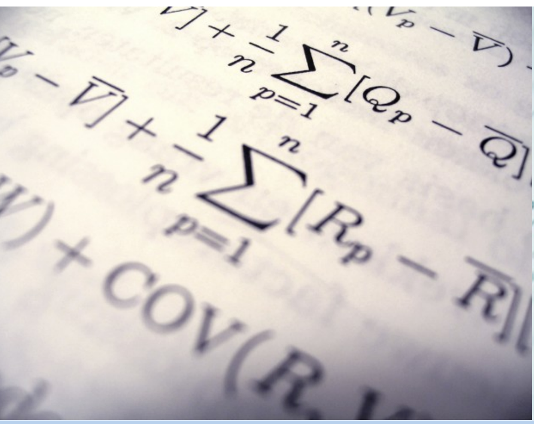
J.P.Morgan

December 2013



Systematic Strategies Across Asset Classes

Risk Factor Approach to Investing and Portfolio Management

Quantitative and Derivatives Strategy

Marko Kolanovic, PhD[AC] (Global)
mkolanovic@jpmorgan.com

Zhen Wei, PhD (Asia)
zhen.wei@jpmorgan.com

See page 203 for analyst certification and important disclosures, including non-US analyst disclosures.

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

December 11, 2013

Dear Investor,

Financial markets today are quite different from those of 20 years ago. Significant developments include an increase in actively managed assets, broad usage of derivative products, and changes in liquidity structure. Some of these developments reduced the amount of alpha available to traditional investors. Additionally, changes in asset volatility and correlations challenged many traditional risk models. For instance, during the recent financial crisis, asset correlations and volatility rapidly rose to historical highs, causing many risk models to fail.

In this guide we will explain a non-traditional approach of **Risk Factor Investing**. The goal of the approach is to create systematic trading strategies that can access **new sources of alpha** while exhibiting **low and stable correlations**. The concept of risk factors is not new **-** it has been used in some form by investors such as Global Tactical Asset Allocation (GTAA), Commodity Trading Advisor (CTA) and Equity Quant Managers.

Risk factors are designed after indentifying a **sound economic rationale**. The risk factor premia can be related to market behavioral effects such as herding behavior, or the persistence of macroeconomic regimes that can cause price **Momentum**. The mean reversion of asset prices to fair-value anchors often leads to **Value** opportunities. Yet another class of risk factors is related to investors mispricing asset yields, which can lead to **Carry** opportunities. In addition to these common risk factor styles, a large derivatives market often provides opportunities to design novel risk factors related to asset **Volatility**.

To create an optimal portfolio of systematic strategies, investors need to define a **risk model**. The risk model will produce weights of individual risk factors with the goal of e.g. maximizing Sharpe ratio, minimizing volatility, or maintaining certain risk factor budgets. Investors can also dynamically rebalance between the risk factor portfolio and risk-free assets, for example to target constant volatility, or protect the principal investment.

A Risk Factor approach has its own risks. Some are related to potential mistakes investors can make in factor design, or failing to understand the lifecycles or capacity limitations of individual risk factors. Allocation models also may have inherent biases and their performance can be influenced by market regimes of volatility, growth, and inflation. By carefully researching risk factor strategies, investors can avoid these pitfalls.

In this guide, we have tried to illustrate various aspects of Risk Factor investing across asset classes. The work presented in this report relies on extensive research of systematic strategies by the J.P. Morgan Research Department over the past decade. We hope this guide will be educative for investors new to the field, and provide a novel perspective to practitioners of risk factor investing.

Marko Kolanovic, PhD
Head of Quantitative and Derivatives Strategy
J.P. Morgan Securities LLC

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Contents

Investing in Risk Factors Across Assets

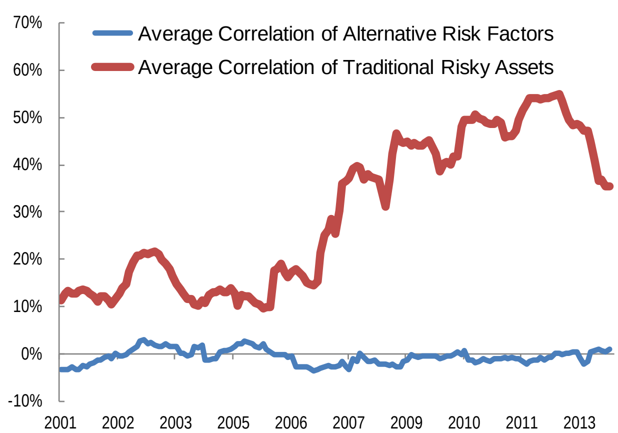
Introduction to Risk Premia Investing

The main task for every fund manager is to deliver stable and positive returns. To generate positive returns, managers are relying on methods such as fundamental and quantitative analysis, shareholder activism, technological edge, superior understanding of macroeconomic or geopolitical developments and others. As most managers can apply leverage to increase the return and risk of their strategies, the task of reducing portfolio correlations (and thus reducing portfolio risk) has become equivalent to seeking new alpha opportunities. Strong growth in active assets under management over the past two decades has therefore led to an **unrelenting search both for alpha and pockets of weakly correlated assets**. For instance, in the 1990s, it was sufficient to include emerging market assets to lower portfolio correlations. An endowment allocation model that included alternative assets (such as Commodities and Real Estate) easily outperformed traditional bond-equity portfolios on a risk adjusted basis. However, the **growth in active assets and increased use of leverage depleted alpha, and increased correlation across all risky assets**.[1] The 2008 market crisis exposed the limited diversification benefits of traditional assets, resulting in a sharp increase in portfolio risk and losses.

Following the lessons of the 2008 crisis, many managers increased focus on forecasting and managing the volatility of traditional asset classes. Having better covariance estimates could certainly improve the performance of traditional risk models. The low yield market environment in the aftermath of the financial crisis forced investors into more risky and higher yielding instruments such as equities, or to sell options to generate yield.

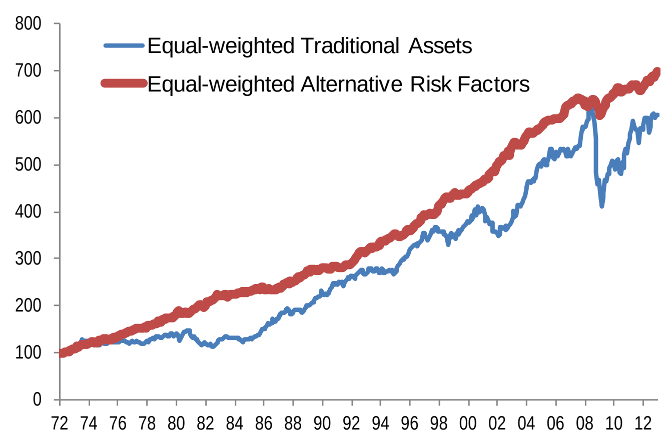
Some investors took a different approach, **moving away from traditional assets and designing new 'alternative' assets.** In an ideal case, these new assets would have lower correlation and be able to tap into new risk premium sources. **These assets are often called 'Alternative Risk Factors'** (also 'Alternative Betas', or 'Exotic Betas'). Unlike traditional assets, risk factors can be designed from any number of instruments and traditional asset classes by applying **specific trading rules**. Risk factors are **defined to access new sources of risk premia, and to have more stable risk and correlation properties**. While the risk factor approach is new to many investors, it has been used for a long time by Quantitative Equity managers, Global Tactical Asset Allocation (GTAA), Commodity Trading Advisors (CTAs), and Global Macro Hedge Fund managers. For instance, Quant Equity managers model portfolios based on equity risk factors (such as: growth, value, earnings momentum, short interest, etc.) instead of traditional sectors. CTAs often exploit momentum patterns in prices of commodities and other assets. The advantage of a risk factor approach can be illustrated by persistently lower correlation between alternative risk factors compared to correlation of traditional risky assets (Figure 1).

Figure 1: Low Average correlation of Cross Asset Alternative Risk Factors (%) vs. High Correlation of Traditional Risky Assets.



Source: J.P. Morgan Quantitative and Derivatives Strategy. Alternative Risk factors included are 16 'Toy models' of Value, Momentum, Carry and Volatility introduced in the next Chapter.

Figure 2: Portfolio of Traditional Assets vs. Portfolio of Alternative Risk Factors (Equal Weighted).



Source: J.P. Morgan Quantitative and Derivatives Strategy. Alternative Risk factors included are 16 'Toy models' of Value, Momentum, Carry and Volatility introduced in the next Chapter.

[1] M. Kolanovic: 'Rise in Cross-Asset Correlations', 2011.

To be a viable investment, **Risk Factors must be expected to generate positive premium**. Ideally, this premium (per unit of risk) compensates an investor more than the premia of traditional assets. In order to generate stable premia, **risk factors are designed after indentifying sound economic rationale for the premium they deliver**. The premia can be related to market behavioral effects such as market overreactions to changes in fundamentals and herding behavior that causes price **Momentum**. Market under-reaction or biases can lead to **Value** opportunities as was demonstrated in equities by Fama and French (1993). Yet another class of risk factors is related to supply and demand imbalances that can lead to **Carry** opportunities. One example of a carry opportunity is related to the failure of uncovered FX parity leading to the popular currency carry trade, or the failure of forward rates expectations (i.e. forward rates overstating future spot rates) leading to a bond carry trade (see the section on Carry factor style). In addition to these well researched examples, strong growth in the usage of derivatives and related supply/demand imbalances often provide opportunities to design novel risk factors related to asset **Volatility**. Examples include products that take advantage of the richness of index options relative to realized volatility, supply/demand distortion of the implied volatility term structure, or the impact of option hedging on cash price patterns (see the section on Volatility factor style).

While risk factors individually may deliver good Sharpe ratios, the true power of risk factor investing comes at the portfolio level, where low correlation between alternative risk factors can significantly reduce portfolio volatility and tail risk. For example, a ‘Momentum’ risk factor in EM Currencies is expected to have low correlation to a ‘Value’ risk factor in equities, unlike EM Currencies and Equities that often have high correlation despite belonging to ‘different’ traditional asset classes (see the next section for definitions of Momentum and Value). Similarly, the correlation between ‘Equity Value’ and ‘Bond Momentum’ risk factors is expected to be more stable, than the correlation between Stocks and Bonds that recently showed instability due to expected tapering of the Quantitative Easing program. Figure 1 shows the average correlation of risk factors across traditional, carry, momentum, value and volatility factor styles. Given the lower average correlation, an equal weight portfolio of alternative risk factors would have delivered significantly higher risk-adjusted returns and lower draw-downs (tail risk) compared to an equal weight portfolio of traditional assets (Figure 2).

The two main advantages of risk factor investing discussed **above are the ability to capture non-traditional sources of premia** (such as behavioral effects, supply-demand imbalances, and market microstructure effects), and the **ability to maintain low average correlation of assets**. The persistent premia and ability to offset factor risk at a portfolio level can lead to portfolio performance and risk profile with similar properties to traditional alpha.

However there are also **potential pitfalls in the risk factor approach**. One is related to **mistakes investors can make in designing risk factors**, and another in **failing to understand the lifecycles and capacity limitations of individual risk factors**. We mentioned that risk factors are defined by a trading rule. However, one can define any number of rules, and even make these rules look profitable in historical backtests. What makes the difference between a trading rule and a valid risk factor is that a risk factor is designed to exploit a particular market inefficiency (e.g. related to behavioral effects, supply demand imbalance, or market microstructure). In other words, behind every risk factor there should be a strong economic rationale explaining the existence of the risk premium. In practice, this means that performance in various market regimes should be consistent with the economic expectation for the risk behind the factor. Besides, a risk factor should not be sensitive to small changes in model parameters (robustness of a factor rule) and it should have a relatively small number of parameters (simplicity of a factor rule – as with a sufficient number of parameters one can reproduce any return profile). The most common mistakes in designing risk factors are related to an in-sample bias in the determination of parameters. These in-sample pitfalls can range from obvious statistical mistakes to more subtle biases introduced by the trading rules that performed well in the recent market environment. Failure to include these considerations in the design of a risk factor will often result in trading rules that look good in a backtest but will likely fail to perform in the future.

Another potential pitfall is an inadequate understanding of risk factor lifecycles. In an ideal world, risk factors have stable premium and risk properties. In reality, **as markets evolve new factors will emerge** alongside products such as derivatives or regulations that will alter investors’ behavior. **Risk factors may also weaken or completely disappear** due to market participants becoming aware of patterns and correcting them, new arbitrage channels, or simply too many assets being invested in a factor. The last reason is particularly important as risk factors are too often designed and tested without properly accounting for market impact and an estimation of how much capital can be employed before the effect disappears.

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

In addition to the emergence and disappearance of factors, the effectiveness of factors may also vary in different market cycles (e.g. demand for protection in a high volatility environment may cause future outperformance of volatility factors). Due to differing levels of market awareness and arbitrage efficiency we may find that the same factors work in one market but not in another. An example is that certain equity factors still generate positive premium in Emerging Markets and US small caps, while they ceased to produce returns in the more efficient US large cap space. Macro regimes can also adversely impact factor performance. An example is the underperformance of carry strategies in a high volatility environment during the recent financial crisis. **Investors should be aware of factor correlations and their behavior in different market regimes.**

Given that risk factors have lifecycles, investors need to constantly research and test new factors, as well as evaluate the effectiveness of old ones. A summary of J.P. Morgan cross-asset risk factor research and related indices is provided in the Appendix.

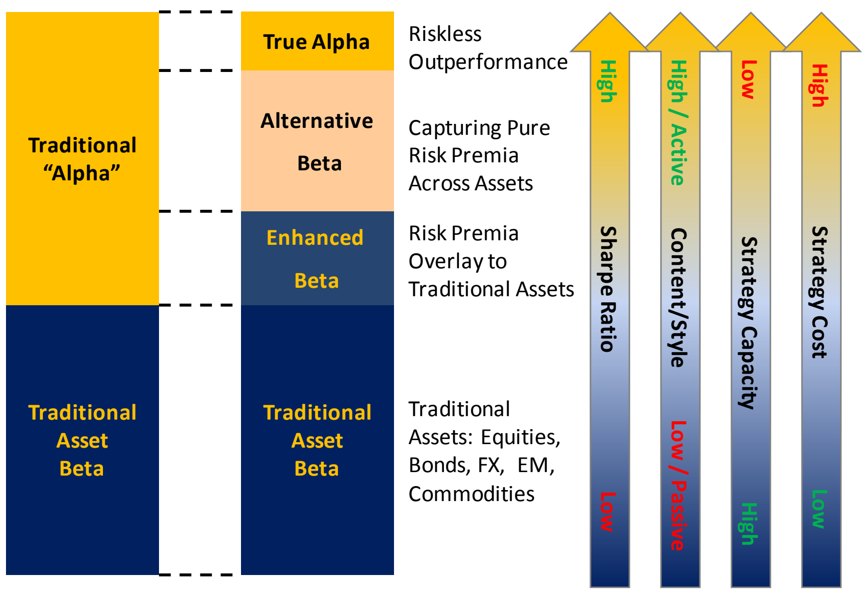
Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

From Risk Factors to Systematic Strategies

Historically, investors explained portfolio returns as a combination of market 'beta' and 'alpha'. As investors learned about various non-traditional sources of risk premia such risk arbitrage, currency carry, equity value effect, etc., part of the old 'alpha' could be explained by premia related to these alternative risk factors or 'alternative betas'. After isolating contributions from 'alternative risk premia', true alpha becomes limited to idiosyncratic returns and the manager's ability to time risk exposures. Moving along the spectrum of returns from traditional beta to pure alpha, the expected Sharpe ratio, complexity and cost of a strategy is expected to increase, while capacity of a strategy is expected to decrease. Note that traditional asset betas such as the S&P 500 index often represent the capitalization of the asset class and hence have plenty of capacity, while the supply of alpha strategies is limited (i.e. every positive alpha opportunity comes at the expense of a market participant experiencing negative alpha).

To create a systematic strategy based on alternative risk premia, investors typically start by setting a goal for the strategy. Unlike **traditional assets** (such as equity, bonds, or commodity indices), strategies based on risk factors are often designed to capture **alternative risk premia** and reduce portfolio risk. Examples are various risk factor styles such as momentum, value, carry, etc. These alternative beta exposures can be mixed with traditional market exposures to provide **enhanced beta strategies**; for example, constructing an equity index that deviates from market capitalization weights by overweighting value and size risk factors, or a broad commodity index that incorporates a momentum overlay. Investors can also neutralize risk factor exposures by creating a long-short portfolio of risk factors, or diversifying away factor risk in a multi-factor portfolio. These approaches would create a portfolio that captures various alternative risk premia but eliminates most of the factor risk, effectively leading to an **alpha strategy**. Risk factors can be also combined with traditional assets to provide cost effective **hedging strategies** for both traditional and alternative portfolios (e.g. volatility risk factors are often designed as hedges).

Figure 3: Beta, Enhanced Beta, Alternative Beta and Alpha



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Once the goal of strategy is set, investors select an appropriate universe of risk factors. Risk factors in a portfolio can be any combination of traditional and alternative (momentum, value, carry, volatility) risk factors that are expected to deliver positive returns and reduce portfolio risk via lower correlations. To create a multi factor portfolio, investors need to define a **risk model to rebalance weights between different factors**. We will denote these models as **cross-sectional risk models**. Investors can also dynamically rebalance the weight between the risk factor portfolio and risk-free assets. We will denote these models as **time-series risk models**.

The simplest example of a weighting scheme would be **fixed weights**. In this approach, an investor periodically (e.g. monthly or quarterly) rebalances factor exposures to maintain constant weights of individual factors. This method involves buying factors that underperformed and selling ones that outperformed – it thus has the properties of a value (reversion) approach. Another popular weighting scheme is **inverse volatility or Equal Marginal Volatility,** in which risk factors are weighted inversely to their past volatility: higher asset historical volatility means a lower asset weight in portfolio. As volatility and performance have an inverse relation, this weighting scheme often increases the weights of assets that performed well and decreases the weights of assets that performed poorly – a property of a momentum-based investment approach. A more elaborate approach to inverse volatility weighting is to weight based on an asset's contribution to portfolio volatility. This approach is similar to inverse volatility, but takes into account the correlation contribution of each asset to portfolio volatility. This weighting approach is called **equal contribution to risk or Risk Parity**.

Investors often optimize the tradeoff between portfolio risk and return. A mathematical approach to optimize the tradeoff (utility) is a **Mean Variance Optimization** under certain assumptions for future asset returns, volatility, and correlations. For instance, a Mean-Variance Optimization (MVO) that assumes equal asset returns would lead to a portfolio with the lowest possible volatility or **Global Minimum Variance portfolio** (GMV). Assuming equal asset Sharpe Ratios would lead to the **Most-Diversified portfolio** (MDP). Investors can also incorporate a customized view of asset performance and combine it with market consensus views. This methodology is captured by the **Black-Litterman** (BL) approach. Each of these risk models will be examined in greater detail in the 3rd Chapter of this report.

Once the multi-factor portfolio with prescribed weight allocation is constructed, investors can decide to manage overall risk of the portfolio by a dynamic allocation between the portfolio and risk free asset. For instance, one can **target a constant volatility** by allocating based on trailing volatility. Another popular method of rebalancing between the portfolio and risk free asset is **Constant Proportional Portfolio Insurance** (CPPI), in which an investor increases exposure following a positive performance, and decreases following negative performance to protect a predetermined floor asset value. Investors can purchase listed and over the counter options to create virtually any risk profile for the underlying multi-factor model. Finally, some investors use **timing models** that can allocate risk based on various macroeconomic or technical signals.

Figure 4 below shows a process of designing a systematic cross-asset strategy. The process starts with an investor defining a strategy goal (alternative beta, enhanced beta, alpha, hedging), designing and selecting risk factors, and finally deciding on a risk management approach for the multi factor portfolio (by assigning relative asset weights, and determining the allocation to the risk-free asset over time).

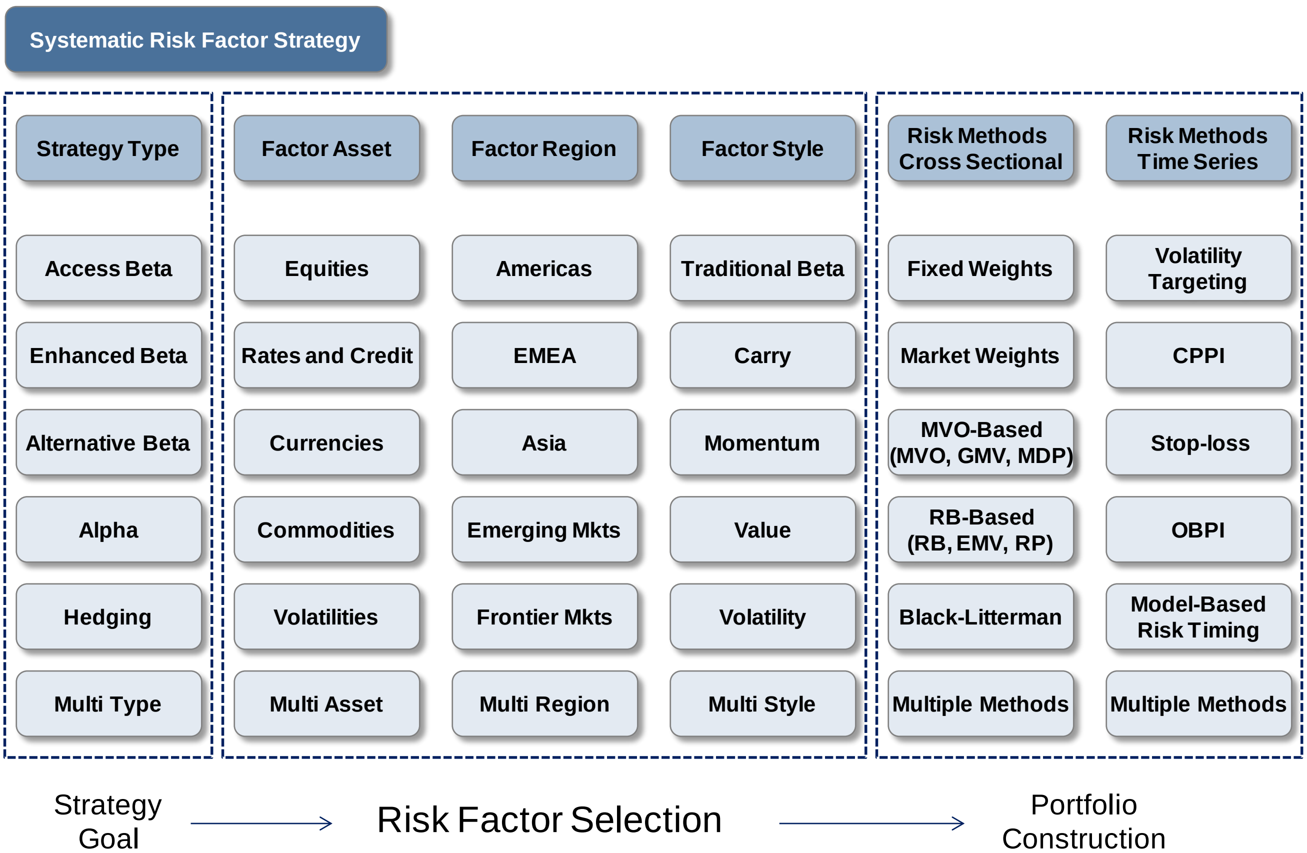
It shows different strategy types, taxonomy of risk factors, and a sample of risk management methods. A process of designing a systematic cross-asset strategy would start with the selection of a strategy type: **access beta, alternative beta, enhanced beta, alpha, or hedging strategy**.

At the core of risk factor investing is the design and selection of risk factors. While there is no unique taxonomy, we classify the main factor styles as: **Traditional Beta, Carry, Momentum, Value and Volatility**. Additionally, many investors designate factors across **traditional asset classes (equities, credit, currency, commodity, volatility) and geographic regions (Americas, Europe, Developed Asia, Emerging Markets and Frontier Markets)** - e.g. US Equity Value, DM Bond Carry, etc. Notice that we have classified Volatility both as a traditional asset and a risk factor style (e.g. to accommodate strategies that focus on cross-asset volatility, single-asset volatility, or even volatility of volatility). Certain factors may have properties of more than one factor style and for this reason we included multi-style, asset and region designations (unlike ideal world 'orthogonal' factors).

The last important step is selecting a **risk methodology or weighing scheme of factors within a portfolio.** Asset relative weighting (cross-sectional risk model) can be as simple as fixed factor weights, or more complex risk optimization techniques based on MVO or Risk Budgeting. Additionally, investors can implement time-series risk management techniques of dynamic allocation between the factor portfolio and risk-free asset. Popular techniques include CPPI-based techniques (such as CPPI and constant volatility) and option based risk methods.

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Figure 4: Designing a Systematic Strategy



Source: J.P. Morgan Quantitative and Derivatives Strategy.

In the **second chapter** of the report we will elaborate on the risk factor taxonomy illustrated in Figure 4 (middle 3 columns). We will construct simple models of traditional, carry, momentum, value and volatility risk factors in each of the asset classes, and illustrate their return, volatility and correlation properties in various market regimes. In the **third chapter** we will focus on risk management and portfolio construction techniques (Figure 4 last column). We will examine the historical behavior of factor portfolios and illustrate the benefits and drawbacks of different portfolio methods. Finally in **the Appendices**, we will provide additional technical details on factor styles and risks methods, provide an overview of existing J.P. Morgan research strategies and tradable products, link our factor styles and popular hedge fund strategies, provide a list of relevant literature and glossary of terms, and more.

Summary

- **Low Alpha / High Correlation Problem**: Diminishing availability of alpha and high cross-asset correlations have prompted investors to seek new investment strategies and styles. In the search for higher risk adjusted returns, finding pockets of low asset correlations can be as important as finding new Alpha. A risk factor investment approach aims to deliver both.

- **Risk Factors**: Also called alternative betas, or exotic betas, are synthetic assets designed to capture risk premia not accessible by traditional assets. Risk factors are defined by a set of trading rules that often involve multiple assets and trading instruments, and a rebalancing strategy. Risk factors are sensible only if there is a strong economic rationale for the premium they deliver. Investors should be able to trace the premium to some specific market inefficiency. This premium can be related to the irrational behavior of market participants, supply/demand friction, change in market micro structure, or other market inefficiencies.

- **Main Advantages of Risk Factor Approach**: There are two main advantages of a risk factor approach: the ability to access new sources of premia (not available to traditional assets), and typically lower correlation between risk factors (compared to the correlation between traditional assets). Given the positive expected premia and lower correlation, the performance of a risk factor portfolio can mimic alpha in a portfolio of traditional assets, with lower volatility and tail risk.

- **Potential Pitfalls**: In an ideal world, risk factors should deliver steady premia and have stable correlation properties. In the real world, this is often not the case. Factors have lifecycles, the level of premia can vary over time, and the correlation between factors can increase in certain market environments. Potential pitfalls in risk factor investing are related to flaws in factor design or failing to understand the lifecycle of individual risk factors. Design mistakes are often related to in-sample biases. Lifecycle issues include factors losing effectiveness due to arbitrage activity or capacity limitations. By carefully researching risk factors, one can avoid these pitfalls.

- **Types of Systematic Strategies**: Risk factors are building blocks for systematic strategies. These strategies can be designed with the aim to generate alpha, enhance performance of traditional assets, provide specific alternative beta exposure or serve as a portfolio hedge.

- **Classification of Risk Factors**: While there is no unique classification of risk factors, the main styles of risk factors are: **Traditional, Carry, Momentum, Value, and Volatility**. In addition to the main style designation, investors often describe a risk factor with traditional asset class or geographical region designations (e.g. US Equity Momentum, EM FX carry, etc.). Some risk factors have properties of more than one style (e.g. Carry may have a negative exposure to Volatility, etc.). Understanding factor premia and correlations under various market regimes enables investor to construct portfolios with lower risk compared to portfolios of traditional assets.

- **Portfolio Construction methods**: To create a viable systematic strategy, an investor needs to select factors and prescribe a weighting methodology. Weights of factors can be selected to minimize portfolio volatility, maximize Sharpe ratio or diversification, equalize risk contribution from each factor, or implement an investor’s specific views on risk and returns. These are called **Cross-Sectional Risk Methods**. Once the factor relative weights are determined, overall portfolio risk can be managed by dynamically allocating risk between the factor portfolio and risk-free asset. These are called **Time-Series Risk Methods** and include volatility targeting, CPPI, stop loss, and option based risk methods.

Classification of Risk Factors

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Risk Factor Framework

The rationale for risk premia of traditional assets such as Equities and Bonds are well documented.[2] For instance, equity premia are often linked to a risk of recession and market crash, and corporate bond premia to a company's default risk. Both Equity and Corporate bond risk premia behave similarly and tend to widen in a high volatility environment. In our **effort to classify alternative risk factors**, we will look for the factors' economic rationale, risk properties, and behavior in various market regimes. A similar approach was used, for instance, in the classification of equity risk factors by Fama and French (1993). Based on these considerations, we will classify risk factors into five broad styles: **Traditional, Carry, Momentum, Value, and Volatility**. In addition to this broad classification, investors often describe a risk factor with traditional asset class or geographical region designations (e.g. US Equity value, EM FX carry, Commodity momentum, etc.).

While there is no unique way to classify risk factors, we think our choice of five main styles is intuitive and consistent with more rigorous academic results. In an idealized world, these risk factor styles should be **independent (orthogonal), deliver positive risk premia, and form a complete set** in the sense that they can explain the risk of any systematic strategy (span all 'dimensions' of risk). In practice, these requirements will hold only approximately. For instance, the correlation between risk factors is almost never zero. However, at a portfolio level correlations can average out to a sufficiently low level to be considered approximately zero. Risk premia are expected to be positive on average, but factors occasionally suffer from draw-downs. Finally, while these five factor styles are expected to form a complete set of risk dimensions, it is quite possible that new market inefficiencies (due to e.g. new products or trading styles) create a need for introducing additional factor styles in the future.

In the rest of the section we will define the factor styles, and analyze their properties. To provide insights into each of the factor styles, we constructed simple illustrative models for each factor style (traditional, momentum, value, carry, volatility) and in each of the traditional asset classes (equities, rates, commodities, currencies). We will study performance, volatility and correlation profiles of these factor style models under different macro-economic environments of GDP growth and inflation, as well as different market technical regimes of volatility, funding liquidity and market liquidity.

The expected return of any trading strategy can be broken down into the return contributions from traditional asset classes such as stocks, bonds, commodities, etc. and an alternative contribution that is not explained by these traditional betas. The expectation for idiosyncratic returns is zero, as these events are by definition unrelated to either traditional or alternative risk factors. Specifically, the expected return (ER) of a trading strategy is given by:

$$\mathrm{ER}(\text{Trading Strategy})_t = \mathrm{ER}(\text{Traditional Assets})_t + \mathrm{ER}(\text{Alternative Factors})_t$$

This expected return is also called the 'ex-ante' return or 'ex-ante' premium at time *t*. As we mentioned earlier, risk premia of **traditional assets** are related to well understood risks such as tail events and economic contraction in equities, inflation risk premium (IRP)[3], business cycles[4] in bonds, market volatility, and corporate defaults in credit. The expected total return of a traditional risk factor itself is given by its expected yield (or net cash flow income yield) and price return (PR) of the asset:

$$\mathrm{ER}(\text{Traditional Asset})_t = \text{Yield}_t + E(\mathrm{PR})_t$$

Price return can capture changes related to changes in asset valuations but also technical drivers such as persistent inflows/outflows of funds to the asset class, covering of short interest, and others. By including yield, valuation and technical contributions, the expected return of a traditional asset can be written as

[2] See, for example, Siegel (1994), Cornell (1999), Dimson–Marsh–Staunton (2002), Fama–Bliss (1987), Campbell–Shiller (1991), Longstaff–Mithal–Neis (2005) and Ilmanen (2003, 2011). See the Appendix for a list of references to relevant academic studies.
[3] Higher inflation uncertainty warrants higher required premia for holding nominal bonds.
[4] The slope of yield curve (YC) is closely related to business cycles. For example, a steep YC usually predicts higher economic growth.

$$\text{ER(Traditional Asset)}_t = \text{ER(Yield)}_t + \text{ER(Valuation)}_t + \text{ER(Technical)}_t$$

This is a natural framework to explain risk premia for asset classes such as equities and real estate (that have well defined yields such as dividend, bond or rental yields, and valuation ratios such as P/E, P/B, Price to rental income ratio, etc.), but it can also be generalized to other asset classes such as commodities and currencies. For instance, commodities and currency have both fundamental valuations (based on inflation levels, GDP growth, etc.), as well as yield components such as commodity futures term structure roll, and cross-currency interest rate differentials.

Alternative risk factors such as **Carry, Momentum and Value** are constructed as long-short portfolios of traditional assets. The choice of asset weights and rebalancing method is such that these alternative risk factors capture risk premia related to certain market inefficiencies, but don't have a direct exposure (beta) to traditional risk factors.

$$\begin{aligned}\text{ER(Alternative Factor)}_t &= \textstyle\sum_i w_{it}\,\text{ER(Traditional Asset}_i)_t \\ &= \textstyle\sum_i w_{it}\,\text{ER(Yield}_i)_t + \sum_i w_{it}\,\text{ER(Valuation}_i)_t + \sum_i w_{it}\,\text{ER(Technical}_i)_t\end{aligned}$$

Carry strategies are constructed by holding long positions in higher yielding assets and short selling lower yielding assets. An example of a carry risk factor is currency carry, where an investor is long high yielding currencies and short low yielding currencies. A portfolio can be diversified across a number of currency pairs to diversify exposure to a single currency or other exposures. Financial theories based on idealized frictionless markets would suggest that any carry advantage would be undermined by subsequent relative price depreciations (uncovered interest rate parity). However, empirical evidence suggests otherwise – higher yielding currencies have delivered persistent outperformance.

Value strategies are constructed by holding long positions in undervalued and short positions overvalued assets based on some valuation model. An example would be a portfolio that is long stocks with a low Price-to-Book ratio (P/B) and short stocks with a high P/B ratio. A long-short value portfolio can be made market neutral, and also be neutral on the carry risk factor (e.g. setting the average dividend yield of high value stocks equal to the average dividend yield of low value stocks). In an efficient market, a value portfolio would not outperform the market, as the premium built into value stocks would compensate for the few stocks that end up defaulting (i.e. value traps). In practice, value stocks tend to outperform the market. This was demonstrated for instance in the work of Fama and French (1993). While simple value factors such as P/B still outperform when applied to emerging market equities, this simple rule is not working well in developed markets. However, more advanced value factors based on corporate earnings and cash flow ratios recently have shown strong performance across emerging and developed market stocks.

Momentum strategies are based on technical signals and tend to be long assets whose price recently appreciated, and short assets whose price depreciated. Momentum patterns develop if there are persistent fund flows or persistent macro trends that cause a serial correlation of asset returns. Momentum can be caused by irrational behavior of investors who extrapolate past performance of an asset: herding into winning assets and abandoning losing ones. An historical example of positive serial correlations during market rallies is the late '90s Tech bubble. Another cause of the momentum effect is a mismatch between asset supply and demand cycles. The mismatch of supply and demand cycles can be illustrated in commodities where the production cycle is often slow to adjust to demand trends (e.g. it takes several years to expand oil production, which may persistently lag increased demand from emerging economies). Momentum factors can be constructed based on absolute or relative return, within or across traditional asset classes.

By constructing a long-short portfolio of traditional assets in such a way to eliminate exposure to traditional market factors, one can create alternative risk exposures such as Carry (long high yield, short low yield), Value (long high value, short low value) and Momentum (long outperformers, short underperformers). This enables us to express the expected return of an alternative risk premia strategy as:

$$\text{ER(Alternative Factor)}_t = \text{ER(Carry)}_t + \text{ER(Momentum)}_t + \text{ER(Value)}_t$$

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

We should note that the momentum and value components are generic terms in this framework: they could include any factor with positive premia that is caused by a particular technical trend or fundamental value anchor. Similarly, carry factors can involve yield, not just from traditional assets, but also derivative yield such as the one from futures and swap term structure roll-down, etc.

Volatility as an Alternative Strategy Style: We defined each of the risk factors (Traditional, Carry, Momentum and Value) via expected risk premia. The actual return of a systematic strategy will in most cases be different than the expected return due to uncertainty embedded in individual risk premia. In other words, each risk factor will exhibit volatility, and actual realized returns ('ex-post' returns) will differ from expected ('ex-ante') premia. For instance, if a value stock in a long-short value portfolio defaults, the factors may deliver a negative return instead of positive expected value premia. Similarly, currency carry return could deviate from ex-ante measures due to inflation, currency devaluation, or a sudden unwind of carry trades. The actual return of any strategy will therefore have uncertainty associated with both traditional and alternative risk factors. This uncertainty can be priced in as additional **Volatility premia** to each of the risk factors.

$$\begin{aligned}\text{Realized Return}_t &= \text{ER(Trading Strategy)}_t + [\text{Realized Return} - \text{ER(Trading Strategy)}]_t \\ &= \text{Traditional Factor}_t + \text{Alternative Factor}_t + [\text{Realized Return} - \text{ER(Trading Strategy)}]_{\text{t}} \\ &= \text{Traditional Factor}_t + \text{Carry}_t + \text{Momentum}_t + \text{Value}_t + \text{Volatility}_t\end{aligned}$$

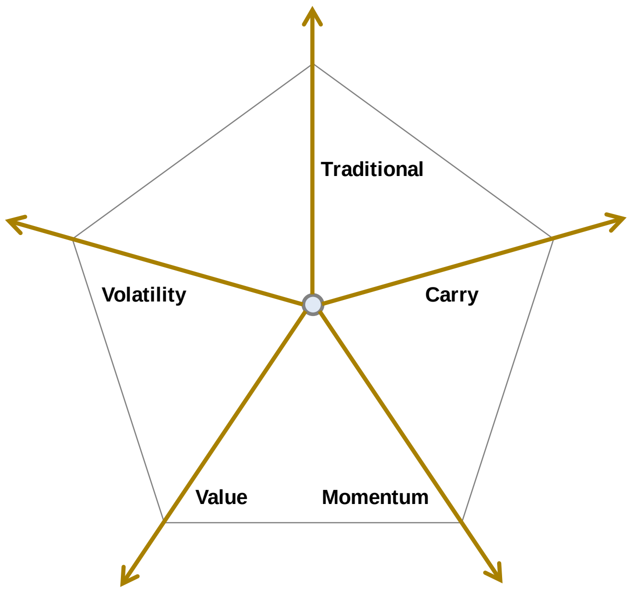
Volatility risk premia can be priced implicitly in the price of an asset, and are often explicitly priced in options and other derivative instruments. Implied volatility often represents the market's expectation of future volatility but also reflects the supply and demand for owning volatility exposure. Implied volatility can be traded indirectly via options (option prices are based on implied volatility) and directly via instruments such as volatility futures and variance swaps. Long volatility positions are negatively correlated with other risky assets such as equity and credit, and can help reduce overall portfolio risk. This benefit comes at a cost, and long volatility positions typically have negative expected premia (negative carry). Volatility factors often sell these expensive volatility premia to generate returns.

The pricing of volatility risk premia can differ for options on various traditional assets. Different levels of volatility risk premia can result from market perceptions of risk, or from supply/demand for protection. For example, equity index volatility tends to trade persistently rich, while currencies often exhibit more balanced levels of volatility premia. The most likely reason for the difference in levels of risk premia is that equities are on balance held long and hedged by investors, while currencies are held both long and short. Given the divergent levels of volatility risk premia, one can construct a portfolio that is systematically short expensive volatility premia, or a portfolio that is short expensive and long cheap volatility premia. In our classifications of alternative risk factors we decided to classify these strategies as Alternative Volatility risk factors rather than, e.g. Value risk factors.[5]

We believe that our categorization of risk factors as Traditional, Carry, Momentum, Value, and Volatility provides a sound framework to analyze cross asset systematic strategies. In an idealized world these factors would be independent (e.g. principal components) and could explain the returns of any strategy (Figure 5 below). While they will often fail to do so in the real world, as a tool they will enable us to identify and capture opportunities in risk factor investing.

[5] There is no broad consensus of how to classify volatility strategies. For instance, many investors consider a long volatility exposure to be one of the traditional asset classes, while some classify short volatility strategies as Carry strategies rather than recognizing them as a separate risk factor. To leave room for different opinions about the classification of volatility strategies, we have included volatility both as one of the main asset classes (alongside, equities, commodities, etc.) as well as one of the Alternative risk factors. We will often refer to simple long volatility strategies as 'traditional factors' and more elaborate premium extraction strategies as 'alternative volatility' risk factors. This dual classification of volatility will also enable us to more precisely identify volatility strategies. For instance a common strategy of selling equity index variance can be either classified as 'Equity Volatility', or 'Volatility Carry' strategy.

Figure 5: Risk premia space spanned by five factor styles



Source: J.P. Morgan Quantitative and Derivatives Strategy.

To illustrate the main properties of risk factors, we designed 'toy models' for the five factor styles in each of the asset classes. Table 1 below shows these simple implementations of Traditional, Carry, Momentum, Value and Volatility factors that we will study in the rest of this section.

Table 1: Stylized examples of risk factors across asset classes

	Traditional	Carry*	Momentum*	Value*	Volatility
Equities	S&P 500	Dividend Yield	Past 12-month price return	Book to Price Ratio	Option Writing on SPX
Rates and Credit	US Treasury Bond	Slope of yield curve	Past 12-month price return	Past 3-year change in yield	Option Writing on UST futures
Currencies	DXY	Short-term deposit rate	Past 12-month price return	Past 5-year loss of PPP	Rolling Currency Vol Swap
Commodities	S&P GSCI	Ex-ante roll yield	Past 12-month price return	Past 5-year average to current price	Option Writing on Gold

Source: J.P. Morgan Quantitative and Derivatives Strategy. * Risk factors are created via long-short portfolio of corresponding assets according to the definitions of Carry, Momentum and Value respectively.

First we will analyze the historical return distributions for these risk factors. This will include simple performance statistics, as well as risk metrics such as standard deviation (volatility), skewness of returns, and tail risk (kurtosis). Additionally we will report common performance ratios such as Sharpe, Sortino, Calmar ratios, as well as factor correlations and co-kurtosis with equities and bonds. For completeness we have included definitions of these measures in the **Mathematical Box** below. Readers who are familiar with these metrics or are not interested in formalism may skip to page 22.

Mathematical Box (Performance-Risk Analytics)

For a time series observation of total returns $\boldsymbol{R} = (r_1, \ldots, r_T)'$ with N observations per annum and the corresponding time series of risk-free rates $\boldsymbol{R_f}$, $\boldsymbol{R_e} = \boldsymbol{R} - \boldsymbol{R_f} = (r_1^e, \ldots, r_T^e)'$ is the excess return. In addition, $\boldsymbol{S_R} = (S_1, \ldots, S_T)^T$ with $S_t = \prod_{i=1}^{t}(1 + r_i)$ is the net asset value (NAV) for the return series $\boldsymbol{R}$.

We define the following "Core Return-Risk Analytics", "Tail Risk Analytics" and "Performance Evaluation Analytics", which will be used and referred throughout the text. Acronyms for each analytics are included in the parentheses right behind the corresponding full name.

Core Return-Risk Analytics

- **Annualized average return (Average):**

$$\boldsymbol{\mu_R} = \frac{N}{T}\sum_{i=1}^{T} r_i$$

- **Annualized compounded return (CAGR):**

$$\boldsymbol{g_R} = \left[\prod_{i=1}^{T}(1 + r_i)\right]^{\frac{N}{T}} - \mathbf{1} = (S_T)^{\frac{N}{T}} - 1$$

- **Annualized standard deviation (StDev):**

$$\boldsymbol{\sigma_R} = \sqrt{N\frac{\sum_{i=1}^{T}(r_i - \bar{r})^2}{T - 1}}$$

  where $\bar{r} = \frac{1}{T}\sum_{i=1}^{T} r_i = \boldsymbol{\mu_R}/N$ is the arithmetic average of the returns.

- **Annualized downside deviation (DownDev):**

$$\boldsymbol{D\sigma_R}(R_{\text{Target}}) = \sqrt{N\frac{\sum_{i=1}^{T}\left[\min(r_i - R_{\text{Target}}, 0)\right]^2}{T}}$$

  where $R_{\textbf{Target}}$ is so-called target return (or Minimum Acceptable Return to evaluate the relative performance). The downside deviation is also called the "loss standard deviation".

- **Annualized upside deviation (UpDev)** or "Gain standard deviation":

$$\boldsymbol{U\sigma_R}(R_{\text{Target}}) = \sqrt{N\frac{\sum_{i=1}^{T}\left[\max(r_i - R_{\text{Target}}, 0)\right]^2}{T}}$$

- **Annualized Covariance (CoVar)** between $\boldsymbol{R}$ and another return series $\boldsymbol{X}$:

$$\mathbf{CoVar}_{\boldsymbol{R,X}} = \frac{N}{T - 1}\sum_{i=1}^{T}(r_i - \bar{r})(x_i - \bar{x})$$

- **Correlation (Correl)** between $\boldsymbol{R}$ and another return series $\boldsymbol{X}$:

$$\mathbf{Correl}_{\boldsymbol{R,X}} = \frac{\mathbf{CoVar}_{\boldsymbol{R,X}}}{\boldsymbol{\sigma_R\sigma_X}}$$

  Covariance and correlation could be calculated either in total returns or excess returns.

Tail Risk Analytics

- **Skewness (Skew)** measures the symmetry of a distribution:

$$\mathbf{Skew}_{\boldsymbol{R}} = \frac{T}{(T-1)(T-2)}\sum_{i=1}^{T}\left(\frac{r_i - \bar{r}}{\boldsymbol{s_R}}\right)^3$$

where $\boldsymbol{s_R} = \boldsymbol{\sigma_R}/\sqrt{N}$ is the (un-annualized) standard deviation of the returns.

- **Kurtosis (Kurt)** characterizes the relative richness of the tail of a distribution compared with a normal distribution:

$$\mathbf{Kurt}_{\boldsymbol{R}} = \frac{T(T+1)}{(T-1)(T-2)(T-3)}\sum_{i=1}^{T}\left(\frac{r_i - \bar{r}}{\boldsymbol{s_R}}\right)^4 - \frac{3(T-1)^2}{(T-2)(T-3)}$$

- **Tail Dependence Coefficient (TDC)** between ***R*** and ***X*** measures the probability of extreme values occurring for ***R*** given that ***X*** assumes an extreme value too. For a return series we are specifically concerned with the "left tail":

$$\mathbf{Left\ TDC}_{\boldsymbol{R,X}} = \mathrm{Prob}(\boldsymbol{R} \text{ is extemely small given } \boldsymbol{X} \text{ is extremely small })$$

Since its estimation involves specific parametric or non-parametric copula models, we don't provide its sample formula here.

- **CoSkewness (CoSkew)** between ***R*** and ***X*** measures the symmetry of the distribution of ***R*** relative to ***X***:

$$\mathbf{CoSkew}_{\boldsymbol{R,X}} = \frac{T}{(T-1)(T-2)}\sum_{i=1}^{T}\frac{(r_i - \bar{r})(x_i - \bar{x})^2}{\boldsymbol{s_R s_X^2}}$$

- **CoKurtosis (CoKurt)** between ***R*** and ***X*** measures the tail dependence of the distribution of ***R*** relative to ***X***:

$$\mathbf{CoKurt}_{\boldsymbol{R,X}} = \frac{T(T+1)}{(T-1)(T-2)(T-3)}\sum_{i=1}^{T}\frac{(r_i - \bar{r})(x_i - \bar{x})^3}{\boldsymbol{s_R s_X^3}} - \frac{3(T-1)^2}{(T-2)(T-3)}$$

The Co-Skewness and Co-Kurtosis statistics are measured relative to a particular benchmark to assess the systematic exposure to skew and tail risks.

- **Drawdown (DD)** measures the current percentage loss of NAV from the previous high water mark (HWM) within a specific time window:

$$\mathbf{DD}_{\boldsymbol{R}}(t_1, t_2) = \frac{S_{t_2}}{\mathrm{HWM}(t_1, t_2)} - 1, \text{where } \mathrm{HWM}(t_1, t_2) = \max_{t_1 \le t \le t_2} S_t$$

- **Maximum Drawdown (MaxDD)** measures the maximum peak to trough percentage change of the NAV during a specific period:

$$\mathbf{MaxDD}_{\boldsymbol{R}}(t_1, t_2) = -\max_{t_1 \le t \le t_2} |\mathbf{DD}_{\boldsymbol{R}}(t_1, t)|$$

As the absolute value of maximum drawdown is higher for longer periods, a reasonable window (e.g. past three years) is usually applied to the calculation so as not to disadvantage managers with longer track records.

- **Drawdown Duration (DDur)** measures the time in years from the last HWM:

$$\mathbf{DDur}_{\boldsymbol{R}}(t_1, t_2) = \frac{t_2 - \tau}{N}, \text{for } t_1 \leq \tau \leq t_2 \text{ such that } S_\tau = \text{HWM}(t_1, t_2)$$

- **Maximum Drawdown Duration (MaxDDur)** measures the maximum amount of time in years to reach previous HWM:

$$\mathbf{MaxDDur}_{\boldsymbol{R}}(t_1, t_2) = \max_{t_1 \leq t \leq t_2} \mathbf{DDur}_{\boldsymbol{R}}(t_1, t)$$

- **Pain Index (PainIdx)** measures the average drawdown from the recent HWM and penalizes on the duration of drawdown:

$$\mathbf{PainIdx}_{\boldsymbol{R}} = -\sum_{t=1}^{T} \frac{\mathbf{DD}_{\boldsymbol{R}}(t)}{T}$$

- **Value at Risk (VaR)** measures a particular percentage quantile of the return distribution. Specifically, given a confidence level δ, the related $\mathbf{VaR}_{\boldsymbol{R}}(\delta)$ is determined such that probability of a return lower than $\mathbf{VaR}_{\boldsymbol{R}}(\delta)$ is δ. We use an empirical estimate from the historical data:

$$\mathbf{VaR}_{\boldsymbol{R}}(\delta) = \text{Quantile}(\boldsymbol{R}, \delta)$$

- **Conditional Value at Risk (CVar)** or expected shortfall evaluates the expected return given the return is below $\mathbf{VaR}_{\boldsymbol{R}}(\delta)$, or

$$\mathbf{CVaR}_{\boldsymbol{R}}(\delta) = E[\boldsymbol{R} | \boldsymbol{R} \leq \mathbf{VaR}_{\boldsymbol{R}}(\delta)]$$

Performance Evaluation Analytics

Performance evaluation usually focuses on certain risk-adjusted return measures. Common measures include alpha and various alternatives of “excess return to risk” ratios:

- **Alpha** measures the risk-adjusted excess return from a factor model:

$$\boldsymbol{R}_e = \boldsymbol{\alpha} + \beta_1 f_1 + \cdots + +\beta_n f_n + \varepsilon,$$

  where $f_1, \dots, f_n$ are n systematic excess return factors and ε is a white noise error term. The regression estimation of $\boldsymbol{\alpha}$ is the **ex-post alpha** to measure portfolio performance after adjusting for systematic factors such as the Fama-French six factors. The regression estimated $\beta_1, \dots, \beta_n$ are the **factor loadings or Betas**, which measure the relative sensitivity of portfolio excess returns to each factor (after controlling for other factors).

- **Sharpe Ratio (SR)**:

$$\text{SR}_{\boldsymbol{R}_e} = \frac{\boldsymbol{\mu}_{\boldsymbol{R}_e}}{\boldsymbol{\sigma}_{\boldsymbol{R}_e}}$$

  When the benchmark used for the calculation of excess return is not a risk-free asset, this is often called **Information Ratio**.

- **Adjusted Sharpe Ratio (ASR)**:

$$\text{ASR}_{\boldsymbol{R}_e} = \text{SR}_{\boldsymbol{R}_e} \times \left[1 + \frac{\mathbf{Skew}_{\boldsymbol{R}_e}}{6} \text{SR}_{\boldsymbol{R}_e} - \frac{\mathbf{Kurt}_{\boldsymbol{R}_e}}{24} \left(\text{SR}_{\boldsymbol{R}_e}\right)^{\mathbf{2}}\right]$$

The adjusted Sharpe Ratio was proposed as an alternative to the standard Sharpe ratio when related performance is not normally distributed. The measure is derived from a Taylor series expansion of an exponential utility function.

- **Sortino Ratio (Sortino):**

$$\mathrm{Sortino}_{\boldsymbol{R}_e} = \frac{\boldsymbol{\mu}_{\boldsymbol{R}_e}}{\boldsymbol{D\sigma}_{\boldsymbol{R}_e}(R_{\mathrm{Target}})}$$

where the target return $R_{\mathbf{Target}}$ is usually set to be 0 for an excess return series.

- **Calmar Ratio (Calmar):**

$$\mathrm{Calmar}_{\boldsymbol{R}_e} = -\frac{\boldsymbol{\mu}_{\boldsymbol{R}_e}}{\mathbf{MaxDD}_{\boldsymbol{R}_e}(\text{Past 3 years})}$$

- **Pain Ratio (PainRatio):**

$$\mathrm{PainRatio}_{\boldsymbol{R}_e} = \frac{\boldsymbol{\mu}_{\boldsymbol{R}_e}}{\mathbf{PainIdx}_{\boldsymbol{R}_e}}$$

- **Reward to VaR Ratio (VaRatio):**

$$\mathrm{VaRatio}_{\boldsymbol{R}_e} = -\frac{\boldsymbol{\mu}_{\boldsymbol{R}_e}}{N \times \mathbf{VaR}_{\boldsymbol{R}_e}(\delta)}$$

- **Reward to CVaR Ratio (CVaRatio):**

$$\mathrm{CVaRatio}_{\boldsymbol{R}_e} = -\frac{\boldsymbol{\mu}_{\boldsymbol{R}_e}}{N \times \mathbf{CVaR}_{\boldsymbol{R}_e}(\delta)}$$

- **Hit Rate** measures the percentage of non-negative returns relative to a certain benchmark:

$$\mathrm{Hit}_{\boldsymbol{R}_e} = \frac{\sum_{i=1}^{T} 1\{r_i^e \geq 0\}}{T}$$

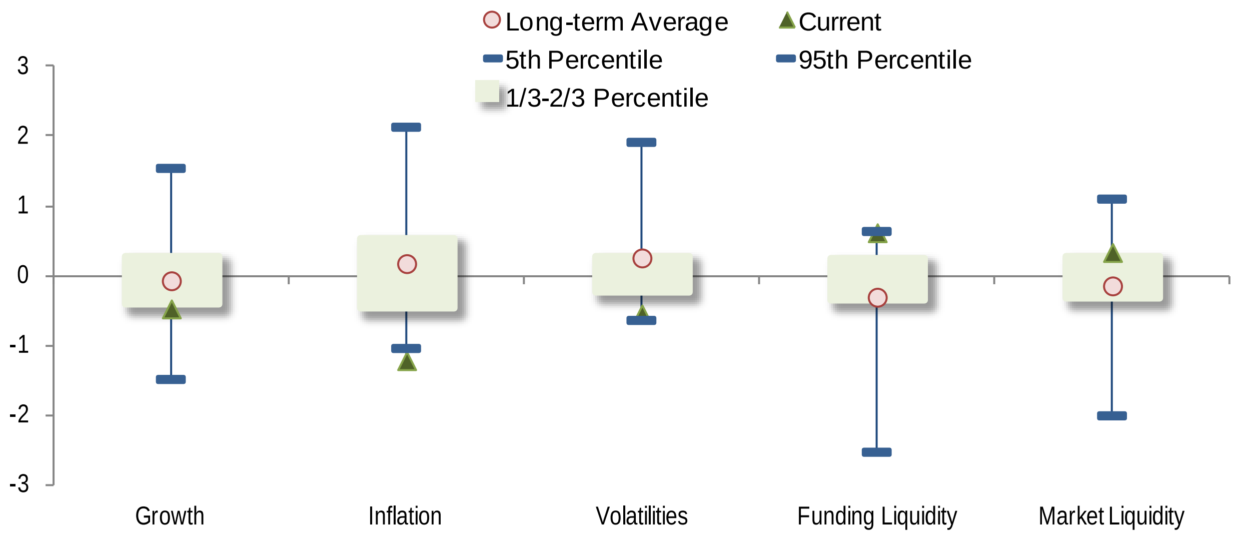
- **Gain to Pain Ratio (GPR)** measures the sum of positive returns to sum of negative returns:

$$\mathrm{GPR}_{\boldsymbol{R}_e} = -\frac{\sum_{i=1}^{T} \max(r_i^e, 0)}{\sum_{i=1}^{T} \min(r_i^e, 0)}$$

To develop a better understanding of traditional and alternative risk factors, we further studied properties of our factors under different macroeconomic and market-technical regimes. In particular, we examined performance, volatility, tail risk, correlations, and other risk properties in different regimes of **Growth** (YoY change of OECD CLI, a leading indicator of global economic growth), **Inflation (**OECD global consumer price inflation indicator), **Volatility** (1-month S&P 500 realized volatility), **Funding Liquidity** (TED Spread, defined as the difference between 3-month Treasury Bill rate and 3-month US$ Libor rate, measures broad US$ funding risk), and **Market Liquidity** (the Pástor-Stambaugh (2003) market liquidity factor, which measures aggregate stock market liquidity in the US). Figure 6 below shows the historical distribution of the five regime indicators[6] - growth, inflation, volatility, funding liquidity and market liquidity during the period from 1972 to 2012, using monthly data.

[6] These indicators were standardized "in-sample" to have unit variance and zeros median for better visualization.

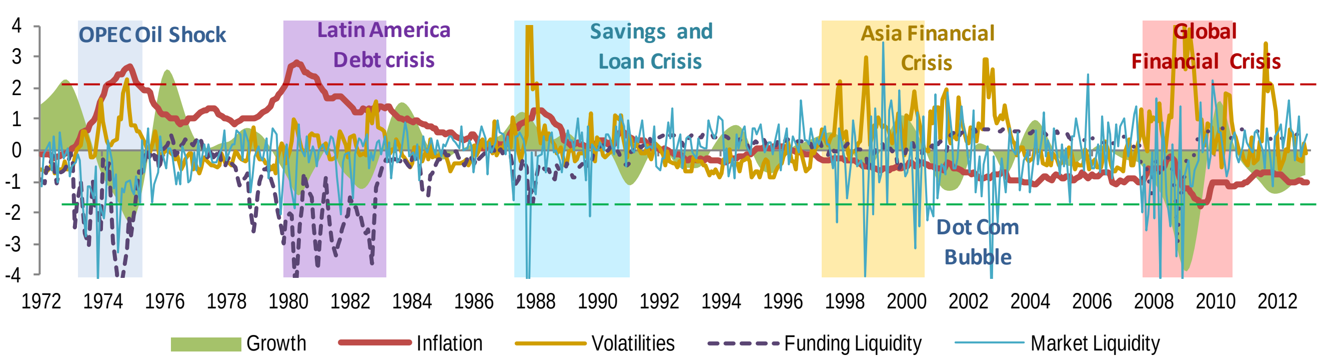
Figure 6: Historical profile of macro economic and market regime factors during 1972-2012



Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg, OECD, and Pástor-Stambaugh (2003). * Regime factors are standardized to unit variance and zero median. ** Current values (green triangles) for Growth, Inflation, Volatilities and Funding Liquidity factors are based on latest available data in 2013 from OECD, Bloomberg and J.P. Morgan Markets as of 10 Dec 2013; Current Value for the Market Liquidity factor refers to the data point in Dec 2012 from the authors' website.

We note that volatility and inflation have a tendency to spike (positive skewness), and the funding and market liquidity measures have tendency to drop (negative skewness). All the measures exhibit a higher likelihood of "tail" events than a normal distribution (positive excess kurtosis). Figure 7 below shows the history of these measures over the past 40 years. Notable features include the growth cycles, recession of '74, '09, strong inflation and funding stress in late 70s, market crash of '87, high volatility and low liquidity during market crises of'02, '08, etc. The Figure shows that we are currently in a low Growth, exceptionally low Inflation, low Volatility, and high Funding and Market Liquidity regime.

Figure 7: Growth, Inflation, Volatility and Liquidity during the past four decades*



Source: J.P. Morgan Quantitative and Derivatives Strategy. * Regime factors are standardized to unit variance and zeros median.

The five macro and market technical regime indicators discussed are not independent of one another. Table 2 below shows the correlation of these regime indicators over the past 40 years, as well as during five crisis periods. For instance, Volatility was negatively correlated with all the other factors, and the negative correlation was most pronounced during crisis periods. Funding Liquidity was significantly negatively correlated with inflation, partly reflecting the secular decline in inflation and improvements in systemic banking credibility and so on.

Table 2: Correlation matrix of Growth, Inflation, Volatility, Funding Liquidity and Market Liquidity Indicators (lower triangular statistics are the all-sample pair-wise correlation, upper triangular are the correlation statistics during crisis periods*)

	Growth	Inflation	Volatilities	Funding Liquidity	Market Liquidity
Growth		47	-69	31	23
Inflation	4		-41	-22	18
Volatilities	-38	-9		-41	-33
Funding Liquidity	17	-71	-20		26
Market Liquidity	10	-14	-43	28	
Full Sample Average	-2	-22	-28	-12	-5
Crisis Average	8	0	-46	-2	8
During GFC	-4	1	-48	-9	3

Source: J.P. Morgan Quantitative and Derivatives Strategy. * Crisis periods we include for the correlation calculation are Oct 1973—Mar 1974 (OPEC Oil Crisis), Aug 1982 – Oct 1983 (Latin America debt crisis), July 1990 - Mar 1991 (US saving & loan crisis), Jul 1997 - Sep 1998 (Asian Financial Crisis, Russian Default and LTCM), and Aug 2007 - Mar 2009 (Global Financial Crisis or GFC). ** Full sample correlations are calculated during the period from Jan 1972 – Dec 2012.

Given that all of these measures show some level of persistence, understanding the performance of cross-asset risk factors in various market regimes (growth, inflation, volatility, etc.) can influence factor selection and risk allocation decisions. For instance, carry strategies typically work well as long as the market is in a low volatility environment. To properly allocate to a carry strategy, an investor doesn't have to know when volatility will decline, but rather increase carry exposure once volatility declined into a new (low volatility) regime. In the next section we analyze the performance and risk properties of risk factor styles (traditional, momentum, value, carry, volatility) and test their performance in various market regimes.

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

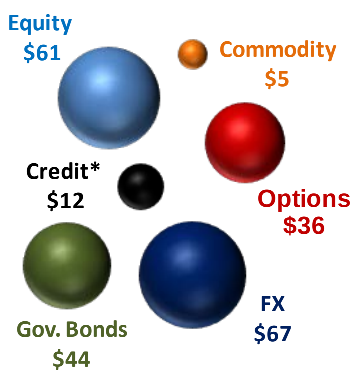
Traditional Assets

The traditional asset classes or ‘betas’ include: Equities, Rates (Government bonds), Credit (Corporate bonds), Commodities, and Currencies. Additionally, many investors classify long Volatility exposure as a traditional asset class. Traditional asset classes represent the core risk factors of most investment portfolios. They are also the building blocks for alternative risk factors. For Equities and Bonds, it is common to introduce geographic designations such as Developed market Americas, Europe and Asia, Emerging Markets and Frontier Markets (see Figure 4 on page 12 for traditional asset and region designations). Commodities can further be classified by type (e.g. Precious metals, Industrial Metals, Energy, Agricultural commodities, etc.). Currency pairs can involve G10 countries, Developed, Emerging market currencies or any cross-regional pair. Given the rapid growth of derivative markets over the past decade, many investors include Volatility in the list of traditional asset classes. Volatility can be traded via options on traditional assets and directly via volatility products (e.g. futures on volatility, variance swaps, etc.).

Figure 8 below shows the market capitalization of publicly traded traditional asset classes. For equities and bonds we show the face value of securities outstanding globally (credit includes non-financial debt only, i.e. excludes ~$35T of financials debt). Commodities include the notional amount of listed and over the counter commodity based financial instruments (e.g. rather than the value of physical reserves) [7]. Currency ‘capitalization’ represents the notional value of currency derivatives such as forwards, swaps and options. Finally, the size of the options market includes notional exposure of all Equity, Bond, Currency and Commodity option contracts (assuming at-the-money options, i.e. 50% exposure to the contract size, i.e. ’50-delta’), rather than the volatility content of options. The volatility content of these options will depend on several factors such as asset volatility, average maturity and strike of each instrument (e.g. the volatility content will be higher for an equity option compared to a rate option of the same specification, due to the higher volatility of equities).

Figure 9 further breaks down Equities and Bonds by geographical designation, Options value by underlying asset, and Currency and Commodities by type of instrument (options and delta one products such as forwards, swaps and futures).

Figure 8: Market Size of Traditional Asset Classes in $T



Source: J.P. Morgan Quantitative and Derivatives Strategy, BIS, Bloomberg.

Figure 9: Market Size for Traditional Assets, Geographical Regions and Product types in $Bn

Equity		Rates		Credit (non-Financial)	
DM Americas	$23,210	DM Americas	$15,680	DM Americas	$6,950
DM Europe	$13,830	DM Europe	$12,020	DM Europe	$2,180
DM Asia	$10,030	DM Asia	$10,680	DM Asia	$1,160
EM	$12,640	EM	$ 5,260	EM	$1,520
FM	$ 770	FM	$ 240	FM	$ 50

Options		Currencies		Commodities	
Rates	$24,180	Delta One	$57,140	Delta One	$2,760
Equity	$ 5,710	Options	$10,220	Options	$2,100
FX	$ 5,110				
Commodity	$ 1,050				

Source: J.P. Morgan Quantitative and Derivatives Strategy, BIS, Bloomberg.

Traditional assets can be traded in many different ways. For instance, investors can directly trade portfolios of stocks and bonds, trade linear derivative products based on these assets such as futures, swaps and ETFs, or trade non-linear derivative products such as options.

[7] An alternative method of estimating the market size of commodities is using the aggregate production value. We estimate global production of all traded commodities to total $10.7T as of 6 Dec 2013. See our report Commodity Flow Monitor for details.

The bulk of traditional assets are held by investors implementing simple buy-and-hold strategies in which risk premia are captured as asset yield or long-term price appreciation. Much is written about traditional asset classes, and the drivers of their prices. For instance, J.P. Morgan research publishes comprehensive annual outlooks for each asset class. These outlooks include an overview of past market developments and performance forecasts for the year ahead, and can be found on the J.P. Morgan Markets site. In the Appendix, we provide some general theoretical considerations for the existence of risk premia based on economic models and investor behavior.

To illustrate the basic properties of traditional risk factors, we examined the performance and risk profiles of these asset classes over the past 40 years. In particular, we examined returns, volatility, tail risk, performance ratios and correlation metrics. In addition, we have compared asset performance under different economic and market regimes. While these properties of traditional assets are well known, readers can compare them to the same metrics for alternative risk factors that we present later in the section.

Our simplified models for traditional asset classes used throughout the report are:

Equities: Excess return of the S&P 500 total return index (index return less 1-month cash yield)[8];

Rates and Credit: Total return of equally weighted monthly rolling positions in 5-year, 10-year and 30-year constant maturity Treasury bonds minus 1-month cash yield;

Currencies: A short position in the US Dollar Index (DXY) as an approximation of an investment in major currencies versus USD.

Commodities: Excess return of S&P GSCI Commodities Index that includes energy, industrial and precious metals, agricultural and livestock products.

Performance and risk properties of traditional asset classes over the past ~40 years (1972 to 2012) are shown in Table 3 below. In our sample, Treasury bonds outperformed all other assets with a 9.3% annual compounded excess return, and a Sharpe ratio of 1.26. Bonds outperformed on other risk-adjusted measures as well (e.g. draw-down, Sortino ratio, Calmar ratio, Pain ratio, etc). The outperformance of bonds was largely due to a secular decline in yields since the early 1980s, stable US inflation and the adoption of US Treasury bonds as the primary global reserve asset. If we examine Treasury bond data on a longer horizon during 1928-2012, the average annual excess return and Sharpe ratio were weaker at 3.7% and 0.45, respectively. This Treasury outperformance will introduce a bias towards models that overweight bond based risk factors (e.g. Bond Beta, or Bond momentum) and risk models that overweight low risk assets (e.g. Risk Parity).

Equities and Commodities beta returned 2.7% and 3.3% per annum respectively, with higher realized volatilities and lower Sharpe ratios. The USD index returned approximately zero with significant volatility.

During the sample period, all traditional beta factors exhibited ‘fat tails’ (positive excess kurtosis), as periodic materialization of financial, geopolitical, and macroeconomic crises resulted in sharp losses for long-only positions in traditional assets. The co-Kurtosis between Treasuries and Equities was negative (suggesting use of Treasury bonds as a safe haven from equity market risks), and Commodities had negative co-Kurtosis with Bonds (suggesting their use as inflation hedge).

[8] We used S&P 500 index due to longest available trading history. The index is highly correlated to a global MSCI All-Country World index (~90% correlation during 1988-2012).

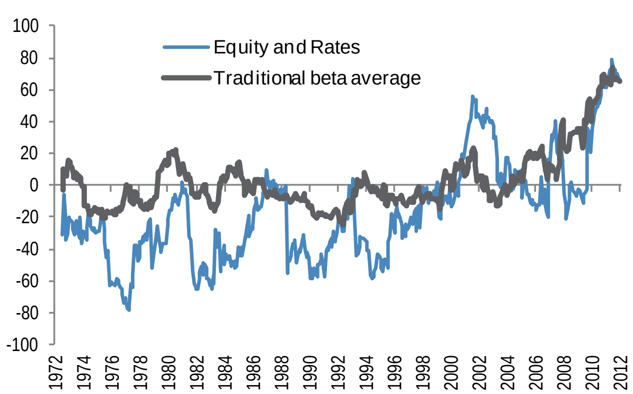
Table 3: Performance-Risk metrics for Cross-Asset Traditional beta Factors during 1972-2012.

	Traditional-Equities	Traditional-Bond	Traditional-Currencies	Traditional-Commodities
Average (%)	3.9	9.2	0.4	5.3
CAGR (%)	2.7	9.3	0.0	3.3
STDev (%)	15.6	7.3	8.9	20.3
MaxDD (%)	-59.0	-17.0	-51.3	-67.8
MaxDDur (in yrs)	14.6	2.0	34.2	13.5
Sharpe Ratio	0.25	1.26	0.05	0.26
Sortino Ratio	0.35	2.58	0.06	0.39
Calmar Ratio	0.24	1.33	0.03	0.24
Pain Ratio	0.16	4.59	0.02	0.19
Reward to 95VaR	0.04	0.33	0.01	0.05
Reward to 95CVaR	0.03	0.22	0.01	0.04
Hit Rate	0.57	0.67	0.52	0.54
Gain to Pain	1.21	2.71	1.04	1.23
Skewness	-0.46	0.64	-0.24	0.05
Kurtosis	1.87	3.87	0.75	2.37
Correl with SPX	1.00	0.13	0.12	0.10
Correl with UST	0.13	1.00	0.17	-0.18
CoSkew with SPX	-0.46	0.05	0.04	-0.21
CoSkew with UST	0.09	0.64	0.12	-0.20
CoKurt with SPX	1.87	-2.58	-2.63	-2.27
CoKurt with UST	-2.18	3.87	-1.50	-4.13

Source: J.P. Morgan Quantitative and Derivatives Strategy.

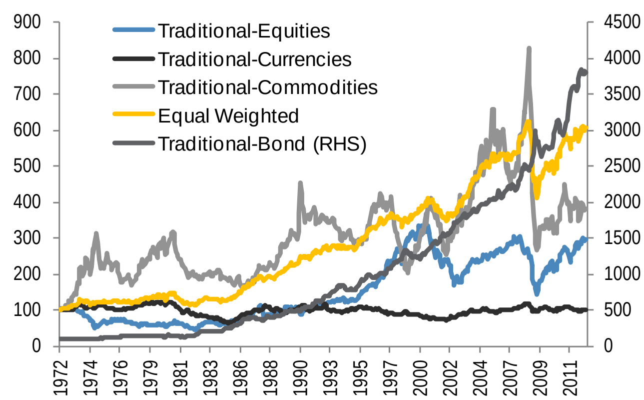
The correlation between traditional assets is a fascinating subject. Levels of correlations are often influenced by macroeconomic, geopolitical, and investor behavioral factors. For a detailed overview of the drivers of cross-asset correlation and developments over the past decades, see our report Rise in Cross Asset Correlations (2011). Changes in market micro-structure such as the introduction of new products and trading styles can also influence correlation between traditional assets [e.g. see our report Why we have correlation bubble (2010)]. Figure 10 shows the trailing 18-month correlation between equities and rates as well as the average correlation among the four traditional beta factors. One can notice a sharp increase of cross-asset correlations during the global financial crisis (since 2008), and a change in rate-equity correlation post 1997/1998 market crisis. Most recently, the correlation of traditional assets declined as a result of the unprecedented Quantitative Easing program by the Federal Reserve. Over the past 6 months, the correlation between bonds, stocks and commodities declined as the fear of tapering impacted investors' behavior (see our Cross-asset correlation June 2013 and October 2013 updates).

Figure 10: Rolling 18m correlation for Cross-Asset Traditional Beta



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 11: Performance of Cross-Asset Traditional Beta Factors



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

The performance of traditional asset classes is heavily influenced by macro economic and market technical regimes. In Table 4 below we summarize annualized average returns (and related *t*-statistics, in parenthesis) for the traditional asset classes under different regimes of growth, inflation, volatility, funding and market liquidity.

Table 4: Performance (t-statistics*) of traditional factor styles under different macro/market regimes

	Growth			Inflation			Volatility			Funding Liquidity			Market Liquidity		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
Traditional-	3.08	3.05	5.57	2.96	11.13	-2.65	8.50	8.85	-5.66	-1.14	7.93	4.90	-12.56	10.72	13.53
Equities	(-0.24)	(-0.25)	(0.48)	(-0.27)	(2.14)	(-1.88)	(1.34)	(1.44)	(-2.79)	(-1.46)	(1.17)	(0.29)	(-4.89)	(1.99)	(2.82)
Traditional -	11.71	10.45	5.34	7.68	12.79	6.92	9.47	6.34	11.69	9.11	9.38	9.01	6.94	11.00	9.56
Bond	(1.59)	(0.80)	(-2.39)	(-0.92)	(2.30)	(-1.38)	(0.19)	(-1.76)	(1.57)	(-0.03)	(0.13)	(-0.10)	(-1.39)	(1.14)	(0.25)
Traditional –	-2.11	3.95	-0.60	2.29	1.05	-2.16	2.33	-0.68	-0.41	-1.42	-0.22	2.89	1.60	-0.17	-0.19
Currencies	(-1.28)	(1.80)	(-0.51)	(0.95)	(0.33)	(-1.29)	(0.97)	(-0.56)	(-0.42)	(-0.93)	(-0.32)	(1.26)	(0.60)	(-0.30)	(-0.31)
Traditional -	-2.77	3.54	15.19	7.84	3.13	5.03	8.42	1.35	6.19	1.41	10.06	4.49	3.04	12.54	0.37
Commodities	(-1.81)	(-0.40)	(2.21)	(0.56)	(-0.50)	(-0.06)	(0.69)	(-0.89)	(0.19)	(-0.87)	(1.06)	(-0.18)	(-0.51)	(1.61)	(-1.10)

Source: J.P. Morgan Quantitative and Derivatives Strategy. * The *t*-statistics shown in parentheses is from a two-sample *t*-test from comparing factor performance under the particular regime versus factor performance out of the regime.

From this Table, we can highlight a few observations. For instance, high growth is positive for commodities and equities and it negatively affected Treasury bonds. USD depreciated during a mid-growth environment and appreciated in low and high growth environments (perhaps due to inflow of capital during high growth and “flight to quality” during low growth). Both high and low inflation was detrimental to equities, and high inflation negatively affected Treasury bonds (consistent with various studies that inflation destroys purchasing power and business sentiment, while deflation usually coincides with recessions). High volatility hurts equities and commodities, but is positive for bonds due to their relative safe-haven status. On the other hand, low volatility generally benefits risky assets and results in bond outflows. Funding and market liquidity measures are both positively related to equities and negatively related to USD.

Table 5 summarizes the exposure of traditional factors to macro/market regime factors over the full time period from 1972 to 2012. We report regression coefficients and *t*-statistics. Results for liquidity factors are after controlling for growth and inflation factors.

Table 5: Traditional factors’ exposures (t-stats*) to macro/market regime factors over the full sample period

	Growth	Inflation	Volatilities	FundLiq	MktLiq
Traditional-Equities	0.21	-0.30	-1.15	1.07	1.22
	(1.03)	(-1.48)	(-5.87)	(3.60)	(6.15)
Traditional-Bond	-0.15	-0.06	0.30	-0.01	-0.04
	(-1.56)	(-0.59)	(3.17)	(-0.08)	(-0.37)
Traditional-Currencies	0.09	-0.17	-0.03	0.09	-0.15
	(0.81)	(-1.42)	(-0.22)	(0.54)	(-1.26)
Traditional-Commodities	0.82	-0.09	-0.92	-0.35	-0.05
	(3.12)	(-0.35)	(-3.51)	(-0.90)	(-0.19)

Source: J.P. Morgan Quantitative and Derivatives Strategy. *The *t*-statistic shown in parentheses is from regression of factor return versus respective regime factor. The results for Funding liquidity and market liquidity are after controlling for growth and inflation factors.

In the rest of this Chapter, we will perform the same performance, risk and regime sensitivity analyses for simple models of alternative risk factors.

Carry

Carry risk factors are designed to take advantage of the outperformance of higher yielding assets over lower yielding assets. Implementation of a Carry strategy typically involves borrowing at a lower cost to fund and hold a higher yielding asset.

Carry strategies are adopted by investors across most asset classes, but are especially popular in currencies and fixed income. In these assets, carry is defined simply as a differential of bond yields, or differential of local interest rates for currencies. Perhaps the most popular Carry strategy is currency carry. The persistence of a total return advantage for higher yielding currencies among major countries was a well-known phenomenon post Brenton-Woods in the early 1970s. Currency carry trades are often implemented on G10 currency pairs, emerging market pairs, or global baskets (see for example Investment Strategies No. 12: JPMorgan Carry-to-Risk Primer, Investment Strategies No. 33: Rotating Between G-10 and EM Carry).

Carry strategies are also common in the fixed income space, where they can be implemented using cash or derivative instruments. For instance, in a popular rates carry strategy, an investor buys the developed market government bonds with the highest yield, and sells those with lowest yield (see Investment Strategies No. 15: A cross-market bond carry strategy) In the Credit space, investors can implement a carry strategy via index credit default swaps to be long high and short low yielding corporate markets in a risk-controlled fashion (see Investment Strategies No. 36: Carry-to-Risk Credit Indices).

In commodities, Carry is often implemented as a **Curve Slide** strategy in which an investor is long the most Backwardated (downward sloping) commodity futures and short contracts that are in Contango (upward sloping). These strategies are often implemented on near term contracts of individual commodities, but can be generalized to take advantage of the slide differential between any pair of commodity contracts. These strategies have been profitable over the past decade, and had a solid performance even during the 2008 crisis. A detailed overview of commodity carry strategies can be found in (Investment Strategies no. 54: Profiting from slide in commodity curves).

Carry risk factors are not commonly used in Equity risk factor investing. The closest proxies for carry are income and dividend based risk factors (see Investment Strategies no. 96: Dividend Yield Factors). Historically, dividend yield has been considered a value strategy, as high yield often implies low growth or reflects a recent price decline. Since the last financial crisis, stock dividend factors have behaved more like a quality factor, as dividend stocks exhibited higher correlation to government bonds. An increasing number of cross-asset investors have started to treat dividend yield as a standalone income generating factor, while neutralizing value and quality exposures. Furthermore, investors look to combine dividend yield with additional forms of income such as call option writing.

Carry strategies are also implemented in the Volatility space. The simplest carry strategies involve selling volatility to capture its risk premium (e.g. see S&P 500 Variance Bonds (2005), and Investment Strategies No. 75: Risk Premia in Volatile Markets). Implied volatility curves are typically upward sloping, so investors can also collect volatility slide carry. Volatility carry strategies often take advantage of the mispricing of volatility risk premia, and despite sharing many features of carry and relative value strategies, we will classify them separately as volatility risk factors.

There are several risks that are common to carry strategies across assets. The first is related to the fact that higher yielding assets tend to be more risky. Hence a portfolio that is long a high yielding asset and short a low yielding asset may have net short volatility exposure. A common approach is thus to compare carry adjusted for the asset's volatility, which is called the Carry-to-risk approach (e.g. see Investment Strategies No. 10: JPM FX and Commodity Barometer, and Investment Strategies No. 12: JPM Carry to Risk Primer).

Carry strategies also tend to underperform due to rising volatility, cycle changes or changes in central bank policies. For instance, a currency carry pair may underperform despite positive carry if the long currency starts depreciating due to a weak economy or declining rates. Simple carry strategies can often be improved by considering not just the levels of carry (e.g. the rate differential in different currencies) but also recent changes in yield differential that may indicate longer dated trends (e.g. see Investment Strategies No. 47: Alternatives to Standard Carry and Momentum in FX).

Despite the common properties of carry trades in various asset classes, carry trade implementation in credit, currencies, rates and commodities may be driven by different sets of fundamental risks. A portfolio of carry trades across asset classes can diversify some of the asset specific carry risk and enhance risk-adjusted return. This was illustrated in a simple model of cross-asset carry strategies Investment Strategies No. 21: Yield Rotator.

Perhaps the most significant risk for carry strategies is the simultaneous unwind of carry positions. This can lead to a tail event for the Carry risk factors, such as the one that occurred on the onset of the 2008 financial crisis. The decline of simple currency carry strategies in 2008 erased years of gains (e.g. see Figure 13 below).

To illustrate the properties of the Carry risk factor, we constructed and tested Carry 'toy models' in equities, fixed income, currencies and commodities over the past 40 years. Our simplified Carry models are:

Carry – Equities: Excess return of a long position in three equity indices with the highest dividend yield and a short position in the three equities indices with the lowest dividend yield (monthly rebalanced). Our index universe consisted of country equity benchmarks for Australia, Canada, France, Germany, HK, Italy, Japan, Netherlands, Spain, Sweden, Switzerland, the UK, and the US.

Carry - Rates and Credit: Excess return of a long position in three 10-year government bonds with the steepest yield curves and a short position in the three 10-year government bonds with the flattest yield curve (monthly rebalanced). Our universe was comprised of government bonds from Australia, Belgium, Canada, Germany, Denmark, Japan, Sweden, the UK and the US.

Carry – Currencies: Excess return of a long position in the top-three yielding currencies and a short position in the bottom-three yielding currencies (monthly rebalanced).We used G10 vs. USD pairs for the currency universe, and domestic short-term deposit rates for yields.

Carry – Commodities: Excess return of a long position in the three most backwardated and a short position in the three least backwardated (steepest contango) commodity futures (monthly rebalanced). The commodity futures universe was: Brent and WTI oil, Heating Oil, Gasoil, Gasoline, Natural Gas, Gold, Silver, Cocoa, Coffee, Cotton, Feeder Cattle, Wheat, Lean Hogs, Live Cattle, Soybeans, Sugar, and Wheat.

Table 6 below shows the risk-reward statistics during the sample period from Jan 1972 to Dec 2012. During this time period, all the Carry strategy factors exhibited better risk-reward profiles than traditional Equity and Commodity assets. Currency and Equity Carry strategies exhibited the highest Sharpe Ratios.

Table 6: Performance-Risk metrics for Cross-Asset Carry Factors during 1972-2012

	Carry-Equities	Carry-Bond	Carry-Currencies	Carry-Commodities
Average (%)	8.1	2.5	5.7	4.4
CAGR (%)	7.5	2.3	5.5	3.6
STDev (%)	13.3	7.4	7.9	12.7
MaxDD (%)	-21.8	-31.8	-31.4	-36.3
MaxDDur (in yrs)	3.1	27.0	5.5	16.8
Sharpe Ratio	0.61	0.34	0.72	0.34
Sortino Ratio	1.26	0.60	1.08	0.53
Calmar Ratio	0.61	0.38	0.60	0.19
Pain Ratio	1.86	0.17	1.29	0.39
Reward to 95VaR	0.15	0.09	0.13	0.06
Reward to 95CVaR	0.11	0.05	0.09	0.05
Hit Rate	0.54	0.53	0.63	0.53
Gain to Pain	1.78	1.37	1.74	1.29
Skewness	3.99	2.27	-0.75	0.04
Kurtosis	44.53	28.36	2.80	0.83
Correl with SPX	-0.14	-0.06	0.22	-0.03
Correl with UST	0.01	-0.15	-0.14	-0.05
CoSkew with SPX	0.28	-0.03	-0.18	-0.10
CoSkew with UST	-0.04	-0.25	0.03	-0.03
CoKurt with SPX	-4.28	-3.24	-1.76	-2.51
CoKurt with UST	-3.22	-4.61	-3.74	-3.49

Source: J.P. Morgan Quantitative and Derivatives Strategy.

The large draw-downs and long draw-down durations experienced by carry strategies were historically comparable to traditional equity and commodity assets.

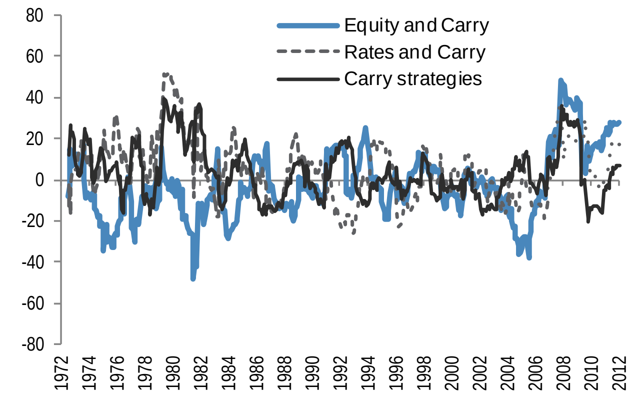
Despite this, carry strategies provide significant diversification benefits to a long-only equity-bond portfolio. For instance, the pairwise correlation between carry strategies and equity/bond betas was close to zero over the whole sample. Similarly, the co-kurtosis between carry strategies and equities and bonds was negative, indicating possible tail risk diversification benefit[9]. However, the Correlation and tail risk benefits of carry strategies were significantly eroded during the global financial crisis of 2008-2009. Figure 12 shows the trailing 18-month average correlation of equities and the four carry strategy factors, between bond beta and carry strategy factors as well as the average correlation among the four carry factors. We note that outside of major crises such as the Latin America Debt Crisis in the early ‘80s and 2008-2009 Global Financial Crisis, the average correlation among carry strategies was fairly low. During the Global Financial Crisis, both the correlation of carry strategies between themselves, and the correlation of carry strategies to equities and market volatility increased significantly.

The poor performance of carry strategies during the financial crisis damaged the perception of carry strategies as a portfolio diversifier. While the correlation between carry strategies has decreased since, the correlation between equities and carry strategies stayed elevated, reducing interest in simple carry strategies.

[9] One may note that the Co-Kurtosis between the G10 Currency Carry factor and Equity beta (SPX) was -1.76 implying that Currency Carry could have provided some tail hedge benefit to SPX during 1972-2012. This may seem counter intuitive at first sight as the correlation between Currency Carry and Equity Traditional beta was at +54% during crisis episodes (see Table 18 on page 47), which suggests the Currency Carry was a poor tail hedge for Equity beta. To explain this, we should note that Currency Carry did provided some tail hedge to SPX during 1972-2001 (first three decades of our sample period) with a co-Kurtosis of -2.8: For example, Equity beta (in excess return) returned -31% during Aug 87-Nov 87 (1987 market crash) and -15% during Apr 98-Aug 98 (Asian Financial Crisis, Russia Default, LTCM), whereas Currency Carry factor didn’t see dramatic sell-offs and returned -0.9% and 0% respectively. However, the tail-hedge ability of Currency Carry disappeared during the 2007-2008 Global Financial Crisis when Equity beta returned -53% during Oct 07-Feb 09 and Currency Carry tumbled -30% during the same period.

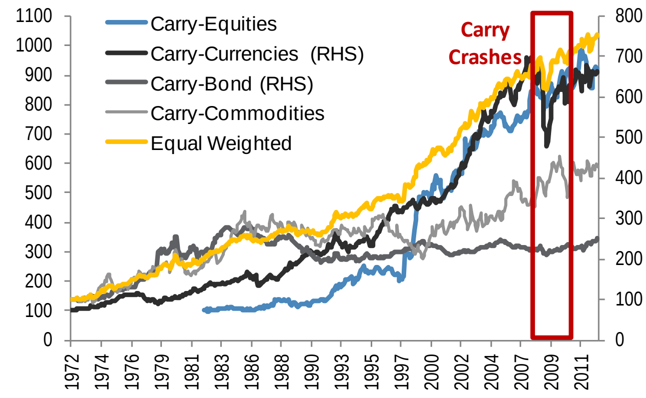
Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Figure 12: Rolling 18m correlation for Cross-Asset Carry factors.



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 13: Performance of Carry Strategies over the past 40 Years



Source: J.P. Morgan Quantitative and Derivatives Strategy.

In addition to performance, volatility and correlation tests, we examined the Carry factors' exposure to macro economic and market regimes of growth, inflation, volatility, funding liquidity and market liquidity. Table 7 below summarizes the annualized average performance for the Carry 'toy models' under different market regimes.

