MSCI

Research Insight

Harvesting Risk Premia with Strategy Indices

From Today's Alpha to Tomorrow's Beta

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1. Introduction

Portfolio returns were traditionally attributed to passive market exposure and active portfolio management. Any return in excess of the market return was considered added value from active management. More recently, many return components that were considered added value (alpha) are increasingly being recognized as risk premia (beta). Systematic risk premia such as value, size or momentum can account for a substantial part of long-term institutional portfolio performance (Ang, Goetzmann and Schaefer, 2009). Over the last few years, we have seen the development of many new indices that reflect systematic risk premia, opening up the possibility to capture risk premia through indexation.

Yet, the institutional asset allocation process continues to focus more heavily on the selection of active managers than the selection and combination of risk premia, despite growing evidence that risk premia contribute more to the long-term performance of the portfolio. In the traditional set-up, the asset owner manages strategy through strategic asset allocation and selection of managers. Alpha is defined broadly: bottom-up security selection, top-down systematic sources and timing. Risk control is principally discharged through asset allocation and manager diversification. The resulting typical organizational structure combines a large line-up of external active managers, often with associated high costs, with a small internal asset owner staff.

We argue that the focus of institutional asset allocation may shift from diversification across managers in multiple alpha mandates towards diversification across strategy betas in multiple index mandates. In this new framework, asset owners would more likely manage the portfolio through beta allocations, while alpha would likely be defined more narrowly by excluding systematic sources, and risk control would principally be accomplished by managing exposures to risk factors. In this environment, active mandates would likely co-exist with beta mandates producing lower overall costs. The resulting typical organizational structure would likely involve a larger internal asset owner investment staff directly managing more assets through beta allocation with a smaller line-up of external active managers.

Our review of the characteristics of various risk premia strategies such as value weighted, risk weighted, equal weighted and minimum volatility over the period 1988 to 2011 reveals that during this period these strategies generated positive active returns (in the case of risk-based strategies, with lower volatility), and hence generally higher Sharpe ratio than the market. Cyclicality in active returns exists though, with periods of underperformance that can last several years. This leads us to believe that a well thought through combination of risk premia could potentially outperform an allocation to a single strategy. Diversifying across strategies may also help to carry the portfolio through the sometimes long periods of underperformance that may occur for any single strategy. The combination of value-based strategies which tend to be riskier in times of crisis with risk-based strategies that experience lower volatility looks particularly interesting. The approach that aims to achieve diversification benefits by combining risk premia is also well suited to combinations of active mandates and risk premia. Our analysis shows that substituting traditional active mandates with risk premia strategies has historically reduced volatility and enhanced the risk-adjusted performance of a sample institutional portfolio.

The remainder of the paper is organized as follows. In section 2, we analyze the performance and characteristics of a broad range of strategy indices. In section 3, we discuss possible explanations behind the historical performance of strategy indices and assess the implications of increasing institutional interest and portfolio allocations for the future performance of risk premia strategies. In section 4, we examine the role of strategy indices in asset allocation and propose a risk budgeting framework for integrating risk premia strategies into institutional portfolios. We summarize our findings and highlight areas for further research in section 5.

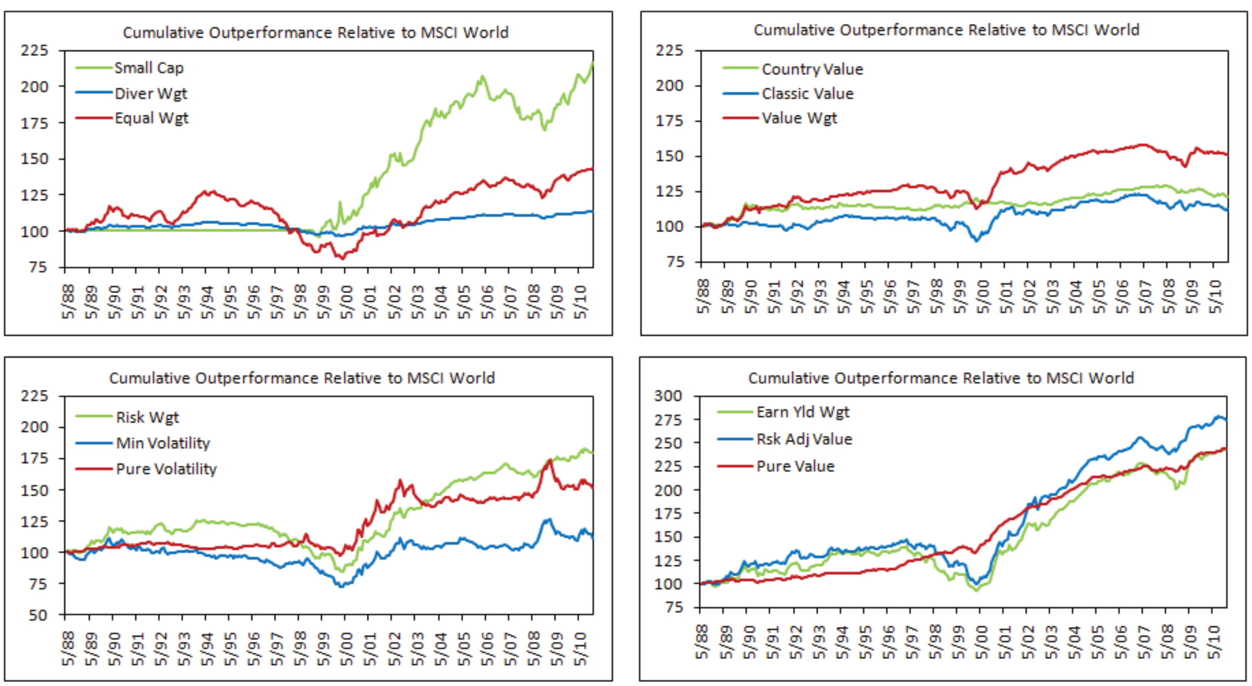
2. Historical Performance

Recently, several new indices have been developed that use alternative weighting schemes. These indices typically maintain long-only exposure to the equity market, therefore reflect the broad equity market performance, and introduce a tilt towards a particular factor to capture additional systematic risk premia or replicate simple investment strategies. We collectively refer to these new alternatively weighted indices as *risk premia strategy indices* or simply *strategy indices*.

