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Risk Factors as Building Blocks for Portfolio Diversification: The Chemistry of Asset Allocation

Asset classes can be broken down into factors that explain risk, return, and correlation characteristics better than traditional approaches. Because seemingly diverse asset classes may have high correlations as a result of overlapping risk factor exposures, factor analysis can improve portfolio diversification. Creating risk factor–based portfolios is theoretically possible, but practically challenging. Nevertheless, factor-based methodologies can be used to enhance portfolio construction and management.

SUMMARY

- Asset classes can be broken down into building blocks, or factors, that explain the majority of the assets' risk and return characteristics. A factor-based investment approach enables the investor theoretically to remix the factors into portfolios that are better diversified and more efficient than traditional portfolios.

- Seemingly diverse asset classes can have unexpectedly high correlations—a result of the significant overlap in their underlying common risk factor exposures. These high correlations caused many portfolios to exhibit poor diversification in the recent market downturn, and investors can use risk factors to view their portfolios and assess risk.

- Although constructing *ex ante* optimized portfolios using risk factor inputs is possible, there are significant challenges to overcome, including the need for active, frequent rebalancing; creation of forward-looking assumptions; and the use of derivatives and short positions. However, key elements of factor-based methodologies can be integrated in multiple ways into traditional asset allocation structures to enhance portfolio construction, illuminate sources of risk, and inform manager structure.

INTRODUCTION

In search of higher returns at current risk levels, institutional investors have expressed intense interest in further diversifying seemingly staid, "traditional" asset allocations constructed using asset class inputs with mean–variance-optimization (MVO) tools. During the past decade, institutional investors have augmented public fixed income and equity allocations with a wide range of strategies—including full and partial long/ short, risk-parity, and low-volatility strategies—and have enlarged allocations to alternative strategies. However, comparatively little has been accomplished at the overall policy level; for most investors, asset classes remain the primary portfolio building blocks.

In this article, I explore portfolio construction by using risk factors, also referred to as "risk premia," as the basic elements. Theoretically, this approach may result in lower correlations between various portfolio components and may lead to more efficient and diversified allocations than traditional methods. However, the practical limitations of policy portfolios constructed with risk factors are significant enough that few investors are embracing full-scale implementation. Yet, much of the intuition of risk factor portfolios can be used to refine and augment traditional allocations and offers a holistic and succinct manner to diversify portfolio risk.

WHY LOOK AT RISK FACTORS?

Recent periods of market stress and dislocation have created considerable interest in credible alternatives to MVO asset allocation methodologies. A multitude of alternative approaches question the quality of the inputs rather than the tools, such as optimizers, that assist in generating asset allocations. From an attribution perspective, many vendors of risk analytics systems use factors to provide a clearer perspective on common exposures across an entire portfolio, rather than simply reporting on siloed asset classes measured with incompatible tools. Practitioners seek inputs that capture essential trade-offs, with logical relationships among components that result in reasonable portfolios. This spawns an interest in a risk factor approach.

Many traditional asset class and sub-asset-class correlations have trended upward over the past decade. These correlations rose to uncomfortable levels during the 2008–09 crisis, driving a desire to find a way to construct portfolios with lower correlations between the various components. High correlations caused many investors to question basic assumptions about traditional models. Seemingly disparate asset classes moved in lockstep during the depths of the crisis, and the distinction in returns between U.S. equity and non-U.S. equity, for instance, was largely immaterial. Because many asset classes, such as equity, fixed income and real estate, have become increasingly correlated, some investors have sought out less correlated, alternative investments, such as hedge funds, commodities, and infrastructure.

Ideally, investors could create portfolios using many components with independent risks that are individually rewarded by the market for their level of risk. Asset classes could be broken down into building blocks, or factors, that explain the majority of their return and risk characteristics. These asset classes would provide an indirect way to invest in factors, but it is also possible to invest in some factors directly. The advantage to a factor-based approach is that factors can, theoretically, be remixed into portfolios that are better diversified and more efficient than traditional methods allow.

Prior to fully defining factors and explaining how they are derived, I review some of the basic tenets of asset class–based portfolio construction, including tools and required inputs, in order to understand how a risk factor–based approach diverges from the traditional asset class approach. The use of risk factors is the next step in the evolution of the policy portfolio.

## THE BASICS OF PORTFOLIO OPTIMIZATION

What Is an Asset Class? Asset classes are bundles of risk exposures divided into categories—such as equities, bonds (or debt), and real assets—based on their financial characteristics (e.g., asset owner versus lender). **Exhibit 1** depicts the asset classes of equity and debt and their sub- and sub-sub-asset classes. Ideally, asset classes are as independent as possible, with little overlap and, in aggregate, cover the investment universe with minimal gaps. In this construct, a myriad of common factor exposures drives the correlations between asset classes. There are important distinctions between asset classes and sub-asset classes. The more granular the difference between various asset classes, the higher the resulting correlations. Typical asset allocation relies heavily on sub-asset classes (e.g., large-cap and small-cap U.S. equity). There are very few actual archetypal asset classes— global equity, global fixed income, cash, and real assets.