Table 7: Performance (t-stats*) of Carry factor styles under different macro/market regimes

	Growth			Inflation			Volatility			Funding Liquidity			Market Liquidity		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
Carry-Equities	11.59	2.81	10.58	8.93	7.39	7.43	6.50	1.03	15.59	3.69	11.74	6.99	12.45	9.55	3.74
	(1.02)	(-1.66)	(0.68)	(0.31)	(-0.24)	(-0.11)	(-0.44)	(-2.02)	(2.39)	(-0.91)	(1.16)	(-0.39)	(1.12)	(0.43)	(-1.45)
Carry-Bond	0.10	2.52	4.90	1.13	-1.44	8.00	5.28	1.71	0.53	2.59	2.13	2.80	1.00	5.50	1.02
	(-1.48)	(0.01)	(1.47)	(-0.85)	(-2.46)	(3.36)	(1.70)	(-0.49)	(-1.21)	(0.05)	(-0.23)	(0.18)	(-0.92)	(1.84)	(-0.91)
Carry-Currencies	4.75	6.09	6.29	5.95	4.60	6.63	5.52	7.22	4.39	4.98	4.62	7.53	4.22	4.28	8.63
	(-0.55)	(0.22)	(0.33)	(0.13)	(-0.64)	(0.51)	(-0.11)	(0.86)	(-0.75)	(-0.42)	(-0.62)	(1.04)	(-0.85)	(-0.81)	(1.67)
Carry-Commodities	7.04	0.20	5.84	4.79	-0.23	8.68	4.43	7.98	0.67	4.48	6.14	2.46	4.50	5.55	3.03
	(0.95)	(-1.48)	(0.53)	(0.15)	(-1.66)	(1.52)	(0.02)	(1.29)	(-1.31)	(0.04)	(0.63)	(-0.68)	(0.05)	(0.42)	(-0.47)

Source: J.P. Morgan Quantitative and Derivatives Strategy. * The *t*-statistics shown in parentheses is from a two-sample *t*-test from comparing factor performance under the particular regime versus factor performance out of the regime.

Table 8 shows the Carry factors' exposures to macro/market regime factors by conducting regression tests over the whole 40 year sample period.

Table 8: Carry factors' exposures (t-stats*) to macro/market regime factors

	Growth	Inflation	Volatilities	FundLiq	MktLiq
Carry-Equities	0.09	-0.11	0.46	-0.25	-0.35
	(0.41)	(-0.38)	(2.51)	(-0.57)	(-1.77)
Carry-Bond	0.13	0.17	-0.12	0.28	0.02
	(1.39)	(1.80)	(-1.28)	(2.00)	(0.17)
Carry-Currencies	0.03	0.03	-0.28	0.14	0.16
	(0.32)	(0.26)	(-2.72)	(0.90)	(1.56)
Carry-Commodities	-0.02	0.09	-0.31	-0.12	-0.06
	(-0.10)	(0.56)	(-1.86)	(-0.51)	(-0.34)

Source: J.P. Morgan Quantitative and Derivatives Strategy. *The *t*-statistic shown in parentheses is from regression of factor return versus respective regime factor. The results for Funding liquidity and market liquidity are after controlling for growth and inflation factors.

Carry strategies in all assets (apart from equities) were negatively impacted by volatility, as higher yielding assets (such as high yielding EM currency or bonds with wide credit spreads) tend to underperform in a high volatility environment. Carry unwinds during market shocks likely contributed to negative exposure to volatility as well. Equity carry strategies outperformed in volatile markets because higher yielding equities are often high-quality, bond-like stocks that outperform low yielding, growth stocks during market crises.

Currency and Bond Carry strategies outperform when market liquidity is ample, as investors rush into higher yielding and riskier assets. This is consistent with academic findings that the crash risk of currency carry strategies often materializes during liquidity dry-ups (e.g. see Brunnermeier, Nagel, and Pedersen (2008)). For the same reason Equity carry underperformed in high market and funding liquidity environments, as investors move from bond-like to high growth stocks.

High growth and inflation was constructive for bond carry strategies. This is likely reflecting the “yield-seeking” behavior during high growth/inflation periods when bond beta performs poorly.

Momentum

Momentum risk factors are designed to buy assets that performed well and sell assets that performed poorly over a certain historical time period. The premise of this investment style is that asset prices trend (i.e. returns have positive serial correlations). The existence of such a price momentum effect would go against the hypothesis of efficient markets which states that past price returns alone can not predict future performance. Despite theoretical arguments against it, price momentum strategies are documented to produce positive returns across a range of assets and are an important part of many investment portfolios.

Reasons for this momentum effect can be found in investors' behavior, supply and demand friction, positive feedback loops between risk assets and the economy, and even in the market microstructure.

The **behavioral** reasons are related to biases of under-reaction and over-reaction to market news as different investors may react to the arrival of new information with different speeds. After initial under-reaction to news, investors often extrapolate past behavior and create price momentum. An example of this was the performance of technology stocks during the late 90s market bubble. In addition, the psychology of "fear and greed" often causes investors to continue selling losing assets and increase exposure to winning assets.

Momentum can also have more **fundamental causes**, which is the positive feedback between risk assets and the economy. For instance, a stronger economy boosts equities which creates wealth effects that in turn boost spending and the economy, which again boost equities, etc. (see The J.P.Morgan View, 28-Nov-2013). Positive feedback between price action and the economy should make momentum in equities and credit longer lasting than in bonds, FX, and commodities, where negative feedback keeps momentum short lived, prone to reversals, and requiring a much shorter investment horizon.

Market Microstructure effects can also create price momentum. Microstructure effects are often closely related to behavioral patterns as investors seek to invest in products and strategies that mimic their behavioral biases. For instance, the trading wisdom of "cut loses and let profits run" causes investors to implement trading strategies such as stop loss, CPPI, dynamical delta hedging, and option based strategies such as protective puts. In all of these trading styles, an investor in advance commits to selling assets when they underperform and buying when they outperform – thus creating a momentum effect. Similarly 'risk parity' strategies tend to buy low volatility assets (often positive performance) and sell high volatility assets (often negative performance). The mechanical rebalance of these strategies and products can further reinforce price momentum.

Another cause of momentum can be in the mismatch of **asset Supply and Demand cycles**. For instance, the commodity production cycle is often slow to adjust to demand trends e.g. it takes several years to expand oil production, which may lag increased demand from a booming economy. Persistent shortages of supply can develop into an upward price momentum.

Momentum in Equities is a well researched topic. One of the early papers to document equity momentum was published by Jegadeesh, and Titman (1993). A detailed description of common equity momentum factors can be found in J.P. Morgan equity factor reference books (see Investment Strategies no. 103: Equity Risk Factor Handbook). Equity Momentum trends manifest themselves globally, and are more prominent in small cap and emerging markets, in part reflecting lower efficiency of these markets. Among the large markets, Japan however has been an exception where momentum has failed since its equity bubble burst in early '90s. While equity momentum tends to exhibit effectiveness across the various time horizons, it shows greatest effectiveness over medium- to longer-term horizons, while over short-term periods the reversal effect is more pronounced. Equity momentum tends to fail during market reversals, such as its failure during the rally of March 2009 (see Figure 15 below). High levels of volatility over the past years added an additional layer of challenge to equity Momentum strategies. Some of the techniques have looked at better controlling momentum risk to take advantage of the momentum over different time horizons, or conditioning momentum based on fundamental and technical data. Examples of such equity momentum strategy improvements can be found in our reports Enhanced Price Momentum, and Trend is Your Friend reports (see also Investment Strategies no. 89: Equity Momentum), The existence of momentum in Commodities is well known to practitioners, with a dedicated group of Commodity Trading Advisors (CTAs) taking advantage of momentum effects over the past 30 years. In addition to behavioral effects, momentum in commodities is also driven by inelastic supply and demand as well as a mismatch between commodity production cycles and business/sector cycles. This has caused the momentum effect in commodities to be more pronounced than in other asset classes (see Table 9 comparing momentum performance across asset classes). For instance, the supply cycle for oil (exploration and production) can be significantly longer than the cyclical or seasonal demands for the commodity. A detailed review of commodity momentum strategies can be found in our report: Investment Strategies No. 25: Momentum in Commodities) as well as in reports by Erb and Harvey (2006) and Miffre and Rallis (2007). In our research, we found that over long time-periods commodity momentum had strong performance when applied to individual commodities (absolute momentum) as well as on a relative basis between commodities (relative momentum). Long-short commodity portfolios constructed by combining absolute and relative momentum signals tend to outperform simple momentum strategies. Further improvements to commodity momentum strategies can be accomplished by including short-term trading rules to minimize the loss in case of a momentum breakdown. More recently (in the past 2-3 years) many commodity strategies failed to deliver the strong returns witnessed before the market crisis. Some potential reasons for this underperformance is the lack of clear trends in commodity demand post global crisis, as well as potential capacity limitations for the simplest commodity momentum strategies.

Momentum effects have also been documented in the Fixed Income space. For instance our report on momentum in German government bonds (Investment Strategies No. 27: Euro Fixed Income Momentum Strategy) demonstrates a strong momentum signal with a 2-3 weeks time horizon, and the report on EM bonds momentum (Investment Strategies No. 44: Momentum in Emerging Markets Sovereign Debt) demonstrates a momentum signal with a slightly longer time horizon (~4 weeks). These studies point to a shorter time scale of fixed income momentum compared to those typical in equities and commodities. The existence of fixed income momentum across global bond markets was shown in the work of Asness, Moskowitz, Pedersen (2008) by using standard ~12-1 month momentum measure. The secular decline in bond yields over the past decade helped the performance of many models based on absolute price momentum. When examining the merits of a bond momentum models, investors should keep in mind that a repeat of similar trends is unlikely.

The momentum effect in Developed Market Currencies was tested and demonstrated for example in the research of Okunev and White (2003). Currency spot momentum strategies have not performed well since the onset of financial crisis. The reasons for poor performance likely include increased market volatility and perhaps capacity issues for these strategies. Improvements to currency momentum strategies can be achieved, for instance, by combining currency and rate momentum (e.g. see spot and rate momentum model in JPM Daily FX Alpha Chart Pack). Currency momentum signals can also be used to allocate between different factor exposures. For instance, in one of our reports we proposed using currency momentum to allocate between EM and DM currency carry strategies (Investment strategies No. 33: Rotating Between G-10 and Emerging Markets Carry).

Given that Volatility is a range-bound, mean reverting measure, Momentum strategies in volatility are not common. The persistence (autocorrelation) of asset returns, in volatility strategies manifests itself as persistence of volatility levels. Strategies that exploit the persistence of volatility levels are often categorized as carry, value or volatility strategies, rather than momentum. However, there are momentum effects that are directly related to, and often caused by, derivative trading strategies. In our report on the Market Impact of Derivatives Hedging, we showed that gamma hedging of equity index options can cause intraday price momentum. The gamma hedging intraday momentum effect is most pronounced during times of high volatility and low liquidity, which complements well other momentum strategies that typically underperform in those market conditions. In addition to intraday momentum, option hedging can cause Price Patterns of Weekly Momentum during option expiry cycles.

To avoid asset specific momentum risk, investors can combine momentum strategies in multiple assets. Cross-sectional Momentum refers to systematic strategies exploring the persistence of relative outperformance/underperformance across a set of assets. In our report on cross-asset momentum (Investment Strategies No. 14: Exploiting Cross-Market Momentum), we explored properties of such a model and showed that a cross-asset momentum model outperformed all of the traditional and alternative assets included in the universe. Applying the Markowitz mean-variance optimization on the composition of this cross-asset momentum portfolio provided further improvements to strategy performance (see Investment Strategies No. 35: Markowitz in tactical asset allocation).

To illustrate some universal properties of momentum strategies, as well as their behavior under different market regimes, we construct simple momentum indices for equities, government bonds, currencies and commodities, using trailing 12 month returns.[10] Specification of our momentum models are:

Momentum – Equities: Excess return of a long position in three equity indices with the highest past 12 month returns and a short position in the three equities indices with lowest past 12 month returns (monthly rebalanced); Our index universe of country equity benchmarks was: Australia, Canada, France, Germany, HK, Italy, Japan, Netherlands, Spain, Sweden, Switzerland, the UK, and the US.

Momentum - Rates and Credit: Excess return of a long position in the three 10-year government bonds with the highest past 12 month returns and a short position in the three 10-year government bonds with lowest past 12 month returns (monthly rebalanced); The universe was comprised of government bonds from Australia, Belgium, Canada, Germany, Denmark, Japan, Sweden, the UK and the US.

Momentum – Currencies: Excess return of a long position in the three G10 currencies with the highest past 12 month returns and a short position in the three G10 currencies with lowest past 12 month returns (monthly rebalanced).

Momentum – Commodities: Excess return of a long position in the three commodity futures with the highest past 12 month returns and a short position in the three commodity futures with lowest past 12 month returns (monthly rebalanced); The commodity futures universe was: Brent and WTI oil, Heating Oil, Gasoil, Gasoline, Natural Gas, Gold, Silver, Cocoa, Coffee, Cotton, Feeder Cattle, Wheat, Lean Hogs, Live Cattle, Soybeans, Sugar, and Wheat.

Table 9 below shows the risk-reward statistics for these momentum strategies during the sample period Jan 1972 to Dec 2012. During this 40 year period, the Commodity momentum factor yielded the highest return, and Bond and Commodity momentum factors exhibited the highest Sharpe ratios.

Table 9: Performance-Risk metrics for Cross-Asset Momentum Factors during 1972-2012

	Momentum-Equities	Momentum-Bond	Momentum-Currencies	Momentum-Commodities
Average (%)	6.2	3.7	2.4	8.2
CAGR (%)	4.7	3.5	2.0	7.2
STDev (%)	18.1	6.5	9.0	15.4
MaxDD (%)	-37.5	-23.5	-27.9	-33.3
MaxDDur (in yrs)	14.4	10.4	13.1	5.7
Sharpe Ratio	0.34	0.56	0.26	0.53
Sortino Ratio	0.54	0.88	0.37	0.86
Calmar Ratio	0.35	0.80	0.19	0.34
Pain Ratio	0.45	0.88	0.25	0.93
Reward to 95VaR	0.07	0.11	0.04	0.11
Reward to 95CVaR	0.05	0.07	0.03	0.08
Hit Rate	0.52	0.60	0.59	0.56
Gain to Pain	1.32	1.57	1.23	1.51
Skewness	0.47	-0.04	-0.35	0.01
Kurtosis	6.02	2.80	1.89	1.36
Correl with SPX	-0.12	0.08	0.00	-0.02
Correl with UST	0.03	0.12	0.01	0.06
CoSkew with SPX	-0.11	-0.15	-0.18	-0.03
CoSkew with UST	-0.05	0.07	0.01	0.08
CoKurt with SPX	-3.39	-2.10	-2.53	-2.58
CoKurt with UST	-3.09	-2.20	-2.87	-2.56

Source: J.P. Morgan Quantitative and Derivatives Strategy.

[10] Another well documented method for cross-sectional momentum on stocks uses the MOM2-12 (based on past 12 month cumulative return, skipping the most recent month's return) method to implement momentum indices to avoid near-month mean-reversion.

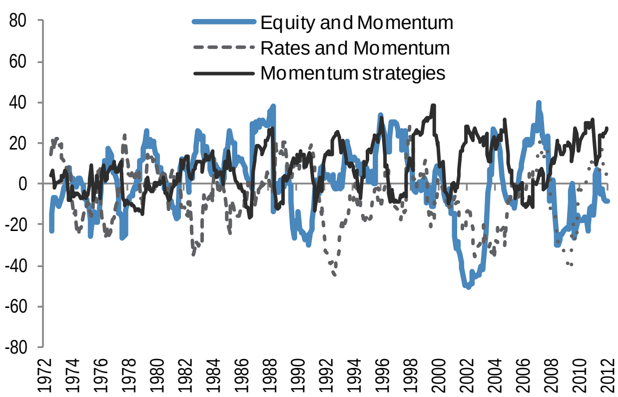
Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

All momentum strategies displayed significant fat-tails (positive excess kurtosis), a property that related to “crash risk”, with equity momentum exhibiting the highest tail risk and draw-downs arising from momentum crashes.

On the positive side, momentum strategies generally provided good diversification benefits and even tail risk diversification to traditional assets. This is evident from low correlation between momentum strategies and traditional assets, and negative Co-kurtosis between momentum strategies and traditional betas for Momentum strategies in all asset classes.

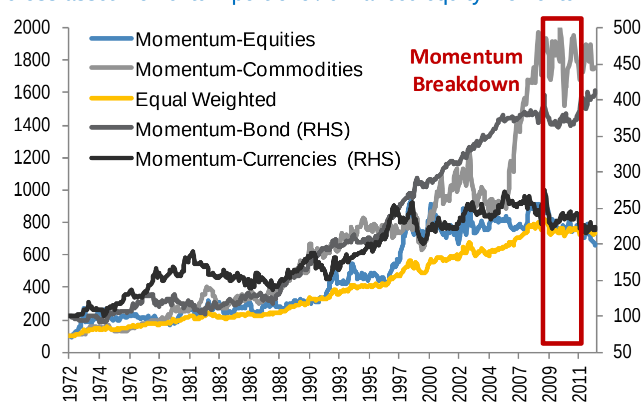
Figure 14 shows the trailing 18-month average correlation between equity beta and the four momentum strategy factors, rates and momentum strategy factors as well as the average correlation between the four momentum factors. Correlation between momentum strategies was relatively low, but on average positive. We note a trend of increasing correlation between the various momentum strategies, especially after the global financial crisis. Historically, momentum strategies provided good diversification to equity portfolios, as the average correlation between equity beta and momentum strategies dropped to -30% during the 1990-1991, and 2001-2003 recessions.

Figure 14: Rolling 18m correlation for Cross-Asset Momentum factors



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 15: Momentum Breakdown of 2009, and performance of cross-asset momentum portfolio / enhanced equity momentum



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 10 below summarizes the average performance (and related *t*-statistics) of our simple momentum strategies in different market macro and technical regimes. We also show a regression test to quantify the Momentum factors' exposures to macro/market regime factors across the full sample period. Relevant sensitivity and *t*-statistics are reported in Table 11.

Table 10: Performance (t-stats*) of Momentum factor styles under different macro/market regimes

	Growth			Inflation			Volatility			Funding Liquidity			Market Liquidity		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
Momentum-Equities	2.66	4.96	11.09	-2.06	15.44	5.15	7.42	10.38	0.90	9.97	5.27	3.47	5.52	9.69	3.50
	(-0.90)	(-0.32)	(1.22)	(-2.09)	(2.35)	(-0.27)	(0.30)	(1.04)	(-1.34)	(0.93)	(-0.24)	(-0.69)	(-0.18)	(0.86)	(-0.69)
Momentum - Bond	2.06	5.48	3.47	3.26	4.51	3.22	4.48	1.73	4.81	2.13	6.09	2.79	0.19	5.98	4.84
	(-1.12)	(1.25)	(-0.14)	(-0.28)	(0.58)	(-0.31)	(0.56)	(-1.34)	(0.78)	(-1.06)	(1.68)	(-0.61)	(-2.42)	(1.60)	(0.81)
Momentum - Currencies	-2.15	4.72	4.58	0.06	4.20	2.86	6.74	2.25	-1.84	1.40	1.12	4.62	-0.83	5.81	2.16
	(-2.28)	(1.17)	(1.10)	(-1.16)	(0.92)	(0.24)	(2.19)	(-0.07)	(-2.12)	(-0.49)	(-0.63)	(1.12)	(-1.61)	(1.72)	(-0.11)
Momentum - Commodities	6.28	9.38	8.91	7.37	7.98	9.24	15.30	5.55	3.71	12.00	7.19	5.37	4.54	12.73	7.29
	(-0.56)	(0.35)	(0.21)	(-0.24)	(-0.06)	(0.31)	(2.10)	(-0.78)	(-1.32)	(1.12)	(-0.29)	(-0.83)	(-1.08)	(1.34)	(-0.26)

Source: J.P. Morgan Quantitative and Derivatives Strategy. * The *t*-statistics shown in parenthesis is from a two-sample *t*-test from comparing factor performance under the particular regime versus factor performance out of the regime.

Table 11: Momentum factors' exposures (t-stats*) to macro/market regime factors

	Growth	Inflation	Volatilities	FundLiq	MktLiq
Momentum-Equities	0.44	0.15	-0.38	-0.68	0.09
	(1.89)	(0.66)	(-1.61)	(-1.94)	(0.39)
Momentum-Bond	-0.01	0.00	-0.03	0.28	0.12
	(-0.08)	(0.03)	(-0.31)	(2.21)	(1.38)
Momentum-Currencies	0.26	0.07	-0.27	0.04	0.06
	(2.21)	(0.63)	(-2.27)	(0.21)	(0.50)
Momentum-Commodities	0.13	0.04	-0.29	-0.64	0.24
	(0.64)	(0.19)	(-1.45)	(-2.17)	(1.19)

Source: J.P. Morgan Quantitative and Derivatives Strategy. *The *t*-statistic shown in parenthesis is from regression of factor return versus respective regime factor. The results for Funding liquidity and market liquidity are after controlling for growth and inflation factors.

We note that high volatility generally hurts momentum strategies. The likely reason is the patterns of mean reversion that risky assets exhibit during times of economic uncertainty. This is true for currency, commodity and equity momentum strategies; however, bond momentum strategies outperformed in high volatility market environments, likely as a result of the persistent demand for safe haven instruments. We also find that momentum strategies tend to exhibit some properties of their underlying traditional assets. For instance, equity and commodity momentum outperformed in high growth environments, inflation was positive for commodity momentum, negative for bond momentum and equity momentum worked best in the mid-inflation regime. All of the momentum strategies exhibited strong performance during “Mid Market Liquidity” environments and experienced significant underperformance during periods of low market liquidity.

Value

Value risk factors are designed to buy assets that are undervalued (cheap) and sell those that are overvalued (expensive) according to a valuation model. For this reason, the core of any value strategy is a model that provides a value anchor or a "fair-value" for the asset. This fair value can be defined as an absolute price level, a spread relative to other assets, or a statistical range in which asset should trade (e.g. within 2-standard deviations). Value strategies are usually implemented as long/short portfolios that have no exposure to other traditional or alternative risk factors.

Value strategies capitalize on the mean-reversion of prices to their 'fair value'. The premise is that prices are only temporarily driven away from 'fair value' by either behavioral effects (over-reaction, herding) or liquidity effects (temporary market impact, long term supply/demand friction). As Value relies on 'mean-reversion to fair value', it often has properties opposite to those of "Momentum" factors. Value factor style encompasses a broad array of systematic strategies that can include fundamental valuation, statistical arbitrage, and cross-asset relative value approaches.

Fundamental Value strategies derive asset fair values based on economic and fundamental indicators. In fixed income, currencies and commodities, these include capital account balance, level and changes in economic activity, inflation, fund flows, etc. In equities and credit, fundamental valuation often relies on corporate metrics such as book value, cash flows, earnings, levels of debt, etc. **Market Value** strategies often rely on statistical models and aim to capture mispricing caused by inefficiencies in liquidity provision. The best examples of this strategy type are Statistical Arbitrage and Index Arbitrage that capture the reversion of temporary market impacts over short time horizons (see Investment Strategies No. 84: Equity Pairs Trading). Over longer time horizons, another example of market value trades includes trading seasonality in equities and commodities (see Investment Strategies No. 87: Equity Factor Seasonality and CMOS: Seasonal spreads at the cyclical crossroads). **Cross-Asset Relative Value** strategies take advantage of relative mispricing of different assets. For instance, Convertible bond arbitrage strategies often involve relative value trading between the stock, credit and volatility of a single company (e.g. see Investment Strategies 85: Investing in Convertible Bonds). Other examples include relative value trading between Credit and Equity Volatility (Investment Strategies No. 38: A Framework for Credit-Equity Investing), using credit signals to trade Equities (Investment Strategies No. 81: Equity-Credit Factors) or relative value trades between commodities and equities (e.g. Investment Strategies No: 68 Commodity equities or futures).

In Equities, the value investment paradigm traces its origin to the work of Graham and Dodd in the 1930s. Some of the common approaches to equity valuation compares a company's market price to its book value, top line sales, bottom line earnings, or various cash-flow metrics.[11] Not all Value factors work equally well across regions. In developed markets like the US, cashflow-based valuations have recently proven most effective, while in the less efficient emerging markets simple Value factors like book-to-price and earnings yield continue to exhibit strong returns. While in Fixed income and commodities Momentum is considered the antipode of Value, in Equities that role is played by Growth – a risk factor specific to companies[12]. Periods where Value worked well are characterized by large cross-sectional dispersion of stock valuations, which create a larger opportunity set for a Value investor (see Investment Strategies No. 94 Equity Value Factors). Value factors can be vulnerable to market cycles – e.g. a classic episode of Value failure was during the Tech bubble (Figure 17 below). Another risk in equity value investing is related to "Value traps" – companies whose valuations are cheap due to rapidly deteriorating fundamentals. To mitigate these risks, investors can combine value factors with equity specific risk factors such as Growth and Quality. Examples of these approaches include growth-at-reasonable-price (GARP) and quality-at-reasonable-price (QARP) factors.

Fair Value models are commonly used in trading government bonds. Value models are often based on fundamental data influencing bond prices – for instance our model in Investment Strategies No. 67: Using unemployment to trade bonds takes advantage of the persistency of unemployment data. Market value signals often look for a reversion of bond yields to their moving averages or interpolated yield curves (Investment Strategies No. 71: Trading Rich / Cheap Signals in EM Sovereigns & Corporates). Most bond value models incorporate a combination of fundamental, market, and cross asset value signals. An example is a model that buys bonds where consensus for a country's growth and inflation is decreasing,

[11] An alternative approach is to take the market price of the company's entire capital structure (equity and debt) and comparing it to comprehensive earnings (EBITDA).

[12] Other examples of equity-specific factors include Earnings-based factors (see Investment Strategies No. 90: Earnings Factors) and Quality factors (see Investment Strategies No. 91: Equity Quality Factors)

and bond yields trade above their long term average (expecting mean reversion) as well as above the earnings yields of a broad local equity index (Investment Strategies No. 5: Profiting from Market Signals).

Currency valuation models can be based on Purchasing Power Parity (assumes constant inflation-adjusted rates), or include a broad number of fundamental value indicators. An example of a fundamental currency model can be found in J.P. Morgan long-term fair value model update. The model produces long term currency fair values based on Productivity, Terms of Trade, Government debt, and Net Investment Income. As with bonds, most successful currency value models include fundamental, market and cross-asset value signals. Additionally currency value models often include value anchors predicted by other alternative factors such as carry and momentum. For instance, a currency model described in the Daily FX Fair Value Regressions Report, includes fundamental variables such as short-term interest rate spreads, commodity prices, equity volatility, and sovereign spreads.

Commodity value models can be based on fundamental signals such as global IP growth and PMIs (Investment Strategies No. 59: Economic and price signals for commodity allocation). Commodity fundamental value models are often related to persistency in economic indicators. For this reason, fundamental value factors can share some similarities with commodity momentum factors (e.g. the IP and PMI based commodity value model was 60% correlated to a commodity momentum model). Despite some overlap, fundamental factors may be quicker to identify macro economic turning points, which often create the greatest risk for trend-following strategies. Other fundamental value signals include demand for shipping capacity, inventories, inflation expectations, and others. Market value indicators in commodities are often simple mean reversion measures such as normalized return (e.g. Assess et al. Value and Momentum Everywhere).

We have decided to classify value strategies based on volatility as a **Volatility** alternative risk factor and will discuss them in the next section. These strategies involve buying cheap and selling rich volatility to capitalize on temporary market dislocations, structural supply and demand imbalances, or fundamental views on the future realized volatility of underlying assets. However, a derivative based Value strategy worth highlighting involves buying Equity Index Dividend swaps. Prices of dividend swaps often trade below their fair value (e.g. aggregated analyst dividend estimates), due to supply via retail structured products (dealers hedging these structured products often need to sell dividends). More details on Dividend swap strategies can be found in Investment Strategy No. 95: Investing in Dividend Swaps.

As with previous factor styles, we created 'Toy Models' of value strategies across asset classes and analyzed their performance over the past 40 years. The definition of our illustrative value models is given below:

Value – Equities: Fama-French (1993) HML value factor. The factor is long the top decile and short bottom decile of US stocks ranked by book to price ratio; the universe covers all non-financial firms listed on the NYSE, AMEX and NASDAQ exchanges.

Value - Rates and Credit: Excess return of monthly rolling a long position in the top-three 10-year government bonds with the largest increase in 10-year yields during the past three years and a short position in the bottom-three 10-year government bonds with the smallest increase (or largest decrease) in 10-year yields during the past three years. Our universe was comprised of government bonds from Australia, Belgium, Canada, Germany, Denmark, Japan, Sweden, the UK and the US.

Value – Currencies: Asness et.al (2013) currency value factor which is a long/short currency portfolio based on the 5-year change in purchasing power parity. The universe covers spot exchange rates of the following G10 currencies: Australia, Canada, Germany (spliced with the Euro), Japan, New Zealand, Norway, Sweden, Switzerland, the United Kingdom, and the United States.

Value – Commodities: Excess return of a long position in the top-three commodity futures with the lowest valuation and a short position in the bottom-three commodity futures with highest valuation, where the valuation metric is defined as the ratio of current price relative to the average price over the past five years (monthly rebalanced). The commodity futures universe was: Brent and WTI oil, Heating Oil, Gasoil, Gasoline, Natural Gas, Gold, Silver, Cocoa, Coffee, Cotton, Feeder Cattle, Wheat, Lean Hogs, Live Cattle, Soybeans, Sugar, and Wheat.

Table 12 below shows the performance, volatility and correlation of value models over the sample period from Jan 1972 to Dec 2012. During this 41 year period, Equity and Bond value factors exhibited the highest reward-to-risk ratios, followed by Currency and Commodity value factors.

Table 12: Performance-Risk metrics for Cross-Asset Value Factors during 1972-2012

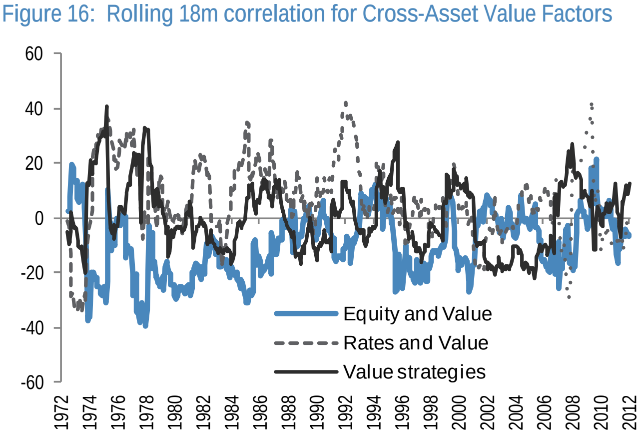
	Value-Equities	Value-Bond	Value-Currencies	Value-Commodities
Average (%)	4.9	4.1	3.7	2.7
CAGR (%)	4.4	4.0	3.3	1.5
STDev (%)	10.5	7.4	8.8	15.1
MaxDD (%)	-44.6	-21.5	-26.9	-59.0
MaxDDur (in yrs)	5.8	23.2	5.6	23.4
Sharpe Ratio	0.46	0.56	0.42	0.18
Sortino Ratio	0.72	1.13	0.67	0.25
Calmar Ratio	0.27	0.71	0.30	0.12
Pain Ratio	0.70	0.47	0.65	0.13
Reward to 95VaR	0.09	0.15	0.09	0.03
Reward to 95CVaR	0.06	0.10	0.06	0.02
Hit Rate	0.56	0.54	0.55	0.53
Gain to Pain	1.44	1.66	1.39	1.14
Skewness	-0.01	2.59	0.22	-0.26
Kurtosis	2.37	21.12	2.97	1.09
Correl with SPX	-0.29	-0.09	0.01	0.06
Correl with UST	0.03	-0.07	-0.09	-0.09
CoSkew with SPX	0.06	0.02	-0.08	0.02
CoSkew with UST	-0.18	-0.05	-0.09	-0.09
CoKurt with SPX	-4.15	-3.20	-2.60	-3.35
CoKurt with UST	-3.10	-2.91	-4.02	-3.93

Source: J.P. Morgan Quantitative and Derivatives Strategy.

All value strategies displayed significant fat-tails (positive excess kurtosis), a property related to the "crash risk" for value strategies – they generally work poorly after the breach of a trading range and subsequent establishment of a trend. Similar to momentum strategies, Value strategies provided good diversification properties for strategies that are long traditional assets. Specifically, the correlation between value strategies and equity/bond betas were either negative or close to zero. The Co-kurtosis between Value strategies and equity and bond traditional factors were also negative. This suggests that value strategies may provide good tail risk diversifications to a traditional equity-bond portfolio.

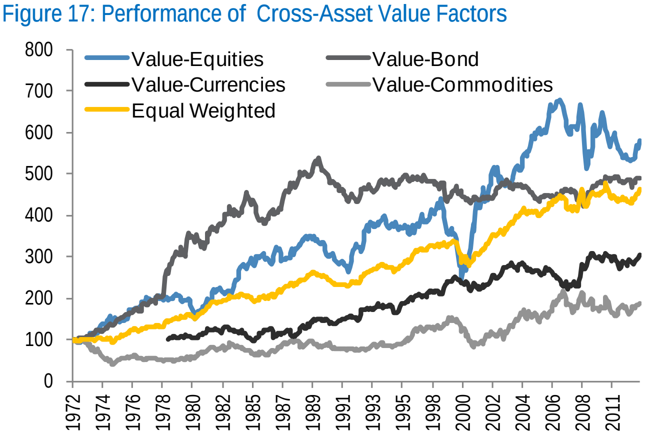
Figure 16 shows the trailing 18-month average correlation between equity and the four value strategy factors, between rates and value factors as well as the average correlation among the four value factors. Given the low or negative average correlation between value factors, investors would benefit from diversifying across value strategies in different asset classes. This is also evident from relatively smooth performance of an equal weighted value portfolio.

Figure 16: Rolling 18m correlation for Cross-Asset Value Factors



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 17: Performance of Cross-Asset Value Factors



Source: J.P. Morgan Quantitative and Derivatives Strategy.

We also conducted statistical tests to examine the Value factor's exposure to macro economic and market technical regimes. Table 13 below summarizes the annualized average performance and related *t*-statistics for our 'Toy' Value models, and Table 14 shows the Value factors' exposures to macro/market regime factors by conducting regression tests over the full sample period.

Table 13: Performance (t-stat*) of Value factor styles under different macro/market regimes

	Growth			Inflation			Volatility			Funding Liquidity			Market Liquidity		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
Value-Equities	3.04	5.63	5.89	2.91	2.87	8.89	7.91	3.92	2.73	3.03	2.08	9.45	6.49	5.77	2.30
	(-0.78)	(0.33)	(0.45)	(-0.84)	(-0.87)	(1.72)	(1.32)	(-0.40)	(-0.91)	(-0.78)	(-1.20)	(1.99)	(0.70)	(0.40)	(-1.10)
Value-Bond	4.42	0.18	7.84	0.98	0.24	11.43	4.64	1.77	6.03	10.29	0.33	1.82	9.74	1.81	0.90
	(0.17)	(-2.44)	(2.27)	(-1.94)	(-2.44)	(4.48)	(0.30)	(-1.46)	(1.15)	(3.81)	(-2.34)	(-1.42)	(3.46)	(-1.43)	(-1.99)
Value-Currencies	7.88	-0.04	3.10	2.40	5.56	2.85	3.40	0.63	6.76	7.24	2.97	1.70	4.55	1.65	4.84
	(2.08)	(-1.84)	(-0.24)	(-0.69)	(0.96)	(-0.30)	(-0.12)	(-1.42)	(1.52)	(1.47)	(-0.33)	(-1.03)	(0.37)	(-0.96)	(0.60)
Value-Commodities	1.83	6.15	0.04	3.75	3.76	0.44	-0.80	6.65	2.18	-1.15	1.24	7.94	0.63	2.88	4.52
	(-0.25)	(1.04)	(-0.79)	(0.32)	(0.33)	(-0.66)	(-1.04)	(1.19)	(-0.15)	(-1.15)	(-0.43)	(1.58)	(-0.61)	(0.06)	(0.55)

Source: J.P. Morgan Quantitative and Derivatives Strategy. * The *t*-statistics shown in parenthesis is from a two-sample *t*-test from comparing factor performance under the particular regime versus factor performance out of the regime.

Table 14: Value factors' exposures (t-stats*) to macro/market regime factors

	Growth	Inflation	Volatilities	FundLiq	MktLiq
Value-Equities	0.25	0.09	-0.21	0.10	-0.20
	(1.83)	(0.67)	(-1.54)	(0.50)	(-1.47)
Value-Bond	0.09	0.34	-0.04	-0.27	-0.03
	(0.95)	(3.62)	(-0.39)	(-1.93)	(-0.32)
Value-Currencies	-0.30	0.05	0.15	-0.06	-0.02
	(-2.11)	(0.39)	(1.29)	(-0.23)	(-0.16)
Value-Commodities	-0.05	-0.10	0.05	0.21	0.04
	(-0.26)	(-0.53)	(0.27)	(0.72)	(0.18)

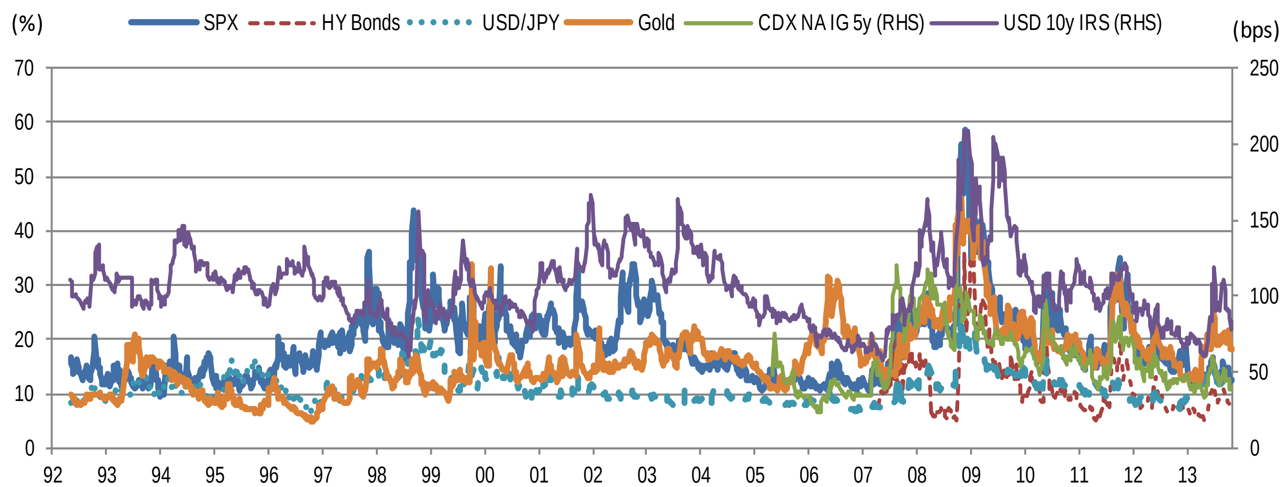
Source: J.P. Morgan Quantitative and Derivatives Strategy. *The *t*-statistic shown in parenthesis is from regression of factor return versus respective regime factor. The results for Funding liquidity and market liquidity are after controlling for growth and inflation factors.

While there were no common patterns for performance of our simple value factors across asset classes, we can make a few asset-specific observations. High growth was constructive for equity and bond value strategies, while low growth generally benefited currency value strategies. The inflation level was positively correlated to the performance of bond value strategies, as during high inflation bond investors likely look for alternatives to going long duration. Equity value strategies worked well during high inflation episodes too. Higher volatility was negative for equity value strategies and good for currency value strategies. High market liquidity was generally negative for equity and bond value strategies. This makes economic sense as value strategies often underperform momentum strategies in high market liquidity environments.

Volatility

Volatility is a key pricing variable for non-linear derivative products such as options. The notional size of the options market is close to $40T, and option volumes and open interest continue to grow (see traditional assets section, page 25). In times of macro-economic uncertainty, realized and asset implied volatility tend to rise. Given that the drivers of volatility are often common to different asset classes, volatility levels tend to be positively correlated. Figure 18 below shows levels of implied volatilities for several traditional asset classes - note the high correlation between volatilities over the past 5 years.[13] Unlike other traditional assets, volatility shows properties of persistence and mean reversion (rather than trending and mean reversion). Volatility tends to stay in a low regime for long periods of time, while transitions to a high regime are quick and difficult to predict. These properties of volatility are common across asset classes, which is one of the reasons why investors often consider Volatility to be a separate asset class.

Figure 18: Implied Volatilities for the Main Asset Classes over the past 20 years



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Supply and demand imbalances for options and patterns of investor behavior often create friction in volatility markets. Investors tend to sell volatility in quiet times, and rush to buy protection in times of high uncertainty. This reinforces the cyclical nature of volatility. As within other asset classes, a volatility investor can capture relative value opportunities between different volatility products, systematically sell volatility to generate carry, or express volatility directional views. Volatility strategies are often directly tied to the microstructure of specific derivative product markets. Derivative products can be complex and quickly evolve. As a result, volatility strategies often require advanced models and are implemented over shorter time horizons.

Due to volatility's tendency to persist in a regime for extended period of time but quickly change regimes, the performance of volatility strategies is often more affected by tail events, rather than day to day volatility. The sensitivity of volatility strategies to tail risk allows investors to express relative value views on the probability of tail events. While many volatility strategies can be classified as carry, relative value or traditional beta, we have decided to classify volatility strategies as a separate 'Volatility' alternative risk factor.

Even for a single underlying (e.g. 10 year treasury rate, S&P 500 index, etc.), volatility is not a single asset but a collection of different assets - for example, the volatility for each option maturity and strike often has different properties (e.g. level, responsiveness to market shocks, etc.). The fair value for volatility based on the expectation for subsequent realized

[13] See Appendix for implied volatilities within each asset class (Equity Indices, Bonds, Interest Rate Swaps, Credit default swaps, Currencies and Commodities) since 1992.

volatility of the underlying asset. Given these common properties of volatility, there are a number of strategies that can be implemented across various asset classes.

Implied – realized volatility arbitrage strategies involve systematically selling volatility that is deemed expensive. Implied volatilities for assets that are broadly held long tend to trade rich. The reason for this is often a supply/demand imbalance in which investors demand protection (for the asset held long), while there is a lack of a natural supply of protection. Perhaps the best examples are S&P 500 and 10-year Treasury options. Given the high liquidity and strong correlation to most investment portfolios, options on these products have traded persistently rich most of the time (see S&P 500 variance bonds (2005) for equities, and Volatility as an Asset Class (2005) for rates volatility).

While implied-realized volatility strategies offer strong returns (especially during periods of low volatility, and in the aftermath of market crises) they tend to be vulnerable to volatility spikes in which they can suffer catastrophic losses. For this reason, implied-realized strategies need to include risk management tools to control leverage and limit tail risk. For instance, one can use the level of the implied-realized volatility spread and level of volatility in other markets as a trading signal to add or remove exposure. This was shown to produce good results in Equity, FX, and gold implied-realized volatility arbitrage strategies (Investment Strategies No.75: Risk Premia in Volatility Markets). The simplest implied-realized volatility strategies include selling of unhedged options (often straddles). These models rely on asset prices being range-bound over certain time periods (e.g. see Investment Strategies No. 86: Range Bound model)

Term structure roll-down is another popular volatility strategy in which an investor takes advantage of the term premium of implied volatility. The term structure premium often has the same origin as the implied-realized volatility premium. When implied volatility trades above realized, investors prefer to buy longer dated options to minimize the cost associated with the time decay of shorter-dated options. At the same time, the supply of long dated options can be scarce. This can cause the implied volatility term structure to be steeply upward sloping (e.g. in Equities the term structure is upward sloping ~85% of the time). Investors can sell the implied volatility term structure to generate positive returns.

The risk of term structure roll-down strategies is the same as for implied-realized strategies – a sharp increase in volatility often causes term structure inversion. For this reason, term structure roll-down strategies should also be risk-managed to adjust leverage based on prevailing market conditions. One example of such a strategy is the J.P. Morgan Macro-hedge that removes roll-down exposure in short term S&P 500 volatility (VIX) as soon as the term structure flattens/begins to invert. Historically, sharp term structure inversion happened only after several days of flattening/mild inversion.

Relative value volatility strategies buy volatility that is deemed cheap and sell volatility deemed rich. Also called ‘spread trading’, these strategies can be applied to the volatility of a single asset, on a portfolio level across similar assets, or between entirely different asset classes. For example, an investor can sell 6M swaption straddles on 10Y rates and buy 6M swaption straddles on 30Y rates. Due to the structural cheapness of short dated options on 30-year rates, and excessive demand for protection on 10-year rates this systematic strategy had strong historical performance (see Volatility as an Asset Class). Further interest rate volatility spreads and relative value metrics can be found in the Fixed Income Analytic Pack that is regularly published by J.P. Morgan research. Additionally, the FX Derivatives Analytics Chartpack warehouses attractive relative value volatility trades in FX.

In equities, relative value volatility trades are very common and often take advantage of structural supply/demand imbalances, or volatility valuation models. An example of a structural relative value trade is selling S&P 500 volatility that is expensive due to insurance industry demand, and buying Nikkei volatility that is cheap due to the volatility supply from retail structured products in Japan. Volatility for individual companies can be valued based on multi factor models that often use fundamental, technical and statistical measures, for example the J.P. Morgan relative value volatility models for European and Asian stocks (Investment Strategies No. 82: Relative Value Model for Implied Volatility).

Relative value volatility strategies can also be implemented on credit volatility such as the strategy of selling iTraxx Main volatility and buying Crossover volatility (Investment Strategies No. 63: CDS Option Strategies), relative value trading between credit and equity volatility (Investment Strategies No. 52: Macro Credit-Equity Trading), and other volatility pairs across asset classes.

Tail Risk Trades take advantage of potential mispricing of tail risk in various derivative instruments. For instance, analysis of skew in FX markets shows that currency pairs in some cases may under-price market tail risk (Investment Strategies No. 62: Tail-risk hedging with FX options). Investors looking to design a systematic tail hedging strategy may look at currency markets for outright or relative value skew opportunities. In most other volatility markets, tail risk tends to be expensive due to excessive demand for protection. This often manifests itself as a steep implied volatility skew. Strategies that take advantage of expensive skew in equities include relative value trading of volatility and variance swaps, and low strike vs. high strike options (e.g. see our report on Nikkei convexity trade, and report on outperformance of put-writing over call writing). Additionally, the richness of equity implied volatility skew was recently analyzed in academic research by Neuberger et.al (2013)[14].

Correlation Trading strategies involve trading correlation between a group of assets. Correlation trades are often implemented as a relative value trade between the volatility of an index and volatilities of its constituents (in this regards, dispersion trading is a special case of a relative value volatility strategy). Correlation trades are popular in the equities space when investors typically sell expensive index volatility and buy volatility on its underlying components, taking advantage of the structural supply/demand imbalance for index protection (Investment Strategies No. 98: Trading Equity Correlations).

Correlation trades can also be implemented in other asset classes. Examples include trading spread options in rates (see yield curve spread option report in Fixed Income Analytic Pack), trading of hybrid options such as FX-equity contingent options, trading of commodity index options vs. options on individual commodities, etc. FX also allows one to imply the market-traded value of correlation between two currency pairs from option prices, thanks to liquidity in 'cross' options (e.g. correlation between EUR/USD and JPY/USD from EUR/USD, USD/JPY and EUR/JPY volatilities, all of which trade liquidly). The availability of implied correlation matrices leads FX investors to routinely use multi-currency/basket options for expressing levered directional views, as well as trade relative value via correlation swaps or baskets of long/short volatility (straddles and/or volatility swaps). See our FX correlation monitor for an analytic tool to monitor correlation opportunities in FX, and Launching the revamped FX Correlation Analyser for details on the monitor.

Volatility and Derivatives data can also be used as a trading signal for assets such as stocks, bonds, and commodities. A well known example is the fact that stocks with low realized volatility have outperformed stocks with high volatility, in contrast to standard market theories. An increasing number of investors describe this effect as the low volatility anomaly, a phenomenon that has persisted for multiple decades across markets globally and has been gaining a lot of interest in the investment community recently (e.g. see our paper on Minimum Variance Strategies). The level of realized volatility can also be used as a signal for allocation between risky and risk-less assets. In one of our previous reports (Investment Strategies No 51: Volatility signals for asset allocation) we documented the benefits of using volatility as a leverage signal for equity, bond and commodity portfolios over the past 20 years (use of volatility to allocate factor risk will be further examined in the next Chapter of this report).

Options data such as put/call ratio and implied volatility skew can also be used to forecast stock returns. Examples of this were given in our report Investment Strategies No. 88: Signals from options market. Derivatives trading and hedging activity can also impact the price of underlying assets. For instance, in our report on the Investment Strategies No. 79: Market Impact of Derivatives Hedging – Daily Patterns, we showed that gamma hedging of options can cause intraday price momentum at the end of the day. Temporary market impact of derivative hedging often dissipates the next day, causing patterns of close-to-close mean reversion. In addition to intraday momentum, option hedging can cause patterns of weekly momentum (see Investment Strategies No. 104: Market Impact of Derivatives Hedging – Weekly Patterns) during option expiry cycles, followed by month-end mean reversion.

To illustrate some properties of volatility risk factors, we created simple 'toy models' of volatility in each traditional asset class. All of our models are based on the most common volatility strategy: implied-realized volatility arbitrage. Inherently these strategies tend to be short volatility, correlation and tail risk. Similar properties may be shared also by some term structure roll-down, correlation, and tail risk volatility strategies. However, not all volatility risk factors behave in such a fashion. For instance, many volatility relative value strategies are designed as pure arbitrage strategies with no residual volatility exposure. There are many tail risk, term structure roll, and volatility signal strategies that are designed to provide

[14] Neuberger, A., Roman Kozhan and Paul Schneider (2013), "The Skew Risk Premium in the Equity Index Market", Review of Financial Studies 26(9), 2174-2203.

protection in volatile markets, and may behave differently than our implied-realized volatility toy models. For this reason investors should avoid generalizing the results below to all volatility strategies.

Our simplified models for volatility premium strategies are:

Volatility – Equities: Equal weighted combination of S&P 500 Buy-write (BXM) and Put-write (PUT) Index;

Volatility - Rates and Credit: Excess return of a short position on 3-month at-the-money straddles (ATM Call plus ATM Put) on near-month US 10-year Treasury Futures, rolled monthly.

Volatility – Currencies: Excess return of an equal weighted position of volatility swaps on USDJPY, USDAUD and USDCHF (receiving implied volatility swap) with unit vega notional, rolled monthly.

Volatility – Commodities: Excess return of a short position on 3-month at-the-money straddles (ATM Call plus ATM Put) on Gold, rolled monthly.

Table 15 below shows the risk-reward statistics during the sample period Jan 1986 to Dec 2012[15]. During this backtest period, the cross asset volatility factors realized positive Sharpe ratios. Steep draw-downs were caused by volatility spikes.

Table 15: Performance-Risk metrics for Cross-Asset Volatility Factors during 1986-2012

	Volatility-Equities	Volatility - Bonds	Volatility - Currencies	Volatility - Commodities
Average (%)	3.0	1.9	6.1	7.2
CAGR (%)	2.8	1.8	5.8	7.1
STDev (%)	5.5	3.7	9.6	8.6
MaxDD (%)	-14.4	-11.2	-54.1	-27.4
MaxDDur (in yrs)	2.8	5.3	5.4	1.8
Sharpe Ratio	0.5	0.5	0.6	0.8
Sortino Ratio	0.7	0.7	0.8	1.2
Calmar Ratio	0.5	0.3	0.4	0.6
Pain Ratio	1.7	0.8	0.6	1.7
Reward to 95VaR	0.1	0.1	0.1	0.1
Reward to 95CVaR	0.1	0.1	0.1	0.1
Hit Rate	62%	57%	67%	69%
Gain to Pain	1.6	1.4	1.7	1.9
Skewness	-1.5	-0.6	-2.6	-0.9
Kurtosis	6.3	0.5	12.7	1.6
Correl with SPX	27%	12%	18%	17%
Correl with UST	-12%	-35%	-34%	3%
CoSkew with SPX	-0.7	-0.1	-0.6	-0.1
CoSkew with UST	0.2	-0.8	-0.9	0.4
CoKurt with SPX	-0.4	-2.7	-1.0	-2.1
CoKurt with UST	-2.2	-7.3	-8.8	-1.1

Source: J.P. Morgan Quantitative and Derivatives Strategy.

These simple volatility strategies had significant negative skewness and fat-tails (positive excess kurtosis). In other words, (short) volatility strategies worked poorly during market distress and/or liquidity crunches. The strategies also exhibited significant positive correlation with Equity beta – our volatility models were susceptible to broad equity market risks given their short volatility exposure.

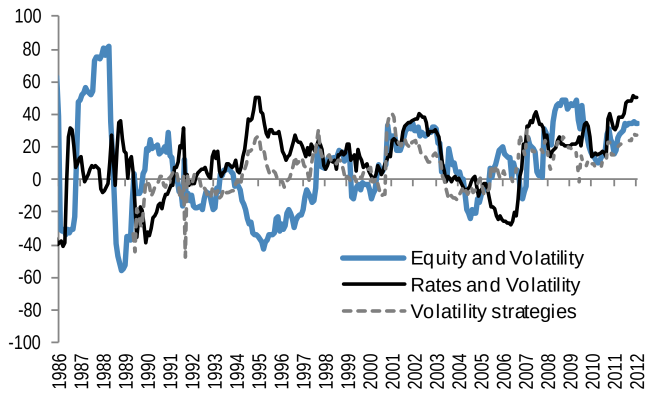
Figure 19 shows the trailing 18-month average correlation between equities and the Volatility factors, between Rates and Volatility factors as well as the average correlation among the Volatility factors. Note that our simple volatility strategies showed increased correlation to risky assets (equities, rates) and between themselves, especially over the past 5 years.

[15] The backtests for Volatility strategies on Rates and Credit, Currencies and Commodities started at Jan 1990 due to limited data availability.

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

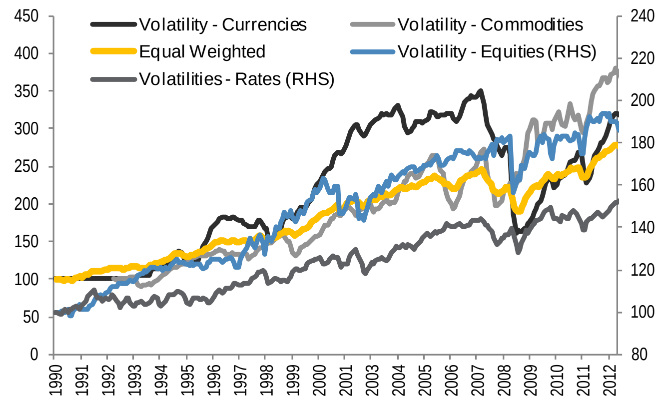
Historical performance was strong, and after the large drawdown during 2008/2009, volatility strategies in most cases recovered to reach new highs.

Figure 19: Rolling 18m correlation for Cross-Asset Volatility Factors



Source: J.P. Morgan Quantitative and Derivatives Strategy .

Figure 20: Performance of Cross-Asset Volatility Factors



Source: J.P. Morgan Quantitative and Derivatives Strategy .

As for other risk factors, we conducted statistical tests to examine the factor's exposure to macro economic/market regimes. Table 16 below summarizes the annualized average performance and related *t*-statistics for the 'Toy' models under different regimes and Table 17 gives exposures to macro/market regimes over the full sample period[16].

Table 16: Performance (t-stat*) of Volatility factor styles under different macro/market regimes

	Growth			Inflation			Volatility			Funding Liquidity			Market Liquidity		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
Volatility-Equities	1.56	3.75	2.78	2.73	2.73	1.73	2.08	2.22	3.46	1.30	3.61	2.44	2.35	1.84	3.53
	(-0.78)	(0.72)	(0.07)	(0.06)	(0.05)	(-0.23)	(-0.36)	(-0.27)	(0.60)	(-0.56)	(0.64)	(-0.20)	(-0.19)	(-0.52)	(0.66)
Volatility - Bond	0.80	1.83	3.93	1.38	2.53	-	1.54	3.85	0.79	-5.22	4.22	1.45	0.77	1.01	3.37
	(-1.16)	(-0.03)	(1.42)	(-0.75)	(0.69)	-	(-0.29)	(1.55)	(-1.12)	(-2.71)	(2.19)	(-0.62)	(-0.94)	(-0.71)	(1.56)
Volatility - Currencies	-0.79	13.80	7.76	4.52	9.36	-	11.61	11.71	-1.52	-47.22	9.86	11.00	-1.83	11.56	9.05
	(-2.85)	(2.58)	(0.44)	(-1.08)	(1.08)	-	(1.90)	(1.47)	(-3.14)	(-8.26)	(1.21)	(2.87)	(-2.71)	(1.63)	(1.09)
Volatility - Commodities	10.17	5.27	4.87	5.96	8.77	-	7.20	7.36	7.19	0.01	10.50	6.30	5.17	6.49	9.42
	(1.38)	(-0.81)	(-0.70)	(-0.86)	(0.69)	-	(-0.02)	(0.04)	(-0.02)	(-1.18)	(1.31)	(-0.60)	(-0.77)	(-0.27)	(0.97)

Source: J.P. Morgan Quantitative and Derivatives Strategy. * The *t*-statistics shown in parenthesis is from a two-sample *t*-test from comparing factor performance under the particular regime versus factor performance out of the regime.

Table 17: Volatility factors' exposures (t-stats*) to macro/market regime factors

	Growth	Inflation	Volatilities	FundLiq	MktLiq
Volatility –Equities	0.05	-0.06	-0.29	0.53	0.04
	(0.48)	(-0.39)	(-3.89)	(2.46)	(0.50)
Volatility –Bond	0.07	-0.01	-0.15	0.13	0.12
	(0.92)	(-0.09)	(-2.58)	(0.76)	(1.98)
Volatility –Currencies	0.76	0.13	-1.30	3.41	0.46
	(4.24)	(0.28)	(-10.06)	(9.20)	(3.00)
Volatility –Commodities	-0.46	-0.28	0.08	0.96	0.06
	(-2.76)	(-0.84)	(0.60)	(2.50)	(0.43)

Source: J.P. Morgan Quantitative and Derivatives Strategy. *The *t*-statistic shown in parenthesis is from regression of factor return versus respective regime factor. The results for Funding liquidity and market liquidity are after controlling for growth and inflation factors.

[16] Due to non-normality of the independent variable(s) in the regressions, it is possible that the regression slope (in Table 17) implies different conclusions from the analysis in 1/3-2/3 percentile regime averages (Table 16). For example, we find the regression slope of the Equity Volatility factor on Volatility regime indicator is significantly negative, implying that higher Volatility leads to lower returns of the Equity Volatility factor. However, the regime study didn't find a significant relationship between the Volatility level and the Equity Volatility factor. This is because the some outliners made the regression coefficient significant – removing them actually makes the regression slope slightly positive (not significant). As a result, we should look for cases where regression and regime analysis make similar conclusions while acknowledge a possible conflict of results due to modeling error (non-normally) as well as insufficient sample size (statistical hypothesis testing is usually based on large sample assumptions).

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Higher economic growth was generally positive for volatility strategies (Bond, Currencies and Equities), while it was negative for the Gold Volatility strategy. The reason for this is the cyclical decline of realized and implied volatility of risky assets during high growth regimes. Almost all volatility strategies had negative correlation to levels of volatility. High volatility negatively impacted strategies, as they were short volatility by construction. Initial under- performance of Equity and Commodity volatility strategies during high market volatility regimes was cushioned by the subsequent pickup in the implied-realized volatility premium. This offset the initial losses due to the volatility increase. In our test, volatility strategies were not very sensitive to inflation regimes. This partly reflects the fact that the back-testing period for most volatility strategies starts from the late 1980s/early 1990s when inflation became low and stable.

Factor Correlations

Over the past several years the correlation between traditional asset classes rose to historical highs and often showed significant instability. High market volatility and unstable correlations damaged many multi asset portfolios. In our previous reports, we documented structural changes in the correlations of traditional assets resulting from market volatility, central bank activities and various asset specific developments (see: Investment Strategies No. 99: Cross-Asset Correlations).

As we discussed in the introduction, two main benefits of risk factor investment approach are providing access to new sources of premia, and reducing portfolio correlation levels. In addition to analyzing asset correlation levels, investors should pay special attention to correlation during periods of high market volatility. It is during volatile markets that hidden correlations between assets may appear and give rise to portfolio downside tail risk. Additionally, breakdowns in correlation (such as the recent decline in equity-rate correlation) can throw off risk allocation models (e.g. recent underperformance of Risk Parity portfolios). The correlation structure of risk factors should be the key input for factor selection, and the construction and risk management of multi-factor portfolios.

The ability of a factor to generate risk premium can be analyzed for each factor separately and performance can then be compared across various factors (e.g. for a performance comparison of our 20 factor 'toy models', see Appendix). To understand the diversification value of a factor, one needs to analyze the factor's relationship to other factors in a portfolio. The correlation of a factor to other assets may also change under different market regimes such as volatility, growth, inflation, etc.

In an idealized world, risk factors are designed to be independent of each other. In the real world, factors will have non-zero correlations and in some cases may have significant overlap with other traditional or alternative factors. We will first study correlation properties of our main factors styles: Traditional, Momentum, Value, Carry, Volatility in each of the main asset classes (Equity, Bond, Currency, and Commodity). We will try to identify correlation patterns between these factors both in times of market stress and in normal market conditions. At the end of the section, we will outline steps to construct fully independent factors.

Table 18 shows a correlation matrix for the 20 risk factors analyzed earlier in this section (our risk factor 'toy' models). Below the diagonal we show correlations calculated for the full sample period (Jan 1972-Dec 2012) and above the diagonal correlation statistics during crisis periods. [17] We also show the average correlation of each factor with all other factors during the full sample period, five episodes of major crises, as well as the latest global financial crisis (Aug 2007-Mar 2009). We note a relatively high level of correlation among the traditional asset classes (with the exception of government bonds), as well as increased correlation between traditional and alternative risk factors during the global financial crisis. However, correlation properties were quite different for different alternative risk factors. For example, carry strategies (especially currency carry), was positively correlated to traditional assets and volatility strategies during periods of market stress. Similarly, volatility strategies were correlated between themselves, and correlated to traditional and carry strategies during the crises. This should come as no surprise if we recall the large carry trade unwind that occurred simultaneously with the equity sell-off and volatility spike during the 2008/2009 crisis.

On the other hand, Value strategies were negatively correlated to most traditional and alternative risk factors. Specifically, during the times of market stress, Value strategies showed consistently negative correlation to Traditional assets, Carry and Momentum strategies. Momentum strategies were also on average negatively correlated to other risk factors during the crises. As we discussed in the description of individual factor styles, we see that Momentum and Value strategies tend to behave in opposite ways, and so do Momentum and Volatility. This is not surprising as many Value strategies are based on mean reversion (opposite of Momentum), and our selection of volatility models (selling unhedged options) performs better in range bound markets. The negative correlation between various blocks of our risk factor correlation matrix can give us a lot of optimism about the risk factor approach - even with very simple factor style models, we can create a well diversified portfolio.

[17] Crisis periods we include for the correlation calculation are Oct 1973—Mar 1974 (OPEC Oil Crisis), Aug 1982 – Oct 1983 (Latin America debt crisis), July 1990 - Mar 1991 (US saving & loan crisis), Jul 1997 - Sep 1998 (Asian Financial Crisis, Russian Default and LTCM), and Aug 2007 - Mar 2009 (Global Financial Crisis or GFC).

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Table 18: Sample correlation between Cross Asset Factor Styles during Jan 1972 to Dec 2012

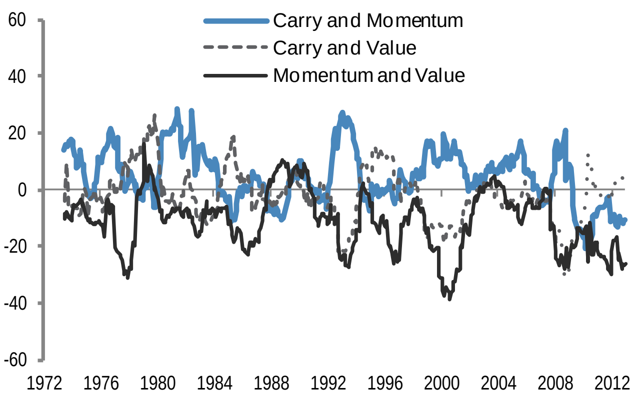
Color Scheme	Less than -30%	-30% to -10%	-10% to +10%	+10% to +30%	Greater than +30%

	Trad'l-Equity	Trad'l - Bond	Trad'l-Curncy	Trad'l - Comdty	Carry-Equity	Carry-Bond	Carry-Curncy	Carry-Comdty	MoM-Equity	MoM - Bond	MoM - Curncy	MoM - Comdty	Value-Equity	Value-Bond	Value-Curncy	Value-Comdty	Vol-Equity	Vol - Bond	Vol - Curncy	Vol - Comdty
Trad'l-Equity		33	18	18	-5	16	54	9	14	26	-18	-22	-8	-14	-23	7	52	7	31	33
Trad'l -Bond	13		28	-24	-5	-6	-4	-5	7	48	12	-1	-7	-15	0	-1	14	-56	-48	29
Trad'l- Curncy	12	17		19	6	11	39	-10	-7	-6	8	6	1	-16	-20	-15	35	-31	2	22
Trad'l -Comdty	10	-18	20		3	10	41	26	1	-11	-22	35	18	-8	-33	-24	31	4	48	-17
Carry-Equity	-14	1	11	2		9	10	-4	-7	-3	3	1	8	10	-10	-10	9	-3	-1	-21
Carry-Bond	-6	-15	-7	0	3		28	-3	-6	-20	-2	-7	-5	13	-10	-2	10	12	12	19
Carry-Curncy	22	-14	8	23	0	11		13	20	-1	-12	1	14	-4	-56	0	38	28	33	28
Carry- Comdty	-3	-5	2	16	-2	-1	2		13	-13	-7	18	14	-11	-14	-50	30	-11	17	-18
MoM- Equity	-12	3	1	8	4	-2	5	12		24	3	9	-6	-33	-10	14	5	23	12	-17
MoM -Bond	8	12	-9	1	0	16	-1	-2	0		18	15	10	-26	-14	15	-14	-7	-51	8
MoM -Curncy	0	1	5	-4	-7	9	-4	1	12	8		5	-7	-27	-30	-11	-35	-26	-48	-12
MoM - Comdty	-2	6	3	16	2	-1	2	27	9	7	5		-6	-15	-12	-46	-19	1	-19	-12
Value- Equity	-29	3	-3	2	1	6	2	-2	-7	3	0	0		4	-4	-9	5	32	23	6
Value-Bond	-9	-7	3	0	1	19	1	-10	-10	-23	-11	-5	7		0	5	-10	9	20	-30
Value-Curncy	1	-9	-20	-9	-8	5	-2	2	-5	9	-32	-10	-7	2		11	-19	21	-13	-6
Value- Comdty	6	-9	-7	-23	1	4	5	-34	-8	2	-6	-58	-5	2	8		-16	37	15	20
Vol- Equity	28	-10	4	23	-4	5	21	9	-5	4	-8	-7	5	-2	8	-7		-14	55	14
Vol -Bond	12	-35	-13	6	-5	-9	8	8	1	-1	-6	3	12	4	7	4	5		30	17
Vol -Curncy	18	-34	3	30	-12	12	29	4	-2	-16	-4	0	15	10	-14	-2	23	25		-2
Vol - Comdty	17	3	7	-1	-7	10	25	-11	-12	1	-11	-9	8	-8	-6	8	12	3	9	
Full Sample Ave	4	-5	2	5	-2	3	7	1	0	1	-3	-1	1	-2	-4	-6	6	1	5	2
Crisis Average	12	0	5	6	-1	4	14	0	3	0	-11	-3	4	-8	-13	-3	9	4	6	3
Ave During GFC	19	-6	15	16	5	12	22	6	2	-7	-14	-2	6	-12	-19	-8	13	5	4	5

Source: J.P. Morgan Quantitative and Derivatives Strategy. * Lower triangular statistics are the all-sample pair-wise correlation and upper triangular are the correlation statistics during crisis periods. ** Crisis periods we include for the correlation calculation are Oct 1973—Mar 1974 (OPEC Oil Crisis), Aug 1982 – Oct 1983 (Latin America debt crisis), July 1990 - Mar 1991 (US saving & loan crisis), Jul 1997 - Sep 1998 (Asian Financial Crisis, Russian Default and LTCM), and Aug 2007 - Mar 2009 (Global Financial Crisis or GFC).

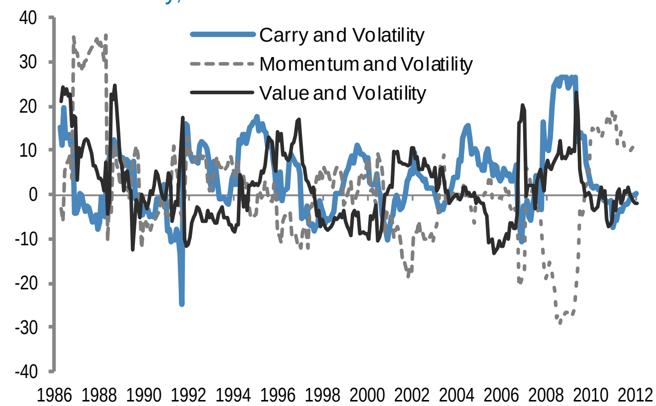
Figure 21 and Figure 22 show rolling 18-month average correlations between the Carry, Momentum, Value and Volatility strategy factor styles.

Figure 21: Rolling 18m average correlation between Cross-Asset Carry, Momentum and Value Factors



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 22: Rolling 18m average correlation between Volatility and Cross-Asset Carry, Momentum and Value Factors

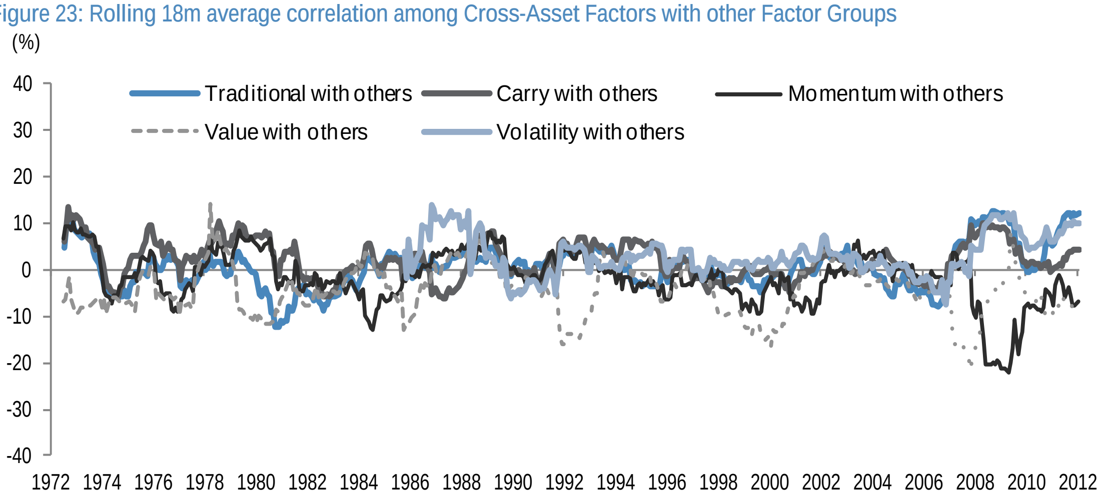


Source: J.P. Morgan Quantitative and Derivatives Strategy.

We note the consistently negative correlation between Momentum and Value factors (-30% to 0% range), average positive correlation between Carry and Volatility (especially during the latest crisis), and positive correlation of Carry and Momentum. The average correlation between Carry and Value, Momentum and Volatility, and Value and Volatility was mean reverting in a ~ -20% to +20% range. In Appendix, we further analyze factor correlation levels in different market regimes of growth, inflation, volatility, funding and market liquidity. We have ranked all of the factors considered according to their historical performance, correlation and portfolio diversification ability.

Figure 23 shows the rolling 18-month average correlation between each factor style group with all other factors, and Figure 24 shows the average correlation of all factors.

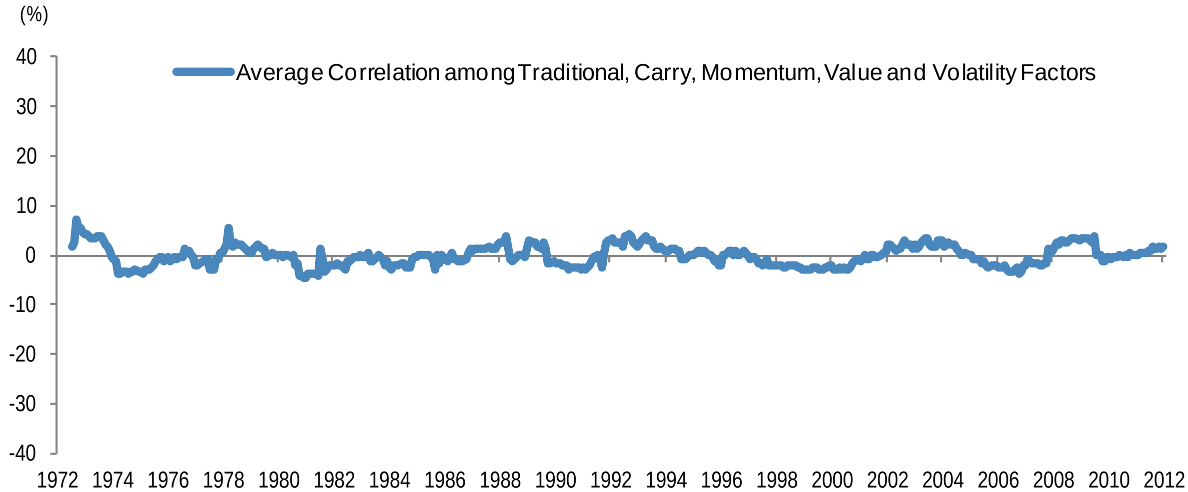
Figure 23: Rolling 18m average correlation among Cross-Asset Factors with other Factor Groups



Source: J.P. Morgan Quantitative and Derivatives Strategy.

We note the average factor correlation was close to zero during the past four decades. This is an important result as it shows that even though we didn't require independent factors (orthogonality), the correlation among the main factor styles and assets cancelled out. Thus the orthogonality of risk factors was achieved cross-sectionally, rather than being imposed in factor construction. The zero average correlation also held up well during crisis periods.

Figure 24: Rolling 18m average correlation among Cross-Asset Traditional, Carry, Momentum, Value and Volatility Factors



Source: J.P. Morgan Quantitative and Derivatives Strategy.

While an understanding of correlations is the key to risk factor investing, we think it is not critical for an investor to ask for an ideal set of orthogonal risk factors. As we have shown, the net zero correlation effect can be achieved in a well diversified portfolio of risk factors. However, it is possible to construct an orthogonal set of new factors, and some investors may prefer to do so. Below we will outline two methods often used to design uncorrelated factors. More formal derivation of these methods is provided in the Appendix on Independent Risk Factors.

A common approach to designing independent factors is **Principal Component Analysis (PCA)**. PCA takes our original risk factor time series (e.g. our 20 'Toy' models) and re-weights them to create new uncorrelated (orthogonal) factors. This is accomplished by diagonalization of a historical covariance matrix. The first principal component is the one that explains the largest portion of data variance (it is the 'vector' corresponding to the highest 'eigenvalue' of the diagonalized covariance matrix). The second principal component by design has zero correlation to the first principal component and explains (the second) largest portion of data variability, and so on. For more details on PCA please see Appendix.

Table 19 and Table 20 below shows the risk contribution profile[18] of the principal components (denoted by PCx) from the 20 Cross-Asset 'Toy' Model risk factors in Traditional, Carry, Momentum, Value and Volatility styles. We could easily identify the major risk contributors to each principal components: Commodity beta for PC1, Equity beta for PC4, Equity Carry for PC5, Commodity Carry for PC6, Equity Volatility for PC19 and Bond Volatility for PC20, just to name a few. Sharpe ratios of the principal components are generally smaller than the original cross asset risk factors.

While PCA is a common simple way to create uncorrelated factors, it does have some drawbacks. The main one is that it generally ranks more volatile factors (such as Equity and Commodity related factors) as more important principal components. This can lead to investors using only the top principal components while ignoring the less volatile but potentially important risk premia[19]. Investors should also be aware that while the correlation between PCA factors is zero by construction, PCA does not always obtain independent factors. This is the case for non-normal data sets (i.e. despite zero correlation, principal components are fully independent only if the data are jointly normally distributed).

[18] See the Chapter on Construction and Risk Management of Factor Portfolios for more details on the calculation of risk contribution profile for a portfolio of risk factors.
[19] One could perform PCA on standardized risk factors (on correlation matrix instead of covariance matrix) to reduce the impact of marginal volatility. However, this could create another bias, namely, the first principal component would overweight the factor with the worst diversification abilities (highest average correlation with others). See Appendix for more on factor diversification abilities.

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Table 19: Risk Contribution Profile (%) for Principal Components of Cross Asset Risk Factors (Jan 1972 – Dec 2012)

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	PC14	PC15	PC16	PC17	PC18	PC19	PC20
Traditional-Equities	0	21	0	57	6	0	2	0	1	0	4	3	0	1	0	1	1	0	1	0
Traditional-Bond	0	0	0	1	1	1	1	5	3	12	0	1	1	6	0	11	48	1	1	6
Traditional-Currencies	1	0	0	0	3	1	0	14	0	3	35	1	15	20	4	0	2	0	0	0
Traditional-Commodities	53	22	7	9	0	0	5	0	0	1	1	0	0	1	0	0	0	0	0	0
Carry-Equities	0	1	0	9	79	2	4	0	0	1	2	0	0	0	0	0	1	0	0	0
Carry-Bond	0	0	0	0	0	0	2	1	1	2	2	12	35	5	11	4	1	21	0	2
Carry-Currencies	0	1	0	0	0	0	8	3	0	0	1	8	1	7	50	18	0	0	1	0
Carry-Commodities	6	2	2	1	2	70	6	2	4	3	0	0	0	1	0	0	0	0	0	0
Momentum-Equities	6	30	51	10	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Momentum-Bond	0	0	0	0	0	0	0	0	0	5	12	3	2	1	8	17	1	48	1	1
Momentum-Currencies	0	1	0	1	0	3	0	23	18	3	16	4	4	5	4	12	7	1	0	0
Momentum-Commodities	15	8	20	3	1	9	0	18	17	5	1	1	0	0	0	1	0	0	1	0
Value-Equities	0	0	0	8	4	4	31	1	5	19	10	12	1	0	0	1	2	1	0	1
Value-Bond	0	0	0	1	0	0	0	1	0	7	5	4	24	25	8	3	0	21	0	0
Value-Currencies	0	0	0	0	1	6	4	21	12	1	2	0	12	20	0	10	11	0	0	0
Value-Commodities	18	7	18	1	0	0	0	6	32	13	1	2	0	0	0	0	1	0	1	0
Volatility-Equities	0	1	0	0	0	0	1	0	1	0	0	0	0	1	0	0	1	1	92	1
Volatility-Bond	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	2	3	3	2	88
Volatility-Currencies	1	3	0	0	2	1	25	2	1	18	1	3	2	3	12	2	20	2	0	0
Volatility-Commodities	0	1	0	0	0	2	8	0	3	8	7	43	3	4	1	16	2	2	0	0

Source: J.P. Morgan Quantitative and Derivatives Strategy. * Each cell (by column) represents the total risk contribution (in percentage) of Cross asset risk factor to each principal component.

Another method, called **Independent Component Analysis (ICA)**, can produce truly independent factors for both normal and non-normal asset returns. This is achieved by optimizing a particular non-normality measure of the factor joint distribution. The idea of ICA arises from 'Blind Source Separation (BSS)' in signal processing applications. The details go beyond the scope of this report, but can be found in technical Appendix on independent risk factors for interested readers.

Table 20 below shows the risk contribution profile of cross asset Traditional, Carry, Momentum, Value and Volatility factors to the ICA independent risk factors. Similar to the case in PCA, we can easily identify the major risk contributors to each independent risk factor: Bond Carry and Bond Value for RF3, Equity Carry for RF7, Currency Carry and Momentum for RF11, Equity Value for RF15, etc.

Table 20: Risk Contribution Profile (%) of Independent Risk Factors from the original Cross Asset Risk Factors (Jan 1972 – Dec 2012)

	RF1	RF2	RF3	RF4	RF5	RF6	RF7	RF8	RF9	RF10	RF11	RF12	RF13	RF14	RF15	RF16	RF17	RF18	RF19	RF20
Traditional-Equities	1	36	0	5	6	26	0	1	2	5	3	0	0	0	10	0	-1	5	2	-1
Traditional-Bond	2	5	0	50	0	0	0	0	8	0	0	0	12	0	2	14	2	5	0	0
Traditional-Currencies	1	8	0	1	0	7	1	2	33	1	0	2	1	6	3	4	17	3	0	9
Traditional-Commodities	12	3	1	0	18	0	1	49	1	3	1	0	0	1	3	2	-1	0	1	5
Carry-Equities	1	0	0	0	0	2	92	0	0	1	0	0	0	0	1	0	0	0	0	1
Carry-Bond	0	0	43	2	0	4	0	1	0	0	0	0	42	0	0	0	0	7	0	0
Carry-Currencies	5	0	1	0	0	0	0	0	4	6	42	36	1	2	0	1	1	0	0	0
Carry-Commodities	2	0	0	1	3	0	0	7	6	2	2	0	1	1	5	1	4	0	28	36
Momentum-Equities	0	2	0	7	0	0	0	0	19	0	1	2	0	0	1	0	67	0	0	0
Momentum-Bond	3	0	2	7	0	8	0	0	0	0	0	0	5	0	0	1	0	73	0	1
Momentum-Currencies	4	0	1	1	0	9	0	0	0	11	36	22	0	0	0	1	8	3	0	3
Momentum-Commodities	2	1	0	3	37	1	0	15	1	0	2	1	0	21	1	0	0	0	21	-5
Value-Equities	0	10	0	0	0	0	1	10	0	1	0	0	0	2	68	0	1	0	0	7
Value-Bond	1	0	53	5	0	1	0	0	1	0	2	1	33	0	0	1	0	1	0	1
Value-Currencies	1	0	0	0	1	19	0	4	14	15	0	32	1	6	1	3	-1	1	0	2
Value-Commodities	0	13	0	0	14	0	0	-5	0	0	0	-1	1	-2	2	4	0	0	44	29
Volatility-Equities	0	17	0	8	11	23	0	3	0	17	3	0	0	4	1	11	0	1	0	2
Volatility-Bond	50	3	0	1	2	0	0	12	1	2	2	0	0	2	1	12	0	2	1	9
Volatility-Currencies	-1	0	0	0	1	1	0	1	8	35	3	2	0	11	1	32	1	0	3	0
Volatility-Commodities	14	0	0	11	7	0	3	0	1	1	3	0	0	45	1	14	0	0	0	0

Source: J.P. Morgan Quantitative and Derivatives Strategy. * Each cell (by column) represents the total risk contribution (in percentage) of Cross asset risk factor to each independent risk factors.

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

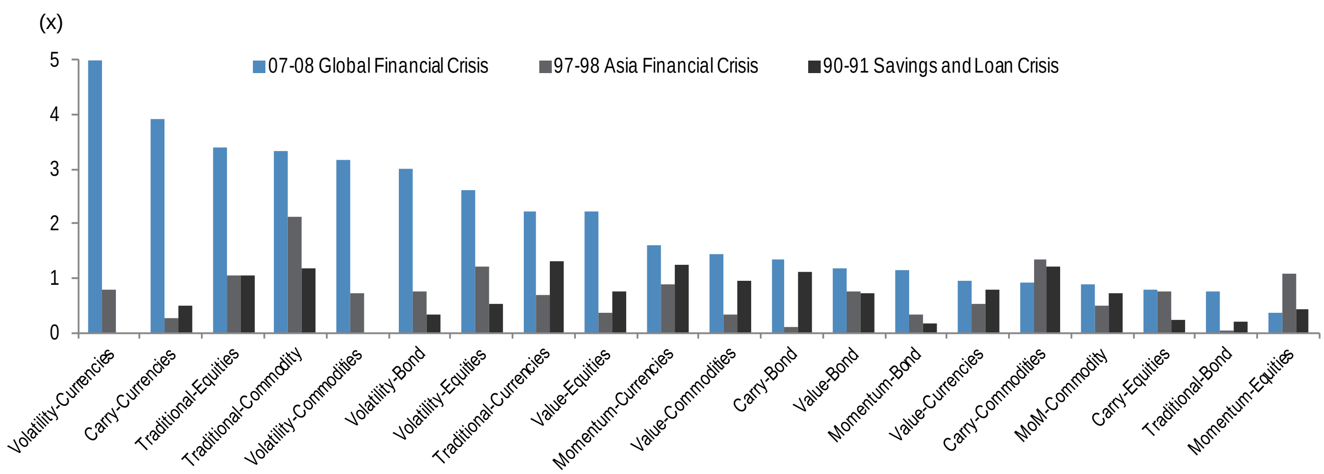
Factor Selection and Factor on Factor

The most likely first step in the factor selection process is to analyze the historical performance of factors. For instance, one can rank a universe of factors based on annualized returns or historical Sharpe ratios. Similarly, investors can rank factors based on their diversification ability, i.e. average correlation to other risk factors. The performance and diversification ranking of our 'Toy model' risk factors is presented in Appendix. Performance and diversification should be compared in different market regimes such as growth, inflation, volatility and liquidity. Investors can then select factors that have attractive properties in the prevailing market regime, or make factor selections based on the market regime forecasts.

More broadly, the selection of risk factors to be included in a portfolio should involve not only assessing factor performance and correlation, but also tail risk properties, liquidity, and estimated capacity of the strategy.

In the aftermath of the global financial crisis, many investors started giving more attention to tail risk properties in their factor selection process. Factor tail risk can emerge as a result of hidden correlations, low liquidity, crowded or low capacity strategies, etc. A simple approach would be to evaluate factors by ranking them according to ratio of maximum drawdown and annualized standard deviation. Figure 25 below shows these rankings for our 20 'Toy' models during the market crises of '90-'91, '97-'98 and '07-'09 (e.g. during the global financial crisis, Commodity beta and Currency Volatility realized the largest draw-downs of -68%, and -54%, or 3.3x, and 5.7x standard deviations, respectively).

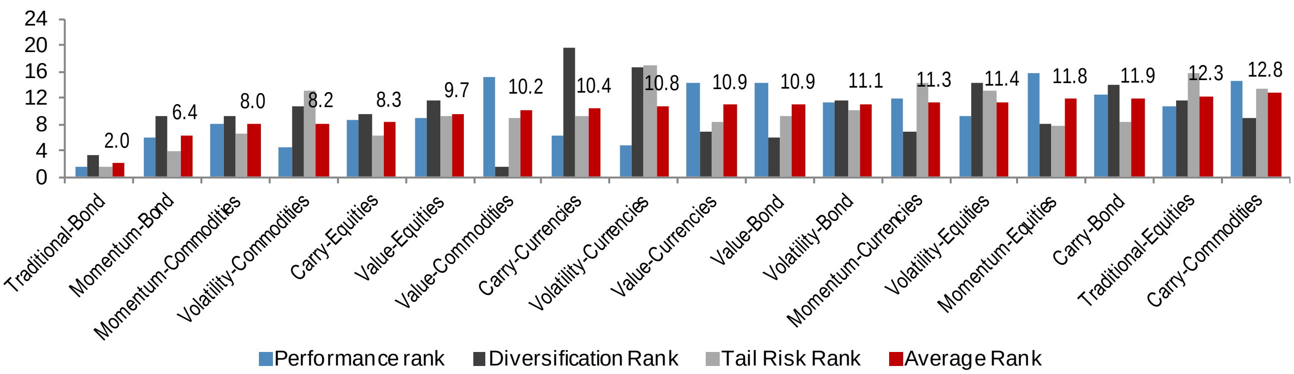
Figure 25: Maximum drawdown for the past three financial crises* measured by number of annualized standard deviations



Source: J.P. Morgan Quantitative and Derivatives Strategy. * July 1990 - Mar 1991 (US saving & loan crisis), Jul 1997 - Sep 1998 (Asian Financial Crisis, Russian Default and LTCM), and Aug 2007 - Mar 2009 (Global Financial Crisis).

To construct a multi-factor portfolio, investors can construct a combined rank for each of the factors by weighting measures such as performance (Sharpe ratio), diversification and tail risk ranks. For example, the chart below provides a stylized factor ranking assuming 50% weight on performance (Sharpe ratio), 25% weight on diversification (average correlation) and 25% weight on tail risks (maximum drawdown divided by standard deviation). A simple multi-factor model could e.g. select the top 10 factors by combining these scores. We should note that the metric used to evaluate factors and assign weights will differ based on investors' risk preference. For instance, unlevered investors will likely use absolute returns rather than Sharpe ratios, and risk-averse investors may put more weight on the tail risk ranking or include additional risk rankings such as duration of draw-down, or co-kurtosis.

Figure 26: Rank of Cross Asset Strategy factors* under Current Macro/Market regime** – The lower the number, the higher the rank



Source: J.P. Morgan Quantitative and Derivatives Strategy. * Performance ranked was performed on Sharpe ratio terms (the higher, the better), Diversification rank was performed on average correlation terms (the lower, the better), Tail risk rank was performed on Maximum drawdown to standard deviations (the lower, the better), where Maximum drawdown were calculated during past three episodes of financial crises: July 1990 - Mar 1991 (US saving & loan crisis), Jul 1997 - Sep 1998 (Asian Financial Crisis, Russian Default and LTCM), and Aug 2007 - Mar 2009 (Global Financial Crisis or GFC). ** In our demonstration, we use low-mid Growth, low Inflation, low Volatility, High Funding Liquidity and Mid-High Market Liquidity as the current regime.

From Figure 26, one can notice that the traditional bond factor scored the highest ranking by performance, tail risk and combined ranking methodology. This simple ranking approach may imply that the factor should be included in any multi-factor model. However, we know that high ranking was likely due to the secular decline of government bond yields over the past few decades, high risk aversion during the global financial crisis, as well as bond buying programs by central banks.

The question for an investor is ‘will the historical performance and risk properties of this factor persist, or mean revert’, for example as a result of improved risk sentiment, scaling back of central bank interventions, and other market developments. In other words, do we expect the bond risk factor to exhibit ‘momentum’, or should we approach the high ranking from the ‘value’ perspective, i.e. expect performance mean reversion. This brings us to the **concept of ‘Factor on Factor’** in which we will apply factor methodologies of momentum, value and carry to rank and select factors themselves.

