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June 2012

Research

Risk Factors as Building Blocks for Portfolio Diversification

The Chemistry of Asset Allocation

- Asset classes can be broken down into building blocks, or factors, which explain the majority of their risk and return characteristics. A factor-based investment approach enables the investor to theoretically remix the factors into portfolios that are better diversified and more efficient than traditional methods.
- 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.
- While constructing ex-ante optimized portfolios using risk factor inputs is possible, there are a significant set of challenges to overcome including: the need for active, frequent rebalancing; creating 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. Over 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—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 paper we explore portfolio construction using risk factors, also referred to as risk premia, as the basic elements. Theoretically, this approach may result in lower correlations among various portfolio components and could 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. Much of the intuition of risk factor portfolios can be used to refine and augment traditional allocations and present 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, which assist in generating asset allocation. From an attribution perspective, many vendors of risk analytics systems employ factors to provide a clearer perspective on common exposures across an entire portfolio, rather than just reporting on siloed asset classes with incompatible tools. Practitioners seek inputs that capture essential tradeoffs, with logical relationships among components that result in reasonable portfolios. This spawns an interest in a risk factor approach.

What are factors?

Factors are the basic building blocks of asset classes and a source of common exposures across asset classes. Factors are the smallest systematic (or non-idiosyncratic) units that influence investment return and risk characteristics. They include elements such as inflation, GDP growth, size, currency, convexity, etc. Using a chemistry analogy: If asset classes are molecules, then factors are atoms. Thus factors help explain the high level of internal correlation among asset classes.

Many traditional asset class and sub-asset class correlations have trended upward over the past decade. These correlations rose to uncomfortable levels during the recent crisis, driving a desire to find a way to construct portfolios with less correlation among 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 can be broken down into building blocks, or factors, which explain the majority of their return and risk characteristics. These asset classes 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, we 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.

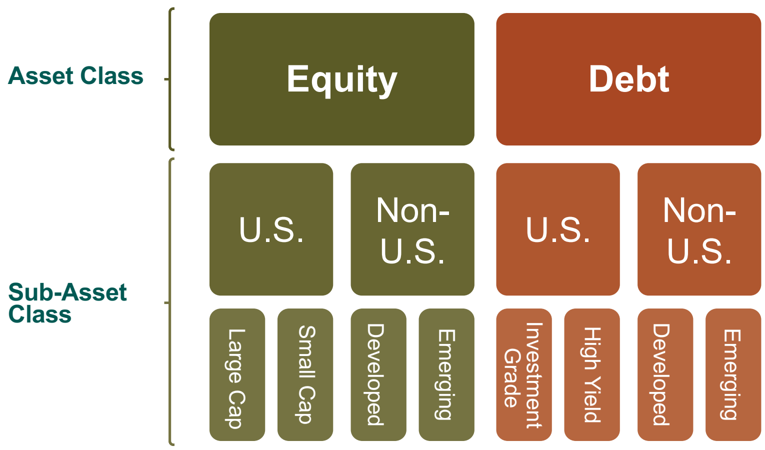
The Basics of Portfolio Optimization

What is an Asset Class?

Asset classes are bundles of exposures divided into categories, such as equities, bonds, real assets, etc., based on their financial characteristics (e.g., asset owner vs. lender) (**Exhibit 1**). Ideally, asset classes should be as independent as possible with little overlap and, in aggregate, should cover the investment universe with minimal gaps. In this construct, a myriad of common factor exposures drive the correlations among 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 and small cap U.S. equity). We believe there are very few actual archetypal asset classes, including global equity, global fixed income, cash and real assets.