Exhibit 1: Historical Performance and Characteristics of Risk Premia Strategies

Period of Analysis 31/05/88 - 31/12/10	MSCI World	Small Cap	Divers Wgt	Equal Wgt	Risk Wgt	Min Vol	Pure Vol	Cntry Value	Classic Value	Value Wgt	Yield Wgt	Rsk Adj Value	Pure Value
Annual Return ($, %)	7.14	10.9	7.74	8.87	9.95	7.64	9.11	8.06	7.70	9.13	11.5	12.0	11.5
Annual Volatility (%)	15.5	17.1	15.5	16.1	13.9	11.8	12.4	15.6	15.6	15.6	16.3	14.1	15.8
Sharpe Ratio	0.21	0.41	0.25	0.31	0.43	0.32	0.42	0.27	0.24	0.34	0.46	0.58	0.48
Active Return (%)	0.00	3.74	0.60	1.74	2.81	0.51	1.97	0.92	0.56	1.99	4.32	4.90	4.32
Tracking Error (%)	0.00	6.47	1.32	5.30	5.39	6.60	5.92	2.62	3.63	3.68	7.07	6.68	2.11
Information Ratio	NA	0.58	0.46	0.33	0.52	0.08	0.33	0.35	0.15	0.54	0.61	0.73	2.05
Annual Turnover (%)	3.93	18.2	8.14	23.4	24.6	20.0	60.0	6.64	21.0	18.6	37.2	35.5	60.0
Max Drawdown (%)	-53.7	-56.2	-54.2	-55.3	-50.9	-42.6	-43.2	-55.0	-56.3	-57.5	-56.7	-52.4	-53.4
Historical Beta	1.00	1.02	1.00	0.98	0.84	0.70	0.75	0.99	0.98	0.98	0.95	0.82	1.01
Japan Crash[1]	-24.1	-24.1	-23.1	-19.6	-18.2	-19.7	-23.6	-18.6	-22.9	-17.7	-16.9	-14.8	-24.7
Dot Com Crash[2]	-45.0	-24.3	-40.7	-28.9	-11.5	-16.4	-14.7	-46.4	-34.5	-32.2	-3.69	7.12	-24.4
Subprime Crisis[3]	-53.7	-56.1	-54.2	-55.3	-50.9	-42.6	-43.2	-55.0	-56.3	-57.5	-56.7	-52.4	-53.4

(1) Total return over 31 Dec 1989 – 30 Sep 1990 (2) Total return over 31 Mar 2000 – 31 Mar 2003 (3) Total return over 31 Oct 2007 – 28 Feb 2009



In this section we review the performance and characteristics of a broad range of strategy indices. Previous efforts to analyze strategy indices either focused exclusively on a particular strategy or used multiple sources of data to make comparisons across selected strategies[1]. Our analysis of risk premia strategies is unique in several important ways. First, we carry out analysis at the global level, while many prior studies focused mainly on US listed securities. Second, we use a consistent set of liquid, investable and widely held securities, namely the constituents of the MSCI World Index, as the starting universe across all the strategies we examine. Third, we use a single source of "as reported" fundamental data[2], ensuring that the results are free from "look-ahead bias" that may affect strategy simulations based on back-filled databases.

The common characteristic of most risk premia strategies is that they aim to achieve superior risk adjusted performance (Sharpe ratio) relative to the market, by either increasing return or by lowering risk. As a result, we can generally classify risk premia strategies in two broad categories reflecting the two primary ways of achieving superior risk adjusted performance: return-based strategies, which aim to increase return through factor tilts, and risk-based strategies, which aim to reduce risk through volatility and correlation tilts.

We review the following risk-based strategies: equal weights, diversity weights[3], risk weights, minimum variance and low volatility. We use the MSCI World Equal Weighted Index, MSCI World Risk Weighted Index and MSCI World Minimum Volatility Index[4] as proxies for equal weighted, risk weighted and minimum variance strategies while we construct diversity weighted portfolios as in Fernholz, Garvy and Hannon (1998)[5]. For illustrative purposes, we also report the performance of a "pure" low volatility strategy by combining the MSCI World Index (equity market return) and the Volatility factor from the Barra Global Equity Model (GEM2). In addition, as risk-based methods typically exhibit a small cap tilt, we show for comparison the performance of the MSCI World Small Cap Index.

With respect to return-based methods, we examine six strategies that target the value factor: value weighting, earnings yield weighting, risk adjusted value, classic value, country value, and pure value. We use the MSCI World Value Weighted Index as a proxy for value weighted strategies. The value weighted index uses fundamental weights such as book value, revenues and earnings that add a value tilt to a market cap index (Asness, 2006). We construct earnings yield weighted and risk adjusted value portfolios using expression 10 derived in Appendix 1. We proxy a pure value strategy by combining the MSCI World Index and the Value factor (value risk premium) from the Barra Global Equity Model (GEM2). Finally, we include two other familiar value-based strategies, namely, "country" value, proxied by the MSCI World GDP Weighted Index, and "classic" value, proxied by the MSCI World Value Index which contains low valuation stocks weighted by market capitalization.

Equal weighted and diversity weighted strategies enhanced return but failed to reduce volatility over the observed period (see Exhibit 1). On the other hand, the simple risk weighted approach that uses the inverse of historical variance to weight stocks and the minimum volatility approach that exploits both variances and covariances to minimize risk were able to reduce realized volatility over the period of

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[1] For example, see Chow, Hsu, Kalesnik, and Little (2011).

[2] The analysis is based on MSCI fundamental data. MSCI began publishing fundamental data for developed market companies in 1969 and for emerging market companies in 1988. MSCI has accumulated a large volume of historical fundamental data during this period. An important feature of the MSCI fundamental data is that they are recorded in the database "as reported". This feature ensures that the database is free from "look-ahead bias".

[3] We classify diversity weighted portfolios together with other risk-based methods in the empirical analysis section as this method reduces concentration risk by interpolating between a market cap weighted and an equally weighted portfolio.

[4] Details regarding the construction methodology of the MSCI Indices we use as proxies for various risk and return-based strategies can be found on www.msci.com.

[5] We set parameter p to the value of 0.76 to construct diversity weighted portfolios, as in Fernholz (1998).

analysis. In addition, both strategies exhibited low beta characteristics and offered downside protection during periods of market turmoil such as the dot com crash of 2000-2003 and the subprime crisis of 2007-2009. The pure volatility strategy that combines a long position in the MSCI World Index and a short position in the Volatility factor from the Barra GEM2 model showed remarkably similar performance and characteristics as the long-only minimum volatility strategy.

With respect to value-based strategies (Exhibit 1), the value weighted index outperformed the MSCI World Index by capturing the value factor premium over the observed period. Performance improved dramatically when the value tilt achieved through value weighting was complemented with a small cap tilt in the earnings yield weighted strategy. Performance improved further when the value and small cap tilts in the earnings yield weighted strategy were combined with a low volatility adjustment in the risk adjusted value strategy. The simple long-only risk adjusted value strategy outperformed the more complicated long-short pure value portfolio by achieving a higher Sharpe ratio and was the only value-based method that experienced lower realized volatility compared to the MSCI World Index.

