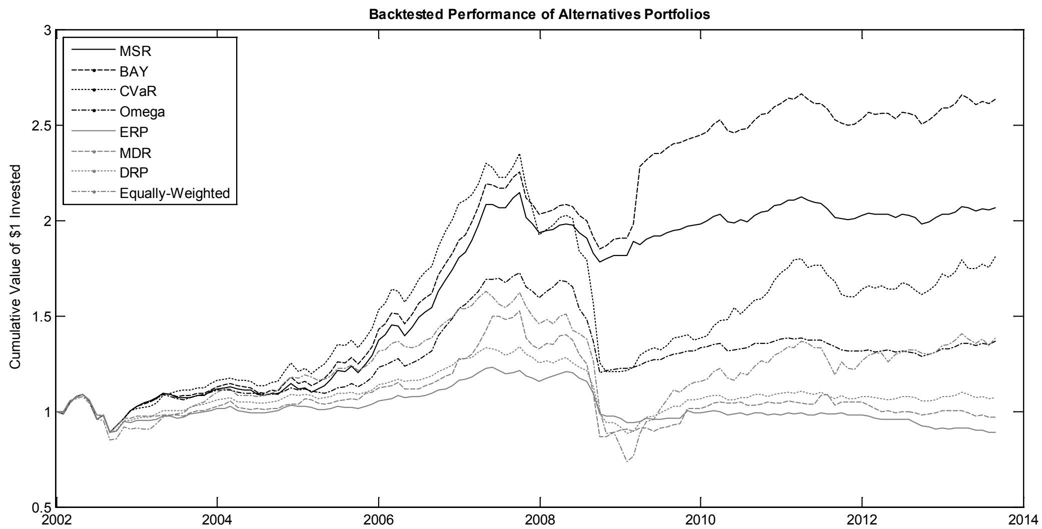


Exhibit 2 Cumulative Returns of Optimized Alternatives Portfolios

Source: Author's calculations