In our previous work, we have already documented the advantage of Multifactor models (see Investment Strategies No. 82: Multifactor Models) and a Factor on Factor approach when applied to Equity risk factors (see Investment Strategies No. 100: Equity Factor Rotation Models). The same approach can be applied to traditional and alternative risk factors across asset classes as illustrated in Table 21 below.

Table 21: Factor Operations on Traditional Assets and Alternative Factors

	Traditional	Carry	Momentum	Value	Volatility
Traditional Asset Assets	Long-only in Traditional Assets	Long (short) higher (lower) yielding assets	Long (short) higher (lower) momentum assets	Long (short) assets with lower (higher) valuation	Selling options (or risk managing) on traditional assets
Alternative Factor Assets	Long-and-hold in Alternative Factors	Long (short) higher (lower) Carry to Risk Factors	Long (short) Factors with higher (lower) Momentum	Long (short) Factors with lower (higher) Valuation	Selling options (or risk managing) on Alternative Factors

Source: J.P. Morgan Quantitative and Derivatives Strategy.

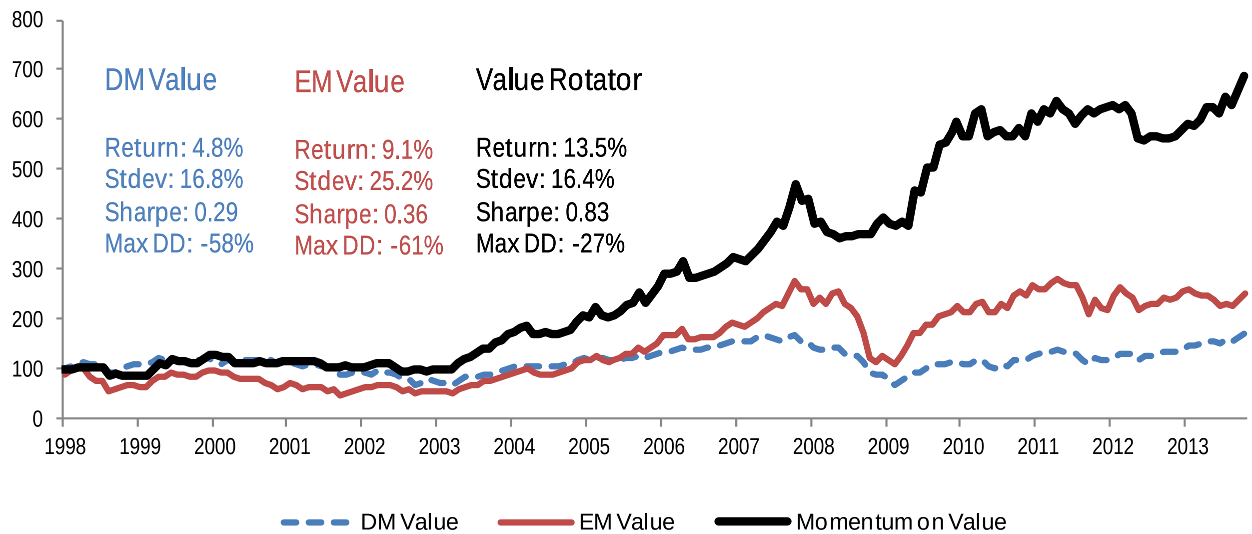
Let’s illustrate the Factor on Factor approach in more details by applying the **Momentum Factor on Factors**. Price momentum of a factor can be defined in the same manner as price momentum of any other underlying. For instance one can use the percentage change of the factor price over some trailing window, Relative Strength Index, or apply some other momentum methodology. Momentum of a factor can also be calculated as a weighted average of momentum scores of all assets comprising the factor:

$$\text{Factor Momentum (Score)} = \sum_i w_i \times \text{Momentum Score}_i$$

where w_i-s are the portfolio weights in the construction of Alternative Factor, and Momentum Score_i are the Momentum scores for the i-th component asset.

A simple example of momentum factor on factor would be an application of Momentum methodology on Value Factors. One can allocate between MSCI DM Equity Value Index and EM Equity Value Index based on the 6-month price momentum score for these indices. This simple application of momentum on value historically improved the Sharpe ratios of the DM and EM Value indices and significantly reduced drawdown as illustrated in the Figure 27 below.

Figure 27: Cumulative excess return of MSCI DM Value index, MSCI EM Value Index and a rotator based on 6-month price momentum



Source: J.P. Morgan Quantitative and Derivatives Strategy. * The Momentum rotator on Equity Value indices compares the total return of MSCI DM value, MSCI EM value and J.P. Morgan US Treasury Bond Index (JPMTUS Index) and takes long position on the best performing index.

Another example where the Momentum factor was effectively applied on factor selection is a Momentum allocation between Currency Carry strategies. The model of momentum allocation between G10 and EM Carry was elaborated in Investment Strategies No. 33: Rotating between G-10 and Emerging Market Carry.

Various risk asset allocation models and risk management techniques also implicitly implement Momentum factor on factors. In the next section we will elaborate on risk management techniques in detail, while here we are discussing them in the context of factor on factor selection approach. For instance, Constant Proportional Portfolio Insurance (CPPI) and Option hedging techniques allocate between risky assets and cash based on the momentum of risky assets. A CPPI managed portfolio of carry strategies will increase exposure to carry when performance is strong and reduce it when the carry strategy starts suffering, thus implementing momentum on Carry.

Another popular asset allocation approach is ‘Risk Parity’. In a Risk Parity approach investors incrementally allocate funds to factors with low or declining volatility. In most cases these are the factors with strong recent performance, and thus Risk Party has elements of a Momentum factor on factor approach. Finally, even a simple mean-variance optimized portfolio of factors often uses 6-12 month trailing returns as estimates of expected future returns, thus building in a momentum assumption in the optimal factor selection process.

Another common approach is to use the **Value Factor on Factors**. Similar to Carry and Momentum factors, one could define aggregate Value scores for factors by either tracking the percentage of components displaying Value or using weighted average Value scores of the assets comprising a factor:

$$\text{Factor Value (Percentage)} = \text{Percentage of Factor Components Displaying Value}$$

$$\text{Factor Value (Score)} = \sum_i w_i \times \text{Value Score}_i$$

An example of the Value approach to factor selection is **Value on Volatility Factors** in which an investor rotates between short Volatility factors for the US, Japan or Europe, based on the level of the implied-realized volatility spread (i.e. a measure of value) for each of the regional volatility factors (Investment Strategies No.75: Risk Premia in Volatility Markets). Similarly, one can allocate between FX, Bond, Commodity and Equity implied-realized volatility carry, based on the level of spreads in these markets.

Many asset allocation schemes implicitly incorporate a Value factor on factor approach. For instance, a simple equal weighting approach to portfolio rebalancing is a Value factor on factor approach. Keeping the asset weights equal involves buying assets that recently underperformed, and selling assets that recently outperformed (which has a mean-reversion or Value bias towards asset expected performance).

The Factor on Factor approach can be generalized to conduct a **multi-dimensional ranking** of factors. For example, Quantitative Equity managers frequently combine the rank of Price Momentum, Earnings Momentum and Valuation in their stock selection process. The concept of multi-dimensional ranking is straightforward to apply to risk factors across assets. An investor would combine Carry, Momentum, Value and Volatility ranks for every factor and select factors with highest weighted average ranking.

$$\text{Multi Factor Rank} = \sum_i w_i \times \text{Individual Factor Rank}_i$$

Weights $\boldsymbol{w_i}$ assigned to ranking according to factor *i* (momentum, value, carry, volatility) can be adjusted based on the investor's preference for the factor bias of a final portfolio (e.g. the portfolio can be biased towards carry, or any other factor).

As we argued, the true power of risk factors comes from their ability to access new sources of risk premia and lower average levels of correlations. The construction and ongoing management of a risk factor portfolio therefore involves researching both the individual factors, as well as their correlation properties under various market regimes. We have shown that simple multi-factor models as well as the factor on factor approach result in dynamic factor weights. Rebalancing factor weights according to these prescriptions can drastically change overall portfolio risk profile over time.

A related approach to constructing a factor portfolio is to start by defining desired portfolio risk properties, and solving for the factor weights and rebalancing prescription. An example would be to target a portfolio of factors that has minimal volatility, maximal diversification level, or the highest Sharpe ratio under certain assumptions for factor returns and covariance. One can also rebalance the portfolio by prescribing a risk budget to individual factors. An example is a simple requirement that each factor contributes equally to the overall portfolio risk (also known as Risk Parity). All of these methods result in a prescription for factor relative weights, and we will refer to them as **cross-sectional risk management** (or risk management of factor weights).

Once a portfolio with the desired factor weighting is constructed, an investor can adjust the allocation between the factor portfolio and risk free asset in order to target a particular level of volatility, protect the principal amount of investment, or implement a timing strategy based on e.g. macro economic or market technical signals. We will refer to these methods as **time-series risk management** (or risk management of total risk).

Methods of portfolio construction and risk management are very broad and important subjects. For this reason, we will focus on them in the rest of this report.

Construction and Risk Management of Factor Portfolios

Introduction

Financial markets today are complex and much different from those of 5, 10 or 20 years ago. Major changes include globalization, shifts in regional economic balance, increase in actively managed assets, broad usage of derivative products and leverage, and changes in regulatory regimes. As the nature of market risks change, investors constantly need to adjust methods to manage portfolio risk.

As early as the market crisis of '87, investors realized limitations of Modern Portfolio Theory, and specifically the assumption of normally distributed returns. It took several more events such as the crisis of 97/98, burst of the tech bubble and the market selloff of 2002 for investors to fully grasp the links between leverage, volatility, and tail risk. These consecutive crises lead to the adoption of more rigorous risk management techniques, and increased the usage of option based portfolio protection. Realizing that it may be easier to forecast volatility and correlation than asset returns, investors shifted focus from return-driven asset allocation models such as Mean Variance Optimization to pure risk-driven models, such as global minimal variance, maximum diversification and equal risk contribution approaches. Furthermore, a generic risk budgeting framework was developed to allow investors to input specific views on risk, while the Black-Litterman framework enabled investors to consistently incorporate specific views on returns.

The global financial crisis of 2008-2009 further challenged investors' understanding of risk. Unprecedented market volatility and rapid changes in cross-asset correlations caused even sophisticated risk-driven models to fail (see Rise in Cross Asset Correlations). Following the crisis, investors further increased focus on tail risk hedging, and on the problem of forecasting correlation and volatility regimes; methods like Risk parity, constant volatility targeting, and low volatility indices approach gained popularity during this time period. Specifically, Risk parity portfolios outperformed fixed weight portfolios, as well as many endowment models that both had too much risk allocated to equity-like investments. [20] However, it did not take too long before the Risk parity approach began to suffer, due to the breakdown of equity-rate correlation and bond underperformance in 2013.

Methods of portfolio risk management also need to evolve as investors expand their investment universe to non-traditional and alternative asset classes. Specifically, the inclusion of Commodities, Private Equity, Hedge Funds, Volatility, and alternative risk factors (Value, Momentum, Carry, and Volatility) can drastically change the distribution of portfolio risk. Many of these assets do not follow normal distributions, and hence the risk methods based on Modern Portfolio Theory may be suboptimal.

In parallel to empirical developments, academics extended the traditional portfolio theories of Markowitz (1952) in several aspects. The original Mean-Variance approach seeks the portfolio with the optimal tradeoff between return and variance. An extension of this concept includes optimization of higher order risks such as tail risk or specific systematic sources of risk such as economic recessions (e.g. Cochrane (1999), Alexander and Baptista (2002), Chung and Schill (2006)). A portfolio optimized to maximize return, minimize variance, but also minimize systematic risk sources, is often quite different from a simple 'mean-variance' portfolio (thus different from Markowitz's market portfolio). Other extensions of the Mean-Variance approach are the inclusion of specific views on expected returns as in the Black-Litterman approach, and the inclusion of specific views on risk as in Risk Budgeting approach.

As the nature of market risks evolves and new assets emerge, investors should be familiar with all available risk methods. Each of the methods will have their own benefits and drawbacks, and may work best under different market conditions. The optimal approach to mange risk will therefore depend not only on the forecast returns and covariances, but also on the understanding of the prevailing market regime and potential tail risks. Investors who are versatile in all risk management methods can stand ready to apply a specific method when it is likely to yield the best results.

In the rest of the report we will discuss methods to construct and risk-manage factor portfolios. We will start with introducing the concept of a mean-variance portfolio. Mean variance optimization (MVO) can be viewed as an approximation for a more generic portfolio optimization (i.e. MVO is a second order approximation of the optimization of

[20] The endowment model was pioneered by Yale endowment CIO David Swensen in his 2000 book "Pioneering Portfolio Management", who advocated the inclusion of alternative assets such as REITs and PE/VC funds into a traditional portfolio to capture liquidity premia.

any utility function). We will then show that various methods such as Market weights, Global Minimal Variance, and Maximal Diversification are simply specific implementations of MVO under certain assumptions for risk and returns of the portfolio components. We will also analyze generic risk budgeting models and specific applications such as Risk Parity and Equal Marginal Volatility. Some of these approaches were studied in greater detail in our previous work, such as in Investment Strategies No. 101: Risk Methods and The Risks of Risk Parity.

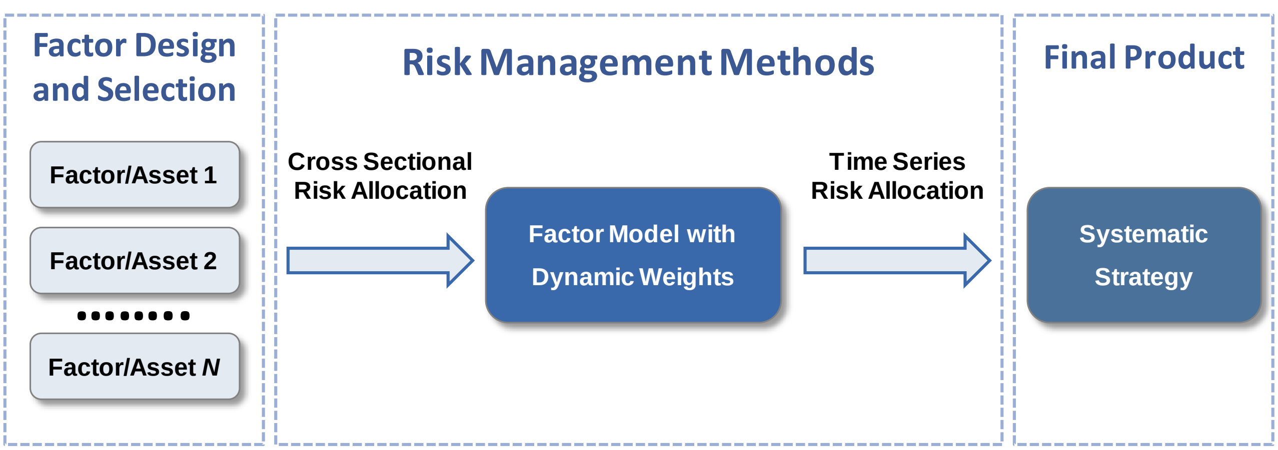
Risk methods that we mentioned have the goal of constructing an optimal portfolio under certain assumptions for asset returns, covariances, and under constraints imposed by an investor (e.g. the portfolio should have the highest Sharpe ratio, minimal variance, each asset should have the same contribution to risk, etc.). We will refer to this process of allocation of risk between different factors as **cross-sectional risk management**. Once the risk weights are allocated across the factors (cross-sectional risk allocation), an investor can dynamically allocate risk between the portfolio and risk-less asset to further modify the risk profile. We will refer to this process as **time-series risk allocation** between the factor portfolio and risk-free assets. For instance, a popular approach is to target constant volatility of a risk factor portfolio. Portfolio losses can be minimized by applying principal protection techniques such as CPPI, or stop loss. The use of options can provide a wide variety of modifications to the risk profile, such as downside protection, tail protection, upside leverage, and collaring.

The construction and risk management of a factor portfolio can be accomplished in three steps:

- *Factor design and selection:* An investor designs (or adopts) factors to access traditional and alternative risk premia. Factors in the universe are then assessed based on their historical performance, volatility, diversification properties, tail risk properties, liquidity, capacity, etc. Factors can be pre-processed to have e.g. standardized volatility, or to be independent.
- *Cross-sectional risk allocation (or risk budgeting at the asset/factor level)*: An investor determines the relative factor weights. This can be based on views (e.g. expected returns, volatility, correlation) and specific risk/reward goals for a portfolio (e.g. maximum Sharpe ratio, equal marginal volatility). Model weights are periodically rebalanced (e.g. monthly or quarterly).
- *Time-series risk allocation (or risk budgeting at the portfolio level)*: An investor determines the optimal allocation of total portfolio risk. This is accomplished by dynamically allocating risk between the factor portfolio and the risk-free asset. A particular methodology is chosen to meet certain requirements such as to target constant volatility, protect principal investment, and stop losses below certain level.

Figure 28 illustrates this process of portfolio design and risk management.

Figure 28: Steps in the Portfolio Construction and Risk Management Process



Source: J.P. Morgan Quantitative and Derivatives Strategy.

The process can be illustrated with a simple example of a constant volatility, risk parity portfolio of equities and bonds. The first step would be to select risk factors, in this case traditional assets: equity and bond indices. This selection was likely based on the historical negative correlation between the two, and positive expected returns. To balance risk contributions between the two assets (of quite different volatility), the investor selects the Risk Parity cross-sectional risk management method. Finally, a time series method of volatility targeting is applied to obtain a constant volatility (e.g. 8% annualized volatility) portfolio.

Through the rest of the report, we will introduce several mathematical concepts related to cross-sectional and time-series risk management. A full derivation of results often requires knowledge of mathematical methods such as linear algebra, matrix theory, and stochastic calculus. We will explain these concepts in simple terms so that they are understandable to readers without a rigorous mathematical background, but will also provide full technical details in the shaded "Mathematical Boxes". These technical notes can be skipped, based on readers' interest and inclination for theory.

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Cross-Sectional Risk Allocation - Theory

The goal of a portfolio optimization process is to create the best possible portfolio for a particular investment objective, given some assumptions for future asset performance. The optimization objective can be to achieve a portfolio with the lowest possible risk, highest Sharpe ratio, smallest tracking error relative to a benchmark, or other objectives specified by an investor. In order to obtain asset weights that will result in an optimal portfolio, an investor often needs to make assumptions on the future asset returns, volatilities and correlation between assets. These assumptions (forecast) are input into an optimizer (e.g. a computer code) or may already be built into a commercial model (such as MSCI Barra).

The optimal portfolio construction is a straightforward mathematical procedure (e.g. see mean-variance optimization method later in this section). However, the forecasts for asset returns, volatilities and correlations are often not accurate, and an expected optimal mathematical solution may not turn out to be a portfolio with the desired properties after the fact. Given that asset returns are not easy to forecast, investors may choose to limit themselves to forecasting volatility and correlations. The rationale behind forecasting volatility and correlations (and not returns) is that these measures tend to exhibit properties of persistence and mean reversion, and their average levels should (in principle) be easier to estimate. To avoid forecasting asset returns, an investor can use simplifying assumptions such as equal expected returns, and equal asset Sharpe ratios.

An investor's objective is often expressed via a utility function ("utility" effectively quantifies an investor's level of satisfaction/happiness with an economic outcome). A utility function quantifies the trade-off between the desired attributes of a portfolio such as high return, and undesirable properties such as high volatility and tail risk. An example of such a utility function is given below.

$$\text{Investor's Utility} = \text{Expected Return} - (\text{Risk Aversion}) \times \text{Variance}$$

To increase the investor's utility, one would need to find asset weights with the best 'trade-off' between high expected return and low contribution to portfolio volatility. The parameter that determines the 'trade-off' between the return and risk parts of the utility function is called 'risk aversion'. Levy and Markowitz (1979) showed that using a simple utility function such as the one above provides optimal solutions for a very broad set of utility functions, i.e. different types of investors (mathematically, the simple utility function above can be viewed as a second-order approximation for any standard utility function). A portfolio constructed by optimizing this utility function would also have the highest possible Sharpe ratio (provided returns, volatility and correlations are accurately forecast).

In reality, the expected returns, volatility and correlations cannot be forecast with high accuracy, and return distributions are often not normal. This can make the optimization method based on a return-volatility trade-off inadequate. For instance, with the expectation of extreme market conditions, a portfolio that minimizes tail risk (rather than volatility) may outperform the maximum Sharpe Ratio portfolio.[21] Readers could also refer to the Mathematical Box on page 19 for commonly used tail risk measures.

The same optimization approach (maximizing the utility function) can be applied by investors whose objective is to outperform a particular benchmark. Instead of absolute return and variance, they would define the optimization objective via the return relative to a benchmark (such as long-term government bonds, or the S&P 500), and substitute portfolio volatility with tracking risk.

In the rest of this Chapter, we will discuss various optimization methods and the properties of the resulting portfolios. We will start with explaining the simple choices of Market-weight and Fixed-weight portfolios and their relationship to generic results of Mean Variance Optimization (MVO). Then we will discuss some special cases of MVO such as Global Minimal Variance and Maximal Diversification. This will be followed by a discussion of generic Risk Budgeting (RB) and its special cases of Risk Parity and Equal Marginal Volatility. We will also introduce the Black-Litterman approach to

[21] This is usually done by including the third and fourth moments (skewness and kurtosis) in the utility function. See Bruder & Roncalli (2012) for a more detailed description of when the risk metric is different from portfolio volatility.

implementing asset return forecasts and briefly address issue of Tail risk. Finally, we will provide a simple summary of these methods and illustrate them in two-, and three-asset portfolio examples.

In the last section of the chapter, we will implement all of the discussed risk models on a more realistic portfolio of traditional and alternative risk factors, as well as on a sample portfolio of J.P. Morgan tradable risk factor indices. We will compare the performance of these risk models under various market regimes, and highlight their pros and cons.

In a series of mathematical boxes, we will provide technical details of the various methods. Readers who are not interested in mathematical formalism may skip these boxes, as they are not required to follow the text. In the first mathematical box we introduce the portfolio matrix notation that will be used in subsequent analyses.

Mathematical Box (Portfolio Risk Notation)

There are N assets in a portfolio[22] . Asset returns are labeled with $r_1, \dots, r_N$, and the risk-free rate is r_f. Superscript T indicates matrix transposition.

- $\boldsymbol{r} = (r_1, \dots, r_N)^T$ is a $N \times 1$ column vector of the marginal excess return,
- $\boldsymbol{\mu} = (\mu_1, \dots, \mu_N)^T = E(\boldsymbol{r})$ is a $N \times 1$ vector so that $E(r_i) = \mu_i$ for any i,
- $\boldsymbol{\sigma} = (\sigma_1, \dots, \sigma_N)^T$ is a $N \times 1$ volatility vector so that $\mathrm{Var}(r_i) = \sigma_i^2$ for any i,
- $\boldsymbol{S} = (s_1, \dots, s_N)^T$ is a $N \times 1$ vector of Sharpe ratios so that $s_i = \mu_i / \sigma_i$ for any i,
- $\boldsymbol{\Lambda} = \mathrm{diag}(\sigma_i)$ is a $N \times N$ diagonal matrix so that $\boldsymbol{\Lambda}^{-1}\boldsymbol{\mu} = \boldsymbol{S}$,
- $\boldsymbol{C} = \left(\rho_{ij}\right)_{N \times N} = \mathrm{Corr}(\boldsymbol{r}, \boldsymbol{r})$ is a $N \times N$ correlation matrix and $\rho_{ii} = 1$ for any i,
- $\boldsymbol{\Sigma} = \left(\sigma_{ij}\right)_{N \times N} = \mathrm{Cov}(\boldsymbol{r}, \boldsymbol{r})$ is a $N \times N$ covariance matrix so that $\sigma_{ij} = \rho_{ij}\sigma_i\sigma_j$,
- $\boldsymbol{w} = (w_1, \dots, w_N)^T$ is a $N \times 1$ column vector of the weights for the assets,
- $\boldsymbol{1} = (1, \dots, 1)^T$ is a $N \times 1$ column vector of ones,
- $\boldsymbol{1}_j = (0, \dots, 1 \dots, 0)^T$ is a $N \times 1$ column vector whose j-th element is 1 and all other elements are 0.

Given the above notations, the portfolio return is given by $r_p = \sum_{i=1}^{N} w_i\, r_i$, whose expected return and variance are given by

- $\mu_p = E\left(r_p\right) = \sum_{i=1}^{N} w_i\, \mu_i = \boldsymbol{w}^T\boldsymbol{\mu}$ (portfolio excess return), and
- $\sigma_p^2 = \mathrm{Var}\left(r_p\right) = \sum_{i=1}^{N}\sum_{j=1}^{N} w_i\, w_j\, \sigma_{ij} = \boldsymbol{w}^T\boldsymbol{\Sigma}\boldsymbol{w}$ (portfolio variance),
- In addition, $\boldsymbol{\beta} = (\beta_1, \dots, \beta_N)^T = \boldsymbol{\Sigma}\boldsymbol{w}/\sigma_p^2$ is a $N \times 1$ vector, so that β_i is the beta of the i-th asset with respect to the portfolio.

The weights $\boldsymbol{w}$ can either be under constraint[23]

$$\sum_{i=1}^{N} w_i = \sum_{i=1}^{N} \boldsymbol{w}^T\boldsymbol{1}_i = \boldsymbol{w}^T\boldsymbol{1} = 1$$

or be *unconstrained* with the inclusion of a risk-free asset that can be lent or borrowed freely.

[22] The underlying instruments could be different asset classes or risk factors giving access to different systematic risk exposures.
[23] Different weight constraints could be imposed to avoid corner portfolio solutions or weight concentration etc.

The sensitivities of the portfolio return and volatility to the asset weights are given by:

$$\frac{\partial \mu_p}{\partial \boldsymbol{w}} = \frac{\partial \boldsymbol{w}^T \boldsymbol{\mu}}{\partial \boldsymbol{w}} = \boldsymbol{\mu}$$

$$\frac{\partial \sigma_p}{\partial \boldsymbol{w}} = \frac{\partial \sqrt{\boldsymbol{w}^T \boldsymbol{\Sigma} \boldsymbol{w}}}{\partial \boldsymbol{w}} = \frac{1}{2\sigma_p} \frac{\partial \boldsymbol{w}^T \boldsymbol{\Sigma} \boldsymbol{w}}{\partial \boldsymbol{w}} = \frac{\boldsymbol{\Sigma} \boldsymbol{w}}{\sigma_p} = \boldsymbol{\beta} \sigma_p$$

Hence, the change of portfolio return with a unit change of marginal weight corresponds to the marginal return, and the change of portfolio volatility with a unit change of marginal weight corresponds to the beta times portfolio volatility.

Mean-Variance Optimization (MVO), Market Portfolio and Fixed Weight Allocation

MVO was first proposed by Markowitz (1952). The goal of the method is to produce a portfolio with the highest Sharpe ratio. Specifically, the method solves the portfolio optimization problem by maximizing a simple utility function aiming for higher returns and lower risk. As a result, Mean Variance Optimization will result in an optimal portfolio with a maximum Sharpe ratio. Specifically, an MVO tries to maximize

$$\text{Expected Portfolio Return} - \frac{\lambda}{2} \times \text{Expected Portfolio Variance}$$

A risk aversion factor (λ, positive value) is used to balance the risk-return tradeoff. The larger the risk aversion factor (λ) is, the higher penalty investor puts on “risk" (i.e. the more risk averse the investor). When λ is equal to 0, an MVO will put 100% weight in the best performing asset without regard to portfolio risk. On the other hand, when the risk aversion factor is very large, MVO will not be concerned with returns, and will simply minimize portfolio risk – resulting in a portfolio with lowest possible volatility (also called the Global Minimum Variance (GMV) portfolio).

MVO is at the center of many traditional asset allocation approaches such as capitalization based allocations (Market Portfolio), and fixed weight investing (e.g. 60 bond / 40 equity portfolio). The Capital Asset Pricing Model (CAPM) introduced separately by Jack Treynor, William Sharpe and John Lintner suggests that the market portfolio is the optimal choice for investors seeking to maximize Sharpe ratio, and an asset’s expected returns are proportional to the asset’s beta to the market and the market’s returns. Under a set of assumptions[24], the CAPM implies that the market portfolio[25] is mean-variance optimal portfolio and that all investors should hold a proportion of the market portfolio as it has the highest Sharpe ratio (the “Two Fund Theorem” suggests investors should allocate between market portfolio and risk-free asset). Currently, most equity investors are benchmarked to capitalization weighted indices – thus implementing a form of the MVO approach. Major equity benchmarks such as MSCI World, S&P 500, or MSCI Europe represent global and regional market portfolios and are thus approximately MVO optimal.

In the mathematical box below we derive the MVO weights and also demonstrate the expected return of an individual security could be calculated through its beta to the market portfolio.

[24] CAPM assumes that:
1) Security markets are perfectly competitive (many small investors as price takers)
2) Markets are frictionless (no taxes or transaction costs; information transparency)
3) Homogenous MVO investors (same one-period horizon; all investors use MVO)
4) All investors can lend and borrow unlimited amounts of the risk free asset

[25] The market portfolio is a portfolio consisting of all assets in the market, weighted proportionately to their market value

Mathematical Box (Mean-Variance Optimization)

If the expected return $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$ could be estimated with a degree of accuracy, the Mean-Variance Optimization (MVO) proposed by Markowitz (1952) maximizes the following utility function by changing the asset weights $\boldsymbol{w}$:

$$\max_{\boldsymbol{w}}\left[E(\boldsymbol{R})-\frac{\lambda}{2}\mathrm{Var}(\boldsymbol{R})\right] \text{ or } \max_{\boldsymbol{w}}\left[\boldsymbol{w}^T\boldsymbol{\mu}-\frac{\lambda}{2}\boldsymbol{w}^T\boldsymbol{\Sigma}\boldsymbol{w}\right]$$

where λ is an investor-specific factor of risk aversion – higher (or lower) λ means more (or less) risk averse.

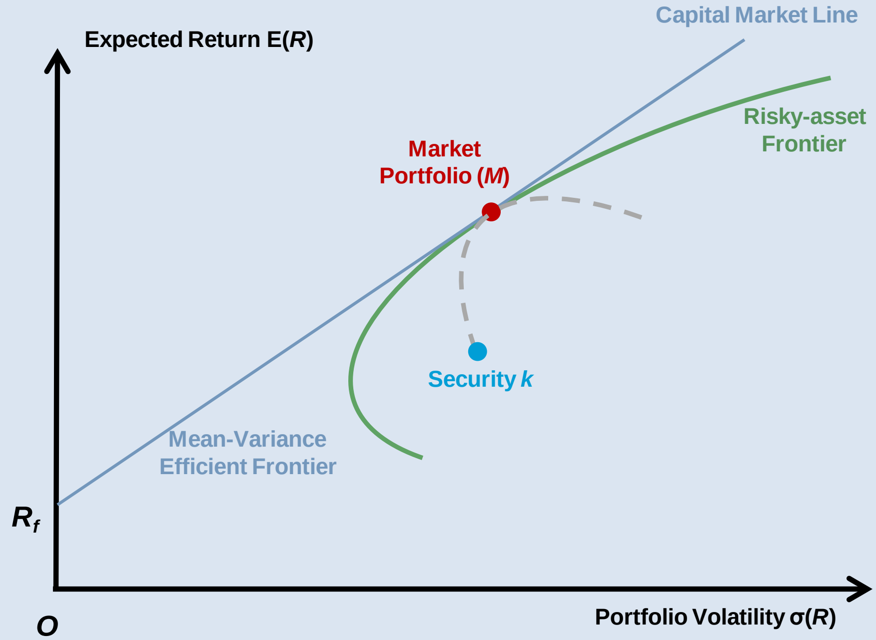
In the unconstrained case, directly solving MVO (taking first derivative with respect to $\boldsymbol{w}$ and equating to zero) results in the MVO portfolio weights:

$$\boldsymbol{w}=(\lambda\boldsymbol{\Sigma})^{-1}\boldsymbol{\mu}$$

It can be shown that under this optimal solution, the ratio of the marginal contribution to portfolio return and the marginal contribution to portfolio risk is the same for all assets and equals the optimal portfolio Sharpe ratio $\sqrt{\boldsymbol{\mu}^T\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu}}=\sqrt{\boldsymbol{S}^T\boldsymbol{C}^{-1}\boldsymbol{S}}$.

Under the CAPM framework, the market portfolio is mean-variance efficient in that it solves the MVO. The market factor of risk aversion (for an average investor) is given by $\lambda_{\mathrm{mkt}}=(\mu_M-R_f)/\sigma_M^2$, where μ_M and σ_M are the expected return and volatility of the market portfolio and R_f is the risk-free rate. Moreover, any efficient portfolio lies on the "Capital Market Line" which crosses the risk-free rate and market portfolio (Figure 29), where $(\mu_M-R_f)/\sigma_M$ is the market price of risk (or market Sharpe Ratio) that determines the slope of the capital market line (CML).

Figure 29: Market Portfolio and CAPM



Source: J.P. Morgan Quantitative and Derivatives Strategy.

To derive the CAPM, let's consider a portfolio $\boldsymbol{P}$ with a fraction of ω invested in the market portfolio with expected return μ_M and variance σ_M^2 and the rest $(1-\omega)$ in an arbitrary security k with expected return μ_k and variance σ_k^2. Suppose the covariance between the security k and the market portfolio is σ_{kM}, the expected return and variance of such a portfolio are given by:

$$\mu_{\boldsymbol{P}} = E(\boldsymbol{P}) = \omega\mu_M + (1-\omega)\mu_k$$

$$\sigma_{\boldsymbol{P}}^2 = \mathrm{Var}(\boldsymbol{P}) = \omega^2\sigma_M^2 + (1-\omega)^2\sigma_k^2 + 2\omega(1-\omega)\sigma_{kM}$$

By the assumptions of CAPM, since the market portfolio is the tangent portfolio on the Capital Market Line as shown in Figure 29 above, the Sharpe ratio of $\boldsymbol{P}$ should be maximized when $\omega = 1$, where the slope of the Capital Market Line (CML) is given by

$$\text{CML Slope} = \left.\frac{\partial\mu_{\boldsymbol{P}}}{\partial\sigma_{\boldsymbol{P}}}\right|_{\omega=1} = \left.\frac{\partial\mu_{\boldsymbol{P}}/\partial\omega}{\partial\sigma_{\boldsymbol{P}}/\partial\omega}\right|_{\omega=1} = \frac{\sigma_M(\mu_M-\mu_k)}{\sigma_M^2-\sigma_{kM}}$$

Equating the above equation with market price of risk $\left(\mu_M - R_f\right)/\sigma_M$ gives:

$$\mu_k = R_f + \frac{\sigma_{kM}}{\sigma_M^2}\left(\mu_M - R_f\right)$$

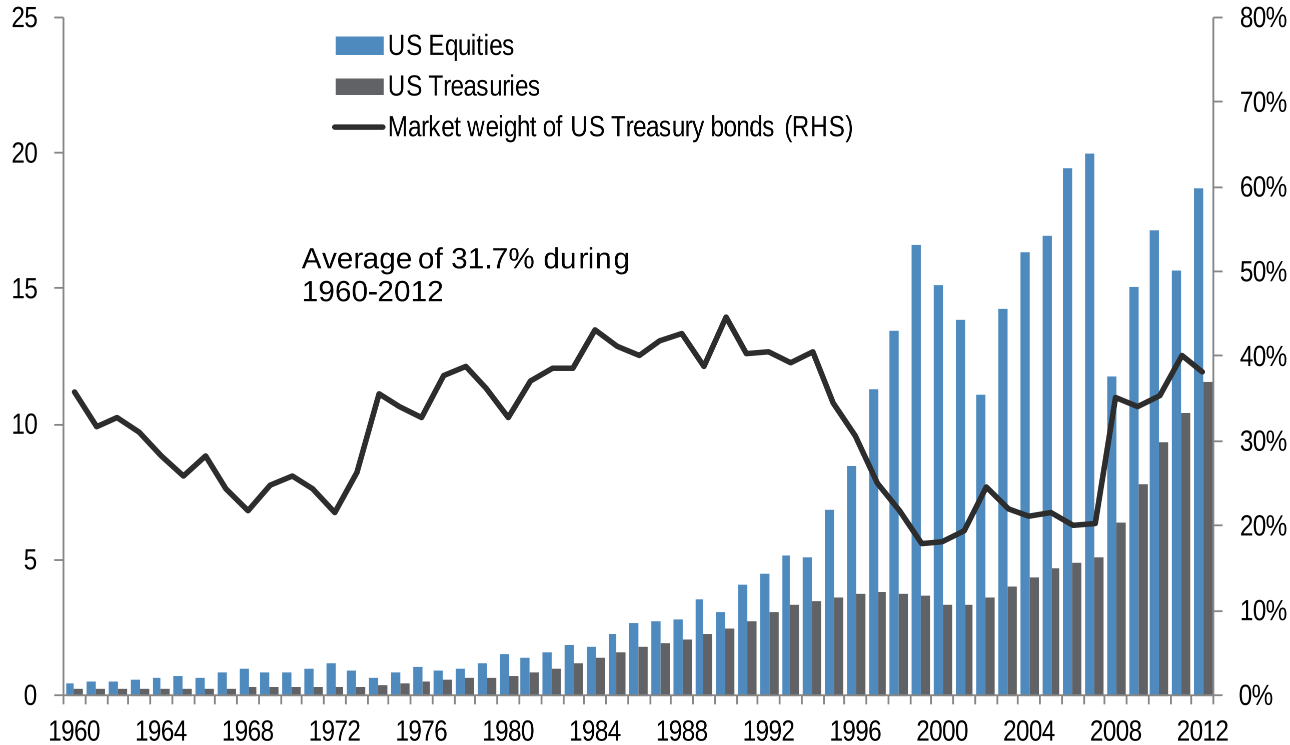
This suggests that, under CAPM, the expected (excess) return of any security k relates to the market portfolio through its beta with respect to the market: $\beta_k = \sigma_{kM}/\sigma_M^2$.

Despite the theoretical elegance of the MVO framework, it can sometimes fail in out-of-sample tactical asset allocation practices. This is mainly due to the high sensitivity of MVO outputs to the input parameters and the difficulties in forecasting expected returns. Possible remedies include: (1) enhancing return forecasts through predictive signals or supplying expected return views, and (2) better risk management to avoid risk concentration. We will also review several proposals including the Black-Litterman approach, Minimum Variance Portfolio, Most Diversified Portfolio, Generic Risk Budgeting and Risk Parity Portfolio.

During 1950s-1960s when the Markowitz portfolio theory and CAPM were introduced, a 60% stock / 40% bond mix roughly represented the market capitalization weights of the universe of investable US assets. The simple bond/stock allocation prescription indirectly follows MVO. In fact, from a domestic US investor's point of view, the "market weight" of Treasury bonds in a Stock-Treasury bond portfolio has actually stood in the 20%-40% range over the past five decades. Based on market size data from the World Bank and US Treasury Department, Figure 30 shows that the market weight for US Treasury bonds averaged 31.7% during 1960 to 2012. If we include corporate bonds, the average market weight for bonds increased to 43.7% during 1960-2012.

Figure 30: Market sizes* of US equities and US Treasury bonds

US$ in trillions

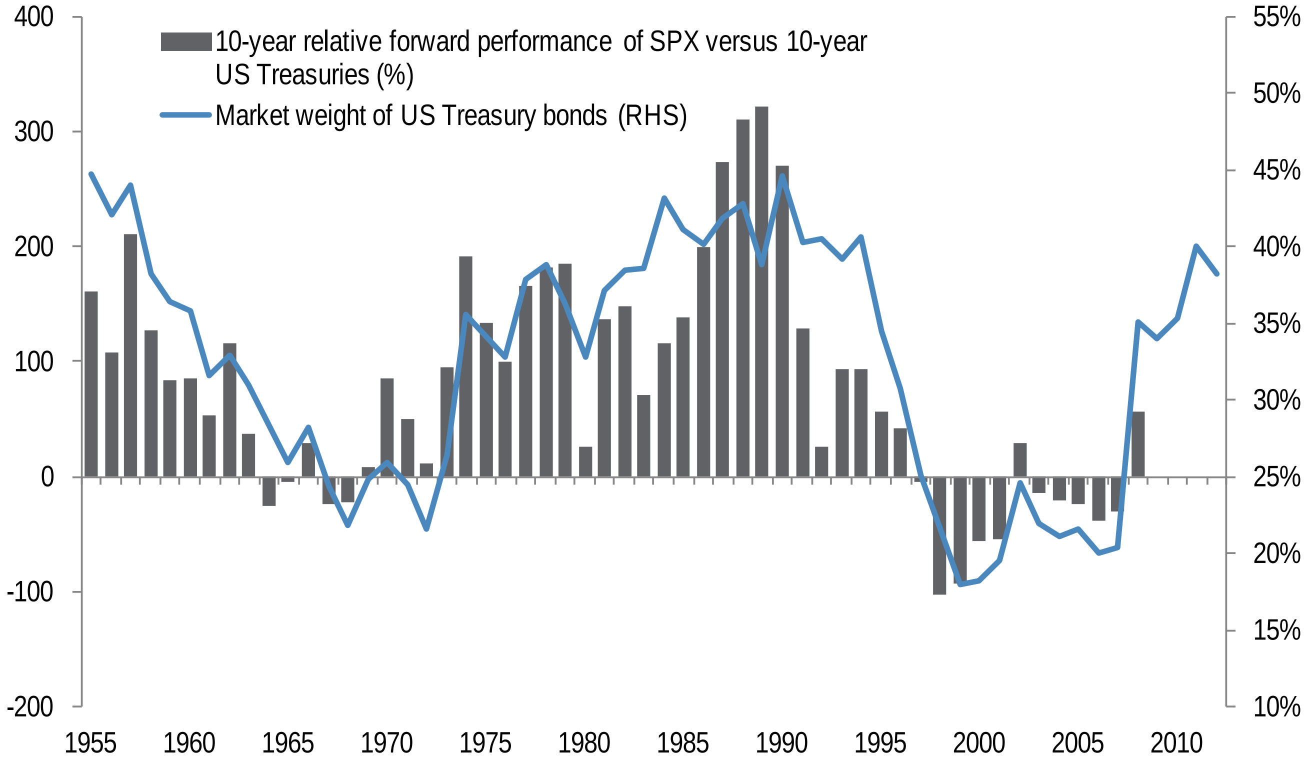


Source: J.P. Morgan Quantitative and Derivatives Strategy, US Treasury. * Market cap data for US equities and Treasury bonds are from the World Bank and US Treasury respectively. Treasury security data includes Treasury Bills, Notes, Bonds, TIPS, United States Savings Bonds, and State and Local Government Series securities.

In addition, historical data suggests that the relative performance of US equities versus Treasury bonds is mean-reverting on a long-term horizon (8-10 years). This is perhaps a good justification of why many traditional mutual funds still use a fixed weight strategic allocation. Figure 31 below shows that the market weight of US equities indeed acted as a contrarian indicator for the relative performance of the S&P 500 relative to 10-year Treasury bonds over a 10-year investment horizon – a high (low) market weight for bonds foreshadowed underperformance (outperformance) of bonds relative to stocks over the subsequent 10 years. Hence, in addition to an element of MVO, a fixed weight investor could enjoy this contrarian investing benefit by periodic portfolio rebalancing.

While one might think that a fixed weight portfolio strategy makes sense when the prices of the assets are mean-reverting relative to market capitalization, Merton (1969) and Samuelson (1969) showed that fixed weight stock/bond portfolios are optimal under broader conditions. A special example of the fixed-weight portfolio method is the “equal weight” (EW) strategy. As its name suggests, EW assigns equal weights to all assets in the portfolio. Recent academic research found empirical evidence that this naïve approach is not inferior to more advanced models under certain market conditions [DeMiguel et.al (2009), Duchin and Levy (2009), and Kritzman et. al (2010)]. However, in our examples from the end of this chapter, we will show that a naïve EW method underperformed most other risk models. The main reason for EW underperformance is the high allocation of risk to volatile assets such as equities. Given these high allocations, EW models tend to underperform during market crises.

Figure 31: Market weight of US Treasuries as a long-term contrarian indicator*



Source: J.P. Morgan Quantitative and Derivatives Strategy, US Treasury, Bloomberg. * Relative performance is calculated as the 10-year forward return difference of the S&P 500 total return and the total return from rolling a 10-year constant maturity Treasury bond contract annually.

Despite its theoretical elegance, the success of MVO is highly dependant on the accuracy of the estimated returns, volatilities and correlations[26] for the individual assets. If one uses incorrect return estimates in the MVO process, the resulting portfolio weights will perform poorly. Moreover, a relatively small change in return and covariance inputs may result in large changes in the output weights. The potential instability of MVO weights is often quoted as the main reason against its broader usage. For traditional assets, expected returns are very difficult to forecast, and the instabilities in the covariance matrix during the recent financial crisis created difficulties for MVO portfolios. MVO may still be the best approach for some of the alternative risk factors, where returns may be easier to forecast and the correlation structure may be more stable. However, MVO is also challenged by the non-normal properties of asset distributions, which could be equally problematic for traditional and alternative risk factor portfolios.

There are many proposed improvements to the MVO approach. Popular methods include simplifying assumptions about expected returns and risk (such as in Global Minimal Variance, Maximal Diversification), directly supplying investor views and combining them with market consensus (such as Black-Litterman), or entirely circumventing return forecasting such as in a Risk Budgeting approach. We discuss all of these methods.

[26] See Appendix for a brief review of popular forecasting models for asset return, volatility and correlation matrix.

Global Minimum Variance (GMV)

Given the potential drawbacks of MVO related to the sensitivity to return forecasts (model inputs), many investors decided to turn to purely risk-based portfolio methods. Focus on risk-based models further increased over recent years, as the global financial crisis shifted investor attention to preventing large losses.

Global Minimum Variance (GMV) is a special case of MVO where an investor has very high risk aversion. In this case "risk avoidance" takes priority to "return maximization" and the optimization tries to find the weights that will result in a portfolio with the lowest possible volatility. As we will show in the mathematical box below, the GMV approach is also equivalent to a special case of an MVO in which the investor simply assumes that the expected returns for all assets are equal. Thus GMV may be an optimal approach for investors that are either highly risk averse, or don't have any differentiating view on the performance of individual assets. An equal return assumption also implies that higher volatility assets have lower Sharpe ratios. While this may contrast with assumptions of efficient markets, there is some recent historical evidence that Sharpe ratios may indeed be lower for higher volatility assets (Volatility anomaly).

Since GMV only depends on the estimated covariance matrix of returns, statistical methods such as multivariate GARCH are usually employed to improve the stability of covariance matrix estimates. Other methods can be used as well such as using option implied volatilities to forecast future realized volatility (see Investment Strategies No. 88: Signals from Options Markets).

Despite the oversimplifying assumptions of GMV, the performance of this method has often been better than e.g. an EW approach. This partly reflects the market performance over the past several years, which was heavily influenced by risky asset draw-downs in 2008 and 2011. Additionally, a more pronounced 'Volatility anomaly' would have benefited GMV due to its assumption of equal returns. At the end of this chapter we will test the performance of risk models applied to realistic portfolios of traditional and alternative factors. While GMV outperformed EW and occasionally other models, its performance over the long time periods was inferior to Risk Budgeting models. The GMV outperformed during times of market stress, due to its disproportionate focus on minimizing risk (as opposed to a more balanced approach between risk and returns).

Mathematical Box (Global Minimum Variance)

In many cases, investors may prefer not to directly offer views on the asset returns. Instead, investors may make simplifying assumptions on the expected returns and focus on forecasting the risk. In the simplest case, a portfolio manager can just assume that the expected excess returns for all the assets are equal to a certain unknown constant c, such that $\boldsymbol{\mu} = c\mathbf{1}$. Under this assumption, the original MVO simply becomes:

$$\max_{\boldsymbol{w}} \left[\boldsymbol{w}^T\boldsymbol{\mu} - \frac{\lambda}{2}\boldsymbol{w}^T\boldsymbol{\Sigma}\boldsymbol{w}\right] = \max_{\boldsymbol{w}} \left[c\boldsymbol{w}^T\mathbf{1} - \frac{\lambda}{2}\boldsymbol{w}^T\boldsymbol{\Sigma}\boldsymbol{w}\right] = \min_{\boldsymbol{w}}[\boldsymbol{w}^T\boldsymbol{\Sigma}\boldsymbol{w}]$$

Maximizing the utility of constant return and negative variance, is equivalent to minimizing the portfolio variance $\boldsymbol{w}^T\boldsymbol{\Sigma}\boldsymbol{w}$, whose solution is given by (we assume weights add to 1 or $\boldsymbol{w}^T\mathbf{1} = 1$):

$$\boldsymbol{w}^* = \frac{\boldsymbol{\Sigma}^{-1}\mathbf{1}}{\mathbf{1}^T\boldsymbol{\Sigma}^{-1}\mathbf{1}}$$

Under the assumption of equal expected excess returns, the Sharpe ratio for each asset is inversely proportional to the corresponding volatility, and the optimal portfolio Sharpe ratio is given by: $c\sqrt{\mathbf{1}^T\boldsymbol{\Sigma}^{-1}\mathbf{1}}$.

As the asset beta is given by $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_N)^T = \boldsymbol{\Sigma}\boldsymbol{w}/\sigma_p^2$, it follows that beta of each asset with respect to portfolio is the same.

Most-Diversified Portfolio (MDP)

Another popular method based entirely on forecasted risk (i.e. does not require return forecasts) is the Most Diversified Portfolio (MDP). MDP maximizes a measure called the 'diversification ratio'. **Diversification ratio** is defined as the ratio of the weighted average asset volatility to overall portfolio volatility. In other words, the portfolio diversification is high when the relatively high volatility of component assets results in overall low portfolio volatility through the offsetting effect of correlations. The simplest example is a portfolio of stocks and bonds. If stocks rally, and bonds crash, both assets exhibit a large move (high asset volatility). However, stock gains may offset bond losses, leading to constant portfolio value (low portfolio volatility). The mathematical box below provides a more precise definition of the diversification ratio.

Although MDP was formally introduced by Choueifaty and Coignard (2008), the concept of maximizing diversification is hardly new. In fact, MDP is just a special case of MVO in which an investor assumes that the Sharpe ratios for all the assets are equal. In fact, if we assume the Sharpe ratios of all assets are equal, the diversification ratio is simply proportional to portfolio Sharpe ratio. In this case, maximizing the Sharpe ratio via MVO is the same as finding the most diversified portfolio.

For uncorrelated assets, MDP gives a simple prescription of weighting the assets inversely to their individual volatility (see mathematical box below). In this specific case (uncorrelated assets), MDP becomes equivalent to another risk-based method called 'Equal Marginal Volatility'.

As we will show later in the chapter, the MDP approach has often outperformed the simplest EW method. On average, MDP performed similar to GMV as both models focused on lowering the portfolio volatility. These models outperformed during risky times (e.g. had lower draw-downs), but they underperformed Risk Budgeting based models such as Risk Parity and Equal Marginal Volatility over full market cycles.

Diversification ratio is related to another theoretical concept called the "number of degrees of freedom" that MDP tries to maximize. This number represents the effective number of independent risk factors (independent assets) in the portfolio risk. [27] For instance, if all the assets are perfectly independent, the number of degrees of freedom is simply equal to the number of assets in the portfolio. In the presence of correlations, the "effective" number of independent risk factors will generally be different from the number of assets depending on the average level of correlation.

Mathematical Box (Most Diversified Portfolio)

Instead of assuming the expected excess returns for all the assets are equal (as in GMV), a portfolio manager could assume the expected Sharpe ratio of all the assets are equal (to a certain unknown constant *c*). In other words, expected return for each asset is proportional to its volatility.

We can replace the expected returns in MVO utility function with the corresponding volatilities, and hence the optimal portfolio solution is given by maximizing

$$\max_{\boldsymbol{w}}\left[\boldsymbol{w}^T\boldsymbol{\mu}-\frac{\lambda}{2}\boldsymbol{w}^T\boldsymbol{\Sigma}\boldsymbol{w}\right]=\max_{\boldsymbol{w}}\left[\boldsymbol{w}^T\boldsymbol{\sigma}-\frac{\lambda}{2}\boldsymbol{w}^T\boldsymbol{\Sigma}\boldsymbol{w}\right]$$

It follows that

$$\boldsymbol{w}=(\lambda\boldsymbol{\Sigma})^{-1}\boldsymbol{\sigma}=(\lambda\boldsymbol{\Lambda}\boldsymbol{C})^{-1}\mathbf{1}$$

The risk aversion factor λ could be determined so that the portfolio weight sums up to 1. It can be verified that the portfolio solution above is mean-variance optimal.

[27] In statistical analysis, "degree of freedom" is usually referred as the trace of the "hat matrix", or the sum of the sensitivities of the fitted values with respect to the observed response values. Some other works use the concept of "entropy" in information theory to define degrees of freedom, usually calculated from variance/volatility contributions of the principal component factors.

Another interpretation is that the MDP portfolio also maximizes the Diversification Ratio (DR). DR is simply the portfolio's Sharpe ratio when the expected returns for all assets are equal to their volatilities:

$$\mathrm{DR}(\boldsymbol{w}) = \frac{\sum_{i=1}^{N}(w_i\sigma_i)}{\sqrt{\sum_{i,j} w_i w_j \rho_{ij}\sigma_i\sigma_j}} = \frac{\boldsymbol{w}^T\boldsymbol{\sigma}}{\sigma_p} = \Big(\rho(\boldsymbol{w})\big(1-\mathrm{CR}(\boldsymbol{w})\big)+\mathrm{CR}(\boldsymbol{w})\Big)^{-1/2}$$

DR can also be expressed as a function of $(\boldsymbol{w})$, the volatility weighted average correlation of all the assets, and $\mathrm{CR}(\boldsymbol{w})$, the volatility weighted concentration ratio (CR) of the portfolio as shown in the final expression above, where:

$$\rho(\boldsymbol{w}) = \frac{\sum_{i,j} w_i\sigma_i w_j\sigma_j\rho_{ij}}{\sum_{i,j} w_i\sigma_i w_j\sigma_j}$$

$$\mathrm{CR}(\boldsymbol{w}) = \frac{\sum_{i=1}^{N}(w_i\sigma_i)^2}{(\sum_{i=1}^{N} w_i\sigma_i)^{\mathbf{2}}}$$

If the weighted average correlation $\rho(\boldsymbol{w}) = 0$, then the maximum diversification weights are obtained via minimizing $\mathrm{CR}(\boldsymbol{w})$ from which we obtain $\boldsymbol{w}^* \propto 1/\boldsymbol{\sigma}$, suggesting portfolio weights are inversely proportional to the assets' individual volatilities. In this case, $\rho(\boldsymbol{w}^*) = \sum_{i,j}\rho_{ij}/N^2$, arithmetic average of the correlation matrix. As a result, under the case of zero average correlation, MDP is identical to another risk management approach called 'Equal marginal volatility' (see later in the report).

A special case of this is uncorrelated assets or zero asset correlations. With zero asset correlation in an MDP portfolio, the concentration ratio simply becomes $1/N$, where N is the number of assets, and the Diversification Ratio grows with number of assets as $\sqrt{N}$. This can be seen from:

$$\mathrm{CR}(\rho(\boldsymbol{w})=0,\mathrm{MDP}) = \frac{\sum_{i=1}^{N}(w_i\sigma_i)^2}{(\sum_{i=1}^{N} w_i\sigma_i)^{\mathbf{2}}} = \frac{\sum_{i=1}^{N}(1)^2}{(\sum_{i=1}^{N} 1)^{\mathbf{2}}} = \frac{N}{(N)^2} = \frac{1}{N}$$

Hence, we have $\mathrm{DR}(\rho(\boldsymbol{w})=0,\mathrm{MDP}) = \mathrm{CR}(\rho(\boldsymbol{w})=0,\mathrm{MDP})^{-1/2} = \sqrt{N}$.

So far, we have explained a generic MVO process and several special cases such as GMV, and MDP. In our discussion of MVO, we maximized an investor's utility function and showed that the resulting portfolio has the highest Sharpe ratio (Capital Asset Pricing Model tangent portfolio). One can approach portfolio optimization from a different angle – maximizing the portfolio's Sharpe ratio from the beginning i.e. without reference to investor's utility.[28]

Mathematically, an optimal condition of a portfolio choice is obtained when any "tweak" of parameters leads to a sub-optimal outcome[29] (e.g. Pareto optimality in Economics is defined as a state when no one could be made better off without making someone else worse off). Below we show that the Maximal Sharpe Ratio (MSR) is achieved when an asset's marginal contribution to return divided by marginal contribution to risk is equal to the portfolio Sharpe ratio (also called a necessary condition for "MSR efficiency"). This condition also implies that the assets' expected return equals the assets' beta to the portfolio times the portfolio's expected return, similar to what we showed for CAPM.

[28] More generally, based on the theory of portfolio choices and Kelly's criterion, an investor's long-run growth rate is maximized by Sharpe ratio. The Kelly's criterion produces optimal betting sizes for a series of risk-taking activities.
[29] Mathematically, this is called the "first-order" condition for an optimization problem.

Mathematical Box (Maximum Sharpe Ratio Portfolios)

The Maximum Sharpe Ratio portfolio satisfies the following condition (portfolio's Sharpe ratio does not change for small changes in asset weights):

$$\frac{\partial\left(\mu_p(\boldsymbol{w})/\sigma_p(\boldsymbol{w})\right)}{\partial w_i} = \frac{\partial\mu_p/\partial w_i}{\sigma_p} - \mu_p\frac{\partial\sigma_p/\partial w_i}{\sigma_p^2} = 0 \text{ for all } i.$$

This is equivalent to the following:

$$\frac{\partial\mu_p/\partial w_i}{\partial\sigma_p/\partial w_i} = \frac{\mu_p}{\sigma_p} \text{ for all } i.$$

In other words, a portfolio having the same ratio of marginal excess return to marginal risk for all the assets, which equals to the portfolio Sharpe ratio is optimal under the mean-variance framework.

Since $\partial\mu_p/\partial w_i = \mu_i$ and $\partial\sigma_p/\partial w_i = \beta_i\sigma_p$, another way to express the condition for the maximal Sharpe ratio of a portfolio is that

$$\mu_i = \beta_i\mu_p \quad \text{for all portfolio assets } i.$$

For an equal-weighted portfolio, $\boldsymbol{w} = \boldsymbol{1}/N$ and $\beta_i \propto \sum_{j=1}^{N}\sigma_{ij}$. It follows that a condition for an equal-weighted portfolio to have maximum-Sharpe ratio is that expected returns μ_i are proportional to $\sum_{j=1}^{N}\sigma_{ij}$ which can be achieved if all the assets have the same expected return, correlation and marginal volatilities.

Risk Budgeting (RB)

Traditional portfolio allocation methods based on MVO use expected returns, volatilities and correlations as inputs to derive optimal portfolio weights. An alternative approach is to start with 'risk budgets' for each of the assets and then solve for portfolio weights. For instance, an investor can require that commodities add to 10% of total portfolio risk, Equities 50%, and so on. Such risk budgets should add to 100%. Risk budgets can be based on the investor's specific view on future performance of assets, or some general principles such as to assign equal risk budget to major asset classes or factor styles.

RB can be used to avoid allocating too much risk to one asset or a group of correlated assets. An often quoted argument in support for risk budgeting is the traditional 60% Equity, 40% Bond allocation; it was argued that such a portfolio has 90% of risk in Equities and only 10% in Bonds, and is therefore prone to equities tail risk. A portfolio with more balanced risk budgets would select a lower allocation to equities and higher allocation to bonds.

The contribution of each asset to portfolio risk is determined by the asset's volatility as well as its correlation to other assets in the portfolio. Adding an uncorrelated asset will increase the volatility of the portfolio only in proportion to the asset's weight and volatility, while adding a highly correlated asset will increase portfolio volatility largely through the correlations with other risky assets.

Detailed derivation of Risk Budget weights and optimal conditions are provided in the mathematical box on the next page. The most important result is that in the Risk Budget approach, asset weights are equal to the risk budget, divided by the beta of the asset with respect to the portfolio. So RB methods rely on the quality of the forecast of the asset's beta to the portfolio. In practice, optimal weights cannot be determined by independently estimating asset betas. Weights are determined in an iterative numerical procedure (e.g. increasing the weight of an asset also changes the betas/weights of all other assets). If an investor believes that realized (ex-post) return contributions of each asset will be in line with the pre-determined risk budget profile, the risk budgeted portfolio will also have the Maximum Sharpe Ratio.

As we will show at the end of this Chapter, when applied on realistic portfolios of traditional and alternative risk factors, RB models have outperformed EW allocation and MVO-based approaches (MVO, GMV and MDP) over the past 40 years. RB models such as Equal Marginal Volatility and Risk Parity struck a good balance between minimizing risk and maximizing returns, while maintaining relatively stable asset weights (unlike MVO that had high asset turnover). Part of the success of risk budgeting methods was in their reliance on more stable volatility and correlation estimates. Additionally, RB models were able to reduce draw-downs through balanced allocation of risk across portfolio components (typically higher weights in low volatility assets such as bonds).

Risk Parity (RP)

A special case of the RB approach is to assign equal risk budgets to all assets in the portfolio. This approach is also called Equal Risk Contribution, or Risk Parity. During recent years, Risk Parity (RP) methods drew a lot of interest because of their strong performance when applied to multi-asset portfolios. Given the higher marginal volatility of stocks, commodities and credit, these models had on average higher allocation to Treasuries. The strong performance of US Treasuries over the past few decades has helped these models to outperform most other asset allocation approaches. The most recent underperformance of Treasuries due to expected Fed tapering, as well as an increase in bond-equity correlations, caused RP portfolios to underperform many other approaches. More detailed analysis of recent underperformance of RP can be found in the report The Risks of Risk Parity.

As we show in the mathematical box below, the total risk contribution of an asset to a portfolio is equal to the corresponding portfolio weight times its beta with the portfolio (the "beta" component incorporates the correlation of an asset to the portfolio). If an investor assumes the return contribution of each asset is equal, the RP portfolio has the highest Sharpe ratio. When all the pair-wise correlations of assets are zero, the RP portfolio allocates weights just based on assets' volatility. This special case is called Equal Marginal Volatility approach (EMV) and is briefly discussed below.

Equal Marginal Volatility (EMV)

EMV assigns portfolio weights based on to the expected volatilities of individual assets. It underweights assets with higher volatility and overweights those with lower volatility so as to achieve an EMV contribution for all assets. However, the EMV approach ignores the contribution to portfolio volatility coming from asset correlations. In that regards, EMV is a special case of the MDP when the average level of correlation is zero, and a special case of RP when all the correlations are zero.

The weight of an asset in the EMV approach is just the inverse of expected asset volatility. Investors often use recent historical volatility to estimate EMV (and more generally RP) weights. However, one can use option-implied volatilities that often have better predictive power than recent realized volatility. Similarly, investors can use option-implied betas to calculate weights in any RB approach. For a discussion on forecasting volatilities and betas from option implied data, see our report Investment Strategies No. 88: Signals from Options Markets.

Mathematical Box (Risk Budgeting and Risk Parity)

Risk of a portfolio is given by

$$R(\boldsymbol{w}) = \sqrt{\boldsymbol{w}^T \boldsymbol{\Sigma} \boldsymbol{w}}$$

where $\boldsymbol{w}$ is a N by 1 vector whose i-th element is w_i such that $\boldsymbol{w}^T \mathbf{1} = 1$.

Given a pre-determined set of risk budgets s_i (so that $\sum_{i=1}^{N} s_i = 1$), a generic risk budgeting is an optimization process to solve $\boldsymbol{w}$ by equating the proportion of total risk contribution (TRC) of the i-th asset with s_i:

$$s_i = \frac{TRC_i}{\sigma_p} = \frac{w_i \frac{\partial R(\boldsymbol{w})}{\partial w_i}}{\sigma_p} = w_i \frac{\sum_j w_j \sigma_i \sigma_j \rho_{ij}}{\sigma_p^2} = w_i \frac{(\boldsymbol{\Sigma w})_i}{\sigma_p^2} = w_i \beta_i$$

It follows that normalized weights are

$$w_i = \frac{s_i/\beta_i}{\sum_{i=1}^{N} s_i/\beta_i}$$

The solution can be obtained by solving a Sequential Quadratic Programming (SQP) problem:

$$\min_{\boldsymbol{w}} \sum_{i=1}^{N} (w_i\beta_i - s_i)^2$$

subject to the constraints that $\boldsymbol{w}^T\mathbf{1} = 1$ and $\mathbf{0} \leq \boldsymbol{w} \leq \mathbf{1}$. In practice, weights could be solved by a gradient descent method or by numerical iterations – one adjusts the weights based on betas, then recalculates betas with new weights, etc. until all of the weights are proportional to risk budgets and inversely proportional to betas.

The Maximum Sharpe ratio condition (optimality) is that $\mu_i = \beta_i\mu_p$ for all i, which implies that

$$\frac{w_i\mu_i}{\mu_p} = s_i$$

In other words, when the ratio of ex-ante total contribution of excess returns for the i-th asset to the total portfolio excess return is equal to s_i (which is the same as ratio of ex-ante total risk contribution of the i-th asset to the total portfolio risk), the risk budgeting portfolio is optimal.

Risk Parity (RP) as a special case

When all the risk budgets s_i-s are equal to $1/N$, the risk budget portfolio becomes a "risk-parity" portfolio (equal total risk contribution from each asset). According to the derivations in the generic risk budgeting case, the portfolio weights satisfy:

$$w_i = \frac{1/\beta_i}{\sum_{i=1}^{N} 1/\beta_i}$$

which could be obtained by solving

$$\min_{\boldsymbol{w}} \sum_{i=1}^{N} (w_i\beta_i - 1/N)^2$$

subject to the constraints that $\boldsymbol{w}^T\mathbf{1} = 1$ and $\mathbf{0} \leq \boldsymbol{w} \leq \mathbf{1}$.

Similar to the generic risk budgeting case, when the ex-ante total contribution of excess returns for all the assets are equal to each other, the risk parity portfolio is optimal.

When all correlations are zero (all off-diagonal elements of correlation matrix ρ_{ij}),

$$s_i = \frac{TRC_i}{\sigma_p} = w_i\frac{\sum_j w_j\sigma_i\sigma_j\rho_{ij}}{\sigma_p^2} = \frac{{w_i}^2{\sigma_i}^2}{\sigma_p^2}$$

the Risk Parity Portfolio becomes Equal Marginal Volatility (or zero-correlation MDP) with optimal weights.

$$w_i = \frac{\sigma_p}{\sigma_i}\frac{1}{\sqrt{N}} = \frac{1/\sigma_i}{\sum_{i=1}^{N} 1/\sigma_i}$$

Black-Litterman (BL)

The BL framework was proposed by Fischer Black and Robert Litterman in 1990[30] to address the challenges of using MVO when there are no reliable return estimates. BL uses proper statistical methods to combine information implied by the market (market portfolio) and investors' views on expected returns. Combining market information and the investor's view results in return and covariance estimates that are then fed into a standard MVO process. The idea is that these estimates will lead to more robust (stable) MVO weights.

The first step of applying the BL framework involves reverse engineering the expected returns from current market portfolio weights (reverse solving MVO for market weights, to obtain 'market implied' asset returns). This step establishes the so called 'market prior' distribution of the expected returns. In addition, investor views on absolute and relative performance of the assets are specified to form an 'active portfolio'. The 'market prior' expected returns and specific investor views are combined in a Bayesian (conditional probability) framework to produce the so-called 'posterior distribution' of portfolio returns. Without investor views, BL is simply reduced to a CAPM market portfolio.

With investor views, the optimal portfolio (the posterior) under the BL framework reflects a combination of market portfolio ('market prior') and a portfolio reflecting optimal application of the investor's views. The investor also needs to set a parameter representing the relative weighting between the 'market prior' and 'investor views'. The BL approach often results in more stable asset weights (as compared to traditional MVO) because the 'posterior' expected returns are anchored to a common 'market prior' returns. Additionally, while the 'market prior' is usually specified as a normal distribution around expected CAPM returns, the BL framework allows for other choices of a 'market prior' distribution.

The BL is a flexible framework as it gives investors the ability to (1) specify the relative uncertainty of prior information e.g. uncertainty of market equilibrium versus investor views, and (2) incorporate other priors such as an EW allocation. The BL framework can be applied to more general scenarios - e.g. the prior distribution may not necessarily be based on CAPM (it could be based on a maximum diversified or risk parity portfolio). The active views do not have to be discretionary – they could be determined based on valuation model forecasts or be based on momentum indicators (i.e. using a factor approach to forecasting returns).

The mathematical box below details the statistical derivation of the BL approach. In practice, most investors will use a simple software package to implement the BL model, and will not need to worry about theoretical considerations.

Mathematical Box (Black-Litterman Approach)

The Black-Litterman approach could be summarized by a four-step process:

Step 1. Define the 'market prior'

We first start with the implied CAPM-Equilibrium asset returns $\boldsymbol{\Pi}$, which result in market weights when used as an input to MVO

$$\boldsymbol{w}_{\mathrm{mkt}} = (\lambda_{\mathrm{mkt}}\boldsymbol{\Sigma})^{-1}\boldsymbol{\Pi}$$

Backing out the returns from market weights gives $\boldsymbol{\Pi} = \lambda_{\mathrm{mkt}}\boldsymbol{\Sigma}\boldsymbol{w}_{\mathrm{mkt}}$. The original BL model assumes that $\boldsymbol{r}$ follows a normal distribution with mean $\boldsymbol{\Pi}$ and covariance matrix $\tau\boldsymbol{\Sigma}$ where the scaling parameter τ describes the relative uncertainty of the market prior with respect to manager views[31]:

$$\boldsymbol{r} \backsim N(\boldsymbol{\Pi}, \tau\boldsymbol{\Sigma})$$

[30] The article was published in the Financial Analysts Journal in September 1992. See Black and Litterman (1992).
[31] See Marco Dion et. al, "The Black-Litterman Model: A Practical Approach to a Complex and Advanced Framework", 19 April 2012 for more details on how to set this scaling factor.

Step 2. Define the view on returns.

Under the BL framework, an investor's views are also normally distributed, with certain expectation and variance. For example, $(r_1 - r_2) \backsim N(3\%, 1\%^2)$ describes a relative view that the first asset will outperform the second asset by 3% with a 1% standard deviation of uncertainty. In general, a return view could be described by the following:

$$\sum_{j=1}^{N} p_{ij}\, r_j = \boldsymbol{p}_i^T \boldsymbol{r} \backsim N(q_i, \omega_i^2)$$

where q_i defines the "base-case" scenario for the *i*-th view, $\boldsymbol{p}_i = (p_1, \dots, r_N)^T$ is an $N \times 1$ column vector of the return weights, and the ω_i determines the related view uncertainty. If there are *k* independent views, they could be simultaneously described by the following matrix form:

$$\boldsymbol{Pr} \backsim N(\boldsymbol{q}, \boldsymbol{\Omega})$$

Where $\boldsymbol{P} = (\boldsymbol{p}_1^T; \dots; \boldsymbol{p}_k^T)$ is a $k \times N$ matrix, with each row representing weights on a particular return view,

- $\boldsymbol{q} = (q_1, \dots, q_k)^T$ is a $k \times 1$ column vector of the base-case scenarios,
- $\boldsymbol{\Omega} = \operatorname{diag}(\omega_i^2)$ is a $k \times k$ diagonal matrix with diagonal elements representing uncertainties with respect to the views.

Conditional on an observation of the returns $\boldsymbol{r}$, the above formulation suggests the base-case scenario vector $\boldsymbol{q}$ describing a total number of *k* investor views follows a multi-variate normal distribution:

$$\boldsymbol{q}|\boldsymbol{r} \backsim N(\boldsymbol{Pr}, \boldsymbol{\Omega})$$

Step 3. Determine the Return Distribution Conditional on Views.

Given market prior returns $\boldsymbol{r} \backsim N(\boldsymbol{\Pi}, \tau\boldsymbol{\Sigma})$ and investor views $\boldsymbol{q}|\boldsymbol{r} \backsim N(\boldsymbol{Pr}, \boldsymbol{\Omega})$, the combined returns i.e. joint vector $(\boldsymbol{r};\ \boldsymbol{q})$ also follows a multi-variate normal distribution. To calculate the distribution of $\boldsymbol{r}|\boldsymbol{q}$ or expected return conditional on investor views, it suffices to determine the expectation and covariance matrix of $(\boldsymbol{r};\ \boldsymbol{q})$. By applying mathematical formulas (1) and (2) below, we have

$$E(\boldsymbol{q}) = E[E(\boldsymbol{q}|\boldsymbol{r})] = E[\boldsymbol{Pr}] = \boldsymbol{P\Pi}$$

$$\operatorname{Cov}(\boldsymbol{r}, \boldsymbol{q}) = \operatorname{Cov}\big(\boldsymbol{r}, E(\boldsymbol{q}|\boldsymbol{r})\big) = \operatorname{Cov}(\boldsymbol{r}, \boldsymbol{Pr}) = \tau\boldsymbol{\Sigma}\boldsymbol{P}^{\boldsymbol{T}}$$

$$\operatorname{Cov}(\boldsymbol{q}, \boldsymbol{q}) = \boldsymbol{\Omega} + \operatorname{Cov}(\boldsymbol{Pr}, \boldsymbol{Pr}) = \boldsymbol{\Omega} + \tau\boldsymbol{P\Sigma P}^{\boldsymbol{T}}$$

It follows that the return distribution conditional on views $\boldsymbol{r}|\boldsymbol{q}$ is also a multi-variate normal distribution, with expectations and covariance matrix determined by:

$$E(\boldsymbol{r}|\boldsymbol{q}) = \boldsymbol{\Pi} - \tau\boldsymbol{\Sigma}\boldsymbol{P}^{\boldsymbol{T}}(\boldsymbol{\Omega} + \tau\boldsymbol{P\Sigma P}^{\boldsymbol{T}})^{-1}(\boldsymbol{P\Pi} - \boldsymbol{q})$$

$$\operatorname{Cov}(\boldsymbol{r}, \boldsymbol{r}|\boldsymbol{q}) = \tau\boldsymbol{\Sigma} - \tau^2\boldsymbol{\Sigma}\boldsymbol{P}^{\boldsymbol{T}}(\boldsymbol{\Omega} + \tau\boldsymbol{P\Sigma P}^{\boldsymbol{T}})^{-1}\boldsymbol{P\Sigma}$$

One can also verify that $\operatorname{Cov}(\boldsymbol{r}, \boldsymbol{r}|\boldsymbol{q}) = [(\tau\boldsymbol{\Sigma})^{-1} + \boldsymbol{P}^T\boldsymbol{\Omega}^{-1}\boldsymbol{P}]^{-1}$. Computationally, if the numbers of views *k* is less than the number of underlying assets *N*, we would prefer to use the first formula given it involves inverting a $k \times k$ matrix; otherwise, the second formula is preferred.

Step 4. Calculate the BL Optimal Portfolio. This is a relatively straightforward step as we can replace the expectation and covariance matrix in the traditional MVO by the conditional returns and covariance from Steps 1-3.

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Mathematical Formula Used in Step 3

(1) *Joint and Conditional Normal Distribution*
Suppose $\boldsymbol{r}$ *is partitioned into* $\boldsymbol{r} = (\boldsymbol{r}_1; \boldsymbol{r}_2)$ *with size* $[q \times 1, (N-q) \times 1]$, *and if* $\boldsymbol{r}_1$ *and* $\boldsymbol{r}_1|\boldsymbol{r}_2$ *are both normally distributed, then they are jointed normally distributed or* $\boldsymbol{r}$ *follows a multi-variate normal distribution; Conversely, if* $\boldsymbol{r}$ *follows a multi-variate normal distribution with mean* $\boldsymbol{\mu} = (\boldsymbol{\mu}_1; \boldsymbol{\mu}_2)$ *and covariance matrix*

$$\boldsymbol{\Sigma} = \begin{bmatrix} \boldsymbol{\Sigma}_{11} & \boldsymbol{\Sigma}_{12} \\ \boldsymbol{\Sigma}_{21} & \boldsymbol{\Sigma}_{22} \end{bmatrix}$$

Then, the distribution of $\boldsymbol{r}_1$*conditional on* $\boldsymbol{r}_2 = \boldsymbol{\alpha}$ *is also a multi-variate normal with mean and covariance matrix below:*

$$E(\boldsymbol{r}_1|\boldsymbol{r}_2 = \boldsymbol{\alpha}) = \boldsymbol{\mu}_1 - \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}(\boldsymbol{\mu}_2 - \boldsymbol{\alpha})$$
$$\mathrm{Cov}(\boldsymbol{r}_1, \boldsymbol{r}_1|\boldsymbol{r}_2 = \boldsymbol{\alpha}) = \boldsymbol{\Sigma}_{11} - \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}\boldsymbol{\Sigma}_{21}$$

(2) *Unconditional Expectation and Law of Total Covariance*
For any random vectors $\boldsymbol{X}$, $\boldsymbol{Y}$ *and* $\boldsymbol{Z}$, *if we know the conditional moments of* $\boldsymbol{X}$ *and* $\boldsymbol{Y}$ *given* $\boldsymbol{Z}$, *then:*

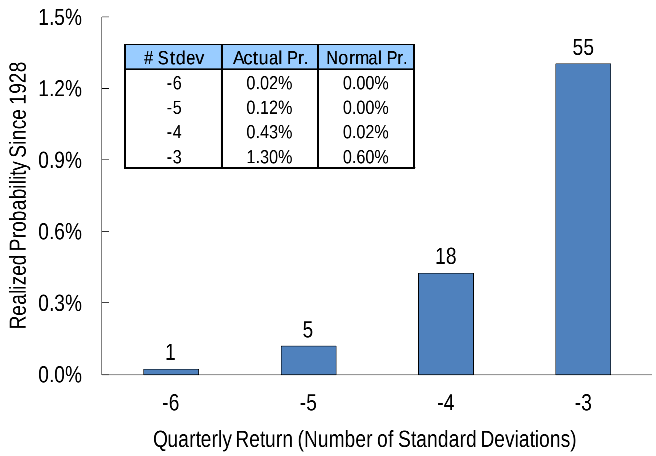
$$E(\boldsymbol{X}) = E[E(\boldsymbol{X}|\boldsymbol{Z})]$$
$$\mathrm{Cov}(\boldsymbol{X}, \boldsymbol{Y}) = E[\mathrm{Cov}(\boldsymbol{X}, \boldsymbol{Y}|\boldsymbol{Z})] + \mathrm{Cov}\big(E(\boldsymbol{X}|\boldsymbol{Z}), E(\boldsymbol{Y}|\boldsymbol{Z})\big)$$

Tail Risk Hedging

'Tail event' is usually defined as an adverse price move larger than 3 standard deviations. This definition is somewhat imprecise as it does not specify how to estimate a 'standard deviation' (e.g. recent asset volatility, long-term average, and option-implied volatility). Historically, tail events were much more frequent than what would be expected based on a normal distribution of asset returns. For instance, the probability of a 4 standard deviation drop in the S&P 500 over three months was ~20 times greater than what would be implied by assuming that quarterly returns are normally distributed (Figure 32, we defined standard deviation as the daily volatility over the trailing quarter)

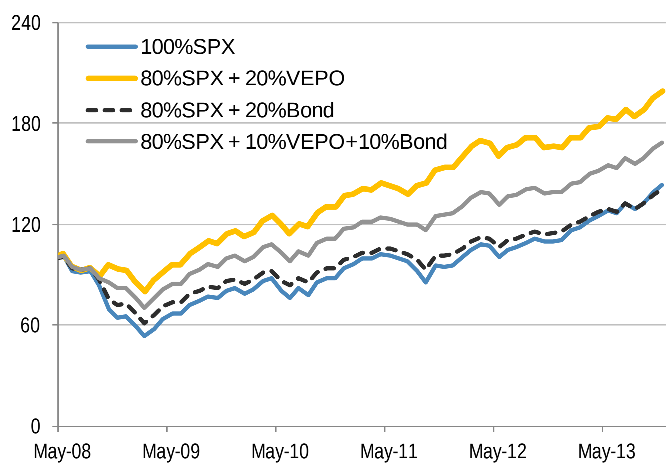
Given the damage caused by the 2008 tail event that impacted many traditional and alternative assets, many investors started adjusting their risk model to reduce tail risk. Another approach is to directly implement option based tail hedges, whose popularity has led to an increase in the cost of tail risk protection across traditional asset classes. Hedging tail risks is certainly a prudent risk management practice. However, investors need to evaluate the effectiveness and cost of tail risk management programs on an ongoing basis.

Figure 32: Frequency of Adverse Quarterly Moves in the S&P 500 (expressed as # of standard Deviations). Table inset compares realized and theoretical probability (based on Normal distribution)



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 33: Tail Risk Reduction through Tail Hedge Diversification (Sep 2006 – Dec 2012)



Source: J.P. Morgan Quantitative and Derivatives Strategy. * VEPO refers to J.P. Morgan Macro Hedge Vepo US Index (Bloomberg Ticker: JPMZVPUS Index) which gives access to volatility premium during normal market conditions and provides tail-risk protection when the VIX futures curve becomes backwardated; Bond refers to J.P. Morgan US Government Bond Index (Bloomberg Ticker: JPMTUS Index) over J.P. Morgan 1-month US$ Cash Index (JPCAUS1M Index)

While the subject of tail risk management is so broad that it would warrant a separate report, we will briefly discuss some of the basic approaches. Tail risk management can be approached from various angles:

- One can change the optimization process to directly impose a penalty for tail risks. This can be accomplished by the inclusion of higher order risk measures directly in the optimization utility function. For instance, one can include Value-at-Risk (VaR), Conditional VaR (CVaR[32]) or Kurtosis, into the utility function, assign tail risk aversion and derive new optimal portfolio weights.
- A simpler approach is to include or overweight assets that had favorable historical tail risk properties. Investors can examine the historical Kurtosis, Draw-down, and co-Kurtosis properties of individual factors. Assuming these tail-hedging properties persist, the investor can simply increase allocation to tail-risk favorable assets.

[32] Conditional VaR is also known as Expected Shortfall or Expected Tail Loss.

- Finally, investors can buy derivative-based tail risk hedges. Examples are out of the money put options on equities and commodities, out of the money swaptions on rates and credit spreads. Many dealers are pricing over the counter options that can provide tail risk protection for custom portfolios of traditional and alternative assets.

The first method extends the mean-variance framework by introducing tail risk measures and it often involves technically complex optimizations. The effectiveness and robustness of the optimization approach is questionable given the lack of reliable tail risk forecasts.

The second method tackles the problem by examining the historical behavior of different tail risks. This practical approach could be implemented more easily by introducing or overweighting instruments with offsetting tail risk properties. The type of tail-risk diversifier can be chosen based on the nature of expected tail risk (e.g. if an investor is hedging against a tail event that includes a high inflation scenario, gold may be a better hedge than treasury bonds). Below we will analyze a simple example of tail hedge diversification with a long volatility position. In the next section we will also briefly discuss option-based tail risk strategies.

Suppose a US fund manager benchmarked against US large-cap equities was trying to reduce portfolio tail risk at the beginning of May 2008 in anticipation of a market crash. By examining the historical episodes of equity draw-down, the manager would have found that the implied volatility index VIX and US Treasury bonds had negative co-Kurtosis with Equities and many other risky assets. These historical findings are also economically justifiable as equity selloffs usually result in increased demand for portfolio protection (volatility) and for US Treasury bonds due to flight to quality.

Hence, the manager can consider four alternatives: (1) a long-and-hold strategy in S&P 500; (2) a balanced portfolio that includes 20% allocation to US Treasury Bonds through J.P. Morgan Treasury Bond Index (JPMTUS Index); (3) a portfolio of 80% in S&P 500, 10% in US Treasury bonds and the remaining 10% in J.P. Morgan MacroHedge Vepo US Index that provides long volatility exposure; (4) a tail-risk hedged portfolio of 80% in the S&P 500 and the remaining 20% in the J.P. Morgan Macro hedge Vepo US Index. Figure 33 shows the historical performance of a US$100 investment in each of the four investment strategies.

From Figure 33, we see that the tail-risk hedged portfolios (3) and (4) delivered the best ex-post performance during May 2008 to Nov 2013. The balanced S&P 500/Bond portfolio outperformed the equity benchmark during 2008-2012 and gave back the out-performance in 2013 due to underperformance of Treasury bonds in anticipation of Fed tapering. Table 22 below shows that the out-performance of (3) and (4) was achieved via reducing tail risks. For example, the maximum drawdown and maximum drawdown durations for portfolio (4) were less than half of those for portfolio (1).

Table 22: Comparisons of Performance and Tail Risk Metrics (May 2008 – Nov 2013)

	100%S&P 500	80%S&P 500 + 20%Bond	80%S&P 500 + 10%VEPO+10%Bond	80%S&P 500 + 20%VEPO
Average (%)	8.1	7.2	10.2	13.2
CAGR (%)	6.6	6.3	9.9	13.2
STDev (%)	18.2	14.4	12.4	12.5
MaxDD (%)	-47.3	-38.9	-30.6	-22.2
MaxDDur (in yrs)	2.8	2.7	1.8	1.2
Sharpe Ratio	0.44	0.50	0.82	1.06
Sortino Ratio	0.62	0.70	1.31	1.81
Calmar Ratio	0.50	0.61	1.69	2.48
Pain Ratio	0.67	0.82	2.12	4.33
Reward to 95VaR	0.08	0.08	0.13	0.20
Reward to 95CVaR	0.05	0.06	0.12	0.15
Hit Rate	0.64	0.63	0.66	0.67
Gain to Pain	1.39	1.45	1.81	2.13
Skewness	-0.82	-0.88	-0.38	-0.35
Kurtosis	1.07	1.35	-0.07	-0.17

Source: J.P. Morgan Quantitative and Derivatives Strategy. * VEPO refers to J.P. Morgan Macro Hedge Vepo US Index (Bloomberg Ticker: JPMZVPUS Index) which gives access to volatility premium during normal market conditions and provides tail-risk protection when the VIX futures curve becomes backwardated; Bond refers to J.P. Morgan US Government Bond Index (Bloomberg Ticker: JPMTUS Index) over J.P. Morgan 1-month US$ Cash Index (Bloomberg Ticker: JPCAUS1M Index). ** Performance-risk analytics are based on monthly excess return data.

The risk of selecting and overweighting assets that historically provided tail risk protection is that these assets may fail to do so in the future. For instance, in an unlikely event of a US dollar crisis and contagion between equities and government bonds, US Treasuries may fail to perform as a tail risk hedge for a risky portfolio. Similarly, it is possible (but unlikely) that a portfolio experiences a decline over an extended time-period (e.g. one quarter) during which time volatility does not increase significantly (and hence volatility fails to provide tail risk protection).

Comparison of Cross-Sectional Risk Models

Before we compare the performance of different risk models on a portfolio of three traditional assets – Stocks, Government Bonds and Credit (and later on in the chapter on a realistic portfolios of alternative risk factors), we wanted to summarize and compare theoretical properties of different risk methods. Table 23 below shows the main objectives of different risk methods as well as conditions under which each of these methods leads to an optimal portfolio. Despite different objectives, each of the methods solves an MVO process under specific assumptions on asset returns and covariance.

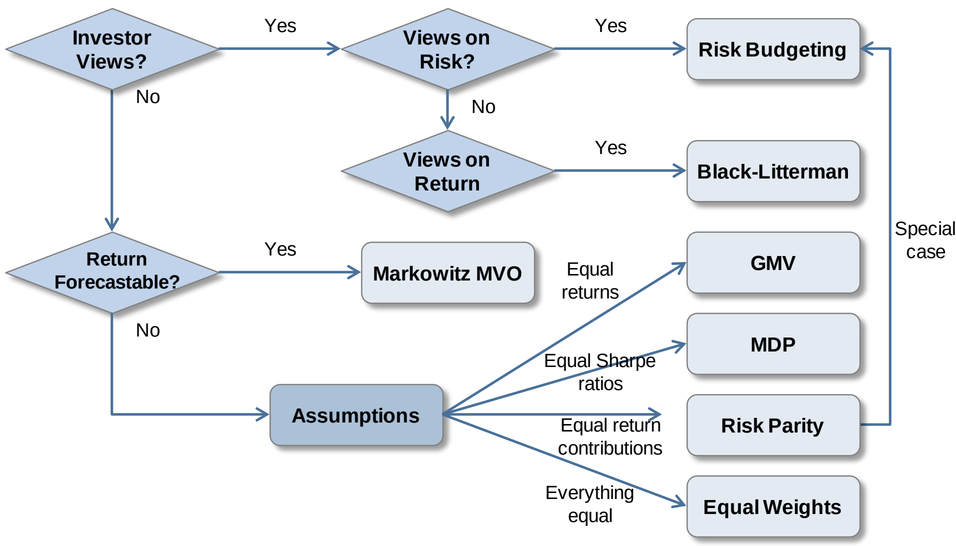
Table 23: Asset Allocation Methodologies, Their Objectives and Conditions for Optimality

Asset Allocation Method	Objective	Conditions for Portfolio to be Mean Variance Optimal
Market weight (MW)	To obtain market portfolio	Efficient market conditions as in CAPM
Equal weight (EW)	Each asset has equal weight	Expected return for the asset is proportional to the sum of the corresponding row of the covariance matrix
Fixed weight (FW)	Specific weights for each of Asset	Expected return for the asset is proportional to the weighted average of the corresponding row of the covariance matrix
Mean-Variance Optimization (MVO)	Achieve Maximum Portfolio Sharpe ratio	Ex Ante always. Ex Post if asset return and covariance forecasts were accurate
Black-Litterman (BL)	Achieve Maximum Sharpe ratio after incorporating expected return views	Posterior expected return is proportional to posterior beta
Global Minimum Variance (GMV)	To obtain minimum variance	Equal expected returns for all assets
Most-Diversified Portfolio (MDP)	To obtain maximum diversification ratio	Equal Sharpe ratios for all assets
Equal Marginal Volatility (EMV)	Each asset has equal marginal volatility	Expected return for the asset is proportional to the correlation weighted marginal volatility
Risk Parity (RP)	Equal total risk contribution for each asset	Equal total return contribution from each Asset
Generic Risk Budgeting (RB)	Specific total risk contribution for each asset	Total return contribution from each Asset is the same with the corresponding total risk contribution

Source: J.P. Morgan Quantitative and Derivatives Strategy.