Exhibit 2: Average Active Country, Sector and Factor Exposure of Risk Premia Strategies

Average Active Exposure 31/05/95 - 31/12/10	Divers Wgt	Equal Wgt	Risk Wgt	Min Vol	Pure Vol	Classic Value	Value Wgt	Yield Wgt	Rsk Adj Value	Pure Value
Active Factor Exposure	Risk Based Strategies					Value Based Strategies				
Growth	0.00	-0.02	-0.11	-0.19	0.00	-0.30	-0.14	-0.07	-0.17	0.00
Leverage	0.04	0.11	0.13	0.03	0.00	0.26	0.19	0.18	0.17	0.00
Liquidity	0.05	0.12	-0.04	-0.23	0.00	-0.11	0.00	0.11	-0.03	0.00
Moment	-0.02	-0.12	-0.09	0.01	0.00	-0.07	-0.14	-0.19	-0.07	0.00
Size	-0.21	-0.92	-0.81	-0.25	0.00	0.02	-0.12	-0.98	-0.86	0.00
Size Non Linearity	0.15	0.61	0.56	0.20	0.00	-0.02	0.08	0.60	0.57	0.00
Value	0.01	0.07	0.14	0.02	0.00	0.39	0.27	0.47	0.38	1.00
Volatility	0.01	0.03	-0.36	-0.73	-1.00	-0.03	0.00	-0.02	-0.38	0.00
Active Country Exposure	Risk Based Strategies					Value Based Strategies				
Europe ex UK	1.3	5.6	5.5	-3.4	0.0	-0.1	2.7	9.4	9.1	0.0
Japan	2.1	8.9	6.2	2.8	0.0	0.1	1.8	1.0	-1.8	0.0
Pacific ex Japan	1.1	6.2	6.9	2.5	0.0	0.0	0.4	7.6	8.7	0.0
United Kingdom	-0.4	-2.0	-1.4	-2.3	0.0	0.0	1.3	0.5	0.3	0.0
USA & Canada	-4.1	-18.6	-17.2	0.3	0.0	-0.1	-6.2	-18.6	-16.4	0.0
Active Sector Exposure	Risk Based Strategies					Value Based Strategies				
Consumer Discretionary	1.4	5.0	2.3	-0.9	0.0	-1.6	1.2	4.1	1.5	0.0
Consumer Staples	-0.3	-1.1	2.2	5.0	0.0	-3.8	-1.4	-1.5	1.2	0.0
Energy	-1.2	-3.3	-3.5	-1.7	0.0	3.0	0.7	-2.8	-3.2	0.0
Financials	-0.1	-3.3	-1.2	-4.2	0.0	12.5	4.7	-0.3	1.4	0.0
Healthcare	-1.3	-4.4	-4.0	3.8	0.0	-5.6	-4.0	-5.5	-5.6	0.0
Industrials	1.6	8.0	6.3	-0.6	0.0	-0.1	0.7	8.3	5.6	0.0
Information Technology	-1.1	-3.3	-7.3	-4.8	0.0	-7.5	-4.8	-6.1	-8.5	0.0
Materials	1.3	5.1	3.7	-1.4	0.0	-0.6	1.0	5.5	4.3	0.0
Telecommunications	-0.8	-3.3	-3.1	-0.2	0.0	1.4	0.3	-3.5	-3.2	0.0
Utilities	0.6	0.6	4.6	5.0	0.0	2.3	1.5	1.8	6.4	0.0

Note: the average active factor exposure statistics reported in this table are based on the eight style risk factors of the latest Barra Global Equity Risk Model (GEM2)

Exhibit 2 shows average exposure to countries, sectors and style factors, relative to the MSCI World Index. This analysis highlights differences in the profile of the various strategies with respect to these important performance drivers. The diversity weighted index has small but significant negative size exposure (bias towards smaller companies), while the equal weighted index has substantial negative exposure to size. The negative size tilt is preserved in risk weighted and minimum volatility strategies. In addition these strategies exhibit significant negative exposure to the volatility factor (bias towards lower volatility companies). This negative exposure is smaller in the risk weighted index and becomes larger in the minimum volatility and pure low volatility strategy, which by construction maintains fixed unit exposure to the Volatility factor. With respect to countries, diversity weighted, equal weighted and risk weighted strategies are underweight in USA and Canada, while the minimum volatility index generally has moderate active country weights due to the active country constraints used in the optimization. In terms of sector weights, most risk-based strategies are overweight in Consumer Goods, Industrials and Utilities, while they are underweight in Energy, Financials and Information Technology.

As expected, all value-based strategies in Exhibit 2 have positive exposure to the Value factor. In addition to maintaining positive exposure to the Value factor, the value weighted index also has small negative exposure to size while the earnings yield weighted and risk adjusted earnings yield weighted strategies have significant negative exposure to size. The risk adjusted earnings yield weighted strategy also has substantial negative exposure to the Volatility factor. In terms of country weights, similar to risk-based methods, all return-based methods (except pure value) exhibit varying degrees of underweight in USA and Canada. With respect to sector exposure, value-based strategies are generally underweight in defensive growth sectors (for example, Health Care) and in cyclical growth sectors (for example, Information Technology), while they are generally overweight in Industrials and Materials.

3. Theoretical Foundations and Possible Future Application

Despite the growing popularity of strategy indices, little effort has gone into understanding their construction methodology and their investment applications by examining them through a robust analytical framework[6]. In this section, we examine strategy indices through the lens of the mean-variance portfolio construction framework. We see that risk premia strategies, when viewed as special cases of mean-variance portfolio construction, aim to achieve higher Sharpe ratio by addressing the two primary investment objectives: return enhancement, achieved through factor tilts (return-based strategies) and risk reduction, achieved through volatility and correlation tilts (risk-based strategies).

Risk-based strategies such as minimum variance, risk weighting, equal weighting, equal risk contribution and maximum diversification can be derived from the mean-variance framework. We can derive the minimum variance portfolio by setting expected returns equal to an arbitrary constant. The risk-weighted portfolio is obtained from the minimum variance portfolio by assuming constant correlations across stocks. Finally, we can derive the equally weighted portfolio from the risk-weighted portfolio by assuming all stocks have the same volatility. Interestingly, the maximum diversification portfolio (Choueifaty and Coignard, 2008) can be derived from the mean-variance solution by substituting returns with volatilities, and the equal risk contribution portfolio (Maillard, Roncalli, and Teiletche, 2010) by solving the minimum variance problem with an additional non-linear constraint.