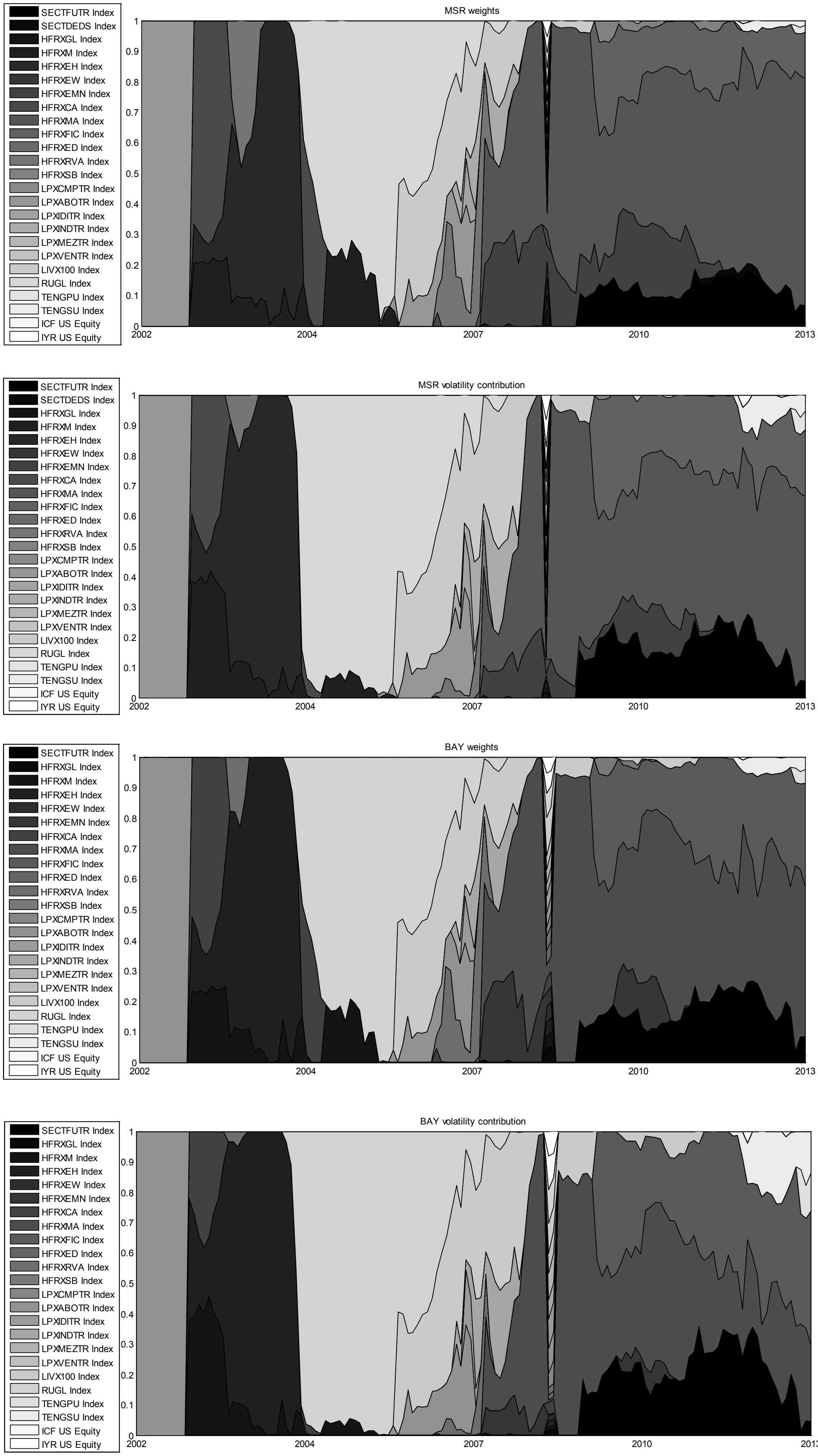
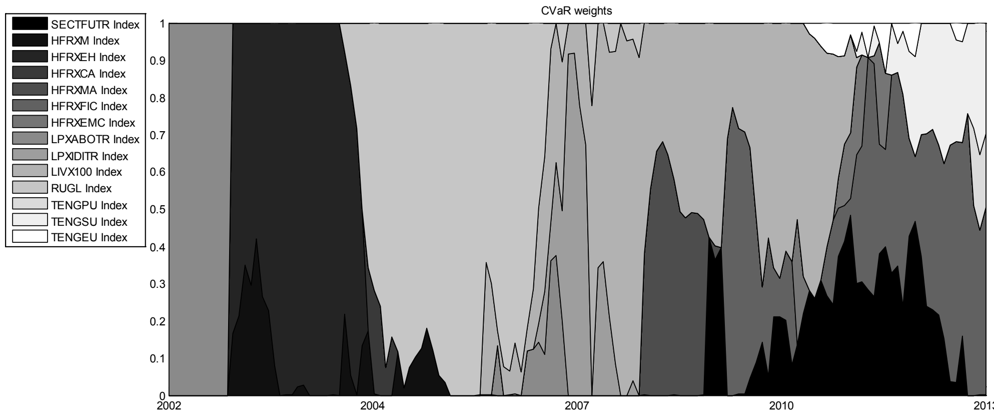
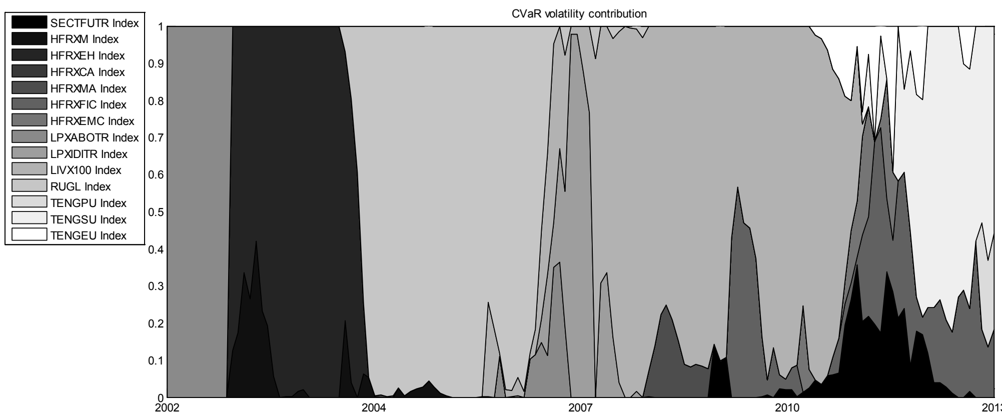
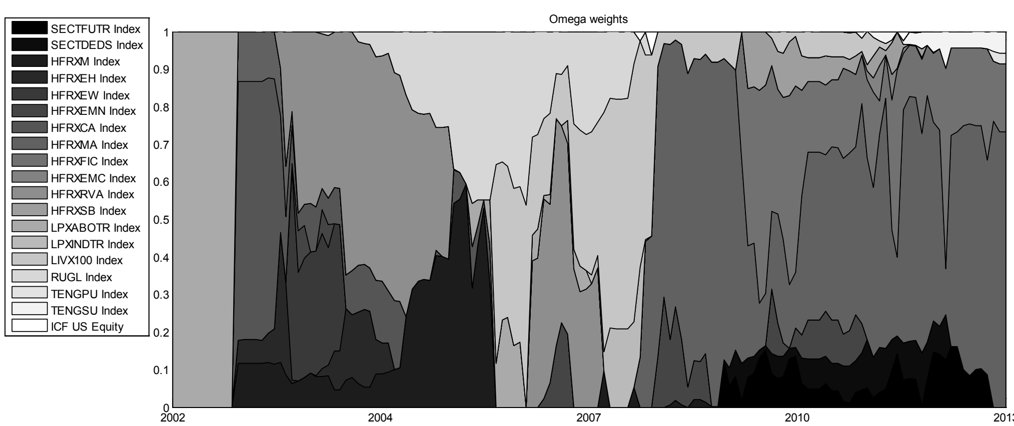