A potential logic behind the selection of a risk method is shown in the diagram on the next page. Decision variables for selection of a risk model include specific views on asset risk, returns, or Sharpe ratio. While assumptions such as ‘equal returns’ or ‘equal Sharpe ratios’ may seem overly simplistic, they do relate to some realistic market regimes. For instance, in an efficient market regime one would expect assets to have similar Sharpe ratios (return proportional to risk), while in the recent ‘Volatility Anomaly’ market regime, assets may have similar returns, i.e. high volatility assets having lower Sharpe ratios than low volatility assets.

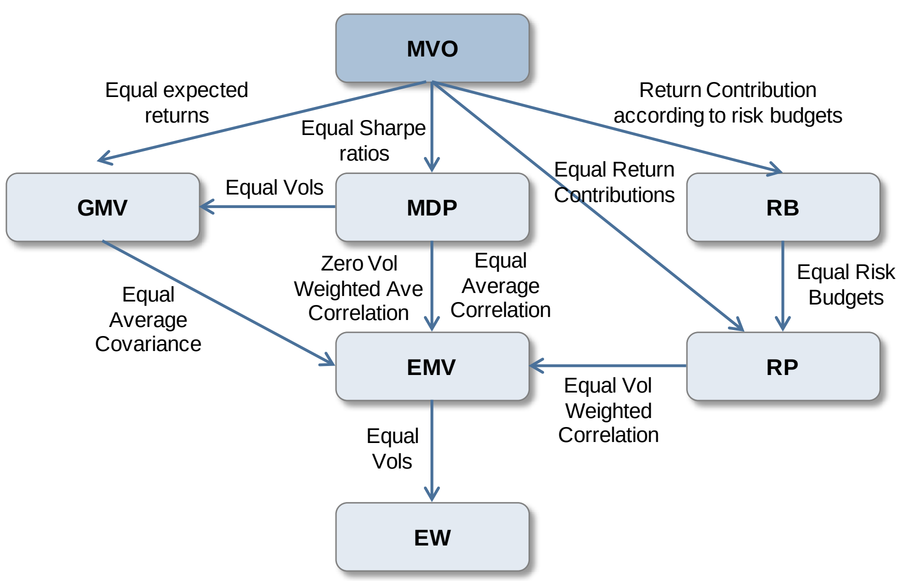
Figure 34: Cross-sectional portfolio risk allocation at an asset/factor level



Source: J.P. Morgan Quantitative and Derivatives Strategy.

All of the risk models discussed are related to each other under certain conditions. As shown in Figure 35 below, each portfolio method discussed is an implementation of MVO under certain assumptions. Working from the bottom of the diagram, EW is an EMV if we assume equal asset volatilities; EMV is an MDP if we assume zero average correlation; and finally MDP is an MVO if we assume equal marginal Sharpe ratios. GMV is an MDP if the asset volatilities are the same, and it is MVO if the expected returns are the same. The condition for the equivalence of MDP and RB is more complicated: it is achieved when the portfolio weight is proportional to the ratio of risk budget to marginal volatility. RP becomes EMV for zero correlation or equal volatility weighted correlations. RP also becomes general RB for non-equal risk budgets, and it becomes MVO for equal return contributions from each asset. We did not include BL in the diagram below as it depends on specific investor views. Detailed technical explanation of links between risk methods is given in the Appendix.

Figure 35: Theoretical Links between Various Portfolio Allocation Methods



Source: J.P. Morgan Quantitative and Derivatives Strategy.

To illustrate the properties of risk methods with a simple example, we design two-asset and three-asset portfolios. The simplest example is a two-asset portfolio of stocks and bonds. We can assume that the expected excess returns of stocks and bonds are 10% and 5%, annualized volatility 20% and 10%, respectively, and correlation coefficient of -10% between the two assets. Under these assumptions, Table 24 below shows the portfolio weights, return contribution, risk contribution as well as Sharpe/diversification ratios for each of the risk methods.[33] In the simplest two asset case, MVO, EMV, MDP and RP generated the same portfolio weights as well as the optimal return/risk contribution profiles. Note that the EW approach had the worst Sharpe ratio as it allocated excessive risk to equities. GMV also lagged as it overweighed Bonds to minimize portfolio risk.

Table 24: A stylized example of stock/bond asset allocation

	Portfolio Weights		Return Contribution		Risk Contribution		Return Contri/ Risk Contribution		Sharpe Ratio	Diversification Ratio
	Stock	Bond	Stock	Bond	Stock	Bond	Stock	Bond		
EW	50%	50%	67%	33%	83%	17%	81%	192%	0.70	1.40
MVO	33%	67%	50%	50%	50%	50%	100%	100%	0.75	1.49
EMV	33%	67%	50%	50%	50%	50%	100%	100%	0.75	1.49
GMV	22%	78%	36%	64%	22%	78%	164%	82%	0.71	1.43
MDP	33%	67%	50%	50%	50%	50%	100%	100%	0.75	1.49
RP	33%	67%	50%	50%	50%	50%	100%	100%	0.75	1.49

Source: J.P. Morgan Quantitative and Derivatives Strategy.

In the three asset example analyzed below, we will find more differentiating properties between the risk models. We will also try to demonstrate some patterns ('Symmetries') exhibited by parameters of each of the models. Selections of assets for the three-asset model are:

- Stock portfolio (**Stock**) with expected excess return of 10% and volatility of 20% (Sharpe ratio: 0.5);
- Government bond portfolio (**Bond**) with expected excess return of 5% and volatility of 10% (Sharpe ratio: 0.5);
- Corporate bond portfolio (**Credit**) with expected excess return of 10% and volatility of 15% (Sharpe ratio: 0.67);

The correlation between the stock index and government bond index is -10%; the correlation between the stock index and corporate bond index is 30%; the correlation between the government bond index and corporate bond index is -30%. Optimized portfolio weights, return/risk contribution, beta, volatility-weighted average correlation (VolCorrel), portfolio Sharpe ratio as well as diversification ratio for the risk models are summarized in Table 25 below for EW, MVO, EMV, GMV, MDP, and RP.

[33] The marginal contribution to return/risk is the sensitivity of portfolio return/risk with respect to its corresponding weight and total contribution to return/risk is the marginal contribution times the corresponding portfolio weight. If we denote MRC marginal contribution to return, MCTR marginal contribution to risk, TRC total contribution to return and, CTR total contribution to risk for an asset, attribution of portfolio return/risk (risk attribution only holds for risk metrics satisfying Euler's homogenous conditions) is

$$\text{Portfolio Return} = \text{TRC}_1 + \text{TRC}_2 + \ \dots \ + \text{TRC}_\text{N}$$

$$\text{Portfolio Risk} = \text{CTR}_1 + \text{CTR}_1 + \cdots + \text{CTR}_\text{N}$$

with $\text{TRC}_i = w_i \times \text{MRC}_i$ and $\text{CTR}_i = w_i \times \text{MCTR}_i$, where w_i stands for portfolio weight for the i-th asset. Since the marginal return contribution for an asset is just its return, the (total) percentage return contribution is equal to portfolio weight times its return and divided by portfolio return. In the Mathematical box on page 63, we showed that the MRC of an asset is proportional to its beta with respect to the portfolio.

Table 25: Portfolio weight, return/risk contribution, beta, volatility-weighted average correlation, portfolio Sharpe ratio and diversification ratio for a stock/gov bond/corp bond portfolio; shaded areas indicate portfolio symmetries specific to different risk models

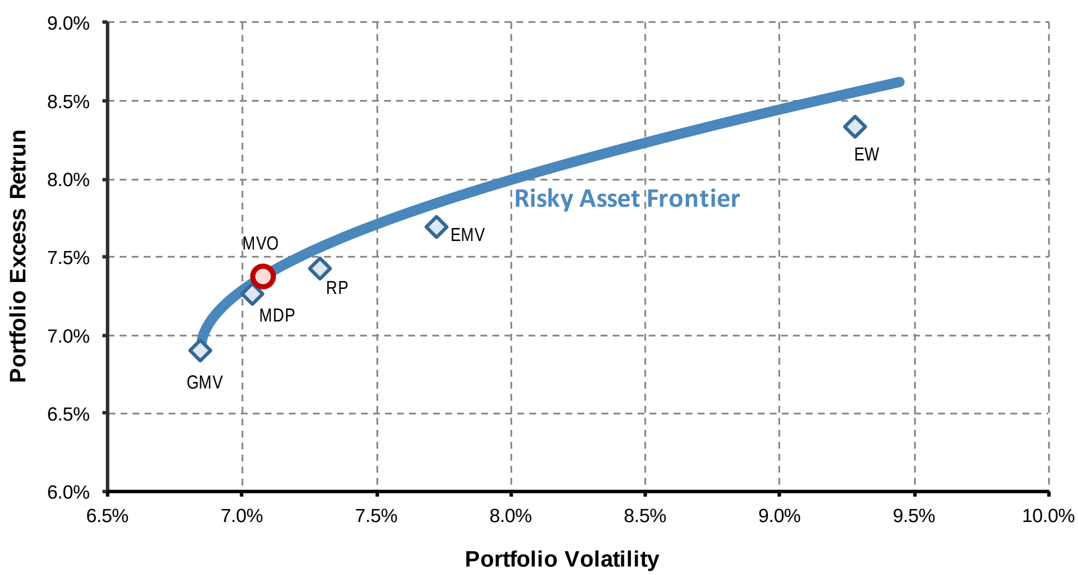
	Portfolio Weight			Return Contribution			Risk Contribution			Return Contr./Risk Contr.			Sharpe Ratio	Divers. Ratio
	Stock	Bond	Credit	Stock	Bond	Credit	Stock	Bond	Credit	Stock	Bond	Credit		
EW	33.3%	33.3%	33.3%	40%	20%	40%	61%	5%	35%	0.7	4.4	1.1	0.90	1.62
MVO	11.5%	52.5%	36.1%	16%	36%	49%	16%	36%	49%	1.0	1.0	1.0	1.04	1.83
EMV	23.1%	46.2%	30.8%	30%	30%	40%	43%	21%	36%	0.7	1.4	1.1	1.00	1.79
GMV	8.1%	62.0%	30.0%	12%	45%	43%	8.1%	62%	30%	1.4	0.7	1.4	1.01	1.80
MDP	14.9%	54.7%	30.3%	21%	38%	42%	23%	42%	35%	0.9	0.9	1.2	1.03	1.85
RP	19.1%	51.5%	29.4%	26%	35%	40%	33%	33%	33%	0.8	1.0	1.2	1.02	1.84

	Asset Beta			Weight x Volatility			Vol Weighted Average Corr			Sharpe Ratio/VolCorrel			Port. Return	Port. Volatility
	Stock	Bond	Credit	Stock	Bond	Credit	Stock	Bond	Credit	Stock	Bond	Credit		
EW	1.8	0.1	1.0	6.7%	3.3%	5.0%	52%	8%	40%	1.0	6.4	1.7	8.3%	9.3%
MVO	1.4	0.7	1.4	2.3%	5.2%	5.4%	26%	26%	35%	1.9	1.9	1.9	7.4%	7.1%
EMV	1.9	0.5	1.2	4.6%	4.6%	4.6%	40%	20%	33%	1.3	2.5	2.0	7.7%	7.7%
GMV	1.0	1.0	1.0	1.6%	6.2%	4.5%	19%	38%	25%	2.6	1.3	2.6	6.9%	6.8%
MDP	1.5	0.8	1.2	3.0%	5.5%	4.6%	29%	29%	29%	1.7	1.7	2.3	7.3%	7.0%
RP	1.7	0.6	1.1	3.8%	5.1%	4.4%	35%	26%	30%	1.4	1.9	2.2	7.4%	7.3%

Source: J.P. Morgan Quantitative and Derivatives Strategy.

To visualize the relationship between different portfolio methods, we also identify each optimized portfolio on the risky-asset efficient frontier, shown in Figure 36. The horizontal axis in the figure is portfolio volatility and the vertical axis is portfolio expected return. Each point in the risky asset efficient frontier is achieved by minimizing portfolio volatility at a certain level of expected return (or equivalently maximizing portfolio expected return at a certain level of portfolio volatility[34]).

Figure 36: Risky asset “efficient” frontier of the Stock, Bond, and Credit portfolio



Source: J.P. Morgan Quantitative and Derivatives Strategy.

[34] In Operations Research, these two optimizations are called “dual problems” that lead to the same set of solutions.

The **Equal Weighted (EW)** portfolio by definition has equal weights (1/3). Although the EW method allocates equal dollar weights to the three assets (and therefore has symmetry in portfolio weights), its return and risk contributions are predominantly from high volatility assets (stocks and corporate bonds return contribution is 80%; and risk contribution 95%). As a result, the EW portfolio is not well diversified - its diversification ratio is 1.6, the smallest among the six portfolio methods under comparison. It also had the worst Sharpe ratio, and highest return and volatility. If expected returns, volatilities and correlations are all the same for all assets, an EW portfolio would be equivalent to MVO, and all the other portfolio methods will be reduced to equal weights.

The **Equal Marginal Volatility (EMV)** portfolio is designed to have equal marginal volatilities. Although the portfolio is weighted to achieve equal marginal volatility – its risk contribution is not equal because of non-zero correlations. In fact, the stock index contributes 43% of the total portfolio risk because of its higher average correlation compared to Bonds and Credit. As marginal volatilities of different assets are usually different, an EMV portfolio is usually a better benchmark than the EW. This can also be noted from the higher Sharpe ratio of EMV compared to EW. Academic researchers commonly use an EMV portfolio as a simple and transparent method to allocate risk between factors. See, for example, Moskowitz et.al (2012) and Asness et.al (2013).

Mean-Variance Optimization (MVO) lies on the ex-ante risk asset efficient frontier as a tangent portfolio with maximum Sharpe ratio. The MVO achieved the highest Sharpe ratio (by definition as we assumed that forecasted returns and volatilities were actually realized) and diversification ratio of 1.83, close to the maximum achievable level of MDP (1.85). The risk symmetry that MVO achieves is manifested in equal ratios of return contribution to risk contribution for all the three underlying assets[35]. Later in this chapter, we will analyze performance of actual risk factor portfolios, and will find that MVO often underperforms other risk model due to discrepancy between forecasted and actually realized performance of individual assets.

The **Global Minimum Variance (GMV)** portfolio resides in the far left hand side of the efficient frontier. It achieves minimum portfolio volatility (as well as the lowest returns) by increasing the weight in less volatile (Bond) and more diversification-capable (Credit) instruments. An interesting fact about GMV is that its total risk contributions for each asset are equal to the asset portfolio weights. For example, Government bonds contribute 62% of the total portfolio volatility in GMV, the same as the Government bonds' portfolio weight. This fact holds in general because GMV assets' betas with respect to the portfolio are the same and equal to one. Since risk contribution is just the asset's portfolio weight times its beta, portfolio weights and asset risk contributions are the same.

Most Diversified Portfolio (MDP) achieved (by definition) the highest diversification ratio, and its Sharpe ratio is very close to MVO (1.03 compared to the maximum achievable level of 1.04). This is because the ex-ante Sharpe ratios of the three assets are very close, and we have previously shown that if the Sharpe ratios of the assets are the same, MDP is equivalent to MVO. When marginal volatilities are equal, the diversification ratio is proportional to the inverse of portfolio volatility. Under such conditions, MDP becomes a GMV portfolio. If the volatility weighted average correlation of the assets is zero, the solution to MDP is the same as an EMV. Moreover, the risk symmetry that MDP achieves is equal volatility-weighted average correlation for the underlying assets (or symmetry in diversification). In our three-asset example, these weighted correlations are the same at 29% for all three assets [36].

[35] Another way to express this symmetry is that MVO achieves equal ratios of asset Sharpe ratio to volatility weighted average asset correlation, i.e. symmetry in risk-adjusted performance vs. diversification abilities.

[36] Because of the dual role of marginal volatility and portfolio weight in the case of MDP, we can also show that the MDP-optimal weights for another portfolio with marginal volatility proportional to the MDP weight is equal to the scaled marginal volatility of the original assets. In our three-asset example, suppose we have another hypothetical portfolio of assets has marginal volatilities of 14.9%, 54.7% and 30.3% (corresponding to the portfolio weight of the MDP portfolio) and the same correlation structure with the original stock/gov bond/corp bond portfolio. The MDP optimal weight for this new portfolio becomes 20%/45% = 44.4%, 10%/45 = 22.2% and 15%/45% = 33.3%, which are proportional to the marginal volatility of the original underlying assets.

Risk Parity (RP) portfolio is defined by equal total risk contributions (risk contribution symmetry). This is achieved by weighting each asset inversely with its beta with the portfolio. Stocks and Credit have higher beta, and hence receive lower weights, while Bonds have lower beta, and hence receive higher weight. Even though RP does not aim to maximize returns, it achieved a high Sharpe ratio as the ratios of return contribution to risk contribution were close to 1, which is a condition for maximum Sharpe ratio.

Table 26 below lists empirical symmetries for each of the methods we studied. For example, MVO aims to achieve symmetry in return contribution versus risk contribution (Return/Risk Sensitivity Symmetry) and GMV to achieve symmetry in portfolio weights and risk contributions.

Table 26: Objectives and symmetries for various asset allocation methodologies

Asset Allocation Method	Objectives to Achieve	Risk Model "Symmetry"
Equal weight (EW)	Equal weights	Equal Portfolio Weights
Mean-Variance Optimization (MVO)	Maximum portfolio Sharpe ratio	Equal Return contribution to Risk contribution Ratios
Global Minimum Variance (GMV)	Minimum variance	Equal Asset Beta, Portfolio Weights vs. Risk Contribution
Most-Diversified Portfolio (MDP)	Maximum diversification ratio	Equal Volatility Weighted Average Correlation
Equal Marginal Volatility (EMV)	Equal Marginal Volatility	Equal Asset Weighted Volatility
Risk Parity (RP)	Equal total risk contribution	Equal Asset Risk Contribution

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Robustness of risk models to changes in leverage and inclusion of similar assets

Risk models can in some cases be 'thrown-off' by the inclusion of similar assets in the portfolio, or change in the leverage of individual assets. For instance, if an investor includes two carry strategies with nearly identical risk properties, will the risk model simply increase the total risk exposure to carry, or will it properly allocate pre-determined carry risk between the two strategies? Another question is how well the model deals with leverage. For instance, if we include an instrument with built-in leverage, will the risk model eliminate the asset entirely based on higher volatility or properly reduce the risk allocation, but keep the potentially important asset in the mix.

The requirement that the optimal portfolio weights are not affected by the introduction of leverage and "redundant" assets [37] is often stated as "portfolio invariance" requirements:

Leverage invariance: Portfolio weights of the unleveraged assets should not be affected by applying leverage on certain assets. For example, suppose a portfolio is constructed with three assets: Stocks, Bonds, and Credit. The "leverage invariance" property requires the same return/risk contribution profile on the three assets if the Credit index were leveraged up by a factor 2.

Redundancy invariance: Portfolio weights of the unleveraged assets should not be affected by introducing one or more combinations of the original assets. Again, for the portfolio with Stocks, Bond and Credit, the "redundancy invariant" property requires the same return/risk contribution profile from the original three assets if another "asset" equal to a "60/30/10%" weighted Stock/Bond/Credit index is added.

A special case of "redundancy invariance" is the "**duplication invariance**" property, which requires that the introduction of a nearly identical asset/factor doesn't change the unlevered weight for the original portfolio. For example, consider a US equity-bond investor originally invested in 60%/40% S&P 500/US Government Bonds through direct cash holdings. After

[37] This is consistent with the rationales in Choueifaty et.al (2013).

introducing a US Government Bond ETF as another "asset" into the portfolio[38] which is nearly 100% correlated with the original bond position, a "duplication invariant" portfolio program should put a total weight of 40% in the new cash + ETF position in US government bonds and the remaining 60% to the S&P 500.

Below we examine the leverage and redundancy properties of risk models on our three asset example. Although our observations are based on a specific model, the conclusions are consistent with more rigorous mathematical proofs and apply to any portfolio.

Leverage Invariance: For the Stock, Bond and Credit portfolio, we introduce 2x leverage on the Credit component. Table 27 below summarizes the portfolio weights for different allocation methods. We find that MVO, EMV, MDP and RP are leverage invariant, while EW and GMV are not.

Table 27: Portfolio weight before and after introducing 2x leverage in Credit

	Weights in "New" Assets			New Effective Weights			Original Weights			Leverage Invariant?
	Stock	Bond	2xCredit	Stock	Bond	Credit	Stock	Bond	Credit	
EW	33%	33%	33%	25%	25%	50%	33%	33%	33%	No
MVO	14%	64%	22%	11%	52%	36%	11%	52%	36%	Yes
EMV	27%	55%	18%	23%	46%	31%	23%	46%	31%	Yes
GMV	14%	75%	12%	12%	67%	21%	8%	62%	30%	No
MDP	18%	64%	18%	15%	55%	30%	15%	55%	30%	Yes
RP	22%	60%	17%	19%	51%	29%	19%	51%	29%	Yes

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Duplication invariance: Similarly, we can introduce to the Stock, Bond and Credit portfolio a "new asset" which is just a duplication of the Credit index (or a nearly identical asset). Table 28 below summarizes the portfolio weights for different allocation methods. We find that MVO, GMV and MDP are duplication invariant, while EW, EMV and RP are not.

Table 28: Portfolio weight before and after introducing a "duplicate" credit asset

	Weights in "New" Assets				New Effective Weights			Original Weights			Duplication Invariant?
	Stock	Bond	Credit	Credit'	Stock	Bond	Credit	Stock	Bond	Credit	
EW	25%	25%	25%	25%	25%	25%	50%	33%	33%	33%	No
MVO	11%	52%	18%	18%	11%	52%	36%	11%	52%	36%	Yes
EMV	18%	35%	24%	24%	18%	35%	47%	23%	46%	31%	No
GMV	8%	62%	15%	15%	8%	62%	30%	8%	62%	30%	Yes
MDP	15%	55%	15%	15%	15%	55%	30%	15%	55%	30%	Yes
RP	16%	48%	18%	18%	16%	48%	36%	19%	51%	29%	No

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Redundancy invariant: Finally, we can introduce to the Stock, Bond and Credit portfolio a "Redundant asset" which is just a weighted combination of in the Stock, Bond and Credit assets with 60%, 30%, 10% weights. Table 29 below summarizes the portfolio weights for different allocation methods. Similar to the "duplication invariant" case, we find that MVO, GMV and MDP are redundancy invariant, while EW, EMV and RP are not.

[38] Although this simplified case rarely happens in empirical portfolio management processes, the case of duplicate assets could happen when the underlying universe is large and different benchmarks for the same asset/factor are used.

Table 29: Portfolio weight before and after introducing a "redundant" asset with 60%, 30%, and 10% allocation to Stocks, Bonds, and Credit, respectively

	Weights in "New" Assets				New Effective Weights			Original Weights			Redundancy Invariant?
	Stock	Bond	Credit	60/30/10	Stock	Bond	Credit	Stock	Bond	Credit	
EW	25%	25%	25%	25%	40%	33%	28%	33%	33%	33%	No
MVO	7%	50%	35%	7%	11%	52%	36%	11%	52%	36%	Yes
EMV	17%	34%	22%	27%	33%	42%	25%	23%	46%	31%	No
GMV	0%	58%	29%	13%	8%	62%	30%	8%	62%	30%	Yes
MDP	15%	55%	30%	0%	15%	55%	30%	15%	55%	30%	Yes
RP	13%	44%	25%	18%	24%	50%	26%	19%	51%	29%	No

Source: J.P. Morgan Quantitative and Derivatives Strategy.

One can further show that show that only MVO and MDP are invariant to a combination of leverage and redundancy changes, while the others are not.

Table 30 below summarizes basic portfolio invariant properties for common allocation methods. Note that the conclusion for more general RB methods has the same invariance properties as the RP method.

Table 30: Summary of invariant properties for portfolio allocation methods

	Leverage Invariant?	Duplication Invariant?	Redundancy Invariant?	Leverage+ Redundancy Invariant?
EW	No	No	No	No
MVO	Yes	Yes	Yes	Yes
EMV	Yes	No	No	No
GMV	No	Yes	Yes	No
MDP	Yes	Yes	Yes	Yes
RP	Yes	No	No	No
RB	Yes	No	No	No

Source: J.P. Morgan Quantitative and Derivatives Strategy.

The fact that the simple EW) model is neither leverage-invariant nor redundancy-invariant makes it potentially problematic for the use on new and untested risk factors. Later in this chapter we will see that the EW model indeed had the worst overall performance when applied to a realistic example of alternative risk factors.

Moreover, despite the broad use of EMV and RP weights in the asset management industry, these two methods are not invariant to an introduction of a duplicate asset or redundant assets. Special attention should be paid when using these models to avoid large risk allocation to assets with similar factor risk (e.g. overweight on Carry strategies that may be highly correlated). One approach would be to construct a portfolio of "non-degenerate" assets[39] by using dimension reduction techniques such as principal component analysis (PCA), independent component analysis (ICA), variable selection, boosting etc (see Appendix for technical details on PCA and ICA).

We also found that the GMV portfolio is not invariant to leverage. This can create instability, as many financial products incorporate a certain degree of leverage. A good practice would be to apply GMV on a set of assets with similar level of volatilities. For assets with dramatically different volatilities, one could pre-process factors to create equal volatility factors before applying GMV (see the next section for the time-series method of volatility targeting).

[39] In Statistics, a "degenerate" set of assets is also called "multicollinearity".

Time Series Risk Allocation - Theory

In the previous section, we discussed the allocation of risk across different assets in a portfolio. These cross-sectional allocations are repeated periodically (e.g. monthly, quarterly rebalances) as the underlying asset/factor performance diverges, and volatility, correlation and performance estimates change. In addition to cross sectional risk allocation, investors can continuously manage the overall portfolio risk by allocating between the factor portfolio and the risk-free asset (e.g. cash or short term bills).

Time-series allocation to the risk-free asset is based on specific prescription for overall portfolio risk. For example, one of the popular methods is to target a constant level of volatility (e.g., 5%, 10% etc. annualized volatility). **Volatility targeting** techniques essentially reduce the risky portfolio position size during volatile periods and leverages up when portfolio volatility is lower than the target. Volatility targeting delivered strong performance during the last financial crisis and has become a popular investment style since (see Investment Strategies No 51: Volatility signals for asset allocation).

Time series risk methods can also be designed to provide upside exposure to a risky portfolio, but protect a specified level of invested assets on the downside. A popular method is **Constant Proportion Portfolio Insurance (CPPI)**. The key parameter for CPPI is the asset floor. As the value of portfolio increases above the floor, the investor increases exposure to the risky portfolio, and when the value of portfolio approaches the floor, the weight of risk-free asset is increased to 100%. In this respect, CPPI acts similar to a **stop-loss** strategy (which can be achieved by a specific selection of CPPI parameters).

Volatility targeting and CPPI-based risk methods are excellent tools to manage downside portfolio risk. One potential challenge these methods face is a risk of tail events. For instance, both volatility targeting and CPPI methods require de-levering when the volatility of assets increases and performance deteriorates. However, if this occurs extremely fast – for instance in one or two days – these strategies will not be able to rebalance quickly enough (e.g. if the strategy rebalances weekly or monthly). For this reason these risk methods may underperform theoretical expectation during extreme tail events. This ‘gap’ risk can also be compared to the failure of a stop-loss strategy, in case of a large overnight drop in asset price. Another challenge is that these strategies tend to buy asset when it is rising and sell it when it is falling i.e. they are ‘short gamma’. This can work well in a trending market, but will not be optimal in volatile, mean reverting markets.

Investors can eliminate the tail risk of volatility targeting and CPPI by implementing **option based risk management**. For instance, an investor that is long a put option on an asset or a portfolio is guaranteed a floor for the asset value. In effect, the put option guarantees a CPPI-type floor for the asset value. In option language, the investor is long ‘gamma’ or protection for large moves in the asset. The advantage of options does come at the cost – options are bought for a premium that decays in time. Option strategies can be designed to allocate between risky and risk-less assets and achieve virtually any risk/reward profile. A popular cost-less strategy for managing portfolio risk is a ‘zero cost collar’, where an investor buys a put option and sells a call option (for net zero premium) and eliminates both left and right tails of the return distribution.

Finally, not all time-series risk methods are based on simple rules to target constant volatility or protect principal. Many investors are allocating risk based on **market timing signals**. With different level of success, market timing models have been designed based on macro data such as the OECD leading indicator, volatility skew and term structure, and are often defined as multi-factor signals (e.g. see Investment Strategies No. 102: Equity Risk Timing).

Table 31 below summarizes common time series portfolio risk allocation methods, their objectives and theoretical conditions under which each approach is optimal. For each of the methods discussed, we will provide a technical description in a series of Mathematical Boxes (readers not interested in technical aspects, can follow the main text and skip these boxes).

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

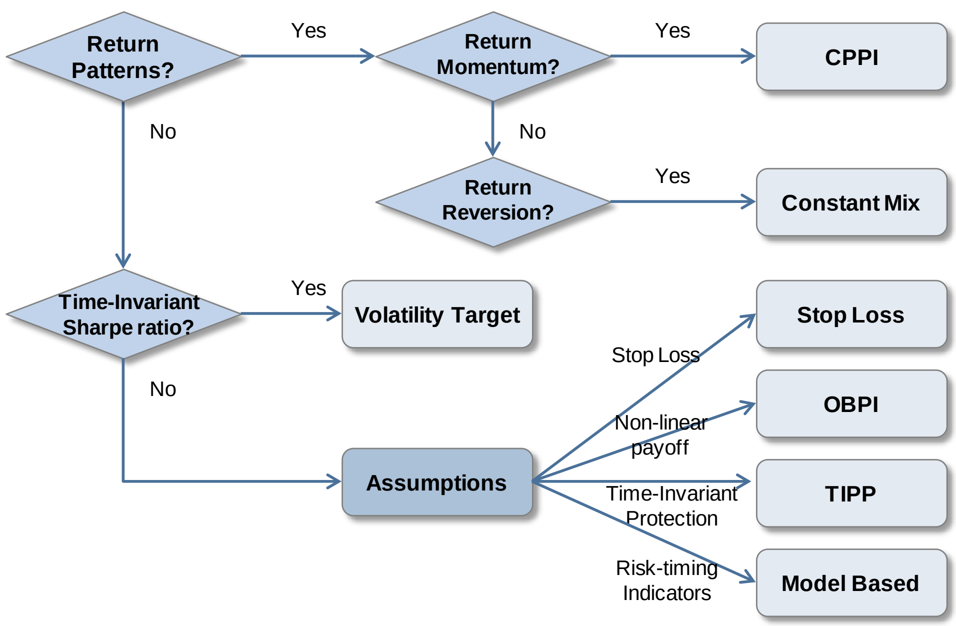
Table 31: Objectives and ex-ante Optimality Conditions for Various Time Series Portfolio Risk Allocation Methodologies

Portfolio Risk Method	Object to Achieve	Risk Method is Optimal When
Volatility Targeting	Constant portfolio volatility	Sharpe ratio is Time Invariant
Constant Proportional Portfolio Insurance (CPPI)	Investing a constant proportion of cushion into risky asset	Risk aversion parameter is proportional to the ratio of cushion to portfolio value
Constant Weight	Constant weight in the risky asset	Risk aversion parameter is constant
Option-based Insurance Strategies (OBPI)	Dynamically replicate protective put strategy	Risk aversion parameter of the risky portfolio is proportional to a time-varying factor depending on risky asset value
Generic Time-Invariant Portfolio Protection (TIPP)	Risky asset weight is a function of the current risky asset value	Risk aversion parameter of the risky portfolio is proportional to a time-varying factor depending on risky asset value

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 37 below describes one example of a decision process for selecting a time series model. The investor selects a risk method based on specific needs (e.g. stop loss, principal protection), and views on future risk and returns (e.g. assuming either momentum or mean-reversion patterns in the assets' returns):

Figure 37: Time series portfolio risk allocation on portfolio level



Source: J.P. Morgan Quantitative and Derivatives Strategy.

In the first Mathematical box of the section, we will show how to determine the dynamic allocation between the risky and risk-free asset that will outperform a simple buy and hold strategy.

Mathematical Box (Theory behind Time Series Risk Methods)

The derivation of dynamic weights that result in an optimal time-series allocation presented below is relevant for many time-series risk methods such as constant volatility, CPPI and stop loss. The derivation of optimal weights involves some basic findings in stochastic calculus which we will adopt as facts, rather than prove.

Let's start with two assets: risky asset *S* representing our factor portfolio and risk-free asset *B* (e.g. cash or treasury bills). Asset prices are described with continuous time series[40] :

$$dS_t = \mu_t S_t dt + \sigma_t S_t dW_t$$

$$dB_t = rB_t dt$$

where μ_t and σ_t are the time-varying expected return and volatility for the risky asset. The risk-free asset has a constant return r, and W_t is a random variable (Wiener process). Randomness of the expected returns for the risky asset are tied to W_t.

Following standard Stochastic Calculus, solutions for the price of risky asset *S* and risk free asset *B* at time *t* are

$$S_t = S_0 \exp\left[\int_0^t (\mu_s - \sigma_s^2/2) ds + \int_0^t \sigma_s dW_s\right] \text{ and } B_t = B_0 \exp(rt)$$

Our time-series risk management process consists of assigning weight w_t to the risky asset at time *t*. The price of a portfolio with w_t of the risky asset and (1-w_t) of the risk-free asset is then given by:

$$dP_t/P_t = w_t dS_t/S_t + (1 - w_t) dB_t/B_t$$

It follows that

$$\frac{dP_t}{P_t} = (r + (\mu_t - r)w_t)dt + \sigma_t w_t dW_t$$

And the solution for the portfolio price at time t is

$$P_t = P_0 \exp\left[\int_0^t (r + (\mu_s - r)w_s - w_s^2 \sigma_s^2/2) ds + \int_0^t \sigma_s w_s dW_s\right].$$

If our dynamically rebalanced strategy P is an optimal choice, it should outperform a strategy that simply holds asset S at the same level of risk. We can now derive the condition under which P will outperform S during time interval [0, *T*], while keeping the volatility of both constant. In other words, if we start with $P_0 = S_0$ and require that $\int_0^T \sigma_t^2 w_t^2 dt = \int_0^T \sigma_t^2 dt$, we need to maximize the non-stochastic component of P

$$R(\boldsymbol{w}) = \int_0^T (r + (\mu_s - r)w_s - w_s^2 \sigma_s^2/2) ds = \int_0^T (r + (\mu_s - r)w_s) ds - \int_0^T \sigma_t^2 dt.$$

To maximize this function while keeping the same level of risk for *P* and *S*, we include the Lagrange multiplier λ. Requiring the first order condition for the maximium (derivative with respect to the dynamic weight to be zero), we find the optimal dynamic weight w_t

$$\Lambda(\boldsymbol{w}) = \int_0^T (r + (\mu_s - r)w_s) ds - \frac{\lambda}{2}\left(\int_0^T \sigma_t^2 w_t^2 dt - \int_0^T \sigma_t^2 dt\right)$$

$$\frac{\partial \Lambda(\boldsymbol{w})}{\partial w_t} = 0 \Leftrightarrow \mu_t - r = \lambda \sigma_t^2 w_t \Leftrightarrow w_t = \frac{\mu_t - r}{\lambda \sigma_t^2}$$

[40] The dynamics are described by continuous time stochastic differential equations for the convenience of expositions. One can think of dS_t/S_t as the continuous time version of returns.

Finally, we need to express the parameter λ as a function of the asset's volatility and performance. This is done from the requirement on variance of P and S

$$\int_0^T \sigma_t^2 dt = \int_0^T \sigma_t^2 w_t^2 dt = \int_0^T \frac{(\mu_t - r)^2}{\lambda^2 \sigma_t^2} dt$$

This gives the value $\lambda = \sqrt{\frac{\int_0^T \frac{(\mu_t - r)^2}{\sigma_t^2} dt}{\int_0^T \sigma_t^2 dt}}$ and $w_t = \frac{\mu_t - r}{\lambda \sigma_t^2}$, which defines the optimal strategy.

Since above definition of λ depends on perfect foresight of μ_t and σ_t^2, we can estimate λ from e.g. historical performance of the portfolio (up to time $t < T$):

$$\lambda_t = \sqrt{\frac{\int_0^t \frac{(\mu_s - r)^2}{\sigma_s^2} ds}{\int_0^t \sigma_s^2 ds}} \text{ and } w_t = \frac{\mu_t - r}{\lambda_t \sigma_t^2}$$

Volatility Targeting

Volatility Targeting is a risk management method in which an investor aims to maintain a constant level of volatility of a portfolio. Volatility targeting is achieved by selecting the weight of the risky asset to be inversely proportional to its expected realized volatility.

In addition to providing exceptional control of portfolio risk (for which reason volatility targeting is also called 'risk control'), the method may also outperform a long only portfolio on a risk adjusted basis. The reason for outperformance is often the negative correlation between volatility and asset performance. Volatility targeting increases leverage to the risky asset in rising markets when volatility is low, and de-levers in volatile markets when large draw-downs are more likely. De-levering during high volatility periods can also significantly reduce the tail risk of a volatility targeting strategy. This resulted in the outperformance of risk controlled portfolios during the recent financial crisis. For a detailed overview of volatility targeting strategies and their performance see Investment Strategies No 51: Volatility signals for asset allocation.

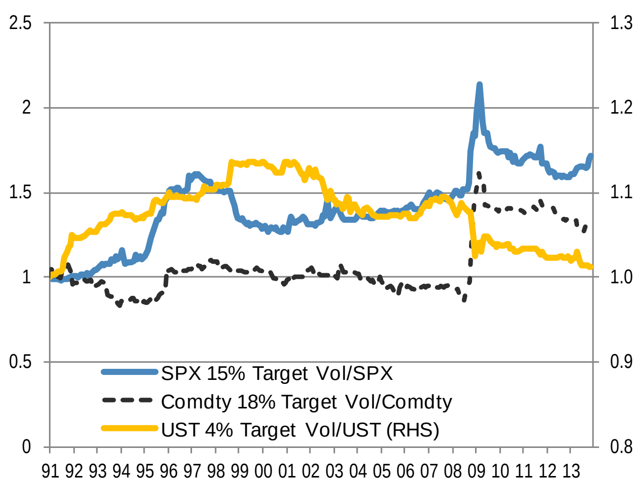
Figure 38 and Figure 39 below show the historical outperformance of volatility-targeting strategies for the S&P 500 (S&P 500T Index), US government bonds (JPMTUS Index), Global Commodities (SPGSCITR Index), EM Equities (MXEF Index), Global Credit (CSIYHYI Index) and G10 FX Carry (AIJPCF1U Index) during the period Jan 1990-Sep 2013. For simplicity, the weights of risky assets are calculated as the targeted volatility, divided by the trailing 60-day realized volatility.

We find volatility-targeting generally outperforms long-only benchmarks given the average negative correlation between the volatility level and future asset performance, as shown in Figure 40 and Figure 41. Volatility targeting worked very well when applied to the S&P 500, Commodities and G10 Carry, which historically had higher volatility and larger draw-downs (compared to bonds). For example, the equity strategy outperformed during the early '90s and during the crisis of 2008-2009. The spike in outperformance in late 2008/early 2009 shows that volatility targeting managed to avoid most of equity drawdown as the market developed downward momentum. However, a portion of the outperformance was given back in the reversion rally started in the spring of 2009. In essence, volatility targeting includes a momentum bias towards asset performance, and will underperform during periods of market reversion. Applying a volatility target on government bonds worked well in the 90s, but didn't work as well since 2000 as the negative correlation between the level of volatility and forward return disappeared, likely due to the secular decline in bond yields that favored a long only bond position.

The performance of Volatility targeting strategies heavily relies on the asset volatility forecast. Many investors use recent historical volatility – assuming that historical volatility is a good predictor of future realized volatility. Other popular approaches include the modification of simple historical volatility obtained from GARCH and Exponentially Weighted

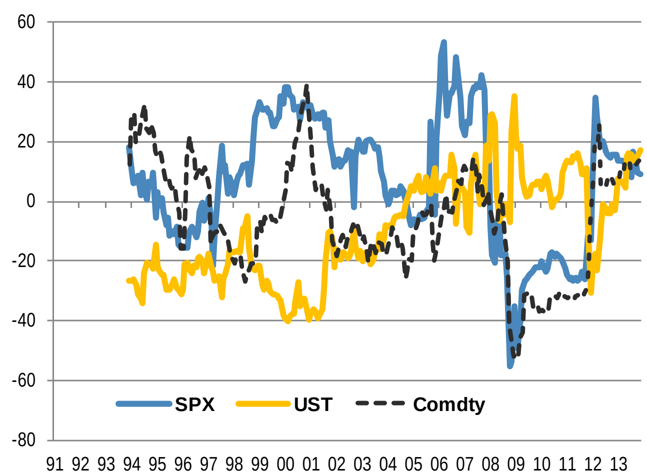
Moving Average (EWMA) models, or the use of high frequency return data. Alternative methods of forecasting volatility can include the use of multi-factor models or option implied volatility measures (see Investment Strategies No. 88: Signals from Options Markets, Investment Strategies No. 82: Equity Volatility Value – RV Model). See the Appendix for a review of popular volatility models. As with other time-series methods, volatility targeting is challenged during quick shifts in volatility regimes during which the model does not have enough time (rebalance frequency) to adjust risky asset weights. Investors need to find balance between responsiveness of the model that is achieved by more frequent rebalancing, and the transaction costs that frequent rebalancing incurs.

Figure 38: Relative performance of volatility targeting strategies for US Equity, US Treasury and Commodities*



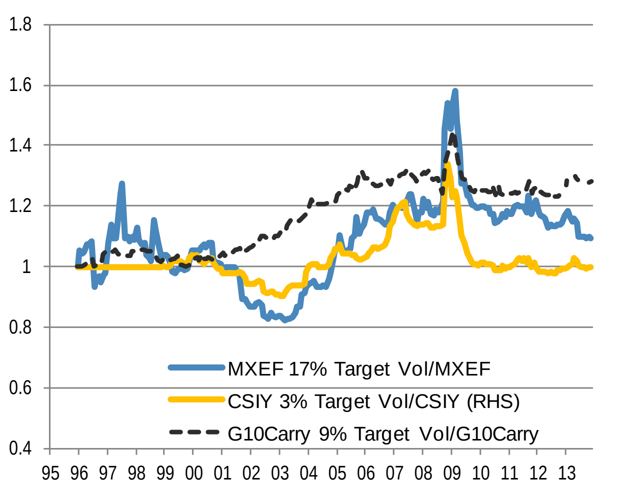
Source: J.P. Morgan Quantitative and Derivatives Strategy. * We use S&P 500 total return Index (S&P 500T Index), J.P. Morgan US Treasury Bond Index (JPMTUS Index) and S&P GSCI total return Commodity Index (SPGSCITR Index) as relevant benchmarks for volatility targeting.

Figure 39: Three-year correlation between 60-day trailing-volatility and 1-month forward performance



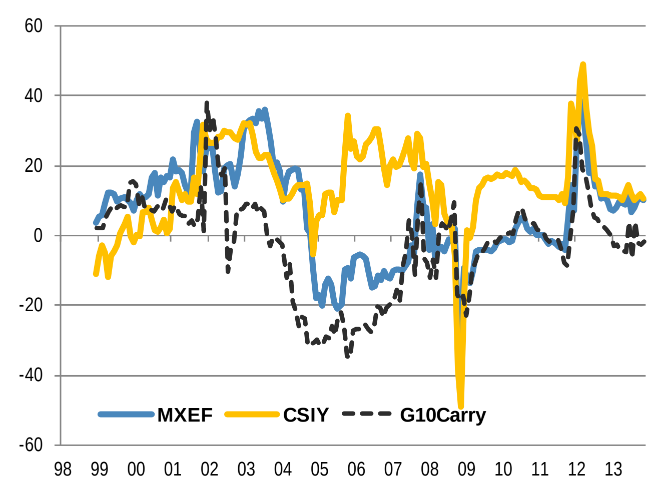
Source: J.P. Morgan Quantitative and Derivatives Strategy. * We use S&P 500 total return Index (S&P 500T Index), J.P. Morgan US Treasury Bond Index (JPMTUS Index) and S&P GSCI total return Commodity Index (SPGSCITR Index) as relevant benchmarks for volatility targeting.

Figure 40: Relative performance of volatility targeting strategies for EM Equities, Global Credit and G10 Carry Strategy*



Source: J.P. Morgan Quantitative and Derivatives Strategy. * We use MXEF Index (MSCI Emerging Market Index), J.P. Morgan Global High Yield Bond Index (CSIYHYI Index) and J.P. Morgan G10 FX Carry Index (AIJPCF1U Index) as relevant benchmarks for volatility targeting.

Figure 41: Three-year correlation between 60-day trailing-volatility and 1-month forward performance



Source: J.P. Morgan Quantitative and Derivatives Strategy. * We use MXEF Index (MSCI Emerging Market Index), J.P. Morgan Global High Yield Bond Index (CSIYHYI Index) and J.P. Morgan G10 FX Carry Index (AIJPCF1U Index) as relevant benchmarks for volatility targeting.

In the Mathematical Box below, we show the theoretical conditions under which a volatility targeting strategy is an optimal choice of risk allocation.

Mathematical Box (Volatility Targeting Strategy)

A strategy that targets constant portfolio volatility $\sigma = w_t \sigma_t$ throughout time has risky asset weight

$$w_t = \sigma / \sigma_t.$$

Using this weight in the expression for the time series and performance of a strategy with dynamically rebalanced weights of the risky and risk-free asset (previous mathematical box) gives for the performance of Volatility targeting strategy

$$\frac{dP_t}{P_t} = \left(r + \frac{\mu_t - r}{\sigma_t} \sigma \right) dt + \sigma dW_t$$

$$P_t = P_0 \exp\left[\int_0^t \left(r + \frac{\mu_s - r}{\sigma_s} \sigma - \sigma^2/2 \right) ds + \sigma W_t \right].$$

To determine when a volatility targeting strategy outperforms long only portfolio, we compare the expected return for a volatility targeting strategy and a long strategy under the condition that both strategies have the same volatility (performance is evaluated over time [0, T]).

Similar to our result for a generic strategy (see previous Mathematical box), we start by allocating the same amount to the volatility target and long only strategies $P_0 = S_0$, and require that they have the same variance $\int_0^T \sigma_t^2 w_t^2 dt = T\sigma^2 = \int_0^T \sigma_t^2 dt$. Requiring that the volatility target strategy outperforms the long only strategy gives the following condition:

$$\int_0^T \left(r + \frac{\mu_t - r}{\sigma_t} \sigma - \sigma^2/2 \right) dt \geq \int_0^T (\mu_t - \sigma_t^2/2) dt \Leftrightarrow \int_0^T \frac{\mu_t - r}{\sigma_t} dt \geq \int_0^T \frac{\mu_t - r}{\sigma} dt$$

A sufficient condition for volatility targeting to outperform long only (i.e. generic condition we derived in previous Mathematical box) is

$$w_t = \frac{\sigma}{\sigma_t} = \frac{\mu_t - r}{\lambda \sigma_t^2} \quad \text{or} \quad \frac{\mu_t - r}{\sigma_t} = \lambda \sigma$$

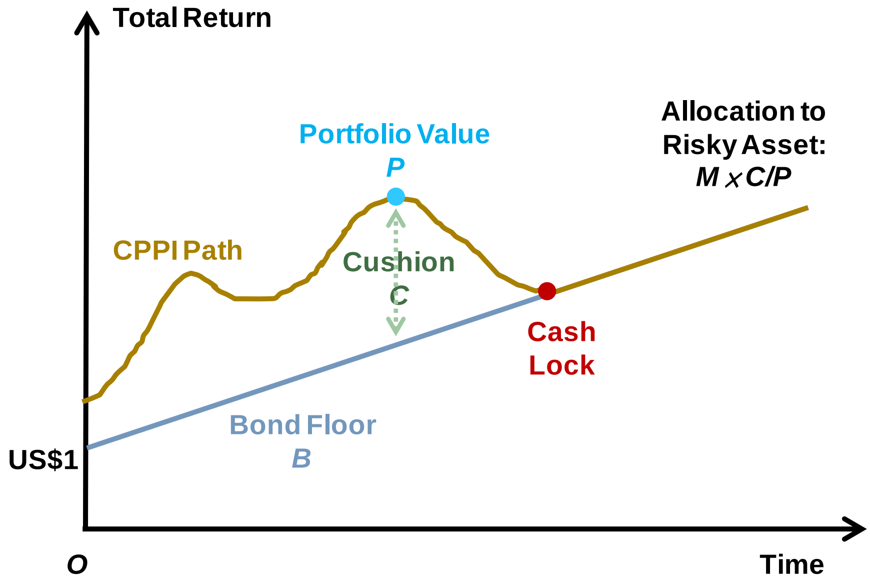
When the risky portfolio has a constant (time-invariant) Sharpe ratio, a volatility-targeting strategy improves the risk-adjusted return.

Constant Proportional Portfolio Insurance (CPPI)

CPPI is a strategy designed to prevent the portfolio value from dropping below a pre-determined floor. The strategy achieves that goal by changing the allocation to the risky asset – increasing it when the performance of the asset is positive, and decreasing exposure to the risky asset when the performance of the risky asset declines. When the level of assets reaches the pre-determined floor, the allocation is entirely to the risk-free asset and it does not change further. This is often called a ‘cash lock’ or CPPI defeasance.

The CPPI strategy is defined with the level of the Cushion ($C = P - B$) which is the difference between the portfolio value (P) and the pre-determined floor (B), and with the leverage Multiplier M (positive number greater than 1). The dollar allocation to the risky asset is given by the Multiplier times the Cushion ($M \times C$). For instance, lets examine a CPPI for which the value of the portfolio P is \$100, the portfolio floor $B = \$80$, and the multiplier $M = 4$. The initial allocation to the risky asset is $4 \times (\$100 - \$80) = \$80$, and the remaining \$20 is allocated to risk free asset. If the portfolio level reaches \$104 due to a 5% increase in risky asset, CPPI will allocate a larger amount, equal to \$96 ($\$96 = 4 \times (\$104 - \$80)$), to the risky asset. If the value of CPPI portfolio drops from \$100 to \$80 (e.g. a 25% drop in value of risky asset), the CPPI Cushion drops to zero and allocation to risky asset becomes zero (the entire portfolio is allocated to the risk free asset). Figure 42 below illustrates an example of the CPPI Cushion, Floor and Allocation to the Risky Asset on a US\$1 initial investment (we assumed the bond floor grows at a positive risk-free rate):

Figure 42: Diagram on CPPI Cushion, Floor and Allocation to Risky Asset on a US\$1 initial investment



Source: J.P. Morgan Quantitative and Derivatives Strategy.

In this respect, CPPI performs similar to a portfolio of a risk free asset (Bond) *B*, and an upside call option on the risky asset. However, there are several important differences between CPPI and a bond plus call option. The first one is the risk of a quick drop in portfolio value, during which CPPI may not be able to reduce exposure to the risky asset. This is called the 'gap risk'. Let's take our previous example of a \$100 CPPI portfolio, floor of \$80 and Multiplier of 4. If the \$80 in the risky asset declines by more than \$20=\$80/4 before CPPI manages to rebalance, the value of the CPPI strategy will gap through the floor value. More generally, the gap return of a risky asset for which the CPPI value will fall below the floor is given as 1 divided by the multiplier (in our case that is 1/4, or 25% drop in the risky asset between rebalances). Additionally, once the portfolio value reaches the floor, CPPI assets will stay invested in the risk free asset and there would be no future exposure to the risky asset even if it subsequently recovers (in that sense, the analogy between CPPI and a call option would be closer to an in-the-money call option that knocks out at its strike level).

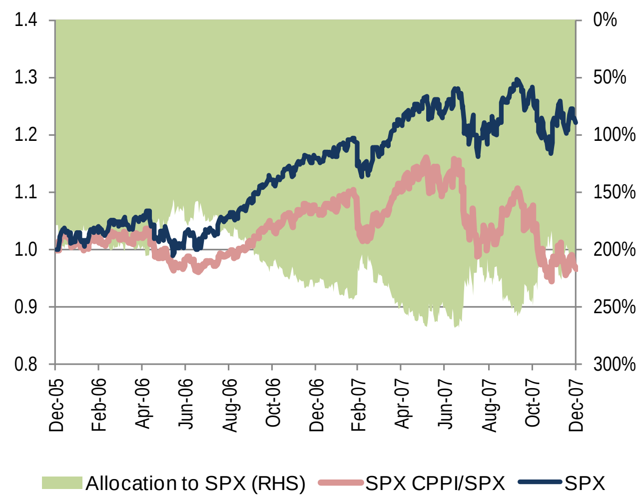
Without a cap/floor on weights, CPPI will increase risky positions when the risky asset sees positive momentum and decrease the risky position when the risky asset sees negative momentum. As a result, CPPI will behave like a momentum strategy in a trending market (similar to a volatility targeting strategy). The performance of a CPPI Strategy relative to a long-only benchmark depends on the relationship between the risky asset weight and asset performance – it outperforms when the asset is trending upward (downward) and CPPI puts more (less) than 100% weight in the asset. Moreover, a CPPI Strategy is inherently short gamma, as during every rebalance it buys the risky asset if it the asset had a positive return (from the previous rebalance) and sells the asset if it had a negative return. For this reason CPPI will generally perform poorly in a volatile mean reverting market as the strategy keeps on buying high and selling low.

For example, Figure 43-Figure 46 illustrate the performance of CPPI strategies (with daily re-balancing) on the S&P 500 and Gold for the period 2006-2007 when both assets were in structural bull markets with periodic draw-downs. We looked at cases with a constant multiplier of 5 with 70% and 100% principal protection respectively over a two-year time horizon

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

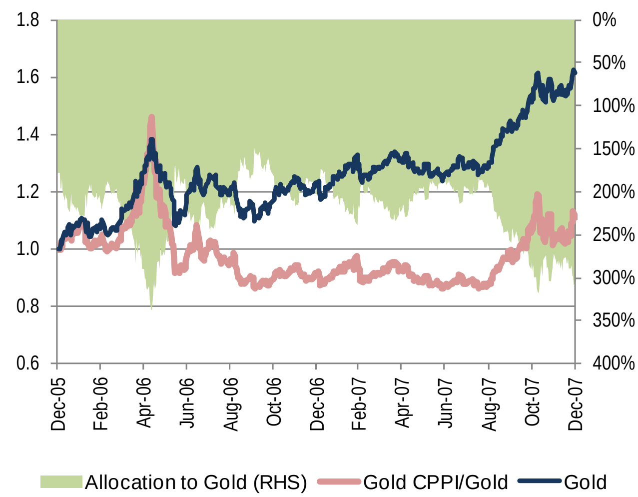
(position initiated on 30 Dec 2005 and matures on 31 Dec 2007). We use the 2-year constant maturity Treasury bond yield as the yield on the risk-free asset (4.4% at the end of 2005, and we assumed linear yield curve roll downs). With 70% principal protection (Figure 43 and Figure 44), CPPI on the S&P 500 and Gold behaved like a leveraged position on the assets and outperformed when the assets exhibited positive momentum (Jun 06-May 07 for S&P 500; Mar 06-April 06 and Aug-Dec 07 for Gold). Both Strategies underperformed during range-bound or declining markets (Jun 07-Dec 07 for S&P 500; May 06-Aug 07 for Gold). On the other hand, with 100% principal protection, both CPPI strategies were conservative in allocating to the risky assets (S&P 500 and Gold respectively) and hence largely underperformed during the 2006-07 bull-run (Figure 45 and Figure 46).

Figure 43: 2-year CPPI on S&P 500 during 2006-07 for M = 5 with 70% principal protection



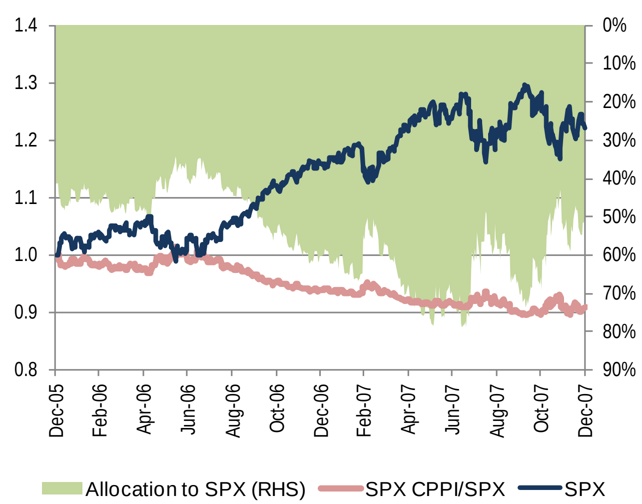
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 44: 2-year CPPI on Gold during 2006-07 for M = 5 with 70% principal protection



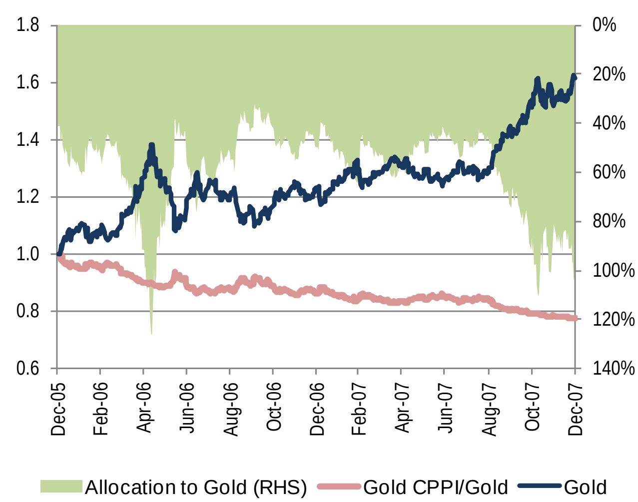
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 45: 2-year CPPI on S&P 500 during 2006-07 for M = 5 with 100% principal protection



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 46: 2-year CPPI on Gold during 2006-07 for M = 5 with 100% principal protection



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Despite drawbacks ('gap risk', defeasance risk), an advantage of CPPI is that it can provide reasonably good downside protection at a low cost - the only costs of CPPI are related to rebalancing transactions and borrow costs when the model prescribes leverage. While option strategies do have better tail risk properties and allow performance recovery (after hitting the floor), options also require spending an upfront premium. Option premium can be viewed as the cost of gap and defeasance risk.

Closely related to CPPI is a simple Stop-loss strategy. Stop-loss is one of the most utilized risk management techniques. The portfolio is fully invested, and instantaneously switches to 100% in the risk-free asset when the portfolio value reaches the stop-loss floor. Theoretically, a stop loss strategy can be approximated by a CPPI strategy in which the multiplier is given by P/C (for $P/C > 0$), and zero otherwise (i.e. $\mathrm{Max}(P/C, 0)$). Holding a put option provides a similar payoff to a Stop-loss strategy; however, unlike a put option, Stop-loss is prone to gap risk. The asset price may jump before stop-loss can manage to sell the asset. A put option 'guarantees' not only an exact stop loss, but also re-purchasing the asset when the price increases above the stop-loss limit. This 'long gamma' exposure of put options is paid via option premium decay.

Mathematical Box (Constant Proportional Portfolio Insurance)

Portfolio Cushion is defined as a difference between the portfolio value and the floor: $C_t = P_t - B_t$. A strategy that invests a constant proportion M ($M > 1$) of the cushion to the risky asset is called a Constant Proportional Portfolio Insurance (CPPI) strategy. In other words, a CPPI strategy allocates

$$w_t = \frac{MC_t}{P_t}$$

to the risky asset and the rest $(1 - w_t)$ to risk-free asset. Time series for the CPPI portfolio P and Cushion C are given by

$$dP_t = P_t\left[w_t \frac{dS_t}{S_t} + (1 - w_t)\frac{dB_t}{B_t}\right] = MC_t\frac{dS_t}{S_t} + (P_t - MC_t)\frac{dB_t}{B_t}$$

and

$$\frac{dC_t}{C_t} = \frac{d(P_t - B_t)}{C_t} = M\frac{dS_t}{S_t} + (1 - M)\frac{dB_t}{B_t} = \big(r + M(\mu_t - r)\big)dt + M\sigma_t dW_t$$

Following Itô's formula, we can calculate the value of Cushion

$$C_t = C_0 \exp\left[\int_0^t \left(r + M(\mu_s - r) - \frac{1}{2}M^2\sigma_s^2\right)ds + M\int_0^t \sigma_s dW_s\right]$$

Since $S_t = S_0 \exp\left[\int_0^t (\mu_s - \sigma_s^2/2)ds + \int_0^t \sigma_s dW_s\right]$, the Cushion can also be written as (by substituting $\int_0^t \sigma_s dW_s$):

$$C_t = C_0 \exp\left[\int_0^t (1 - M)\left(r + \frac{1}{2}M\sigma_s^2\right)ds\right]\left(\frac{S_t}{S_0}\right)^M$$

A condition for the CPPI strategy to generate better risk-adjusted return than a long only portfolio is expressed in terms of portfolio risky allocation

$$w_t = \frac{MC_t}{P_t} = \frac{\mu_t - r}{\lambda\sigma_t^2}$$

A CPPI strategy implicitly assumes "momentum" in portfolio performance – the higher the Cushion, the higher the allocation to the risky asset.

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Constant weight strategy

A constant weight strategy allocates a fixed weight to risk free and risky assets. If the risky asset performs well, it is sold and the allocation to the risk-free asset is increased, and if the risky asset underperforms, leverage is increased. A constant weight approach will outperform when the performance of the risky asset is mean-reverting, and the frequency of mean reversion roughly coincides with the re-balancing schedule. A strategy that invests a constant proportion of the portfolio to the risky asset: $w_t = w$ corresponds to a CPPI with zero floor $B = 0$ and the leverage factor $M = w$ (note that in contrast to CPPI, leverage w is smaller than 1). When the value of the risky asset/portfolio is rising, a CPPI strategy (with leverage greater than 1 and non-zero floor) increases portfolio risk. On the other hand, the constant mix strategy acts in a contrarian fashion by selling the risky asset to maintain its relative weight to the risk-free asset. According to our theoretical conditions for optimality of a strategy with dynamic weights (the first Mathematical box in this section), a constant weight strategy will be an optimal choice when the portfolio Sharpe ratio is proportional to the portfolio's volatility. $w_t = w = (\mu_t - r)/\lambda\sigma_t^2$. Intuitively this implies mean reversion of asset prices: following the asset price declines and increases in volatility, one would expect reversion and a higher Sharpe ratio.

Option-based Portfolio Insurance (OBPI)

Based on the large notional size of derivative markets (~$36T in options outstanding), options are likely the most popular tool used to manage portfolio risk nowadays. Exchange listed options trade on many individual assets and asset benchmarks. Additionally, investors are increasingly using over the counter options, that can provide protection for any custom portfolio including options on alternative risk factors.

The simplest option strategy is buying a put as an overlay to a risky portfolio. This is equivalent to buying a call option on a portfolio and holding the value of the portfolio in the risk free asset. A protective put strategy meets the same goal as CPPI and Stop-loss (protecting the floor), but without exposing the portfolio to gap risk or defeasance, and without the need for rebalancing. Additionally, a protective put strategy has long gamma exposure that provides positive portfolio convexity, and long vega exposure that can provide additional protection during the asset price decline. A drawback of a simple protective put strategy is that the price of options often trades at a premium. In fact, in our discussion of volatility risk factors, we have shown that systematic selling of options across markets often generates positive premium.

Given the average richness of put options, investors often employ 'cheaper' option strategies such as put-spreads, and collars. In a put-spread strategy, a portfolio floor is guaranteed only within a range of prices. This is achieved by buying a higher strike put option and selling a lower strike put option. Given the typical richness of implied volatility skew, put-spread strategies provide a good alternative to protective puts. Collaring a position involves buying a put option and selling a call option. The portfolio floor is protected with a put, but the upside is capped at the strike of the call option that is sold. An advantage of collars is that the investor is often not outright buying volatility, and hence can significantly reduce the cost of risk management.

More generally, an investor can tailor any risk-reward profile via use of options. Protection or leverage can be obtained in any range of prices and over many different time horizons. Other popular risk reduction option strategies include: put-spread collars, put calendar spreads, butterflies, put-ratios, put-ladders, covered-calls, and others.

Similar to CPPI, volatility target and constant weight methods, deciding on a particular option strategy depends on the investor's view on momentum and mean reversion in the market. Additionally, the choice of option strategy depends on the assessment of the fair value for volatility. The volatility view is often conditional on the time horizon (implied volatility term structure) and the likely price range of the asset (implied volatility skew).

Options and other derivative products are also used for portfolio tail risk hedging. Historically, buying far-out of the money put options was one of the most common tail risk hedges. Given the richness of implied volatility, and implied volatility skew, investors are often looking for alternative products to manage portfolio tail risk. Some alternatives include volatility products based on VIX futures, and VIX option strategies, which can also be effective tools to manage portfolio tail risk. As a first step in tail hedge design, the investor needs to define the tail risk scenario that is being hedged. The second step is to find the cheapest derivative product that can achieve that goal. Relative value between tail hedges may be due to market mispricing (value opportunity), but can also be due to tracking risk of the instrument relative to the hedged asset. Instead of looking for the cheapest instrument that can achieve the hedging goal, an investor can also define the premium they are willing to spend on tail hedges (e.g. 0.5% of the portfolio per annum), and then look for the products that provide the most effective tail protection within this budget.

When tail hedging a portfolio with options, an investor should also examine the correlations of their portfolio assets under different tail scenarios. For instance, in a case of moderate economic downturn, the correlation between bonds and equities is expected to be negative. An investor holding a portfolio of bonds and stocks likely needs to hedge only equity tail risk in this scenario. In the scenario of a severe crisis leading to bond-equity contagion (e.g. foreign investors abandoning USD assets), both equity and bonds are expected to suffer losses, and the investor should buy protection on both asset classes (e.g. S&P 500 out of the money puts, and out of the money Swaptions on the 10-year rate).

Generic Time-Invariant Portfolio Protection (TIPP)

For readers interested in the theory of time-series risk methods, it may be worth noting that the concept of CPPI can be extended to a broader class of time-invariant portfolio insurance strategies. Brennan and Schwartz (1988) showed that under certain assumptions all of the discussed strategies (Volatility targeting, CPPI, Constant weight, and Option Based Portfolio insurance) are special cases of a more general Time-Invariant Portfolio Protection (TIPP) approach.

Model-based Risk Timing Strategies

An investor can also employ various fundamental and statistical models to decide on the allocation between risky and risk-free assets. Similarly, timing models can be used to allocate between more risky and less risky factors (in this case, risk timing can also be also regarded as a part of cross-sectional risk management).

A simple risk timing model would, for instance, rotate between risky factors and the risk-free asset based on a collection of market sentiment indicators. Models that have many free parameters are often at risk of implicit or explicit in-sample biases ("over-fitting") and may have poor out-of-sample performance. Hence, in constructing a model-based risk allocation strategy, one should balance between considerations such as the economic rationale for the signal, historical performance, and model simplicity. For an overview of specific risk timing models in equities, see our report Investment Strategies No. 102: Equity Risk Timing.

As an illustration of a risk timing strategy, we create a simple model aimed to enhance the performance of G10 carry strategies. The model is based on the historical 1-month trailing volatility of the S&P 500. The model allocates risk to a G10 carry strategy, and rotates to US Treasury bonds during market crises. The signal for a market crisis is triggered if the trailing 1-month average realized volatility on the S&P 500 is greater than 30% or the z-score of realized volatility is greater than 2. In other words, a crisis mode is defined when either the absolute level of S&P 500 volatility is high or the volatility significantly increased. Figure 47 below shows the historical performance of the “Risk Timed G10 Carry Strategy” compared with the G10 Carry, and Table 32 summarizes related performance-risk analytics.

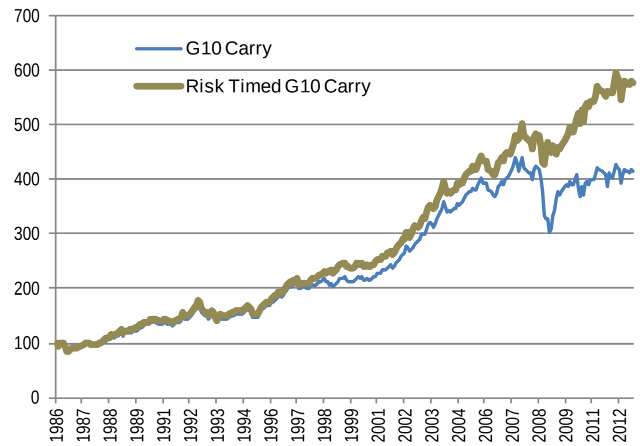
As is shown in Table 32, the risk-timed G10 Carry strategy had a higher annualized excess return, higher Sharpe ratio and smaller maximum drawdown than the G10 Carry strategy. Significant outperformance of the risk-timed strategy was achieved during crisis times (1998-1999 and 2008-2009). An investor can certainly question how robust is our selection of a 30% volatility level and z-score of 2, and if the same choice will continue to perform well in the future. Despite these concerns, we note that the z-score was used as an out of sample signal, and the portfolio was rebalanced only once a month.

Table 32: Performance-Risk Summaries

	G10 Carry	US Treasury	Risk Timed G10 Carry
Average (%)	5.8	2.7	7.0
CAGR (%)	5.6	2.6	6.9
STDev (%)	8.7	4.8	7.7
MaxDD (%)	-31.4	-9.4	-19.6
MaxDDur (in yrs)	5.5	5.0	3.3
Sharpe Ratio	0.67	0.56	0.90
Sortino Ratio	0.97	0.90	1.38
Calmar Ratio	0.61	0.91	0.86
Pain Ratio	1.25	0.96	2.15
Reward to 95VaR	0.12	0.11	0.16
Reward to 95CVaR	0.08	0.08	0.11
Hit Rate	0.64	0.57	0.65
Gain to Pain	1.67	1.52	1.96
Skewness	-0.92	-0.05	-0.78
Kurtosis	2.67	0.71	1.73

Source: J.P. Morgan Quantitative and Derivatives Strategy. * Statistics are calculated during Jan 1986 – Dec 2012.

Figure 47: Performance Comparison between G10 Carry and a Risk-Timed G10 Carry Strategy



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Another example of a volatility-based market timing signal is embedded in the J.P. Morgan Macro-hedge family of indices. These indices remove risk (remove short S&P 500 volatility exposure) when the term structure of the S&P 500 implied volatility inverts. Historically, inversion of the implied volatility term structure occurred (and lasted for several days) before all major market selloffs. This, however, does not guarantee the same relationship between term structure and market behavior in the future.

From a purely theoretical angle, we have shown (see Mathematical box) that the optimal portfolio leverage of a timing strategy corresponds to the ex-ante factor of risk aversion. If a market timing signal can consistently provide such foresight, a model-based time series risk allocation would deliver optimal risk adjusted returns.

Practical Application of Risk Factor Portfolios

After introducing the theory behind portfolio construction and risk management, we will apply these methods on an actual portfolio of cross-asset risk factors. Analyzing the historical performance of each of the methods can give further insights into their benefits and drawbacks, as well as model performance under different macro economic and market regimes.

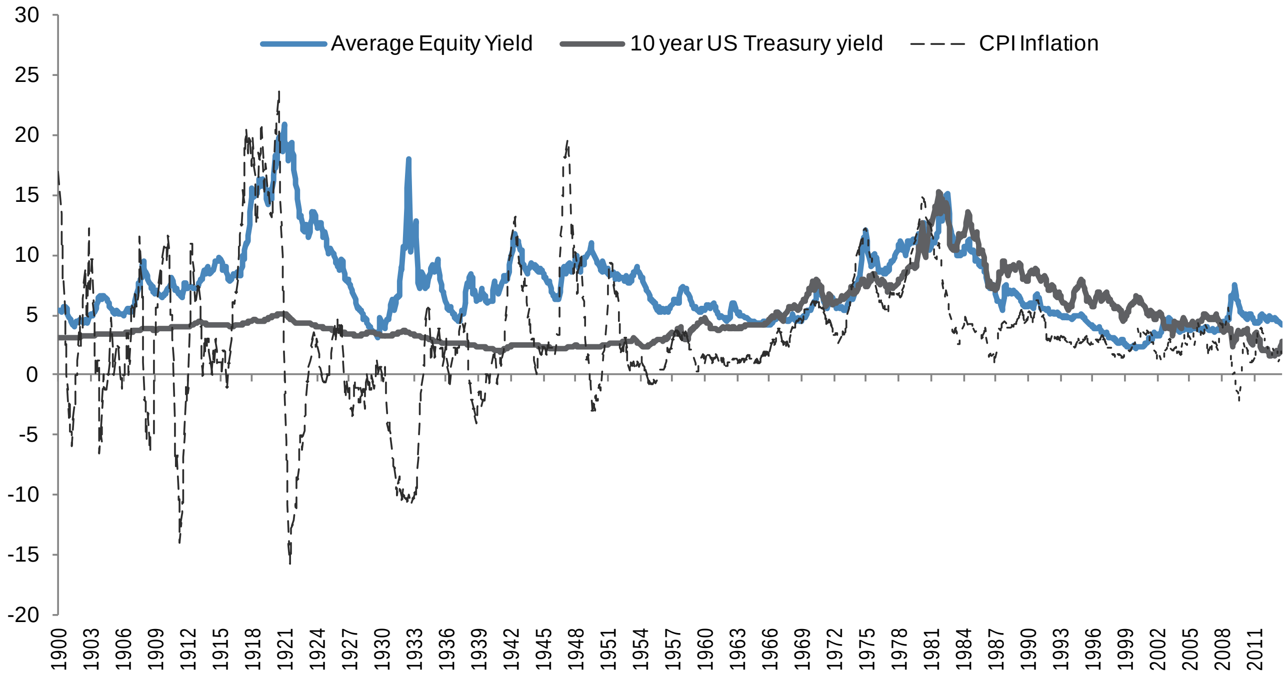
In particular, we will apply cross-sectional risk management models on the portfolio of 12 traditional and alternative risk factors introduced in the Chapter on the classification of risk factors. We selected 3 risk factors from each of the main factor styles: Traditional, Value, Momentum, and Carry. We have omitted the volatility factors, as our backtest goes over 40 years back (from Jan 1972), and derivative based risk factors generally have much shorter time history available (e.g. the first listed option on equity indices started trading in 1983). Within each of the factor styles, we have selected examples from different traditional asset classes:

- **Traditional Beta – Equities:** S&P 500 total return index minus 1-month cash yield;
- **Traditional Beta - Rates and Credit:** Total return of a hypothetical monthly rolling position in 5-year, 10-year and 30-year constant maturity Treasury bonds minus 1-month cash yield;
- **Traditional Beta - Commodities:** Excess return of the S&P GSCI Commodities Index;
- **Carry - Rates and Credit:** Excess return of a monthly rolling a long position in the top-three 10-year government bonds with the steepest yield curves and a short position in the bottom-three 10-year government bonds;
- **Carry - Currencies:** Excess return of a monthly rolling a long position in the top-three yielding currencies and a short position in the bottom-three yielding currencies;
- **Carry - Commodities:** Excess return of a monthly rolling long position in the top-three backwardated commodity futures and a short position in the bottom-three backwardated (or most contangoed) commodity futures;
- **Momentum - Equities:** Excess return of a monthly rolling long position in the top-three equity indices with the highest past 12 month returns and a short position in the bottom-three equities indices with lowest past 12 month returns;
- **Momentum - Rates and Credit:** Excess return of a monthly rolling long position in the top-three 10-year government bonds with the highest past 12 month returns and a short position in the bottom-three 10-year government bonds with lowest past 12 month returns;
- **Momentum - Commodities:** Excess return of a monthly rolling long position in the three commodity futures with the highest past 12 month returns and a short position in the three commodity futures with lowest past 12 month returns;
- **Value - Equities:** Fama-French (1993) HML value factor;
- **Value - Rates and Credit:** Excess return of a monthly rolling long position in the top-three 10-year government bonds with the largest increase in 10-year yields during the past three years and a short position in the bottom-three 10-year government bonds with smallest increase (or largest decrease) in 10-year yields during the past three years;
- **Value – Commodities:** Excess return of a monthly rolling long position in the top-three commodity futures with the lowest valuation and a short position in the bottom-three commodity futures with the highest valuation, where valuation is defined as the ratio of average price over the past five years to the current price.

Before we analyze the performance of allocation methods under different macro regimes, we should first note that the past two decades exhibited specific secular trends in inflation, stock and bond performance that could have influenced the performance of different risk models. Figure 48 below shows inflation levels, and average Equity and Government bond yields over the past 100 years. For instance, Treasury bonds had strong performance in recent decades, because low and stable inflation as well as accommodative central bank policies helped a secular decline in bond yields. Specifically, inflation was relatively low and stable over the past 20 years (compared to the most of the 20th century). Hence, any investment strategy with strategic tilts towards low risk assets would have overweight bonds, likely improving risk adjusted returns (such as Risk Parity, Equal Marginal Volatility).

Equity yields declined during 1982-2000, and then rose sharply into the financial crisis of 2008. Hence, any investment strategy that would have overweighed equities, but managed to avoid the 2008 drawdown, would have shown better risk adjusted returns.

Figure 48: Long-term US Equity earnings yield, Treasury bond yields and Inflation (%)



Source: Robert Shiller, J.P. Morgan Quantitative and Derivatives Strategy. * Average Equity yield is calculated as the inverse of CAPE10 proposed by Robert Shiller.

We will start with providing simple performance and correlation properties of individual factors in our 12-asset portfolio. (For a more detailed analysis of factors in different market regimes, see the Section on Classification of Risk Factors). Table 33 highlights basic risk-performance analytics for our factor selection.

Table 33: Performance-Risk metrics for popular portfolio allocation methods during 1972-2012

	Trad'l-Equity	Trad'l - Bond	Trad'l - Comdty	Carry-Bond	Carry-Curncy	Carry-Comdty	Mom'm-Equity	Mom'm-Bond	Mom'm-Comdty	Value-Equity	Value-Bond	Value-Comdty
Average (%)	3.9	9.2	5.3	2.5	5.7	4.4	6.2	3.7	8.2	4.9	4.1	2.7
CAGR (%)	2.7	9.3	3.3	2.3	5.5	.6	4.7	3.5	7.2	4.4	4.0	1.5
STDev (%)	15.6	7.3	20.3	7.4	7.9	12.7	18.1	6.5	15.4	10.5	7.4	15.1
MaxDD (%)	-59.0	-17.0	-67.8	-31.8	-31.4	-36.3	-37.5	-23.5	-33.3	-44.6	-21.5	-59.0
MaxDDur (in yrs)	14.6	2.0	13.5	27.0	5.5	16.8	14.4	10.4	5.7	5.8	23.2	23.4
Sharpe Ratio	0.25	1.26	0.26	0.34	0.72	0.34	0.34	0.56	0.53	0.46	0.56	0.18
Sortino Ratio	0.35	2.58	0.39	0.60	1.08	0.53	0.54	0.88	0.86	0.72	1.13	0.25
Calmar Ratio	0.24	1.33	0.24	0.38	0.60	0.19	0.35	0.80	0.34	0.27	0.71	0.12
Skewness	-0.46	0.64	0.05	2.27	-0.75	0.04	0.47	-0.04	0.01	-0.01	2.59	-0.26
Kurtosis	1.87	3.87	2.37	28.36	2.80	0.83	6.02	2.80	1.36	2.37	21.12	1.09

Source: J.P. Morgan Quantitative and Derivatives Strategy.

The factor correlation matrix is shown in Table 34 below, with the statistics below diagonal showing values for the full sample period and above the diagonal for market crises. The average correlation of a factor with all other factors during the full sample period (Jan 1972-Dec 2012), five episodes of major crises[41], as well as the latest global financial crisis (Aug 2007-Mar 2009) is shown at the bottom of the table.

Table 34: Correlation matrix during 1972-2012 using monthly excess returns

	Trad'l-Equity	Trad'l - Bond	Trad'l-Comdty	Carry-Bond	Carry-Curncy	Carry-Comdty	Mom'm-Equity	Mom'm-Bond	Mom'm-Comdty	Value-Equity	Value-Bond	Value-Comdty
Trad'l-Equity		33	18	16	54	9	14	26	-22	-8	-14	7
Trad'l -Bond	13		28	-6	-4	-5	7	48	-1	-7	-15	-1
Trad'l -Comdty	10	-18	20	10	41	26	1	-11	35	18	-8	-24
Carry-Bond	-6	-15	-7		28	-3	-6	-20	-7	-5	13	-2
Carry-Curncy	22	-14	8	11		13	20	-1	1	14	-4	0
Carry- Comdty	-3	-5	2	-1	2		13	-13	18	14	-11	-50
Mom'm- Equity	-12	3	1	-2	5	12		24	9	-6	-33	14
Mom'm-Bond	8	12	-9	16	-1	-2	0		15	10	-26	15
Mom'm- Comdty	-2	6	3	-1	2	27	9	7		-6	-15	-46
Value- Equity	-29	3	-3	6	2	-2	-7	3	0		4	-9
Value-Bond	-9	-7	3	19	1	-10	-10	-23	-5	7		5
Value- Comdty	6	-9	-7	4	5	-34	-8	2	-58	-5	2	
Full Sample Avg	0	-3	3	3	5	0	0	2	0	-2	-3	-11
Crisis Average	12	2	7	2	15	1	5	6	-2	2	-9	-8
Avg During GFC	20	-7	17	9	22	7	0	-7	-3	4	-17	-15

Source: J.P. Morgan Quantitative and Derivatives Strategy. * Lower triangular statistics are the all-sample pair-wise correlation and upper triangular are the correlation statistics during crisis periods.

For instance, Currency Carry and Commodity Beta had the highest average correlation with other factors, and the average correlation increased during crisis periods. On the other hand, the Treasury bond beta and Value strategies across asset classes had the lowest average correlation both in the full sample and during market crises.

For these twelve risk factor benchmarks (three benchmarks in each of the four systematic factor styles among Traditional, Carry, Momentum, and Value), we tested the following risk methodologies:

1. Equal weighted portfolio (EW),
2. Equal marginal volatility portfolio (EMV),
3. Mean-Variance Optimized portfolio with expected returns estimated from trailing average returns (MVO),
4. Global Minimum Variance portfolio (GMV),
5. Most Diversified Portfolio (MDP),
6. Risk Parity Portfolio (RP),
7. Risk Budgeting portfolio with active risk view based on momentum[42] (RB).
8. Black-Litterman portfolio with ex-ante equilibrium set at the risk parity portfolio and an active view based on momentum[43] (BL);

---

[41] Crisis periods we include for the correlation calculation are Oct 1973—Mar 1974 (OPEC Oil Crisis), Aug 1982 – Oct 1983 (Latin America debt crisis), July 1990 - Mar 1991 (US saving & loan crisis), Jul 1997 - Sep 1998 (Asian Financial Crisis, Russian Default and LTCM), and Aug 2007 - Mar 2009 (Global Financial Crisis or GFC).
[42] We dynamically allocate total risk contribution proportional to the trailing 12 month performance, floored at 5% and capped at 20%.
[43] For illustration purpose, we simply assume an investor view that the expected return difference between the best vs worst performance to be inline with the past 12 months, capped at 10% per month.

To calculate model weights, we used simple methods to estimate the marginal volatility, correlation matrix and expected returns. Specifically, we used trailing three-year monthly data to estimate asset volatilities and correlations and the average trailing 12-month return to estimate the expected future return. These simplistic volatility and correlation assumptions could be easily enhanced with e.g. a GARCH-based forecast. Interested readers could also refer to the Appendix for a brief review of forecasting models for expected return, volatility and correlation matrix.

Evaluating Model Performance

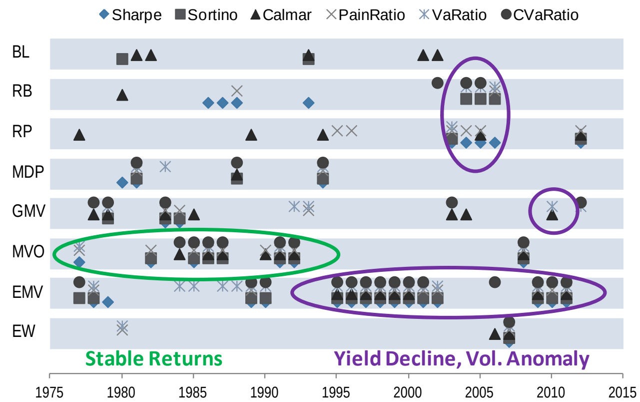
Figure 49 shows the best and Figure 50 the worst performing allocation methods according to different reward/risk metrics. In addition, we show the same performance rankings for the risk methods after applying a volatility targeting time series approach (8% constant volatility target).

Our first finding is that no single allocation method was best under all market regimes. On average, simplistic allocation methods such as equal weight underperformed, and risk based methods such as Equal Marginal Volatility outperformed. However, the performance ranking of methods was largely dependent on market regimes such as the trending or reversal of assets (e.g. momentum favoring models such as risk parity), persistence or reversion of volatility (e.g. stable volatility and returns favoring MVO), and volatility anomaly (e.g. outperformance of low volatility assets favoring EMV).

Some more specific observations about risk model performance are listed below:

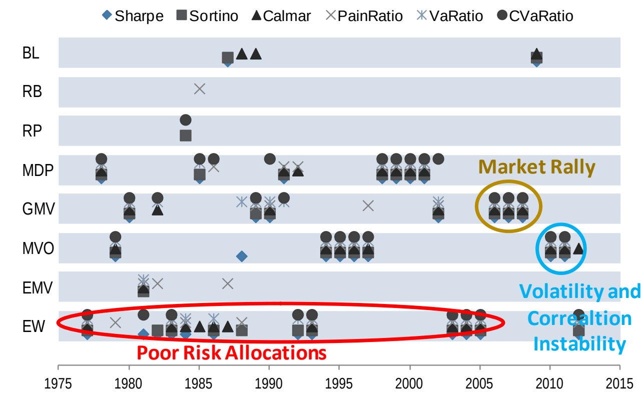
- MVO was consistently one of the top performing strategies in the 1980s and early 1990s. However, its performance was eroded afterwards, likely due to the inability to forecast returns based on historic performance (e.g. tech bubble burst). Specifically, MVO was the worst performing model in the last several years, likely due to the significant instability of correlations in 2009-2011, and asset performance divergence in 2011-2013.
- Equal marginal volatility (EMW) was one of the top performing models since the mid-1990s. This is likely due to the negative correlation between volatility and performance. This relationship between volatility and performance is contemporaneous, but often has forward looking implications that low volatility assets continue to outperform high volatility assets (‘Volatility anomaly’). Additionally, EMW overweighed bond-based risk factors, which performed well due to the secular decline in bond yields.
- Similar to EMW, Risk parity (RP) as well as our versions of Risk Budgeting (RB) and Black-Litterman (BL) had strong performance in the 2000s. These models also overweighted low risk assets, and took advantage of persistent momentum in several traditional and alternative risk factors.
- The performances of GMV and MDP were not strong, as these models relied on the persistence of volatility and correlations to minimize the risk (or maximize diversification). These approaches often underperformed by e.g. missing out on equity-like allocations during the market rally of 2000s. However, in select years (e.g. 2010, 2012) these models performed well.
- The Equal Weight (EW) model was one of the worst performing models. The reason for its underperformance was an overly simplistic allocation to risk that ignored asset volatility and correlations.

Figure 49: Best performing portfolio allocation method based on trailing 3-year reward/risk ratios – No portfolio volatility targeting



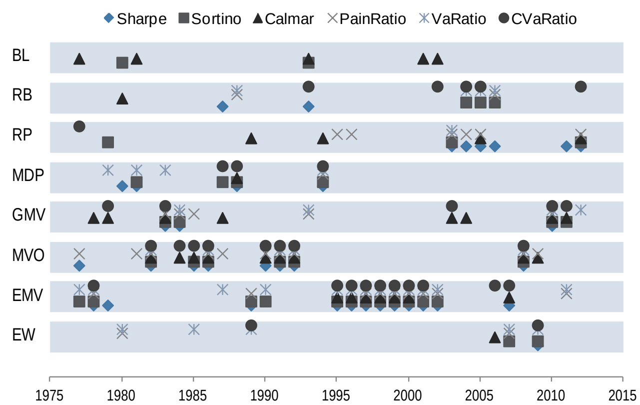
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 50: Worst performing portfolio allocation method based on trailing 3-year reward/risk ratios – No portfolio volatility targeting



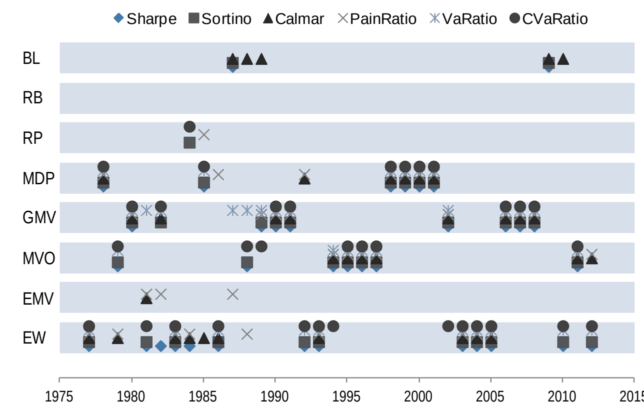
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 51: Best performing portfolio allocation method based on trailing 3-year reward/risk ratios – With an 8% annual volatility target



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 52: Worst performing portfolio allocation method based on trailing 3-year reward/risk ratios – With an 8% annual volatility target



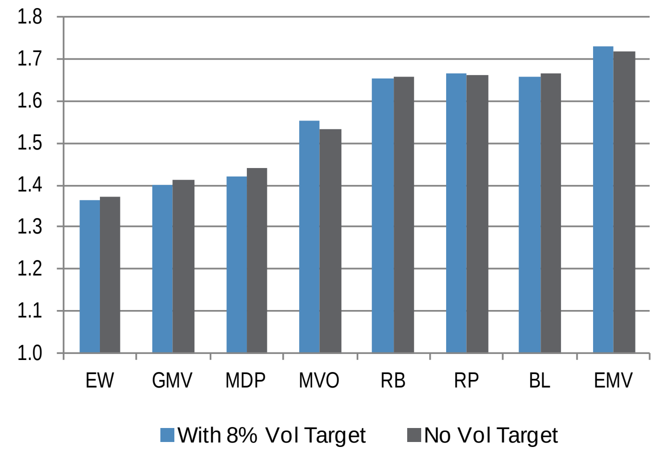
Source: J.P. Morgan Quantitative and Derivatives Strategy.