Exhibit 1

Examples of Asset Classes and Sub-Asset Classes



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) primary optimization inputs include:

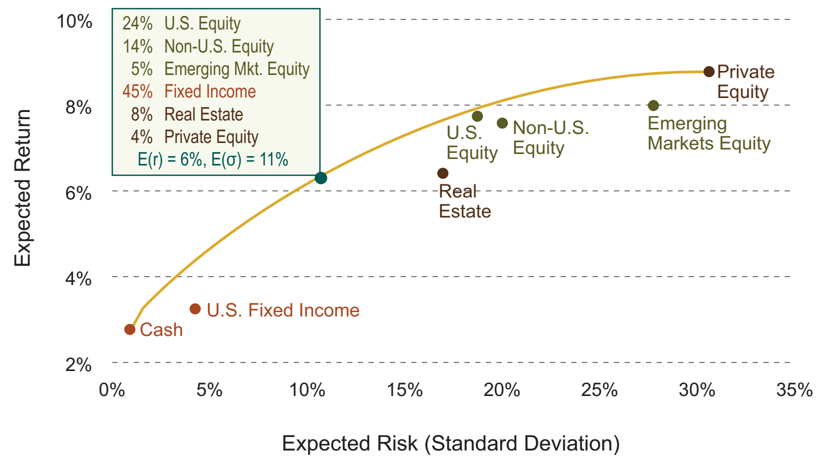
- **E(r)** Expected return
- **E(σ)** Expected standard deviation, a proxy for risk
- **E(ρ)** Expected correlations among all assets

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 (et al.) extended and simplified MPT by compressing security characteristics into asset class groupings where a single market factor (beta) serves as a proxy for a multitude of security-level characteristics.

The objective of MPT and the resulting Capital Asset Pricing Model (CAPM) is to generate mean-variance efficient portfolios via quadratic optimization, represented by the efficient frontier (**Exhibit 2**). 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.

Exhibit 2

Traditional Asset Class Efficient Frontier



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 non-linear curve of the frontier is due to imperfect (less than 100%) correlations across 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.

Arbitrage Pricing Theory (APT) extends CAPM by allowing for multiple factors instead of just one "beta" factor as a proxy for the market. It states that:

The expected return of a given asset

The weight of factor **1**

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

The return on risk factor **1**

The risk-free rate

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.

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

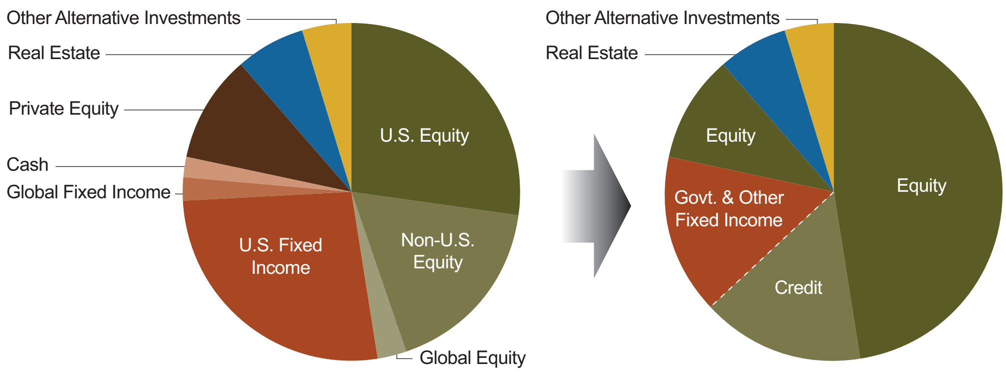
Diversification in Name Only?

Modern Portfolio Theory, 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 sub-styles, can nonetheless suffer from surprisingly high levels of internal correlation within each block. This is the manifestation of diversification in name only.