Exhibit 3 Optimal Weights and Volatility Contribution for Alternatives Portfolios

Source: Data as listed in the legend and author's calculations







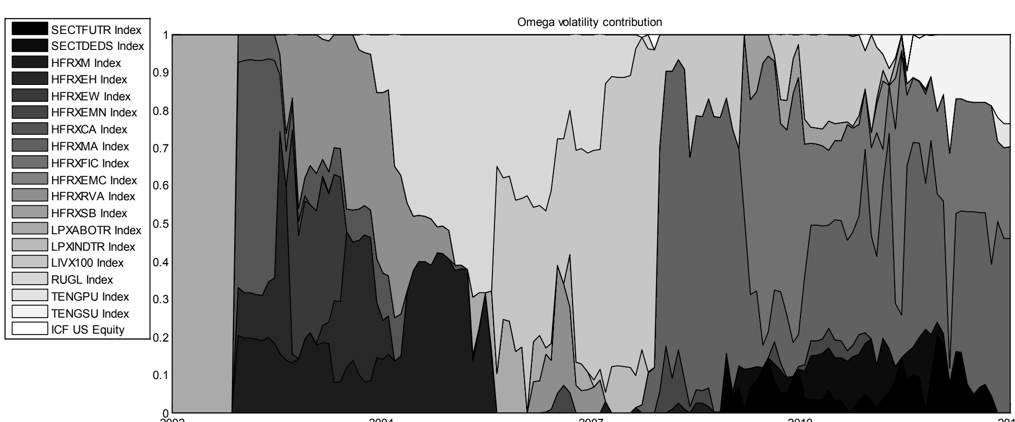


Exhibit 3 (Cont'd) Optimal Weights and Volatility Contribution for Alternatives Portfolios