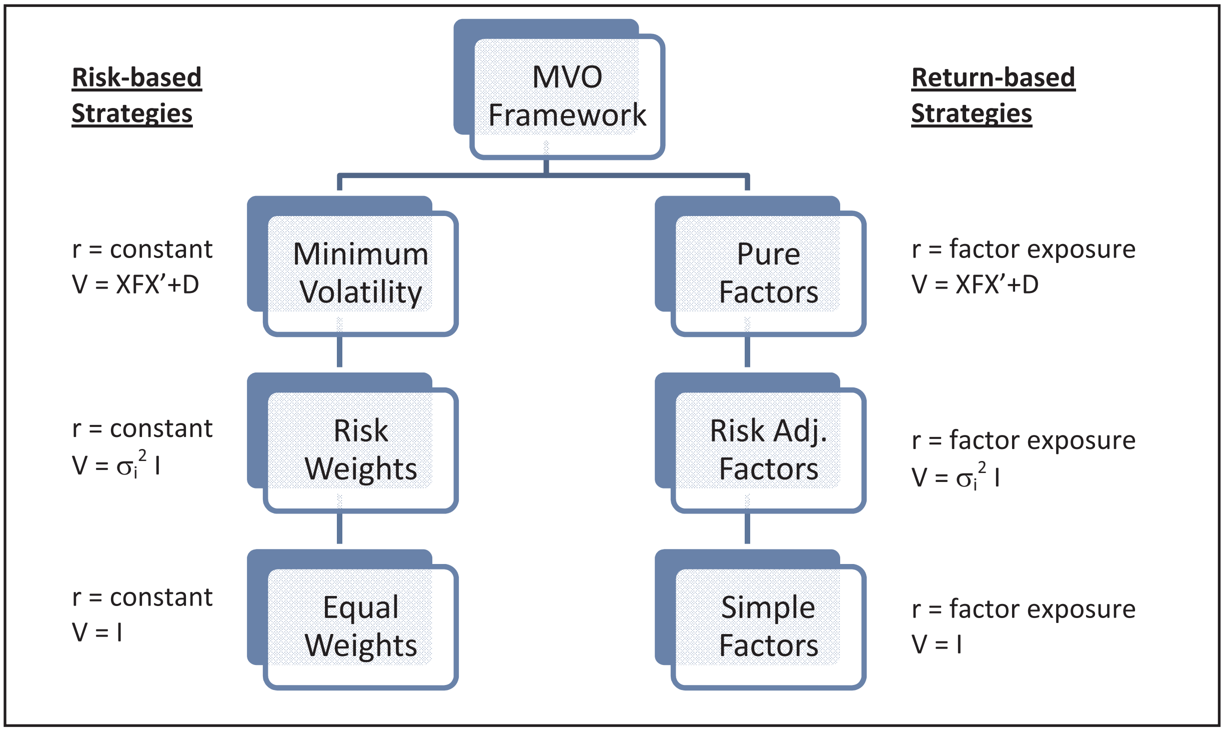
Many familiar return-based heuristics can also be embedded into the classical mean-variance framework. For example, many active managers forecast returns using industry and company analysis and then weight the portfolio in proportion to the expected return of each asset. We can proxy this approach by simply setting the covariance matrix equal to the identity matrix in the mean-variance solution. In fact, this simple approach of ignoring volatilities and correlations and weighting assets in proportion to expected return can also describe many alternative index methodologies. For example, we can derive the weights of fundamental indices (Arnott, Hsu and Moore, 2005) from the mean-variance

[6] See Appendix 1 for full analytical derivations.

solution by setting the covariance matrix equal to the identity matrix, substituting returns with the book value of each asset and setting risk aversion equal to the total book value of all assets.

In general, by ignoring the covariance matrix and setting returns equal to asset exposures to a risk factor, we can construct simple factor portfolios that proxy the returns to any systematic factor. These simple factor portfolios provide a first approximation to the underlying factors as they focus exclusively on expected return (factor exposure) and ignore volatilities and correlations. An incrementally more sophisticated approach for constructing factor tilted portfolios is to take into account both returns and volatilities and weight assets according to their expected return to volatility ratios (Sharpe ratios). We can derive the weights of these risk adjusted factor portfolios directly from the mean-variance solution by using a diagonal covariance matrix. Finally, we can use optimization to create pure factor portfolios which capture a target factor while eliminating exposure to other factors and minimizing specific risk. Melas, Suryanaryanan and Cavaglia (2010) investigated different approaches for constructing pure factor portfolios in practice and highlighted passive and active investment management applications of pure factor portfolios. Exhibit 3 shows schematically the links between different systematic risk-based and return-based strategies and their relationship with the general mean variance framework.

Exhibit 3: A Mean Variance Based Framework for Understanding Risk Premia Strategies



In the historical performance section, we observed that many risk premia strategies tend to have significant exposure to the Value, Size, and Volatility factors. In the remainder of this section, we discuss possible explanations behind the empirically observed performance patterns associated with these factors and the implications of increasing interest and allocations into risk premia strategies for the future performance of these factors.

Many studies have reported that value and small cap stocks have historically outperformed the market portfolio. A possible explanation is that these stocks have higher systematic risk and therefore portfolios that overweight them earn a risk premium in compensation for bearing higher systematic risk (Fama and French, 1993). An alternative explanation is that value and small cap stocks are mispriced and that portfolios that overweight these stocks earn higher return by exploiting this mispricing (Lakonishok, Schleifer and Vishny, 1994). A more recent hypothesis links the empirically observed value and size premia to momentum and reversal effects due to delegated portfolio management. According to this theory (Vayanos & Woolley, 2010), fund flows push prices away from fundamental value, resulting in subsequent reversal effects.

Several studies have reported evidence of a negative relationship between idiosyncratic volatility and subsequent returns (for example, Ang, Hodrick, Xing, and Zhang, 2006). The superior performance of low volatility stocks has been a puzzle and is yet another empirical critique of the CAPM (Blitz and Vliet, 2007). These studies report that the low volatility effect persists across regions and after adjusting for a range of other explanatory variables such as size, book-to-market, liquidity, leverage, different economic regimes and high and low volatility regimes. Explanations behind the low volatility effect focus on behavioral biases leading to excess demand for high volatility stocks, combined with limits on arbitrage (Baker, Bradley and Wurgler, 2011).

From a macro equilibrium perspective, as long as there are large groups of institutional investors that avoid cheap, small, or illiquid stocks, either due to perceived higher risk or due to behavioral biases (for example, institutional neglect, lack of coverage, focus on glamour stocks, etc.) institutional investors that are prepared to hold these stocks may continue to earn a long-term premium. However, as factor-based strategies become increasingly popular, institutional investors may over time begin to experience relatively lower factor returns in the future.