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

Exhibit 3

Average Large Plan Allocation

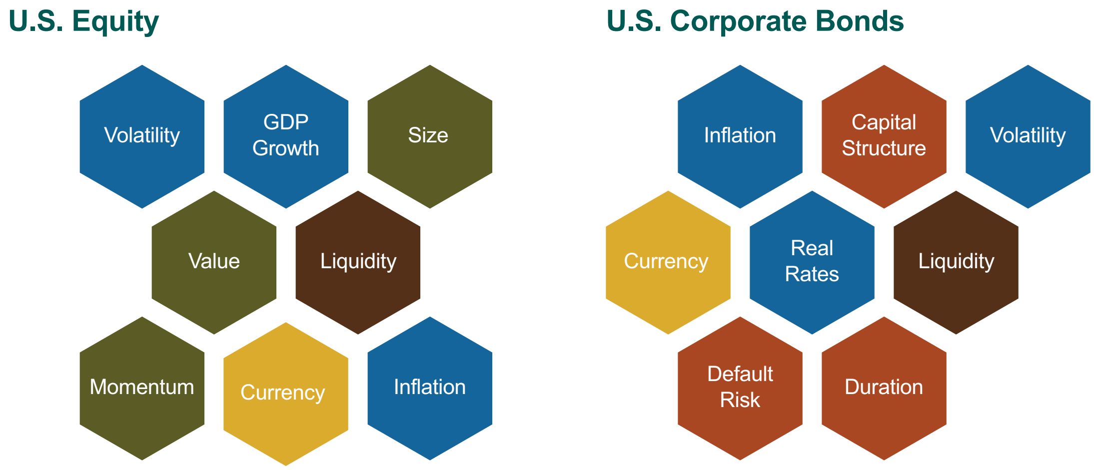


Source: Pensions & Investments.

The credit component of fixed income can be thought of as "equity-light," and, by definition, features a positive correlation with equities (this is somewhat tempered by government and other non-credit 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 it would initially seem.

Exhibit 4

Common Factor Exposure Across Asset Classes



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

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 across different categories. (These sample factors could be grouped in a myriad of ways, depending on the investor's needs.) For example, macroeconomic factors are applicable to

Exhibit 5

Illustrative Sampling of Factors 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

most asset classes while equity and fixed income factors deconstruct characteristics within those two broad asset classes. 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—this 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 using a long nominal Treasuries and short TIPS position. A few other examples of how to capture specific factor exposures include:

Inflation: Long Nominal Treasuries Index, Short TIPS Index
Real Interest Rates: Long TIPS Index
Volatility: Long VIX Futures Index
Value: Long Developed Equity Value Index, Short Developed Equity Growth Index
Size: Long Developed Equity Small Cap Index, Short Developed Equity Large Cap Index
Credit Spread: Long U.S. High Quality Credit Index, Short U.S. Treasury/Government Index
Duration: Long U.S. Treasury 20+ Year Index, Short U.S. 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 problematic 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, in order to create a portfolio constructed with risk factors we selected 10 factors with investable proxies (**Exhibit 6**). We introduce a "Developed Economic Growth"

Exhibit 6

Historical Risk and Return for Selected Factors

Periods Ended 12/31/2011

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

Source: MSCI, Barclays, CBOE and Callan.

factor, represented by long exposure to the MSCI World Index, which folds together global developed GDP growth, productivity, liquidity and other characteristics. Other equity-related factors include spreads to value, size (both 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. We select real rates, inflation and volatility from the macroeconomic arena.

Exhibit 7

Factor Correlations (Five-, 10- and 15-Year)

Periods Ended 12/31/2011

10 YEAR (above diagonal) / 5 YEAR (below diagonal)

	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.

In **Exhibits 6 and 7**, we present returns, standard deviations and correlations over five-, 10- and 15-year periods ending December 31, 2011, to illustrate how factor portfolios evolve. These factor characteristics are based on 60, 120 and 180 monthly observations of long and short positions (except for developed economic growth, real rates and volatility, which can be accessed via long-only instruments or derivatives).

1 The Fama-French factor model is a model designed by Eugene Fama and Kenneth French to describe stock returns. 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. In contrast, 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 caps and (2) stocks with a high book-to-market ratio—value stocks as opposed to growth stocks. They then added these two factors to the CAPM.