Modern Portfolio Theory and the Efficient Frontier In 1952, Markowitz and other contributors created a framework for constructing portfolios of securities by quantitatively considering each investment in the context of a portfolio rather than in isolation. Modern portfolio theory's (MPT's) primary optimization inputs include:

- $E(r)$ for expected return

- $E(\sigma)$ for expected standard deviation, a proxy for risk

- $E(\rho)$ for expected correlations between assets

One of the key insights of MPT is that correlations less than 100% lead to diversification benefits, which are considered the only free lunch in finance. Sharpe (1963,

Exhibit 1. **Examples of Asset Classes and Sub-Asset Classes**
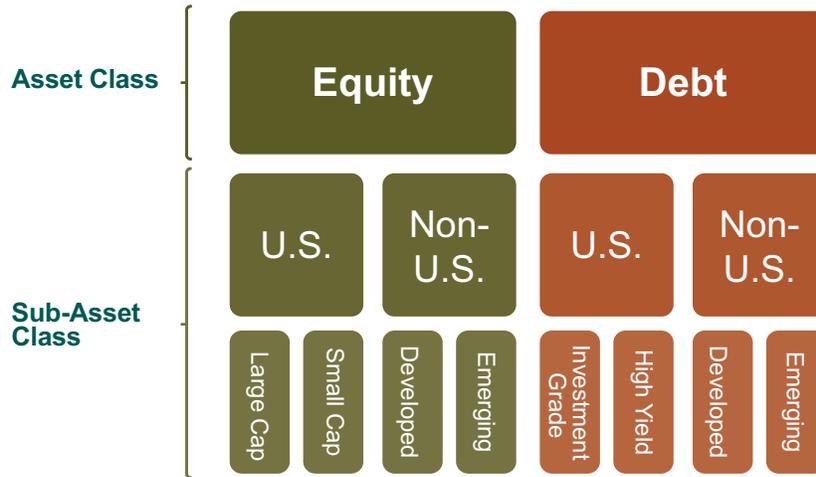
1964) and others extended and simplified MPT by compressing security characteristics into asset class groupings for which a single market factor (beta) serves as a proxy for a multitude of security-level characteristics.

The objective of MVO, as informed by MPT and the resulting capital asset pricing model (CAPM), is to generate mean–variance-efficient portfolios via quadratic optimization, represented by the efficient frontier. Portfolios are classified as efficient if they provide the greatest expected return for a given level of expected risk. This type of optimization and the efficient portfolios it generates rely heavily on the quality of the inputs. Robust forward-looking capital market forecasts are the basis of this model when asset classes are the inputs.

Arbitrage pricing theory (APT) extends the CAPM by allowing for multiple factors instead of only one beta factor as a proxy for the market. It states:

The expected return
of a given asset

The weight
of factor **1**

Where α = 0

$$E(r_j) = r_f + b_{j1}RP_1 + b_{j2}RP_2 + b_{j3}RP_3 + \ldots + b_{jn}RP_n + \alpha$$

The risk-free rate

The return on
risk factor **1**

Put simply, this means the expected return of a given asset is equal to the risk-free rate plus risk factor return

#1 times the weight of factor #1, summed for multiple factors. An example of a mean–variance-efficient frontier is provided in **Exhibit 2**.

The efficient frontier's length is composed of mean–variance-efficient portfolios. Portfolios below the frontier are termed "inefficient" because they are dominated by those on the frontier, and those above the frontier are unattainable within the parameters of the model. The signature nonlinear curve of the frontier is caused by imperfect (less than 100%) correlations between asset classes. The optimizer seeks to maximize these diversification benefits. The sample portfolio in Exhibit 2 has an expected annual geometric return of 6% and an expected annual standard deviation of 11%. There is not a more efficient portfolio at this level of expected risk, nor a less risky portfolio at this level of return.

Next, I identify and classify various factors and explore how they can be used to build portfolios.

Diversification in Name Only? MPT, APT, the CAPM, and MVO approaches are flexible enough to work with a variety of inputs. But most institutional market participants have embraced asset class characteristics as the basic unit of interest. Portfolios that appear to have diversified exposure to the major components of equity and fixed income, as well as the full range of possible substyles, may nonetheless suffer from surprisingly high levels of internal correlation within each block. This is the manifestation of diversification in name only.

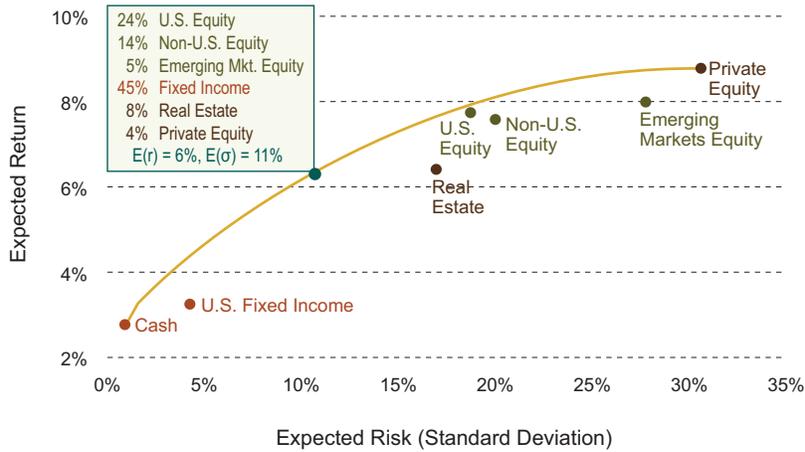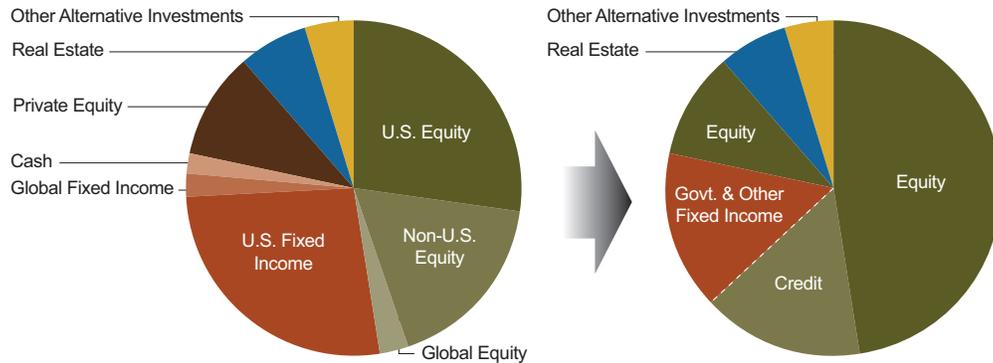Exhibit 2.   Traditional Asset Class Efficient Frontier