Exhibit 4: Long Term Annual Mean Returns of Various Barra Model Factors and MSCI Strategy Indices

Long Term Factor Return Over Different Horizons	30 Yrs to 12/2010	10 Yrs to 12/1990	10 Yrs to 12/2000	10 Yrs to 12/2010	5 Yrs to 12/1985	5 Yrs to 12/1990	5 Yrs to 12/1995	5 Yrs to 12/2000	5 Yrs to 12/2005	5 Yrs to 12/2010
Barra US Equity Model (USE3) Factors										
SIZE	-2.13%	-2.60%	-0.32%	-3.31%	-3.88%	-1.64%	-0.75%	0.11%	-3.77%	-2.85%
VALUE (EARNINGS YLD)	4.12%	5.22%	3.73%	3.34%	5.90%	4.66%	4.06%	3.41%	5.69%	0.98%
VOLATILITY	-0.27%	-3.72%	1.93%	0.90%	-2.46%	-4.84%	0.97%	2.88%	0.97%	0.84%
GROWTH	-0.93%	-1.57%	-0.90%	-0.31%	-1.04%	-2.10%	-0.11%	-1.70%	-0.84%	0.22%
LEVERAGE	-0.45%	-0.79%	0.27%	-0.89%	-0.94%	-0.51%	0.71%	-0.16%	0.71%	-2.49%
Barra UK Equity Model (UKE7) Factors										
SIZE	-2.13%	-3.16%	-0.92%	-2.29%	-1.64%	-4.67%	-0.85%	-1.02%	-3.45%	-1.12%
VALUE	3.27%	4.32%	2.51%	3.04%	3.67%	4.96%	2.49%	2.41%	4.94%	1.13%
VOLATILITY	-0.70%	0.14%	-0.54%	-2.12%	0.84%	-0.56%	-0.29%	0.05%	-2.78%	-1.47%
GROWTH	-1.17%	-1.58%	-1.29%	-0.88%	-1.22%	-1.95%	-2.89%	0.82%	-0.63%	-1.13%
LEVERAGE	-0.02%	0.70%	-0.24%	-0.54%	0.98%	0.43%	-0.26%	-0.21%	1.12%	-2.20%
MSCI Strategy Indices										
Risk Weighted Index	2.44%	3.68%	-1.35%	5.37%	3.30%	3.27%	0.77%	-3.47%	8.50%	2.25%
Value Weighted Index	1.46%	1.36%	1.35%	1.76%	2.18%	0.34%	2.04%	0.65%	3.33%	0.20%

The table presents annual average factor returns for the Barra factors and annual average outperformance for the MSCI Strategy Indices
We analyzed USE3 and UKE7 factor returns as these are the two Barra models with factor return history extending back to the late 1970s
Full details of the estimation process of the Barra models and the index construction process of MSCI indices can be found on msci.com

One way to assess the potential impact of increasing allocations to risk premia strategies would be to examine factor returns over different historical periods and try to detect trends suggesting diminishing factor premia over time. Exhibit 4 presents Barra factor returns and MSCI Strategy Indices outperformance over different 5 and 10 year periods during the last 30 years. Even though the value, size and low volatility effects were reported extensively in the literature in the early 1980s (for example, Banz, 1981, for the size effect, Basu, 1983, or even Graham & Dodd, 1934, for the value effect) looking at distinct 5 and 10 year periods during the last 30 years we see little evidence of diminishing size, value or low volatility effects. In addition, the data in Exhibit 4 shows that factors have time varying risk premia and certain factors had negative returns over the entire 30 year period, for example the Growth and Leverage factors. Systematically tilting an equity portfolio towards any random fundamental factor cannot automatically guarantee long-term outperformance over the market portfolio!

As allocations to risk premia strategies represent active decisions relative to the market cap benchmark, it is interesting to contrast the new approach with more traditional passive strategies. Broad-based cap weighted indices represent objectively the entire investment opportunity set by reflecting the aggregate holdings of all market participants. In the absence of active views, broad- based cap weighted indices are seen by most institutional investors as the natural starting point for asset allocation (policy benchmarks) and the appropriate reference point for performance analysis (performance benchmarks). Despite empirical critiques against the Capital Asset Pricing Model (CAPM), broad-based cap weighted indices will continue to play a central role in the institutional investment process as they offer unique theoretical and practical advantages, including automatic rebalancing, low turnover, low transaction costs, easy implementation, low maintenance, high trading liquidity, high investment capacity and macro consistency (Siegel, 2003).

The issue of macro consistency is particularly important for assessing the future role of strategy indices in institutional portfolios. Risk premia strategies cannot fully substitute broad-based cap weighted allocations in all institutional portfolios as they lack macro consistency. An index or a portfolio is macro consistent if it can be held by all institutional investors without disturbing market prices. This is a unique property of free-float market capitalization weighted indices. If all institutional investors tried to hold the same strategy index, this index would experience diminishing active returns relative to the market and would eventually become market cap weighted.

The interplay of investor flows and factor premia is complex particularly when viewed over time. While the idea that increasing popularity will over time diminish subsequent returns is widely appreciated, there are phasing issues at work. Generally, increased capital flows going into a popular strategy produce tailwind to the strategy's performance over the medium term, prior to any reversal at some future date.

The generalized framework to analyze this interaction is set out in the reflexivity concept popularized by Soros (2008). The phasing can often be seen in a sequence starting with new investor beliefs that impact investor behaviors and flows which then affect investment conditions producing further feedback and iterations. So institutional investors' observation of capital markets and strategy opportunities (the cognitive function) and participation in the capital markets (the manipulative function) influence both valuations and fundamental conditions and outcomes. This feedback loop in the process explains the 'reflexive' description used by Soros. The reflexivity concept is generally supportive to invoking early mover advantages to attain cycles of strong performance so institutional investors should judge which factor premia might be in this phase. It also warns of the dangers of using empirical results alone to support future performance assumptions, given that the pricing of factor premia cannot be considered to be in equilibrium for long enough for these assumptions to be robust. That is why allocations to risk premia strategies will require a higher share of the governance budget of the asset owner to be dedicated to the selection and the monitoring of these strategies.

4. Asset Allocation

In this section we discuss a risk budgeting framework for determining the appropriate allocation to risk premia strategies. We take the hypothetical example of an institutional portfolio that uses a core passive mandate tracking the MSCI ACWI Index, a global equity index consisting of developed and emerging market countries, in order to capture the broad equity market beta as well as three satellite active mandates to generate active returns. For the sake of this analysis, we assume a sample allocation of 40% to the core passive ACWI mandate, 20% allocation to a low active risk mandate (for example, a quant or enhanced index fund), 20% allocation to a medium active risk mandate (for example, a fundamental active fund) and 20% allocation to a high active risk mandate (for example, an absolute return fund, thematic fund or hedge fund).