Our expectation is that the building blocks individually produce modest returns. In Exhibit 6, we observe 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%. Correlations among factors are low, typically ranging from -0.50 to +0.60. Somewhat highly correlated factors include developed economic growth vs. high yield and high yield vs. default. The average correlation for the 10 factors in Exhibit 7 is +0.02. This is significantly less than many asset class correlations, which range from -0.15 to more than +0.90. Sub-asset classes like U.S. small cap vs. U.S. large cap are the most correlated while relatively unrelated pairings such as U.S. 1-3 Year Treasuries vs. private equity have a low correlation.

Factor returns and risks are extremely time sensitive, as evidenced by the multiple time horizons defined above. Changing the observation window can materially impact 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 proven erratic as well, with annualized returns ranging from -0.17% over 10 years to 15.15% over the past five years.

If factors are properly specified and isolated, they generally have very little correlation with each other because all of the systematic risk has been stripped out.

Exhibit 7 details the correlation characteristics. The correlation matrix is shaded to show pair-wise relationships with various degrees of diversification: dark tints for low correlations (less than -0.30), medium for close to uncorrelated (between -0.30 and +0.30), light for modestly positive (between +0.30 and +0.60), and white for significantly positive (above +0.60). Volatility and inflation demonstrate very low, often negative, correlations with most of the other factors. If factors are properly specified and isolated, they generally have very 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. Within the broad ranges described above, we observe that fundamental economic relationships appear to hold over multiple time periods. The average correlations for these 10 factors across three observation periods vary within a very small range, from -0.0021 to +0.0092.

Constructing Factor Portfolios

Taking the 10 factors assessed above, we construct a simple, equally-weighted portfolio with monthly rebalancing **(Exhibit 8)**. This is compared with a “traditional” portfolio consisting of 40% Russell 3000, 20% MSCI ACWI ex US and 40% Barclays Aggregate, also rebalanced monthly. We ignore fees and costs (including rebalancing costs) in this example. Given the historical risk, return and correlation inputs, we expect a factor portfolio with a modest return and risk. This contrasts with the traditional portfolio, where the majority of the risk budget is spent on equity-like assets. 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 (Exhibit 8).

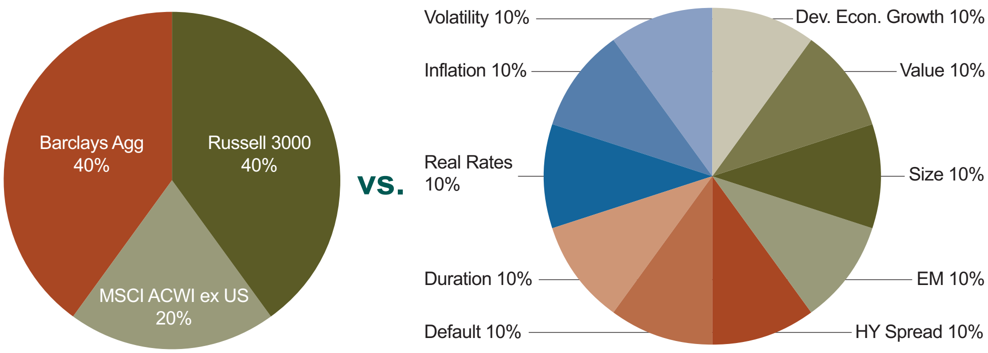
Converting standard deviation to variance (which is the term of interest for an optimizer), we observe that the factor portfolio has 34 units of variance compared to the 119 units in the traditional portfolio over 15 years. The simple factor portfolio historically achieved a slightly higher level of 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.