Exhibit 2. Traditional Asset Class Efficient Frontier

Legend:
24% U.S. Equity
14% Non-U.S. Equity
5% Emerging Mkt. Equity
45% Fixed Income
8% Real Estate
4% Private Equity
E(r) = 6%, E(σ) = 11%

Y-axis: Expected Return (2% to 10%)
X-axis: Expected Risk (Standard Deviation) (0% to 35%)

Data points: Cash, U.S. Fixed Income, Real Estate, U.S. Equity, Non-U.S. Equity, Emerging Markets Equity, Private Equity

Exhibit 3.   Average Large Plan Allocation

Exhibit 3. Average Large Plan Allocation

Left pie chart labels: Other Alternative Investments, Real Estate, Private Equity, Cash, Global Fixed Income, U.S. Fixed Income, Non-U.S. Equity, Global Equity, U.S. Equity

Right pie chart labels: Other Alternative Investments, Real Estate, Equity, Govt. & Other Fixed Income, Credit, Equity

To understand the limitations of the traditional MVO inputs (asset classes) and resulting efficient frontier portfolios, consider a typical institutional portfolio as represented by the 2012 Pensions & Investments average of the Top 200 defined-benefit plan allocations, shown in the left pie chart of **Exhibit 3**. Many of the multicolor pie slices are highly correlated with one another. The chart on the right aggregates the exposures into more basic asset classes. Equity-like exposures in one hue and credit exposures in another reveal a less diverse mix.

The credit component of fixed income can be thought of as "equity light"; by definition, it features a positive correlation with equities (this is somewhat tempered by government and other, noncredit fixed income sectors). Many traditionally constructed portfolios are dominated by allocations to equity and equity-like assets and thus are prominently exposed to equity risk. Even though the asset classes in the left pie chart appear diverse, their exposures are not as different as would initially seem.

Correlations between portfolio components—asset classes in this case—can be high because many of the asset classes are exposed to similar risks which, in combination, drive the majority of returns of each asset class. For example, as depicted in **Exhibit 4**, U.S. equity and U.S. corporate bonds share some common risk exposures, such as currency, volatility, and inflation risk. The significant overlap in factor exposures is the primary driver of unexpectedly high correlations between seemingly diverse asset classes. Thus, decomposing the portfolio into factor exposures broadens our understanding of the relationships between asset classes.

Exhibit 4.   Common Factor Exposure across Asset Classes

U.S. Equity

U.S. Corporate Bonds

Exhibit 5.   Illustrative Sampling of Factor and Potential Groupings

Macroeconomic	Regional	Dev. Econ. Grth.	Fixed Income	Other
GDP Growth	Sovereign Exposure	Size	Duration	Liquidity
Productivity	Currency	Value	Convexity	Leverage
Real Interest Rates	Emerging Markets *(Institutions + Transparency)*	Momentum	Credit Spread	Real Estate
Inflation			Default Risk	Commodities
Volatility			Capital Structure	Private Markets

WORKING WITH FACTORS

Factors come in a nearly infinite number of flavors. **Exhibit 5** presents an illustrative sampling of factors, grouping them by type of exposure among various categories. (These sample factors could be grouped in a myriad of ways, depending on the investor's needs.) Note that macroeconomic factors are applicable to most asset classes, whereas equity and fixed income factors deconstruct characteristics within those two broad asset classes. The "Developed Economic Growth" factor

folds together global developed GDP growth, productivity, liquidity, together with other characteristics. Other types of factors include liquidity, leverage, and private markets, for which marketable proxies are challenging to find. It is possible to reconstitute an asset class from these building blocks. Cash would be the combination of real interest rates and inflation. Core bonds would add some of the elements under the "fixed income" heading. Investors can gain exposure to factors via investable proxies, although some factors are easier to access than others.

Factor Exposures Gaining exposure to factors is rather challenging—which is one reason they are seldom applied in institutional portfolios. Ironically, even though risk factors are the basic building blocks of investments, there is no "natural" way to invest in many of them directly. For instance, much debate revolves around obtaining exposure to GDP growth. Although many studies explore the existence of a link between equity market returns and GDP growth, consensus is lacking. Establishing exposures to some other factors is simpler. Many factors necessitate derivatives and/or long/short positions in order to capture a spread. For instance, exposure to inflation can be constructed by using a long nominal U.S. Treasuries position and short TIPS (Treasury

Inflation-Protected Securities) position. Other examples of how to capture specific factor exposures are

- **Inflation:** Long a nominal Treasuries index, short a TIPS index

- **Real interest rates:** Long a TIPS index

- **Volatility:** Long the VIX Futures Index

- **Value:** Long a developed country equity value index, short a developed country equity growth index

- **Size:** Long a developed country equity small-cap index, short a developed country equity large-cap index

- **Credit spread:** Long a U.S. high-quality credit index, short a U.S. Treasury/government index

- **Duration:** Long a Treasury 20+ year index, short a Treasury 1–3 year index

Deriving Factor Characteristics: Return, Risk and Correlation Practical considerations and shortcomings become apparent as soon as we cross from theory to actual construction of factor-based portfolios. As mentioned, it is difficult, if not impossible, to gain exposure to some factors, and we cannot yet model all of the granular factors presented in Exhibit 5 because effective investable proxies are lacking. Thus, to create a portfolio constructed on