We observed a very similar performance ranking of strategies after applying volatility targeting. For example, portfolio Sharpe ratios for each method stand very similar whether we applied constant portfolio volatility targeting or not (Figure 53). Other performance measures such as Sortino Ratio, Reward to VaR ratios were also quite similar. A possible explanation for this is that the across-asset risk factors used in our portfolio construction example displayed relatively stable covariance structure during the past 40 years, and hence the portfolios themselves already achieved roughly constant volatility levels.

Interestingly, we did find some minor differences in some measures related to tail risks. For example, Figure 54 below shows that applying volatility targeting could reduce the maximum draw-down durations for MVO, while increasing the maximum draw-down durations for EW and EMV. This could be due the fact that a momentum on momentum strategy[44] (volatility-targeting on MVO) could further reduce the negative impact of draw-down for this factor portfolio, while momentum on mean-reversion (volatility-targeting on EW) worked less well (momentum on mean-reversion is ill-defined). The reason for the increase in the draw-down duration for volatility-targeted EMV may be because of that fact that an increase in factor correlations didn't lead to poor average factor performance as it did for a traditional asset portfolio (volatility targeting on EMV will weight EMV less when there was an increase in average factor correlation).

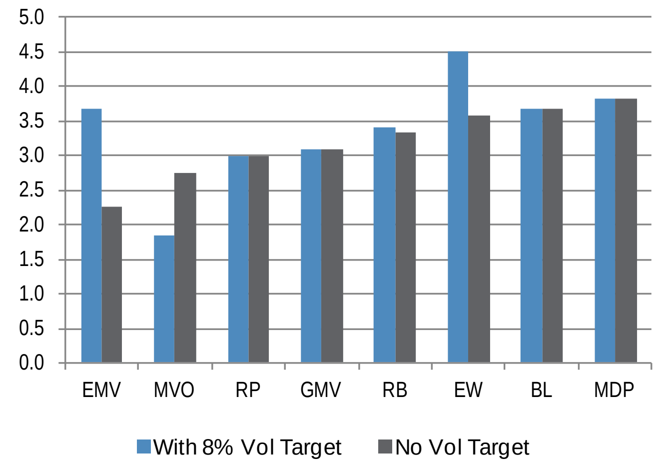
[44] See more on the section on "Factor on Factor" in Chapter 2 of the primer.

Figure 53: Comparing portfolio Sharpe ratios for different portfolio methods with and without volatility targeting



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 54: Comparing maximum drawdown durations (in years) for different portfolio methods with and without volatility targeting



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Given that the relative performance of models was not changed, we will continue our analysis of portfolio allocation methods without applying volatility targeting. Table 35 below summarizes the performance and risk analytics for the eight portfolio construction methods with twelve underlying factors described in the previous section for the out of sample period Jan 1975 – Dec 2012[45].

Table 35: Performance-Risk metrics for popular portfolio allocation methods during 1972-2012

	EW	MVO	GMV	MDP	EMV	RP	RB	BL
Average (%)	4.8	5.9	3.9	4.2	4.4	4.3	4.6	4.5
CAGR (%)	4.8	6.0	3.9	4.3	4.5	4.3	4.6	4.5
STDev (%)	3.5	3.8	2.8	2.9	2.6	2.6	2.8	2.7
MaxDD (%)	-14.6	-6.3	-4.6	-4.9	-7.1	-5.2	-5.3	-5.5
MaxDDur (in yrs)	3.6	2.8	3.1	3.8	2.3	3.0	3.3	3.7
Sharpe Ratio	1.4	1.5	1.4	1.4	1.7	1.7	1.7	1.7
Sortino Ratio	2.5	3.2	3.0	3.1	3.6	3.6	3.6	3.7
Calmar Ratio	1.4	1.8	2.7	4.8	3.3	5.7	4.8	4.2
Pain Ratio	4.7	8.6	6.7	5.0	9.6	8.5	6.8	7.6
Reward to 95VaR	0.32	0.38	0.40	0.40	0.47	0.49	0.49	0.46
Reward to 95CVaR	0.21	0.26	0.25	0.25	0.30	0.29	0.29	0.30
Hit Rate	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
Gain to Pain	2.8	3.4	3.2	3.2	3.8	3.7	3.7	3.7
Skewness	-0.4	0.5	0.7	0.7	0.1	0.4	0.4	0.4
Kurtosis	2.6	3.4	5.2	4.2	1.8	3.1	2.9	2.7
Correl with SPX	39.9%	11.2%	8.6%	14.6%	29.1%	20.8%	21.2%	18.6%
Correl with UST	9.0%	25.1%	23.9%	17.9%	25.7%	23.4%	22.6%	20.3%
CoSkew with SPX	-0.5	-0.3	-0.1	-0.1	-0.4	-0.2	-0.3	-0.3
CoSkew with UST	-0.1	0.2	0.1	0.1	0.0	0.1	0.1	0.1
CoKurt with SPX	-0.2	-1.6	-2.0	-1.7	-0.6	-1.2	-1.1	-1.1
CoKurt with UST	-2.6	-1.4	-1.2	-1.6	-1.4	-1.2	-1.3	-1.5

Source: J.P. Morgan Quantitative and Derivatives Strategy.

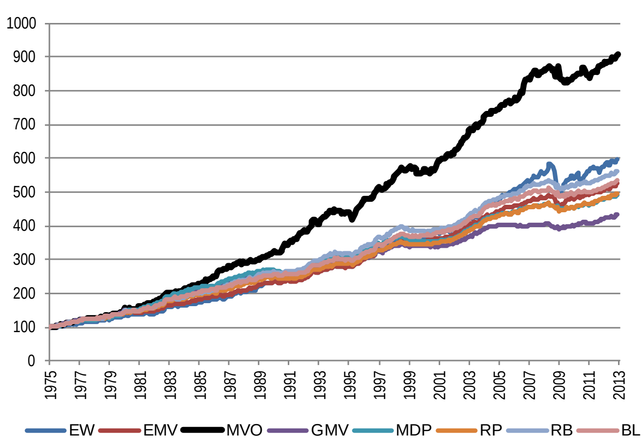
[45] We used three years of trailing data to estimate the marginal volatilities and correlation matrix.

Based on the historical test of risk models, we can observe:

- EW had the lowest Sharpe ratio, worst drawdown (-14.6%), and relatively high correlation to the performance of risky assets (S&P 500).
- MVO generated the highest return (CAGR); however, this was more than offset by the volatility, leading to a below average Sharpe ratio. On the positive side, MVO had low correlation to risky assets and negative co-kurtosis to bonds and equities.
- GMV and MDP generated low CAGRs, which also led to the lowest Sharpe ratios for these models. These models were obviously focused on minimizing downside risk, and that resulted in the best (smallest) draw-downs, and lowest correlation and co-kurtosis to risky asset.
- EMV, RP, RB and BL had the highest Sharpe and Pain to Gain ratios. This was achieved by a good trade-off between returns, risk and draw-downs. RP, RB and BL had somewhat better risk properties than EMV as the model suffered from high correlation to risky assets, and relatively high draw-downs (-7.1%).
- Except EW, all the other seven allocation methods achieved positive skewness and more than 3x Gain-to-Pain ratios, which dramatically improved the risk properties of the portfolios as compared to each underlying factor separately. All allocation methods had negative co-kurtosis with Equity beta and bond beta, suggesting various levels of ability to provide tail hedges to a traditional risky asset portfolio.
- Generally speaking, EMV, RP, RB and BL had the highest reward to tail risk ratios.

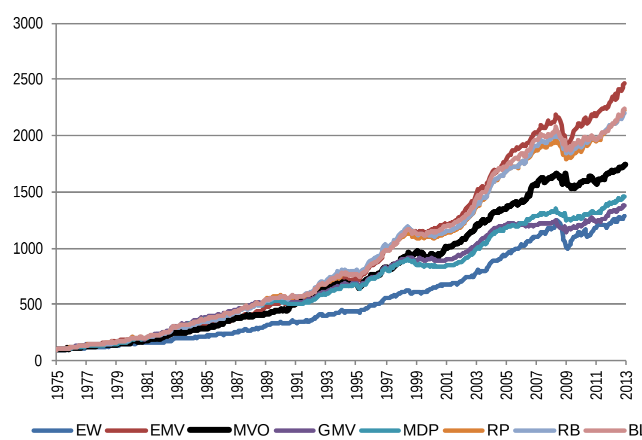
The P/Ls of US$100 (uncollateralized) investments in each of the methods on Dec 1974 are shown in Figure 55 below, with the ending P/L reflecting the CAGR for each method. We also show the P/Ls of each method under 5% in-sample volatility (we scaled each portfolio to have equal full-sample volatility) in Figure 56, with ending P/L reflecting the Sharpe ratios for each method.

Figure 55: P/Ls of a US$100 (uncollateralized) investment on Dec 1974



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 56: P/Ls of a US$100 (uncollateralized) investment on Dec 1974 with 5% in-sample volatility



Source: J.P. Morgan Quantitative and Derivatives Strategy.

One can see that the performances of different methods were closely correlated to each other – this can be verified by examining the correlation matrix shown in Table 36. The average correlation coefficients between methods were above 60%, which didn't show material change during the 2007-2009 Global Financing Crisis. This is also understandable since all the models had long exposures to our selection of 12 risk factors

Table 36: Correlation matrix among different portfolio allocation methods on a same set of assets

(%)	EW	EMV	MVO	GMV	MDP	RP	RB	BL
Equal Weights (EW)		91	55	35	50	70	72	71
Equal Marginal Volatility (EWV)	89		74	63	75	90	91	89
Mean-Variance Optimization (MVO)	59	70		59	76	83	88	80
Global Minimum Variance (GMV)	48	71	67		95	86	80	87
Most Diversified Portfolio (MDP)	60	74	69	92		95	91	94
Risk Parity (RP)	75	89	74	89	94		99	98
Risk Budgeting (RB)	78	89	81	83	90	97		96
Black-Litterman (BL)	77	89	79	84	91	97	97	
Ave Correl - All Sample	69	82	71	76	81	88	88	88
Ave Correl - 07-08 GFC	63	82	73	72	82	89	88	88

Source: J.P. Morgan Quantitative and Derivatives Strategy. * Lower triangular statistics are the all-sample pair-wise correlation and upper triangular are the correlation statistics during Global Financial Crisis (Aug 2007 - Mar 2009).

Portfolio Weights Time Series

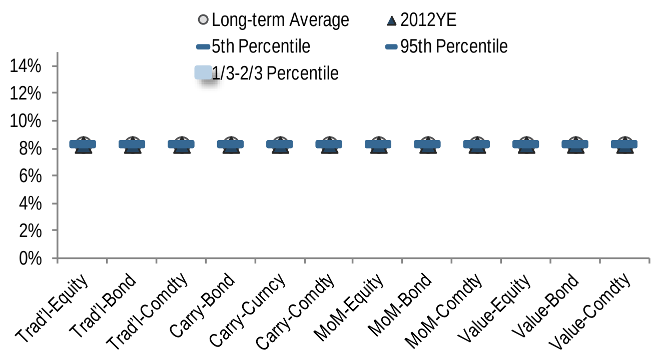
We next examine the how asset weights, risk contributions and diversification ratios for the eight portfolio allocation methods varied in time. Figure 57-Figure 72 shows the times-series of the asset weights assigned by different portfolio methods. We make a few observations below.

The Equal-Weight (EW) method by definition gives constant weights, while MVO displayed the highest volatility of asset weights. This is understandable as our version of MVO uses simplistic return and covariance forecasts (e.g. past 12-month factor return as an estimate of the future return). Hence, MVO weights will reflect estimation error from both expected returns and the covariance matrix, and give the most volatile weights.

We can see that all methods put the highest weight in bond factors. The main reason for this is the low volatility of bond factors (e.g. as in EMV) and good diversification properties (e.g. as in MDP and RP). Additionally, models that aim to reduce total risk and increase diversification, often overweight value factors due to their low levels of correlation to other factor styles.

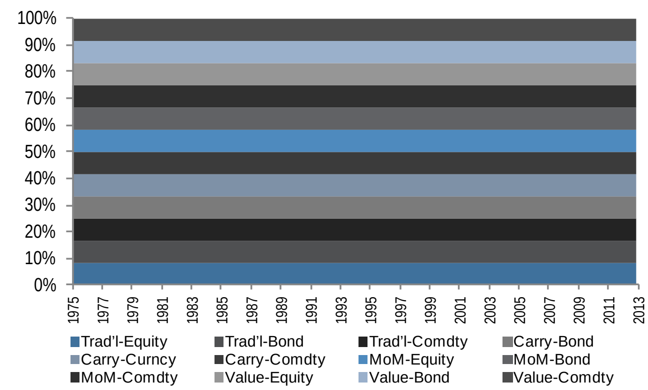
As was evident from the performance and risk summary, GMV and MDP show similar asset weights patterns (aimed to minimize risk and draw-downs). Risk-Parity (RP), and our momentum-based version of Risk-Budgeting (RB) and Black-Litterman (BL) also show similar portfolio weight variations. The Equal-Marginal Volatility (EMV) method is by construction underweight in the more volatile factors and overweight in less volatile ones. As EMV doesn't involve estimation on expected return or correlations, its weights tend to be more stable than the other methods.

Figure 57: EW - Distribution of portfolio weights



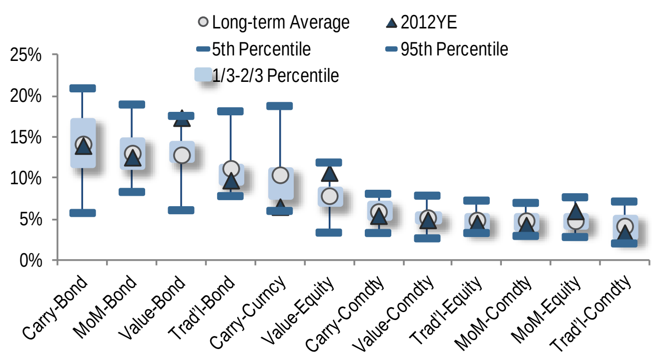
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 58: EW - Time-varying portfolio weights



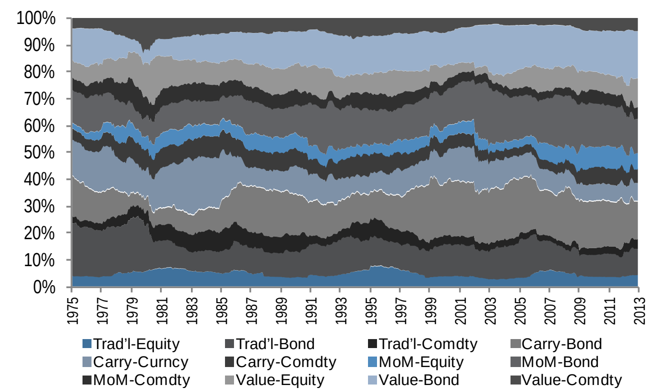
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 59: EMV - Distribution of portfolio weights



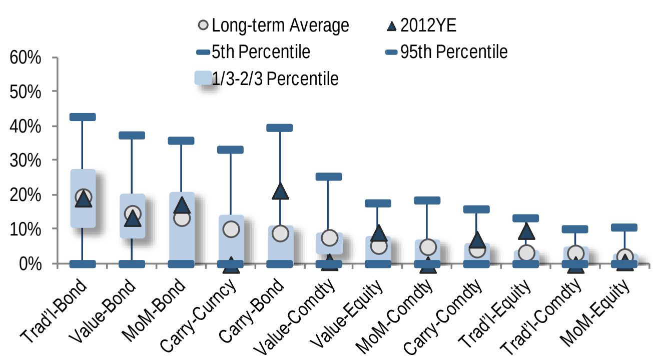
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 60: EMV - Time-varying portfolio weights



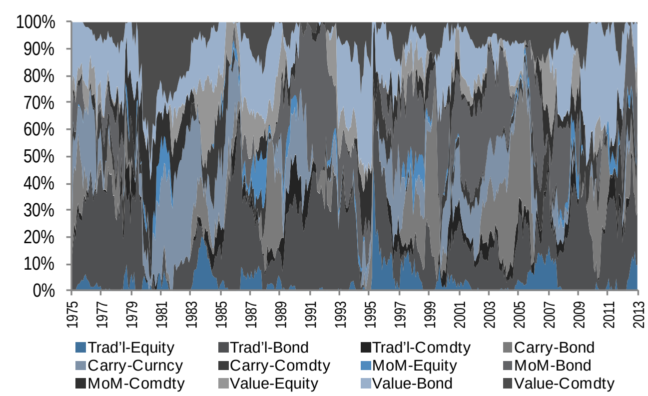
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 61: MVO - Distribution of portfolio weights



Source: J.P. Morgan Quantitative and Derivatives Strategy.

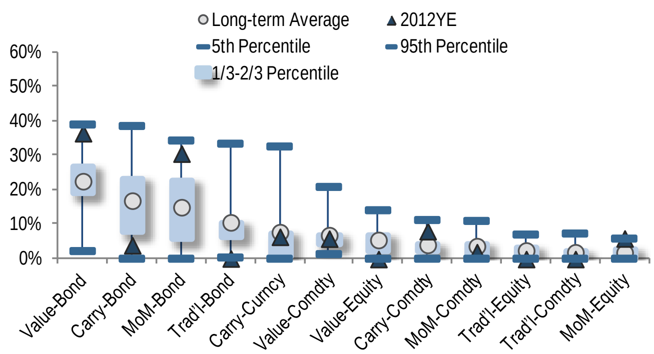
Figure 62: MVO - Time-varying portfolio weights



Source: J.P. Morgan Quantitative and Derivatives Strategy.

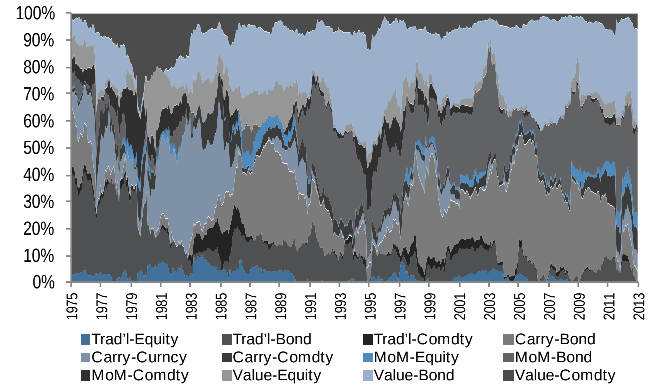
Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Figure 63: GMV - Distribution of portfolio weights



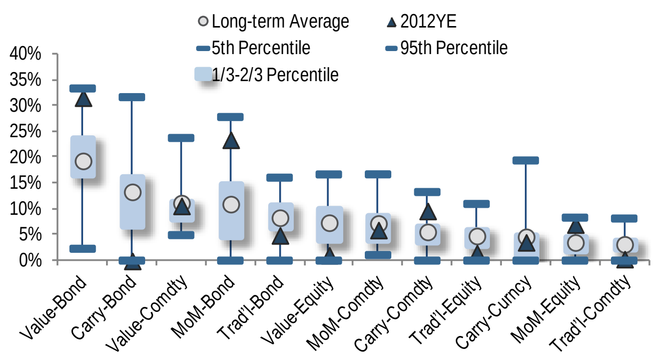
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 64: GMV - Time-varying portfolio weights



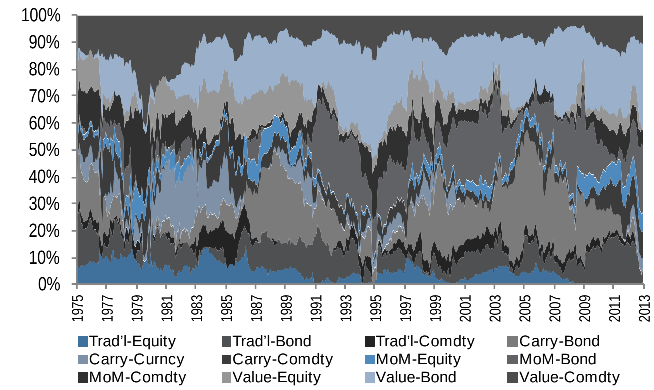
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 65: MDP - Distribution of portfolio weights



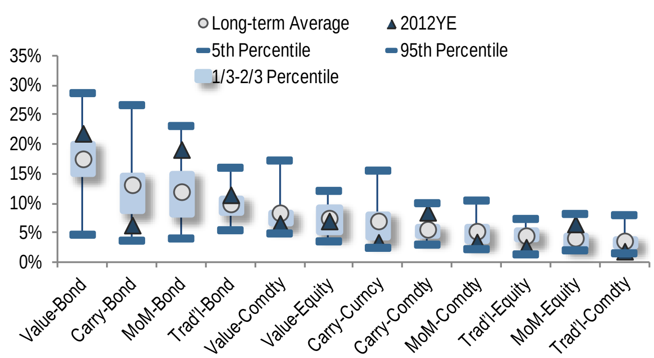
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 66: MDP - Time-varying portfolio weights



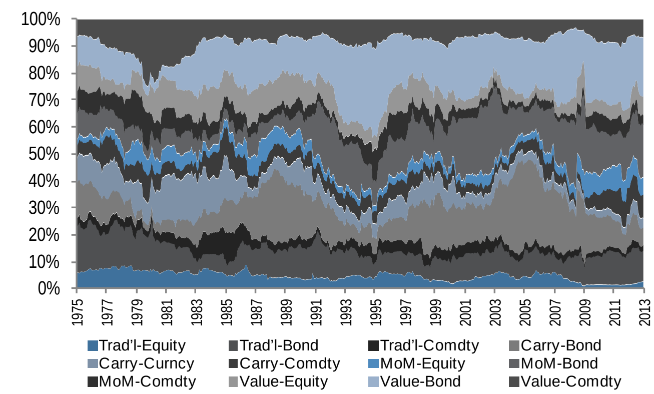
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 67: RP - Distribution of portfolio weights



Source: J.P. Morgan Quantitative and Derivatives Strategy.

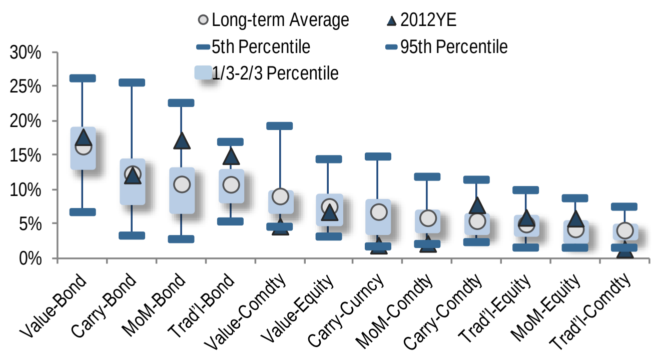
Figure 68: RP - Time-varying portfolio weights



Source: J.P. Morgan Quantitative and Derivatives Strategy.

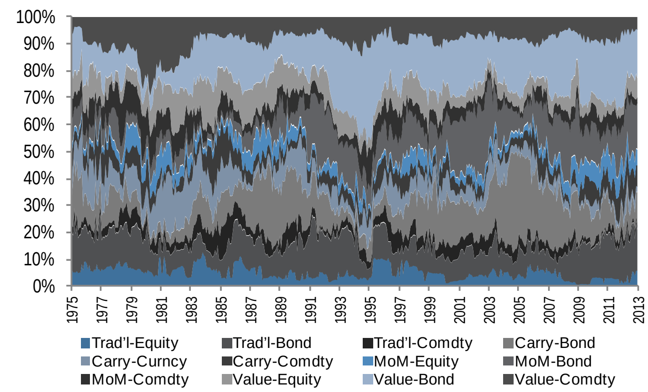
Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Figure 69: RB - Distribution of portfolio weights



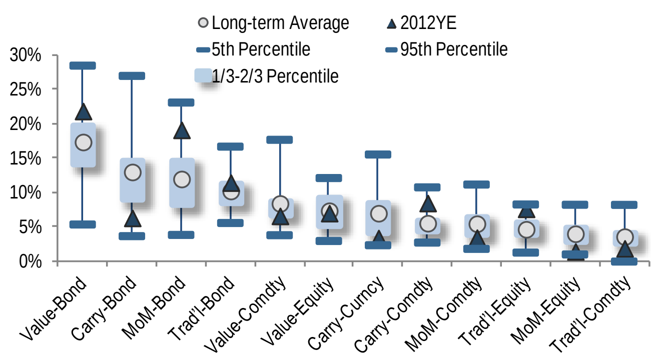
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 70: RB - Time-varying portfolio weights



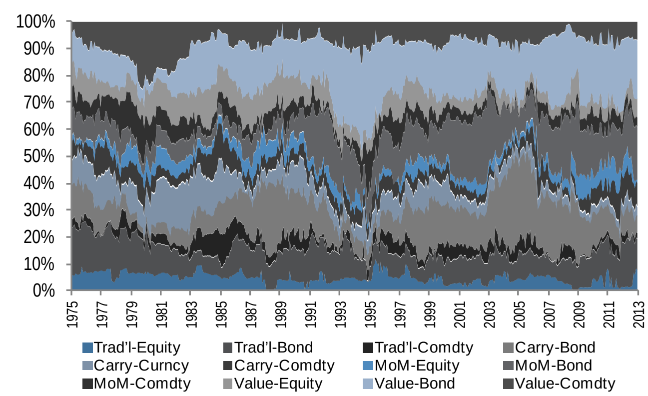
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 71: BL - Distribution of portfolio weights



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 72: BL - Time-varying portfolio weights



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Portfolio Risk Time Series

Changes in asset weights are important to understand the model's stability and estimate transaction costs. Perhaps an even more important metric to understand is the time series of portfolio risk attribution. Figure 73-Figure 88 show the time-series distribution of the ex-ante total risk contribution profiles for different portfolio methods. We can make several simple observations.

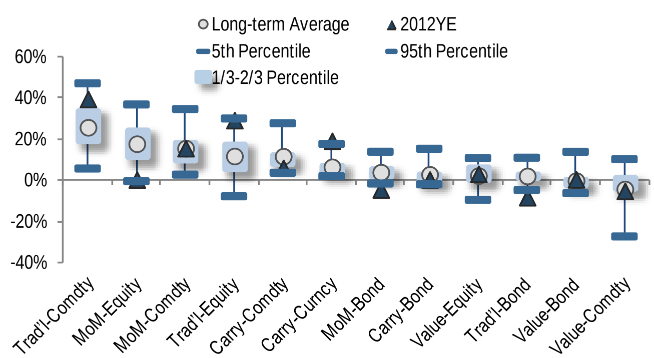
The Equal Weight (EW) method over-allocates to equity risk, given the simplistic approach of giving equal weights to all risk factors. On the other hand, EMV allocates risk in a fairly balanced way between different asset classes and factor styles.

Given the high Sharpe ratios and low volatility of bond factors, MVO's allocation to these factors is high. GMV allocates an even higher portion of risk to Bond factors due to their low volatility and correlation. MDP allocates most of the risk to value factors across assets, given the low correlation of value factors to the rest of the portfolio.

By construction, the Risk Parity (RP) portfolio assigns equal ex-ante risk contribution to each asset. The Risk Budgeting (RB) and Black-Litterman (BL) portfolios' risk contribution follows the RP risk allocation, but modifies it based on specific views (in our case price momentum). For instance, one can notice a balanced ex-ante risk attribution of RB and BL, with higher recent equity allocation due to the strong performance of the asset class.

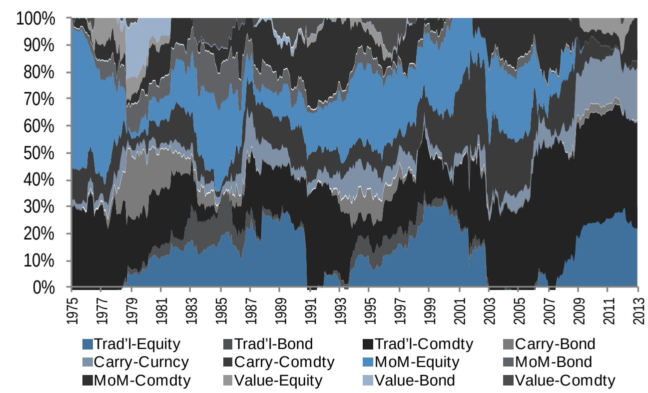
Consistent with our previous theoretical analysis, the ex-ante total risk contribution profile of GMV is equivalent to its portfolio weights (see Figure 64 and Figure 80), and for MDP its ex-ante total risk contribution profile is equivalent to the product of its portfolio weights and volatilities. Note that the total risk contribution for some risk factors can be negative (if the assets' average correlation with other factors is negative). For example, the average ex-ante risk-contribution from the Commodity Value risk factor was -1.6% during the out-of-sample period from Jan 1975 to Dec 2012.

Figure 73: EW - Distribution of ex-ante total risk contributions



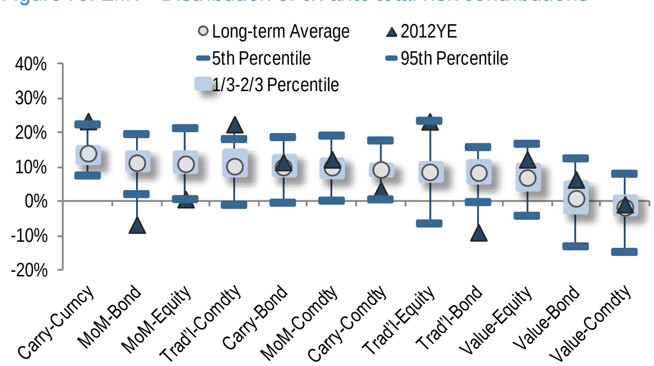
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 74: EW - Time-varying ex-ante total risk contributions



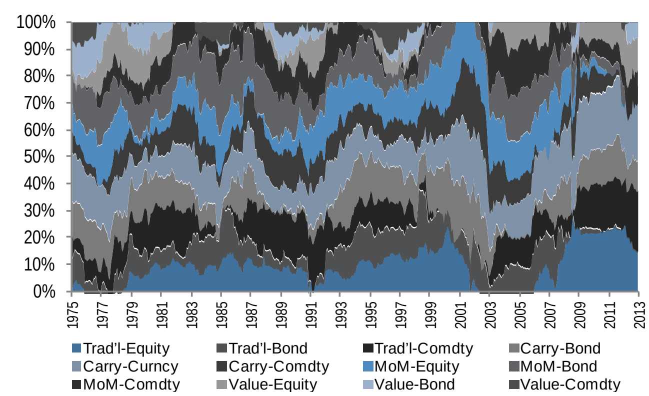
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 75: EMV - Distribution of ex-ante total risk contributions



Source: J.P. Morgan Quantitative and Derivatives Strategy.

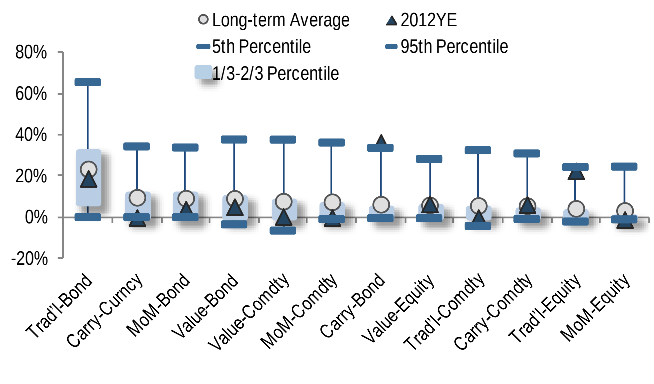
Figure 76: EMV - Time-varying ex-ante total risk contributions



Source: J.P. Morgan Quantitative and Derivatives Strategy.

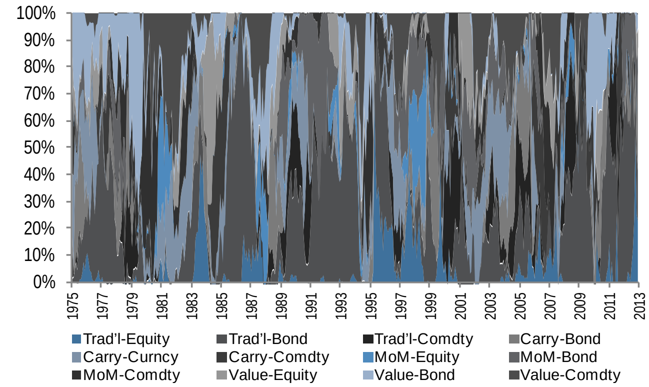
Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Figure 77: MVO - Distribution of ex-ante total risk contributions



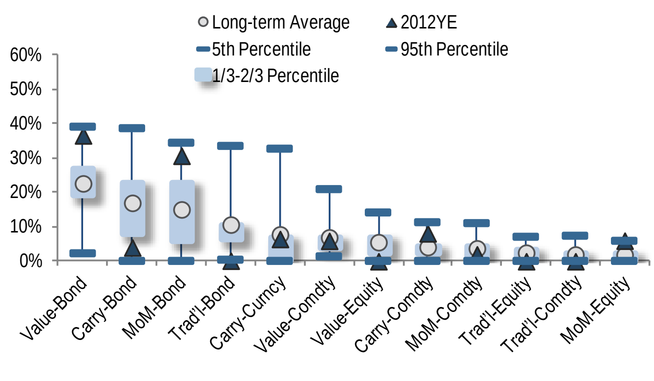
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 78: MVO - Time-varying ex-ante total risk contributions



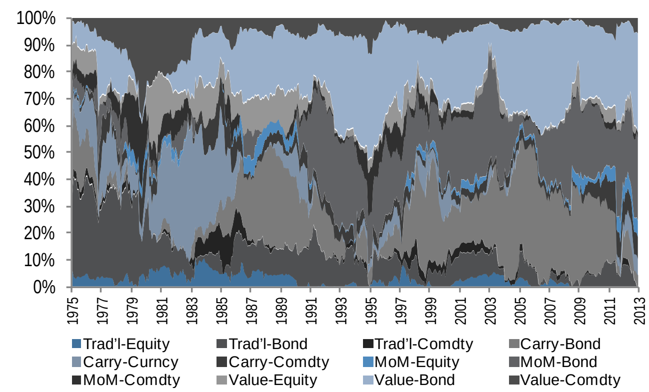
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 79: GMV - Distribution of ex-ante total risk contributions



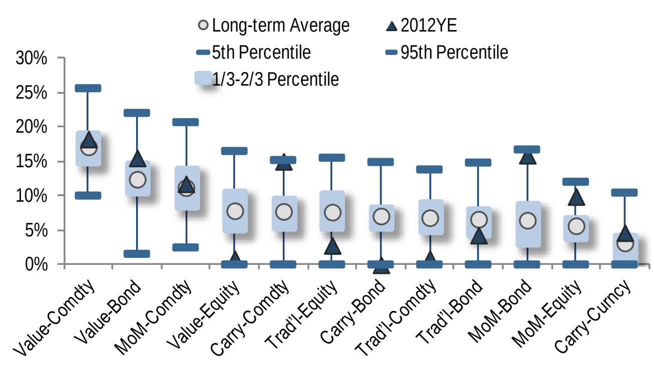
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 80: GMV - Time-varying ex-ante total risk contributions



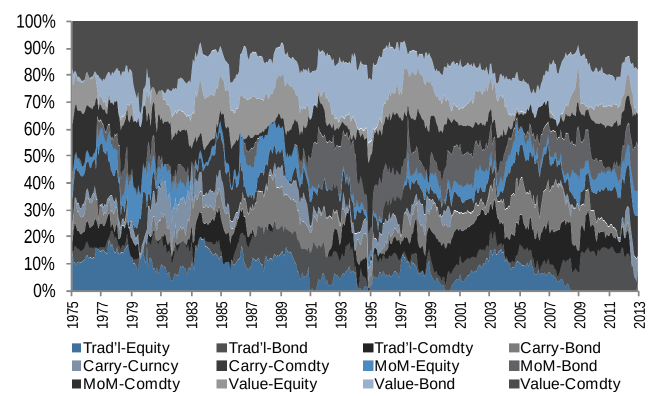
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 81: MDP - Distribution of ex-ante total risk contributions



Source: J.P. Morgan Quantitative and Derivatives Strategy.

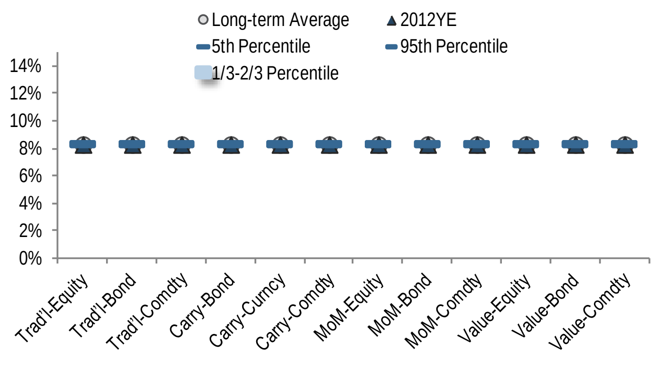
Figure 82: MDP - Time-varying ex-ante total risk contributions



Source: J.P. Morgan Quantitative and Derivatives Strategy.

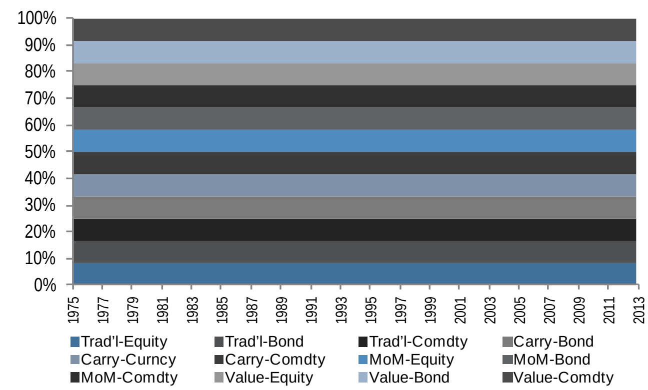
Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Figure 83: RP - Distribution of ex-ante total risk contributions



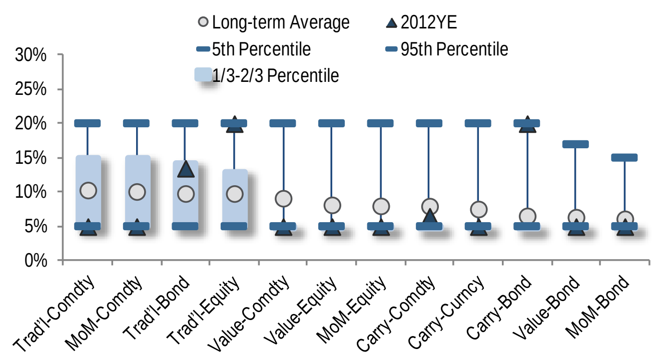
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 84: RP - Time-varying ex-ante total risk contributions



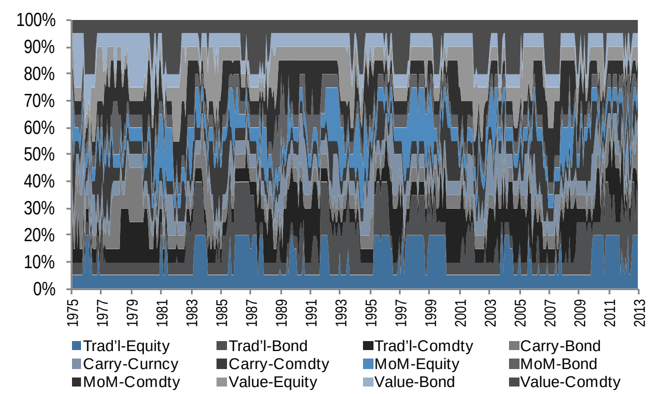
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 85: RB - Distribution of ex-ante total risk contributions



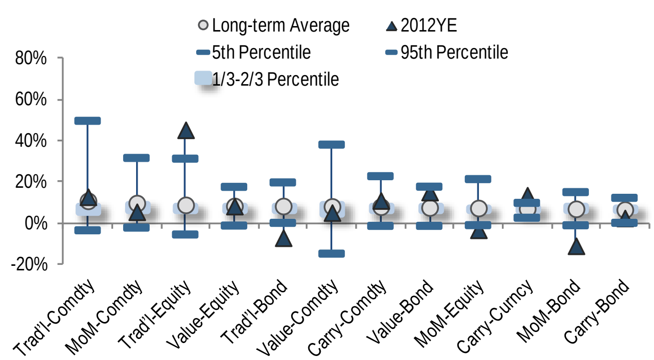
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 86: RB - Time-varying ex-ante total risk contributions



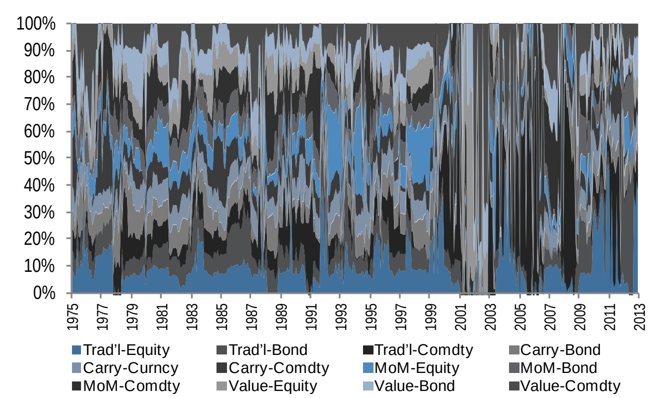
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 87: BL - Distribution of ex-ante total risk contributions



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 88: BL - Time-varying ex-ante total risk contributions



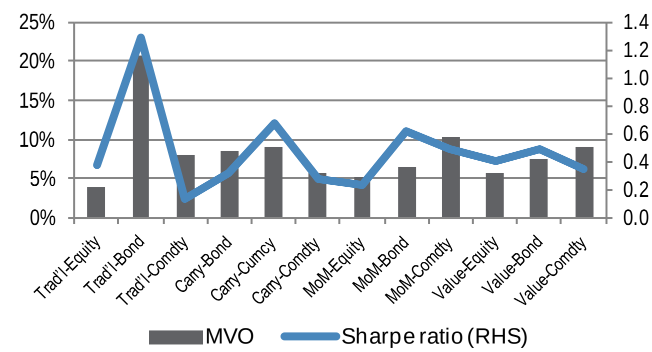
Source: J.P. Morgan Quantitative and Derivatives Strategy.

To examine how the ex-post total risk contributions compared to the ex-ante expectations, we calculate the realized risk contributions from Jan 1975 to Dec 2012. The results are shown in Figure 89-Figure 92. We make several observations:

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

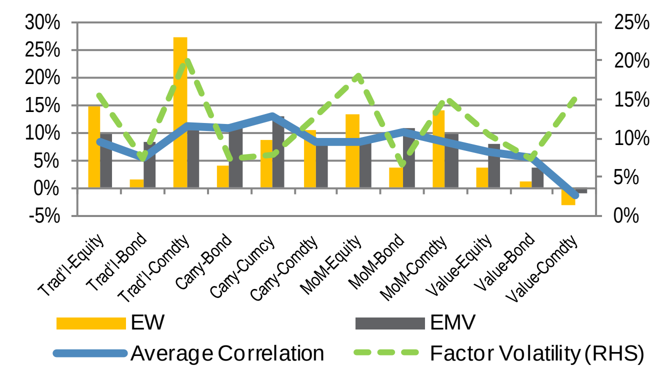
- Despite high volatility of weights and ex-ante risk contribution, MVO allocated risk **roughly according to the ex-post Sharpe ratio of the individual assets**. In other words, MVO allocated more risk to assets with higher Sharpe ratios.
- As expected, the equal-weight (EW) portfolio realized high risk exposures in high volatility and low correlation factors such as commodity beta and equity momentum. On the other hand, it realized too little risk exposure (underweight) in low volatility and low correlation factors such as bond beta and commodity value.
- By construction, EMV's ex-ante risk allocations are proportional to average factor correlations (note that the total risk contribution is proportional to beta, which becomes average correlation as EMV weights are inverse to the assets' volatility). From Figure 90, we find that this objective was met in ex-post terms
- GMV and MDP allocated high weights to factors with better diversification abilities (such as the Value factors). The difference between the risk contributions in these two models is that the GMV put more weight on low volatility factors, as the MDP is indifferent to marginal volatility (Figure 91).
- Despite its ex-ante objective to achieve equal risk contribution, RP put a slight risk overweight in value factors and underweight in risky factors like traditional equities and commodities, and currency carry (Figure 92).

Figure 89: Ex-post total risk allocation of MVO and factor Sharpe ratios



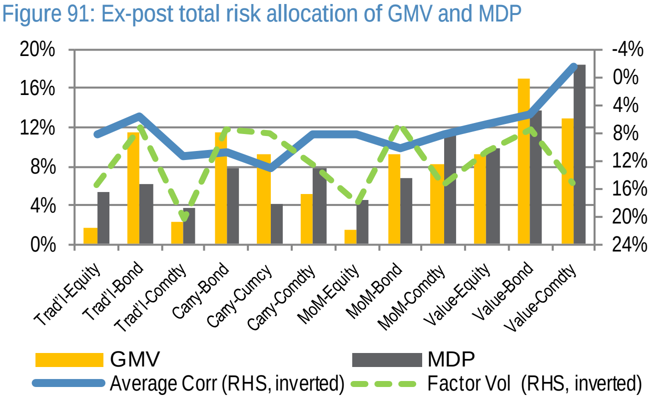
Source: J.P. Morgan Quantitative and Derivatives Strategy. * Statistics are calculated during the period Jan 1975—Dec 2012.

Figure 90: Ex-post total risk allocation of EW/EMV vs factor average correlation and factor volatility



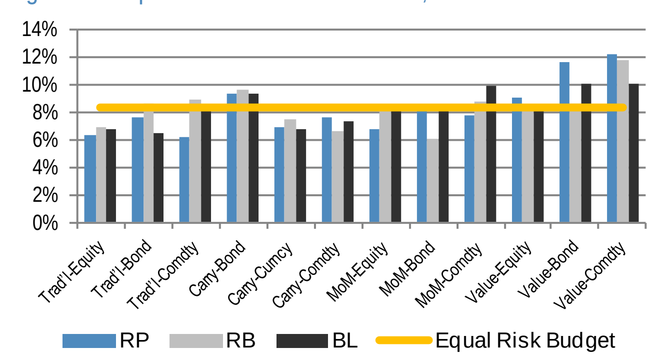
Source: J.P. Morgan Quantitative and Derivatives Strategy. * Statistics are calculated during the period Jan 1975—Dec 2012.

Figure 91: Ex-post total risk allocation of GMV and MDP



Source: J.P. Morgan Quantitative and Derivatives Strategy. * Statistics are calculated during the period Jan 1975—Dec 2012.

Figure 92: Ex-post total risk allocation of RP, RB and BL



Source: J.P. Morgan Quantitative and Derivatives Strategy. * Statistics are calculated during the period Jan 1975—Dec 2012.

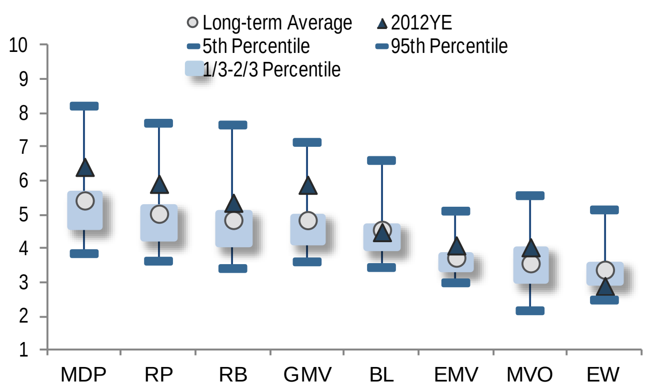
Diversification ratios and Degrees of Freedom

The ability of a portfolio to maintain low risk through low correlations is measured by the diversification ratio (DR). In our introduction to portfolio risk methods, we have showed that the value of the diversification ratio (squared) can be regarded as the effective number of independent risk factors (or degrees of freedom) of the portfolio.

We will first compare the “ex-Ante” diversification for different risk methods. For instance, the Most Diversified Portfolio (MDP) will have the best "ex-ante" diversification ratio by construction. ‘Ex-Post’ diversification ratios that are actually realized may differ substantially due to uncertainty in model inputs.

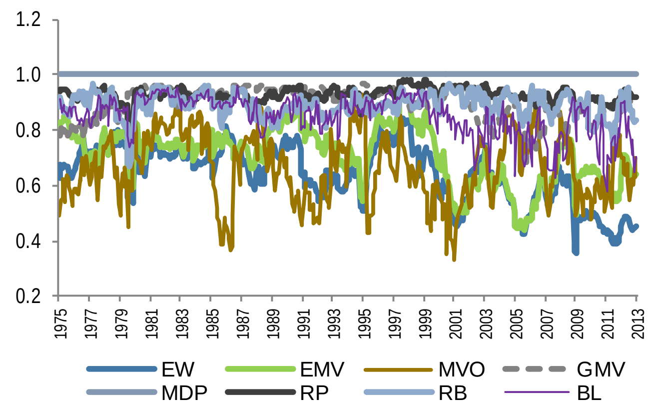
Figure 93 shows the distribution of ex-ante diversification ratios for different portfolio methods and Figure 94 shows the time-series of ex-ante diversification ratio relative to that of MDP. We find that GMV, RP, and RB achieved similar ex-ante diversification ratios to that of MDP, while EW, EMV and MVO trailed behind.

Figure 93: Distribution of ex-ante diversification ratios



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 94: Time-varying ex-ante diversification ratios*

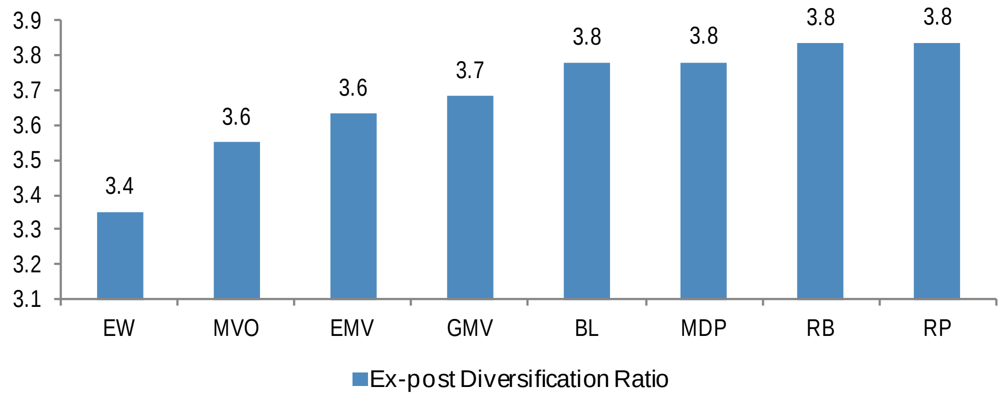


Source: J.P. Morgan Quantitative and Derivatives Strategy. * Relative to the diversification ratio of MDP.

MDP had an ‘ex-ante’ average diversification ratio of 5.4, translating to roughly 30 degrees of freedom, which is much higher than the total number of assets (12). We will see that the ‘ex-post’ DR of the MDP was indeed much lower. On the other hand, the equal-weighted (EW) method had the lowest average diversification ratio at 3.4, translating to 11.5 degrees of freedom, roughly the same as the number of assets.

The ‘ex-post’ diversification ratios are calculated from realized volatilities and correlations over the full-sample period from Jan 1975 to Dec 2012. Figure 95 shows that MDP, RP, BP and GMV all realized lower ‘ex-post’ DRs as compared to ex-ante values. MDP even realized lower diversification than RP and RB. Interestingly, the ex-post diversification ratios for EW, MVO, and EMV were roughly equal to their respective historical average ex-ante diversification ratios.

Figure 95: Ex-post diversification ratios during 1975-2012



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Market Regimes for Portfolio Methods

We next examine the performance of risk allocation methods under different macro-economic and market regimes defined in the previous Chapter. Models are compared based on their Sharpe ratios (assumes portfolio returns follow a normal distribution) and reward-to-CVaR ratios (purely focuses on tail risk defined by CVaR).

Table 37 and Table 38 show the Sharpe ratios and Reward-to-CVaR ratios for the eight portfolio methods under different regimes of Growth, Inflation, Volatility, Funding and Market Liquidities. As certain market conditions may benefit or hurt all the models (e.g. higher growth, higher inflation, lower volatility and higher funding liquidity will generally benefit each portfolio allocation method), we also rank the performance of models in each of the market regimes in Table 39 and Table 40.

Table 37: Overall Sharpe ratios of popular portfolio allocation methods amid different Economic/Market Regimes

	Growth			Inflation			Volatility			Funding Liquidity			Market Liquidity		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
Equal Weighted (EW)	0.83	1.80	1.78	1.08	1.54	1.56	2.12	1.85	0.57	0.90	1.63	1.71	0.35	2.43	1.66
Equal Marginal Vol (EMV)	1.33	2.01	1.93	1.47	1.74	1.99	2.47	1.72	1.12	1.30	1.81	2.28	0.84	2.40	2.04
Mean-Variance Opt (MVO)	1.47	1.69	1.44	1.19	1.64	1.78	1.90	1.51	1.19	1.33	1.64	1.84	1.07	2.02	1.46
Global Min Var (GMV)	1.21	1.34	1.72	1.17	1.09	2.02	1.71	1.33	1.19	1.38	1.37	1.76	1.06	1.79	1.35
Max Diver (MDP)	1.24	1.52	1.63	1.23	1.21	1.94	1.78	1.54	1.04	1.44	1.22	2.02	0.95	2.07	1.29
Risk Parity (RP)	1.38	1.79	1.90	1.51	1.54	2.04	2.16	1.71	1.19	1.45	1.55	2.40	1.03	2.30	1.65
Risk Budgeting (RB)	1.38	1.88	1.81	1.34	1.70	2.00	2.19	1.84	1.05	1.40	1.58	2.36	0.95	2.34	1.69
Black Litterman (BL)	1.44	1.76	1.85	1.41	1.58	2.07	2.20	1.81	1.08	1.37	1.75	2.16	0.94	2.39	1.70

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 38: Overall Reward-to-CVaR ratios of popular portfolio allocation methods amid different Economic/Market Regimes

	Growth			Inflation			Volatility			Funding Liquidity			Market Liquidity		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
Equal Weighted (EW)	0.11	0.35	0.30	0.13	0.29	0.26	0.48	0.35	0.07	0.12	0.28	0.27	0.04	0.66	0.25
Equal Marginal Vol (EMV)	0.20	0.42	0.37	0.21	0.37	0.34	0.57	0.31	0.16	0.20	0.36	0.44	0.11	0.62	0.38
Mean-Variance Opt (MVO)	0.22	0.31	0.26	0.17	0.29	0.32	0.37	0.26	0.18	0.22	0.30	0.30	0.14	0.49	0.22
Global Min Var (GMV)	0.18	0.25	0.38	0.18	0.19	0.37	0.42	0.24	0.17	0.24	0.25	0.35	0.13	0.45	0.24
Max Diver (MDP)	0.20	0.26	0.32	0.17	0.20	0.37	0.46	0.29	0.15	0.26	0.20	0.34	0.13	0.51	0.21
Risk Parity (RP)	0.22	0.32	0.38	0.22	0.30	0.37	0.55	0.32	0.17	0.24	0.27	0.50	0.13	0.64	0.29
Risk Budgeting (RB)	0.22	0.32	0.36	0.19	0.31	0.38	0.48	0.37	0.16	0.24	0.27	0.48	0.13	0.68	0.28
Black Litterman (BL)	0.24	0.34	0.35	0.22	0.32	0.38	0.53	0.36	0.16	0.24	0.32	0.45	0.13	0.65	0.30

Source: J.P. Morgan Quantitative and Derivatives Strategy.

The shaded area in these tables corresponds to the current market regime of low volatility, low inflation, high liquidity and low/medium growth. We also show the average ranking of risk models in all market regimes as well as the average performance in the current market regime.

Table 39: Sharpe ratio ranks (from high to low) of popular portfolio allocation methods amid different Economic/Market Regimes

	Growth			Inflation			Volatility			Funding Liquidity			Market Liquidity			Average Rank	
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High	All	Current
EW	8	3	5	8	5	8	5	1	8	8	4	8	8	1	4	5.6	5.3
EMV	5	1	1	2	1	5	1	4	4	7	1	3	7	2	1	3.0	2.1
MVO	1	6	8	6	3	7	6	7	1	6	3	6	1	7	6	4.9	5.4
GMV	7	8	6	7	8	3	8	8	3	4	7	7	2	8	7	6.2	7.4
MDP	6	7	7	5	7	6	7	6	7	2	8	5	5	6	8	6.1	6.3
RP	3	4	2	1	6	2	4	5	2	1	6	1	3	5	5	3.3	3.3
RB	4	2	4	4	2	4	3	2	6	3	5	2	4	4	3	3.5	3.1
BL	2	5	3	3	4	1	2	3	5	5	2	4	6	3	2	3.3	3.0

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 40: Reward-to-CVaR ratio ranks (from high to low) of popular portfolio allocation methods amid different Economic/Market Regimes

	Growth			Inflation			Volatility			Funding Liquidity			Market Liquidity			Average Rank	
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High	All	Current
EW	8	2	7	8	6	8	5	3	8	8	4	8	8	2	5	6.0	5.4
EMV	5	1	3	3	1	6	1	5	5	7	1	4	7	5	1	3.7	2.9
MVO	2	6	8	7	5	7	8	7	1	6	3	7	1	7	7	5.5	6.3
GMV	7	8	1	5	8	3	7	8	3	5	7	5	2	8	6	5.5	6.6
MDP	6	7	6	6	7	4	6	6	7	1	8	6	6	6	8	6.0	6.4
RP	4	4	2	1	4	5	2	4	2	2	5	1	3	4	3	3.1	2.7
RB	3	5	4	4	3	2	4	1	6	4	6	2	5	1	4	3.6	3.3
BL	1	3	5	2	2	1	3	2	4	3	2	3	4	3	2	2.7	2.4

Source: J.P. Morgan Quantitative and Derivatives Strategy.

We find that EMV and RP had the highest average Sharpe ratios across all market regimes as well as under the current regime. BL and RP had the highest average Reward-to-CVaR ratio ranks (both overall and under the current regime). EW, GMV and MDP were on average lowest ranked, however they did outperform under certain market conditions. For instance, GMV and MVO outperformed in low liquidity and high volatility environments, and EW outperformed in mid liquidity and mid volatility environments.

Sample Portfolio of J.P. Morgan Indices

To further illustrate the performance of portfolio allocation methods, we tested the hypothetical historical performance of portfolios consisting of 14 Traditional, Carry, Momentum, Value and Multi-Style indices created by J.P. Morgan. The performance time series of these models are available on Bloomberg and strategy details are available to J.P. Morgan clients. Table 41 below lists a brief description of these risk factors.

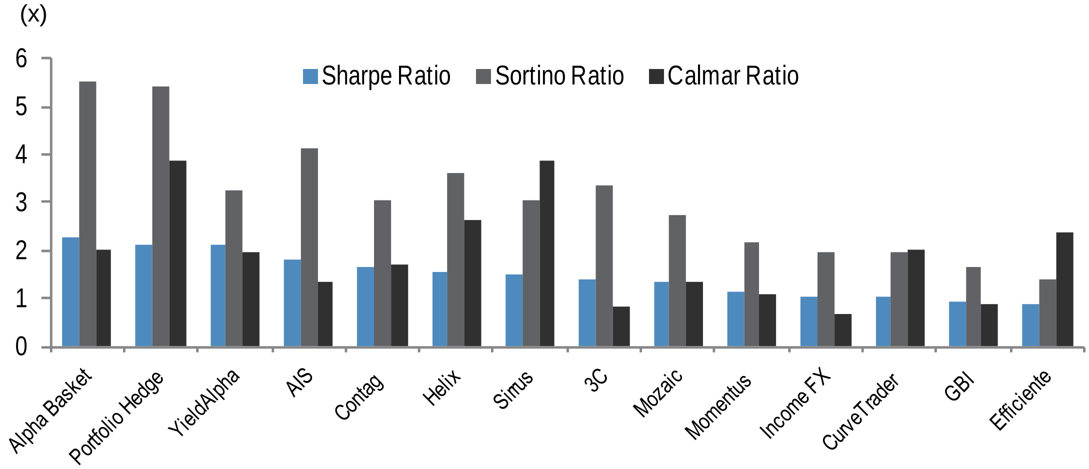
Table 41: Description of J.P. Morgan indices used for a portfolio allocation exercise

Ticker	Index Name	JPM Index Family	Asset Class	Strategy Style
JHDCGBIG	Global Government Bond Index[46] (GBI)	GBI	Rates	Traditional
JCTAADJE	Alpha S&P GSCI Light Energy	Contag	Commodities	Carry
IFXJAM30	IncomeAsia 3.0	Income FX	Currencies	Carry
YAJPMUS2	JPM Yield Alpha USD Index	YieldAlpha	Multi Asset	Carry
EEJPUS5E	ETF Efficiente 5	Efficiente	Multi Asset	Momentum
JMOZUSD	Mozaic USD	Mozaic	Multi Asset	Momentum
JHLXH2US	Helix2 - Basket Hedged in USD	Helix	Rates	Momentum
JMOMQTO	Momentus Quattro in USD	Momentus	Rates	Momentum
JMAB3CER	3C	3C	Commodities	Value
JPOLARE	Polaris Equal Weighted	Portfolio Hedge	Commodities	Value
JMAB008E	Commodity Alpha Basket 8	Alpha Basket	Commodities	Multi Style
AIJPB1U5	J.P.Morgan AI Top 20 Sharpe	AIS	Multi Asset	Multi Style
JPCVTOUS	CurveTrader M+ USD Index	CurveTrader	Rates	Multi Style
JMSIRRUS	Sirrus	Sirrus	Rates	Multi Style

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 96 below shows the Sharpe ratio, Sortino Ratio and Calmar Ratio for the individual risk factor indices (performance metrics calculated before commissions and bid-offer spreads). During the 13-year period from Jan 2000 to Dec 2012, these indices on average achieved better risk-adjusted rewards than the simple factor models we introduced in our introduction to Risk Factor Classification Chapter.

Figure 96: An example of superior risk-adjusted reward profiles for J.P. Morgan tradable indices



Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg. *Statistics were calculated during Jan 2000 to Dec 2012.

A correlation matrix for the 14 factors during the full sample period and during the recent Global Financial Crisis (August 2007-March 2009), as is shown in Table 42.

[46] Excess return is calculated by adjusting for 1-month US$ Libor rate.

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

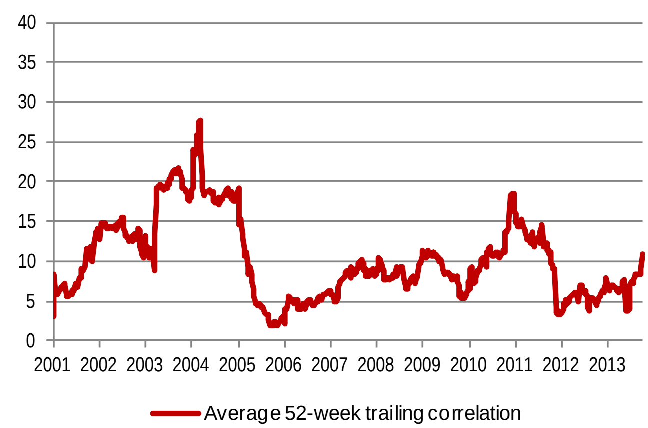
Table 42: Correlation among J.P. Morgan tradable indices during Jan 2000 – Dec 2012 (below diagonal) and During GFC (above diagonal).

	Alpha Basket	Yield Alpha	Portfolio Hedge	AIS	GBI	Contag	3C	Helix	Curve Trader	Sirrus	Mozaic	Efficiente	Income FX	Momentus
Alpha Basket		66	5	4	-12	56	-25	30	-31	14	4	36	8	11
YieldAlpha	13		52	-15	2	39	-72	15	-23	14	22	65	52	27
Portfolio Hedge	9	5		-8	65	26	-57	51	-13	44	40	63	34	80
AIS	31	13	-5		27	29	45	26	-21	-7	34	25	-5	-7
GBI	-11	-8	0	23		40	-8	45	-10	42	49	45	8	58
Contag	68	7	13	36	-2		-14	40	-19	22	26	49	35	24
3C	6	-28	10	27	-6	1		1	-1	-17	2	-45	-60	-35
Helix	-8	10	9	26	33	-17	-1		16	19	44	27	4	63
CurveTrader	-8	-9	-9	7	24	-2	-2	37		-23	17	-30	17	-21
Sirrus	-5	-5	-4	4	27	0	-18	27	11		37	44	-13	44
Mozaic	10	21	13	38	35	5	19	36	16	9		65	32	27
Efficiente	6	41	12	25	37	10	-4	19	2	2	65		49	52
Income FX	7	39	-4	13	-8	5	-19	14	7	-12	31	31		10
Momentus	-3	0	10	4	33	-1	-6	48	30	25	20	15	2	
Full Sample Ave	9	8	4	19	14	9	-1	18	8	5	24	20	8	14
During GFC	13	19	29	10	27	27	-22	29	-11	17	31	34	13	26

Source: J.P. Morgan Quantitative and Derivatives Strategy. * Lower triangular statistics are the all-sample pair-wise correlation and upper triangular are the correlation statistics during GFC.

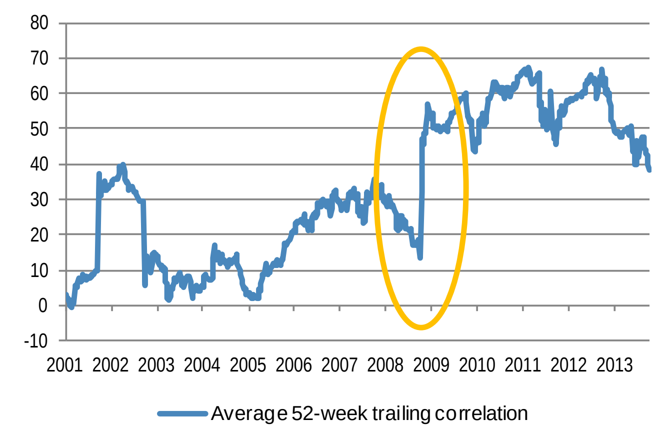
Most of the factors were positively correlated to each other over the full sample period and the correlation increased during the Global Financial Crisis. However, some of the factors showed significant negative correlation (e.g. 3C, and CurveTrader^{M+}). The selection of assets had a tilt to bond-based factors, as the average correlation between GBI (J.P. Morgan Global Government Bond Index) and other factors was 14%, which further increased to +27% during global financial crisis. This has likely contributed to the strong performance over the backtest time-period. Figure 97 below shows the 1-year average correlation of the portfolio assets, which can be compared with Figure 98 that shows the average correlation of US equities (S&P 500), US High yield bond (CSIYUS), Commodities (SPGSCIP) and Real Estate (REIT Index). We find that the average correlation among the 14 factor indices has been range bound between +5% and +20%. Furthermore, correlation did not increase during the crisis, unlike the correlation between traditional assets.

Figure 97: Rolling 52-week average correlation among a basket of J.P. Morgan tradable indices



Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg.

Figure 98: Rolling 52-week average correlation among risky asset portfolio of US equities, US credit, commodities and REIT



Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg.

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

We further apply the eight portfolio allocation methods in the previous sections to the above 14 tradable indices during the out-of-sample period Jan 2001-Dec 2012. For risk model estimates, we used trailing 12-month returns, trailing 60-day realized volatility, and trailing 1-year correlations, and applied a volatility target of 5%.

Table 43 below summarizes the performance (before commissions and spreads) and risk metrics for different allocation methods, and compares them with Traditional Equities, Bonds and a Hedge Fund Index[47].

Table 43: Performance-Risk metrics for portfolio allocation methods, with Equity, Treasury bond and Hedge Fund beta, during 2001-2012

	EW	EMV	MVO	GMV	MDP	RP	RB	BL	Equity	Bonds	Hedge Funds
Average (%)	15.9	18.1	21.3	17.1	19.7	19.3	20.3	19.5	1.9	2.8	3.7
CAGR (%)	17.0	19.5	23.3	18.3	21.4	20.9	22.1	21.2	0.5	2.7	3.5
STDev (%)	5.0	5.0	5.4	4.6	5.5	5.2	5.4	5.2	16.8	3.1	6.4
MaxDD (%)	-2.1	-2.7	-4.0	-6.3	-4.6	-5.0	-3.4	-4.4	-55.8	-5.5	-24.4
MaxDDur (in yrs)	0.3	0.2	0.2	0.3	0.3	0.3	0.3	0.3	5.2	3.3	3.1
Sharpe Ratio	3.2	3.6	4.0	3.7	3.6	3.7	3.8	3.7	0.1	0.9	0.6
Sortino Ratio	11.1	13.0	13.8	10.5	12.8	12.5	14.4	13.0	0.2	1.5	0.8
Calmar Ratio	9.1	12.5	13.4	16.9	12.6	12.5	14.0	12.3	0.1	0.8	0.4
Pain Ratio	91.1	120.5	166.6	100.1	109.5	115.9	140.9	122.2	0.1	2.1	0.8
Reward to 95VaR	1.1	1.6	2.0	1.7	1.7	1.7	1.8	1.7	0.0	0.2	0.1
Reward to 95CVaR	0.8	0.9	1.0	0.9	1.0	0.9	1.0	1.0	0.0	0.2	0.1
Hit Rate	82.6%	88.2%	88.9%	86.8%	85.4%	86.8%	87.5%	86.8%	56.3%	61.8%	62.5%
Gain to Pain	11.7	14.8	17.4	13.3	13.9	14.7	17.1	15.2	1.1	1.9	1.5
Skewness	0.1	-0.1	-0.3	-0.6	-0.1	-0.2	-0.1	-0.2	-0.7	0.0	-0.9
Kurtosis	0.2	-0.1	0.7	1.8	0.1	0.5	0.0	0.4	1.4	-0.1	1.9
Correl with Equity	10.3%	9.5%	17.5%	28.5%	16.9%	16.1%	14.0%	15.5%	100.0%	-32.7%	87.6%
Correl with Bond	35.7%	42.0%	28.5%	37.5%	37.3%	42.4%	41.3%	41.8%	-32.7%	100.0%	-34.0%
CoSkew with Equity	-0.2	-0.3	-0.3	-0.5	-0.3	-0.4	-0.3	-0.4	-0.7	0.1	-0.7
CoSkew with Bond	-0.1	-0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	0.0	0.0
CoKurt with Equity	-2.6	-2.3	-2.3	-0.9	-1.7	-1.7	-2.0	-1.8	1.4	-3.9	0.9
CoKurt with Bond	-1.9	-1.8	-2.1	-1.8	-1.9	-1.8	-1.7	-1.8	-3.8	-0.1	-4.0

Source: J.P. Morgan Quantitative and Derivatives Strategy.

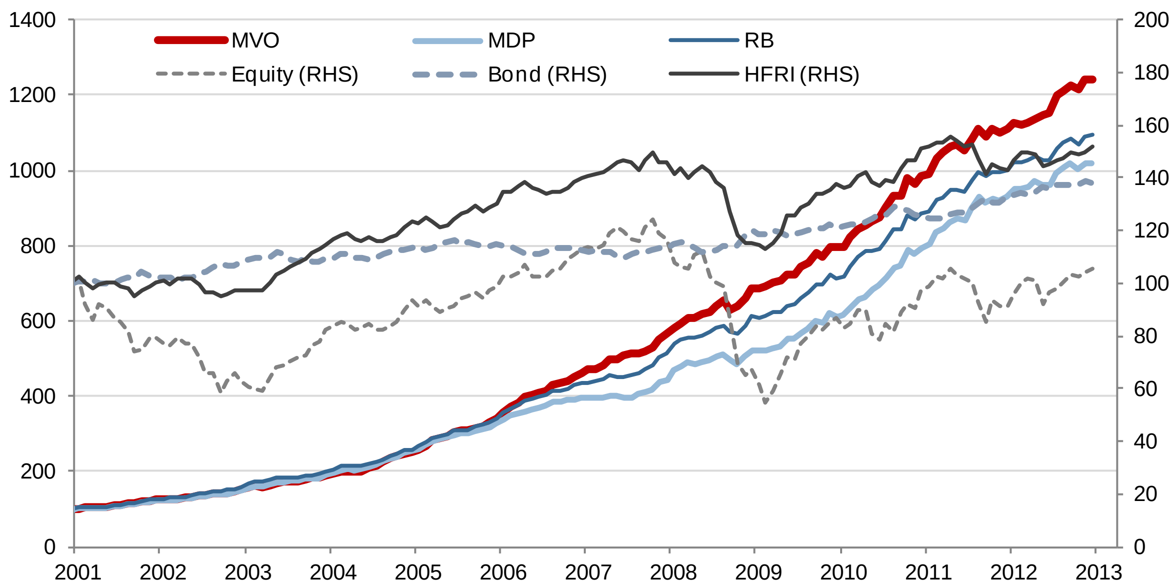
During 2001-2012, a risk-managed portfolio of J.P. Morgan alternative indices achieved attractive risk-reward profiles. The MVO portfolio generated the highest return (+23.3%) and Sharpe ratio (4.0) with only a -4% maximum drawdown during this twelve-year period including the 2007-08 Global Financing Crisis.

Comparatively, global equities, bonds and hedge funds annual returns were +0.5%, +2.7% and +3.5%, with maximum draw-downs of -55.8%, -5.5% and -24.4%, respectively, The Gain-to-Pain ratio for the MVO portfolio was very high at 17.4, compared to 1.1, 1.9 and 1.5 for global equities, bonds and hedge funds.

The overall strong outperformance of alternative indices (relative to traditional assets) was primarily due to uncorrelated yield (alpha) as well as the 'bond' bias in the original selection of risk factors. For example, the full sample correlation of the portfolios with bonds was highly significant, with the Risk-Parity (RP) portfolio 42% correlated to Bonds.

[47] We use MSCI All-Country World Net total return index (NDDUWI Index) minus cash yield for global equity beta, J.P. Morgan Global Aggregate Bond total return Index (JHDCGBIG Index) minus cash yield for global bond beta, and HFR Weighted Composite Hedge Fund Index (HFRIFWI Index) minus cash yield for global hedge fund beta.

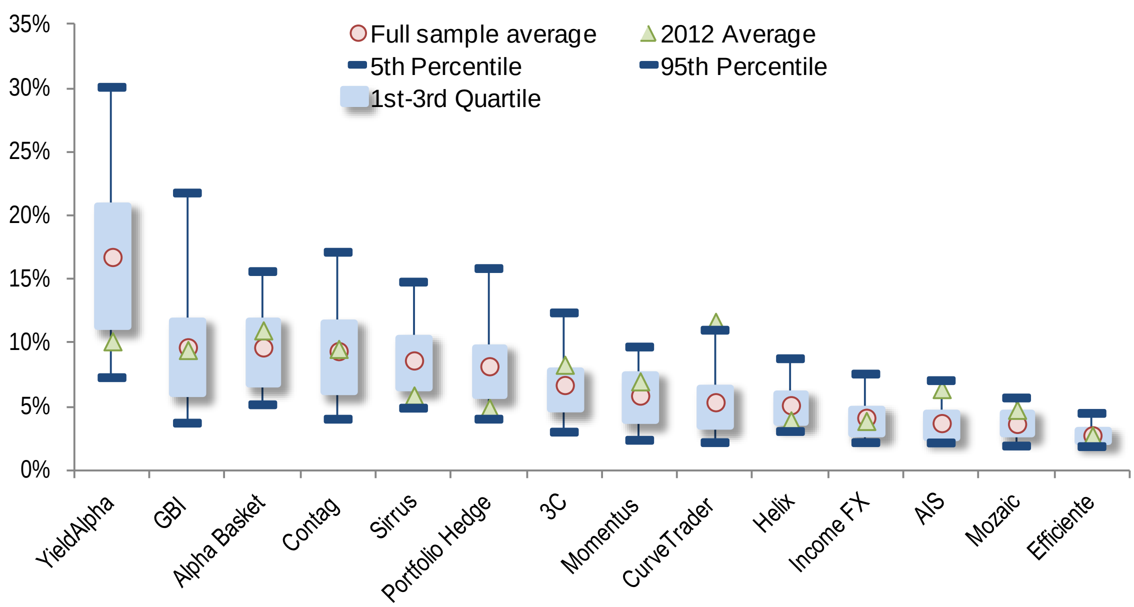
Figure 99: Performance (before commissions and spreads) of risk managed portfolios of J.P. Morgan risk factor Indices (left hand side) compared with Equities, Bonds and Hedge Funds (right hand side)



Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg. * Past performance is no indication of future results.

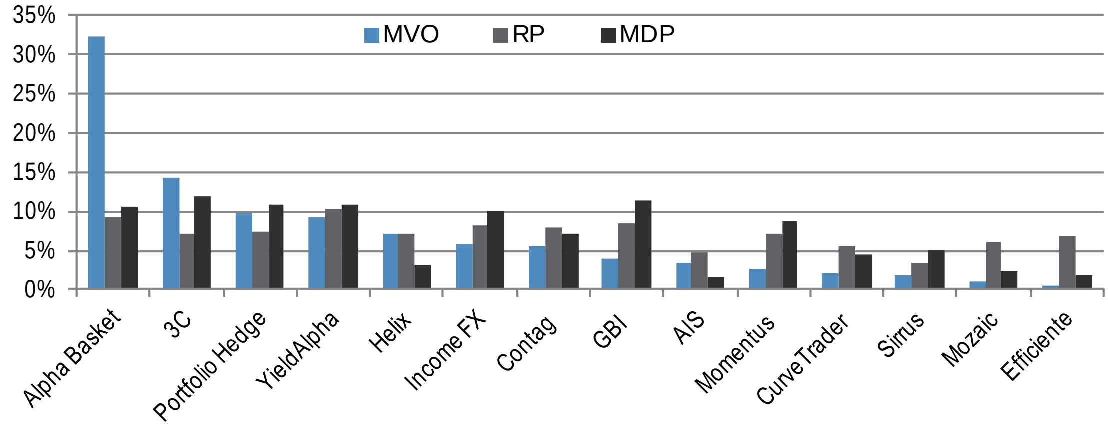
Figure 100 shows the allocation weights for the Risk-Parity portfolio, and Figure 101 ex-post total contribution to risk for each of the factors (for RP, MDP, MVO).

Figure 100: Statistical distributions of the unlevered weights of the assets for a Risk Parity Portfolio during 2001-2012



Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg

Figure 101: Ex-post Total Risk Contribution for a portfolio of J.P. Morgan tradable indices



Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg. *Statistics were calculated during the out-of-sample period from Jan 2001 to Dec 2012.

From the total risk allocation chart, we can see that MVO out-performance was in part due to the allocation of risk towards the best-performing index (Alpha Basket), and was further helped by the stable returns and correlations of alternative indices over the backtest sample. Despite the high risk-adjusted performance of MVO, we would prefer a method with a more balanced allocation of risk (such as RP). Concentrated allocations to individual strategies can introduce idiosyncratic risks – should the overweighted factor fail to deliver past returns, MVO would likely underperform other models.

To confirm the risk managed portfolio indeed generated alpha, we perform two regression analyses while controlling for the systematic factors contributing to the portfolio return. In the first regression, the excess return of the MVO portfolio is regressed on the Fama-French (2012) four factors of global equities, plus the excess return of J.P. Morgan Global Government Bond Index (the global Bond factor) and the excess return of J.P. Morgan EMBI Global Index (the global EM/Credit factor).

In the second regression, we replaced the Fama-French, Bond and Credit factors with Traditional, Carry, Momentum, Value and Volatility factors. Each factor is an equal marginal volatility (EMV) weighted index on cross-asset factors within each style during the period Jan 2001 to Dec 2012.

Table 44: Regression of MVO portfolio of J.P. Morgan tradable indices on Fama-French Global four factors, plus Global Bond and Credit factors

	Alpha	Mkt-RF	SMB	HML	WML	GBI	EMBI
Coefficients	1.56	0.04	0.01	0.00	0.00	0.42	0.14
t-Stat	11.64	1.37	0.15	0.09	0.02	2.94	3.13

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 45: Regression of MVO portfolio of J.P. Morgan tradable indices on Cross Asset Systematic Style factors

	Alpha	Traditional	Carry	Momentum	Value	Volatility
Coefficients	1.57	0.33	0.08	0.37	0.20	-0.24
t-stats	12.15	4.64	0.72	4.07	1.54	-2.20

Source: J.P. Morgan Quantitative and Derivatives Strategy.

In both cases, the Alpha component was the most statistically significant contribution. The MVO portfolio also had significant positive exposures to Bond factors, as well as to Traditional and Momentum factors in the second regression. Exposure to volatility was negative, a likely result of long bond exposure. In addition to alpha, strong and persistent (momentum) performance of bonds over the sample period contributed to the strong performance of the specific choice of J.P. Morgan risk factor indices. In the Appendix of the report, we provide a comprehensive list of traditional and alternative investable risk factor indices published by J.P. Morgan.

Appendices

J.P. Morgan Investment Strategies Research

Over the past decade, the cross-asset research teams at J.P. Morgan have put together a rich collection of papers on traditional as well as cutting edge issues related to Cross-Asset Systematic Strategies. Table 46 below maps the number of our research papers into the Asset Class versus Factor Style matrix for easy reference of the readers who may be interested in a particular topic such as Currency Carry or Multi Asset Momentum.

Table 46: List of J.P. Morgan Research Papers on Cross Asset Systematic Strategies

JPM Paper No.	Traditional Beta	Carry	Value	Momentum	Volatility	Multi-Strategy
Equities	9, 23, 78, 83, 103	21, 68, 96, 103	11, 16, 38, 52, 58, 66, 78, 79, 81, 84, 85, 87, 91, 94, 95, 103, 104	14, 26, 35, 41, 42, 53, 56, 58, 65, 69, 79, 89, 90, 103, 104	28, 51, 75, 85, 86, 88, 99, 101, 103	9, 11, 14, 16, 21, 26, 35, 38, 41, 42, 52, 53, 56, 58, 65, 66, 69, 78, 79, 80, 87, 88, 91, 92, 93, 97, 100, 101, 102, 103, 104
Rates	9, 18	15, 21, 31	2, 5, 11, 13, 16, 22, 64, 66, 72	14, 27, 32, 34, 35, 43, 48, 65, 67, 69	51, 75, 88, 99, 101	2, 5, 11, 14, 16, 18, 21, 32, 39, 43, 65, 66, 67, 69, 72, 74, 101
Credit	9, 19, 20, 49, 63, 70, 85	21, 36, 50	1, 11, 29, 30, 37, 38, 52, 64, 71, 81	14, 35, 44, 69, 76	24, 51, 75, 88, 99, 101	1, 9, 11, 19, 20, 29, 30, 39, 45, 61, 69, 76, 101
Currencies	9, 17, 60, 62	12, 21, 33, 77	3, 4, 6, 7, 8, 10, 55, 66	14, 35, 69	51, 75, 88, 99, 101	3, 4, 6, 7, 8, 9, 10, 17, 21, 33, 39, 47, 60, 62, 101
Commodities	9, 23, 73	21, 54, 68	59, 10	14, 25, 35, 40, 59, 69	51, 75, 88, 99, 101	9, 21, 23, 39, 40, 54, 59, 68, 69, 101
Volatility	9, 24, 28, 88, 99	21, 75, 88	24, 28, 82, 86, 88, 95	14, 35, 69, 88	51, 75, 88, 99, 101	24, 28, 39, 79, 85, 88, 104
Multi Asset	9, 17, 18, 19, 23, 24, 28, 39, 46, 57, 70, 95	12, 15, 21, 31, 33, 39, 54, 68, 75, 77	1-8, 10, 11, 16, 38, 39, 52, 65, 66, 95	14, 25, 26, 27, 35, 39, 41, 42, 43, 44, 51, 69	24, 28, 39, 51, 75, 88, 99, 101	9, 10, 11, 14, 16, 21, 23, 35, 38, 39, 51, 52, 65, 66, 68, 69, 70, 81, 88, 101

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 47 below lists all our previous investment strategy papers according to the paper numbers.

Table 47: List of J.P. Morgan Research Papers on Cross Asset Systematic Strategies

Publication Date (dd/mm/yyyy)	Headline	Abstract/Highlights
10/12/2013	Investment Strategies No. 104: Market Impact of Derivatives Hedging - Weekly Patterns	Investigates the impact of expiry week delta hedging and month-end asset rebalances on weekly S&P 500 price patterns. Also included is a 'momentum-enhanced' S&P 500 overwriting strategy that mitigates this market impact.
10/12/2013	Investment Strategies No. 103: Equity Factor Reference Handbook	A compilation of quant factor reference books across the US, Europe, Asia ex-Japan, Australia and GEM regions.
10/12/2013	Investment Strategies No. 102: Equity Risk Timing	These reports provide the ingredients for building a Market Timing tool. A direct implementation of this is dynamic Beta neutralization using a risk timing model.
10/12/2013	Investment Strategies No. 101: Risk Methods	Looks at risk-based portfolio construction approaches and suggests changes to improve risk adjusted returns. Also included is a deep-dive into the J.P Morgan Risk Platform.

10/12/2013	Investment Strategies No. 100: Equity Factor Rotation Models	Research on topics such as style switching, regime timing, macro factor rotation and dynamic factor rotation modeling.
10/12/2013	Investment Strategies No. 99: Cross-Asset Correlations	Examines the reasons behind the rise in cross-asset correlations, such as central bank monetary stimulus. We also show how to implement cross-asset views directly through OTC “hybrid” derivatives.
10/12/2013	Investment Strategies No. 98: Trading Equity Correlations	Investigate the reasons behind recent high levels of correlation and explains how dispersion trading can be used to capture correlation risk premium.
10/12/2013	Investment Strategies No. 97: Event-Driven Equity Factors	These reports investigate underlying equity returns following various event-driven catalysts, such as changes in dividend policies, and M&A announcements.
10/12/2013	Investment Strategies No. 96: Dividend Yield Factors	We show how volatility can be reduced substantially by the integration of Dividend Yield as a Factor in Quant models. The reports also explore a new Factor classified as ‘Shareholder Yield’ in academic papers.
10/12/2013	Investment Strategies No. 95: Investing in Dividend Swaps	Analyzes opportunities in global dividends and discusses the market, mechanics, long-term economic drivers and uses of dividend swaps.
10/12/2013	Investment Strategies No. 94: Equity Value Factors	Focuses on identifying effective equity valuation factors and includes analysis that shows that expensive P/E stocks are better short candidates from a valuation-based perspective.
10/12/2013	Investment Strategies No. 93: Equity Country Selection	Details the development of a quantitative model which aims to select between emerging markets. Also included is analysis on the growing relevance of sector selection in Asia and GEM.
10/12/2013	Investment Strategies No. 92: Equity Sector Models	Macro domination of stock returns has been a recurring theme since the financial crisis. These reports focus on factors and investment styles to be considered in building a successful sector allocation model.
10/12/2013	Investment Strategies No. 91: Equity Quality Factors	We investigate how various equity factors, such as Return on Equity and Accruals, can be augmented to contribute to quantitative alpha.
10/12/2013	Investment Strategies No. 90: Earnings Factors	Examines the relationship between Earnings Momentum and Price Momentum and outline s strategies that can be developed to improve earnings-based signals. Also included is an analysis of how investing based on changes in analyst target prices has proved to be a profitable strategy.
10/12/2013	Investment Strategies No. 89: Equity Momentum	Reviews various enhancements to a basic Price Momentum strategy. Also includes a backtest of the Trend Factor in various markets to understand the effect of momentum on stock returns.

10/12/2013	Investment Strategies No. 88: Signals from Options Markets	Illustrates how signals from the options market, such as implied volatility skew, can be used to improve risk management of a portfolio.
10/12/2013	Investment Strategies No. 87: Equity Factor Seasonality	Examines the impact of implementing periodic seasonality in Factor returns. A seasonality-based trading model can work as a stand-alone strategy as well as be integrated into a Multi-Factor model framework.
10/12/2013	Investment Strategies No. 86: Equity Volatility Value - Range Bound Model	The Range-Bound report ranks stocks that, relative to their volatility, appear likely to remain in a tight trading range. These mean reverting stocks make good candidates for selling options via range bound strategies such as straddles, strangles, or call overwrites.
10/12/2013	Investment Strategies No. 85: Investing in Convertible Bonds	Looks at the impact of convertibles on the performance of underlying equities. Also included is a screen that provides a list of convertibles that can be used as additions (or substitutes) to bond and stock portfolios to either enhance yield, provide equity upside, or hedge downside risk.
10/12/2013	Investment Strategies No. 84: Equity Pairs Trading	Discusses the various methods of identifying pairs, noting the need to avoid spurious correlations. Also included is a sample trade triggered by the Pairs Trade Model.
10/12/2013	Investment Strategies No. 83: Equity Indexation Strategies	These reports analyze the performance of stocks following their inclusion in or exclusion from (globally accepted) benchmarks. Also included in this compilation is our annual Index Handbook – an overview of passive indexation, a summary of index methodologies employed by major index providers and a detailed schedule of index rebalance events every year.
10/12/2013	Investment Strategies No. 82: Equity Volatility Value - RV Model	The Relative Value (RV) Score is a quantitative framework for screening relative value opportunities in single stock volatility based on a combination of fundamental and technical factors.
10/12/2013	Investment Strategies No. 81: Equity - Credit Factors	CDS spreads have gained widespread acceptance as an important indicator of distress and more specifically of credit risk. These reports analyze the impact of single-name CDS on stock returns and the impact of credit ratings on stock performance.
10/12/2013	Investment Strategies No. 80: Equity Multi-factor Models	We introduce the Q-Snapshot - a standardized, easy-to-read summary of Quantitative metrics condensed into an overall company Q-score from a universe of more than 3,000 listed companies in Europe.
10/12/2013	Investment Strategies No. 79: Market Impact of Derivatives Hedging - Daily Patterns	This compilation of reports estimates the market impact of gamma hedging of derivative products (options and levered ETFs) and discusses how to construct systematic trading strategies around this.
31/10/2013	Investment Strategies No. 78: A country model for equities	We develop a trading model for allocating between 16 major equity markets across both DM and EM. We find that changes in manufacturing PMIs, changes in exchange rates, and value, proxied by the price-to-cashflows ratio, generate profitable signals for rotating between countries.
18/01/2013	Investment Strategies No. 77: Optimizing FX reserve management	Central bank reserve managers hold almost $11tr of FX reserves. Currently, their portfolio likely yields around 30bp, likely well below funding costs for many from EM, and thus raising pressure to seek better returns.
12/12/2012	Investment Strategies No. 76: Using review ratios to trade corporate credit	We analyze US and European credit investment strategies based on rating review ratios.