Source: Data as listed in the legend and author's calculations

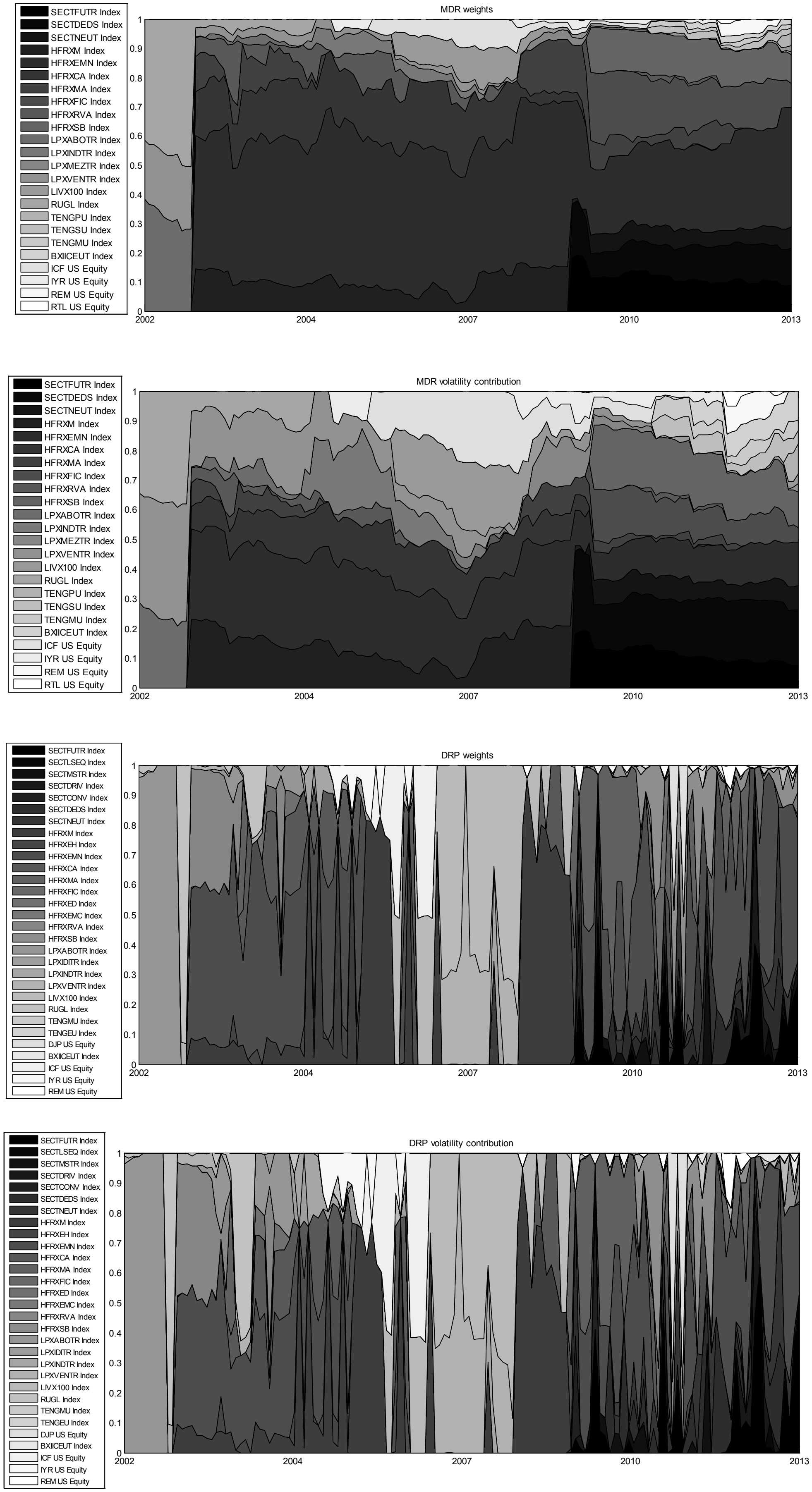


Exhibit 3 (Cont'd) Optimal Weights and Volatility Contribution for Alternatives Portfolios