Exhibit 6.	Historical Risk and Return for Selected Factors (periods ending 31 December 2011)							
Factor Exposure	**Long/Short Position**	**5 Year**		**10 Year**		**15 Year**	
		Return	**Risk**	**Return**	**Risk**	**Return**	**Risk**
Dev. Econ. Grth.	MSCI World	-2.37%	20.47%	3.62%	16.96%	4.20%	16.69%
Value	MSCI World Value / MSCI World Growth	-3.84%	6.39%	0.38%	5.87%	0.28%	8.36%
Size	MSCI World Small Cap / MSCI World Large Cap	2.43%	6.82%	5.19%	7.27%	3.35%	9.08%
EM	MSCI Emerging Markets / MSCI World	6.55%	13.56%	11.17%	11.97%	3.76%	15.04%
HY Spread	Barclays HY / Barclays Int Credit (IG)	1.46%	11.58%	2.97%	9.58%	0.66%	8.88%
Default	Barclays Aaa / Barclays BBB	1.79%	6.81%	1.32%	5.13%	0.54%	4.34%
Duration	Barclays 20+ Yr Treasuries / 1-3 Yr Treasuries	7.27%	15.51%	5.86%	12.88%	4.50%	11.34%
Real Rates	Barclays TIPS	7.95%	7.41%	7.57%	6.85%	7.16%	5.86%
Inflation	Barclays Treasuries / Barclays TIPS	-1.43%	6.74%	-1.98%	5.21%	-1.02%	4.64%
Volatility	CBOE VIX	15.15%	82.23%	-0.17%	68.46%	0.75%	67.06%

Source: MSCI, Barclays, CBOE, and Callan.
Risk is defined as annualized standard deviation.

the basis of risk factors, I selected 10 factors with investable proxies, which are shown in **Exhibit 6** together with data for their long-term returns and standard deviations. I introduced a "developed economic growth" factor represented by long exposure to the MSCI World Index. Other equity-related factors include spreads to value and size (both of which are Fama–French style factors[1]) and emerging markets (which could also be classified in a regional bucket). The fixed income universe offers a more granular menu of investable factors, including high-yield spread, default, and duration. From the macroeconomic arena come real rates, inflation, and volatility.

Exhibit 7 provides the correlations between these factors for 5-, 10- and 15-year periods ending December 31, 2011. These factor characteristics are based on 60, 120, and 180 monthly observations of long and

Exhibit 7. Factor Correlations for 5-, 10-, and 15-Year Periods (periods ending 31 December 2011)

10 YEAR (upper triangle) / 5 YEAR (lower triangle)

	Dev Econ Growth	Value	Size	EM	High-Yield Spread	Default	Duration	Real Rates	Inflation	Volatility
Dev Econ Grth	1.00	0.23	0.30	0.39	0.71	0.56	-0.27	0.12	-0.45	-0.69
Value	0.12	1.00	0.02	-0.16	0.12	0.02	0.12	-0.11	0.18	-0.06
Size	0.44	-0.04	1.00	0.37	0.40	0.38	-0.09	0.14	-0.32	-0.25
EM	0.44	-0.37	0.32	1.00	0.34	0.35	-0.11	0.22	-0.38	-0.29
HY Spread	0.74	-0.02	0.56	0.40	1.00	0.77	-0.45	-0.01	-0.51	-0.49
Default	0.58	-0.10	0.52	0.44	0.81	1.00	-0.32	0.22	-0.61	-0.40
Duration	-0.27	0.20	-0.24	-0.17	-0.47	-0.41	1.00	0.50	0.17	0.20
Real Rates	0.31	-0.19	0.11	0.30	0.22	0.31	0.31	1.00	-0.69	-0.04
Inflation	-0.55	0.35	-0.38	-0.46	-0.67	-0.68	0.30	-0.75	1.00	0.31
Volatility	-0.71	0.03	-0.32	-0.27	-0.51	-0.42	0.21	-0.16	0.37	1.00

15 YEAR

	Dev Econ Growth	Value	Size	EM	High-Yield Spread	Default	Duration	Real Rates	Inflation	Volatility
Dev Econ Grth	1.00									
Value	-0.06	1.00								
Size	0.04	0.09	1.00							
EM	0.33	-0.06	0.36	1.00						
HY Spread	0.64	0.02	0.30	0.38	1.00					
Default	0.48	0.00	0.31	0.33	0.73	1.00				
Duration	-0.22	0.04	-0.06	-0.15	-0.40	-0.33	1.00			
Real Rates	0.07	-0.02	0.09	0.12	-0.03	0.18	0.50	1.00		
Inflation	-0.35	0.03	-0.22	-0.34	-0.48	-0.59	0.23	-0.63	1.00	
Volatility	-0.68	0.08	-0.12	-0.31	-0.47	-0.37	0.20	0.00	0.28	1.00

Legend (5 10 15):
- Correlation < -0.30
- Correlation between -0.30 and 0.30
- Correlation between 0.30 and 0.60
- Correlation > 0.60

Source: MSCI, Barclays, CBOE, and Callan.
EM = emerging markets.

short positions (except for developed country economic growth, real interest rates, and volatility, which can be accessed via long-only instruments or derivatives).

The expectation is that the building blocks individually will produce modest returns. Exhibit 6 shows that factor returns (or premiums) are fairly low; most have returned less than 5% over the past decade. Factor standard deviations range widely, from 4% to 82%.

Exhibit 6 illustrates how factor portfolios evolve. Factor returns and risks are extremely time sensitive. Changing the observation window can materially affect the observed risk and return relationships. For instance, the emerging markets spread returned an annualized 3.76% over 15 years, 11.17% over 10 years, and 6.55% over five years. Volatility, as its name suggests, has also proven erratic, with annualized returns ranging from −0.17% over 10 years to 15.15% over the past five years.

The correlation matrix in Exhibit 7 is shaded to show pair-wise relationships with various degrees of diversification benefits: dark tints for low correlations (less than −0.30), medium tints for factors that are close to uncorrelated (between −0.30 to +0.30), light tints for modestly correlated (between +0.30 and +0.60), and white for significantly correlated (above +0.60).

Correlations between factors are low, typically ranging from −0.50 to +0.60. Volatility and inflation demonstrate very low, often negative, correlations with most of the other factors. Somewhat highly correlated factors are developed economic growth with high-yield spread and high-yield spread with default. Sub-asset classes, such as U.S. small cap and U.S. large cap, are the most correlated, whereas relatively unrelated pairings, such as U.S. 1–3 year Treasuries and private equity, have low correlations.