28/11/2012	Investment Strategies No.75: Risk Premia in Volatility Markets	We find that we can enhance the performance of volatility carry strategies. These carry strategies exploit the difference between implied and realized volatility via trading variance swaps, delta-Risk Management straddles or similar payoffs.
2/10/2012	Investment Strategies No. 74: Simple rules to trade duration	In this paper, we describe a range of simple systematic rules for trading duration, through futures on 10-year US, German, Japanese and UK government bonds. These rules provide a complement to more qualitative and discretionary judgments on...
11/7/2012	Investment Strategies No. 73: Gold in asset allocation	There is no consensus on how much gold you should own in your portfolio. Some investors hold a lot. Most hold nothing. In this paper, we take an asset allocation approach to assess how much gold one should hold strategically in a portfolio that...
9/3/2012	Investment Strategies No. 72: Exploiting reversals in cross-market yield spreads	Overweighting duration in markets where yield curves have steepened most, against those where curves have steepened least, would have produced a return to risk of up to 0.9, net of transactions costs, across DM swap markets since 1995, with little...
13/02/2012	Investment Strategies No. 71: Trading Rich / Cheap Signals in EM Sovereigns & Corporates	We introduce a simple and intuitive method for highlighting relative value among Emerging Markets Sovereign and Corporate US$-denominated bonds of an issuer
13/02/2012	Investment Strategies No. 70: Playing Away from Home in the Credit markets	Investing in a different currency exposes an investor to large foreign exchange risk which they may be unwilling to bear. We show that simple hedging strategies involving either FX swaps or cross currency basis swaps allow investors to remove most of their foreign currency exposure.
12/1/2012	Investment Strategies No. 69: REVISITING: Using the Global PMI as trading signal	In Sep 2009, we published a trading rule that goes long Global Cyclical vs. Defensive sectors if the Global Manufacturing PMI improves and vice versa. Out of sample, since mid 2009, this trading rule has performed well but only when using the...
9/12/2011	Investment Strategies No. 68: Commodity Equities or Futures?	Measures of relative value/carry of commodity equities and commodity futures are reliable signals when deciding whether to be long commodity equities or futures. Relative carry is determined by the shape of the futures curves and yield measures of...
16/11/2011	Investment Strategies No. 67: Using unemployment to trade bonds	Unemployment rates provide a profitable signal for trading government bonds. Overweighting government bonds in countries where unemployment is rising most against those where unemployment is rising least would have produced a return to risk of up...
24/06/2011	Investment Strategies No. 66: Trading the US vs. Europe	We develop a set of fair value and trading models for allocating between US and Euro assets. We find that fundamental variables provide profitable low-frequency trading signals for trading the 10-year US-EU swap rate difference, the relative equity...
28/03/2011	Investment Strategies No. 65: Trading on economic data releases: What works? What does not?	We examine the profitability of a range of signals for trading stock and bond markets in a half-hour window around major US data releases. Basic models can predict data surprises, but this is not exploitable for trading as the market seems to...

9/2/2011	Investment Strategies No.64: Evaluating bond markets in a world of rising debt	We assess the relative riskiness of 19 different bond sectors, i.e. sovereign, local government, bank and corporate, based on 6 universal metrics: debt/income, interest expense/income, yield volatility, debt redemptions/debt, foreign ownership,...
26/01/2011	Investment Strategies No. 63: CDS Options Strategies - Strategies for every investor	CDS options are liquid, high volume products that provide attractive investment opportunities for many classes of investor. Typical trades include buying out-of-the-money payer options and selling receiver options (asset managers), hedging against...
10/1/2011	Investment Strategies No. 62: Tail-risk hedging with FX options	In this study we assess the empirical efficiency of using FX option strategies to Risk Management against market tail risk events We extract a benchmark set composed of 12 currency pairs most reactive to risk markets A comparison of various option strategies...
18/11/2010	Investment Strategies No. 61: Sector rotation in corporate bonds	A strategy that rotates between US Cyclical and Defensive corporate bond sectors using the Global PMI new orders-to-stock ratio produced a return-to-risk of 1.1 since 2000. Momentum is also useful but only in absolute return, not relative....
28/05/2010	Investment Strategies No. 60: Managing FX Risk Management ratios - A framework for strategic and tactical decisions	Unprecedented volatility over the past two years has heightened investor and corporate attention towards managing FX Risk Management ratios. For investors, four issues predominate: (1) how to determine the long-term, optimal Risk Management ratio; (2) how to time...
28/10/2009	Investment Strategies No. 59: Economic and Price Signals for Commodity Allocation	Economic activity signals, such as global IP growth and global manufacturing PMI, are leading indicators of future commodity performance. Simple rules that use economic activity signals have performed well in the past decade, delivering Sharpe...
8/9/2009	Investment Strategies No.58: Trading Cyclical vs Defensive equity sectors	A trading rule that goes long Global Cyclical vs Defensive sectors if the global manufacturing PMI new orders-to-stocks ratio rises and vice versa, produced a good information ratio of 0.65 since 1998. The global PMI has also provided a profitable...
22/06/2009	Investment Strategies no. 57: Longevity Risk and Portfolio Allocation	The value of pension fund and life annuity liabilities increases with life expectancy. These institutions are in effect short longevity. Longevity-linked securities, such as mortality forwards and longevity swaps, allow these institutions to...
29/04/2009	Investment Strategies No. 56: The EM vs Developed Markets equity allocation	A return momentum strategy that goes long EM equities vs Developed Markets (DM) if the former outperformed in the previous 2 months and vice versa, produced an information ratio of 0.86 since 1988 An economic momentum strategy based on the...
29/04/2009	Investment Strategies No. 55: Trading and Hedging Long-Term FX Fundamentals	At the beginning of April, G10 currencies were misaligned by nearly 10% on average against the USD, with EUR and JPY crosses misaligned by more than 12% and 14% on average. Misalignments are statistically and economically significant in predicting...
24/04/2009	Investment Strategies no. 54: Profiting from slide in commodity curves	The slope of the futures curve is a profitable signal for long-short strategies on commodities futures contracts. The slope of the curve also helps in deciding where along the curve to position. Simple strategies have information ratios around 1.5...

26/02/2009	Investment Strategies No. 53. Combining Directional and Sector Momentum	We use a simple directional momentum signal to determine whether to invest in the long-only or the long-short sector momentum strategy, and obtain Sharpe ratios of up to 0.9 since 1996 vs 0.0 for the MSCI World index.
24/11/2008	Investment Strategies No 52: Macro Credit-Equity Trading	We introduce a top down framework that expands JPMorgan's Credit-Equity CEV model to analyze the relationship between the Euro Stoxx 50 Index and iTraxx Main. The JPM CEV model uses equity prices and volatility surfaces to calculate default...
20/11/2008	Investment Strategies No 51: Volatility signals for asset allocation	Deleveraging in periods of high volatility, and releveraging in periods of low volatility, i.e., risk-budgeting, generates higher risk-adjusted returns with lower tail risk for equities, commodities, and bonds.
25/09/2008	Investment Strategies No. 50: Timing carry in US municipal markets	Simple economic signals - level of carry, monetary policy expectations, and momentum - help in timing the profitability of muni carry trades
3/9/2008	Investment Strategies No. 49: Hedging Default Risk in Portfolios of Credit Tranches	As default concerns rise, credit tranche investors need to know if their books have name concentrations that expose them to large losses from multiple defaults.
14/08/2008	Investment Strategies No. 48: Global bond momentum	An equally-weighted basket of individual bond momentum strategies across countries produces high information ratios of up to 1.2
8/8/2008	Investment Strategies No. 47: Alternatives to standard carry and momentum in FX	Carry and momentum are the most commonly followed trading strategies in currency markets, and probably in any asset class.
29/07/2008	Investment Strategies No. 46: Hedging Illiquid Assets	Illiquidity distorts relative price relationships, playing havoc with hedging strategies that work smoothly in liquid markets.
2/6/2008	Investment Strategies No. 45: Active Strategies for 130/30 Emerging Markets Portfolios	The 130/30 class of portfolios present opportunities for investment managers to grow their assets under management
13/05/2008	Investment Strategies No. 44: Momentum in Emerging Markets Sovereign Debt	Momentum in Emerging Markets is particularly pervasive because of difficulty in assessing value and higher information search costs across various economies, in our opinion
20/05/2008	Investment Strategies No. 43: Trading the US Curve	Monetary policy momentum, curve momentum, positions on 10y UST and economic sentiment are profitable signals in trading the US curve
19/05/2008	Investment Strategies No. 42: Cross-momentum for EM equity sectors	We find evidence of momentum in EM equity sectors, but it is more profitable to invest across EM sectors according to past global sector performance
9/5/2008	Investment Strategies No. 41: Momentum in Global Equity Sectors	Active momentum-based strategies in global equity sectors offer high returns to risk, and perform well in both bull and bear markets; Buying the top-third performing global sectors over the past year outperforms an equal sector allocation by...
29/04/2008	Investment Strategies No. 40: Optimizing Commodities Momentum	We show that dynamic mean-variance optimization enhances the return to risk of commodities momentum strategies
10/3/2008	Investment Strategies No. 39: Risk Management Fund Alternatives	We analyze the pros and cons of Risk Management fund replication and rule-based investing.
12/12/2007	Investment Strategies No. 38: A Framework for Credit-Equity Investing	The relationship between Credit and Equity markets is an important signal for both markets but not simple to capture.

10/10/2007	Investment Strategies No. 37: Learning Curves - Curve Trading Using Model Signals	In this note we analyze our model for predicting the steepness of single name CDS curves and test the effectiveness of its predictions.
25/09/2007	Investment Strategies No. 36: Carry-to-Risk Credit Indices	Credit Carry-to-Risk is a relative value framework for comparing credits. It aims to highlight value across different credits by identifying those that provide the highest Carry (income return) for the Risk taken (volatility of return).
7/8/2007	Investment Strategies No. 35: Markowitz in tactical asset allocation	Classical mean variance portfolio optimization, conceived by Harry Markowitz in 1952, is used frequently for long-term strategic asset allocation, but not for tactical asset allocation.
2/8/2007	Investment Strategies No. 34: A simple rule to trade the curve	The strategy: invest in flatteners when central banks tighten and steepeners when central banks ease, look for carry when policy rates are on hold
9/7/2007	Investment strategies No. 33: Rotating Between G-10 and Emerging Markets Carry	Carry trade performance has been impressive this year, both for G-10 and emerging market currencies.
17/05/2007	Investment Strategies No. 32: Momentum in Money Markets	Momentum-based trading strategies offer attractive risk-adjusted returns on Euro area and US money markets.
11/1/2007	Investment Strategies No. 31: Exploiting carry with cross-market and curve bond trades	The strategy: enter into a spread trade-cross market or curve- that offers the highest carry-to-risk
17/11/2006	Investment Strategies No.30: Relative Value in Tranches II	In this short note we apply the results from our return-to-risk analysis for tranches
17/11/2006	Investment Strategies 29: Relative Value in Tranches I	We have developed an approach to analyze return-to-risk in tranches. We think this framework can be used to identify long-short tranche trade opportunities in general and tranche curve trades in particular.
17/11/2006	Investment Strategies No 28: Variance Swaps	Variance swaps offer straightforward and direct exposure to the volatility of an underlying
10/11/2006	Investment Strategies Series No.27: Euro Fixed Income Momentum Strategy	Momentum-based strategies provide attractive risk-adjusted trading returns in European fixed income.
8/11/2006	Investment Strategy Series No. 26: Equity Style Rotation	We evaluate index-based equity style rotation strategies using momentum, valuations and macro data in the search for the most robust and profitable rules...
19/09/2006	Investment Strategies No. 25: Momentum in Commodities	Active momentum-based strategies in commodities offer high returns to risk and outperform passive investment in the asset class
3/8/2006	Investment Strategies No. 24: Trading Credit Volatility	The introduction of a liquid market in credit options has given investors the opportunity to trade volatility. By doing so, market participants have at their disposal a new strategy that can generate alpha in both volatile and range-bound markets
31/07/2006	Investment Strategies No. 23: Hedging Inflation with Real Assets	Rising inflation and the focus on pension underfunding are heightening interest in real assets, both as a Risk Management for broader market volatility (short-term investors) and to preserve purchasing power (long-term investors).
8/6/2006	Investment Strategies No. 22: Relative Value on Curve vs. Butterfly Trades	We show that slope spreads at the front end of the yield curve are highly correlated to fly spreads at the long end of the curve and vice-versa
19/05/2006	Investment Strategies: No. 21: Yield Rotator	The strategy: Buy the assets with the highest yield pickup per unit of risk against those with the lowest

5/4/2006	Investment Strategies No. 20: Trading Credit Curves II	Trading credit curves has become part of the standard repertoire for many credit investors. We introduce a framework to fully understand the factors impacting the P+L in curve trading.
5/4/2006	Investment Strategies No. 19 Trading Credit Curves I	We introduce our framework for understanding the P+L drivers in credit curve trades. This first note looks at the theory behind credit curves to set the foundations for our analysis.
28/03/2006	Investment Strategies No. 18: Index Linked Gilts Uncovered	A unique market within the inflation-linked universe. Investors should be aware of idiosyncrasies of this market.
23/03/2006	Investment Strategies No. 17: JPMorgan FX Hedging Framework	An intuitive, fundamental approach to analyzing medium-term currency risk across developed and emerging markets
17/03/2006	Investment Strategies No. 16: Bonds, Bubbles and Black Holes	We use the dividend discount model as a framework for considering the relative valuation of index linked bonds against equity. Our analysis suggests the stock-bond real-yield ratio should be around 2:1, at equilibrium. In the UK this yield ratio...
9/3/2006	Investment Strategies No. 15: A cross-market bond carry strategy	The strategy: buy the 10-year where carry is highest, against the market where it is lowest, currency Risk Management
8/2/2006	Investment Strategies No. 14: Exploiting Cross-Market Momentum	We propose an innovative strategy that achieves high returns with low risk by exploiting momentum in relative returns across a wide set of asset classes.
1/2/2006	Investment Strategies No. 13: Valuing cross-market yield spreads	Yields spreads and term premia across the curve have virtually disappeared in many markets as curves flattened. But the existence of still large yield spreads across countries points to large cross-market risk premia that one should try to exploit.
23/02/2005	Investment Strategies No. 12: JPMorgan Carry-to-Risk Primer	A simple, systematic and intuitive approach to analyze and invest in emerging market currencies. JPMorgan Emerging Market Carry-to-Risk Model provides a systematic approach to analyze expected risk-adjusted returns on currency positions.
26/01/2005	Investment Strategies No. 11: A Fair Value Model for US Bonds, Credit and Equities	This fair value model allows investors to translate a view on fundamentals into a view on markets
22/09/2004	Investment Strategies No. 10: JPMorgan's FX and commodity Barometer	JPMorgan's FX & Commodity Barometer is a multi-factor, signaling model for currency and metals markets. The model's chief enhancement over existing frameworks is the combination of indicator breadth and flexible weights.
7/1/2004	Investment Strategies No. 9: Which Trade?	Investors positioning across many markets face the question of which trade best expresses a given macro view, such as a change in growth, inflation or central bank expectations.
8/1/2003	Investment Strategies No.8: Alternative LCVI trading strategies	* Trading emerging-market currencies in line with LCVI signals generates very attractive returns even after transaction costs, albeit with greater volatility than FX CACI * Trading the three most liquid crosses among the G10 according to LCVI...
1/10/2002	Investment Strategies No.7: Using equities to trade FX: Introducing the LCVI	* Equities playing a bigger role as a driver of markets * LCVI adds the VIX - a measure of implied volatility in the equity market - to the LCPI * The LCVI generates higher returns and information ratios for our FX CACI trading basket

12/4/2002	Investment Strategies No.6: A Framework for Long-term Currency Valuation	This paper describes a framework for assessing currency valuation from a long-term point of view and for producing long-term currency forecasts that are consistent with fundamental historical relationships.
6/3/2002	Investment Strategies No. 5: Profiting from Market Signals	JPMorgan's Bond Barometer tracks four key market drivers: fundamentals, value, risk appetite and technical; and combines them into a single, directional signal on bonds.
24/01/2002	Investment Strategies No. 4: FX positioning with JPMorgan's exchange rate model	This paper introduces JPMorgan's methodology to measure expected Emerging Markets currency moves and evaluates trade performance based on such measures.
19/12/2001	Investment Strategies No. 3: New LCPI trading rules - Introducing FX CACI	FXCI returns fell during 2001 as yield differences narrowed. This paper shows that combining current accounts with yield differentials enhances returns and resolves issues. Shorting risk-appetite trades when LCPI shifts from risk-seeking to neutral...
6/12/2001	Investment Strategies No. 2: Understanding and trading swap spreads	This paper identifies the key driving factors of swap spreads (yield curve shape, budget expectations and risk aversion), and describes profitable trading rules to take advantage of the level of swap spreads and their future direction.
15/11/2001	Investment Strategies No:1: Rock-Bottom Spreads	The Investment Strategies series aims to offer new approaches and methods on investing and trading profitably in financial markets. The objective is to explain completely the methods and models behind the investment recommendations you are receiving...

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

J.P. Morgan Tradable Risk Factor Indices

J.P. Morgan Tradable Risk Factor Indices - Equities

Ticker	Index Name	JPM Family	Launch Date	Strategy Type	Asset Class	Regional Focus	Strategy Style	Risk Method	Curncy
ARJPEMU5	Emerging Mkts ARC 15% ER	Adaptive Risk Control	Dec-10	Enhanced Beta	Equities	Emerging Mkts	Traditional	Portfolio Level	USD
CIJPCAV2	China A-shares Vol controlled Index 20%	Risk Control	Feb-10	Enhanced Beta	Equities	Emerging Mkts	Traditional	Portfolio Level	HKD
CIJPCAVC	China A-shares Vol controlled Index 20%	Risk Control	Feb-10	Enhanced Beta	Equities	Emerging Mkts	Traditional	Portfolio Level	HKD
FTJGUSEE	US Equity Futures (G) Tracker	RollingFutures	Aug-09	Access Beta	Equities	Americas	Traditional	None	USD
FTJGUSSE	US Small Cap Equities Futures (G) Tracker	RollingFutures	Aug-09	Access Beta	Equities	Americas	Traditional	None	USD
FTJPUSEE	J.P. Morgan US Equity Futures	RollingFutures	Jun-09	Access Beta	Equities	Americas	Traditional	None	USD
FTJMCHEE	J.P. Morgan Swiss Equity Futur	RollingFutures	Jan-12	Access Beta	Equities	EMEA	Traditional	None	CHF
FTJFDEEE	J. P. Morgan German Equity Fut	RollingFutures	Jan-12	Access Beta	Equities	EMEA	Traditional	None	EUR
FTJGEUEE	European Equity Futures (G) Tracker	RollingFutures	Jun-09	Access Beta	Equities	EMEA	Traditional	None	EUR
FTJPEUEE	European Equity Futures Index	RollingFutures	Jun-09	Access Beta	Equities	EMEA	Traditional	None	EUR
RFJPEUEE	J.P. Morgan European Equity Futures Tracker	RollingFutures		Access Beta	Equities	EMEA	Traditional	None	EUR
FTJPEPEE	J. P. Morgan Pan European Equity Futures Tracker	RollingFutures	Oct-13	Access Beta	Equities	EMEA	Traditional	None	EUR
FTJGUKEE	J.P. Morgan UK Equity Futures (G) Tracker	RollingFutures		Access Beta	Equities	EMEA	Traditional	None	GBP
FTJPUKEE	UK Equity Futures Index	RollingFutures	Jun-09	Access Beta	Equities	EMEA	Traditional	None	GBP
RFJPUKEE	UK Equity Futures Tracker	RollingFutures	Jun-09	Access Beta	Equities	EMEA	Traditional	None	GBP
FTJMTREE	Turkish Equity Futures Tracker	RollingFutures	Nov-11	Access Beta	Equities	EMEA	Traditional	None	TRY
FTJMAUEE	J.P. Morgan Australian Equity Futures Tracker	RollingFutures		Access Beta	Equities	Asia	Traditional	None	AUD
FTJMHKEE	J.P. Morgan Hong Kong Equity Futures Tracker	RollingFutures		Access Beta	Equities	Asia	Traditional	None	HKD
FTJGJPEE	Japanese Equity Futures (G) Tracker	RollingFutures	Jun-09	Access Beta	Equities	Asia	Traditional	None	JPY
FTJPJPEE	Japanese Equity Futures Index	RollingFutures	Jun-09	Access Beta	Equities	Asia	Traditional	None	JPY
RFJPJPEE	Japanese Equity Futures Tracker	RollingFutures	Jun-09	Access Beta	Equities	Asia	Traditional	None	JPY
FTJMSKEE	J.P. Morgan Korean Equity Futures Tracker	RollingFutures		Access Beta	Equities	Asia	Traditional	None	KRW
FTJMSGEE	J.P. Morgan Singaporean Equity Futures Tracker	RollingFutures		Access Beta	Equities	Asia	Traditional	None	SGD
CIJPIDEE	J.P. Morgan Indian Equity Futures Tracker	RollingFutures	Aug-11	Access Beta	Equities	Emerging Mkts	Traditional	None	USD
FTJFEMUE	J. P. Morgan Emerging Mkts Futures Tracker (G)	RollingFutures		Access Beta	Equities	Emerging Mkts	Traditional	None	USD
FTJMEMUE	EM Futures Tracker	RollingFutures	May-12	Access Beta	Equities	Emerging Mkts	Traditional	None	USD
FTJPEAEE	J. P. Morgan International Equity Futures Tracker	RollingFutures	Oct-13	Access Beta	Equities	Multi Region	Traditional	None	USD

YAJPEBE8	JPM Equity Alpha 8 Broad EUR	YieldAlpha	Aug-08	Alternative Beta	Equities	Multi Region	Carry	Risk Optimizing	EUR
YAJPEEU2	Equity Alpha EUR	YieldAlpha	Aug-06	Alternative Beta	Equities	Multi Region	Carry	Risk Optimizing	EUR
YAJPEEU8	Equity Alpha 8 EUR	YieldAlpha	Aug-06	Alternative Beta	Equities	Multi Region	Carry	Risk Optimizing	EUR
YAJPEBJ8	Equity Alpha 8 Bunsan JPY	YieldAlpha	Aug-07	Alternative Beta	Equities	Multi Region	Carry	Risk Optimizing	JPY
YAJPEJP2	JPM Equity Alpha JPY Index	YieldAlpha	Aug-08	Alternative Beta	Equities	Multi Region	Carry	Risk Optimizing	JPY
YAJPEJP8	JPM Equity Alpha 8 JPY Index	YieldAlpha	Aug-08	Alternative Beta	Equities	Multi Region	Carry	Risk Optimizing	JPY
YAJPEBUX	Equity Alpha Broad X (USD)	YieldAlpha	Aug-08	Alternative Beta	Equities	Multi Region	Carry	Risk Optimizing	USD
YAJPEUS2	JPM Equity Alpha US Index	YieldAlpha	Aug-08	Alternative Beta	Equities	Multi Region	Carry	Risk Optimizing	USD
YAJPEUS8	Equity Alpha 8 USD	YieldAlpha	Aug-06	Alternative Beta	Equities	Multi Region	Carry	Risk Optimizing	USD
CIJPKAE5	Asia Pacific Equity Rotator Index (KRW)	Aero	Jan-12	Alternative Beta	Equities	Asia	Momentum	Portfolio Level	KRW
CIJPAER5	Asia Pacific Equity Rotator Index (USD)	Aero	Aug-11	Alternative Beta	Equities	Asia	Momentum	Portfolio Level	USD
CIJPAERO	J.P. Morgan Asia-Pacific Equity Rotator 10 Index	Aero		Alternative Beta	Equities	Asia	Momentum	Portfolio Level	USD
CIJPAEB5	Asian EM Equity Rotator 5	Aero	Mar-12	Alternative Beta	Equities	Emerging Mkts	Momentum	Portfolio Level	USD
AIJPMEUU	Equity Momentum US	AIS	Nov-09	Alternative Beta	Equities	Americas	Momentum	None	USD
AIJPMEEE	Equity Momentum Europe	AIS	Nov-09	Alternative Beta	Equities	EMEA	Momentum	None	EUR
AIJPMEJJ	Equity Momentum Japan	AIS	Nov-09	Alternative Beta	Equities	Asia	Momentum	None	JPY
SEJPML3S	Momentum (SEK) Index	Efficiente	Apr-11	Multi Type	Equities	Multi Region	Momentum	None	SEK
JPMZKRMO	J.P.Morgan Kronos Index - Momentum	Kronos	Jun-13	Alternative Beta	Equities	Americas	Momentum	None	USD
JPUSSCTE	J.P.Morgan U.S. Sector Rotator	SectorRotator	Jun-13	Alternative Beta	Equities	Americas	Momentum	None	USD
JPUSSC5E	J.P.Morgan U.S. Sector Rotator 5% Vol Budget	SectorRotator	Jun-13	Alternative Beta	Equities	Americas	Momentum	Portfolio Level	USD
AIJPCE1U	Equity Value Carry USD	AIS	Nov-09	Alternative Beta	Equities	Americas	Value	None	USD
AIJPCE2U	Equity Small Cap Carry US	AIS	Nov-09	Alternative Beta	Equities	Americas	Value	None	USD
AIJPSR1U	Mean Reversion US	AIS	Nov-09	Alternative Beta	Equities	Americas	Value	None	USD
AIJPSR1E	Mean Reversion Europe	AIS	Nov-09	Alternative Beta	Equities	EMEA	Value	None	EUR
AIJPSR1J	Mean Reversion Japan	AIS	Nov-09	Alternative Beta	Equities	Asia	Value	None	JPY
EQJPG2MU	Equity Edge Global Emerging Market (USD)	Equity Edge	Jan-11	Alternative Beta	Equities	Emerging Mkts	Value	None	USD
EQJPA1MU	Equity Edge Asia	Equity Edge	Oct-10	Alternative Beta	Equities	Asia	Value	None	USD
EQJPG1LU	Global Large Cap	Equity Edge	Oct-10	Alternative Beta	Equities	Multi Region	Value	None	USD
JPMZKRMR	J.P.Morgan Kronos Index - Mean Reversion	Kronos	Jun-13	Alternative Beta	Equities	Americas	Value	None	USD
AIJPSV1U	Satellite Short Volatility US	AIS	Nov-09	Alternative Beta	Equities	Americas	Volatility	None	USD
JPMZMHEN	J.P.Morgan Macro Hedge Enhanced	Macro Hedge	Dec-11	Multi Type	Equities	Americas	Volatility	None	USD
JPMZMHLO	Macrohedge Systematic Long Index	Macro Hedge	Mar-11	Multi Type	Equities	Americas	Volatility	None	USD
JPMZMHUS	Macrohedge Long-Short US	Macro Hedge	Aug-10	Multi Type	Equities	Americas	Volatility	None	USD

JPMZMHVC	J.P. Morgan Macrohedge US Curve	Macro Hedge	Dec-11	Multi Type	Equities	Americas	Volatility	None	USD
JPUSSTSL	JPM Strategic Volatility Long	Macro Hedge	Feb-12	Multi Type	Equities	Americas	Volatility	None	USD
JPUSSTVD	Strategic Volatility Dynamic Beta	Macro Hedge	Aug-12	Multi Type	Equities	Americas	Volatility	None	USD
JPUSSTVL	JPM Strategic Volatility Index	Macro Hedge	Jun-11	Multi Type	Equities	Americas	Volatility	None	USD
JPUSSTLF	Strat Vol Long Flat	Macro Hedge	May-11	Multi Type	Equities	Americas	Volatility	None	USD
JPMZVPUS	J.P.Morgan Macro Hedge Vepo US	Macro Hedge	Apr-12	Multi Type	Equities	Americas	Volatility	Portfolio Level	USD
JPMZVTU3	Macro Hedge Vega Target 3%	Macro Hedge	Jun-13	Multi Type	Equities	Americas	Volatility	Portfolio Level	USD
JPMZMHCE	J.P. Morgan Macrohedge Curve (EUR) Index	Macro Hedge		Multi Type	Equities	Multi Region	Volatility	None	EUR
JPMZMHH6	JP Morgan Macrohedge Hybrid Risk Control 6	Macro Hedge	Aug-11	Multi Type	Equities	Multi Region	Volatility	None	EUR
JPMZMHHT	J.P. Morgan Macrohedge Dual TR Index	Macro Hedge	Mar-12	Multi Type	Equities	Multi Region	Volatility	None	EUR
JPMZVEC5	J.P. Morgan Macrohedge Curve VT 5% (EUR)	Macro Hedge	Jul-13	Multi Type	Equities	Multi Region	Volatility	None	EUR
JPMZMHCL	J.P.Morgan Macro Curve LO USD	Macro Hedge	Jun-12	Multi Type	Equities	Multi Region	Volatility	None	USD
JPMZMHCO	J.P.Morgan Macro Curve LO Euro	Macro Hedge	Jun-12	Multi Type	Equities	Multi Region	Volatility	None	USD
JPMZMHCU	J.P. Morgan Macrohedge Curve	Macro Hedge	Feb-12	Multi Type	Equities	Multi Region	Volatility	None	USD
JPMZMHE6	JP Morgan Macrohedge Enhanced Risk Control 6 US	Macro Hedge	Mar-11	Multi Type	Equities	Multi Region	Volatility	None	USD
JPMZMHHG	J.P.Morgan Macrohedge Dual Enhanced	Macro Hedge	Mar-11	Multi Type	Equities	Multi Region	Volatility	None	USD
JPMZMHHY	Macrohedge Hybrid	Macro Hedge	Sep-10	Multi Type	Equities	Multi Region	Volatility	None	USD
JPMZVTC5	J.P. Morgan Macrohedge Curve VT 5% (USD)	Macro Hedge	Jul-13	Multi Type	Equities	Multi Region	Volatility	None	USD
JPMZVTD3	J.P. Morgan Macrohedge Dual VT 3% (USD)	Macro Hedge	Jul-13	Multi Type	Equities	Multi Region	Volatility	None	USD
JPMZVTD4	J.P. Morgan Macrohedge Dual VT 4% (USD)	Macro Hedge	Jul-13	Multi Type	Equities	Multi Region	Volatility	None	USD
JPTC80UL	TECH 80 Long Index	Tech 80	Aug-13	Hedging	Equities	Americas	Volatility	Option-based	USD
JPTC80UE	TECH US 80 Index	Tech 80	Aug-13	Hedging	Equities	Americas	Volatility	Option-based	USD
JPTC80UL	TECH US 80 Long Index	Tech 80	Aug-13	Hedging	Equities	Americas	Volatility	Option-based	USD
JPTC90UE	TECH US 90 Index	Tech 80	Aug-13	Hedging	Equities	Americas	Volatility	Option-based	USD
JPTC90UL	TECH US 90 Long Index	Tech 80	Aug-13	Hedging	Equities	Americas	Volatility	Option-based	USD
JPMZSSUS	Systematic Short Strangle European Equity Delta Hedge Mechanism Index	Volatility Strategies	Jun-13	Alternative Beta	Equities	Americas	Volatility	Portfolio Level	USD
JPMZSSEU	Systematic Short Strangle European Equity Delta Hedge Mechanism Index	Volatility Strategies	Jan-13	Alternative Beta	Equities	EMEA	Volatility	Portfolio Level	USD
JPVOLUSA	Volemont-US Equities	Volemont	May-13	Alternative Beta	Equities	Americas	Volatility	Portfolio Level	USD
JPVOLEMA	Volemont Asia Strategy	Volemont	Jun-12	Alternative Beta	Equities	Asia	Volatility	Portfolio Level	USD
JPVOLEEG	Volemont Global Strategy (EUR)	Volemont	Dec-12	Alternative Beta	Equities	Multi Region	Volatility	Portfolio Level	EUR
JPVOLEME	J.P. Morgan Volemont (EUR)	Volemont	Nov-11	Alternative Beta	Equities	Multi Region	Volatility	Portfolio Level	EUR
JPVOLEM6	J.P. Morgan Volemont Risk Cont	Volemont	Apr-12	Alternative Beta	Equities	Multi Region	Volatility	Portfolio Level	USD

JPVOLEMG	Volemont Global Strategy	Volemont	Dec-12	Alternative Beta	Equities	Multi Region	Volatility	Portfolio Level	USD
JPVOLEMO	J.P. Morgan Volemont Index	Volemont	Nov-11	Alternative Beta	Equities	Multi Region	Volatility	Portfolio Level	USD
JPVOLGU2	J.P. Morgan Volemont Global Series 2	Volemont		Alternative Beta	Equities	Multi Region	Volatility	Portfolio Level	USD
JPVOLGU3	J.P. Morgan Volemont Global Series 3	Volemont		Alternative Beta	Equities	Multi Region	Volatility	Portfolio Level	USD
YAJPVUS2	JPM Variance Alpha USD Index	YieldAlpha	Aug-08	Alternative Beta	Equities	Americas	Volatility	Risk Optimizing	USD
YAJPVUS8	Variance Alpha 8 USD	YieldAlpha	Aug-06	Alternative Beta	Equities	Americas	Volatility	Risk Optimizing	USD
JPMZKRNS	J.P.Morgan Kronos Index	Kronos	Jun-13	Alternative Beta	Equities	Americas	Multi Factor	None	USD

J.P. Morgan Tradable Risk Factor Indices - Rates and Credit

Ticker	Index Name	JPM Family	Launch Date	Strategy Type	Asset Class	Regional Focus	Strategy Style	Risk Method	Curncy
JPVUC210	2s10s Curve Index	Curve tracker	Jun-11	Access Beta	Rates	Americas	Traditional	None	USD
JPVEC2XU	EUR 2s-10s Curve Index	EUR Curve	Jan-00	Access Beta	Rates	EMEA	Traditional	None	USD
JPFSIEUR	European Funding Spread Index (FSI)	FSI	Jan-12	Multi Type	Rates	EMEA	Traditional	None	EUR
JPFSMUEU	FSI - Multiplicative in EUR	FSI	Feb-12	Multi Type	Rates	EMEA	Traditional	None	EUR
JPFSMUUS	FSI - Multiplicative in USD	FSI	Feb-12	Multi Type	Rates	EMEA	Traditional	None	USD
JPMGEMLC	EMU Government Bond Index (GBI)	GBI	Jan-01	Access Beta	Rates	EMEA	Traditional	None	EUR
JHDCGBIG	Global Government Bond Index (GBI)	GBI	Dec-89	Access Beta	Rates	Multi Region	Traditional	None	USD
JPINUS03	3Y USCPI ZC Swap Tracker in USD	Inflation Swap Trackers		Access Beta	Rates	Americas	Traditional	None	USD
JPINUS05	5Y USCPI ZC Swap Tracker in USD	Inflation Swap Trackers		Access Beta	Rates	Americas	Traditional	None	USD
JPINUS07	7Y USCPI ZC Swap Tracker in USD	Inflation Swap Trackers		Access Beta	Rates	Americas	Traditional	None	USD
JPINUS10	10Y USCPI ZC Swap Tracker in USD	Inflation Swap Trackers		Access Beta	Rates	Americas	Traditional	None	USD
JPINUS20	20Y USCPI ZC Swap Tracker in USD	Inflation Swap Trackers		Access Beta	Rates	Americas	Traditional	None	USD
JPINEU03	3Y HICPxT ZC Swap Tracker in EUR	Inflation Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	EUR
JPINEU05	5Y HICPxT ZC Swap Tracker in EUR	Inflation Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	EUR
JPINEU07	7Y HICPxT ZC Swap Tracker in EUR	Inflation Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	EUR
JPINEU10	10Y HICPxT ZC Swap Tracker in EUR	Inflation Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	EUR
JPINEU20	20Y HICPxT ZC Swap Tracker in EUR	Inflation Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	EUR
JPINGB03	3Y UKRPI ZC Swap Tracker in GBP	Inflation Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	GBP
JPINGB05	5Y UKRPI ZC Swap Tracker in GBP	Inflation Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	GBP
JPINGB07	7Y UKRPI ZC Swap Tracker in GBP	Inflation Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	GBP
JPINGB10	10Y UKRPI ZC Swap Tracker in GBP	Inflation Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	GBP

JPINGB20	20Y UKRPI ZC Swap Tracker in GBP	Inflation Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	GBP
JPINE03U	3Y HICPxT ZC Swap Tracker in USD	Inflation Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	USD
JPINE05U	5Y HICPxT ZC Swap Tracker in USD	Inflation Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	USD
JPINE07U	7Y HICPxT ZC Swap Tracker in USD	Inflation Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	USD
JPINE10U	10Y HICPxT ZC Swap Tracker in USD	Inflation Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	USD
JPINE20U	20Y HICPxT ZC Swap Tracker in USD	Inflation Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	USD
JPING03U	3Y UKRPI ZC Swap Tracker in USD	Inflation Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	USD
JPING05U	5Y UKRPI ZC Swap Tracker in USD	Inflation Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	USD
JPING07U	7Y UKRPI ZC Swap Tracker in USD	Inflation Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	USD
JPING10U	10Y UKRPI ZC Swap Tracker in USD	Inflation Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	USD
JPING20U	20Y UKRPI ZC Swap Tracker in USD	Inflation Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	USD
JFLFBA1C	Canadian Bank Bill 1st contract in CAD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	CAD
JFLFBA2C	Canadian Bank Bill 2nd contract in CAD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	CAD
JFLFBA3C	Canadian Bank Bill 3rd contract in CAD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	CAD
JFLFBA4C	Canadian Bank Bill 4th contract in CAD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	CAD
JFLFBA5C	Canadian Bank Bill 5th contract in CAD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	CAD
JFLFBA6C	Canadian Bank Bill 6th contract in CAD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	CAD
JFLFBA7C	Canadian Bank Bill 7th contract in CAD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	CAD
JFLFBA8C	Canadian Bank Bill 8th contract in CAD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	CAD
JFLFUS1E	Eurodollar 1st contract in EUR	RollingFutures		Access Beta	Rates	Americas	Traditional	None	EUR
JFLFUS2E	Eurodollar 2nd contract in EUR	RollingFutures		Access Beta	Rates	Americas	Traditional	None	EUR
JFLFUS3E	Eurodollar 3rd contract in EUR	RollingFutures		Access Beta	Rates	Americas	Traditional	None	EUR
JFLFUS4E	Eurodollar 4th contract in EUR	RollingFutures		Access Beta	Rates	Americas	Traditional	None	EUR
JFLFUS5E	Eurodollar 5th contract in EUR	RollingFutures		Access Beta	Rates	Americas	Traditional	None	EUR
JFLFUS6E	Eurodollar 6th contract in EUR	RollingFutures		Access Beta	Rates	Americas	Traditional	None	EUR
JFLFUS7E	Eurodollar 7th contract in EUR	RollingFutures		Access Beta	Rates	Americas	Traditional	None	EUR
JFLFUS8E	Eurodollar 8th contract in EUR	RollingFutures		Access Beta	Rates	Americas	Traditional	None	EUR
JFBU10GB	10Y Note in GBP	RollingFutures		Access Beta	Rates	Americas	Traditional	None	GBP
FTJFUTBE	JPM US 30Y Treasury Bond Futures Tracker (G)	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
FTJMUTBE	JPM US 30Y Treasury Bond Futur	RollingFutures	Jan-12	Access Beta	Rates	Americas	Traditional	None	USD
FTJPUS2E	J.P. Morgan 2-Year US Treasury notes Futures Tracker (Net)	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
RFJGUSBE	US Treasury Note Futures (G) Tracker	RollingFutures	Jun-09	Access Beta	Rates	Americas	Traditional	None	USD

RFJGUSME	US Money Market Futures (G) Tracker	RollingFutures	Aug-09	Access Beta	Rates	Americas	Traditional	None	USD
RFJPUS2E	US 2Y Treasury Note Futures Tracker	RollingFutures	May-09	Access Beta	Rates	Americas	Traditional	None	USD
RFJPUSBE	10Y US Treasury Note Futures Tracker	RollingFutures	Jun-09	Access Beta	Rates	Americas	Traditional	None	USD
JFLFUS1U	Eurodollar 1st contract in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JFLFUS2U	Eurodollar 2nd contract in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JFLFUS3U	Eurodollar 3rd contract in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JFLFUS4U	Eurodollar 4th contract in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JFLFUS5U	Eurodollar 5th contract in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JFLFUS6U	Eurodollar 6th contract in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JFLFUS7U	Eurodollar 7th contract in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JFLFUS8U	Eurodollar 8th contract in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JFLFBA1U	Canadian Bank Bill 1st contract in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JFLFBA2U	Canadian Bank Bill 2nd contract in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JFLFBA3U	Canadian Bank Bill 3rd contract in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JFLFBA4U	Canadian Bank Bill 4th contract in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JFLFBA5U	Canadian Bank Bill 5th contract in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JFLFBA6U	Canadian Bank Bill 6th contract in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JFLFBA7U	Canadian Bank Bill 7th contract in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JFLFBA8U	Canadian Bank Bill 8th contract in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JFBU2USD	2Y Note in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JFBU5USD	5Y Note in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JFBU10US	10Y Note in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JFBULBUS	Long Bond in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JFBUSBUS	Ultralong in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JPVU0210	USD 2s10s Curve Index in USD	RollingFutures		Access Beta	Rates	Americas	Traditional	None	USD
JPVUC210	USD 2s10s Curve Index, Vol Capped, in USD	RollingFutures		Enhanced Beta	Rates	Americas	Traditional	Risk Budgeting	USD
FTJMCHBE	J.P. Morgan Swiss Bonds Futures Tracker	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	CHF
JFLFSF1S	Euroswissie 1st contract in CHF	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	CHF
JFLFSF2S	Euroswissie 2nd contract in CHF	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	CHF
JFLFSF3S	Euroswissie 3rd contract in CHF	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	CHF
JFLFSF4S	Euroswissie 4th contract in CHF	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	CHF
JFLFSF5S	Euroswissie 5th contract in CHF	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	CHF

JFLFSF6S	Euroswissie 6th contract in CHF	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	CHF
JFLFSF7S	Euroswissie 7th contract in CHF	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	CHF
JFLFSF8S	Euroswissie 8th contract in CHF	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	CHF
FTJPEU2E	J P Morgan Euro Schatz Futures Tracker (Net)	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	EUR
RFJGEUBE	Euro Bund Futures (G) Tracker	RollingFutures	Jun-09	Access Beta	Rates	EMEA	Traditional	None	EUR
RFJGEUME	European Money Market Futures (G) Tracker	RollingFutures	Aug-09	Access Beta	Rates	EMEA	Traditional	None	EUR
RFJPEU2E	Euro Schatz Future (G)	RollingFutures	May-09	Access Beta	Rates	EMEA	Traditional	None	EUR
RFJPEUBE	Euro Bund Futures Tracker	RollingFutures	Jun-09	Access Beta	Rates	EMEA	Traditional	None	EUR
JFLFEU1E	Euribor 1st contract in EUR	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	EUR
JFLFEU2E	Euribor 2nd contract in EUR	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	EUR
JFLFEU3E	Euribor 3rd contract in EUR	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	EUR
JFLFEU4E	Euribor 4th contract in EUR	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	EUR
JFLFEU5E	Euribor 5th contract in EUR	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	EUR
JFLFEU6E	Euribor 6th contract in EUR	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	EUR
JFLFEU7E	Euribor 7th contract in EUR	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	EUR
JFLFEU8E	Euribor 8th contract in EUR	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	EUR
JFBEDUEU	Schatz in EUR	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	EUR
JFBEBLEU	Bobl in EUR	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	EUR
JFBERXEU	Bund in EUR	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	EUR
JFBEBXEU	Buxl in EUR	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	EUR
JFBEOTEU	French OAT in EUR	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	EUR
JFBEBPEU	Italian BP in EUR	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	EUR
J10EGBEU	10Y Gilt in EUR	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	EUR
JPVE0210	EUR 2s10s Curve Index in EUR	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	EUR
RFJPUKBE	UK GILT Futures Tracker	RollingFutures	Jun-09	Access Beta	Rates	EMEA	Traditional	None	GBP
JFLFGB1G	Short Sterling 1st contract in GBP	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	GBP
JFLFGB2G	Short Sterling 2nd contract in GBP	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	GBP
JFLFGB3G	Short Sterling 3rd contract in GBP	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	GBP
JFLFGB4G	Short Sterling 4th contract in GBP	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	GBP
JFLFGB5G	Short Sterling 5th contract in GBP	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	GBP
JFLFGB6G	Short Sterling 6th contract in GBP	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	GBP
JFLFGB7G	Short Sterling 7th contract in GBP	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	GBP

JFLFGB8G	Short Sterling 8th contract in GBP	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	GBP
J10EGBUK	10Y Gilt in GBP	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	GBP
JFLFEU1U	Euribor 1st contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFEU2U	Euribor 2nd contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFEU3U	Euribor 3rd contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFEU4U	Euribor 4th contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFEU5U	Euribor 5th contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFEU6U	Euribor 6th contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFEU7U	Euribor 7th contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFEU8U	Euribor 8th contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFGB1U	Short Sterling 1st contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFGB2U	Short Sterling 2nd contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFGB3U	Short Sterling 3rd contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFGB4U	Short Sterling 4th contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFGB5U	Short Sterling 5th contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFGB6U	Short Sterling 6th contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFGB7U	Short Sterling 7th contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFGB8U	Short Sterling 8th contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFSF1U	Euroswissie 1st contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFSF2U	Euroswissie 2nd contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFSF3U	Euroswissie 3rd contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFSF4U	Euroswissie 4th contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFSF5U	Euroswissie 5th contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFSF6U	Euroswissie 6th contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFSF7U	Euroswissie 7th contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFLFSF8U	Euroswissie 8th contract in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFBEDUUS	Schatz in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFBEBLUS	Bobl in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFBERXUS	Bund in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFBEBXUS	Buxl in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFBEOTUS	French OAT in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD
JFBEBPUS	Italian BP in USD	RollingFutures	Access Beta	Rates	EMEA	Traditional	None	USD

J10EGBUS	10Y Gilt in USD	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	USD
JPVEU210	EUR 2s10s Curve Index in USD	RollingFutures		Access Beta	Rates	EMEA	Traditional	None	USD
JPVEC210	EUR 2s10s Curve Index, Vol Capped, in EUR	RollingFutures		Enhanced Beta	Rates	EMEA	Traditional	Risk Budgeting	EUR
JPVEC2XU	EUR 2s10s Curve Index, Vol Capped, in USD	RollingFutures		Enhanced Beta	Rates	EMEA	Traditional	Risk Budgeting	USD
JFLFAU1A	Aussie Bank Bills 1st contract in AUD	RollingFutures		Access Beta	Rates	Asia	Traditional	None	AUD
JFLFAU2A	Aussie Bank Bills 2nd contract in AUD	RollingFutures		Access Beta	Rates	Asia	Traditional	None	AUD
JFLFAU3A	Aussie Bank Bills 3rd contract in AUD	RollingFutures		Access Beta	Rates	Asia	Traditional	None	AUD
JFLFAU4A	Aussie Bank Bills 4th contract in AUD	RollingFutures		Access Beta	Rates	Asia	Traditional	None	AUD
JFLFAU5A	Aussie Bank Bills 5th contract in AUD	RollingFutures		Access Beta	Rates	Asia	Traditional	None	AUD
JFLFAU6A	Aussie Bank Bills 6th contract in AUD	RollingFutures		Access Beta	Rates	Asia	Traditional	None	AUD
JFLFAU7A	Aussie Bank Bills 7th contract in AUD	RollingFutures		Access Beta	Rates	Asia	Traditional	None	AUD
JFLFAU8A	Aussie Bank Bills 8th contract in AUD	RollingFutures		Access Beta	Rates	Asia	Traditional	None	AUD
J10EAUAU	Aussie 10Y Note in AUD	RollingFutures		Access Beta	Rates	Asia	Traditional	None	AUD
RFJGJPBE	Japanese Government Bond Futures (G) Tracker	RollingFutures	Jun-09	Access Beta	Rates	Asia	Traditional	None	JPY
RFJGJPME	Japanese Money Market Futures (G) Tracker	RollingFutures	Aug-09	Access Beta	Rates	Asia	Traditional	None	JPY
RFJPJPBE	Japanese Govt Bond Futures Tracker	RollingFutures	Jun-09	Access Beta	Rates	Asia	Traditional	None	JPY
JFLFJP1J	Euroyen 1st contract in JPY	RollingFutures		Access Beta	Rates	Asia	Traditional	None	JPY
JFLFJP2J	Euroyen 2nd contract in JPY	RollingFutures		Access Beta	Rates	Asia	Traditional	None	JPY
JFLFJP3J	Euroyen 3rd contract in JPY	RollingFutures		Access Beta	Rates	Asia	Traditional	None	JPY
JFLFJP4J	Euroyen 4th contract in JPY	RollingFutures		Access Beta	Rates	Asia	Traditional	None	JPY
JFLFJP5J	Euroyen 5th contract in JPY	RollingFutures		Access Beta	Rates	Asia	Traditional	None	JPY
JFLFJP6J	Euroyen 6th contract in JPY	RollingFutures		Access Beta	Rates	Asia	Traditional	None	JPY
JFLFJP7J	Euroyen 7th contract in JPY	RollingFutures		Access Beta	Rates	Asia	Traditional	None	JPY
JFLFJP8J	Euroyen 8th contract in JPY	RollingFutures		Access Beta	Rates	Asia	Traditional	None	JPY
J10EJPJP	TSE 10Y JGB's in JPY	RollingFutures		Access Beta	Rates	Asia	Traditional	None	JPY
FTJMSKBE	Korean Treasury Bond Futures Tracker	RollingFutures	Jan-12	Access Beta	Rates	Asia	Traditional	None	KRW
JFLFAU1U	Aussie Bank Bills 1st contract in USD	RollingFutures		Access Beta	Rates	Asia	Traditional	None	USD
JFLFAU2U	Aussie Bank Bills 2nd contract in USD	RollingFutures		Access Beta	Rates	Asia	Traditional	None	USD
JFLFAU3U	Aussie Bank Bills 3rd contract in USD	RollingFutures		Access Beta	Rates	Asia	Traditional	None	USD
JFLFAU4U	Aussie Bank Bills 4th contract in USD	RollingFutures		Access Beta	Rates	Asia	Traditional	None	USD
JFLFAU5U	Aussie Bank Bills 5th contract in USD	RollingFutures		Access Beta	Rates	Asia	Traditional	None	USD
JFLFAU6U	Aussie Bank Bills 6th contract in USD	RollingFutures		Access Beta	Rates	Asia	Traditional	None	USD

JFLFAU7U	Aussie Bank Bills 7th contract in USD	RollingFutures	Access Beta	Rates	Asia	Traditional	None	USD
JFLFAU8U	Aussie Bank Bills 8th contract in USD	RollingFutures	Access Beta	Rates	Asia	Traditional	None	USD
JFLFJP1U	Euroyen 1st contract in USD	RollingFutures	Access Beta	Rates	Asia	Traditional	None	USD
JFLFJP2U	Euroyen 2nd contract in USD	RollingFutures	Access Beta	Rates	Asia	Traditional	None	USD
JFLFJP3U	Euroyen 3rd contract in USD	RollingFutures	Access Beta	Rates	Asia	Traditional	None	USD
JFLFJP4U	Euroyen 4th contract in USD	RollingFutures	Access Beta	Rates	Asia	Traditional	None	USD
JFLFJP5U	Euroyen 5th contract in USD	RollingFutures	Access Beta	Rates	Asia	Traditional	None	USD
JFLFJP6U	Euroyen 6th contract in USD	RollingFutures	Access Beta	Rates	Asia	Traditional	None	USD
JFLFJP7U	Euroyen 7th contract in USD	RollingFutures	Access Beta	Rates	Asia	Traditional	None	USD
JFLFJP8U	Euroyen 8th contract in USD	RollingFutures	Access Beta	Rates	Asia	Traditional	None	USD
J10EUSAU	Aussie 10Y Note in USD	RollingFutures	Access Beta	Rates	Asia	Traditional	None	USD
J10EUSJP	TSE 10Y JGB's in USD	RollingFutures	Access Beta	Rates	Asia	Traditional	None	USD
JPIRUS03	USD 3Y Swap in USD	Swap Trackers	Access Beta	Rates	Americas	Traditional	None	USD
JPIRUS05	USD 5Y Swap in USD	Swap Trackers	Access Beta	Rates	Americas	Traditional	None	USD
JPIRUS07	USD 7Y Swap in USD	Swap Trackers	Access Beta	Rates	Americas	Traditional	None	USD
JPIRUS10	USD 10Y Swap in USD	Swap Trackers	Access Beta	Rates	Americas	Traditional	None	USD
JPIRUS20	USD 20Y Swap in USD	Swap Trackers	Access Beta	Rates	Americas	Traditional	None	USD
JPIRCH03	CHF 3Y Swap in CHF	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	CHF
JPIRCH05	CHF 5Y Swap in CHF	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	CHF
JPIRCH07	CHF 7Y Swap in CHF	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	CHF
JPIRCH10	CHF 10Y Swap in CHF	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	CHF
JPIRCH20	CHF 20Y Swap in CHF	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	CHF
JPIRDK03	DKK 3Y Swap in DKK	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	DKK
JPIRDK05	DKK 5Y Swap in DKK	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	DKK
JPIRDK07	DKK 7Y Swap in DKK	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	DKK
JPIRDK10	DKK 10Y Swap in DKK	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	DKK
JPIRDK20	DKK 20Y Swap in DKK	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	DKK
JPIREU03	EUR 3Y Swap in EUR	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	EUR
JPIREU05	EUR 5Y Swap in EUR	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	EUR
JPIREU07	EUR 7Y Swap in EUR	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	EUR
JPIREU10	EUR 10Y Swap in EUR	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	EUR
JPIREU20	EUR 20Y Swap in EUR	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	EUR

JPIRGB03	GBP 3Y Swap in GBP	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	GBP
JPIRGB05	GBP 5Y Swap in GBP	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	GBP
JPIRGB07	GBP 7Y Swap in GBP	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	GBP
JPIRGB10	GBP 10Y Swap in GBP	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	GBP
JPIRGB20	GBP 20Y Swap in GBP	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	GBP
JPIRSK03	SEK 3Y Swap in SEK	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	SEK
JPIRSK05	SEK 5Y Swap in SEK	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	SEK
JPIRSK07	SEK 7Y Swap in SEK	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	SEK
JPIRSK10	SEK 10Y Swap in SEK	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	SEK
JPIRSK20	SEK 20Y Swap in SEK	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	SEK
JPIRE03U	EUR 3Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD
JPIRE05U	EUR 5Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD
JPIRE07U	EUR 7Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD
JPIRE10U	EUR 10Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD
JPIRE20U	EUR 20Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD
JPIRG03U	GBP 3Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD
JPIRG05U	GBP 5Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD
JPIRG07U	GBP 7Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD
JPIRG10U	GBP 10Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD
JPIRG20U	GBP 20Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD
CPIRC03U	CHF 3Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD
CPIRC05U	CHF 5Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD
CPIRC07U	CHF 7Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD
CPIRC10U	CHF 10Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD
CPIRC20U	CHF 20Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD
DPIRD03U	DKK 3Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD
DPIRD05U	DKK 5Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD
DPIRD07U	DKK 7Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD
DPIRD10U	DKK 10Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD
DPIRD20U	DKK 20Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD
SPIRS03U	SEK 3Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD
SPIRS05U	SEK 5Y Swap in USD	Swap Trackers	Access Beta	Rates	EMEA	Traditional	None	USD

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

SPIRS07U	SEK 7Y Swap in USD	Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	USD
SPIRS10U	SEK 10Y Swap in USD	Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	USD
SPIRS20U	SEK 20Y Swap in USD	Swap Trackers		Access Beta	Rates	EMEA	Traditional	None	USD
JPIRAU03	AUD 3Y Swap in AUD	Swap Trackers		Access Beta	Rates	Asia	Traditional	None	AUD
JPIRAU05	AUD 5Y Swap in AUD	Swap Trackers		Access Beta	Rates	Asia	Traditional	None	AUD
JPIRAU07	AUD 7Y Swap in AUD	Swap Trackers		Access Beta	Rates	Asia	Traditional	None	AUD
JPIRAU10	AUD 10Y Swap in AUD	Swap Trackers		Access Beta	Rates	Asia	Traditional	None	AUD
JPIRAU20	AUD 20Y Swap in AUD	Swap Trackers		Access Beta	Rates	Asia	Traditional	None	AUD
JPIRJY03	JPY 3Y Swap in JPY	Swap Trackers		Access Beta	Rates	Asia	Traditional	None	JPY
JPIRJY05	JPY 5Y Swap in JPY	Swap Trackers		Access Beta	Rates	Asia	Traditional	None	JPY
JPIRJY07	JPY 7Y Swap in JPY	Swap Trackers		Access Beta	Rates	Asia	Traditional	None	JPY
JPIRJY10	JPY 10Y Swap in JPY	Swap Trackers		Access Beta	Rates	Asia	Traditional	None	JPY
JPIRJY20	JPY 20Y Swap in JPY	Swap Trackers		Access Beta	Rates	Asia	Traditional	None	JPY
JPIRJ03U	JPY 3Y Swap in USD	Swap Trackers		Access Beta	Rates	Asia	Traditional	None	USD
JPIRJ05U	JPY 5Y Swap in USD	Swap Trackers		Access Beta	Rates	Asia	Traditional	None	USD
JPIRJ07U	JPY 7Y Swap in USD	Swap Trackers		Access Beta	Rates	Asia	Traditional	None	USD
JPIRJ10U	JPY 10Y Swap in USD	Swap Trackers		Access Beta	Rates	Asia	Traditional	None	USD
JPIRJ20U	JPY 20Y Swap in USD	Swap Trackers		Access Beta	Rates	Asia	Traditional	None	USD
APIRA03U	AUD 3Y Swap in USD	Swap Trackers		Access Beta	Rates	Asia	Traditional	None	USD
APIRA05U	AUD 5Y Swap in USD	Swap Trackers		Access Beta	Rates	Asia	Traditional	None	USD
APIRA07U	AUD 7Y Swap in USD	Swap Trackers		Access Beta	Rates	Asia	Traditional	None	USD
APIRA10U	AUD 10Y Swap in USD	Swap Trackers		Access Beta	Rates	Asia	Traditional	None	USD
APIRA20U	AUD 20Y Swap in USD	Swap Trackers		Access Beta	Rates	Asia	Traditional	None	USD
JVOLE1AE	EUR 1Y10Y in EUR	Swaption Trackers		Access Beta	Rates	EMEA	Traditional	None	EUR
JVOLEAAE	EUR 10Y10Y in EUR	Swaption Trackers		Access Beta	Rates	EMEA	Traditional	None	EUR
JVOLU1AU	USD 1Y10Y in USD	Swaption Trackers		Access Beta	Rates	EMEA	Traditional	None	USD
JVOLUAAU	USD 10Y10Y in USD	Swaption Trackers		Access Beta	Rates	EMEA	Traditional	None	USD
JVOLE1AU	EUR 1Y10Y in USD	Swaption Trackers		Access Beta	Rates	EMEA	Traditional	None	USD
JVOLEAAU	EUR 10Y10Y in USD	Swaption Trackers		Access Beta	Rates	EMEA	Traditional	None	USD
AIJPCB1U	Bond 2Y Carry USD	AIS	Nov-09	Alternative Beta	Rates	Americas	Carry	None	USD
AIJPCB2U	Bond 2Y Long-Short Carry USD	AIS	Nov-09	Alternative Beta	Rates	Americas	Carry	None	USD
AIJPCB3U	Bond 10Y Carry USD	AIS	Nov-09	Alternative Beta	Rates	Americas	Carry	None	USD

AIJPCB4U	Bond 10Y Long-Short Carry USD	AIS	Nov-09	Alternative Beta	Rates	Americas	Carry	None	USD
JCMXHUS	CarryMAX	CarryMAX	Jul-06	Alternative Beta	Rates	Multi Region	Carry	None	USD
JGCTRCBU	Govt Bond Carry to Risk (GBCTR)	GBCTR	May-12	Alternative Beta	Rates	Multi Region	Carry	None	USD
JMPLTUS	Pilot	Pilot	Aug-12	Alternative Beta	Rates	Americas	Carry	Portfolio Level	USD
JMPLTB2U	Pilot Basket of 2	Pilot	Aug-12	Alternative Beta	Rates	Multi Region	Carry	Portfolio Level	USD
YAJPBBE8	Bond Alpha 8 Broad EUR	YieldAlpha	May-08	Alternative Beta	Rates	Multi Region	Carry	Risk Optimizing	EUR
YAJPBEU2	Bond Alpha EUR	YieldAlpha	Aug-06	Alternative Beta	Rates	Multi Region	Carry	Risk Optimizing	EUR
YAJPBEU8	Bond Alpha 8 EUR	YieldAlpha	Aug-06	Alternative Beta	Rates	Multi Region	Carry	Risk Optimizing	EUR
YAJPBBJ8	Bond Alpha 8 Bunsan JPY	YieldAlpha	Aug-07	Alternative Beta	Rates	Multi Region	Carry	Risk Optimizing	JPY
YAJPBJP2	JPM Bond Alpha JPY Index	YieldAlpha	Aug-08	Alternative Beta	Rates	Multi Region	Carry	Risk Optimizing	JPY
YAJPBJP8	JPM Bond Alpha 8 JPY Index	YieldAlpha	Aug-08	Alternative Beta	Rates	Multi Region	Carry	Risk Optimizing	JPY
YAJPBBUX	Bond Alpha Broad X (USD)	YieldAlpha	Aug-08	Alternative Beta	Rates	Multi Region	Carry	Risk Optimizing	USD
YAJPBUS2	JPM Bond Alpha US Index	YieldAlpha	Aug-08	Alternative Beta	Rates	Multi Region	Carry	Risk Optimizing	USD
YAJPBUS8	Bond Alpha 8 US	YieldAlpha	Aug-06	Alternative Beta	Rates	Multi Region	Carry	Risk Optimizing	USD
AIJPMMUU	Momentum Money Market US	AIS	Nov-09	Alternative Beta	Rates	Americas	Momentum	None	USD
AIJPMMEE	Momentum Money Market Europe	AIS	Nov-09	Alternative Beta	Rates	EMEA	Momentum	None	EUR
AIJPMMJJ	Momentum Money Market Japan	AIS	Nov-09	Alternative Beta	Rates	Asia	Momentum	None	JPY
JPFSMMEU	FSI - Multi.Momentum EUR	FSI	Feb-12	Multi Type	Rates	EMEA	Momentum	None	EUR
JPFSMMLE	FSI - Multi Momentum Long Only EUR	FSI	Feb-12	Multi Type	Rates	EMEA	Momentum	None	EUR
JPFSGMUS	FSI - Gemini in USD	FSI	Feb-12	Multi Type	Rates	EMEA	Momentum	None	USD
JHLXH2US	Helix2 - Basket Hedged in USD	Helix	Feb-13	Alternative Beta	Rates	Multi Region	Momentum	Portfolio Level	USD
JHLXHUS	Helix - Basket Hedged in USD	Helix	May-09	Alternative Beta	Rates	Multi Region	Momentum	Portfolio Level	USD
JMOMQTO	Momentus Quattro in USD	Momentus	Jun-07	Alternative Beta	Rates	Multi Region	Momentum	None	USD
JMOMUUU	Momentus Quattro Duo in USD	Momentus	Jun-07	Alternative Beta	Rates	Multi Region	Momentum	None	USD
JMOZFIGU	Mozaic Global Rates	Mozaic	Jul-12	Alpha	Rates	Multi Region	Momentum	Multi Methods	USD
JVOLTS1U	SigmaTY in USD - additive	SigmaTY	Feb-13	Alternative Beta	Rates	Americas	Volatility	Portfolio Level	USD
JVOLTS2U	SigmaTY in USD - multiplicative	SigmaTY	Feb-13	Alternative Beta	Rates	Americas	Volatility	Portfolio Level	USD
JVOLU1AU	Swaption Tracker - $1y10y	VOLT	Sep-12	Access Beta	Rates	Americas	Volatility	Portfolio Level	USD
JVOLB01U	Swaption Alpha	VOLT	Sep-12	Enhanced Beta	Rates	Americas	Volatility	Portfolio Level	EUR
JVOLENSE	Swaption VOLT index – no switch	VOLT	Sep-12	Enhanced Beta	Rates	Americas	Volatility	Portfolio Level	EUR
JPCVTOEU	CurveTrader M+ sub EUR Index	CurveTrader	Feb-08	Alpha	Rates	Multi Region	Multi Factor	None	EUR
JPCVHUS	Curve Trader H+ USD	CurveTrader	Jan-10	Alpha	Rates	Multi Region	Multi Factor	None	USD

JPCVTOUS	CurveTrader M+ sub USD Index	CurveTrader	Feb-08	Alpha	Rates	Multi Region	Multi Factor	None	USD
JPCVTUS	CurveTrader M+ USD	CurveTrader	Feb-08	Alpha	Rates	Multi Region	Multi Factor	None	USD
JMSIRRUS	Sirrus	Sirrus	May-12	Alpha	Rates	Multi Region	Multi Factor	Portfolio Level	USD
JCMDCOMP	CEMBI Narrow Diversified	EMBI	Dec-07	Access Beta	Credit	Emerging Mkts	Traditional	None	USD
JPEMCOMP	Emerging Mkts Bond Index Plus (EMBI+)	EMBI	Jul-95	Access Beta	Credit	Emerging Mkts	Traditional	None	USD
IBOXHY	iBoxx $ Liquid High Yield	iBoxx	Nov-06	Access Beta	Credit	Multi Region	Traditional	None	USD
ERIXCDIG	Markit iTraxx CDX NA Inv Grade 5yr Excess Return	itraxx	Mar-07	Access Beta	Credit	Americas	Traditional	None	USD
ERINCDHY	Markit iTraxx CD NA HighYeild 5yr Excess Return	itraxx	Mar-07	Access Beta	Credit	Americas	Traditional	None	USD
ERIXITXO	Markit iTraxx Europe Crossover 5yr Excess Return	itraxx	Mar-07	Access Beta	Credit	EMEA	Traditional	None	EUR
ERIXITEU	Markit iTraxx Europe Main 5yr Excess Return	itraxx	Mar-07	Access Beta	Credit	EMEA	Traditional	None	EUR
JCRERCHY	Credit NA HY Risk Control Carry	Credit Strategy	Jan-12	Alternative Beta	Credit	Americas	Carry	Portfolio Level	USD
JCRERCIG	Credit NA IG Risk Control Carry	Credit Strategy	Jan-12	Alternative Beta	Credit	Americas	Carry	Portfolio Level	USD
JCRERCEU	Credit Europe Main Risk Control Carry	Credit Strategy	Jan-12	Alternative Beta	Credit	EMEA	Carry	Portfolio Level	EUR
JCRERCXO	Credit Europe Crossover Risk Control Carry	Credit Strategy	Jan-12	Alternative Beta	Credit	EMEA	Carry	Portfolio Level	EUR
JCREMOHY	Credit NA HY Momentum	Credit Strategy	Jan-12	Alternative Beta	Credit	Americas	Momentum	None	USD
JCREMOIG	Credit NA IG Momentum	Credit Strategy	Jan-12	Alternative Beta	Credit	Americas	Momentum	None	USD
JCREMOEU	Credit Europe Main Momentum	Credit Strategy	Jan-12	Alternative Beta	Credit	EMEA	Momentum	None	EUR
JCREMOXO	Credit Europe Crossover Momentum	Credit Strategy	Jan-12	Alternative Beta	Credit	EMEA	Momentum	None	EUR

J.P. Morgan Tradable Risk Factor Indices - Currencies

Ticker	Index Name	JPM Family	Launch Date	Strategy Type	Asset Class	Regional Focus	Strategy Style	Risk Method	Curncy
JFBXCADU	CAD FX Tracker in USD	FX Trackers		Access Beta	Currencies	Americas	Traditional	None	USD
JFBXEURU	EUR FX Tracker in USD	FX Trackers		Access Beta	Currencies	EMEA	Traditional	None	USD
JFBXGBPU	GBP FX tracker in USD	FX Trackers		Access Beta	Currencies	EMEA	Traditional	None	USD
JFBXCHFU	CHF FX Tracker in USD	FX Trackers		Access Beta	Currencies	EMEA	Traditional	None	USD
JFBXJPYU	JPY FX Tracker in USD	FX Trackers		Access Beta	Currencies	Asia	Traditional	None	USD
JFBXAUDU	AUD FX Tracker in USD	FX Trackers		Access Beta	Currencies	Asia	Traditional	None	USD
JFBXNZDU	NZD FX Tracker in USD	FX Trackers		Access Beta	Currencies	Asia	Traditional	None	USD
FTJFTRYE	J.P. Morgan USDTRY Futures Tracker	RollingFutures	May-12	Access Beta	Currencies	EMEA	Traditional	None	TRY
RFJPCHCE	CHF FX Futures Tracker	RollingFutures	May-09	Access Beta	Currencies	EMEA	Traditional	None	USD

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

RFJPJPCE	JPY/USD FX Futures Index	RollingFutures	Jun-09	Access Beta	Currencies	Asia	Traditional	None	USD
RFJPEUCE	J.P. Morgan USD FX Futures Tracker	RollingFutures		Access Beta	Currencies	Multi Region	Traditional	None	USD
AIJPCF1U	G10 FX Carry USD	AIS	Nov-09	Alternative Beta	Currencies	Multi Region	Carry	None	USD
IFXJAM20	Income Asia 2.0	Income FX	Jul-07	Alternative Beta	Currencies	Asia	Carry	Portfolio Level	USD
IFXJAM30	Income Asia 3.0	Income FX	Jul-07	Alternative Beta	Currencies	Asia	Carry	Portfolio Level	USD
IFXJEMUS	Income EM	Income FX	Aug-07	Alternative Beta	Currencies	Emerging Mkts	Carry	Portfolio Level	USD
IFXJ2MUS	Income FX 2	Income FX	Oct-07	Alternative Beta	Currencies	Multi Region	Carry	Portfolio Level	USD
IFXJPMUS	Income FX	Income FX	Jan-06	Alternative Beta	Currencies	Multi Region	Carry	Portfolio Level	USD
YAJPFEU2	FX Alpha EUR	YieldAlpha	Aug-06	Alternative Beta	Currencies	Multi Region	Carry	Risk Optimizing	EUR
YAJPFEU8	FX Alpha 8 EUR	YieldAlpha	Aug-06	Alternative Beta	Currencies	Multi Region	Carry	Risk Optimizing	EUR
YAJPFJP2	JPM FX Alpha JPY Index	YieldAlpha	Aug-08	Alternative Beta	Currencies	Multi Region	Carry	Risk Optimizing	JPY
YAJPFJP8	FX Alpha 8 JPY	YieldAlpha	Aug-06	Alternative Beta	Currencies	Multi Region	Carry	Risk Optimizing	JPY
YAJPFUS2	JPM FX Alpha US Index	YieldAlpha	Aug-08	Alternative Beta	Currencies	Multi Region	Carry	Risk Optimizing	USD
YAJPFUS8	FX Alpha 8 US	YieldAlpha	Aug-06	Alternative Beta	Currencies	Multi Region	Carry	Risk Optimizing	USD
YAJPFUSX	FX Alpha X (USD)	YieldAlpha	Aug-08	Alternative Beta	Currencies	Multi Region	Carry	Risk Optimizing	USD
AIJPMF3U	Momentum FX EURJPY	AIS	Nov-09	Alternative Beta	Currencies	Americas	Momentum	None	USD
AIJPMF1U	Momentum FX EURUSD	AIS	Nov-09	Alternative Beta	Currencies	EMEA	Momentum	None	USD
AIJPMF5U	Momentum FX AUDUSD	AIS	Nov-09	Alternative Beta	Currencies	EMEA	Momentum	None	USD
AIJPMF6U	Momentum FX EURGBP	AIS	Nov-09	Alternative Beta	Currencies	EMEA	Momentum	None	USD
AIJPMF2U	Momentum FX USDJPY	AIS	Nov-09	Alternative Beta	Currencies	Asia	Momentum	None	USD
AIJPMF4U	Momentum FX USDCAD	AIS	Nov-09	Alternative Beta	Currencies	Asia	Momentum	None	USD
JPVOLFFS	FX Futures Volemont	Volemont	Jun-13	Alternative Beta	Currencies	Multi Region	Volatility	Portfolio Level	USD
JPVOLFXS	Volemont FX	Volemont	Apr-13	Alternative Beta	Currencies	Multi Region	Volatility	Portfolio Level	USD

J.P. Morgan Tradable Risk Factor Indices - Commodities

Ticker	Index Name	JPM Family	Launch Date	Strategy Type	Asset Class	Regional Focus	Strategy Style	Risk Method	Curncy
JMABRCGA	Relative Carry Index Alpha	Relative Carry	Aug-13	Alpha	Commodities	Multi Region	Carry	Multi Methods	USD
JPVOLBRT	Brent Volemont	Volemont	Jul-13	Alternative Beta	Commodities	Multi Region	Volatility	Portfolio Level	USD
JPVOGLVP	J.P. Morgan Gold Volatility Premium Index	Volatility Strategies	Jul-13	Alternative Beta	Commodities	Multi Region	Volatility	Portfolio Level	USD
JPVOLWTI	WTI Volemont	Volemont	Apr-13	Alternative Beta	Commodities	Multi Region	Volatility	Portfolio Level	USD

JMABALOC	Commodity Allocator	Allocator	Apr-13	Alpha	Commodities	Multi Region	Multi Factor	Portfolio Level	USD
JPVOGLVO	Gold Volemont Strategy	Volemont	Mar-13	Alternative Beta	Commodities	Multi Region	Volatility	Portfolio Level	USD
JPMZSSGD	Systematic Short Strangle Gold ETF Delta Hedge Mechanism Index	Volatility Strategies	Jan-13	Alternative Beta	Commodities	Multi Region	Volatility	Portfolio Level	USD
JMABSSPE	Seasonal Spreads Portfolio	Seasonal Spreads	Sep-12	Alpha	Commodities	Multi Region	Value	Multi Methods	USD
JMEBDJST	Enhanced Beta Select DJUBS Weights	Beta Select	Jan-12	Enhanced Beta	Commodities	Multi Region	Traditional	None	USD
JMABDJSE	DJUBS Select Alpha	Curve Alpha	Jan-12	Enhanced Beta	Commodities	Multi Region	Carry	Multi Methods	USD
JMABDJF3	DJUBS F3 Alpha	Curve Alpha	Nov-11	Enhanced Beta	Commodities	Multi Region	Carry	Multi Methods	USD
JMAB052E	Fast Continuum	Technical Momentum	Nov-10	Alternative Beta	Commodities	Multi Region	Momentum	Multi Methods	USD
JMABCCLE	WTI Continuum	Technical Momentum	Nov-10	Alternative Beta	Commodities	Multi Region	Momentum	None	USD
CMZSLSTR	C-IGAR Sigma	C-IGAR	Jun-10	Alternative Beta	Commodities	Multi Region	Momentum	None	USD
AIJPCC1U	Commodity Carry USD	AIS	Nov-09	Alternative Beta	Commodities	Multi Region	Carry	None	USD
AIJPMCEU	Commodity Momentum Energy	AIS	Nov-09	Alternative Beta	Commodities	Multi Region	Momentum	None	USD
AIJPMCNU	Commodity Momentum Non-Energy	AIS	Nov-09	Alternative Beta	Commodities	Multi Region	Momentum	None	USD
JCTAADJE	Contag Alpha Alternative Benchmark	Contag	May-09	Alpha	Commodities	Multi Region	Carry	Multi Methods	USD
JCTAAFEE	Contag Alpha Full Energy	Contag	May-09	Alpha	Commodities	Multi Region	Carry	None	USD
JCTAALEE	Contag Alpha Light Energy	Contag	May-09	Alpha	Commodities	Multi Region	Carry	None	USD
JCTABDJT	Contag Beta Alternative Benchmark TR	Contag	May-09	Alternative Beta	Commodities	Multi Region	Carry	Multi Methods	USD
JCTABFET	Contag Beta Full Energy TR	Contag	May-09	Alternative Beta	Commodities	Multi Region	Carry	None	USD
JCTABLET	Contag Beta Light Energy TR	Contag	May-09	Alternative Beta	Commodities	Multi Region	Carry	None	USD
JCTABDJE	Contag Beta Alternative Benchmark	Contag	May-09	Enhanced Beta	Commodities	Multi Region	Carry	Multi Methods	USD
CMDT9CER	C-IGAR 9 Conditional Long Short	C-IGAR	May-09	Alternative Beta	Commodities	Multi Region	Momentum	None	USD
CMDT9SER	C-IGAR 9 Long Short	C-IGAR	May-09	Alternative Beta	Commodities	Multi Region	Momentum	None	USD
CMDT9YER	C-IGAR 9 Long Only	C-IGAR	May-09	Alternative Beta	Commodities	Multi Region	Momentum	None	USD
JCTABFEE	Contag Beta Full Energy	Contag	May-09	Enhanced Beta	Commodities	Multi Region	Carry	Multi Methods	USD
JMCXEXTR	Commodity Curve Index ex-Front Month	JPMCCI	Jun-08	Enhanced Beta	Commodities	Multi Region	Traditional	None	USD
JMCXEXER	Commodity Curve Index ex-Front Month	JPMCCI	Jun-08	Enhanced Beta	Commodities	Multi Region	Traditional	None	USD
CMDTO1ER	Optimax Alternative 1	Optimax	May-08	Alternative Beta	Commodities	Multi Region	Momentum	Portfolio Level	USD
CMDTOMER	Optimax Market-Neutral	Optimax	May-08	Alternative Beta	Commodities	Multi Region	Momentum	Portfolio Level	USD
CMDTOPER	Optimax Plus	Optimax	May-08	Alternative Beta	Commodities	Multi Region	Momentum	Portfolio Level	USD
JMCXER	Commodity Curve Index	JPMCCI	Nov-07	Access Beta	Commodities	Multi Region	Traditional	None	USD
JMCXTR	Commodity Curve Index	JPMCCI	Nov-07	Access Beta	Commodities	Multi Region	Traditional	None	USD

J.P. Morgan Tradable Risk Factor Indices - Volatilities

Ticker	Index Name	JPM Family	Launch Date	Strategy Type	Asset Class	Regional Focus	Strategy Style	Risk Method	Curncy
JPMZMHEN	J.P.Morgan Macro Hedge Enhanced	Macro Hedge	Dec-11	Multi Type	Volatilities	Americas	Carry	None	USD
JPMZMHLO	Macrohedge Systematic Long Index	Macro Hedge	Mar-11	Multi Type	Volatilities	Americas	Carry	None	USD
JPMZMHLO	Macrohedge Systematic Long Index	Macro Hedge	Mar-11	Multi Type	Volatilities	Americas	Carry	None	USD
JPMZMHUS	Macrohedge Long-Short US	Macro Hedge	Aug-10	Multi Type	Volatilities	Americas	Carry	None	USD
JPMZMHVC	J.P. Morgan Macrohedge US Curve	Macro Hedge	Dec-11	Multi Type	Volatilities	Americas	Carry	None	USD
JPUSSTSL	JPM Strategic Volatility Long	Macro Hedge	Feb-12	Multi Type	Volatilities	Americas	Carry	None	USD
JPUSSTVD	Strategic Volatility Dynamic Beta	Macro Hedge	Aug-12	Multi Type	Volatilities	Americas	Carry	None	USD
JPUSSTLF	Strat Vol Long Flat	Macro Hedge	May-11	Multi Type	Volatilities	Americas	Carry	None	USD
JPMZVPUS	J.P.Morgan Macro Hedge Vepo US	Macro Hedge	Apr-12	Multi Type	Volatilities	Americas	Carry	Portfolio Level	USD
JPMZVTU3	Macro Hedge Vega Target 3%	Macro Hedge	Jun-13	Multi Type	Volatilities	Americas	Carry	Portfolio Level	USD
JPMZMHCE	J.P. Morgan Macrohedge Curve (EUR) Index	Macro Hedge		Multi Type	Volatilities	Multi Region	Carry	None	EUR
JPMZMHH6	JP Morgan Macrohedge Hybrid Risk Control 6	Macro Hedge	Aug-11	Multi Type	Volatilities	Multi Region	Carry	None	EUR
JPMZMHHT	J.P. Morgan Macrohedge Dual TR Index	Macro Hedge	Mar-12	Multi Type	Volatilities	Multi Region	Carry	None	EUR
JPMZVEC5	J.P. Morgan Macrohedge Curve VT 5% (EUR)	Macro Hedge	Jul-13	Multi Type	Volatilities	Multi Region	Carry	None	EUR
JPMZMHCL	J.P.Morgan Macro Curve LO USD	Macro Hedge	Jun-12	Multi Type	Volatilities	Multi Region	Carry	None	USD
JPMZMHCO	J.P.Morgan Macro Curve LO Euro	Macro Hedge	Jun-12	Multi Type	Volatilities	Multi Region	Carry	None	USD
JPMZMHCU	J.P. Morgan Macrohedge Curve	Macro Hedge	Feb-12	Multi Type	Volatilities	Multi Region	Carry	None	USD
JPMZMHE6	JP Morgan Macrohedge Enhanced Risk Control 6 US	Macro Hedge	Mar-11	Multi Type	Volatilities	Multi Region	Carry	None	USD
JPMZMHHG	J.P.Morgan Macrohedge Dual Enhanced	Macro Hedge	Mar-11	Multi Type	Volatilities	Multi Region	Carry	None	USD
JPMZMHHY	Macrohedge Hybrid	Macro Hedge	Sep-10	Multi Type	Volatilities	Multi Region	Carry	None	USD
JPMZVTC5	J.P. Morgan Macrohedge Curve VT 5% (USD)	Macro Hedge	Jul-13	Multi Type	Volatilities	Multi Region	Carry	None	USD
JPMZVTD3	J.P. Morgan Macrohedge Dual VT 3% (USD)	Macro Hedge	Jul-13	Multi Type	Volatilities	Multi Region	Carry	None	USD
JPMZVTD4	J.P. Morgan Macrohedge Dual VT 4% (USD)	Macro Hedge	Jul-13	Multi Type	Volatilities	Multi Region	Carry	None	USD
JPMZSSUS	Systematic Short Strangle US Equity Index Delta Hedged	Volatility Strategies	Jun-13	Alternative Beta	Volatilities	Americas	Carry	Portfolio Level	USD
JPMZSSEU	Systematic Short Strangle European Equity Delta Hedge Mechanism Index	Volatility Strategies	Jan-13	Alternative Beta	Volatilities	EMEA	Carry	Portfolio Level	USD
JPMZSSGD	Systematic Short Strangle Gold ETF Delta Hedge Mechanism Index	Volatility Strategies	Jan-13	Alternative Beta	Volatilities	Multi Region	Carry	Portfolio Level	USD
JPVOGLVP	J.P. Morgan Gold Volatility Premium Index	Volatility Strategies	Jul-13	Alternative Beta	Volatilities	Multi Region	Carry	Portfolio Level	USD
JPVOLUSA	Volemont-US Equities	Volemont	May-13	Alternative Beta	Volatilities	Americas	Carry	Portfolio Level	USD
JPVOLEMA	Volemont Asia Strategy	Volemont	Jun-12	Alternative Beta	Volatilities	Asia	Carry	Portfolio Level	USD
JPVOLEEG	Volemont Global Strategy (EUR)	Volemont	Dec-12	Alternative Beta	Volatilities	Multi Region	Carry	Portfolio Level	EUR
JPVOLEME	J.P. Morgan Volemont (EUR)	Volemont	Nov-11	Alternative Beta	Volatilities	Multi Region	Carry	Portfolio Level	EUR

JPVOGLVO	Gold Volemont Strategy	Volemont	Mar-13	Alternative Beta	Volatilities	Multi Region	Carry	Portfolio Level	USD
JPVOLBRT	Brent Volemont	Volemont	Jul-13	Alternative Beta	Volatilities	Multi Region	Carry	Portfolio Level	USD
JPVOLEM6	J.P. Morgan Volemont Risk Cont	Volemont	Apr-12	Alternative Beta	Volatilities	Multi Region	Carry	Portfolio Level	USD
JPVOLEMG	Volemont Global Strategy	Volemont	Dec-12	Alternative Beta	Volatilities	Multi Region	Carry	Portfolio Level	USD
JPVOLEMO	J.P. Morgan Volemont Index	Volemont	Aug-11	Alternative Beta	Volatilities	Multi Region	Carry	Portfolio Level	USD
JPVOLFFS	FX Futures Volemont	Volemont	Jun-13	Alternative Beta	Volatilities	Multi Region	Carry	Portfolio Level	USD
JPVOLGU2	J.P. Morgan Volemont Global Series 2	Volemont	Mar-13	Alternative Beta	Volatilities	Multi Region	Carry	Portfolio Level	USD
JPVOLGU3	J.P. Morgan Volemont Global Series 3	Volemont		Alternative Beta	Volatilities	Multi Region	Carry	Portfolio Level	USD
JPVOLWTI	Volemont WTI	Volemont	Apr-13	Alternative Beta	Volatilities	Americas	Carry	Portfolio Level	USD
JPVOLFXS	Volemont FX	Volemont	Apr-13	Alternative Beta	Volatilities	Multi Region	Carry	Portfolio Level	USD
JVOLB01U	Swaption Alpha	VOLT	Feb-13	Enhanced Beta	Volatilities	Americas	Carry	Portfolio Level	EUR
JVOLENSE	Swaption VOLT index – no switch	VOLT	Feb-13	Enhanced Beta	Volatilities	Americas	Carry	Portfolio Level	EUR
YAJPVUS2	JPM Variance Alpha USD Index	YieldAlpha	Aug-08	Alternative Beta	Volatilities	Americas	Carry	Risk Optimizing	USD
YAJPVUS8	Variance Alpha 8 USD	YieldAlpha	Aug-06	Alternative Beta	Volatilities	Americas	Carry	Risk Optimizing	USD

J.P. Morgan Tradable Risk Factor Indices - Multi Asset

Ticker	Index Name	JPM Family	Launch Date	Strategy Type	Asset Class	Regional Focus	Strategy Style	Risk Method	Curncy
YAJPMEU2	JPM Yield Alpha EUR Index	YieldAlpha	Aug-08	Alpha	Multi Asset	Multi Region	Carry	Multi Methods	EUR
YAJPMEU8	Yield Alpha 8 EUR	YieldAlpha	Aug-06	Alpha	Multi Asset	Multi Region	Carry	Multi Methods	EUR
YAJPMBJ8	Yield Alpha 8 Bunsan JPY	YieldAlpha	Aug-07	Alpha	Multi Asset	Multi Region	Carry	Multi Methods	JPY
YAJPMJP2	JPM Yield Alpha JPY Index	YieldAlpha	Aug-08	Alpha	Multi Asset	Multi Region	Carry	Multi Methods	JPY
YAJPMJP8	Yield Alpha 8 JPY Index	YieldAlpha	Aug-08	Alpha	Multi Asset	Multi Region	Carry	Multi Methods	JPY
YAJPMQAU	Quattro Alpha (USD)	YieldAlpha	Aug-08	Alpha	Multi Asset	Multi Region	Carry	Multi Methods	USD
YAJPMUS2	JPM Yield Alpha USD Index	YieldAlpha	Aug-08	Alpha	Multi Asset	Multi Region	Carry	Multi Methods	USD
YAJPMUS8	Yield Alpha 8 USD	YieldAlpha	Aug-06	Alpha	Multi Asset	Multi Region	Carry	Multi Methods	USD
EEJPR5SW	Efficient Allocation (CHF)	Efficiente	Jan-12	Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	CHF
EFJPEH8E	Efficiente (EUR Hedged)	Efficiente	Aug-07	Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	EUR
EFJPEH8I	Efficace (EUR Hedged)	Efficiente	Mar-08	Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	EUR
EFJPEH8T	J.P. Morgan Efficiente TR (EUR Hedged) Index	Efficiente		Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	EUR
EFJPGH8T	J.P. Morgan Efficient Frontier (GBP) Index	Efficiente		Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	GBP
EEJPDS5E	ETF Efficiente Daily Series 5	Efficiente	Nov-12	Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	USD

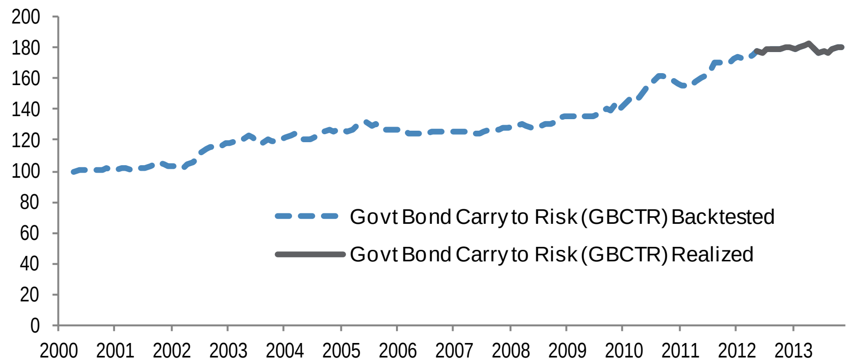
EEJPDS8E	J.P.Morgan ETF Efficiente Daily Series 8 Index	Efficiente		Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	USD
EEJPRC5E	J.P. Morgan ETF Efficiente 5 RC Index	Efficiente	Jan-13	Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	USD
EEJPRC8E	ETF Efficiente 8 RC	Efficiente	Nov-12	Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	USD
EEJPUS5E	ETF Efficiente 5 Index	Efficiente	Oct-10	Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	USD
EEJPUS5M	ETF Efficiente 5 MOD	Efficiente	Mar-12	Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	USD
EEJPUS5P	ETF Efficiente 5 Price Return	Efficiente	May-12	Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	USD
EEJPUS5T	ETF Efficiente 5 Total Return	Efficiente	May-12	Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	USD
EEJPUS8E	ETF Efficiente 8 Index	Efficiente	Oct-10	Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	USD
EFJP5GUE	Efficiente Global 5% (USD)	Efficiente	May-12	Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	USD
EFJPEM5E	Efficiente EM 5	Efficiente	May-13	Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	USD
EFJPIU8E	Efficiente Islamic	Efficiente	Jun-09	Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	USD
EFJPUS8E	Efficiente (USD)	Efficiente	Aug-07	Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	USD
EFJPUS8T	J.P. Morgan Efficiente TR USD Index	Efficiente		Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	USD
IEJPRC4E	ETF Efficiente Income Focus DS 4	Efficiente	Aug-12	Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	USD
IEJPRC6E	J.P. Morgan Income Focus Efficiente DS 6 Risk Control	Efficiente	Aug-12	Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	USD
IEJPUS4E	J.P. Morgan Income Focus Efficiente DS 4 Index	Efficiente	Aug-12	Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	USD
IEJPUS6E	J.P.Morgan Income Focus Efficiente DS 6 Index	Efficiente	Aug-12	Enhanced Beta	Multi Asset	Multi Region	Momentum	Risk Optimizing	USD
JMOZ5USD	Mozaic 5	Mozaic	Jul-12	Alpha	Multi Asset	Multi Region	Momentum	Multi Methods	USD
JMOZUSD	Mozaic USD	Mozaic	Apr-09	Alpha	Multi Asset	Multi Region	Momentum	Multi Methods	USD
JPCORLIS	Coriolis	Call Overwrite	May-12	Alternative Beta	Multi Asset	Multi Region	Value	None	USD
AIJPB1E5	Alternative Index Series Top 20 Sharpe	AIS	Mar-10	Alpha	Multi Asset	Multi Region	Multi Factor	Portfolio Level	EUR
AIJPB1EX	Alternative Index Series Top 20 Sharpe	AIS	Mar-10	Alpha	Multi Asset	Multi Region	Multi Factor	Portfolio Level	EUR
AIJPV5HE	Alternative Index Series 5 Volatility Enhanced (HUF)	AIS	Jan-11	Alpha	Multi Asset	Multi Region	Multi Factor	Portfolio Level	HUF
AIJPVTHE	Alternative Index Series 10 Volatility Enhanced (HUF)	AIS	Jan-11	Alpha	Multi Asset	Multi Region	Multi Factor	Portfolio Level	HUF
AIJPB1U5	J.P.Morgan AI Top 20 Sharpe	AIS	Mar-10	Alpha	Multi Asset	Multi Region	Multi Factor	Portfolio Level	PLN
AIJPM5EE	Alternative Multi-Strategy 5	AIS	Nov-09	Multi Type	Multi Asset	Multi Region	Multi Factor	Multi Methods	EUR
AIJPM5JE	Alternative Multi-Strategy 5	AIS	Nov-09	Multi Type	Multi Asset	Multi Region	Multi Factor	Multi Methods	JPY
AIJPM5UE	Alternative Multi-Strategy 5	AIS	Nov-09	Multi Type	Multi Asset	Multi Region	Multi Factor	Multi Methods	USD
AIJPMTUE	Alternative Multi-Strategy 10	AIS	Nov-09	Multi Type	Multi Asset	Multi Region	Multi Factor	Portfolio Level	USD
QSJP5FEE	Quintet Balanced 5 (EUR)	YieldAlpha	Dec-12	Alpha	Multi Asset	Multi Region	Multi Factor	Multi Methods	EUR
CIJPAIMS	Asia Multi Factor Index	YieldAlpha		Alpha	Multi Asset	Multi Region	Multi Factor	Multi Methods	USD
QSJP4FUE	J.P. Morgan Quartet Balanced (USD)	YieldAlpha	Jan-12	Alpha	Multi Asset	Multi Region	Multi Factor	Multi Methods	USD

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Examples of J.P. Morgan Tradable Risk Factor Indices

J.P. Morgan GCBTR – Rates Carry

Strategy Index Profile	
Index Name	GBCTR
Strategy Type	Alternative Beta
Asset Class	Rates
Regional Focus	Multi Region
Strategy Style	Carry
Risk Method	None
Launch Date	May 2012
Bloomberg Ticker	JGCTRCBU Index



Perf/Risk Summary	Past 1-year	Past 3-year	Past 5-year	Since 2000	Since Launch	During GFC
Average (%)	1.2	4.0	6.4	4.5	2.0	5.4
CAGR (%)	1.1	4.0	6.5	4.5	1.9	5.5
STDev (%)	3.7	3.8	4.4	4.1	3.3	2.4
MaxDD (%)	-3.3	-3.7	-3.9	-5.7	-3.3	-1.6
MaxDDur (in yrs)	0.5	0.6	0.7	3.3	0.5	0.5
Sharpe Ratio	0.3	1.0	1.5	1.1	0.6	2.2
Sortino Ratio	0.5	2.1	3.2	2.1	1.0	5.4
Calmar Ratio	0.4	1.1	1.8	1.2	0.6	3.4
Pain Ratio	1.0	4.4	9.3	3.1	2.3	19.7
Reward to 95VaR	0.1	0.2	0.4	0.3	0.1	0.6
Reward to 95CVaR	0.1	0.2	0.3	0.2	0.1	0.5
Hit Rate	58.3%	55.6%	61.7%	62.3%	55.6%	80.0%
Gain to Pain	1.3	2.2	3.0	2.3	1.6	5.1
Skewness	-0.5	0.3	0.1	0.1	-0.5	0.1
Kurtosis	-0.6	-0.3	0.0	0.5	-0.2	1.0
Correl with Equity	32.5%	-32.3%	-32.6%	-31.4%	0.0%	-26.4%
Correl with Bond	74.1%	54.8%	42.9%	53.8%	60.8%	55.5%
CoSkew with Equity	-0.4	0.1	0.2	0.2	0.3	0.2
CoSkew with Bond	-0.5	-0.3	-0.4	-0.1	-0.7	0.3
CoKurt with Equity	-2.8	-4.5	-4.0	-4.0	-4.9	-4.5
CoKurt with Bond	-0.3	-0.7	-1.3	-1.3	0.1	-2.0

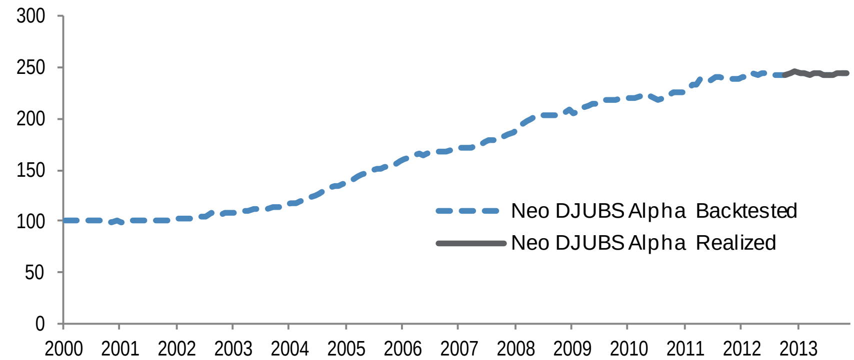
Strategy Description

- The Government Bond Carry-To-Risk USD-denominated Index follows a rule-based strategy ("Strategy") that provides synthetic exposure to a basket of bond futures from the United States, Europe and Japan. The Strategy can synthetically take long or short exposure of up to 7 of its eligible constituents via the relevant Futures Trackers, each selected on the basis of recent "Carry-to-Risk" and each subject to a volatility target.

Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg. * Performance calculated as of Oct 2013.

J.P. Morgan Neo DJUBS Alpha – Commodity Carry

Strategy Index Profile	
Index Name	Neo DJUBS Alpha
Strategy Type	Alpha
Asset Class	Commodities
Regional Focus	Multi Region
Strategy Style	Carry
Risk Method	Multiple Methods
Launch Date	October 2012
Bloomberg Ticker	JMABNEO1 Index



Perf/Risk Summary	Past 1-year	Past 3-year	Past 5-year	Since 2000	Since Launch	During GFC
Average (%)	0.2	2.7	3.7	6.5	0.5	10.2
CAGR (%)	0.2	2.7	3.7	6.7	0.5	10.6
STDev (%)	1.3	2.4	2.6	2.8	1.3	3.6
MaxDD (%)	-1.4	-1.4	-2.0	-2.0	-1.4	-1.3
MaxDDur (in yrs)	0.8	0.8	0.8	1.3	0.8	0.2
Sharpe Ratio	0.2	1.1	1.4	2.3	0.4	2.8
Sortino Ratio	0.2	2.5	3.1	6.7	0.5	9.3
Calmar Ratio	0.2	2.0	2.7	4.8	0.4	8.0
Pain Ratio	0.4	5.9	8.4	21.1	0.9	62.3
Reward to 95VaR	0.0	0.3	0.3	0.8	0.1	1.0
Reward to 95CVaR	0.0	0.2	0.3	0.5	0.1	0.7
Hit Rate	58.3%	66.7%	68.3%	75.2%	61.5%	80.0%
Gain to Pain	1.1	2.6	3.1	6.1	1.3	8.3
Skewness	-1.0	0.9	0.5	0.3	-1.1	-0.1
Kurtosis	0.7	1.7	0.8	0.0	1.0	-0.8
Correl with Equity	2.6%	16.7%	33.4%	6.9%	-6.5%	35.4%
Correl with Bond	38.4%	29.2%	46.6%	21.2%	37.3%	57.3%
CoSkew with Equity	0.0	-0.2	-0.2	-0.3	0.1	-0.2
CoSkew with Bond	0.0	0.1	0.2	0.1	-0.1	0.1
CoKurt with Equity	-4.3	-2.9	-2.2	-2.5	-4.4	-2.2
CoKurt with Bond	-3.5	-2.3	-0.7	-2.2	-3.3	-1.6

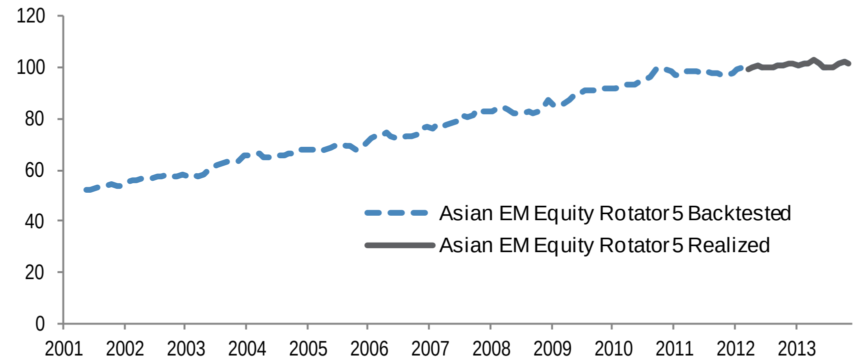
Strategy Description

- Equal risk weights are applied to two dynamically rebalanced portfolios of curve alpha strategies on individual commodities
- Each portfolio is optimized and rebalanced monthly to the weights that have historically generated the maximum return for 5% volatility: Portfolio One: 1 month lookback; Portfolio Two: 6 month lookback
- The portfolios select from a universe of 40 curve alpha strategies across 25 commodities, where strategies are chosen to reflect sector specific curve profiles: (1) Long CCI ex-FM vs. short benchmark for all commodities; (2) Long Contag for Metals and Energy, Seasonal for Ags and Livestock vs short the benchmark in both cases. (3) To preserve liquidity, weights are capped at 10% per strategy, 20% per commodity.

Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg. * Performance calculated as of Oct 2013.

J.P. Morgan Asian EM Equity Rotator 5 – Equity Momentum

Strategy Index Profile	
Index Name	Asian EM Rotator 5
Strategy Type	Alternative Beta
Asset Class	Equities
Regional Focus	Emerging Markets
Strategy Style	Momentum
Risk Method	Risk Timing
Launch Date	March 2012
Bloomberg Ticker	CIJPAEB5 Index



Perf/Risk Summary	Past 1-year	Past 3-year	Past 5-year	Since 2001	Since Launch	During GFC
Average (%)	1.0	0.7	4.3	5.5	1.2	3.8
CAGR (%)	1.0	0.7	4.3	5.6	1.2	3.7
STDev (%)	3.3	2.9	3.6	3.8	2.9	4.8
MaxDD (%)	-3.1	-3.1	-3.1	-3.1	-3.1	-2.8
MaxDDur (in yrs)	0.5	1.3	1.3	1.3	0.5	0.7
Sharpe Ratio	0.3	0.2	1.2	1.4	0.4	0.8
Sortino Ratio	0.5	0.3	2.3	3.0	0.6	1.5
Calmar Ratio	0.3	0.2	1.4	1.8	0.4	1.3
Pain Ratio	0.9	0.5	4.8	7.6	1.6	3.1
Reward to 95VaR	0.0	0.0	0.3	0.3	0.1	0.2
Reward to 95CVaR	0.0	0.0	0.2	0.2	0.1	0.1
Hit Rate	58.3%	58.3%	68.3%	69.1%	60.0%	55.0%
Gain to Pain	1.3	1.2	2.5	2.9	1.4	1.8
Skewness	-0.3	-0.3	0.3	0.2	-0.3	0.4
Kurtosis	-0.1	-0.5	0.7	0.5	0.0	-0.4
Correl with Equity	30.2%	1.3%	23.7%	14.5%	0.8%	19.1%
Correl with Bond	76.3%	42.9%	63.6%	42.6%	70.9%	62.2%
CoSkew with Equity	-0.6	-0.4	0.0	0.0	-0.1	0.1
CoSkew with Bond	-0.1	-0.4	0.1	0.0	-0.2	0.3
CoKurt with Equity	-3.0	-3.6	-2.3	-2.8	-3.9	-3.3
CoKurt with Bond	-1.0	-1.6	-0.4	-1.6	-0.8	-1.4

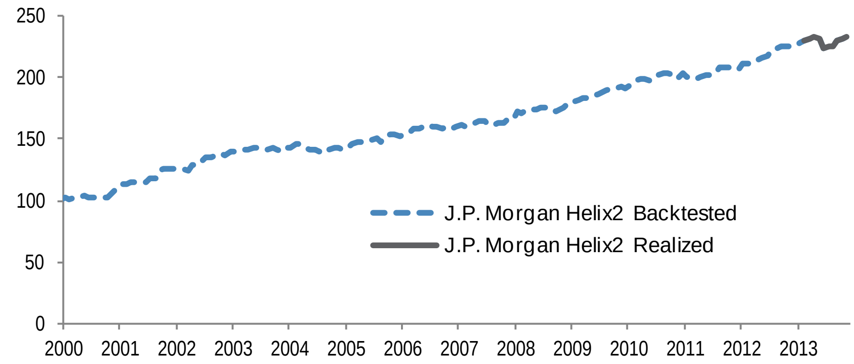
- The Index is a notional rules-based proprietary index that tracks the excess return of a synthetic portfolio of up to five constituents that are each an Asian/EM equity index or a futures tracker (selected from Asian/EM equity indices or equity futures trackers) and, if fewer than five Equity Constituents have been selected, the J.P. Morgan U.S. Treasury Notes Futures Tracker (the "Bond Constituent") above the return of the J.P. Morgan Cash Index USD 3 Month.
- The Index rebalances the synthetic portfolio monthly. Each month, the Index will select the top five positive performing Equity Constituents based on their past month's performance for inclusion in the synthetic portfolio.
- As part of this rebalancing process, the Index will assign weights to the Basket Constituents. The Index uses a volatility budgeting approach to assign weights to the Non-Cash Constituents based on a total volatility allocation of 5%.

Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg. * Performance calculated as of Oct 2013.

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

J.P. Morgan Helix2 – Rates Momentum

Strategy Index Profile	
Index Name	J.P. Morgan Helix2
Strategy Type	Alternative Beta
Asset Class	Rates
Regional Focus	Multi Region
Strategy Style	Momentum
Risk Method	Risk Timing
Launch Date	February 2013
Bloomberg Ticker	JHLXH2US Index



Perf/Risk Summary	Past 1-year	Past 3-year	Past 5-year	Since 2000	Since Launch	During GFC
Average (%)	2.9	4.5	5.7	6.0	1.5	7.3
CAGR (%)	2.8	4.5	5.8	6.1	1.4	7.5
STDev (%)	4.7	4.1	3.7	4.1	5.2	3.8
MaxDD (%)	-4.4	-4.4	-4.4	-4.4	-4.4	-1.8
MaxDDur (in yrs)	0.5	0.5	0.8	0.9	0.5	0.3
Sharpe Ratio	0.6	1.1	1.6	1.5	0.3	2.0
Sortino Ratio	0.8	1.7	2.8	3.1	0.4	5.1
Calmar Ratio	0.7	1.0	1.3	1.4	0.3	4.1
Pain Ratio	2.3	6.0	11.7	9.7	0.9	33.8
Reward to 95VaR	0.1	0.2	0.4	0.4	0.0	0.6
Reward to 95CVaR	0.1	0.1	0.2	0.2	0.0	0.4
Hit Rate	75.0%	69.4%	75.0%	67.9%	77.8%	70.0%
Gain to Pain	1.6	2.3	3.3	3.3	1.3	4.8
Skewness	-2.0	-0.8	-0.8	0.3	-2.1	0.2
Kurtosis	4.8	2.0	2.4	1.5	4.4	0.3
Correl with Equity	59.4%	15.5%	9.1%	-14.0%	54.5%	-3.6%
Correl with Bond	52.6%	56.5%	55.9%	36.1%	63.0%	59.1%
CoSkew with Equity	-0.2	0.2	0.1	0.2	-0.3	0.0
CoSkew with Bond	-0.2	-0.5	-0.1	0.1	-0.3	0.5
CoKurt with Equity	-2.4	-3.5	-3.1	-3.6	-3.0	-3.6
CoKurt with Bond	-1.9	-0.7	-0.6	-1.5	-2.4	-1.6

Strategy Description

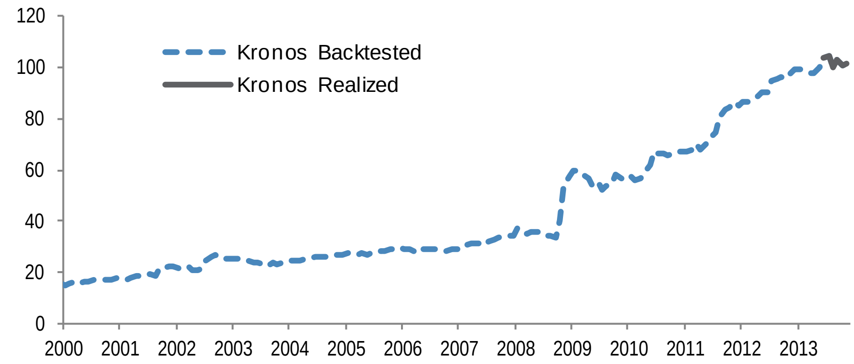
- Seeks to take advantage of trends in short-term EUR and USD interest rates by creating exposure to a synthetic basket of EURIBOR and Eurodollar futures trackers.
- Index can provide dynamic long and/or short exposure to the front four EURIBOR and Eurodollar exchange-traded quarterly money market futures.
- Stop loss cut-out feature if returns are persistently negative over a rolling 1-week observation window.
- Volatility target of 3.5%.
- Leverage factor determined as a function of the index's volatility.

Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg. * Performance calculated as of Oct 2013.

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

J.P. Morgan Kronos – Equity Momentum/Value

Strategy Index Profile	
Index Name	Kronos
Strategy Type	Alternative Beta
Asset Class	Equities
Regional Focus	Americas
Strategy Style	Momentum/Value
Risk Method	None
Launch Date	June 2013
Bloomberg Ticker	JPMZKRNS Index



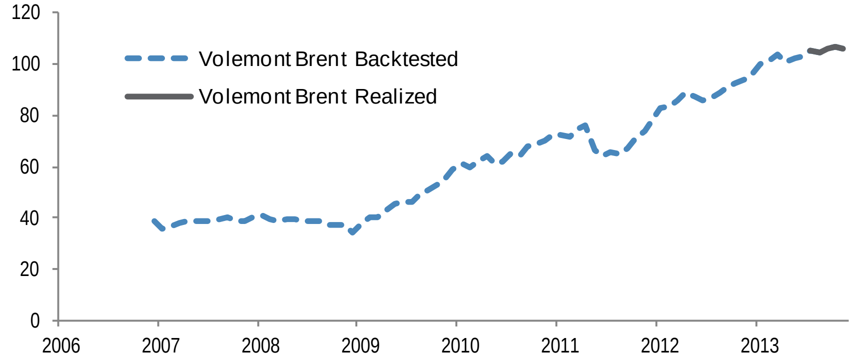
Perf/Risk Summary	Past 1-year	Past 3-year	Past 5-year	Since 2000	Since Launch	During GFC
Average (%)	5.8	14.3	19.8	14.8	2.2	39.8
CAGR (%)	5.7	14.9	20.1	14.8	1.7	42.4
STDev (%)	7.5	8.0	17.6	14.5	10.8	30.8
MaxDD (%)	-3.8	-3.8	-12.7	-15.6	-3.8	-9.6
MaxDDur (in yrs)	0.3	0.3	1.2	2.0	0.3	0.7
Sharpe Ratio	0.8	1.8	1.1	1.0	0.2	1.3
Sortino Ratio	1.3	4.3	4.2	3.1	0.3	8.1
Calmar Ratio	1.5	3.8	5.2	3.9	0.6	4.1
Pain Ratio	5.6	26.4	11.1	6.0	1.3	17.5
Reward to 95VaR	0.1	0.4	0.5	0.4	0.0	1.1
Reward to 95CVaR	0.1	0.4	0.3	0.3	0.0	1.0
Hit Rate	66.7%	72.2%	68.3%	61.8%	60.0%	60.0%
Gain to Pain	1.8	3.9	3.7	2.9	1.2	5.2
Skewness	-0.4	0.5	4.4	3.7	-0.1	2.6
Kurtosis	-0.1	2.0	27.4	24.2	-1.7	7.5
Correl with Equity	-1.0%	-39.6%	-47.7%	-37.0%	9.6%	-40.9%
Correl with Bond	-16.8%	-5.3%	13.9%	10.7%	-3.3%	16.0%
CoSkew with Equity	-0.6	0.4	0.3	0.5	-0.6	0.4
CoSkew with Bond	0.5	0.2	0.3	0.3	0.7	0.6
CoKurt with Equity	-2.5	-4.6	-4.5	-5.2	-6.0	-5.5
CoKurt with Bond	-5.1	-4.0	-2.2	-2.6	-9.4	-3.1

Strategy Description

- "Kronos" provides exposure to the S&P 500 end-of-month mean reversion strategy and the S&P 500 options expiry momentum strategy using E-mini S&P 500 Futures.
- One week before the end of month, if the front month E-mini S&P 500 Futures contract (Bloomberg: ES1 <Index>) is:
  - Below the front month contract's level on the last day of the previous month, then go long the futures contract
  - Above the front month contract's level on the last day of the previous month, then go short the futures contract
  - The index is fully invested for the next 5 business days
- Three business days before S&P 500 options expiry, if the front month E-mini S&P 500 Futures contract is:
  - Above the front month contract's level on the previous expiry, then go long the futures contract
  - Below the front month contract's level on the previous expiry, then go short the futures contract
  - The index is fully invested for the next 3 business days

J.P. Morgan Volemont Brent – Commodities Volatility

Strategy Index Profile	
Index Name	Volemont Brent
Strategy Type	Alternative Beta
Asset Class	Commodities
Regional Focus	Multi Region
Strategy Style	Volatility
Risk Method	Risk Timing
Launch Date	July 2013
Bloomberg Ticker	JPVOLBRT Index



Perf/Risk Summary	Past 1-year	Past 3-year	Past 5-year	Since 2006	Since Launch	During GFC
Average (%)	14.0	15.5	21.9	15.2	11.0	1.9
CAGR (%)	14.8	15.9	23.3	15.6	11.5	1.2
STDev (%)	5.9	11.5	12.4	11.7	4.8	12.4
MaxDD (%)	-2.3	-15.8	-15.8	-15.8	-0.7	-15.2
MaxDDur (in yrs)	0.3	0.6	0.6	1.2	0.1	1.2
Sharpe Ratio	2.4	1.3	1.8	1.3	2.3	0.2
Sortino Ratio	5.8	1.9	3.0	2.1	8.6	0.3
Calmar Ratio	6.1	1.0	1.4	1.0	14.9	0.1
Pain Ratio	35.0	6.1	11.9	6.3	59.5	0.4
Reward to 95VaR	0.5	0.5	0.5	0.3	1.2	0.0
Reward to 95CVaR	0.5	0.2	0.2	0.2	1.2	0.0
Hit Rate	83.3%	75.0%	75.0%	72.6%	75.0%	50.0%
Gain to Pain	5.6	3.0	3.8	2.8	6.0	1.1
Skewness	-0.1	-2.3	-1.2	-0.9	-0.5	0.9
Kurtosis	1.5	9.7	4.5	3.7	-3.4	2.3
Correl with Equity	51.0%	32.9%	17.2%	21.8%	73.9%	-26.6%
Correl with Bond	-19.3%	4.3%	-20.6%	-8.1%	78.2%	-53.6%
CoSkew with Equity	-0.1	0.2	0.3	0.2	-1.5	0.1
CoSkew with Bond	-0.2	0.2	-0.1	-0.1	-1.2	-0.3
CoKurt with Equity	-1.9	-1.9	-3.1	-2.5	-0.4	-4.1
CoKurt with Bond	-4.2	-3.4	-5.4	-4.6	-0.2	-6.1

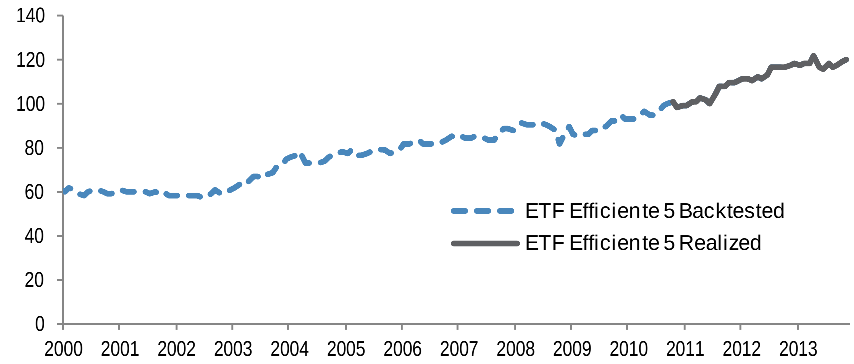
Strategy Description

- The Strategy aims to monetize any positive difference between implied and realized volatility in Brent crude oil.
- Each business day, the strategy may initiate a synthetic short ATM straddle position on the second nearby listed Brent options contract: (1) Strikes are diversified to limit gamma exposure and mitigate spot dependency; (2) The aggregate position is delta hedged daily on the close to capture the volatility premium
- Aims to improve risk-return characteristics and mitigate drawdown by employing a Risk Overlay, which suspends the sale of straddles in periods of macro market stress
- The strategy targets 0.5% vega.

Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg. * Performance calculated as of Oct 2013.

J.P. Morgan ETF Efficiente 5 – Multi Asset Momentum

Strategy Index Profile	
Index Name	ETF Efficient 5
Strategy Type	Enhanced Beta
Asset Class	Multi Asset
Regional Focus	Multi Region
Strategy Style	Momentum
Risk Method	Risk Budgeting
Launch Date	October 2010
Bloomberg Ticker	EEJPUS5E Index



Perf/Risk Summary	Past 1-year	Past 3-year	Past 5-year	Since 2006	Since Launch	During GFC
Average (%)	2.3	5.8	7.6	5.2	5.8	2.4
CAGR (%)	2.1	5.8	7.7	5.1	5.8	2.0
STDev (%)	6.3	5.3	5.8	6.2	5.2	8.7
MaxDD (%)	-5.1	-5.1	-5.1	-10.3	-5.1	-10.3
MaxDDur (in yrs)	0.5	0.5	0.5	2.8	0.5	1.1
Sharpe Ratio	0.4	1.1	1.3	0.8	1.1	0.3
Sortino Ratio	0.5	1.9	2.5	1.3	1.9	0.4
Calmar Ratio	0.4	1.1	1.5	1.0	1.1	0.2
Pain Ratio	1.2	6.4	7.6	2.8	6.6	0.9
Reward to 95VaR	0.0	0.3	0.3	0.2	0.3	0.0
Reward to 95CVaR	0.0	0.2	0.2	0.1	0.2	0.0
Hit Rate	66.7%	69.4%	70.0%	63.0%	70.3%	55.0%
Gain to Pain	1.3	2.4	2.8	1.9	2.4	1.2
Skewness	-1.1	-0.4	-0.1	-0.5	-0.4	-0.4
Kurtosis	2.6	2.0	1.2	1.7	2.1	1.2
Correl with Equity	30.7%	8.3%	20.9%	26.9%	8.3%	52.5%
Correl with Bond	87.3%	73.3%	78.3%	61.2%	72.9%	82.8%
CoSkew with Equity	-0.2	0.2	-0.2	-0.4	0.2	-0.7
CoSkew with Bond	-0.8	-0.6	0.0	-0.2	-0.7	0.2
CoKurt with Equity	-2.6	-3.0	-2.3	-1.5	-3.0	-0.9
CoKurt with Bond	0.3	-0.1	0.6	-0.6	-0.1	-0.2

Strategy Description

- The index seeks to provide exposure to a range of asset classes and geographic regions based on the modern portfolio theory approach to asset allocation.
- The Index selects from a basket of 12 cross asset ETFs and the J.P. Morgan Cash Index USD 3 Month. The ETF universe includes SPY, IWM, EFA, TLT, LQD, HYG, EEM, EMB, IYR, GSG, GLD and TIP.
- The Index seeks to identify the weights for each Basket Constituent that would have resulted in the hypothetical portfolio with the highest return over the previous six months while realizing an annualized volatility over the same period of 5% or less.

Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg. * Performance calculated as of Oct 2013.

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Theory of Risk Premia

Risk premium is commonly regarded as the difference between the expected return of a risky investment and the riskless return (e.g. US Treasury bill return for a US$ investment). In general, risk premium is the expected compensation (or excess return) for bearing the risk of losses on an investment. From the perspective of a rational investor, requiring a positive risk premium is related to his/her risk aversion, characterized by a concave utility function.

Economic and financial theories based on investor rationality and market efficiency relate risk premia with macro/liquidity risk factors, investor risk-aversion and its covariance with "bad times[48]". More recent developments in behavioral theories links the persistence of market anomalies to investors' psychological traits such as anchoring, herding, over-confidence, over-reaction and frame dependence, which are not captured by traditional finance theories. We believe both rational and irrational psychological factors contribute to the time-varying nature of different risk premia. Swinging investor sentiment between bullishness and bearishness is probably more important in determining tactical trends and reversals in different investment strategies, while rational financial theories could provide some general guidance on the "intrinsic values" of the risk factors. These two forces together determine risk factor cycles.

Risk averse investors require positive risk premia

In order to understand why there are risk premia, we start by describing an average investor through the use of a utility function. In Economics terms, a utility function quantifies the satisfaction of an individual from consuming a given amount of goods and services. Conceptually, it maps a person's wealth or consumption in dollar terms (the total value that he/she might receive or consume in goods/services) into a numeric measure of "happiness".

Generally speaking, there are two "agreed" properties for the utility function of an average investor that is assumed to be risk-averse: (1) More wealth leads to higher level of satisfaction, and (2) Additional satisfaction acquired by a given increase of wealth decreases when one obtains more wealth. The first property is called "monotonicity" and the second "decreasing marginal utility". These two fundamental properties make the utility function upward sloping and concave[49].

For an expected utility maximizer[50] with unit investment capital and a concave utility function u, any investment opportunity with one-period return R should satisfy:

$$E[u(1+R)] \geq u\left(1+r_f\right)$$

where $E[\cdot]$ is the expectation of a random variable and r_f is the risk-free return with the same investment horizon. The inequality above simply states that "the investor is rationally requiring a higher expected utility".

As the utility function is concave, by Jensen's inequality,

$$u(E[1+R]) \geq E[u(1+R)]$$

Putting the two equations together, we have

$$u(E[1+R]) \geq E[u(1+R)] \geq u\left(1+r_f\right)$$

---

48 Typically, "bad times" could refer to adverse economic and market scenarios such as faltering economic growth, high inflation/deflation, banking/liquidity crises, volatility spikes, and other economic/financial turbulences. For historical records of various financial crises in 66 countries, see Reinhart and Rogoff (2009).

49 Logarithmic and quadratic utility functions are frequently used by academia and practitioners.

50 According to *von Neumann–Morgenstern (VNM) Utility Theorem*, a (VNM-) rational decision maker must be an expected utility maximize for some utility function. The famous "Kelly criterion" used in the gaming and trading community is a special case with logarithmic utility function.

Because the utility function u is monotonically increasing, the required risk premium ($E[R] - r_f$) must be positive. Despite our simple illustration of a one-period investment choice, similar logic works for multi-horizon investment opportunities.

Risk premia defined by its covariance with "bad times"

A central idea among modern asset pricing theories is that the no-arbitrage price of an asset at time t (denoted by P_t) is given by the conditional expectation of its payoff at (t+1) (denoted by X_{t+1}) discounted to t:

$$P_t = E_t[X_{t+1} m_{t+1}]$$

where m is a "stochastic discount factor" (SDF) reflecting a time-varying discount rate and $E_t[\cdot]$ is the conditional expectation of a random variable. The SDF is intuitively a measure of "bad times": it is high during "bad times" such as macro-economic recessions and/or market distress and it is low during "good times" such as economic booms and/or market richness. In other words, assets that pay off well in bad times are valuable to investors.

With some re-arrangement of the above equation[51], we can get

$$E_t\left[R_{t+1} - r_f\right] = -\left(1 + r_f\right)\mathrm{cov}_t\left(R_{t+1} - r_f, m_{t+1}\right)$$

which states that the risk premium for any investment is inversely related to its covariance with SDF, the index of "bad times".

With this in mind, it is not difficult to understand why traditional long-only investments in risky asset classes like equity, credit and commodities may demand high risk premia, while long-only investment in safe-haven assets such as US Treasuries could command low or even negative risk premia. Moreover, systematic strategies like FX carry and equity index volatility selling could justify high risk premia as they tend to lose money in bad times.

Monetizing "crash-risk" or tail-risk for liquidity providers

A more generic explanation for the risk premia of different systematic strategies is that these strategies behave like a lottery-ticket selling strategy that monetize premium income in normal market conditions, but are subject to infrequent but large losses when related "tail" events materialize. Rational liquidity providers for these systematic strategies such as currency carry and commodity momentum thus demand extra compensation for bearing these "crash" risks.

Note that the "crash" events cover broader market situations than the "bad times" terminology in the previous section and the "crash" events may differ for different strategies[52]. Due to different implementation details, the "crash" events may even differ for the same type of strategies, e.g. among carry and momentum strategies for different asset classes. With the benefits of hindsight, different macro/micro indicators could be created to time or forecast these "crash" events in order to improve strategy performances. We cover more empirical details of the "crash risks" of cross-asset systematic strategy styles in Chapter 2 of the main text.

Irrational behaviors

Although the assumption of a "rational" investor is theoretically appealing to financial economics researchers, empirical evidence suggests that market participants make systematic errors. The outbreak of the 2008 global financial crisis (GFC) reinforced the perception that investors could behave irrationally for a sustained period of time.

Behavioral finance theories suggest that market prices also reflect the shifting demands from irrational investors. In other words, the time-varying risk premia reflect both the rational and irrational nature of financial markets. As economist Robert Shiller puts it, "The Efficient Market Hypothesis (EMH) is one of the most egregious errors in the history of economic thought - It's a half-truth." Strategies that are designed to explore investor behavior related market inefficiencies could be

[51] See, for example, Cochrane (2001).
[52] See Brunnermeier, Nagel and Pedersen (2008) and Daniel and Moskowitz (2013).

rewarded. For example, the observed short-term/long-term mean-reversion and medium-term momentum in many asset classes are linked to investors' initial under-reaction, subsequent over-reaction and final realization cycles. Different systematic strategies across asset classes are designed to capture these "behavioral cycles".

Not all risks get compensated at all times

It is well understood that idiosyncratic risks could be diversified away, but systematic risks cannot. While the traditional Capital Asset Pricing Model (CAPM)[53] predicts only systematic risk sources carry risk premia, more recent papers[54] suggest idiosyncratic risk could also explain cross sectional stock returns. Risk premium investing is about exploring sources of risks that get rewarded over the medium to long term.

However, not all risk-taking activities are compensated. For example, it is well-known that casinos gain a consistent edge over gamblers and hence gambling is a long-run losing activity despite its risk-taking nature. Even strategies that are proved to gain positive risk premia could suffer extended periods of drawdown.

For example, the "Magic Formula" propagated by Hedge Fund manager Joel Greenblatt[55], which employs quantitative stock screens to purchase stocks with high earnings yields and high return on capital, suffered steep a drawdown during the GFC[56]. However, this doesn't mean the "Magic Formula" is not a valid source of long-run risk premium. In the same vein, despite the fact that the cross-asset strategy factors introduced in Chapter 2 earned positive risk premia during the 41-year sample period, many strategies suffered dramatic and extended periods of drawdown that may result in the strategies falling out of favor with investors.

As a result, there should be sound economic rationale behind a successful risk premium strategy. Besides establishing economic explanations, an understanding of the time-varying and regime-shifting natures of different risk premia is essential for successful cross-asset systematic investing. Moreover, one may attempt to implement various dynamic risk timing strategies to enhance the "vanilla" risk premia strategies in the hope that future drawdowns could be avoided.

Market inefficiencies and Arbitrage Opportunities

The Efficient Market Hypothesis (EMH) suggests that the market prices of traded assets reflect all known information at any time. However, this contradicts with the observed fact that security prices sometimes fluctuate wildly even during periods with no new market information. Moreover, EMH-advocators argue that even if there are temporary market inefficiencies due to liquidity or legal constraints, smart investors will exploit them and arbitrage them away. Again, this also cannot withstand the well-known phenomenon that events like company earnings announcements, FOMC meetings, key economic data releases, rating agencies' guidance on credit upgrade/downgrades, etc, presented persistent arbitrage opportunities in equity, rates and credit markets.

The astonishing long-run track records of many *Market Wizards*[57] interviewed by Jack D. Schwager also present strong cases against the EMH. One common trait of success for these Market Wizards is a strict enforcement of risk management rules that reduces the negative impact of "tail events". Actually, it is these managers' ability to avoid "crash events" that generates long-run alpha for star fund managers. We examined the details for different risk management systems that could be employed to improve risk-adjusted returns in Chapter 3.

Over-fitting and Data Mining Biases

Data-mining bias involves selecting attractive trading strategies with high return-risk profiles among many candidate strategies. It usually occurs when the same database is used repeatedly to search for patterns or trading rules by fine-tuning

[53] See Sharpe (1964) and Lintner (1965).
[54] See Miffre et al. (2011) and Heaton and Deborah (1996).
[55] Detailed performance and implementation could be found in Greenblatt's best-seller series "The Little Book That Beats the Market" and "The Little Book That Still Beats the Market".
[56] See Gray and Carlisle (2012).
[57] See the "Market Wizards" book series (1988, 1992, 2001, 2012) by Jack D. Schwager.

parameters such as buy/sell thresholds, lookback-window length, and exponential decay weights, etc. Only the best result is shown on a specific combination of signals and/or sample periods. In fact, the frequently claimed “out-of-sample” tests in many investment-related studies were calibrated "in-sample". Even though “sensitivity studies” were provided to prove the consistency of a strategy, they could only be performed on parameters that are not the key inputs to the relevant strategy.

Increasing the number of parameters for a systematic strategy often improves back-test results. However, this usually leads to the so-called “over-fitting” problem that often precludes strategy crashes once it goes live (which is a true out-of-sample test). One should recognize the reality that any simulated (back-tested) performance likely overstates future prospects. A useful test of data-mining and over-fitting biases is to examine the sensitivity of the strategy’s Sharpe ratio to the key input parameters and to various data series/sample periods.

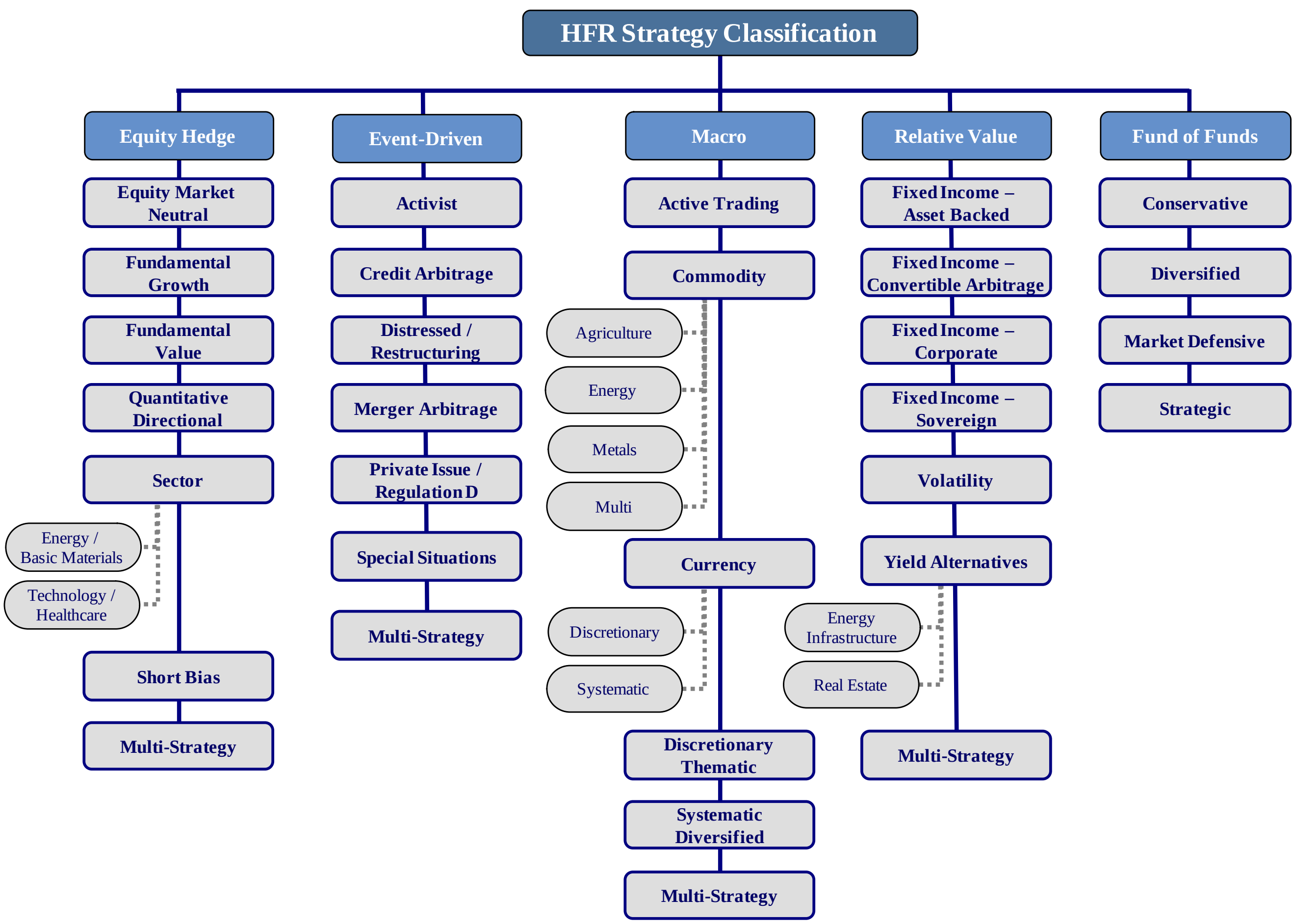
Factor Styles and HFR Classification

According to hedge fund index and database provider Hedge Fund Research (HFR), the total assets under management (AUM) for the hedge fund industry reached a record high of US$2.51 trillion as of Q3 2013. Given the increasing public awareness of the hedge fund industry, investors may be interested in how different hedge fund strategies may fit into our framework of "Traditional Beta/Carry/Momentum/Value/Volatility" fundamental risk factor style classifications. Short Q&As are presented in this Appendix to help readers better understand their differences and commonalities.

Q: What are the popular Hedge Fund Strategies?

A: Hedge fund database/index providers classify reporting hedge funds via certain strategy style tilts from collected responses. The popular hedge fund strategies include Long/Short Equity, Equity Market Neutral, Event Driven, Global Macro, Fixed Income Arbitrage, and Volatility Strategies among others. The chart below gives additional granularity of hedge fund strategies according to HFR classifications. Other popular hedge fund databases such as DJCS, BarclayHedge and Eurekahedge use a similar system of strategy classifications.

Figure 102: HFR Strategy Classifications



Source: HFR.

Q: What are the pros and cons of existing Hedge Fund strategy classification?

A: Pros: The existing strategy classifications from Hedge Fund Database/Index providers give some generic descriptive insights into otherwise mysterious strategy styles. For example, HFR defines Global Macro as "a broad range of strategies in which the investment process is predicated on movements in underlying economic variables and the impact these have on equity, fixed income, hard currency and commodity markets".

Cons: It is well documented that hedge fund managers often deviated from their stated strategy style ("Style Drift") and hence the related indices may not be representative. Moreover, the hedge fund database is **fragmented** (different managers may report to different databases) and is subject to **self-reporting biases** (managers may only want to show the performance of certain strategies and/or periods) as well as **survivorship bias** (closed funds were dropped out of the index). Hence, the categorization **may not be consistent** and related benchmarks **may not be broadly representative** of the stated investment styles.

Q: How is the performance of popular Hedge Fund strategies compared to traditional assets like Stocks and Government bonds?

A: As mentioned in the previous Q/A, all existing hedge fund benchmarks suffer from different degree of biases. We select major benchmarks for HFRI (non-investable) indices for illustration purposes. To be sure, traditional asset benchmarks such as MSCI equity indices and J.P. Morgan global government indices are more representative of asset returns.

Table 48 compares return/risk characteristics for HFRI indices versus Global Equities and Government Bonds[58] during the 23-year period from Dec 1989 to Dec 2012. With the exception of Global Macro, we find all hedge fund strategies exhibited negative skewness and high excess kurtosis (fat tail), a property exhibited by tail-risk selling strategies like Currency-Carry and Cross asset Volatility factors.

Table 48: Performance-Risk metrics for HFRI Strategies during Dec 1989 to Dec 2012, compared with Global Equities and Government Bonds

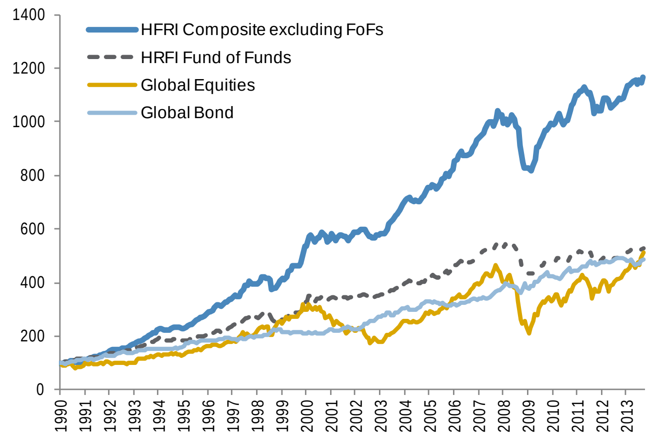
	Composite ex-FoFs	Fund of Funds	Equity Hedge	Event Driven	Global Macro	Relative Value	Emerging Market	Global Equities	Global Bond
Average (%)	7.0	3.5	8.7	7.5	8.1	6.2	9.1	4.1	3.3
CAGR (%)	7.0	3.4	8.6	7.5	8.1	6.2	8.4	2.8	3.2
STDev (%)	7.0	5.8	9.2	6.9	7.5	4.4	14.3	15.9	5.9
MaxDD (%)	-24.1	-24.8	-33.0	-28.1	-11.6	-20.7	-47.2	-56.3	-16.7
MaxDDur (in yrs)	3.3	5.2	5.2	3.5	2.8	2.2	6.3	7.3	4.2
Sharpe Ratio	1.01	0.61	0.95	1.09	1.07	1.41	0.64	0.26	0.57
Sortino Ratio	1.59	0.89	1.57	1.63	2.20	2.10	0.93	0.35	0.93
Calmar Ratio	0.77	0.45	0.65	0.82	1.12	1.50	0.55	0.20	0.86
Pain Ratio	1.96	0.58	1.65	2.38	2.83	4.65	0.71	0.25	0.82
Reward to 95VaR	0.21	0.11	0.19	0.22	0.29	0.46	0.13	0.04	0.12
Reward to 95CVaR	0.14	0.08	0.13	0.13	0.19	0.18	0.08	0.03	0.09
Hit Rate	0.66	0.63	0.64	0.69	0.58	0.77	0.63	0.58	0.57
Gain to Pain	2.10	1.61	2.04	2.28	2.34	3.22	1.62	1.21	1.51
Skewness	-0.76	-0.77	-0.29	-1.33	0.47	-2.12	-0.88	-0.66	0.14
Kurtosis	2.56	4.09	1.77	4.12	0.98	13.76	3.66	1.46	0.41
Correl with Equity	0.09	0.06	0.09	0.12	-0.03	0.15	0.06	1.00	0.26
Correl with Bond	-0.15	-0.10	-0.15	-0.14	-0.01	-0.10	-0.16	0.26	1.00
CoSkew with Equity	-0.45	-0.39	-0.41	-0.51	-0.24	-0.48	-0.36	-0.66	-0.09
CoSkew with Bond	-0.22	-0.31	-0.17	-0.29	0.01	-0.38	-0.20	-0.11	0.14
CoKurt with Equity	-1.51	-1.55	-1.52	-1.48	-2.68	-0.86	-1.80	1.46	-1.69
CoKurt with Bond	-3.83	-3.71	-3.78	-3.83	-3.32	-3.92	-3.75	-2.06	0.41

Source: HFR, J.P. Morgan Quantitative and Derivatives Strategy. * Calculations are based on monthly excess returns over 1-month US$ Libor rates.

[58] We select MSCI All-Country World total return index and J.P. Morgan Global Government Bond (unhedged) index as benchmarks for Global Equities and Global Government Bonds.

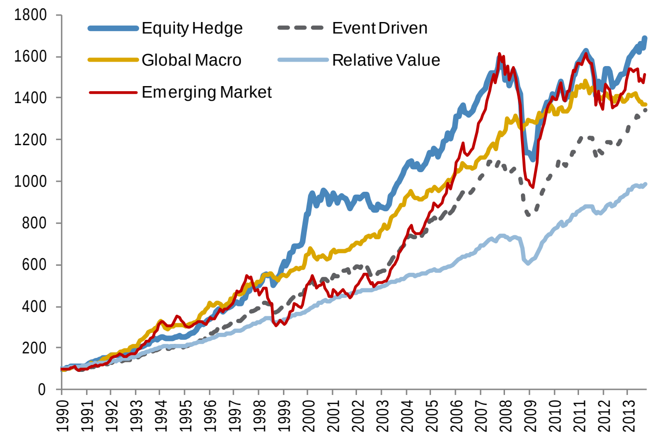
Figure 103 and Figure 104 below shows the historical total return of HRFI indices and the sub-Strategy Style categories (scaled to US$100 at Dec 31, 1989). We find that all hedge fund strategies (after deduction of fees) displayed superior Sharpe ratio than the traditional assets like Global Equities and Global Government Bonds during this specific sample period.

Figure 103: Total returns of HFRI weighted composite (ex FoFs) index, HFRI Fund of Fund index and Global Equities/Govt Bond



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 104: Total returns of HFRI major strategies: Equity Hedge, Event Driven, Global Macro, Relative Value and Emerging Markets.



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Q: Are Hedge Fund strategies good diversifiers to an Equity/Bond Portfolio?

A: Table 49 below shows the correlation among HFRI strategies as well as between Global Equities and Government Bonds. We find significant positive correlation among HFRI sub-strategies and these strategies became nearly perfectly correlated during the GFC (except Global Macro) - one possible explanation is that all hedge funds were significantly exposed to some common risk factors that materialize during crises.

Moreover, the hedge fund strategies' diversification abilities to Global Equities during crisis were generally eroded except Global Macro. On the other hand, with the exception of Global Macro, the correlation between Hedge funds strategies and Global Government bonds remained low or negative during the GFC. This is not surprising as all Hedge Fund indices behaved like equities during the GFC, whereas government bonds benefited from policy rate cuts and global QE programs.

Table 49: Correlation Matrix of HFRI Strategies, Global Equities and Government Bonds during Dec 1989—Dec 2012 (lower diagonal) and during the GFC (upper diagonal)

	Composite ex-FoFs	Fund of Funds	Equity Hedge	Event Driven	Global Macro	Relative Value	Emerging Market	Global Equities	Global Bond
Composite ex-FoFs		97	99	96	44	91	97	29	1
Fund of Funds	87		94	94	49	91	92	26	10
Equity Hedge	95	82		96	36	90	98	32	-2
Event Driven	90	76	83		25	95	93	28	-12
Global Macro	64	67	55	50		16	36	-2	42
Relative Value	72	66	67	76	32		89	28	-11
Emerging Market	87	80	74	76	57	62		39	6
Global Equities	9	6	9	12	-3	15	6		44
Global Bond	-15	-10	-15	-14	-1	-10	-16	26	

Source: HFR, J.P. Morgan Quantitative and Derivatives Strategy. * Calculations are based on monthly excess returns over 1-month US$ Libor rates.

Q: How can major Hedge Fund strategies fit into our risk factor framework?

A: The framework we develop in this primer is concerned with systematic strategies, while most hedge fund strategy categories involve combinations of discretionary and systematic elements. For the systematic part of each generic hedge fund strategy category, it could be classified as a "Multi Region" and "Multiple Risk Method" strategy that is supposed to deliver Alpha. Table 50 below gives some stylized classification of the generic HFR strategies under our framework.

Table 50: Classification of HFR Strategies

HFR Strategies	Strategy Type	Asset Class	Regional Focus	Strategy Style	Risk Method
Equity Hedge					
Equity Market Neutral	Alpha	Equities	Multi Region	Multi Strategy	Multiple Methods
Fundamental Growth	Alpha	Equities	Multi Region	Multi Strategy	Multiple Methods
Fundamental Value	Alpha	Equities	Multi Region	Value	Multiple Methods
Quantitative Directional	Alpha	Equities	Multi Region	Value	Multiple Methods
Short Bias	Alpha	Equities	Multi Region	Value	Multiple Methods
Event Driven					
Credit Arbitrage	Alpha	Rates and Credit	Multi Region	Value	Multiple Methods
Distressed Restructuring	Alpha	Rates and Credit	Multi Region	Value	Multiple Methods
Merger Arbitrage	Alpha	Equities	Multi Region	Value	Multiple Methods
Special Situations	Alpha	Multi Asset	Multi Region	Value	Multiple Methods
Macro					
Active Trading	Alpha	Multi Asset	Multi Region	Multi Strategy	Multiple Methods
Commodity	Alpha	Commodities	Multi Region	Multi Strategy	Multiple Methods
Currency	Alpha	Currencies	Multi Region	Multi Strategy	Multiple Methods
Systematic Diversified	Alpha	Multi Asset	Multi Region	Multi Strategy	Multiple Methods
Relative Value					
Fixed Income	Alpha	Rates and Credit	Multi Region	Value	Multiple Methods
Volatility	Alpha	Volatilities	Multi Region	Value	Multiple Methods
Yield Alternatives	Alpha	Multi Asset	Multi Region	Value	Multiple Methods
Fund of Funds					
Fixed Income	Alpha	Rates and Credit	Multi Region	Multi Strategy	Multiple Methods
Volatility	Alpha	Volatility	Multi Region	Multi Strategy	Multiple Methods
Emerging Market	Alpha	Multi Asset	Emerging Market	Multi Strategy	Multiple Methods

Source: J.P. Morgan Quantitative and Derivatives Strategy.

For specific reporting hedge funds, we could have a more detailed classification of its regional focus and strategy style by examining both the reported style tilts as well as realized risk factor attributions. For example, Table 51 below gives some examples of hedge funds by examining their public disclosure of asset class focus/investment styles:

Table 51: Illustrative Classification of Hedge Funds under the J.P. Morgan Cross Asset Risk Factor Framework

Bloomberg Ticker	Hedge Fund Name	AUM (US$ mn)	Launch Date	Fund Currency	Strategy Type	Asset Class	Regional Focus	Strategy Style
STAMWIF VI	Winton Futures Fund Ltd	9,692	9/30/1997	USD	Alpha	Multi Asset	Multi Region	Multi Factor
LANUEUI KY	Lansdowne Developed Markets	8,150	7/31/2001	USD	Alpha	Equities	EMEA	Value
CAPULAD KY	Capula Global Relative Value	5,452	10/3/2005	USD	Alpha	Rates and Credit	Multi Region	Value
TARPALE US	Tarpon All Equities Fund LLC	3,170	9/29/2006	USD	Alpha	Equities	Emerging Markets	Multi Factor
CCPQUAN KY	CCP Quantitative Fund	2,300	3/1/2007	USD	Alpha	Multi Asset	Multi Region	Momentum and Value
IRISLOW GU	Managed Investments PCC Ltd - IRIS Low Volatility Cell	1,792	7/31/2007	USD	Alpha	Multi Asset	Multi Region	Volatility
ARMAJCU KY	Armajaro Commodities Fund	968	4/19/2004	USD	Alpha	Commodities	Multi Region	Momentum

Source: Bloomberg, J.P. Morgan Quantitative and Derivatives Strategy. * For illustration purpose only.

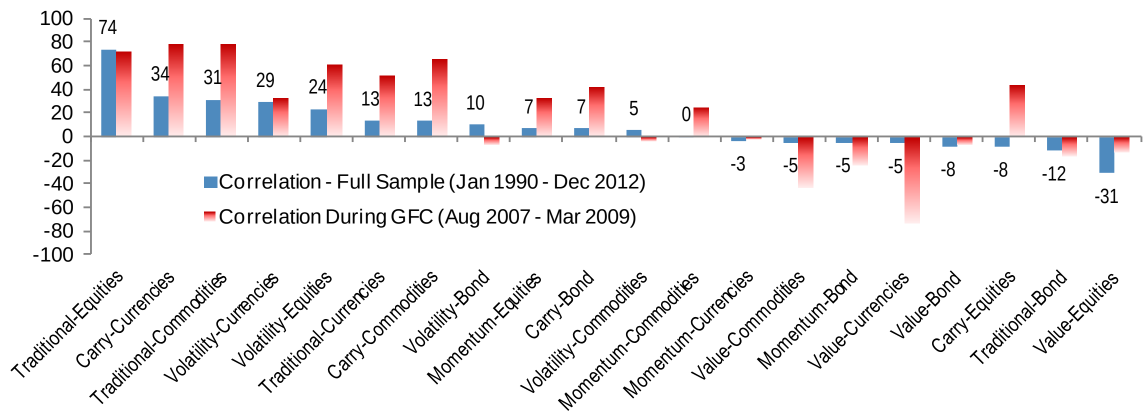
Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Q: Can Hedge Fund strategies being systematically replicated?

A: This is an area that deserves future research efforts and the answer so far is a qualified "yes". Most existing hedge fund replicators strive to balance between absolute performance and tracking error against some benchmarks. Theoretically, if the hedge fund indices (before fees) cannot deliver alpha after controlling for a systematic replicator, it could reflect that discretionary judgment of the hedge fund managers may not add value on average.

A simple illustration of the ex-post replicability of hedge strategies is to examine the sample correlation between hedge fund indices with Cross Asset risk factors. For example, Figure 105 below plots the pairwise correlation between the HFRI composite index with the cross-asset risk factors we introduced in Chapter 2. Consistent with our previous intuitions, on average hedge funds were significantly exposed to Traditional Equity and Commodities beta, Currency Carry, Equity Volatility and Carry Volatility risk factors, which performed poorly during realizations of tail events (see the increased correlation during the GFC). On the other hand, the hedge fund index's negative correlation with Bond beta and Value factors may reflect these factors' systematic diversification abilities rather than hedge fund's negative factor exposures.

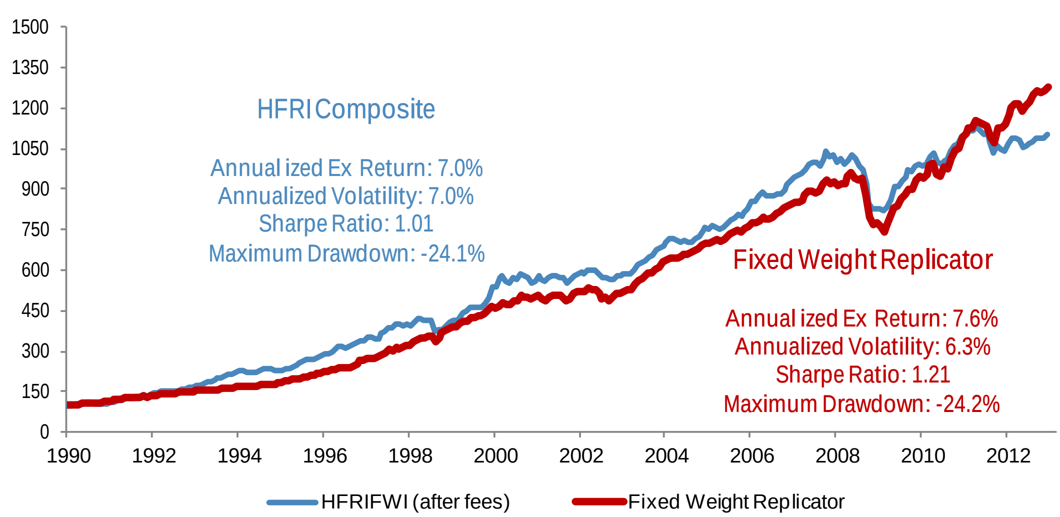
Figure 105: Correlation between HFRI composite (ex-FoFs) and Cross Asset Strategy Factors



Source: J.P. Morgan Quantitative and Derivatives Strategy, HFR.

Based on these findings, we create a simple Hedge Fund replicator using a fixed weight portfolio of 30% in Traditional Equity Beta (SPX), 5% in Traditional Commodities Beta (S&P GSCI), 10% in S&P 100 Index Implied-Realized Volatility Swap, and the rest in 1-month US$ Libor.

Figure 106: HFRI composite index compared with a simple three-factor fixed weight replicator (Jan 1990 – Dec 2012)



Source: J.P. Morgan Quantitative and Derivatives Strategy, HFR.

Figure 106 above compares the historical performance of HFRI composite index and our fixed weight (FW) replicator. Despite the simplicity of our portfolio, it achieved a +77% historical correlation with the HFRI composite index, similar drawdowns and a higher Sharpe ratio during the period from Jan 1990 to Dec 2012.

In reality, hedge funds are switching among different strategies according to their assessment of macro/market environments and fund managers' timing/selection abilities. These dynamic features are not captured by the full-sample correlation coefficients or multiple regression betas. The issue of dynamic replication/super-replication of Hedge Fund sub-strategies under a more general economic/statistical framework is a topic for future research.

Factor Rankings

Table 52 reports the Sharpe ratios of the cross-asset factors introduced in Chapter 2, during different periods of Growth, Inflation, Volatility, and Funding/Market Liquidity regimes. For example, the traditional Commodities beta achieved a Sharpe ratio of 0.9 during "High Growth" regimes; while its Sharpe ratio was reduced to -0.1 during "Low Growth" regimes.

Table 52: Overall Sharpe ratios of Cross-Asset factors amid different Economic/Market Regimes

	Growth			Inflation			Volatility			Funding Liquidity			Market Liquidity		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
Traditional-Equities	0.17	0.23	0.37	0.18	0.85	-0.16	0.90	0.67	-0.27	-0.06	0.51	0.38	-0.63	0.82	1.16
Traditional-Bond	1.26	1.65	0.95	1.14	2.15	0.79	1.70	0.83	1.40	0.98	1.48	1.56	0.89	1.54	1.39
Traditional-Currencies	-0.23	0.44	-0.07	0.27	0.11	-0.24	0.30	-0.07	-0.04	-0.14	-0.02	0.37	0.16	-0.02	-0.02
Traditional-Commodities	-0.11	0.20	0.90	0.33	0.19	0.25	0.52	0.08	0.24	0.06	0.52	0.24	0.12	0.80	0.02
Carry-Equities	1.02	0.31	0.57	0.86	0.43	0.82	0.63	0.12	0.87	0.32	0.68	0.72	0.97	0.56	0.39
Carry-Bond	0.01	0.40	0.60	0.31	-0.29	0.72	0.63	0.24	0.08	0.24	0.37	0.63	0.13	0.62	0.20
Carry-Currencies	0.54	0.79	0.86	0.67	0.53	1.09	0.74	1.05	0.47	0.61	0.58	0.98	0.47	0.59	1.14
Carry-Commodities	0.49	0.02	0.47	0.36	-0.02	0.63	0.42	0.64	0.05	0.32	0.52	0.20	0.31	0.46	0.26
Momentum-Equities	0.14	0.34	0.54	-0.16	0.76	0.26	0.47	0.55	0.05	0.43	0.33	0.25	0.26	0.56	0.24
Momentum-Bond	0.29	0.96	0.51	0.73	0.90	0.35	0.69	0.27	0.70	0.25	1.02	0.66	0.02	0.96	0.85
Momentum-Currencies	-0.22	0.58	0.51	0.01	0.45	0.32	0.89	0.26	-0.17	0.14	0.12	0.66	-0.08	0.70	0.26
Momentum-Commodities	0.38	0.60	0.65	0.43	0.57	0.63	1.22	0.36	0.21	0.81	0.44	0.36	0.27	0.90	0.49
Value-Equities	0.25	0.65	0.56	0.25	0.29	0.89	1.06	0.44	0.20	0.29	0.18	1.04	0.51	0.60	0.26
Value-Bond	0.63	0.03	0.90	0.23	0.05	1.06	0.53	0.26	0.92	1.02	0.05	0.41	1.26	0.21	0.17
Value-Currencies	0.85	0.00	0.32	0.30	0.64	0.28	0.39	0.09	0.66	0.65	0.33	0.26	0.44	0.20	0.60
Value-Commodities	0.11	0.42	0.00	0.22	0.31	0.03	-0.07	0.44	0.12	-0.07	0.08	0.53	0.04	0.20	0.34
Volatility-Equities	0.23	0.88	0.53	0.42	0.76	0.25	0.81	0.60	0.44	0.17	0.72	0.49	0.32	0.38	0.82
Volatility-Bond	0.19	0.54	1.28	0.36	0.71	-	0.47	1.26	0.18	-0.93	1.37	0.39	0.17	0.26	1.16
Volatility-Currencies	-0.06	2.46	1.14	0.43	1.29	-	1.74	1.62	-0.13	-2.42	1.40	1.63	-0.16	1.90	0.94
Volatility-Commodities	1.04	0.72	0.57	0.60	1.42	-	0.95	1.02	0.70	0.00	1.34	0.79	0.51	0.78	1.25

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 53 ranks the factors under each regime with respective to their Sharpe ratios[59] **from high to low** and calculates the average ranks for each factor style under all regimes and under the current regime (shaded columns).

Table 53: Sharpe ratio ranks (from high to low) of Cross-Asset factors amid different Economic/Market Regimes

	Growth			Inflation			Volatility			Funding Liquidity			Market Liquidity			Average Rank	
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High	All	Current
Traditional-Equities	13	16	17	18	5	16	6	6	20	16	11	14	20	5	4	12.5	10.9
Traditional-Bond	1	2	3	1	1	5	2	5	1	2	1	2	3	2	1	2.1	1.6
Traditional-Curncy	20	11	20	14	17	17	19	20	17	18	20	15	13	20	20	17.4	17.0
Traditional-Comdty	18	17	5	11	16	13	14	19	9	14	9	19	15	6	19	13.6	14.9
Carry-Equities	3	15	10	2	13	4	11	17	3	7	7	6	2	12	11	8.2	8.6
Carry-Bond	16	13	8	12	20	6	12	16	14	11	13	9	14	9	17	12.7	12.6
Carry-Currencies	6	5	6	4	11	1	9	3	7	5	8	4	6	11	5	6.1	6.3
Carry- Comdty	7	19	16	9	19	7	17	7	16	8	10	20	9	14	15	12.9	14.4
Momentum-Equities	14	14	12	20	6	12	15	9	15	6	15	18	11	13	16	13.1	15.7
Momentum-Bond	9	3	15	3	4	9	10	13	4	10	5	8	17	3	7	8.0	6.1
Momentum-Curncy	19	9	14	19	12	10	7	14	19	13	17	7	18	8	14	13.3	11.9
Momentum- Comdty	8	8	7	7	10	8	3	12	10	3	12	16	10	4	10	8.5	8.0
Value-Equities	10	7	11	15	15	3	4	10	11	9	16	3	4	10	13	9.4	8.9
Value-Bond	5	18	4	16	18	2	13	15	2	1	19	12	1	17	18	10.7	14.1
Value-Currencies	4	20	18	13	9	11	18	18	6	4	14	17	7	18	9	12.4	14.1
Value-Commodities	15	12	19	17	14	15	20	11	13	17	18	10	16	19	12	15.2	15.0
Volatility-Equities	11	4	13	8	7	14	8	8	8	12	6	11	8	15	8	9.4	9.3
Volatility-Bond	12	10	1	10	8	-	16	2	12	19	3	13	12	16	3	9.8	11.4
Volatility-Currencies	17	1	2	6	3	-	1	1	18	20	2	1	19	1	6	7.0	4.7
Volatility- Comdty	2	6	9	5	2	-	5	4	5	15	4	5	5	7	2	5.4	4.6

Source: J.P. Morgan Quantitative and Derivatives Strategy.

---

59 We calculated the Reward-to-CVaR ratios under different regimes as well and find the results are broadly similar.

We find that our plain vanilla implementation of Traditional Bond beta, Currency Carry, Equity Carry, Bond Momentum, Currency Volatility and Commodity Volatility factors fared relatively well in Sharpe ratio terms on average. On the other hand, the performances of Commodity beta, Currency beta, Commodity Carry, Currency Momentum and Commodity Value did not perform as strongly. Similarly, Table 54 reports the average correlation of Cross-Asset factors with all the other factors, according to different periods of Growth, Inflation, Volatility, and Funding/Market Liquidity regimes. For example, the average correlation between Currency Carry with other factors was +11.8% during a “Low Inflation” regime; while the average correlation was reduced to a mild +3% during a "Mid Inflation" regime.

Table 54: Average correlation (%) of Cross-Asset factors with other factors amid different Economic/Market Regimes

	Growth			Inflation			Volatility			Funding Liquidity			Market Liquidity		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
Traditional-Equities	7.1	-3.8	3.2	5.5	-1.7	0.5	-1.5	-2.1	6.0	8.9	0.0	1.3	5.8	-0.5	1.7
Traditional-Bond	-7.3	-1.3	-3.1	-6.1	-2.2	-1.3	-3.2	-2.0	-6.2	-4.7	-1.5	-5.9	-7.3	-2.6	-5.4
Traditional-Currencies	6.2	-1.8	-2.0	6.3	1.3	-4.4	0.5	-2.0	3.8	0.9	1.7	4.1	4.0	2.0	-1.0
Traditional-Commodities	7.6	-0.2	5.7	6.7	2.9	1.4	3.0	4.9	5.9	8.7	0.4	5.7	6.3	3.5	4.7
Carry-Equities	-2.6	1.7	-3.4	-1.6	-0.8	-8.1	-1.3	2.0	-2.5	-1.9	-3.0	-0.3	-3.3	0.4	-2.7
Carry-Bond	1.2	2.3	3.8	2.0	2.0	2.6	5.9	0.9	0.2	4.6	1.2	0.9	2.2	4.0	0.4
Carry-Currencies	11.8	3.0	4.4	10.6	4.4	3.0	5.3	2.9	9.7	10.7	3.4	8.1	9.7	4.2	6.8
Carry-Commodities	1.3	0.1	0.9	-0.6	1.4	2.6	-1.6	0.9	1.5	4.7	-0.4	-1.2	3.4	-0.1	-2.6
Momentum-Equities	-2.8	0.3	1.2	-1.4	0.7	2.4	-2.5	1.0	-0.2	1.3	-1.3	1.3	1.0	-2.3	-1.2
Momentum-Bond	-2.9	0.9	7.5	-3.5	0.9	7.4	1.7	4.2	-0.3	0.7	0.6	-1.0	1.8	2.7	-5.5
Momentum-Currencies	-6.5	-0.2	1.7	-6.0	0.9	-0.6	-0.6	0.0	-4.9	-6.7	-4.8	1.2	-4.2	-3.5	-1.9
Momentum-Commodities	-0.7	-2.1	2.2	-0.6	1.4	-0.5	0.3	0.1	-1.2	-3.8	-2.1	1.4	0.0	-2.3	-0.9
Value-Equities	1.7	0.9	-3.1	3.2	-3.7	-3.6	-0.7	0.7	0.6	2.0	-2.4	2.6	0.5	-3.8	4.3
Value-Bond	-4.4	-8.1	3.1	-6.0	-5.1	-1.9	-2.6	0.5	-4.9	-0.3	-4.2	-4.0	-6.1	2.9	-1.1
Value-Currencies	-10.4	1.0	0.7	-8.8	-2.3	2.9	-2.4	-2.0	-5.5	-5.6	-1.1	-4.0	-8.3	-0.2	-0.7
Value-Commodities	-8.3	-5.4	-5.4	-8.3	-5.6	-6.3	-4.5	-6.9	-7.7	-3.6	-5.9	-8.3	-7.7	-5.6	-5.0
Volatility-Equities	5.6	2.4	5.9	5.6	0.5	7.9	-4.1	1.6	8.3	12.9	1.8	2.6	8.3	0.4	5.3
Volatility-Bond	2.6	-0.1	-0.6	4.1	-4.6	-	-2.5	-1.2	4.0	4.0	-4.8	2.3	0.7	-1.0	4.9
Volatility-Currencies	6.0	3.7	1.7	4.9	4.4	-	4.9	0.0	5.4	2.8	2.2	4.1	3.7	-0.8	8.5
Volatility-Commodities	5.3	-1.1	-0.7	4.1	-3.0	-	-0.5	2.1	2.9	6.3	2.9	-0.4	5.5	-1.8	0.6

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 55 ranks the factors under each regime with respective to their average correlation with all the other factors **from low to high** and calculates the average ranks for each factor style for the current regime (shaded columns).

Table 55: Average correlation ranks (from low to high) of Cross-Asset factors amid different Economic/Market Regimes

	Growth			Inflation			Volatility			Funding Liquidity			Market Liquidity			Average Rank	
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High	All	Current
Traditional-Equities	18	3	15	16	8	9	9	2	18	18	12	12	17	10	14	12.1	11.7
Traditional-Bond	3	6	4	3	7	6	3	4	2	3	8	2	3	4	2	4.0	3.3
Traditional-Curncy	17	5	5	18	14	3	15	3	14	9	16	17	15	15	9	11.7	13.7
Traditional-Comdty	19	8	18	19	18	10	17	20	17	17	13	19	18	18	16	16.5	16.6
Carry-Equities	8	16	2	7	9	1	10	16	6	6	5	8	6	14	4	7.9	9.6
Carry-Bond	10	17	16	11	17	12	20	13	10	14	15	9	12	19	12	13.8	14.0
Carry-Currencies	20	19	17	20	19	15	19	18	20	19	20	20	20	20	19	19.0	19.6
Carry- Comdty	11	11	9	10	15	13	8	12	12	15	11	5	13	12	5	10.8	8.9
Momentum-Equities	7	12	10	8	11	11	6	14	9	10	9	11	10	5	7	9.3	8.0
Momentum-Bond	6	13	20	6	12	16	16	19	8	8	14	6	11	16	1	11.5	9.1
Momentum-Curncy	4	9	11	5	13	7	12	8	4	1	2	10	5	3	6	6.7	7.0
Momentum- Comdty	9	4	13	9	16	8	14	9	7	4	7	13	7	6	10	9.1	9.3
Value-Equities	12	14	3	12	4	4	11	11	11	11	6	15	8	2	15	9.3	11.6
Value-Bond	5	1	14	4	2	5	4	10	5	7	4	4	4	17	8	6.3	6.1
Value-Currencies	1	15	8	1	6	14	7	5	3	2	10	3	1	11	11	6.5	7.0
Value-Commodities	2	2	1	2	1	2	1	1	1	5	1	1	2	1	3	1.7	1.7
Volatility-Equities	15	18	19	17	10	17	2	15	19	20	17	16	19	13	18	15.7	14.1
Volatility-Bond	13	10	7	14	3	-	5	6	15	13	3	14	9	8	17	9.8	11.6
Volatility-Currencies	16	20	12	15	20	-	18	7	16	12	18	18	14	9	20	15.4	16.6
Volatility- Comdty	14	7	6	13	5	-	13	17	13	16	19	7	16	7	13	11.9	10.6

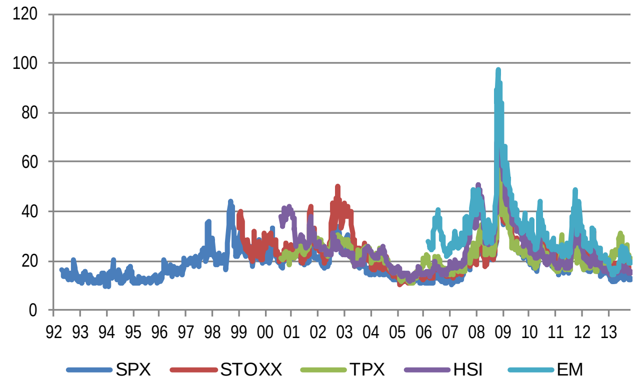
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

We find that Cross Asset Value strategies and the Traditional bond beta factor had the lowest average correlation with other factors on average and under the current macro/market regime. Consequently, they provided good diversification to a cross-asset multi-strategy portfolio. On the other hand, Traditional equity, currency, commodity beta factors, Cross Asset Carry factors, and Volatility factors had the highest average correlation with other factors - they provided the least diversification benefits.

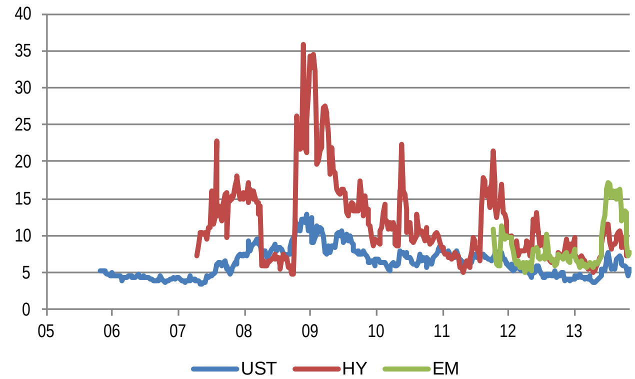
Implied Volatilities Across Assets

Figure 107: 3M ATM Implied Volatilities for Equity Indices (%)



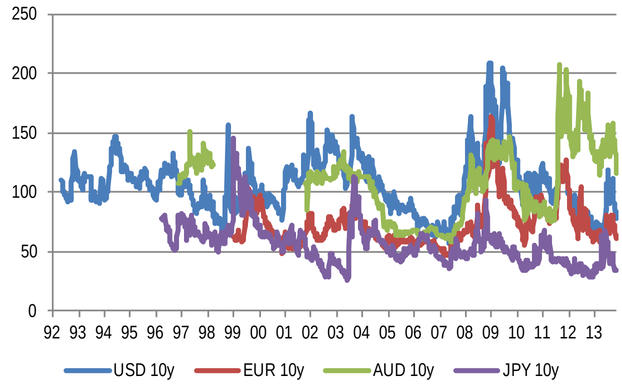
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 108: 3M ATM Implied Volatilities for Bonds (%)



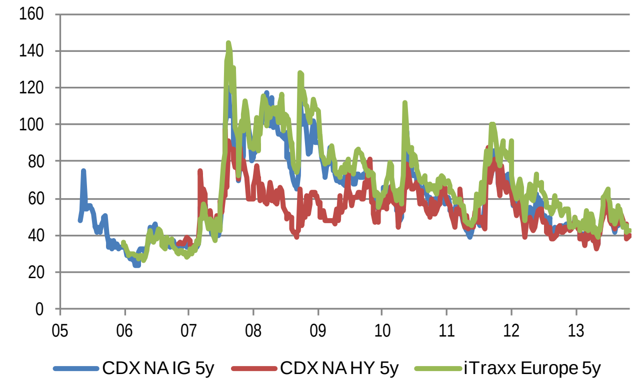
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 109: 3M ATM Implied Vols for Interest Rate Swaps (bps)



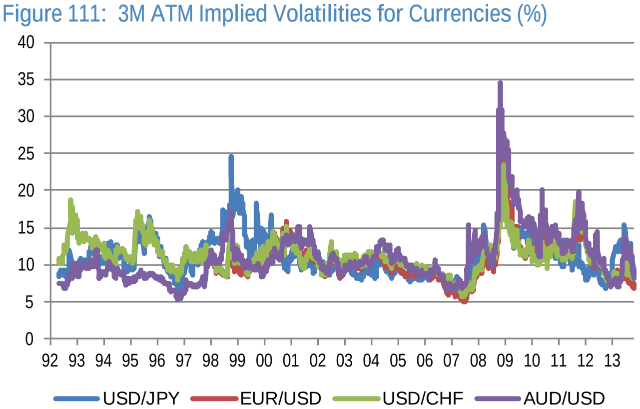
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 110: 3M ATM Implied Volatilities for CDS Indices (bps)



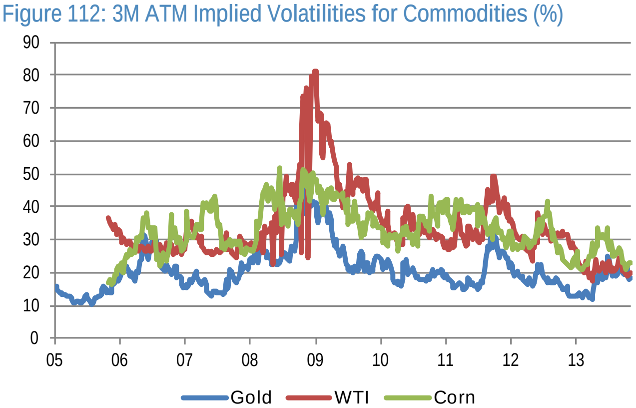
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 111: 3M ATM Implied Volatilities for Currencies (%)



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 112: 3M ATM Implied Volatilities for Commodities (%)



Source: J.P. Morgan Quantitative and Derivatives Strategy.

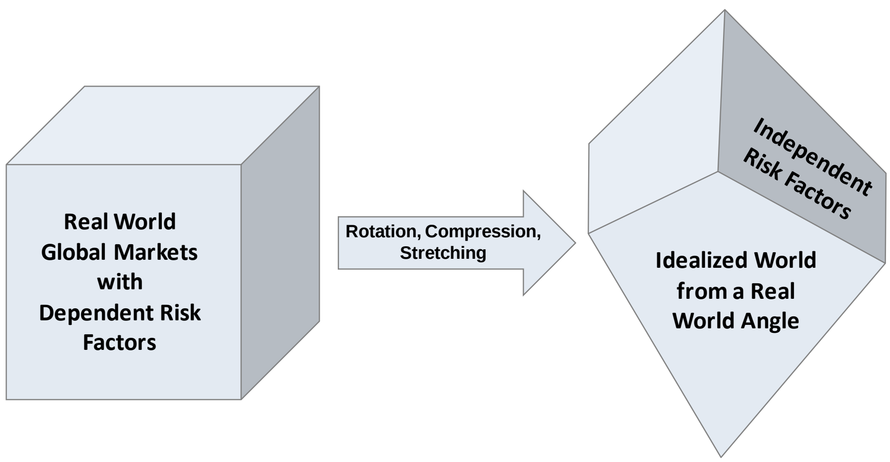
Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Independent Risk Factors

Introduction

In Chapter 2 of the main text, we constructed cross asset risk premium factors to represent generic Traditional, Carry, Momentum, Value and Volatility risk factor styles and studied the long-run risk-return properties, inter-correlations as well as tail risks of the related Toy Models. We hypothesize that these cross-asset risk factors represent independent sources of systematic risk premia in an "idealized world", which is usually different from the "real world"[60]. To visualize their connections, one could imagine the idealized world as some rotation and compression/stretching of the real world financial markets (and vice versa).

Figure 113: Independent Risk Factors in an idealized world become dependent in Real World



Source: J.P. Morgan Quantitative and Derivatives Strategy.

As investors are most concerned with performance and risk in the real world, one may wish to construct real-world independent risk factors. The requirement of risk factor independence in the real financial world is relevant in both understanding the source of risk and in effective portfolio diversification/risk management. The 2007-08 Global Financial Crisis exemplifies investors' poor understanding of risks as the failure to truly diversify led to widespread negative portfolio returns when many assets/investment strategies become highly correlated. Many investments were exposed to common risk factors at a time when diversification was most needed. Instead, portfolios with exposure to multiple independent risk premia sources could fare well even during financial turbulence. Moreover, there are two general benefits from investing in additional independent factors: (1) investors could also achieve better risk-adjusted rewards and, (2) risk hedging is more straightforward with independent factors.

How do we define the Independence of Risk Factors? One important economic rationale is that the distribution of each risk factor should represent **the distribution of some insurance-selling** on a specific type of risk. This property guarantees collection of insurance premium on the associated risk in "normal" times with the promise of suffering losses when such risk materializes and the insurance payment is due. Moreover, the long-term insurance **premium collected in normal times should more than compensate for the loss** in bad times, so that investment managers could justifiably own the corresponding risk and collect the long-term associated premia by providing such liquidity. Since the "bad time" for each independent risk factor is usually independent as well, the insurance payments for all risk factors should not come due simultaneously, yielding a better diversified portfolio. Based on these assumptions, we could design some statistical procedure to estimate the independent risk factors from the original set of cross-asset risk factors. Interested readers can refer to our mathematical derivations in the subsequent sections for more technical details.

[60] Similarly, asset pricing theories suggest that discounted security prices are martingales in a "risk-neutral" world, which is usually different from the real world characterized by average risk aversion. A change of measure is needed to move between the "risk-neutral" world and the real world.

The first step towards independent risk factors is to estimate the **principal component factors** or uncorrelated risk factors. As described Chapter 2, this can be done by finding the eigenvectors of the factor covariance matrix. Besides the risk contribution profile of the principal components in the main text, Table 56 below shows the reward-risk metrics of the principal components (denoted by PCx) of the 20 Cross-Asset Toy Model factors.

We find that the Sharpe ratios of the principal components are generally smaller than the original cross asset risk factors and that the drawdown was generally more severe. This comes at no surprise, as principal components are by construction only concerned with explaining the core risk (variance) of the original risk factors and they are not designed to achieve reasonable risk premia factor profiles.

Table 56: Principal Components of Cross Asset Risk Factors ranked by % of variance explained (Jan 1972 – Dec 2012)

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
Average (%)	8.9	1.0	2.9	3.1	5.6	1.0	8.0	4.3	1.6	8.1
CAGR (%)	6.5	-0.8	1.4	1.8	5.1	0.4	7.8	3.9	1.1	8.0
STDev (%)	22.8	18.7	17.6	15.6	11.9	11.5	9.6	10.1	9.7	8.5
MaxDD (%)	-63.8	-72.1	-56.8	-57.2	-34.6	-37.3	-47.9	-39.0	-37.4	-26.8
MaxDDur (in yrs)	9.1	30.2	24.6	18.8	15.1	23.3	5.4	9.0	23.9	4.1
Sharpe Ratio	0.39	0.05	0.16	0.20	0.47	0.09	0.83	0.43	0.16	0.96
Sortino Ratio	0.61	0.07	0.24	0.28	0.92	0.13	1.37	0.66	0.24	1.67
Calmar Ratio	0.31	0.02	0.18	0.30	0.47	0.07	0.58	0.47	0.14	1.08
Pain Ratio	0.39	0.03	0.09	0.10	0.47	0.05	1.26	0.57	0.09	1.99
Correl with SPX	0.23	-0.54	-0.03	0.22	0.20	0.54	0.00	-0.20	-0.07	0.30
Correl with UST	0.09	0.14	0.01	0.68	0.11	-0.03	0.05	-0.01	0.27	-0.01
Skewness	0.05	0.20	0.00	-0.50	3.16	0.03	-0.35	-0.26	-0.18	-0.12
Kurtosis	2.28	2.98	2.00	2.10	32.65	1.11	2.69	2.77	0.57	0.97

	PC11	PC12	PC13	PC14	PC15	PC16	PC17	PC18	PC19	PC20
Average (%)	2.0	0.1	6.5	2.7	2.6	0.8	8.6	3.2	1.1	2.1
CAGR (%)	1.7	-0.2	6.4	2.5	2.4	0.6	8.8	3.1	1.0	2.1
STDev (%)	8.7	7.5	7.8	7.0	6.6	6.2	5.7	5.3	4.2	2.8
MaxDD (%)	-30.3	-46.3	-24.1	-41.8	-21.0	-28.4	-8.0	-17.0	-14.1	-6.3
MaxDDur (in yrs)	11.8	32.8	4.9	27.8	12.8	14.1	1.8	8.0	9.5	3.8
Sharpe Ratio	0.23	0.02	0.84	0.38	0.39	0.13	1.50	0.61	0.26	0.74
Sortino Ratio	0.35	0.02	1.81	0.64	0.59	0.19	3.05	0.97	0.38	1.25
Calmar Ratio	0.16	0.02	0.85	0.56	0.14	0.13	1.55	1.19	0.17	0.55
Pain Ratio	0.22	0.00	1.89	0.14	0.48	0.08	7.58	0.98	0.30	1.77
Correl with SPX	-0.12	0.08	0.04	-0.09	-0.18	0.07	-0.09	0.19	0.14	0.04
Correl with UST	-0.01	-0.07	0.38	0.05	0.05	0.48	-0.10	0.13	-0.08	-0.03
Skewness	-0.06	-0.26	3.05	0.83	-0.15	0.00	0.00	-0.34	-0.14	-0.08
Kurtosis	1.94	3.44	30.97	5.71	0.86	1.85	0.55	4.09	1.32	0.63

Source: J.P. Morgan Quantitative and Derivatives Strategy.