Source: Data as listed in the legend and author's calculations

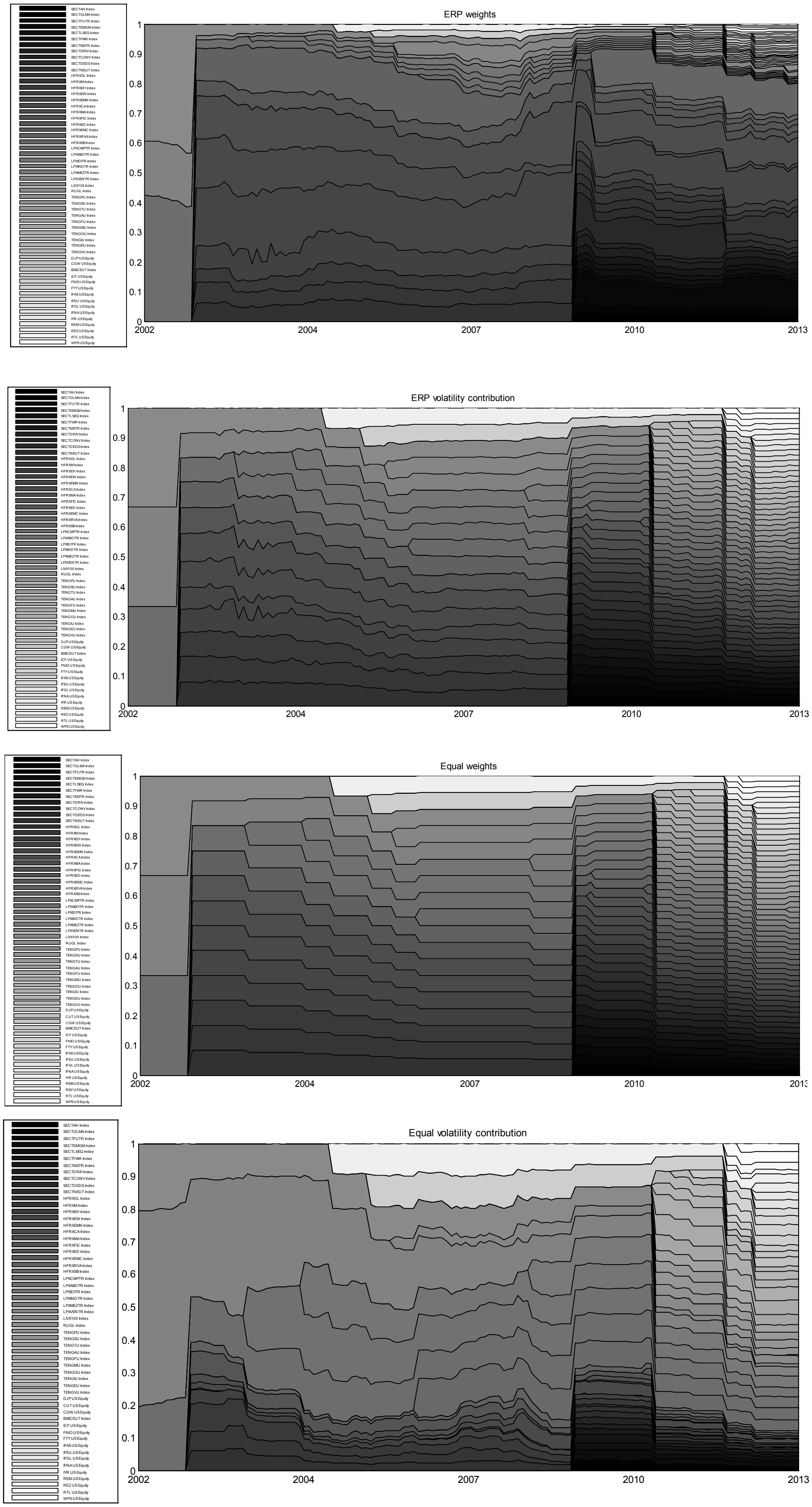


Exhibit 3 (Cont'd) Optimal Weights and Volatility Contribution for Alternatives Portfolios

Source: Data as listed in the legend and author's calculations

	Geometric Average Return (p.a.)	Std Dev (p.a.)	Max.DD	Sharpe Ratio*	Share of Alternatives
MSR	6.6%	6.3%	18.1%	0.81	0.80
BAY	8.9%	7.7%	18.5%	0.89	0.81
CVaR	5.4%	11.6%	48.9%	0.35	0.78
Omega	4.8%	5.4%	18.5%	0.62	0.69
MDR	1.3%	4.4%	20.3%	-0.01	0.76
DRP	6.3%	9.0%	19.9%	0.54	0.69
ERP	2.6%	6.1%	29.9%	0.19	0.73
EW	4.3%	12.1%	51.1%	0.24	0.77

**Risk-free rate has been averaged over the whole period.*

Exhibit 4 Performances of the Traditional/Alternatives Assets Portfolios
Source: Author's calculations