The average correlation for the 10 factors in Exhibit 7 is +0.02. This figure is significantly less than many asset class correlations, which range from −0.15 to more than +0.90. If factors are properly specified and isolated, they generally have little correlation with each other because all of the systematic risk has been stripped out.

The correlation relationships exhibit greater stability over time than return and standard deviation do. Within the broad ranges described here, the fundamental economic relationships appear to hold over multiple time periods. The average correlations for these 10 factors for the three observation periods vary within a small range, from −0.0021 to +0.0092.

CONSTRUCTING FACTOR PORTFOLIOS

The 10 factors have been used to construct a simple equal-weighted portfolio with monthly rebalancing. **Exhibit 8** allows a comparison of this portfolio with a traditional portfolio consisting of 40% the Russell 3000 Index, 20% the MSCI All Country World Index (ACWI) ex USA, and 40% the Barclays US Aggregate Bond Index, all also rebalanced monthly. Fees and costs (including rebalancing costs) are ignored in this example.

Given the historical risk, return, and correlation inputs, we would expect the factor portfolio to have modest return and risk—in contrast to the traditional portfolio, where the majority of the risk budget is spent on equity-like assets.

In fact, Exhibit 8 shows that the simple factor portfolio features equity-like returns (between 5% and 7% annualized over multiple time periods) with considerably less volatility. The traditional portfolio produces broadly similar returns (between 2.5% and 6%) but with considerably greater risk.

When standard deviation is converted into variance (which is the term of interest for an optimizer), Exhibit 8 shows that the factor portfolio has 34 units of variance compared with the 119 units in the traditional portfolio over 15 years. The simple factor portfolio historically achieved a slightly higher level of return than the traditional portfolio while taking on about one quarter of the volatility. Interestingly, the two portfolios are only slightly uncorrelated (−0.29) with each other.

Examining the data for the trailing 10-year period in Exhibit 8, we see a similar relationship; both portfolios returned roughly 6% but at very different risk levels. The factor portfolio variance is one-quarter of the traditional portfolio's variance. During the more dramatic previous five-year period, the factor portfolio returned 6.74% (helped significantly by the high return of the volatility factor), once again at roughly one-quarter the volatility of the traditional portfolio.
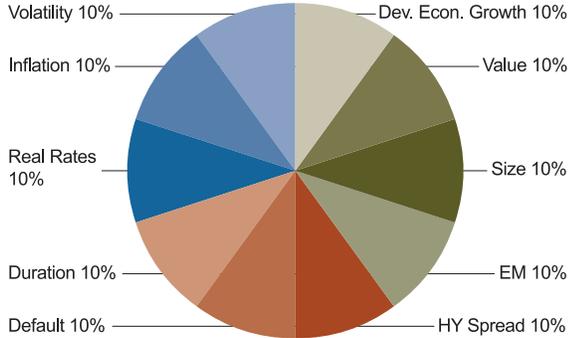
Factor characteristics appear to be time-period dependent; if different start or end dates were selected, both factor and traditional portfolios would have different risk and return characteristics. This simple exercise demonstrates,

Exhibit 8. Portfolio Comparison (periods ending 31 December 2011)

"Traditional" 60/40 Portfolio
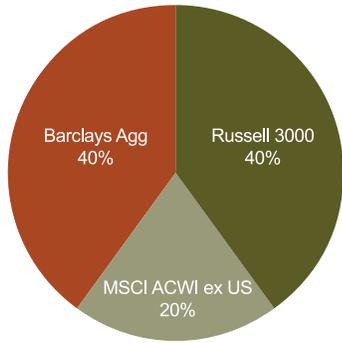
	5 Year	10 Year	15 Year
Historical Return:	2.52%	6.01%	5.98%
Historical Risk:			
Standard Dev. (σ)	13.75%	11.14%	10.90%
Variance (σ²)	189.18	124.06	118.83

Simple Factor Portfolio

	5 Year	10 Year	15 Year
Historical Return:	6.74%	5.97%	4.75%
Historical Risk:			
Standard Dev. (σ)	6.84%	5.79%	5.81%
Variance (σ²)	46.74	33.48	33.77

however, that a factor portfolio can be constructed that has fundamentally diverse characteristics from a traditional asset class portfolio—and has less volatility.

Several methods can be used to refine the simple equal-weighted portfolio. The preferred approach involves forecasting forward-looking, expected factor returns, which can be used in various optimization models. One of the hardest challenges in asset allocation is to forecast expected returns, however, and moving from asset classes to factors compounds this challenge because data may be difficult to obtain and interpret.

Another approach involves forecasting *ex ante* risk-to-return or Sharpe ratios for each factor and imputing expected returns based on a historical covariance matrix, which is assumed to have some explanatory power.

For the purposes of this study, I used historical, backward-looking inputs as detailed in Exhibits 6 and 7 in a forward-looking model, thus sacrificing predictive power for understandability. I also selected a portfolio from the factor efficient frontier with the same standard deviation as the simple factor portfolio for each time period. Using historical inputs rather than forecasted, forward-looking projections, the
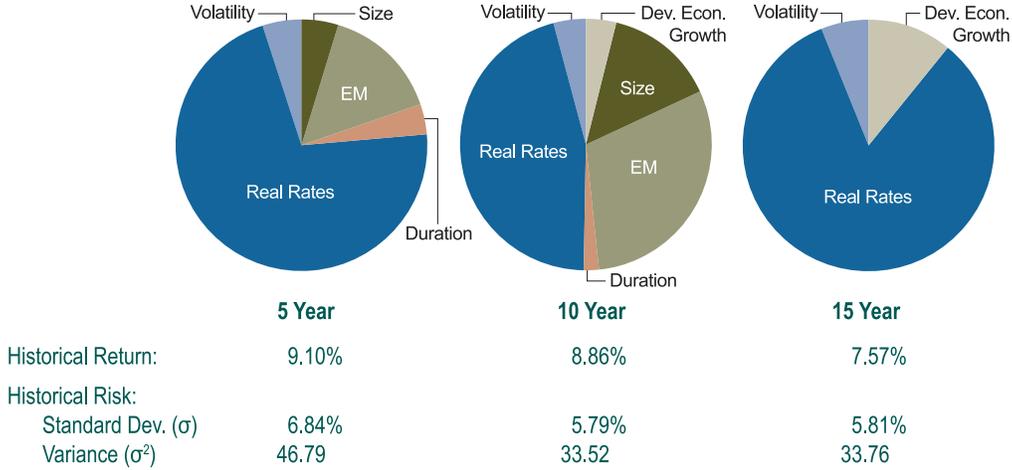
"optimized" portfolio, shown in **Exhibit 9** produces a "best fit" portfolio specifically tuned for the 5-, 10- and 15-year windows. This example illustrates that using traditional mean–variance tools is possible with factors but that high-quality forward-looking inputs are still necessary.