Exhibit 5: Historical Performance of Sample Active Mandates and Selected Risk Premia Strategies

Historical Performance of Individual Strategies	MSCI ACWI Index	Low Active Risk Mandate	Medium Active Risk Mandate	High Active Risk Mandate	Value Weighted Strategy	Risk Weighted Strategy	Minimum Volatility Strategy
Panel A: 5 Years to 31 Dec 2005							
Annual Return ($, %)	3.41	3.09	8.41	14.4	7.22	14.2	7.25
Annual Volatility (%)	14.9	14.8	16.5	17.6	15.3	13.0	10.5
Sharpe Ratio	0.10	0.08	0.40	0.71	0.35	0.96	0.51
Active Return (%)	0.00	-0.32	5.00	11.0	3.82	10.8	3.84
Tracking Error (%)	0.00	1.05	6.31	9.76	2.63	5.93	7.11
Information Ratio	NA	-0.31	0.79	1.12	1.45	1.83	0.54
Return in 2001	-15.9	-15.7	-10.7	-17.0	-9.76	-7.33	-7.73
Return in 2002	-19.0	-18.8	-16.3	-9.9	-16.7	-3.50	-11.4
Return in 2003	34.6	33.7	43.0	52.3	41.5	48.2	29.9
Return in 2004	15.8	15.6	16.0	46.4	18.9	27.4	21.8
Return in 2005	11.4	10.0	20.8	17.4	12.0	15.3	9.77
Panel B: 5 Years to 31 Dec 2010							
Annual Return ($, %)	3.98	3.88	3.74	6.62	3.99	8.27	6.38
Annual Volatility (%)	20.1	19.2	20.7	23.6	21.9	19.8	13.4
Sharpe Ratio	0.11	0.11	0.09	0.20	0.10	0.32	0.34
Active Return (%)	0.00	-0.10	-0.24	2.65	0.01	4.29	2.40
Tracking Error (%)	0.00	1.69	5.91	8.09	3.15	3.17	8.06
Information Ratio	NA	-0.06	-0.04	0.33	0.00	1.35	0.30
Return in 2006	21.5	20.6	26.8	31.1	24.2	27.4	24.5
Return in 2007	12.2	8.17	20.7	15.9	9.61	11.8	7.61
Return in 2008	-41.8	-38.6	-44.8	-50.4	-43.3	-38.8	-25.1
Return in 2009	35.4	32.4	27.4	53.7	39.9	43.2	18.0
Return in 2010	13.2	14.1	11.7	18.9	12.7	19.3	15.0

We proxy the performance of these three active mandates using data from the eVestment Alliance database. First, we classify global mandates in the database into three groups according to their active risk: low active risk group represented by the bottom quartile, medium active risk group represented by the second and third quartile, and high active risk group represented by the top quartile. Then from each of the three active risk groups we select the fund with median performance over the 10 years to December 2010. The performance of these sample active mandates along with three risk premia strategies is shown in Exhibit 5.

Exhibit 6: Sample Allocation to Risk Premia Strategies Funded from Passive and Active Mandates

Historical Performance of Sample Asset Allocations	Initial Portfolio	Allocation to Risk Premia Funded from Active Mandates			Allocation to Risk Premia Funded from Passive Mandates			Allocation to Risk Premia Funded from Both Mandates		
		Eq Wgt	Risk Wgt	Perf Wgt	Eq Wgt	Risk Wgt	Perf Wgt	Eq Wgt	Risk Wgt	Perf Wgt
Panel A: Average Weights - Updated Annually, Based on Trailing 5 Year Performance Data										
MSCI ACWI Passive	40.0	40.0	40.0	40.0	0.0	0.0	0.0	0.0	0.0	0.0
Low Act Rsk Mandate	20.0	10.0	10.3	4.7	16.7	17.2	7.9	0.0	0.0	0.0
Med Act Rsk Mandate	20.0	10.0	8.7	9.1	16.7	14.5	15.2	0.0	0.0	0.0
High Act Rsk Mandate	20.0	10.0	7.9	12.6	16.7	13.2	20.9	0.0	0.0	0.0
Value Weighted Strategy	0.00	10.0	9.4	6.4	16.7	15.7	10.6	33.3	28.4	19.5
Risk Weighted Strategy	0.00	10.0	10.2	14.2	16.7	17.0	23.7	33.3	30.9	42.2
Min Volatility Strategy	0.00	10.0	13.4	13.0	16.7	22.4	21.7	33.3	40.7	38.3
Panel B: Subsequent Performance - Based on Data Over 5 Years to 31 Dec 2010										
Annual Return ($, %)	4.53	4.96	4.96	4.97	5.62	5.61	5.62	6.30	6.27	5.68
Annual Volatility (%)	20.4	19.6	19.3	19.3	19.3	18.8	18.8	18.2	17.6	17.2
Sharpe Ratio	0.13	0.16	0.16	0.16	0.19	0.20	0.20	0.24	0.25	0.22
Sharpe Ratio % Gain	0.00	21.0	22.6	23.3	48.5	52.0	52.6	86.5	91.1	69.7
Active Return (%)	0.55	0.98	0.98	0.99	1.64	1.63	1.64	2.32	2.29	1.70
Tracking Error (%)	2.00	1.20	1.28	1.69	2.00	2.13	2.82	2.98	3.47	3.94
Information Ratio	0.27	0.82	0.76	0.59	0.82	0.76	0.58	0.78	0.66	0.43
Information Ratio % Gain	0.00	200.0	179.7	114.5	199.4	178.9	113.0	185.3	141.1	58.3
Total Return in 2006	24.3	24.1	23.9	24.8	25.8	25.6	27.0	25.4	25.4	25.9
Total Return in 2007	13.8	12.2	11.9	12.4	12.3	11.8	12.5	9.7	9.6	9.9
Total Return in 2008	-43.5	-41.0	-40.3	-41.0	-40.5	-39.3	-40.5	-36.1	-35.1	-35.8
Total Return in 2009	36.7	35.5	34.4	34.3	35.5	33.7	33.5	33.4	31.4	27.6
Total Return in 2010	14.2	14.5	14.5	14.8	15.4	15.3	15.9	15.8	15.7	16.4
Active Return in 2006	2.76	2.53	2.42	3.24	4.24	4.06	5.44	3.84	3.84	4.35
Active Return in 2007	1.63	0.06	-0.25	0.19	0.09	-0.43	0.31	-2.50	-2.61	-2.25
Active Return in 2008	-1.70	0.82	1.53	0.80	1.37	2.56	1.33	5.75	6.70	6.01
Active Return in 2009	1.34	0.08	-1.03	-1.13	0.12	-1.73	-1.92	-1.97	-3.99	-7.84
Active Return in 2010	1.03	1.30	1.26	1.63	2.16	2.09	2.70	2.54	2.53	3.18

We maintain the initial passive allocation of 40% to the MSCI ACWI Index and introduce risk premia strategies to the portfolio by reducing the allocation to active mandates. Specifically, we examine three different portfolio allocations: equal allocation, equal risk allocation, and risk-adjusted performance (Sharpe ratio) allocation. The equal allocation has 10% weight in each of the three active mandates and in each of the three risk premia strategies. The equal risk allocation uses the inverse of historical volatility to determine the weights of active strategies. Ignoring correlations, this approach is equivalent to constructing a risk parity, or equal risk contribution portfolio (Ruban and Melas, 2011). Finally, the risk-adjusted performance allocation uses risk-adjusted performance (Sharpe ratio) to determine the weights of the active strategies. To ensure that the results are not affected by in-sample bias, we update asset allocation weights annually, based on the risk and performance of the various strategies over trailing 5-year periods, and we compute subsequent portfolio performance over the 5-year period to

December 31, 2010. The sample portfolio allocations before and after the introduction of risk premia strategies are presented in Exhibit 6.