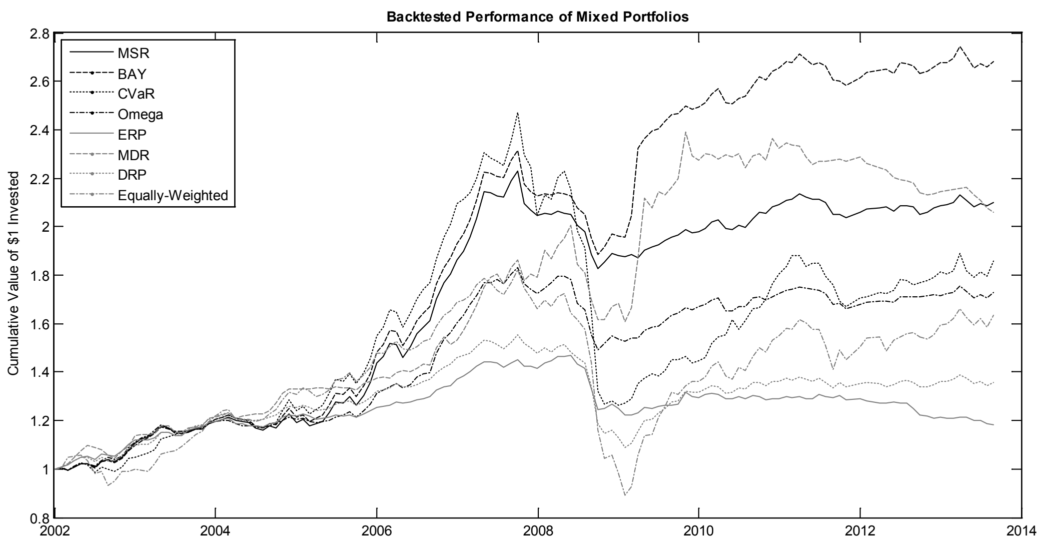


Exhibit 5 Evolution of the Performance of the Optimized Mixed Portfolios
Source: Author's calculations

Portfolio Optimization Frameworks

We build unleveraged long-only optimized portfolios without imposing an upper bound on the assets weights, using the following objective functions.

Risk-Adjusted Expected Returns

Modified Sharpe Ratio

The Modified Sharpe ratio is a variation of the standard Sharpe ratio taking non-normality into account. The MSR replaces the standard deviation in the denominator with the Modified VaR as follows:

$$MSR = \frac{r - r_f}{MVaR} \quad (1)$$

$$\text{with } MVaR = \mu - \left\{ z_c + \frac{1}{6}(z_c^2 - 1)s + \frac{1}{24}(z_c^3 - 3z_c)k - \frac{1}{36}(2z_c^3 - 5z_c)s^2 \right\}\sigma \quad (2)$$

where r represents past return, r_f is the return of the risk-free asset, μ is the arithmetic mean, σ is the standard deviation, z_c is the number of standard deviations at the VaR_α, s is the skewness, and k is the (excess) kurtosis.

Bayes-Stein Estimator

To address estimation error in the expected returns, the Bayes-Stein estimator uses a shrinkage method where the sample means are multiplied by a coefficient lower than one. We follow Jorion (1985) and shrink the expected returns towards the Minimum Variance Portfolio (MVP) average returns as follows:

$$\bar{r}(\hat{w}) = \hat{w} * \hat{r}_0 + (1-\hat{w}) * \bar{r}_j \quad (3)$$

$$\hat{w} = \frac{\hat{\lambda}}{T+\hat{\lambda}} \quad (4)$$

$$\hat{\lambda} = \frac{(N+2)(T-1)}{(r-r_0 1)' \Sigma^{-1} (r-r_0 1)(T-N-2)} \quad (5)$$

Where $\hat{r}_0$ and $\hat{w}$ are estimated from the data. The average is "shrunk" toward the new mean $\bar{r}(\hat{w})$. Since the variance-covariance matrix Σ is not known in practice, it is replaced by the shrinkage estimate given by Ledoit and Wolf (2003). (See below.)

Risk Measures

Conditional Value-at-Risk

To take into account the skewness and kurtosis, we implement the Cornish-Fisher expansion of the $CVaR_\alpha$ as:

$$CVaR_\alpha(X) = \mu - \frac{1}{1-\alpha} f(\hat{z}_\alpha)\sigma \quad (6)$$

$$with\ \hat{z}_\alpha = z_\alpha + \frac{1}{6}(z_\alpha^2 - 1)s + \frac{1}{24}(z_\alpha^3 - 3z_\alpha)k - \frac{1}{36}(2z_\alpha^3 - 5z_\alpha)s^2 \quad (7)$$

Where *f(.)* is the standard normal density, μ is the arithmetic mean, σ is the standard deviation, z_α is the number of standard deviations at the VaR_α, *s* is the skewness, and *k* is the (excess) kurtosis.

The Omega Model

Keating and Shadwick (2002) developed the Omega measure, which consider returns below and above a specific loss threshold, providing a ratio of total probability weighted losses and gains.

$$\grave{U}(r) = \frac{\int_{r_f}^{+\infty} (1-F(x))dx}{\int_{-\infty}^{r_f} F(x)dx} \quad (8)$$

Where r_f is the return level regarded as a loss threshold (risk-free rate), and *F(•)* the cumulative distribution function of the assets returns.