Comparison of Exhibit 8 and Exhibit 9 indicates that the optimized factor portfolio's historical return is considerably higher than that of the simple factor portfolio. When the 15-year history is used, only three of the ten factors have allocations in the new portfolio and most of the allocation is to real interest rates. When the 10-year history is used, six factors receive allocations, with the largest weights to real rates and emerging markets. For the shortest period, five factors have allocations, dominated by real rates. It is no coincidence that these particular factors, given their strong performance over the past 15 years, feature prominently in the optimized portfolio.

These optimized portfolios are useful in helping us understand the relative robustness of simpler approaches. For instance, over the 15-year horizon, the best-fit, optimized portfolio returned 7.57% whereas the simple

Exhibit 9. Optimized Factor Portfolio Comparisons (periods ending 31 December 2011)

"Optimized" Factor Portfolio

	5 Year	10 Year	15 Year
Historical Return:	9.10%	8.86%	7.57%
Historical Risk:			
Standard Dev. (σ)	6.84%	5.79%	5.81%
Variance (σ²)	46.79	33.52	33.76

equal-weighted portfolio returned 4.75%. The 2.82 percentage point return difference is achievable only, however, with extraordinarily prescient forecasting skills. Over 10 years, the difference is 2.89 percentage points, and over 5 years, 2.36 percentage points. The optimized portfolios clearly are a product of their times. We would expect similar best-fit results from using backward-looking returns over these periods also for optimizing asset classes and sub-asset classes. Fixed income rallied during the long decline in rates, and emerging markets surged during their bull market run.

CHALLENGES IN FACTOR-BASED PORTFOLIO CONSTRUCTION

Although the diversification benefits of factors is appealing in theory, the practical challenges are difficult to ignore. These challenges have prevented the widespread adoption of risk factor–based policy portfolios among asset owners. At the strategy (rather than policy) level, some asset managers have incorporated risk factor portfolio construction into hedge fund-type products, including hedge fund beta replication.

Some of the practical challenges of constructing portfolios with factors may be insurmountable. For one, no theoretical opportunity set encompasses all of the significant factors. With asset classes, we can rely on the concept of the complete market portfolio, even if some of the underlying components, such as residential housing and human capital, fall outside our modeling ability. Another issue is that many factors—even basics such as global GDP growth or momentum—have poor investable proxies.

Another challenge and area for further research is how to properly weight factors within a portfolio. Without a consensus on how to weight factors, many academic studies use equal weights—a naive but pragmatic assumption also adopted in this study.

Frequent and attentive rebalancing is necessary to maintain the desired factor exposures over time. Institutions wishing to pursue such asset allocations would need the resources for nearly continuous rebalancing (long and short), which is a far cry from standard quarterly or monthly rebalancing schedules. Additionally, a policy implemented through factors may have 20 or more exposures, each of which must be managed. Putting it all together, a policy described through factors resembles the global macro hedge fund style.

As previously demonstrated, we have the tools to construct factor portfolios, including using MVO. Forward-looking assumptions are hard to develop, however, because our example portfolios are best suited to historical data. While some factors, such as GDP growth,

real rates, and inflation, have a wide base of analysts and economists generating forecasts, most others do not.

A practical limitation of portfolios constructed with factors is that they must be implemented by using long and short exposures, often via derivatives. Synthetic instruments are, by definition, the price of admission in factor portfolio construction. Using synthetics, however, will be counter to some asset owners' guidelines that prohibit the use of derivatives at the policy level. Also, typical investment policies are crafted with long-only proxies for market exposures and are implemented accordingly. When using factors in a portfolio optimization model, however, the long-only constraint must be lifted. (Indeed, portfolios constructed with asset classes might produce different results from those explored here if short positions were allowed.)

PORTFOLIO APPLICATIONS

Given the challenges of constructing pure factor-based portfolios, we can take a step back and, instead, apply the insights gained from these approaches to more traditional portfolios assembled from asset classes. One hybrid approach is to examine asset classes through a factor lens during the policy portfolio construction process and group like asset classes together under various macroeconomic scenarios. By understanding how to group asset classes that behave similarly, we can implicitly understand the drivers of their correlations with one another.

Another method is to analyze the behavior of asset classes under various inflation and economic growth scenarios, as illustrated in **Exhibit 10**. Incorporating additional variables would generate an even more granular and robust model.

We can also examine the economic roles of various asset classes. By bucketing asset classes based on their response to macroeconomic scenarios, we can combine the transparency of investing through asset classes with the granularity of factor-based approaches. As shown in **Exhibit 11**, broad buckets might include

- **Growth assets**, such as equity-like instruments

- **Low-risk assets**, such as cash, government obligations, and investment-grade bonds

- **Strategies intended to benefit from skillful active management**, such as hedge funds and other absolute return investments

- **Real assets that support purchasing power**, such as real estate and TIPS.

Each bucket includes exposure to a number of factors but is organized thematically.