Exhibit 8

Portfolio Comparison

Periods Ended 12/31/2011

"Traditional" 60/40 Portfolio vs. Simple Factor Portfolio



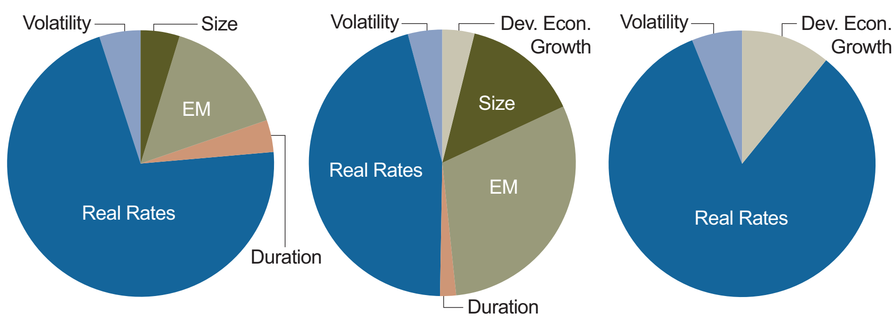
	"Traditional" 60/40 Portfolio 5 Year	10 Year	15 Year	Simple Factor Portfolio 5 Year	10 Year	15 Year
Historical Return:	2.52%	6.01%	5.98%	6.74%	5.97%	4.75%
Historical Risk:						
Standard Dev. (σ)	13.75%	11.14%	10.90%	6.84%	5.79%	5.81%
Variance (σ^2)	189.18	124.06	118.83	46.74	33.48	33.77

Exhibit 9

Optimized Factor Portfolio Comparisons

Periods Ended 12/31/2011

"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 (σ^2)	46.79	33.52	33.76

Examining the trailing 10-year period 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. 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-fourth the volatility of the traditional portfolio.

This simple exercise demonstrates that it is possible to construct a factor portfolio that has fundamentally diverse characteristics from a traditional asset class portfolio, and with less volatility.

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. However, this simple exercise demonstrates that it is possible to construct a factor portfolio that has fundamentally diverse characteristics from a traditional asset class portfolio, and with less volatility.

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

Another approach involves forecasting ex-ante risk/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 we employ historical, backward-looking inputs as detailed in Exhibits 6 and 7 in a forward-looking model, sacrificing predictive power for understandability. We select 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 produces a “best fit” portfolio specifically tuned for the five, 10- and 15-year windows. This example illustrates that using traditional mean-variance tools are possible with factors, but that high quality forward-looking inputs are still necessary.

We observe that the “optimized” factor portfolio’s historical return is considerably higher than that of the simple factor portfolio (**Exhibit 9**). Only three out of the 10 factors have allocations in the new portfolio using the 15-year history, and most of the allocation is to real rates, with smaller allocations to developed economic growth and volatility. Over 10 years, 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 feature prominently in the optimized portfolio, given their strong performance over the past 15 years.

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

While the diversification benefits of factors looks very appealing in theory, the practical challenges are difficult to ignore. These challenges have prevented the widespread adoption of risk factor-based policy portfolios across 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.

Challenges in Factor-Based Portfolio Construction

Many practical challenges arise when constructing portfolios with factors—some 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 like global GDP growth or momentum—have poor investable proxies. Another 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, which is a naïve but pragmatic assumption that we have also adopted here.

Frequent and attentive rebalancing is necessary to maintain the desired factor exposures over time.

Frequent and attentive rebalancing is necessary to maintain the desired factor exposures over time. Institutions wishing to pursue such asset allocations would require the resources for near-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. However forward-looking assumptions are hard to develop, as 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.