Exhibit 6 shows that during the observed period introducing risk premia strategies to a sample institutional portfolio by reducing the allocation to active mandates enhanced the risk-adjusted performance of the portfolio. Based on the sample allocations analyzed, the improvement in risk-adjusted performance (Sharpe ratio) ranged between 21.0%, for the equal allocation, to 23.3% for the performance allocation. Another approach would be to fund an allocation to risk premia strategies by reducing or completely eliminating the passive mandate from the portfolio. This analysis is also presented in Exhibit 6. Based on the sample allocations analyzed, the historical improvement in risk adjusted performance ranged between 48.5%, for the equal allocation, to 52.6% for the performance allocation. Finally, we examined the case of eliminating both passive and active mandates from the portfolio and replacing them with risk premia strategies. In this case, the gain in risk adjusted performance ranged between 69.7%, for the performance allocation, to 91.1% for the risk allocation.

It is worth highlighting that from a total risk perspective, all sample allocations analyzed in Exhibit 6 led to a reduction in total portfolio volatility. The risk-weighted allocations in particular resulted in significant risk reduction across all three funding methods. The diversification benefits were also very apparent when looking at performance in times of crisis such as the subprime crisis of 2008 where the positive relative performance of risk-based strategies compensated for the under-performance of higher beta strategies (active and passive).

The decision of whether to fund an allocation to risk premia strategies by reducing allocations to active or passive mandates could be driven by active risk budgeting considerations. A broad cap weighted index such as the MSCI ACWI Index that reflects the entire standard equity investment opportunity set in an objective and transparent manner is the most natural starting point for asset allocation (policy benchmark) as well as the reference point for performance analysis (performance benchmark). Maintaining a passive allocation to ACWI helps to reduce the overall active risk of the portfolio: based on the sample allocations in Exhibit 6, this approach resulted in total portfolio active risk ranging between 1.2% to 2.0%. On the other hand, eliminating completely the core passive allocation and using the proceeds to increase exposure to active mandates and strategy indices lead to portfolio active risk ranging between 2.0 to 3.9%.While the second approach may result in superior long-term performance, it also entails significantly higher levels of active risk.

The choice of allocation strategy (equal weights, equal risk, risk-adjusted performance) depends on the investment beliefs and capabilities of a particular institutional investor. An investor that does not have views on the risk and performance of different strategies could allocate equally across a range of strategies to reduce concentration risk. An investor who can forecast the risk of different strategies but has no views on future performance could use equal risk allocation to ensure that different strategies contribute equally to the risk of the portfolio. Finally, an investor that has views on both the risk and the performance of different strategies could tilt the portfolio towards strategies with expected superior risk-adjusted performance.

The shift in the institutional asset allocation process from diversification across managers in multiple alpha mandates towards diversification across strategy betas in multiple index mandates has important implications for the evaluation and selection of strategy indices. As these indices will increasingly be viewed as potential substitutes for active mandates they are likely to be scrutinized in a similar manner. Important due diligence topics underpinning the evaluation of strategy indices include: Are the investment beliefs behind the strategy index methodology based on sound economic and financial rationale? Is the risk premium or behavioral anomaly likely to persist in the future? Is the methodology robust and consistent in capturing the risk premium? Is the methodology transparent and does it address investability issues? Can the index be replicated cost effectively (moderate turnover and fees)? Are the various facets of risk addressed properly? Are there model dependency, operational and production risks? How robust is the governance framework? Is there an independent index rebalancing and calculation agent? Addressing these due diligence questions underpinning strategy index evaluation and selection is likely to become increasingly important for institutional investors.

5. Concluding Remarks

We analyzed the historical performance and characteristics of a range of strategy indices using a unique and consistent data set. In addition to the broad equity market return, value-based indices such as a fundamental index capture the value effect. Risk-based indices such as a risk weighted index reflect the small cap and low volatility effects. Combining value-based and risk-based strategies can lead to improved risk adjusted performance. Our analysis shows that historically the performance of value-based indices such as a fundamental index could be enhanced significantly when combined with simple risk adjustments.

Gaining a deeper understanding of the relationship between different strategy indices could have significant implications for new index development and institutional portfolio management. We described an analytical framework for understanding the links between many new risk premia strategies. This framework shows that many strategy indices are special cases of mean-variance portfolio construction, subject to various assumptions for expected risk and return. Embedding strategy indices into the mean-variance framework provides a solid theoretical foundation and demonstrates that these indices are not arbitrary portfolio proxies. In addition, this framework leads to an intuitive classification of strategy indices into risk-based and return-based variants and offers a roadmap for future strategy index development.

We discussed possible explanations behind the historical performance of strategy indices and the possible implications of increasing allocations into risk premia strategies for the future performance of these indices. Even though the value, size and volatility effects were reported extensively in the finance literature in the early 1980s we found little evidence of diminishing factor returns in the subsequent 30 years. From an equilibrium perspective, as long as there are large numbers of institutional investors that avoid stocks with certain characteristics either due to perceived higher risk or due to behavioral biases (for example, institutional neglect, lack of coverage, focus on glamour stocks, etc.), institutional investors that are prepared to hold these stocks may continue to earn a long-term premium. Growing popularity and increasing allocations into risk premia strategies may remain powerful tailwinds for the performance of these strategies for the foreseeable future. However, as these strategies start to attract increasing amounts of capital they may start to reflect diminishing factor premia over time.

Finally, we examined the role of strategy indices in asset allocation and discussed a risk budgeting framework for integrating risk premia into institutional portfolios. Allocations to risk premia are predicated upon the investment beliefs and research capabilities of specific institutional investors and could be based on the expected risk and performance characteristics of different strategies. Our analysis shows that substituting traditional mandates with risk premia strategies has historically reduced volatility and enhanced long-term risk adjusted performance of a sample institutional portfolio.

Increasing adoption of risk-based asset allocation, growing realization of the potential impact of systematic risk factors on long-term portfolio performance and the need to capture these factors through transparent and cost effective vehicles are likely to continue to drive research, innovation and new product development in the indexing arena, both within equities and across asset classes[7]. In addition to expanding the lineup of asset allocation tools, future research efforts are also likely to focus on the application of these new tools in portfolio construction and risk management. We highlighted important transformations currently affecting the institutional asset allocation process that could have far-reaching implications. The increasing realization that systematic factors are key drivers of long-term portfolio performance could lead to a redefinition of active management and provide further justification and motivation for the adoption of risk-based asset allocation. Adoption of risk-based asset allocation could lead to increasing use of global policy benchmarks and growing demand for new strategy indices to serve the needs of the new asset allocation risk groupings. Indexation can play a crucial role in redefining risk-based portfolio construction by providing low cost easily accessible building blocks for strategic and tactical asset allocation.