Asset classes are still the primary tool for most institutional portfolios, but the groupings illustrate many of the residual factor exposures. An example of such an approach can be found in **Exhibit 12**, where four broad buckets include exposure to multiple asset classes for a fictional corporate defined-benefit plan pursuing a

Exhibit 10.	Macroeconomic Scenarios

Inflation

Economic Growth

Low or Falling Growth High or Rising Inflation
Inflation linked bonds (TIPS)
Commodities
Infrastructure

High Growth High Inflation
Real assets: real estate, timberland, farmland, energy

Low Growth Low Inflation or Deflation
Cash
Government bonds

High Growth Low Inflation
Equity
Corporate debt

Exhibit 11.   Sample Groupings

CAPITAL ACCUMULATION
Grow assets through relatively high long-term returns
Global public equity
Private equity

ABSOLUTE RETURN
Earn returns between stocks and bonds while attempting to protect capital
Absolute return hedge funds

FLIGHT TO QUALITY
Protect capital in times of market uncertainty
U.S. fixed income
Cash equivalents

INFLATION LINKED
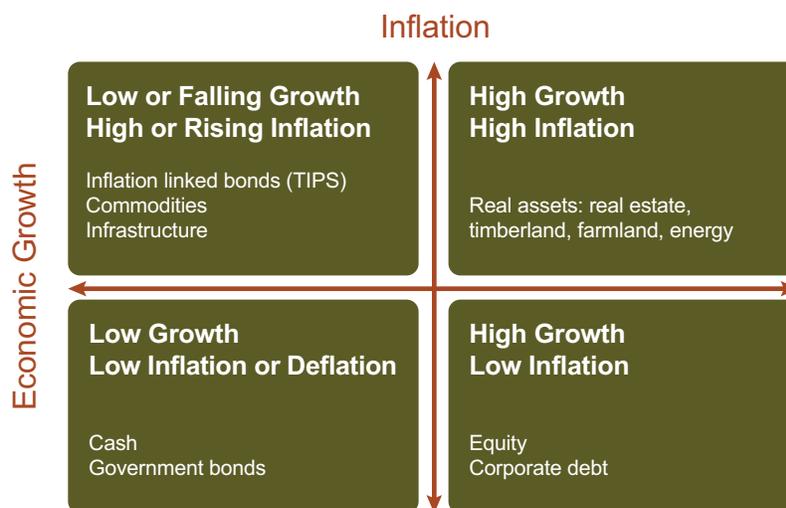*Support the purchasing power of assets*
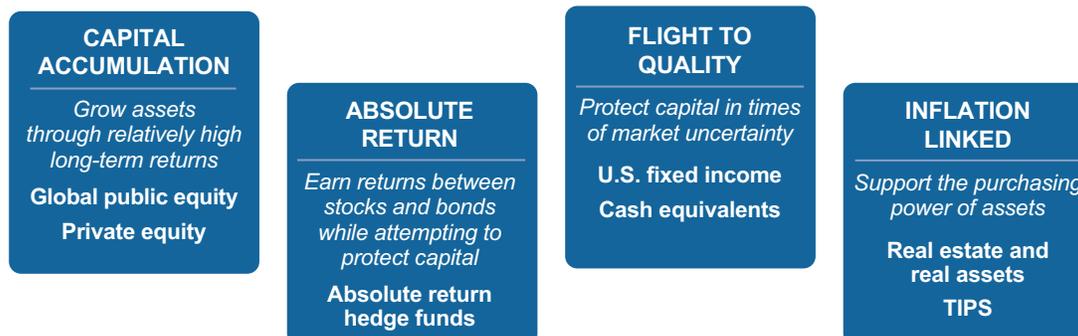**Real estate and real assets**
TIPS

Exhibit 12.   Asset Allocation through a New Lens: Sample of Defined-Benefit Plan Viewed with Risk Factors

Economic Role	Asset Class	Target	Economic Growth	Real Interest Rates	Inflation	Duration	Credit Spread	Private Markets	Leverage	Manager Skill
Liability Hedge		45%								
	U.S. Government Bonds (Long Dur.)	14%		✓	✓	✓				
	U.S. Credit (Long Dur.)	31%	✓	✓	✓	✓	✓			
Capital Preservation		5%								
	Cash	1%		✓						
	U.S. Government Bonds (Int. Dur.)	4%		✓	✓	✓				
Capital Growth		35%								
	Global Public Equity	25%	✓							
	Global Private Equity	6%	✓					✓	✓	✓
	Hedge Funds	4%								✓
Real Assets		15%								
	U.S. Private Real Estate	7%	✓	✓	✓				✓	✓
	Commodities	4%	✓		✓					✓
	Global Inflation-Linked Bonds	4%		✓		✓				

liability-matching strategy. The four categories are liability hedge, capital preservation, capital growth, and real assets. The factors of interest are economic growth, real rates, inflation, duration, credit spread, private markets, leverage, and manager skill. To create this portfolio, the investor would begin by identifying the broad economic roles and would then match the asset classes that fit those roles. The risk factor classifications do not necessarily apply to policy portfolio construction but are helpful in identifying the allocation of risk during the process.

Derisking Factor-based approaches are conducive to attenuating common sources of risk in traditional portfolios—that is, derisking. For instance, the prevalence of risk stemming from equity can be reduced by introducing factors such as those under the macroeconomic and fixed income headings in Exhibit 5. Additionally, one can readily incorporate liability-driven investing (LDI) by treating the liability as an asset held short and allocating appropriate weights to interest rate, duration, inflation, credit spread, and other factors that mimic the liability profile. Such an approach could also incorporate

the credit exposure essential to hedging liabilities discounted by corporate bond curves.

An LDI approach is also applicable to asset portfolios set up to match other types of liabilities, including those found in areas such as health care and education. Factors specific to medical and higher education inflation could be isolated and incorporated into appropriate matching factor portfolios.