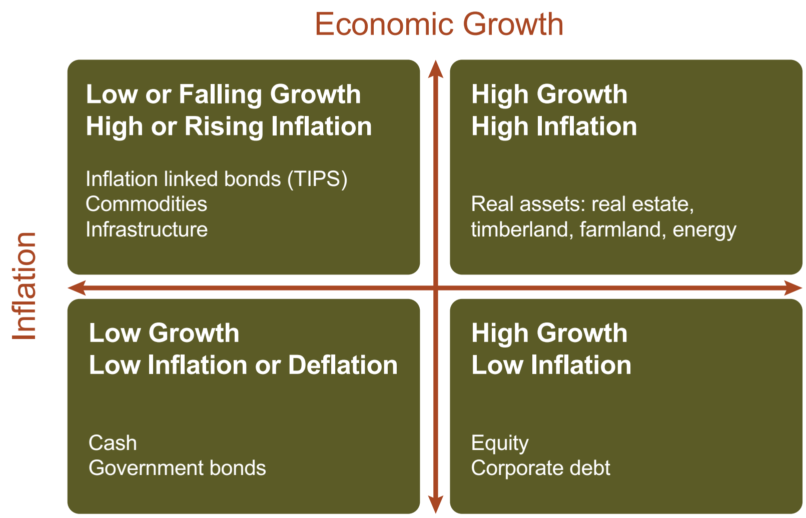
A practical limitation of portfolios constructed with factors is that they must be implemented using long and short exposures, often via derivatives. Synthetic instruments are, by definition, the price of admission in factor portfolio construction. This may be counter to some asset-owner’s guidelines, which prohibit the use of derivatives or short exposures at the policy level. This implies that we release the long-only constraint when using factors in a portfolio optimization model. Typical investment policies are crafted with long-only proxies for market exposures, and are implemented accordingly. Portfolios constructed with asset classes may produce different results from those explored above if short positions were allowed.

Portfolio Applications

Given the challenges of constructing purely factor-based portfolios, we can 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 with similar behaviors, we can implicitly understand the drivers of their correlations to one another. Another method is to analyze the behavior of asset classes under various inflation and economic growth scenarios (**Exhibit 10**). Incorporating additional variables generates a more granular and robust model.

Exhibit 10

Macroeconomic Scenarios



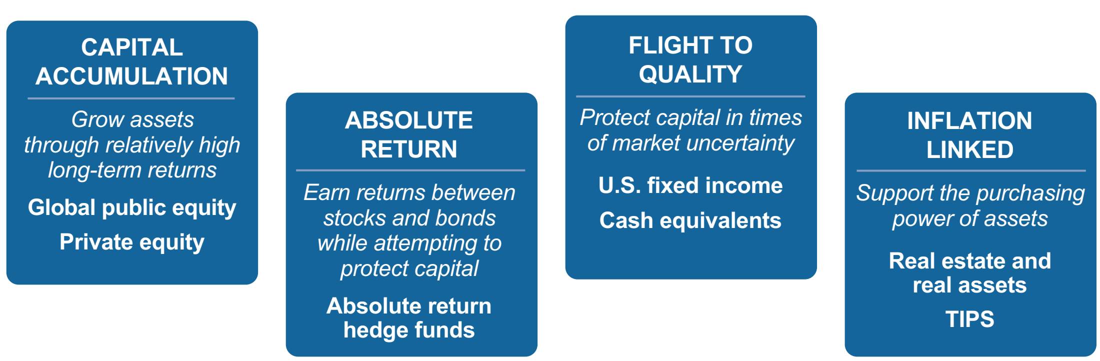
We can also examine the economic roles of various asset classes. By bucketing asset classes based on their response to macroeconomic scenarios (**Exhibit 11**), it is possible to combine the transparency of investing through asset classes with the granularity of factor-based approaches. Broad buckets may include:

- Growth assets such as equity-like instruments,
- Less-risky assets such as cash, government obligations and investment grade bonds,
- Strategies which aim to benefit from skillful active management, such as hedge funds and other absolute return investments, and
- Real assets that support purchasing power like real estate and TIPS.

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

Exhibit 11

Sample Groupings



Asset classes are still the primary tool for most institutional portfolios, but the groupings illustrate many of the residual factor exposures. One illustrative 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 liability matching strategy. These four categories are: liability hedge, capital preservation, capital growth, and real assets. Factors of interest include 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 accordingly. The risk factor classifications do not necessarily apply to policy portfolio construction but are helpful in identifying the allocation of risk during the process.