Appendix 1: embedding alternative beta strategies into the mean-variance framework

The standard mean-variance problem for a fully funded portfolio can be expressed as follows[8]:

$$\max_h \left\{ h' r - \frac{1}{2} \lambda h' V h \right\} \quad s.t. \quad h' e = 1 \tag{1}$$

The solution can be computed analytically (appendix 2) and is given by the following expression:

$$h^* = \frac{1}{\lambda} V^{-1} \left(r - \frac{e' V^{-1} r - \lambda}{e' V^{-1} e} e \right) \tag{2}$$

We can derive the maximum diversification portfolio (Choueifaty and Coignard, 2008) from the solution to the mean-variance problem by substituting returns with volatilities in equation 2:

$$h^* = \frac{1}{\lambda} V^{-1} \left(\sigma - \frac{e' V^{-1} \sigma - \lambda}{e' V^{-1} e} e \right) \tag{3}$$

We can derive the minimum variance portfolio from the solution to the mean-variance problem by setting expected returns in equation 2 equal to an arbitrary constant:

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[7] See Bender, Briand, Nielsen, and Stefek (2010) for examples of portfolio construction using multi asset class risk premia strategies.

[8] In this equation, *n*-vectors *h* and *r* denote portfolio weights and expected returns, *V* is the asset by asset covariance matrix, λ is the risk aversion coefficient and *e* represents a vector of ones.

$$h_{MV}^{*} = \frac{1}{e'V^{-1}e}V^{-1}e \qquad (4)$$

We can derive the risk weighted portfolio from the last expression by simply assuming constant correlations across all stocks. Using a diagonal covariance matrix, the last expression becomes:

$$h_{RW,i}^{*} = \frac{\frac{1}{\sigma_i^2}}{\sum_{i=1}^{n}\frac{1}{\sigma_i^2}} \qquad (5)$$

Finally, we can derive the equally weighted portfolio by assuming that all assets have the same variance, in other words, by setting variances in the last expression equal to an arbitrary constant:

$$h_{EW,i}^{*} = \frac{1}{n} \qquad (6)$$

Many familiar return-based heuristics can also be embedded into the classical mean-variance framework. For example, many active managers weight the portfolio in proportion to the expected return of each asset. We can proxy this active management approach by replacing the covariance matrix with the identity matrix in the mean-variance solution given by equation 2:

$$h_{FM,i}^{*} = \frac{1}{\lambda}(r_i - \bar{r}_i) + \frac{1}{n} \qquad (7)$$

In fact, this simple approach of ignoring volatilities and correlations and weighting assets in proportion to expected return can also describe many alternative index methodologies. For example, we can derive the weights of fundamental indices (Arnott, Hsu and Moore, 2005) from equation 2 by setting the covariance matrix equal to the identity matrix, substituting returns with the book value of each asset and setting risk aversion equal to the total book value of all assets:

$$h_{FW,i}^{*} = \frac{B_i}{\sum_{i=1}^{n} B_i} \qquad (8)$$

Likewise, we can derive the diversity weighted index (Fernholz, Garvy, and Hannon, 1998) from the mean-variance solution (equation 2) by replacing return with the p-power capitalization of each asset and setting risk aversion equal to the total p-power capitalization of all assets, where p is a constant between zero and one:

$$h_{DW,i}^{*} = \frac{M_i^p}{\sum_{i=1}^{n} M_i^p} \tag{9}$$

In general, by ignoring the covariance matrix and setting returns equal to asset exposures to a risk factor, we can construct simple factor portfolios that proxy the returns to any systematic factor. These simple factor portfolios provide a first approximation to the underlying factors as they focus exclusively on expected return (factor exposure) and ignore volatilities and correlations. An incrementally more sophisticated approach for constructing factor tilted portfolios is to take into account both returns and volatilities and weight assets according to their expected return to volatility ratios (Sharpe ratios). We can derive the weights of these risk adjusted factor portfolios directly from the mean-variance solution (equation 2), by using a diagonal covariance matrix[9]:

$$h_{RA,i}^{*} = \frac{\frac{r_i}{\sigma_i^2}}{\sum_{i=1}^{n} \frac{r_i}{\sigma_i^2}} \tag{10}$$

Finally, pure factor portfolios can be computed from a multivariate cross sectional regression of asset returns against factor exposures or as solutions to a constrained optimization problem. Melas, Suryanaryanan and Cavaglia (2010) specify the pure factor portfolio construction problem as follows. Given a factor model, we would like to construct portfolios that have maximum exposure to a target factor, zero exposure to all other factors, and minimum portfolio risk:

$$\max_h \left\{ h' X_\alpha - \frac{1}{2}\lambda h' V h \right\} \quad s.t. \quad h' X_\sigma = 0 \tag{11}$$

Here, X_α and X_σ represent exposures to the target factor and to all other factors. This optimization problem can be solved analytically. The optimal weights are given by the following expression:

$$h_{PF}^{*} = \frac{1}{\lambda} V^{-1} \left[X_\alpha - X_\sigma \left(X_\sigma ' V^{-1} X_\sigma \right)^{-1} \left(X_\sigma ' V^{-1} X_\alpha \right) \right] \tag{12}$$

[9] We set the risk aversion coefficient to the average Sharpe ratio multiplied by the number of assets.

Appendix 2: solving the mean variance optimization problem using Lagrange multipliers

The Lagrangian corresponding to the optimization problem defined by equation (1) is:

$$h'r - \frac{1}{2}\lambda h'Vh - \mu\left(h'e - 1\right) \qquad (13)$$

By computing the partial derivative with respect to vector h and setting it equal to zero we have:

$$h^* = \frac{1}{\lambda}V^{-1}(r - \mu e) \qquad (14)$$

By substituting the last expression into the constraint of the optimization problem we have:

$$e'\frac{1}{\lambda}V^{-1}(r - \mu e) = 1 \qquad (15)$$

By solving the last equation for the Lagrange multiplier μ we obtain the following expression:

$$\mu = \frac{e'V^{-1}r - \lambda}{e'V^{-1}e} \qquad (16)$$

Finally, by substituting μ into equation (A.2) we obtain the solution of the optimization problem:

$$h^* = \frac{1}{\lambda}V^{-1}(r - \frac{e'V^{-1}r - \lambda}{e'V^{-1}e}e) \qquad (17)$$

In certain applications it is more appropriate to consider an unfunded portfolio where the investor starts with zero initial endowment. In this case, portfolio weights in equation 2 would sum to zero. The solution of the unfunded mean variance problem is given by the following expression:

$$h^* = \frac{1}{\lambda}V^{-1}(r - \frac{e'V^{-1}r}{e'V^{-1}e}e) \qquad (18)$$

Finally, the simplest version of the mean variance portfolio optimization problem ignores the budget constraint completely. In this case optimal weights are given by the following expression:

$$h^* = \frac{1}{\lambda} V^{-1} r \tag{19}$$

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