Diverfication Measures

Most Diversified Portfolio

Choueifaty and Coignard (2008) define the diversification ratio as the ratio of the weighted average of volatilities divided by the portfolio volatility. The Most Diversified Portfolio is then computed by maximizing this ratio:

$$w_{MDP} = \text{argmax}_w D(w) = \frac{w'.\sigma}{\sqrt{w'\Sigma w}} \quad (9)$$

Maximum Diversification

Using principal component analysis, Meucci (2009) intends to extract the main drivers of the assets' variability. The principal components represent then the uncorrelated risk sources inherent in the portfolio assets. Meucci (2009) defines the risk contributions of these components as:

$$p_i = \frac{w_i^2 \lambda_i}{Var(R_w)} \quad (10)$$

Where λ_i are the principal portfolio's variances, $Var(R_w)$ is the variance of the portfolio, and the p_i's sum to one.

A portfolio is well diversified when the distribution is uniform, i.e. when the p_i's are equal to *1/N*.

A distribution or diversification metric (see Exhibit 8) is derived and equal to:

$$\mathbb{N}_{Ent} = \exp\left(\sum_{i=1}^{N} p_i \ln p_i\right) \quad (11)$$

It is straightforward to see that when all the p_i's are all equal to *1/N*, the entropy is maximized and equal to *N*.

With the budget constraints, we then solve the following problem:

$$w_{DRP} = \underset{w}{\text{argmax}}\ \mathbb{N}_{Ent} \quad (12)$$

Heuristics

Equal Risk Contribution

The ERC portfolio is designed such that each constituent has the same weighted marginal contribution to risk. We follow Maillard, Roncalli, and Teiletche (2010) :

$$w_{ERP} = \underset{w}{\text{argmin}} \sum_{i=1}^{N}\sum_{j=1}^{N} (w_i(\Sigma w)_i - w_j(\Sigma w)_j)^2 \quad (13)$$

which essentially minimizes the variance of the risk contributions.

Sample Variance-Covariance Matrix

Ledoit and Wolf (2003) define the shrinkage estimator of the covariance matrix as

$$\hat{\Sigma}_{\text{Shrink}} = \hat{\delta}^* * F + \left(1 - \hat{\delta}^*\right) * S \qquad (14)$$

Where S is the sample covariance matrix and F is the constant correlation covariance matrix calculated as follows:

Given the sample correlations on assets i and j:

$$r_{ij} = \frac{s_{ij}}{\sqrt{s_{ii} s_{jj}}} \qquad (15)$$

And the average sample correlation:

$$\overline{\mathrm{r}} = \frac{2}{(\mathrm{N}-1)\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}-1} \sum_{\mathrm{j}=\mathrm{i}+1}^{\mathrm{N}} \mathrm{r}_{\mathrm{ij}} \qquad (16)$$

We define the sample constant correlation matrix F by means of the sample variances and the average sample correlation:

$$\mathrm{f}_{\mathrm{ii}} = \mathrm{s}_{\mathrm{ii}} \quad \textit{and} \quad \mathrm{f}_{\mathrm{ij}} = \overline{\mathrm{r}} * \sqrt{\mathrm{s}_{\mathrm{ii}} \mathrm{s}_{\mathrm{jj}}} \qquad (17)$$

Endnotes

1. See http://investments.yale.edu.
2. There is no attempt to allocate funds dynamically and funds are selected through due diligence in order to reduce extreme risks due to operational issues (e.g. fraud, bankruptcy), rather than for their hypothetical future potential returns. As a result, both management and incentive fees tend to be significantly lower for investable hedge fund indices than for FoHF. (Gehin & Vaissié, 2004).
3. We do not use the trackers, but the main indices series.
4. We do not report either the descriptive statistics or the correlation matrix due to the large number of assets involved. (We can provide them to interested readers.)

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Philip Boigner is Vice President of TIG Ecosystem at the Dubai Silicon Oasis Authority. He has over 10 years of experience in the investments industry. His resumé includes assignments at a German buy-out fund, an Australian Venture Capital company, a Dubai-based Alternative Investments Fund-of-Funds, and a Swiss alternative assets advisory firm among others. Mr Boigner has a DBA from the University of Nice Sophia Antipolis and the International University of Monaco. He holds an MBA degree from the University of Southern California's Marshall School of Business in Los Angeles. His research concentrates on hedge fund return replication, asset allocation, and sovereign wealth funds.

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