Exhibit 12

Asset Allocation Through a New Lens: Sample Defined Benefit Plan Viewed with Risk Factors

			Factor Exposures							
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%		✓		✓				

De-Risking and LDI

Factor-based approaches are very conducive to attenuating common sources of risk in traditional portfolios. For instance, it is possible to reduce the prevalence of risk stemming from equity by introducing alternative factors, such as those under the macroeconomic and fixed income headings in Exhibit 5. Additionally, one can readily incorporate liability-driven investing (LDI) approaches 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 would also be able to incorporate credit exposure essential to hedging liabilities discounted by corporate bond curves. In this section we focus on derisking from a pension plan perspective, but 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 matching factor portfolios alongside those mentioned above.

Liability-driven investing approaches have evolved through three distinct phases—each further progression has more fully embraced risk factor approaches (**Exhibit 13**). 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, which 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. One common factor that typically overlaps between the return-seeking and liability-hedging portfolios is credit, which is related to equity.

Exhibit 13

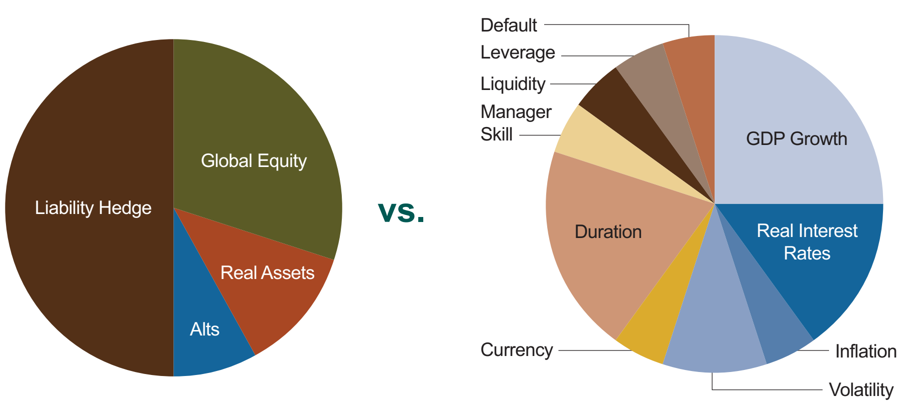
The Evolution of LDI

	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, etc.
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, etc.
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

Instead of constructing the liability-hedging portfolio separately from the return-seeking portfolio, it is possible to employ granular risk factors to bind all of the exposures together in a single, unified portfolio. **Exhibit 14** presents an illustrative example. The single lens of risk factors, as illustrated in the right pie chart, provides the practitioner with a view of all risk factors. Overlaps and gaps become more readily apparent. To some extent, portfolios that have already embraced LDI approaches are explicitly using factor exposures to measure duration, 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.

Exhibit 14

Bringing the Two Portfolios Together



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 overlap and diversified skills. The same is true across other asset classes. Whether looking at style, regions, capitalization, duration, convexity or vintage years, factors are already employed when structuring portfolios of managers. While this is a good first step, it can be expanded by linking the silos encompassing each of these asset class structures so that multi-asset cross correlations are considered as well.

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 strategic asset allocation thinking. Practitioners will place more emphasis on understanding the reaction of different 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 above-mentioned environments. Liquidity will also be an explicit consideration in strategic policy development and implementation.

While building purely factor-based portfolios is challenging and largely impractical for most asset owners, using factors to understand traditionally constructed portfolios is very useful.

Conclusion

While building purely factor-based portfolios is challenging and largely impractical for most asset owners, using factors to understand traditionally constructed portfolios is very useful. 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.

However, factors offer immediate, potentially beneficial applications. One of these is enhancing the way we monitor exposures and attribute risk on both an asset class and individual strategy level, including providing a useful way to group traditional asset classes in macroeconomic buckets. Simple insights, such as the relationship between equity and credit, are reinforced. 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. When implementing 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 among active strategies.

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