LDI approaches have evolved through three distinct phases. As **Exhibit 13** describes, each progression more fully embraces a risk factor approach. LDI 1.0 consists of simply extending bond duration and using traditional bond benchmarks for the liability-hedging portfolio. The remainder of the portfolio, tasked with seeking return, is structured in a total-return manner. LDI 2.0 involves a more sophisticated liability hedge, one that uses factors to match specific liability characteristics, including duration and credit quality. Aside from greater liquidity requirements, the return-seeking portfolio changes little from the 1.0 implementation. The latest iteration, LDI 3.0, features a more granular expression of the liability benchmark. It uses an expanded collection of risk factors and constructs the return-seeking portfolio with factors to prevent overlap with the liability hedge. (A common factor that typically appears in the return-seeking and the liability-hedging portfolios is credit, which is related to equity.)

Instead of constructing the liability-hedging portfolio separately from the return-seeking portfolio, one could use granular risk factors to bind all of the exposures together in a single, unified portfolio. **Exhibit 14** presents an example in the pie chart on the right. The single lens of risk factors in that chart provides a view of all risk factors. Overlaps and gaps then become more readily apparent.

To some extent, portfolios that have already embraced LDI approaches are explicitly using factor exposures to measure duration, inflation, credit quality, and other curve characteristics. Performing a surplus optimization using factors rather than asset classes simply extends this approach and leads to greater consistency in portfolio construction.

Using Factors within Manager Structure Incorporating risk factors *within* a particular asset class is common today. For instance, many of the factors listed under the equity or fixed income headings in Exhibit 5 are explicitly incorporated in a portfolio that features managers with minimal style overlaps and diversified skills. The same is true for other asset classes. Whether looking at style, regions, capitalization, duration, convexity, or vintage years, factors are already used when investors are structuring portfolios of managers. Although this approach is a good first step, it can be expanded, however,

Exhibit 13.	The Evolution of LDI	
	Liability-Hedging Portfolio	**Return-Seeking Portfolio**
LDI 1.0 *Long-Duration Bonds*	Longer duration physical bonds (no derivatives), traditional bond benchmarks	Total-return oriented including global public and private equity, real estate, hedge funds
LDI 2.0 *Long Bonds and Derivatives*	Long-duration physical bonds and derivatives, benchmarked to liability characteristics	Dominated by liquid public equity exposure but typically includes semi-liquid strategies such as hedge funds
LDI 3.0 *Risk Factors*	Liability factor exposures expressed through physical bonds and derivatives, benchmarked to a granular liability benchmark	Portfolio of risk factor exposures constructed to minimally overlap with the liability hedge

Exhibit 14. **Bringing the Two Portfolios Together**
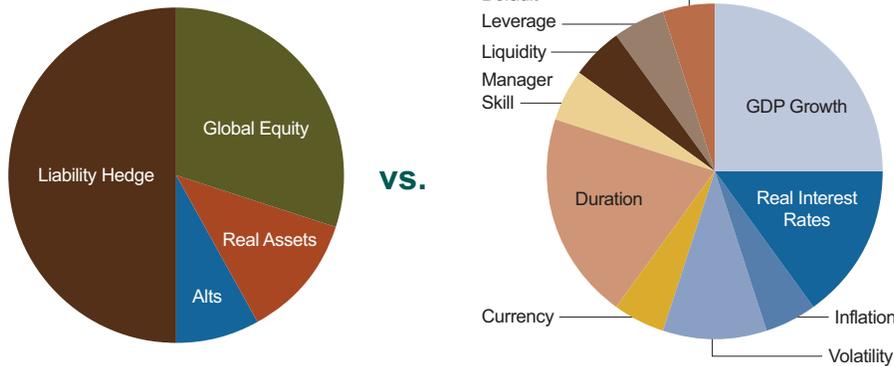
by linking the silos encompassing each asset class structure so that multiasset cross-correlations are considered.

Next Steps in Asset Allocation Merely using risk, return, and correlation forecasts is insufficient to create robust portfolios. Better inputs that provide deeper portfolio insights exist to guide our thinking about strategic asset allocation. In the future, therefore, practitioners will place more emphasis on understanding the reaction of various portfolios to specific economic and capital market outcomes, such as high or rapidly rising inflation, flight to quality, liquidity events, and rapidly changing interest rates or deflation. New techniques will augment traditional deterministic and stochastic forecasting methods. Asset classes will be increasingly defined by their expected reactions to the economic and capital market environments. Liquidity will also be an explicit consideration in strategic policy development and implementation.

CONCLUSION

Building pure factor-based portfolios is challenging and largely impractical for most asset owners, but using factors to understand traditionally constructed portfolios is possible and recommended. Factor approaches offer immediate potentially beneficial applications. One of these is enhancing the way we monitor exposures and attribute risk on the level of asset classes and the level of individual strategies; factors provide a useful way to group traditional asset classes in macroeconomic buckets. Simple insights, such as the relationship between equity and credit, are reinforced by analyzing factors.

More complex interactions, such as those between liability-hedging and return-seeking portfolios, can be expressed with greater clarity through the lens of risk factors. In a policy portfolio, many factor exposures are already explicitly incorporated within manager structure analysis (e.g., liquidity, leverage, duration, currency, size, and momentum). For equity or fixed income portfolios, factors can shed new light on the multifaceted relationships between active strategies.

The application of risk factors to policy portfolio construction is relatively new. Areas for further research include identifying a set of significant factors, mapping this set to investable instruments, developing a forward-looking return forecasting methodology, and considering transaction costs and other messy, but important, practical details.

NOTES

1   The Fama–French factor model was designed by Eugene Fama and Kenneth French to describe stock returns (see Fama and French 1992). The traditional asset pricing model, the CAPM, uses only one variable, beta, to describe the returns of a portfolio or stock with the returns of the market as a whole. The Fama–French model uses three variables. Fama and French observed that two classes of stocks have tended to perform better than the market as a whole: (1) small-cap stocks and (2) stocks with a high book-to-market ratios—that is, value stocks (as opposed to growth stocks). They added these two factors to the CAPM.

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