While investors frequently use the top principal components to conduct analysis, they may have ignored the less volatile but potentially more important risk premium sources. Moreover, the principal components were sometimes falsely regarded as independent factors, which could lead to misunderstanding and misjudgment when the original risk sources are significantly non-normal. Based on the principal components of cross asset risk factors, we move a step further to pursue independent sources of priced systematic risks. The independent factors are generated via maximizing a certain non-normality measure of the joint distribution. Each factor targeted a 10% volatility level for easy comparisons.

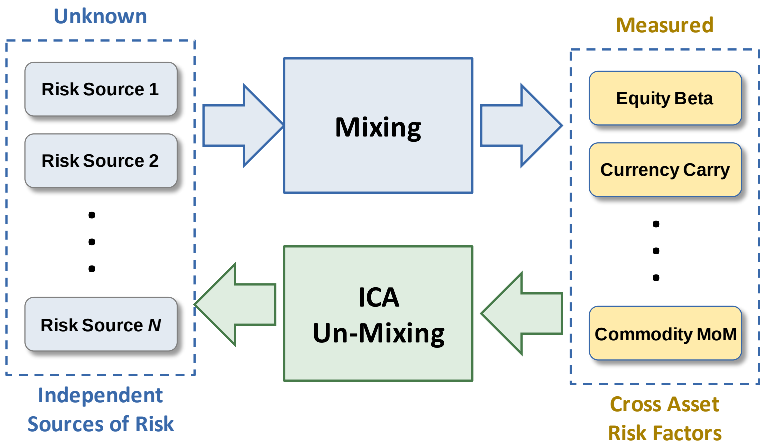
Independent Factors in Portfolio Applications

Consider that we have multiple sources emitting signals that are interfering with each other (e.g. people speaking at the same time in a room) and only mixed signals are recorded. The task of Blind Source Separation (BSS) is to find the "un-mixing matrix" that could restore the original sources of signals. If we consider the original signals as the sources of risk premia, the ICA ("Independent Component Analysis") method[61] exactly fits our purpose in identifying independent risk factors (Figure 114). To simplify the expositions here, we leave the technical details for estimating the independent risk factors to the next section.

[61] See Jutten and Hérault (1991) and Comon (1994).

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Figure 114: From Cross Asset Risk Factors to Independent Factors



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 57 shows the historical risk-reward profiles of the independent risk factors (labeled as RFx) during the period from Jan 1972 to Dec 2012. Compared with Top 10 principal components, the Top 10 independent factors had higher Sharpe ratio, less drawdown and higher excess kurtosis (or fatter tail distribution). On the other hand, the bottom 5 independent risk factors were rewarded poorly and exhibited significant drawdowns. As a result, gaining positive exposures to the top independent risk factors and hedging against the bottom independent risk factors could be a viable solution for a better long-term portfolio. In Table 58, we show the correlation matrix of the 20 independent risk factors: These independent factors had zero correlation during the full sample period (by construction) and their average correlations during crises (and during the recent GFC) were generally close to 0 or slightly negative.

Table 57: Performance-Risk Metrics for Independent Risk Factors ranked by historical Sharpe ratio (Jan 1972 – Dec 2012)

	RF1	RF2	RF3	RF4	RF5	RF6	RF7	RF8	RF9	RF10
Average (%)	10.6	10.0	8.3	7.1	6.8	6.5	5.7	5.6	5.2	4.6
CAGR (%)	10.6	10.0	8.1	6.8	6.5	6.2	5.3	5.2	4.9	4.1
STDev (%)	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
MaxDD (%)	-26.5	-18.4	-19.6	-33.9	-28.4	-31.1	-13.0	-31.9	-37.5	-58.4
MaxDDur (in yrs)	2.0	2.1	6.3	4.8	7.0	3.2	3.2	5.7	7.4	6.6
Sharpe Ratio	1.06	1.00	0.83	0.71	0.68	0.65	0.57	0.56	0.52	0.46
Sortino Ratio	1.81	1.74	2.20	1.22	1.18	0.93	1.24	0.89	0.84	0.58
Calmar Ratio	0.53	0.55	1.37	0.74	0.73	0.53	0.44	0.42	0.66	0.45
Pain Ratio	4.18	3.35	2.38	1.16	1.12	1.72	1.93	0.74	0.61	0.66
Correl with SPX	0.23	-0.54	-0.03	0.22	0.20	0.54	0.00	-0.20	-0.07	0.30
Correl with UST	0.09	0.14	0.01	0.68	0.11	-0.03	0.05	-0.01	0.27	-0.01
Skewness	-0.60	-0.17	6.02	0.31	0.57	-2.09	5.67	-0.06	0.06	-5.11
Kurtosis	5.98	0.99	76.28	1.87	3.49	19.49	77.28	0.84	0.38	61.19

	RF11	RF12	RF13	RF14	RF15	RF16	RF17	RF18	RF19	RF20
Average (%)	4.6	4.4	4.3	3.7	3.7	3.3	2.0	1.9	1.2	0.1
CAGR (%)	4.2	4.0	3.9	3.2	3.2	2.8	1.5	1.4	0.7	-0.4
STDev (%)	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
MaxDD (%)	-34.2	-26.9	-26.9	-56.3	-29.1	-36.6	-33.5	-40.4	-34.9	-66.0
MaxDDur (in yrs)	7.1	5.2	11.0	17.9	16.2	13.3	17.1	23.7	18.3	39.3
Sharpe Ratio	0.46	0.44	0.43	0.37	0.37	0.33	0.20	0.19	0.12	0.01
Sortino Ratio	0.67	0.69	0.74	0.52	0.58	0.60	0.30	0.28	0.17	0.02
Calmar Ratio	0.27	0.33	0.52	0.30	0.53	0.16	0.14	0.20	0.11	0.01
Pain Ratio	0.48	0.73	0.83	0.28	0.29	0.29	0.16	0.12	0.08	0.00
Correl with SPX	-0.12	0.08	0.04	-0.09	-0.18	0.07	-0.09	0.19	0.14	0.04
Correl with UST	-0.01	-0.07	0.38	0.05	0.05	0.48	-0.10	0.13	-0.08	-0.03
Skewness	-0.55	-0.23	1.94	-0.84	0.42	3.12	0.69	0.13	-0.24	0.33
Kurtosis	2.35	7.03	20.36	2.96	5.75	31.17	10.89	3.35	3.24	1.44

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Table 58: Sample correlation between Independent Risk Factors during Jan 1972 to Dec 2012

Color Scheme	Less than -30%	-30% to -10%	-10% to +10%	+10% to +30%	Greater than +30%

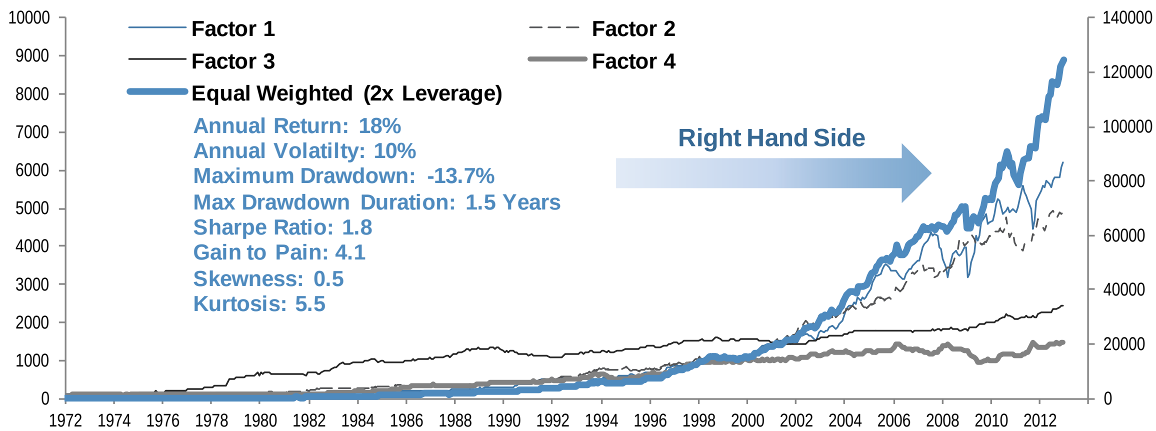
	Risk Factor 1	Risk Factor 2	Risk Factor 3	Risk Factor 4	Risk Factor 5	Risk Factor 6	Risk Factor 7	Risk Factor 8	Risk Factor 9	Risk Factor 10	Risk Factor 11	Risk Factor 12	Risk Factor 13	Risk Factor 14	Risk Factor 15	Risk Factor 16	Risk Factor 17	Risk Factor 18	Risk Factor 19	Risk Factor 20
Risk Factor 1		2	7	-4	34	-15	-2	2	-23	-5	-3	29	-13	4	-17	5	0	-5	6	0
Risk Factor 2	0		-10	-4	12	16	-8	-10	13	10	-29	0	21	0	18	-15	17	-13	6	15
Risk Factor 3	0	0		16	6	-13	4	-6	-2	-1	5	7	6	-1	-2	2	-35	9	0	-1
Risk Factor 4	0	0	0		10	36	-5	3	-16	12	-2	0	20	-10	-19	-3	17	-15	20	-8
Risk Factor 5	0	0	0	0		-5	-13	-10	-18	-20	-13	7	15	20	12	6	4	-24	3	1
Risk Factor 6	0	0	0	0	0		-6	-19	8	25	-26	-9	15	7	-3	4	15	-5	14	-8
Risk Factor 7	0	0	0	0	0	0		-2	1	9	16	-3	-10	-4	5	-2	-13	-2	-2	5
Risk Factor 8	0	0	0	0	0	0	0		4	-10	-5	-26	-4	-27	8	-11	-21	-5	-11	7
Risk Factor 9	0	0	0	0	0	0	0	0		-3	-16	13	1	22	4	0	3	18	-23	22
Risk Factor 10	0	0	0	0	0	0	0	0	0		-2	-4	-4	-4	2	-10	8	11	10	3
Risk Factor 11	0	0	0	0	0	0	0	0	0	0		-35	0	-22	-21	7	7	-9	1	-12
Risk Factor 12	0	0	0	0	0	0	0	0	0	0	0		1	6	-11	5	11	23	6	-8
Risk Factor 13	0	0	0	0	0	0	0	0	0	0	0	0		1	-2	3	-15	-35	7	3
Risk Factor 14	0	0	0	0	0	0	0	0	0	0	0	0	0		-7	1	-5	15	12	-12
Risk Factor 15	0	0	0	0	0	0	0	0	0	0	0	0	0	0		-6	-13	17	-14	21
Risk Factor 16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	-4	4	6
Risk Factor 17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		1	-1	-1
Risk Factor 18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		6	2
Risk Factor 19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		-14
Risk Factor 20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Full Sample Ave	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Crisis Average	0	2	0	2	1	2	-2	-8	0	1	-8	1	0	0	-1	0	-1	-1	2	1
Ave During GFC	-2	1	-6	-4	-6	-2	-11	-9	1	-1	-7	0	-7	-1	-7	-4	1	4	-1	0

Source: J.P. Morgan Quantitative and Derivatives Strategy. * Lower triangular statistics are the all-sample pair-wise correlation and upper triangular are the correlation statistics during crisis periods. ** Crisis periods we include for the correlation calculation are Oct 1973—Mar 1974 (OPEC Oil Crisis), Aug 1982 – Oct 1983 (Latin America debt crisis), July 1990 - Mar 1991 (US saving & loan crisis), Jul 1997 - Sep 1998 (Asian Financial Crisis, Russian Default and LTCM), and Aug 2007 - Mar 2009 (Global Financial Crisis or GFC).

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Figure 115 below shows the historical P/L (in excess return) of US$100 in Dec 1971 for an equal weighted (with 2x leverage) position on the top 4 independent risk factors. Annual excess returns from 1972 to 2012 for such a strategy are also listed below the figure and we find that one could achieve absolute return by exposure to only four independent factors.

Figure 115: P/Ls of Top 4 Independent Risk Factors and a leveraged Equal Weighted portfolio (with annual excess returns since 1972)



1972	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985
16.1	25.3	4.5	29.3	26.9	24.0	24.1	16.1	-2.7	21.5	53.8	20.8	16.8	32.4
1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
22.1	0.4	32.2	16.4	12.4	19.2	23.2	27.9	5.5	18.0	34.3	27.9	15.6	2.6
2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	
24.4	13.7	32.7	25.2	19.7	21.1	14.1	6.5	11.4	4.6	11.0	25.5	21.4	

Source: J.P. Morgan Quantitative and Derivatives Strategy.

In Chapter 3, we have shown the risk contribution of cross asset factors to the independent risk factors in order to identify their connections. In addition, we could examine the source of cross asset factor correlations by identifying their related risk exposure to independent factors in Table 59. As explained in the next section, these risk contributions are proportional to the squared value of correlations to the corresponding risk factor. As a result, the risk contribution could also be derived from the correlation matrix between cross asset risk factor and the independent risk factors, in Table 60.

Table 59: Risk Contribution Profile (%) of Cross Asset Risk Factors from their Independent Components (Jan 1972 – Dec 2012)

	RF1	RF2	RF3	RF4	RF5	RF6	RF7	RF8	RF9	RF10	RF11	RF12	RF13	RF14	RF15	RF16	RF17	RF18	RF19	RF20
Traditional-Equities	5	29	0	5	4	29	0	4	1	9	2	1	0	1	3	1	1	4	2	0
Traditional-Bond	1	2	0	46	1	0	0	0	7	0	0	0	14	0	0	23	1	2	1	0
Traditional-Currencies	2	11	0	0	0	8	0	1	27	5	0	1	4	6	2	6	15	2	0	9
Traditional-Commodities	11	5	0	0	17	0	1	39	1	14	0	0	0	3	2	2	1	0	0	3
Carry-Equities	1	0	0	0	0	6	87	0	0	1	0	0	0	0	1	0	0	1	0	1
Carry-Bond	0	0	51	1	0	2	0	0	0	0	0	0	41	0	0	0	0	3	0	0
Carry-Currencies	9	0	1	0	0	0	0	0	5	16	30	34	2	1	0	0	0	0	0	0
Carry-Commodities	1	0	0	1	1	0	0	10	6	2	1	0	3	4	8	1	6	0	16	39
Momentum-Equities	0	2	1	7	0	0	0	0	16	0	0	1	0	0	4	0	67	0	0	0
Momentum-Bond	5	1	1	13	0	9	0	0	0	1	0	1	13	0	0	2	0	54	0	0
Momentum-Currencies	3	1	1	0	0	5	0	0	0	9	33	30	2	0	1	2	11	2	0	2
Momentum-Commodities	2	0	0	1	20	1	0	15	1	0	1	1	1	17	3	0	1	0	30	4
Value-Equities	1	19	0	0	2	2	1	9	1	1	0	0	0	3	52	0	1	0	1	7
Value-Bond	2	0	56	6	0	0	0	0	1	0	1	2	28	0	0	2	0	0	1	0
Value-Currencies	3	1	0	0	1	18	0	2	8	14	4	37	2	4	1	3	0	0	0	1
Value-Commodities	0	7	0	0	5	0	0	6	3	1	0	1	0	1	4	5	2	0	39	27
Volatility-Equities	0	10	0	6	12	28	0	2	0	27	2	0	0	2	0	8	0	1	0	1
Volatility-Bond	45	2	0	3	1	1	0	10	1	1	2	0	0	1	0	21	0	1	1	10
Volatility-Currencies	0	0	0	0	0	2	1	1	4	43	3	2	1	8	0	32	1	0	2	0
Volatility-Commodities	15	0	0	9	6	0	4	0	1	4	2	2	0	41	0	14	0	0	0	0

Source: J.P. Morgan Quantitative and Derivatives Strategy. * Each cell (by row) represents the total risk contribution (in percentage) of independent risk factors to each Cross asset risk factor.

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Table 60: Correlation between Cross Asset Risk Factors and Independent Risk Factors (Jan 1972 – Dec 2012)

	RF1	RF2	RF3	RF4	RF5	RF6	RF7	RF8	RF9	RF10	RF11	RF12	RF13	RF14	RF15	RF16	RF17	RF18	RF19	RF20
Traditional-Equities	23	-54	-3	22	20	54	0	-20	-7	30	-12	8	4	-9	-18	7	-9	19	14	4
Traditional-Bond	9	14	1	68	11	-3	5	-1	27	-1	-1	-7	38	5	5	48	-10	13	-8	-3
Traditional-Currencies	16	-33	4	-5	-5	-28	-5	-10	52	23	1	11	20	-24	-15	25	38	-13	1	30
Traditional-Commodities	33	-23	5	-1	-41	2	-11	63	-7	38	-5	-1	-1	-17	15	-14	9	-3	4	16
Carry-Equities	10	-2	-2	-7	3	-25	93	5	2	9	-2	3	-3	2	12	4	-3	-8	3	12
Carry-Bond	-2	6	71	8	2	-14	-1	-6	-6	6	0	6	-64	0	-5	3	2	18	-3	6
Carry-Currencies	30	2	-7	-5	3	6	-7	0	-22	39	55	58	-14	-11	-6	5	-6	2	-4	5
Carry-Commodities	-12	-6	-4	-9	12	4	-1	31	25	15	10	2	-16	-19	28	9	25	6	40	-63
Momentum-Equities	1	16	-9	27	2	-3	5	1	-40	-3	-4	11	4	-4	20	-4	82	3	-6	-3
Momentum-Bond	21	9	12	36	3	30	3	0	2	-8	-5	-8	-36	0	0	14	-5	-74	1	-5
Momentum-Currencies	18	-8	7	-4	0	23	3	0	2	-29	57	-55	-14	1	-7	15	33	13	-2	13
Momentum-Commodities	15	3	-2	-12	45	9	0	39	12	4	-10	-8	-7	-42	19	6	8	2	-55	-20
Value-Equities	11	44	4	-4	-14	-12	7	30	11	9	0	-3	0	18	-72	-3	7	-2	-10	-27
Value-Bond	-15	0	75	-25	-3	3	3	1	-7	4	10	15	52	3	-2	-15	-4	-3	-9	-7
Value-Currencies	-18	9	-1	3	-10	42	4	13	29	-37	-21	61	-14	20	10	-18	-4	6	3	9
Value-Commodities	1	26	5	6	21	-3	-3	-23	-16	-9	2	7	7	7	-21	-22	-14	-6	63	52
Volatility-Equities	-3	31	-3	-25	-34	53	4	-15	3	52	-16	0	-7	-13	5	28	4	10	6	11
Volatility-Bond	67	16	-1	-17	-11	8	-1	-32	10	-8	-14	4	0	-10	6	-46	1	11	8	-32
Volatility-Currencies	6	7	-3	0	5	13	-12	-9	21	66	17	-13	-9	27	5	-56	9	4	-13	3
Volatility-Commodities	39	0	-2	-30	25	-3	-20	-2	-7	21	-15	13	-4	64	5	38	0	0	5	7

Source: J.P. Morgan Quantitative and Derivatives Strategy.

From Table 59 and Table 60 (two Tables above), we could identify interesting sources of cross asset and cross factor correlations. For example, we find that the Currency Carry, Currency Momentum and Currency Value Strategies are significantly exposed to RF10, RF11 and RF12 factors: the Currency Carry factor had long exposure to RF10, RF11 and RF12; Currency Momentum factor is long RF11 while short RF10 and RF12; Currency Value is long RF12 while short RF10 and RF11. Moreover, while the significant positive correlation between the Equity beta and Equity Volatility factors mainly arose from their common positive exposure to RF6 and RF10 factors, the positive correlation between Equity beta and Currency carry was because of their common exposure to RF1 and RF10 factors. In summary, the independent risk factors can shed additional light to the sources of risk and correlations of alternative risk factors.

Mathematical Derivations

For interested readers, we provide some high-level mathematical derivations on principal components as well as independent factors in this section. It covers the calculation of risk contributions, factor correlations, factor hedging, as well as optimal portfolio Sharpe ratios with independent factors.

Following the notations from the section on Portfolio Construction Methodologies, we examine the technicalities in examining Independent Component Analysis (ICA) of Cross Asset Risk Factors. Suppose we have N time series of factor returns $\boldsymbol{R} = (\boldsymbol{r}_1, \ldots, \boldsymbol{r}_N)$, our aim to is find a weighting matrix $\boldsymbol{W} = (\boldsymbol{w}_1, \ldots, \boldsymbol{w}_N) = \left(w_{ij}\right)_{N \times N}$ so that the mixed factors

$$\boldsymbol{F} = (\boldsymbol{f}_1, \ldots, \boldsymbol{f}_N) = \boldsymbol{R} \times \boldsymbol{W} = (\boldsymbol{R}\boldsymbol{w}_1, \ldots, \boldsymbol{R}\boldsymbol{w}_N)$$

are independent sources of systematic risks. Suppose the weighting matrix $\boldsymbol{W}$ is invertible (the factors represent a non-degenerate set of mixed risks) and $\boldsymbol{V} = \boldsymbol{W}^{-1}$, then the factor returns could be represented by linear combinations of independent risk premia:

$$\boldsymbol{R} = \boldsymbol{F} \times \boldsymbol{V} = (\boldsymbol{F}\boldsymbol{v}_1, \ldots, \boldsymbol{F}\boldsymbol{v}_N)$$

Principal Components and Uncorrelated Factors

The first step towards independence is to create principal components, which are orthogonal transformations (or rotations) of original factors so that the "principal components" are uncorrelated. By definition, the principal components of the factors are created by its eigenvector rotations so that the "rotated" factors are uncorrelated and the variance of factor principal components corresponds to the eigen-values of the factor covariance matrix $\boldsymbol{\Sigma} = \mathrm{Cov}(\boldsymbol{R}, \boldsymbol{R}) = \left(\sigma_{ij}\right)_{N\times N}$.

Specifically, suppose the eigen-value decomposition of $\boldsymbol{\Sigma}$ is given by

$$\boldsymbol{\Sigma} = \boldsymbol{E}\boldsymbol{D}\boldsymbol{E}^{\boldsymbol{T}}$$

where $\boldsymbol{E} = (\boldsymbol{e}_1, \dots, \boldsymbol{e}_N)$ are the eigen-vectors so that $\boldsymbol{E}\boldsymbol{E}^{\boldsymbol{T}} = \boldsymbol{E}^{\boldsymbol{T}}\boldsymbol{E} = \boldsymbol{I}$ (identity matrix) and $\boldsymbol{D} = \mathrm{diag}(d_1, \dots, d_N)$ is a diagonal matrix of eigen-values (usually ranked by descending order). Since the covariance matrix $\boldsymbol{\Sigma}$ is positive semi-definite, the diagonal elements of $\boldsymbol{D}$ are non-negative.

By construction, the covariance matrix of the "rotated" factors or "principal components" $\boldsymbol{P}^c = \boldsymbol{R} \times \boldsymbol{E} = (\boldsymbol{R}\boldsymbol{e}_1, \dots, \boldsymbol{R}\boldsymbol{e}_N)$ is given by

$$\mathrm{cov}(\boldsymbol{P}^c, \boldsymbol{P}^c) = \boldsymbol{E}^{\boldsymbol{T}}\boldsymbol{\Sigma}\boldsymbol{E} = \boldsymbol{D}$$

As a result, the principal components as linear combinations of original factors are uncorrelated and their variances are given by the diagonal elements of matrix $\boldsymbol{D}$ or the eigen-values.

Risk Contribution of Principal Components

To understand how the principal components relate to the original set of risk factors, we can evaluate their risk contribution profiles. By definition, the *i*-th principal component of the risk factors is given by $\boldsymbol{R}\boldsymbol{e}_i$ where the *i*-th eigen-vector $\boldsymbol{e}_i$ represents the (leveraged) weights. Furthermore, from the identity $\boldsymbol{E}^{\boldsymbol{T}}\boldsymbol{\Sigma}\boldsymbol{E} = \boldsymbol{D}$, we have $\boldsymbol{\Sigma}\boldsymbol{e}_i = d_i\boldsymbol{e}_i$ and $\boldsymbol{e}_i^T\boldsymbol{\Sigma}\boldsymbol{e}_i = d_i$ for all *i*.

In the section on Portfolio Construction Methodologies, we suggested that the risk contribution (in percentage) is equal to beta times weight. The beta vector (on the original factors) for the *i*-th principal component is given by

$$\boldsymbol{\beta}(\boldsymbol{P}_i^c \text{ relative to } \boldsymbol{R}) = \frac{\boldsymbol{\Sigma}\boldsymbol{e}_i}{\boldsymbol{e}_i^T\boldsymbol{\Sigma}\boldsymbol{e}_i} = \frac{d_i\boldsymbol{e}_i}{d_i} = \boldsymbol{e}_i$$

which is exactly the i-th eigen-vector, the same as the corresponding factor weights.

As a result, the vector $\boldsymbol{e}_i \cdot \boldsymbol{e}_i = (e_{1i}^2, \dots, e_{Ni}^2)^T$ describes the risk contribution of the original risk factors on the *i*-th principal component.

Moreover, we could also evaluate the risk contribution of the principal components to the original risk factors by noting the fact that

$$\boldsymbol{R} = \boldsymbol{P}^c \times \boldsymbol{E}^{\boldsymbol{T}} = (\boldsymbol{P}^c\boldsymbol{e}_1^r, \dots, \boldsymbol{P}^c\boldsymbol{e}_N^r)$$

where $\boldsymbol{e}_i^r$ is the *i*-th column of the transposed eigen-vector matrix (or the *i*-th row vector of $\boldsymbol{E}$). Furthermore, from the identity $\boldsymbol{\Sigma} = \boldsymbol{E}\boldsymbol{D}\boldsymbol{E}^{\boldsymbol{T}}$, we have $(\boldsymbol{e}_i^r)^T\boldsymbol{D}\boldsymbol{e}_i^r = \sigma_i^2$ for all *i*.

Hence, the beta vector (on the principal components) for the *i*-th factor is given by

$$\boldsymbol{\beta}(\boldsymbol{r}_i \text{ relative to } \boldsymbol{P}^c) = \frac{\boldsymbol{D}\boldsymbol{e}_i^r}{(\boldsymbol{e}_i^r)^T\boldsymbol{D}\boldsymbol{e}_i^r} = \frac{\boldsymbol{D}\boldsymbol{e}_i^r}{\sigma_i^2}$$

As a result, the vector $(\boldsymbol{D}\boldsymbol{e}_i^r \cdot \boldsymbol{e}_i^r)/\sigma_i^2 = (d_1 e_{i1}^2/\sigma_i^2, \dots, d_N e_{iN}^2/\sigma_i^2)^T$ describes the risk contribution of the principal components on the i-th risk factor component.

Independent Risk Factors and Non-Normality

It is well known that zero-correlation does not necessarily lead to independence, and hence the principal components are not necessarily the independent risk factors we are looking for. In Mathematical terms, the two factors $\boldsymbol{f}_1$ and $\boldsymbol{f}_2$ are independent if and only if their joint probability density function can be written as the product of the marginal density functions:

$$p_{\boldsymbol{f}_1,\boldsymbol{f}_2}(\boldsymbol{f}_1, \boldsymbol{f}_2) = p_{\boldsymbol{f}_1}(\boldsymbol{f}_1) \times p_{\boldsymbol{f}_2}(\boldsymbol{f}_2)$$

In effect, we need to identify another transformation $\boldsymbol{G}$ of the principal components into truly independent risk factors:

$$\boldsymbol{F} = (\boldsymbol{f}_1, \dots, \boldsymbol{f}_N) = \boldsymbol{P}^c \times \boldsymbol{G} = (\boldsymbol{R} \times \boldsymbol{E}) \times \boldsymbol{G} = \boldsymbol{R} \times (\boldsymbol{E} \times \boldsymbol{G})$$

So we can finally arrive at the loading matrix on the original set of factors $\boldsymbol{W} = \boldsymbol{E} \times \boldsymbol{G}$.

While the criterion for principal components derives naturally from eigen-values of factor covariance/correlation matrix (or Singular Value Decomposition of the factors), the criterion for independent risks could be hard to define statistically. Instead, we first define an independent risk premium (or risk factor) by its economic and financial market meaning and then use an optimization program to derive factors satisfying such a definition.

One important economic rationale for the definition of **independent risk source** is that the distribution of each risk factor should represent **the distribution of some insurance-selling** on a specific type of risk the corresponding factor represents. This property guarantees collection of insurance premium on the associated risk in "normal times" at the promise of incurring large losses when such risk materializes and the insurance payment is due. Moreover, the long-term insurance **premium should more than compensate for the loss** in bad times so that investment managers could justifiably own the corresponding risk and collect the long-term associated premia. Based on these assumptions, two basic statistical properties of an independent risk factor are: (1) it should have a long-term positive average return and (2) it should follow some fat-tail distribution (tail fatness is usually benchmarked against a comparable normal distribution).

Statistically, while the first requirement is easy to satisfy, the second requirement needs some measurement of "Non-Normality". By the Central Limit Theorem, the sum of many independent fat-tailed risk factors has a distribution that is closer to a normal distribution than the individual risk factors. As a result, the principal components should be closer to normal distributions than the independent components. With regard to our targeted independent factors, there are two basic measurements of normality:

(1) Excess kurtosis defined by $\mathbf{Kurt}(\boldsymbol{X}) = \boldsymbol{E}\left[\left(\boldsymbol{X} - \boldsymbol{E}(\boldsymbol{X})\right)^4\right] / \left(\mathbf{Var}(\boldsymbol{X})\right)^2 - 3$

(2) Negative Entropy defined by $\mathbf{NegEntropy}(\boldsymbol{X}) = \boldsymbol{H}(\boldsymbol{X}_{\text{Normal}}) - \boldsymbol{H}(\boldsymbol{X})$, where $\boldsymbol{H}(\boldsymbol{X}) = \boldsymbol{E}[-\log(p(\boldsymbol{X}))]$ is the entropy function on factor $\boldsymbol{X}$ and $\boldsymbol{H}(\boldsymbol{X}_{\text{Normal}})$ is the entropy function for a normal variable of the same covariance matrix as $\boldsymbol{X}$.

Since the negative entropy function is always non-negative and is zero only if the underlying factor is a normal variable, one could design some optimization program (e.g. based on a generalized Newton-Raphson procedure) to maximize the negative entropy to achieve non-normality of risk factors. In our demonstration of independent risk factors, we use the popular FastICA algorithm to estimate the parameters. Once the rotation matrix $\boldsymbol{W}$ is estimated, factor risk contribution profiles could be calculated similar to the case of principal components.

Optimal Portfolio Sharpe Ratio

In the section on Portfolio Construction Methodologies, we showed that the optimal portfolio Sharpe ratio for a set of factors is given by: $\sqrt{\boldsymbol{\mu}^T\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu}} = \sqrt{\boldsymbol{S}^T\boldsymbol{C}^{-1}\boldsymbol{S}}$, where $\boldsymbol{\Sigma}$ and $\boldsymbol{C}$ are the covariance and correlation matrices of the underlying factors; $\boldsymbol{S} = (s_1, \ldots, s_N)^T$ be a $N \times 1$ vector of Sharpe ratios so that $s_i = \mu_i/\sigma_i$ for any i.

In the case of independent factors, the correlation matrix $\boldsymbol{C}$ is an identify matrix and hence we have

$$\text{Optimal Sharpe Ratio} = \sqrt{\boldsymbol{S}^T\boldsymbol{C}^{-1}\boldsymbol{S}} = \sqrt{\boldsymbol{S}^T\boldsymbol{S}} = \sqrt{\sum_{i=1}^{N} s_i^2}$$

As a result, adding an independent risk factor would always improve portfolio Sharpe ratio as long as factors are optimally weighted.

Common Risk exposure to Independent Factors

Financial researchers usually attribute correlation between asset classes, risk factors, investment strategies, etc to their common exposure to certain independent sources of risk. Here, we provide a framework to quantify that correlation.

We have shown in the last section that the factor sensitivity of an arbitrary portfolio (or risk factor, asset class) with respect to a certain independent risk factor of unit variance is given by portfolio volatility times corresponding factor correlation, which hold in the presence of multiple independent risk factors as well. As a result, for any two portfolios $\boldsymbol{P}_1$ and $\boldsymbol{P}_2$, we can write them as representations of the independent factors:

$$\boldsymbol{P}_1 = \sum_{i=1}^{N} \beta_{1i}\boldsymbol{f}_i + \epsilon_1 \quad \text{and} \quad \boldsymbol{P}_2 = \sum_{i=1}^{N} \beta_{2i}\boldsymbol{f}_i + \epsilon_2$$

where $\beta_{1i} = \sigma_{\boldsymbol{P}_1}\text{Corr}(\boldsymbol{P}_1, \boldsymbol{f}_i) = \sigma_{\boldsymbol{P}_1}\boldsymbol{\xi}_{1i}$ and $\beta_{2i} = \sigma_{\boldsymbol{P}_2}\text{Corr}(\boldsymbol{P}_2, \boldsymbol{f}_i) = \sigma_{\boldsymbol{P}_2}\boldsymbol{\xi}_{2i}$.

If we assume ϵ_1 and ϵ_2 are independent with $\sigma(\epsilon_i) = \sigma_{\boldsymbol{P}_i}\boldsymbol{\xi}_{\epsilon i}$, it follows that

$$\text{Corr}(\boldsymbol{P}_1, \boldsymbol{P}_2) = \frac{\text{Cov}(\boldsymbol{P}_1, \boldsymbol{P}_2)}{\sqrt{\text{Var}(\boldsymbol{P}_1)\text{Var}(\boldsymbol{P}_2)}} = \frac{\sum_{i=1}^{N}\beta_{1i}\beta_{2i}}{\sqrt{\left(\sum_{i=1}^{N}\beta_{1i}^2 + \sigma^2(\epsilon_1)\right)\left(\sum_{i=1}^{N}\beta_{2i}^2 + \sigma^2(\epsilon_2)\right)}} = \frac{\sum_{i=1}^{N}\boldsymbol{\xi}_{1i}\boldsymbol{\xi}_{2i}}{\sqrt{(\sum_{i=1}^{N}\boldsymbol{\xi}_{1i}^2 + \boldsymbol{\xi}_{\epsilon 1}^2)(\sum_{i=1}^{N}\boldsymbol{\xi}_{2i}^2 + \boldsymbol{\xi}_{\epsilon 2}^2)}}$$

since the factors $\boldsymbol{F} = (\boldsymbol{f}_1, \ldots, \boldsymbol{f}_N)$ are independent.

The equation above quantifies the correlation between two arbitrary strategies/portfolios through their correlation to a common set of independent risk factors $\boldsymbol{\xi}_{1i}$ and $\boldsymbol{\xi}_{2i}$. Common exposure suggested by correlations with the same signs (co-positive or co-negative) increases factor correlation while offsetting exposures suggested by correlations with the opposite signs decreases factor correlation.

The failure of diversification generally happens when different investment strategies/portfolios load up common exposures to independent risk factors, which usually happens right before risk factor crashes (materialization of risks). The reasons for this investor behavior could be over-confidence and over-extrapolation of past performance which push fund inflows (outflows) into (out of) related risk premia to extremes, and lead to waning demand for protection.

Risk Hedging with Independent Factors

Suppose an investor does not want to be exposed to certain sources of risk; a hedging overlay could be formed through examining the multi-variate sensitivity of the portfolio with respect to selected factors through regression analysis. In the case of independent factors, individual factor sensitivity could be simply derived from one-by-one single variable regression.

Without loss of generality, we assume the independent factors $\boldsymbol{F} = (\boldsymbol{f}_1, \dots, \boldsymbol{f}_N)$ have unit marginal variance each and the pair-wise correlation with a portfolio $\boldsymbol{P}$ is given by:

$$\boldsymbol{\xi}_i = \mathrm{Corr}(\boldsymbol{P}, \boldsymbol{f}_i) \ \text{ for } 1 \le i \le N$$

Assume a portfolio volatility of $\sigma_{\boldsymbol{P}}$, the sensitivity or "beta" of portfolio $\boldsymbol{P}$ with respect to $\boldsymbol{f}_i$ is given by:

$$\boldsymbol{\beta}_i = \mathrm{Cov}(\boldsymbol{P}, \boldsymbol{f}_i)/\mathrm{Cov}(\boldsymbol{f}_i, \boldsymbol{f}_i) = \sigma_{\boldsymbol{P}} \boldsymbol{\xi}_i$$

Moreover, the proportion of portfolio variance explained by performing a single-variable regression on $\boldsymbol{f}_i$ is given by:

$$R_i^2(\boldsymbol{f}_i) = \boldsymbol{\xi}_i^2$$

In the case of multiple-independent-factor hedging, the portfolio sensitivities are still given by $\boldsymbol{\beta} = (\boldsymbol{\beta}_1, \dots, \boldsymbol{\beta}_N)$ and the proportion of portfolio variance explained by performing a multiple regression on

$$R^2(\boldsymbol{f}_1, \dots, \boldsymbol{f}_N) = \frac{\sum_{i=1}^N \boldsymbol{\beta}_i^2}{\sigma_{\boldsymbol{P}}^2} = \sum_{i=1}^N \boldsymbol{\xi}_i^2$$

In other words, the multiple regression R-Squared (measuring explanatory power or goodness of fit) increases by a factor of squared correlation if an independent factor is added.

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Equivalent Portfolio Methods

In our introduction of Cross-Sectional Portfolio Risk Methods in Chapter 3, we have shown already that GMV is equivalent to an MVO when the expected returns of the assets are equal. We have also shown that MDP is equivalent to an MVO when the Sharpe ratios of the assets are equal. The following mathematical derivations are aimed to help better understand the connection among different methods in Figure 35 of the main text.

To start with, we can write a Diversification ratio (DR) of an MDP via vector $\boldsymbol{\psi} = \boldsymbol{w} \cdot \boldsymbol{\sigma}$, ($\psi_i = w_i\sigma_i$ for all i) as

$$\mathrm{DR}(\boldsymbol{w}) = \frac{\boldsymbol{w}^T\boldsymbol{\sigma}}{\sigma_p} = \frac{\boldsymbol{\psi}^T\mathbf{1}}{\sqrt{\boldsymbol{\psi}^T\boldsymbol{C}\boldsymbol{\psi}}}$$

Hence, maximizing DR is equivalent to minimizing its denominator – which is just variance if all the asset volatilities are equal.

We have also shown that if the volatility weighted average correlation for all assets is zero or

$$\rho(\boldsymbol{w}) = \frac{\sum_{i,j} w_i\sigma_i w_j\sigma_j\rho_{ij}}{\sum_{i,j} w_i\sigma_i w_j\sigma_j} = 0$$

an MDP becomes an EMV portfolio. Furthermore, since

$$\boldsymbol{w}^T\boldsymbol{\Sigma}\boldsymbol{w} = \boldsymbol{\psi}^T\boldsymbol{C}\boldsymbol{\psi}$$

the optimal solution to an MDP in $\boldsymbol{\psi}$ terms is given by $\boldsymbol{\psi}^* \propto \boldsymbol{C}^{-1}\mathbf{1}$. As a result, an MDP is equivalent to an equal-marginal volatility (EMV) portfolio if the arithmetic average correlations for each asset are equal to each other. Similarly, as the solution for GMV is given by $\boldsymbol{w} \propto \boldsymbol{\Sigma}^{-1}\mathbf{1}$, it is equivalent to an EMV portfolio if the average covariance for each asset with others are equal.

Finally for a Risk parity (RP) portfolio, portfolio weights are inversely proportional to the beta. As a result, an RP portfolio is equivalent to an EMV portfolio if $\boldsymbol{\beta} \propto \boldsymbol{\sigma}$ or in other words, if

$$\boldsymbol{\Sigma}\boldsymbol{w} \propto \boldsymbol{\sigma}$$

Since $(\boldsymbol{\Sigma}\boldsymbol{w})_i = \sum_{\boldsymbol{j}} w_j\sigma_j\sigma_i\rho_{ij}$, the above-mentioned condition could be achieved if the marginal volatility weighted average correlation $\sum_j w_j\sigma_j\rho_{ij} \,/ \sum_j w_j\sigma_j$ are equal for all the assets, which suggests that if an Equal Marginal Volatility Portfolio is also Maximally Diversified, it is a Risk Parity Portfolio. More generally, a Risk Budgeting (RB) portfolio is equivalent to EMV if $\sum_{\boldsymbol{j}} w_j\sigma_j\rho_{ij}$ are proportional to the pre-specified risk budgets s_i.

For a RB portfolio to be equivalent to MVO, it needs to satisfy the MSR condition that $\boldsymbol{w} \cdot \boldsymbol{\mu} \propto \boldsymbol{s}$. In other words, when return contributions of the assets are according to the risk budgets, a risk budgeting portfolio is also mean-variance optimized.

Finally, we examine the relationship between MDP, EMV and RB. First of all, since MDP is a volatility-invariant version of GMV, the solution to MDP satisfies:

$$\boldsymbol{C}(\boldsymbol{w} \cdot \boldsymbol{\sigma}) = \frac{\varsigma\mathbf{1}}{\mathbf{1}^T\boldsymbol{C}\mathbf{1}}$$

Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Let's denote the constant $\frac{\varsigma}{\mathbf{1}^T \boldsymbol{C}\mathbf{1}}$ by η which is solely determined by the correlation matrix of the assets, the above equation means:

$$\sum_j w_j \sigma_j \rho_{ij} = \eta \text{ for all } i$$

Now, for an RB portfolio, since its weights are determined by $w_i \beta_i = s_i$ for all i, which is equivalent to:

$$w_i \sigma_i \sum_j w_j \sigma_j \rho_{ij} = s_i \sigma_p^2 \text{ for all } i$$

It follows that for MDP to be equivalent to RB, it is necessary and sufficient to have:

$$w_i \sigma_i \eta = s_i \sigma_p^2 \text{ for all } i$$

or

$$w_i = \frac{s_i / \sigma_i}{\sum_j s_j / \sigma_j} \text{ for all } i$$

This suggests that when the portfolio weight is proportional to the ratio of risk budget to marginal volatility, RB is equivalent to MDP.

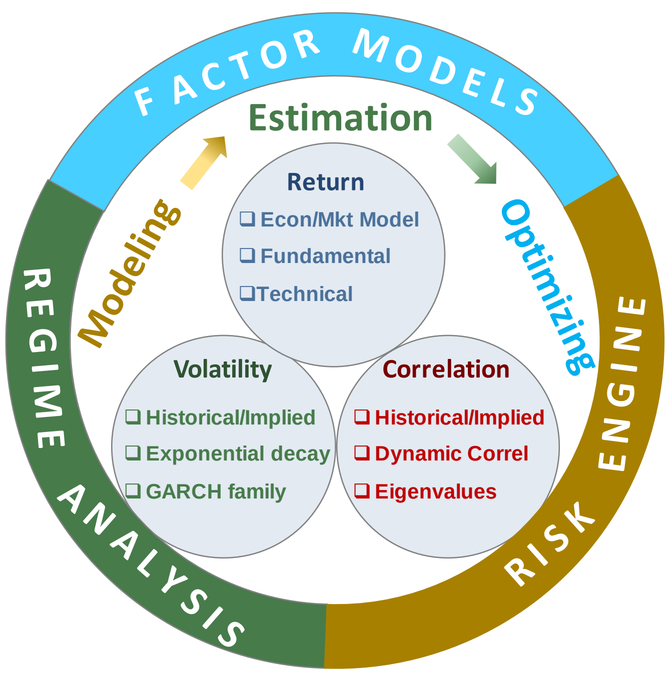
Marko Kolanovic
(1-212) 272-1438
marko.kolanovic@jpmorgan.com

Implementing Portfolio Methods

Generally, there are three important processes during the implementation of a Portfolio Method on a set of assets. **Factor Models** are built to monitor the return exposure of the assets to key macro economic/market variables as well as other systematic risk factors (such as credit risk, liquidity risk, exchange order flows, foreign/domestic fund flows, insider/smart investor actions). **Regime Analysis** is a process of determining the future macro/market regimes (growth, inflation, volatility, funding and market liquidity etc) for better assessment of risk factors and portfolio performance/risk. The **Risk Engine** is a continuous monitoring process that takes various inputs (assets, factors, regimes, etc) in order to assess and manage portfolio risk (risk measurement, stop-loss triggers, policy requirements, etc). In practice, these three processes could be implemented together within an integrated risk management framework. As a matter of fact, many practical risk engines take care of factor modeling and regime switching analysis.

Once these guiding procedures are in place, one needs to **construct a model to estimate the distributions** of the assets, so that an **optimization procedure** can be applied to obtain the portfolio weights by maximizing an expected utility function[62]. Under the mean-variance framework assuming approximate normal distributions, investors need only be concerned with **three elements**: (1) Expected Returns, (2) Marginal Volatilities, and (3) the Correlation Matrix. As a result, a systematic way of forecasting/estimating these elements is essential for successful implementation of Portfolio Methods. A summary of the key procedures/elements in implementing portfolio risk methods is given in Figure 116 below.

Figure 116: Key Elements in Implementing Portfolio Risk Methods



Source: J.P. Morgan Quantitative and Derivatives Strategy.

There are three general types of systematic models used to estimate **expected returns**. **Economic/Market Models** use economic/market-based variables such as GDP growth, unemployment, PMI, yield curve, dividend yield, etc to forecast asset/factor returns. See Ilmanen (2011) for more details. **Fundamental Models** use security fundamentals such as balance sheet quality, cash flow projections as well as sector/industry cycle analysis to assess expected returns. Although

[62] In our introduction on Portfolio Construction Methods, we assumed that distributions of the assets are given.

Fundamental Models are more often used by Equity or Credit analysts on individual companies, the idea could be applied to market indices as well. **Technical Models** use trend (momentum), reversion, seasonality, and/or other charting techniques. Despite receiving strong attention and efforts, tactical return forecasting has achieved only limited success.

As cross asset volatilities display short-term persistence, their near-term levels (not changes) are relatively easier to forecast than returns. There are three popular types of models in forecasting **volatility**: (1) One could directly use **historical volatility**[63], which could also include exponential decay or other smoothing methods (e.g. based on volatility on volatility) could be used to better account for recent (or more important) information ; (2) using **Implied volatility** (if available) which reflects the derivatives market's estimate of future realized volatility; (3) Various extensions of Generalized autoregressive conditional heteroskedasticity (**GARCH**) could be used to better account for the statistical behaviors of volatility. The idea of autoregressive conditional heteroskedasticity (ARCH) was originally introduced by Engle (1982) and Bollerslev (1988) and extended by many researchers to stochastic/jump diffusion volatility models.

The last element is the **correlation matrix** of the assets. While simultaneous estimation of volatilities and the correlation matrix is possible through multivariate GARCH models such as Orthogonal GARCH discussed in Kariya (1988) and Alexander and Chibumba (1997), there are usually too many model parameters to obtain robust results so this method is rarely used by practitioners. Instead, there are three general empirical treatments of correlation matrices: (1) **Historical correlation or implied** correlations (if available) could be used by assuming persistence; (2) **Dynamic models** (such as auto-regressive) could be used to capture the time-series dependence structure of correlation. Correlations could also be calculated through factor exposures in a dynamic multi-factor model similar to our treatment in our introduction of independent risk factors; (3) **Eigenvalue methods** refers to estimation of the closest positive definite correlation matrix when a sample or model estimation fails to produce positive eigenvalues[64]. Robust estimation of the correlation matrix is a valid concern when the sample size is small compared with the number of assets[65].

After estimating the asset/factor distributions, we can move forward to implement a portfolio method. While most portfolio methods have explicit solutions in an unconstrained case, empirical implementation may involve constraints on asset/factor weights or group (such as industry/sector/region) weights. This could arise from considerations on the robust estimation of weights or from regulatory/policy/liquidity requirements. Moreover, methods like Risk Budgeting don't have explicit solutions to start with. As a result, we usually need an **optimization program** to find the **portfolio weights** of the assets $\boldsymbol{w}$ according to some iterative procedure. In practice, there are several concerns in implementing such optimization programs, such as: which operating system and **program language** to use, which **optimization method** to deploy, and how **scalable** each Portfolio Method is by using a particular optimization procedure.

While it may be desirable for more efficient implementation to use a multi-threading Unix/Linux system with a lower-level programming language such as C++/C#/JAVA, in practice most investors may only have access to Windows/Mac OS systems with higher level programming languages such as R, Matlab or Excel VBA.

The choice/design of **optimization method** is a practical concern for large-scale problems with hundreds or thousands of assets, as computation time usually decays cubic to the asset dimension. As introduced in Chapter 3, each portfolio method could be regarded as a weight-searching program by minimizing or maximizing a certain non-linear objective function under specific constraints. In general, such a constrained non-linear optimization could be formulated by:

$$\mathbf{min} \underset{\boldsymbol{w}}{\text{or}} \mathbf{max}\ \text{Objective Function}(\boldsymbol{w})$$

$$\text{Subject to constraints on portfolio weights } \boldsymbol{w}$$

[63] Unlike returns, volatility is not directly measurable. Practitioners usually use the trailing standard derivations of daily returns or range-based estimators such as the Yang-Zhang estimator in Yang and Zhang (2000).
[64] Theoretically, a correlation matrix of a non-degenerating set of assets should be a positive definite matrix with positive eigenvalues.
[65] Statistically, when sample size is less than the number of assets (e.g. one-year trailing correlation for the constituents of S&P 500), the sample correlation matrix will have zero eigenvalues as the number of principal components is less than the number of assets.

There are two general types of optimization methods for objective functions with continuous parameters. [66] **Active set methods** (ASM) start from a feasible point and search for directions that can optimize the objective function. For example, the popular sequential quadratic programming (SQP) and gradient projection methods belong to ASM. **Interior point methods** (IPM) create the so-called “prime-dual” problem sets, based on which an optimal path could be followed to achieve convergence. Both types of algorithms could be designed to solve medium to large sized optimization problems. Depending on the specific details in numerical implementation, ASM may become slower near to the optimal solution, in which case it could be computationally expensive. On the other hand, IPM usually requires a strictly feasible starting point which may be hard to determine in some cases. Interested readers could find more details on optimization in Polak (1971) and Fletcher (1987).

The light blue box below illustrates a simple example in implementing a Mean-Variance Optimization with an active-set method. In this example we use Matlab’s optimization toolbox function `fmincon`, with a negative portfolio Sharpe ratio as the objective function to be minimized (to achieve maximum Sharpe ratio). One could replace the definition of objective function to reach other optimal portfolios.

```
function [AssetWeights, Portvol, fval, exitflag] = PortMVO(Sigma, mu, MinMarginalWeight,
MaxMarginalWeight)

if (nargin<2 || nargin>4)
    error('Wrong Number of Arguments');
end

options = optimoptions('fmincon','Algorithm','active-set','Display', 'off', 'TolFun', 1e-8);

N = size(Sigma, 2);

[AssetWeights, fval,exitflag] = fmincon(@(w) -PortMaxSharpeObj(w, Sigma, mu), ones(N,1)/N , ...
,[],[], ones(1, N), 1,  ones(N,1) * MinMarginalWeight, ones(N,1) * MaxMarginalWeight,[], options);

Portvol = sqrt(AssetWeights' * Sigma * AssetWeights);

function objFunction = PortMaxSharpeObj(w, Sigma, mu)

portvar = w' * Sigma * w;

objFunction = w' * mu ./ sqrt(portvar);
```

The performance of an optimization procedure also leads to the topic on scalability of different portfolio methods – whether a method is only suited to small problems with, say, less than 20 assets, or can be scaled up to a large program with more than 1000 assets. For example, in risk-based indexing of stocks, some researchers suggested using the Global Minimum Variance or Risk Parity methods to replace the market-weight methods widely implemented in global equity benchmarks such as S&P 500 index. In this case, it is desired that portfolio weights could be generated within seconds.

We conduct some simulation studies on the computing time needed for typical portfolio methods on an average personal computer (dual-core 2.4GHz) with Windows 7 64-bit operating system. Table 61 below summarizes the results using the active-set method in Matlab: for a given number of assets, we simulate a positive definite covariance matrix and a vector of expected returns, based on which we test the time (in seconds) it takes to reach a solution. We include Mean-Variance Optimization (MVO), Global Minimum Variance (GMV) and Risk Parity (RP) as examples because they represent three distinct types of objective functions in our demonstration of portfolio methods.

---

[66] For objective functions with discrete parameters, one could simply evaluate the objective function on all possible combination of parameters and find the best combination. Since discrete optimization is usually easier to implement, practitioners occasionally use parameter-discretization (e.g. assume asset weights can only take values in {0, 0.1, 0.2, …, 1}) to find the optimal set of parameters.

Table 61: Time (in seconds) needed to solve a one-period optimal portfolio using active-set methods

		MVO	GMV	RP
Number of Assets	5	0.04	0.02	0.05
	50	0.51	0.09	3.11
	200	43	1	249
	500	1,461	2	2,457

Source: J.P. Morgan Quantitative and Derivatives Strategy.

For less than 50 assets, each method comfortably reaches a solution within seconds. Moreover, we find that for a GMV type method with quadratic objective functions, it only took 2 seconds in Matlab to solve the solution for 500 assets, while MVO took 1461 seconds (24 min) and Risk Parity took the longest (2457 seconds, or 41 min). It is possible to further optimize the results by using interior point methods or running programs using lower-level compiling languages. For example, using Matlab's implementation of the interior point method, it only took 6.5 seconds to reach a solution for MVO with 2000 assets, which makes the method suitable for large-scale portfolio management purposes.

Academic References

Adrian, T. and J. Rosenberg (2008), "Stock Returns and Volatility: Pricing the Short-Run and Long-Run Components of Market Risk," Journal of Finance 63, 2997-3030.

Ahn, D. H.; Conrad, J.; and Dittmar, R. F. (2003), "Risk adjustment and trading strategies," Review of Financial Studies 16(2), 459–485.

Alexander, C.O.; Chibumba, A.M. (1997), "Multivariate orthogonal factor GARCH", Mimeo, University of Sussex

Alexander, G.J. and A.M. Baptista (2002), "Economic implications of using a mean-VaR model for portfolio selection: A comparison with mean–variance analysis", Journal of Economic Dynamics and Control 26, 1159–1193.

Ang, A.; R. Hodrick; Y. Xing; and X. Zhan (2006), "The Cross-Section of Volatility and Expected Returns," Journal of Finance, 61, 259-299.

Asness, Clifford S.; Tobias J. Moskowitz; and Lasse Heje Pedersen (2013), "Value and Momentum Everywhere," The Journal of Finance, 68(3), 929-985

Baquero, G.; J. Ter Horst; and M. Verbeek (2005), "Survival, Look-Ahead Bias, and Persistence in Hedge Fund Performance", Journal of Financial and Quantitative Analysis 40, 493-518.

Barberis, N.; A. Shleifer; and R. Vishny (1998), "A model of investor sentiment", Journal of Financial Economics 49(3), 307–343

Barberis, N.; and A. Shleifer (2003), "Style Investing", Journal of Financial Economics 68, 161-199.

Baberis, N. and R. Thaler (2003), "A survey of behavioral finance," Handbook of Behavioral Economics of Finance, 1052-1090.

Black F.; and Litterman R. (1992), "Global Portfolio Optimization", Financial Analysts Journal 48(5), 28–43.

Bollerslev, T. (1986), "Generalized autoregressive conditional heteroskedasticity", Journal of Econometrics, 31, 307-327.

Bollerslev, T.; G. Tauchen; H. Zhou (2009), "Expected Stock Returns and Variance Risk Premia," Review of Financial Studies 22, 4463-4492.

Brennan, Michael J.; and Eduardo Schwartz S. (1988), "Time invariant portfolio insurance strategies," The Journal of Finance, June, 283-299

Bruder, Benjamin; and Roncalli, Thierry (2012), "Managing Risk Exposures Using the Risk Budgeting Approach," working paper, available at SSRN: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2009778

Brunnermeier, Markus K.; Stefan Nagel; and Lasse H. Pedersen (2008), "Carry trades and currency crashes," NBER Macroeconomics Annual.

Burnside, C.; Eichenbaum, M.; and Rebelo, S. (2011), "Carry trade and momentum in currency markets", Annual Review of Financial Economics 3(1), 511–535.

Campbell, John Y. (1987), "Stock Returns and the Term Structure", Journal of Financial Economics 18, 373-399.

Campbell, John Y.; and Robert J. Shiller (1991), “Yield spreads and interest rate movements: A bird’s eye view,” Review of Economic Studies 58, 495–514.

Campbell, John Y.; Adi Sunderam; and Luis M. Viceira (2010), “Inflation bets or deflation hedges? The changing risks of nominal bonds,” Harvard University working paper.

Carhart, Mark M. (1997), “On persistence in mutual fund performance,” Journal of Finance 52, 57-82.

Carr, P.; L. Wu (2009), “Variance Risk Premiums," Review of Financial Studies, 22, 1311-1341.

Chang, B. Y.; P. Christoersen and K. Jacobs (2013), “Market skewness risk and the cross section of stock returns," Journal of Financial Economics, 107, 46-68.

Choueifaty, Yves; Tristan Froidure; and Julien Reynier (2013), "Properties of the Most Diversified Portfolio”, Journal of Investment Strategies 2(2), 49-70.

Choueifaty, Yves; and Yves Coignard (2008), “Toward Maximum Diversification,” Journal of Portfolio Management 34, 40 – 51.

Churm, Rohan; and Nikolaos Panigirtzoglou (2005), “Decomposing credit spreads,” Bank of England working paper 253.

Chung, Y. Peter; and Michael J. Schill (2006), “Asset Pricing When Returns Are Nonnormal: Fama-French Factors versus Higher-Order Systematic Co-Moments”, Journal of Business 79(2), 923-940

Cochrane, John H. (1999), “Portfolio Advice for a Multifactor World,” Economic Perspectives, Federal Reserve Bank of Chicago 23, 59-78.

Cochrane, John H. (2001), Asset Pricing, Princeton University Press.

Cochrane, John H.; and Monika Piazzesi (2005), “Bond Risk Premia,” American Economic Review 95, 138-160.

Cochrane, John H. (2011), “Discount Rates,” The Journal of Finance, August, 1048-1108

Cochrane, John H.; and Monika Piazzesi (2008), “Decomposing the yield curve,” University of Chicago working paper.

Cornell, Bradford (1999), The Equity Risk Premium, New York: John Wiley & Sons, Inc.

Daniel, Kent; and Tobias Moskowitz (2013), “Momentum Crashes,” Columbia Business School working paper

DeMiguel, V.; Garlappi, L.; and R. Uppal (2009), “Optimal Versus Naive Diversification: How Inefficient is the 1/N Portfolio Strategy?” Review of Financial Studies 22(5), 1915-1953

Dimson, Elroy; Paul Marsh; and Mike Staunton (2002), Triumph of the Optimists: 101 Years of Global Investment Returns, Princeton, NJ: Princeton University Press.

Duchin, R. and H. Levy (2009), “Markowitz versus the Talmudic Portfolio Diversification Strategies,” Journal of Portfolio Management 7(4), 70-74.

Elton, Edwin J.; Martin J. Gruber; Deepak Agrawal; and Christopher Mann (2001), “Explaining the rate spread on corporate bonds,” Journal of Finance 56, 247–277.

Engle, R. F. (1982), “Autoregressive conditional heteroskedasticity with estimates of variance of U.K. inflation,” Econometrica 50, 987-1008.

Erb, Claude, and Campbell Harvey (2006), "The strategic and tactical value of commodity futures," Financial Analysts Journal 62, 69–97.

Fama, Eugene F. (1965), "The behavior of stock market prices," Journal of Business 38, 34-105.

Fama, Eugene F. (1970), "Efficient capital markets: A review of theory and empirical work," The Journal of Finance 25, 383-417.

Fama, Eugene F. (1991), "Efficient capital markets: II," The Journal of Finance 46, 1575-617.

Fama, Eugene F.; and Robert R. Bliss (1987), "The information in long maturity forward rates," American Economic Review 77, 680–692.

Fama, Eugene F.; and Kenneth R. French, (1993), "Common risk factors in the returns on stocks and bonds," Journal of Financial Economics 33, 3–56.

Fama, Eugene F.; and Kenneth R. French, (1998), "Value versus growth: The international evidence," Journal of Finance 53(6), 1975–1999.

Fama, Eugene F.; and Kenneth R. French (2001), "Disappearing dividends: Changing firm characteristics or lower propensity to pay," Journal of Financial Economics 60, 3–43.

Fama, Eugene F.; and Kenneth R. French (2002), "The equity premium," Journal of Finance 57 (April), 637–659.

Fama, Eugene F.; and Kenneth R. French (2012), "Size, value, and momentum in international stock returns," Journal of Financial Economics 105, 457–472.

Frazzini, A.; and Lamont, O. A. (2008), "Dumb money: Mutual fund flows and the cross-section of stock returns", Journal of Financial Economics 88(2), 299–322.

Fung, W. and D. A. Hsieh (2001), "The risk in hedge fund strategies: Theory and evidence from trend followers", Review of Financial Studies 14(2), 313-341.

Fung, W.; and D.A. Hsieh (2004), "Hedge Fund Benchmarks: A Risk Based Approach", Financial Analyst Journal 60, 65-80.

Fletcher R. (1987), Practical Methods of Optimization, John Wiley & Sons, New York

Granger, C. W. J. (1992), "Forecasting stock market prices: Lessons for forecasters", International Journal of Forecasting 8, 3-13.

Gray, Wesley; and Garlisle, Tobias (2012), Quantitative Value: A Practitioner's Guide to Automating Intelligent Investment and Eliminating Behavioral Errors, (The Wiley Finance Series), Wiley

He, Hua (2000), "Modeling term structures of swap spreads," Yale School of Management working paper, available at SSRN: http://ssrn.com/abstract=233963

Heaton, John, and Deborah J. Lucas (1996), "Evaluating the Effects of Incomplete Markets on Risk Sharing and Asset Pricing", Journal of Political Economy, Vol.104, No. 3, pp. 443-87.

Hong, H. and J. C. Stein (1999), "A unified theory of underreaction, momentum trading, and overreaction in asset markets", Journal of Finance 54(6), 2143–2184.

Ilmanen, Antti (2003), "Expected returns on stocks and bonds," Journal of Portfolio Management 29(2), 7–27.

Ilmanen, Antti (2011), Expected returns: An investor's guide to harvesting market rewards (The Wiley Finance Series), Wiley

Jegadeesh, Narasimhan, and Sheridan Titman (1993), "Returns to buying winners and selling losers: Implications for stock market efficiency", Journal of Finance 48, 65–91.

Johnson, T. C. (2002), "Rational momentum effects", Journal of Finance 57, 585–608

Kandel, S. and R. F. Stambaugh (1996), "On the predictability of stock returns: An asset-allocation perspective", Journal of Finance 51, 385-424.

Kariya T. (1988), "MTV model and its application to the prediction of stock prices," In *Proceedings of the Second International Tampere Conference in Statistics*, Pullila T, Puntanen S (eds). University of Tampere, Finland.

Kritzman, M.; Page, S.; and D. Turkington (2010), "In Defense of Optimization: The Fallacy of 1/N," Financial Analysts Journal 66(2), 31-39.

Levy, H.; and Markowitz, H.M. (1979), "Approximating expected utility by a function of mean and variance," American Economic Review 69, 308–317.

Lintner, J. (1965), "The Valuation of Risky Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets." Review of Economics and Statistics, 47, 13-37.

Lo, A. (2004), "The adaptive markets hypothesis: Market efficiency from an evolutionary perspective", Journal of Portfolio Management 30, 15-29.

Lohre, H.; Opfer, H.; and Orszag, G. (2012), "Diversifying Risk Parity," working paper, available at SSRN: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1974446

Longstaff, Francis A.; Sanjay Mithal; and Eric Neis (2005), "Corporate yield spreads: Default risk or liquidity? New evidence from the credit-default swap market," Journal of Finance 60, 2213–2253.

Maillard, Sebastien; Thierry Roncalli; and Jerome Teiletche (2010), "On the Properties of Equally-Weighted Risk Contribution Portfolios," Journal of Portfolio Management 36, 60 – 70.

Markowitz, H. (1952), "Portfolio Selection," Journal of Finance 7(1), 77-91.

Markowitz, H. (1952), "The Utility of Wealth," Journal of Political Economy, 6 (2), 151-158.

Merton, Robert C. (1973), "An intertemporal capital asset pricing model", Econometrica 41(5), 867-887.

Merton, Robert C. (1980), "On estimating the expected return on the market: An exploratory investigation," Journal of Financial Economics 8, 323–361.

Meucci, A. (2009), "Managing diversification," Risk 22, 74–79.

Miffre, Joelle; Chris Brooks; Xiafei Li (2011), "Idiosyncratic Risk and the Pricing of Poorly-Diversified Portfolios", EDHEC-Risk Institute working paper, available at SSRN: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1855944

Miffre, Joelle and Georgios Rallis (2007), "Momentum strategies in commodity futures markets," Journal of Banking and Finance 31, 1863-1886.

Moskowitz, T.; Ooi, Y. H.; and Pedersen, L. H. (2012), “Time series momentum”, Journal of Financial Economics 104(2), 228 – 250.

Naik, N. Y.; Ramadorai, T.; and Stromqvist, M. (2007), “Capacity constraints and hedge fund strategy returns”, European Financial Management 13(2), 239–256.

Nelson, C.; and Siegel, A. (1987), “Parsimonious Modelling of Yield Curve,” Journal of Business 60(3), 473-489.

Neuberger, A. (2012), "Realized Skewness," Review of Financial Studies 25, 3423-3455.

Okunev, J.; and White, D.R. (2003), “Do momentum-based strategies still work in foreign currency markets?” Journal of Financial and Quantitative Analysis 38, 425–447.

Pesaran, M. H. (1987), The Limits to Rational Expectations, Oxford: Basil Blackwell.

Pesaran, M. H. and A. Timmermann (1994), “Forecasting Stock Returns: An Examination of Stock Market Trading in the Presence of Transaction Costs”, Journal of Forecasting 13, 335-367.

Polak E. (1971), Computational Methods in Optimization: A United Approach, Academic Press Inc, London.

Qian, E. (2006), “On the financial interpretation of risk contribution: Risk budgets do add up,” Journal of Investment Management 4, 1–11.

Reinhart, Carmen and Rogoff , Kenneth (2009), This Time is Different: Eight Centuries of Financial Folly, Princeton, NJ: Princeton University Press.

Ross, S.A. (1976), “The Arbitrage Theory of Capital Asset Pricing,” Journal of Economic Theory 13, 341-360.

Samuelson, P. (1965), “Proof that properly anticipated prices fluctuate randomly,” Industrial Management Review Spring 6, 41-49.

Samuelson, Paul A. (1969), “Lifetime portfolio selection by dynamic stochastic programming”, Review of Economics and Statistics 5, August, 239-246.

Scherer, Bernd. (2007), Portfolio Construction & Risk Budgeting, Riskbooks, Third Edition.

Siegel, Jeremy J. (2002), Stocks for the Long Run (Third Edition), New York: McGraw-Hill.

Shiller, R. J. (2005), Irrational Exuberance (Second edition), Princeton University Press.

Sortino F.; and van der Meer, R. (1991), “Downside risk”, Journal of Portfolio Management 17(4), 27-31.

Swensen, D.F. (2000), Pioneering Portfolio Management, The Free Press, New York.

Szakmary, A. C.; Q. Shen; and S. C. Sharma (2010), “Trend-following trading strategies in commodity futures: A re-examination”, Journal of Banking and Finance 34(2), 409–426.

Yang, D.; and Zhang Q. (2000), “Drift independent volatility estimation based on high, low, open and close prices”, Journal of Business 73, 477-491.

Glossary

Absolute return

Absolute return strategies aim to produce a positive return regardless of the performance of the general market. This is usually achieved by taking positions in a portfolio of diversified risk premium factors with prudent risk management.

Algorithm

An algorithm is a set of formulaic steps that uses a series of inputs to arrive at an output. An algorithm could be implemented as an automatic process that takes input data into some calculation engine and produces the outputs.

Annualized return

An annualized rate of return is the return on an underlying converted into an annual equivalent. For example, a 1 month return of 1% could be stated as an annualized rate of return of 12%. Or a five year return of 10% could be stated as an annualized rate of return of 2%.

Asset allocation

The mechanism of allocating investment capital across different underlying asset classes, such as equities, bonds and commodities. The assets could also be cross-asset risk premium factors introduced in this primer.

Asset Class

An asset class is a set of financial instruments that show similar characteristics or follow a common theme. Examples of asset classes are equities, commodities, government bonds, corporate bonds, real estate, etc. Volatility is recently recognized as a separate asset class.

Back-testing

The analysis of an algorithm or model using historical data. Many of the cross-asset risk premium factor indices contain back-tested data, which shows how the model would have performed under historical market conditions.

Benchmark

A reference index or underlying against which performance of another index is compared with.

Beta

The beta of an asset measures how much it moves compared with a benchmark. In other words, it measures sensitivity of returns with respect to the benchmark. For example, stocks with a high beta tend to have larger positive returns when the broader market rises, and conversely, have a larger negative return when the broader market declines.

Black-Litterman (BL)

The BL methodology employs a Bayesian framework to tackle portfolio allocation after incorporating investor views on expected returns.

Bond

A bond is a financial instrument that companies or governments use to raise capital. The purchaser of a bond effectively lends the issuer (e.g. the company or government) money, in return for coupons and a repayment of principal at maturity.

Carry Strategy

A systematic strategy that stays overweight in higher yielding instruments and/or underweight in lower yielding instruments.

Correlation

Correlation is a measure of the degree to which changes in two underlyings are related. It is a number that takes a value between plus one (meaning that they both move in tandem) and minus one (which means they move in opposite directions).

Covered call

Selling a call option while owning the underlying security on which the option is written. The technique is often used by fund managers to generate income by receiving the option premium. Typically, they would sell slightly out of the money options on the asset, which gives them some upside exposure to the asset.

Constant Mix

Constant Mix is a portfolio risk management technique that invests a constant proportion of capital in the underlying asset/factor and the rest to risk free asset.

Constant Proportional Portfolio Insurance (CPPI)

Constant Proportional Portfolio Insurance (CPPI) is a dynamic portfolio risk management technique that invests a constant proportion of the cushion above a guaranteed floor to the risky asset/factor and the rest to risk free asset.

Currency forward

An agreement between two parties to exchange a defined amount of one currency for another at a particular date in the future, at a price that is agreed today.

Derivative

A derivative is a financial product, the value of which depends on the value of other financial (or non financial) instruments.

Directional

A directional strategy is one which has outright long or short positions in some underlying financial instruments. For e.g. a strategy with a long position would be described as a bullish (or long) strategy and will deliver positive returns if the underlying financial instrument displays positive returns.

Downside risk

The risk of losses that an investor may experience if there is a decline in the price on an underlying investment.

Drawdown

Drawdown is calculated as the percentage return from the peak level of the index to some reference position. **Maximum Drawdown** measures the largest Drawdown of the index over some history.

Excess return

The difference between a fully collateralized total return and the risk-free rate. More generally, it is the fully financed return of an investment (e.g. the P/L of being long a portfolio of stocks financed by shorting another portfolio of stocks).

Equal Marginal Volatility (EMV)

Equal Marginal Volatility (or Volatility Parity) is a portfolio allocation technique that weights each asset according the inverse of its volatility.

Fundamental Analysis

Refers to a type of analysis, typically used in the context of stocks, which involves analyzing company assets and liabilities, cash flows, management structure and competitive advantages, along with competitors and markets. It is performed on historical and current data with the aim of making forecasts about the securities. The term is used to distinguish such analysis from other types of investment analysis, such as quantitative or technical analysis.

Factors

Factors can refer to certain macro economic or market indicators. They can also refer to some systematic strategies capturing different risk premia. See also “Risk Factors” and “Risk Premia”.

Future

A future is a contract between two parties to buy or sell a standard quantity of a given instrument, at a price agreed today, on a specific date in the future. Futures are traded on a range of underlying instruments including commodities, bonds, currencies and stock indexes.

Global Minimum Variance (GMV)

Global Minimum Variance is a risk-based portfolio allocation technique that minimizes the portfolio variance under various weight constraints.

Growth Stocks

Refers to stocks that have higher earnings growth potential than the market average. These stocks typically have a high share price compared with their earnings (i.e. high P/E ratio). The opposite of growth stocks are **value stocks**.

Historical volatility

Historical volatility refers to the volatility of an index or financial instrument over some period in the past. This compares with implied volatility, which is an expectation of the future level of volatility priced into a derivative contract.

Implied volatility

Implied volatility refers an expectation of the future level of volatility fo an underlying instrument priced into a derivative contract. It is typically derived from the prices of options on the instrument by backing out the volatility parameter from a pricing formula like the Black-Scholes equation.

Interest rate swap

A derivative between two counterparties where one counterparty agrees to exchange a stream of interest payments for the other party's fixed cash flows. They can be used by hedgers to manage their liabilities, or they can be used by investors to replicate bond positions. They are amongst the most liquid and popular derivative instruments.

Leverage

Refers to the exposure of an index (or position) to another underlying index. A position is said to be leveraged if the exposure is greater than 100%, meaning that a 1% change in the underlying index will generate a greater than 1% change in the value of the position.

Leverage invariant

Portfolio weights on the unleveraged assets are not affected by leveraging up or down on a certain subset of assets.

Libor

The London inter-bank offered rate (LIBOR) is a daily reference rate based on the interest rates at which banks borrow unsecured funds from other banks in the London wholesale interbank market. This rate is typically set every business day.

Liquidity

Liquidity is a measure of the ease of trading in and out of financial instruments. An instrument is said to be liquid if the costs to enter and exit that position are low.

Mean-Variance Optimization (MVO)

MVO solves one-period portfolio optimization by using only the first two moments of the underlying return series. It achieves minimum variance given a certain expected return target.

Mean reversion

The tendency of a certain metric (price, yield, portfolio etc) to revert to its short-term or long-term fair value determined by technicals or fundamentals variables. It can work in either absolute or relative terms. Mean reversion belongs to Value style in systematic strategy terms.

Momentum

The tendency of a trend to continue or the best (worst) performance assets to continue to outperform (underperform).

Most-Diversified Portfolio (MDP)

Most-Diversified Portfolio is a portfolio allocation technique which maximizes the diversification ratio defined by the ratio of weighted average marginal volatility to portfolio volatility. It is equivalent to Mean-Variance Optimization (MVO) when the Sharpe ratios for all the assets are equal to a certain positive constant.

Option

An option is a contract that gives the holder the right, but not the obligation, to buy or sell an underlying at a certain price in the future. In exchange for this right, the purchaser of the option has to pay the seller a premium. Options which are exercisable at only at a specific point in the future (the options expiry date) are called European options, while those which are exercisable at any point in time before expiry (from the date of purchase) are termed American options.

Option-Based Portfolio Insurance Strategies (OBPI)

Option-Based Portfolio Insurance (OBPI) is a portfolio risk management technique that synthetically replicates a “protective put” on the underlying risky asset/portfolio.

Overlay

A strategy designed to tweak the return profile of a portfolio using derivatives or other financial instruments, but generally leaving the securities in the underlying portfolio unchanged. For example, a fund manager may wish to implement a covered call overlay which generates extra income from the sale of options, but reduces the maximum upside potential of his portfolio.

Price return

The price return is the return on an underlying over some period, where the return measure takes into account only the appreciation in price of underlying and not any income or distributions generated over the period. Often, indices like the S&P 500 are described as price return, as they only measure the price changes of the component securities (and not any dividends paid by these components).

Quantitative Strategies

Quantitative (or "Quant") strategies are investment strategies that use large amounts of financial and market data with the aim of looking for trading patterns to make investment decisions. They are typically employed by more sophisticated fund managers or hedge funds.

Replication

Replication of an index refers to the purchase of securities whose returns match the returns of the index. For example, to replicate the performance of S&P 500 Index, one would need to purchase all 500 securities within the S&P 500, in their respective weightings. One could also exercise partial replication or statistical replication to match the risk/return profile of an index.

Redundancy invariant

Portfolio weights on the unleveraged assets are not affected by introducing one or more linear combinations of the original assets.

Risk Budgeting (RB)

Risk Budgeting (RB) is a generalized version of Risk Parity, which allows for a pre-specified total contribution to risk of the marginal assets. See also “Risk Parity”.

Risk Factors

Also called alternative betas, or exotic betas, risk factors are synthetic assets designed to capture risk premia not accessible by traditional assets. Risk factors are defined by a set of trading rules that often involve multiple assets/trading instruments, and a rebalancing strategy.

Risk Parity (RP)

Risk Parity (RP) or equal contribution to total risk (equal-CTR) is a portfolio allocation technique that achieves equal total contribution to risk of all the marginal assets.

Risk Premium

Risk premium is generally defined as excess compensation for taking a certain risk, such as macro risks, liquidity risks or tail risks. They are usually implemented as different investable risk factors. See also "Excess Return".

Sharpe ratio

A measure that aims to capture the potential return of an underlying per unit of risk. It is calculated as the Excess Return of an underlying divided by its Volatility.

Sortino ratio

Similar to a Sharpe Ratio, the Sortino Ratio measures the excess return of an underlying divided by Downside Volatility. Downside Volatility refers to the volatility of the underlying measured by considering only returns below a certain target. It is a metric that focuses on the downside risk of a portfolio.

Stock index future

Refers to a futures contract on a stock index (see "Futures" definition above). For example, the S&P 500 has listed futures which allow professional investors to replicate the returns of the index in a cost efficient manner.

Stop Loss

A stop loss strategy is a portfolio risk management technique that is full invested in a risky portfolio but unwinds this investment and switches to 100% allocation to the risk-free asset when the portfolio value touches a designated floor level.

Systematic Strategy

An investment strategy that runs using an algorithm, typically with little or no investor discretion. Systemic strategies can run on virtually any set of assets.

Time-Invariant Portfolio Protection (TIPP)

Time-Invariant Portfolio Protection (TIPP) is a class of generic portfolio risk management techniques that aims to maintain a minimum value of the portfolio. See also "CPPI" and "OBPI".

Total return

The total return of an investment is the return of the investment including price appreciation and income generated. A total return stock index reflects the price return of the stocks in addition to the reinvested dividends paid by the stocks within the index.

Type of Strategies

Risk factors are building blocks for systematic strategies. These strategies can be designed with the aim of generating **alpha**, **enhancing performance** of traditional assets, providing specific **alternative beta** exposure or serving as a **portfolio hedge**.

Value-at-risk

Refers to a measurement that aims to calculate the worst case loss of a portfolio over a particular holding period, with a particular degree of confidence. For example, a "99%, 1 day Value at Risk (VaR) of US$1 million" for a given portfolio means that the there is a 99% probability that the return of that portfolio over a given day will be at least greater than negative US$1 million.

Value Investing

Refers to an investment strategy that involves buying stocks that appear underpriced on the basis of some form of fundamental analysis.

Value Strategies

Refers to systematic strategies which go long assets/factors that are cheaply valued and short assets/factors with expensive valuation. See also “Mean Reversion”.

Variance

Variance is a statistical measure that refers to how "spread out" a distribution is. For example, the returns of a factor can be described as having high variance if the returns are fairly wide ranging and dispersed.

Variance swap

A contract between two parties to exchange a pre-agreed variance level for the actual amount of variance realized over a period for a certain asset. The payoff to the "long" party is proportional to the difference between the realized variance of the designated asset and the strike variance.

Volatility

Volatility usually refers to the standard deviation of the returns of a financial instrument within a specific time horizon. It is a widely used measure to express the risk of the financial instrument over the specified time period. Volatility is normally expressed in annualized terms as a percentage. For example, emerging market equities historically exhibit high volatility. On the other hand, short-term treasury bills would be classified as an asset with low volatility.

Volatility Premium

Refers to the long-term positive average spread between implied and realized volatility (variance).

Volatility Targeting

Volatility Targeting is a dynamic portfolio risk management technique that targets a constant portfolio/factor volatility via periodic rebalancing.

Zero coupon bond

A debt instrument which pays no coupons but redeems at par at the maturity date. It will typically be sold at a discount to par.

Contacts

J.P. Morgan Global Research

Thomas Schmidt	Global Head of Research
Joyce Chang	Global Head of Fixed Income Research
Bruce Kasman	Chief Economist
Marko Kolanovic	Global Head of Quantitative and Derivatives Strategy
Jan Loeys	Global Asset Allocation
Noelle Grainger	Director of Americas Equity Research
Paul Huxford	Director of EMEA Equity Research
Sunil Garg	Director of Asia Pacific Equity Research
Colin Fenton	Global Commodities Research
John Normand	Global FX Strategy and International Rates Research
Matthew Jozoff	Structured Products and U.S. Rates Research
Eric Beinstein	U.S. High Grade Strategy and Credit Derivatives Research
Stephen Dulake	International Credit Research
Peter Acciavatti	U.S. High Yield Credit Research

Additional Contributors to the Report

Dubravko Lakos-Bujas
Bram Kaplan
Arjun Mehra

Quantitative and Derivatives Strategy

Global Head
Marko Kolanovic

Americas
Bram Kaplan
AJ Mehra
Dubravko Lakos-Bujas
David (Sang) Han
Min Moon

EMEA
Davide Silvestrini
Peng Cheng
Sahil Manocha
Viquar Shaikh
Angelo Pessaris
Rahil Iqbal

Asia Pacific
Tony Lee
Michiro Naito
Zhen Wei
Sue Lee
Haoshun Liu
Robert Smith
Berowne Hlavaty
Christopher Ma

GRC
Pankaj Gupta
Vivek Shah
Arfi Khan
Arun Jain
Priyanka Saraf
Rahul Dalmia

Disclaimers

Risks of Common Option Strategies

Risks to Strategies: Not all option strategies are suitable for investors; certain strategies may expose investors to significant potential losses. We have summarized the risks of selected derivative strategies. For additional risk information, please call your sales representative for a copy of "Characteristics and Risks of Standardized Options." We advise investors to consult their tax advisors and legal counsel about the tax implications of these strategies. Please also refer to option risk disclosure documents.

Put Sale. Investors who sell put options will own the underlying stock if the stock price falls below the strike price of the put option. Investors, therefore, will be exposed to any decline in the stock price below the strike potentially to zero, and they will not participate in any stock appreciation if the option expires unexercised.

Call Sale. Investors who sell uncovered call options have exposure on the upside that is theoretically unlimited.

Call Overwrite or Buywrite. Investors who sell call options against a long position in the underlying stock give up any appreciation in the stock price above the strike price of the call option, and they remain exposed to the downside of the underlying stock in the return for the receipt of the option premium.

Booster. In a sell-off, the maximum realised downside potential of a double-up booster is the net premium paid. In a rally, option losses are potentially unlimited as the investor is net short a call. When overlaid onto a long stock position, upside losses are capped (as for a covered call), but downside losses are not.

Collar. Locks in the amount that can be realized at maturity to a range defined by the put and call strike. If the collar is not costless, investors risk losing 100% of the premium paid. Since investors are selling a call option, they give up any stock appreciation above the strike price of the call option.

Call Purchase. Options are a decaying asset, and investors risk losing 100% of the premium paid if the stock is below the strike price of the call option.

Put Purchase. Options are a decaying asset, and investors risk losing 100% of the premium paid if the stock is above the strike price of the put option.

Straddle or Strangle. The seller of a straddle or strangle is exposed to stock increases above the call strike and stock price declines below the put strike. Since exposure on the upside is theoretically unlimited, investors who also own the stock would have limited losses should the stock rally. Covered writers are exposed to declines in the long stock position as well as any additional shares put to them should the stock decline below the strike price of the put option. Having sold a covered call option, the investor gives up all appreciation in the stock above the strike price of the call option.

Put Spread. The buyer of a put spread risks losing 100% of the premium paid. The buyer of higher ratio put spread has unlimited downside below the lower strike (down to zero), dependent on the number of lower struck puts sold. The maximum gain is limited to the spread between the two put strikes, when the underlying is at the lower strike. Investors who own the underlying stock will have downside protection between the higher strike put and the lower strike put. However, should the stock price fall below the strike price of the lower strike put, investors regain exposure to the underlying stock, and this exposure is multiplied by the number of puts sold.

Call Spread. The buyer risks losing 100% of the premium paid. The gain is limited to the spread between the two strike prices. The seller of a call spread risks losing an amount equal to the spread between the two call strikes less the net premium received. By selling a covered call spread, the investor remains exposed to the downside of the stock and gives up the spread between the two call strikes should the stock rally.

Butterfly Spread. A butterfly spread consists of two spreads established simultaneously. One a bull spread and the other a bear spread. The resulting position is neutral, that is, the investor will profit if the underlying is stable. Butterfly spreads are established at a net debit. The maximum profit will occur at the middle strike price, the maximum loss is the net debit.

Pricing Is Illustrative Only: Prices quoted in the above trade ideas are our estimate of current market levels, and are not indicative trading levels.

Disclosures

This report is a product of the research department's Global Equity Derivatives and Quantitative Strategy group. Views expressed may differ from the views of the research analysts covering stocks or sectors mentioned in this report. Structured securities, options, futures and other derivatives are complex instruments, may involve a high degree of risk, and may be appropriate investments only for sophisticated investors who are capable of understanding and assuming the risks involved. Because of the importance of tax considerations to many option transactions, the investor considering options should consult with his/her tax advisor as to how taxes affect the outcome of contemplated option transactions.

Analyst Certification: The research analyst(s) denoted by an "AC" on the cover of this report certifies (or, where multiple research analysts are primarily responsible for this report, the research analyst denoted by an "AC" on the cover or within the document individually certifies, with respect to each security or issuer that the research analyst covers in this research) that: (1) all of the views expressed in this report accurately reflect his or her personal views about any and all of the subject securities or issuers; and (2) no part of any of the research analyst's compensation was, is, or will be directly or indirectly related to the specific recommendations or views expressed by the research analyst(s) in this report. For all Korea-based research analysts listed on the front cover, they also certify, as per KOFIA requirements, that their analysis was made in good faith and that the views reflect their own opinion, without undue influence or intervention.

Important Disclosures

Company-Specific Disclosures: Important disclosures, including price charts, are available for compendium reports and all J.P. Morgan–covered companies by visiting https://jpmm.com/research/disclosures, calling 1-800-477-0406, or e-mailing research.disclosure.inquiries@jpmorgan.com with your request. J.P. Morgan's Strategy, Technical, and Quantitative Research teams may screen companies not covered by J.P. Morgan. For important disclosures for these companies, please call 1-800-477-0406 or e-mail research.disclosure.inquiries@jpmorgan.com.

Explanation of Equity Research Ratings, Designations and Analyst(s) Coverage Universe:
J.P. Morgan uses the following rating system: Overweight [Over the next six to twelve months, we expect this stock will outperform the average total return of the stocks in the analyst's (or the analyst's team's) coverage universe.] Neutral [Over the next six to twelve months, we expect this stock will perform in line with the average total return of the stocks in the analyst's (or the analyst's team's) coverage universe.] Underweight [Over the next six to twelve months, we expect this stock will underperform the average total return of the stocks in the analyst's (or the analyst's team's) coverage universe.] Not Rated (NR): J.P. Morgan has removed the rating and, if applicable, the price target, for this stock because of either a lack of a sufficient fundamental basis or for legal, regulatory or policy reasons. The previous rating and, if applicable, the price target, no longer should be relied upon. An NR designation is not a recommendation or a rating. In our Asia (ex-Australia) and U.K. small- and mid-cap equity research, each stock's expected total return is compared to the expected total return of a benchmark country market index, not to those analysts' coverage universe. If it does not appear in the Important Disclosures section of this report, the certifying analyst's coverage universe can be found on J.P. Morgan's research website, www.jpmorganmarkets.com.

J.P. Morgan Equity Research Ratings Distribution, as of September 30, 2013

	Overweight (buy)	Neutral (hold)	Underweight (sell)
J.P. Morgan Global Equity Research Coverage	43%	44%	12%
IB clients*	57%	49%	39%
JPMS Equity Research Coverage	42%	50%	8%
IB clients*	76%	65%	57%

*Percentage of investment banking clients in each rating category.
For purposes only of FINRA/NYSE ratings distribution rules, our Overweight rating falls into a buy rating category; our Neutral rating falls into a hold rating category; and our Underweight rating falls into a sell rating category. Please note that stocks with an NR designation are not included in the table above.

Equity Valuation and Risks: For valuation methodology and risks associated with covered companies or price targets for covered companies, please see the most recent company-specific research report at http://www.jpmorganmarkets.com, contact the primary analyst or your J.P. Morgan representative, or email research.disclosure.inquiries@jpmorgan.com.

Equity Analysts' Compensation: The equity research analysts responsible for the preparation of this report receive compensation based upon various factors, including the quality and accuracy of research, client feedback, competitive factors, and overall firm revenues.

Registration of non-US Analysts: Unless otherwise noted, the non-US analysts listed on the front of this report are employees of non-US affiliates of JPMS, are not registered/qualified as research analysts under NASD/NYSE rules, may not be associated persons of JPMS, and may not be subject to FINRA Rule 2711 and NYSE Rule 472 restrictions on communications with covered companies, public appearances, and trading securities held by a research analyst account.

Conflict of Interest
This research contains the views, opinions and recommendations of J.P. Morgan research analysts. J.P. Morgan has adopted research conflict of interest policies, including prohibitions on non-research personnel influencing the content of research. Research analysts still may speak to J.P. Morgan trading desk personnel in formulating views, opinions and recommendations. Trading desks may trade, or have traded, as principal on the basis of the research analysts' views and research. Therefore, this research may not be independent from the proprietary interests of J.P. Morgan trading desks which may conflict with your interests. As a general matter, J.P. Morgan and/or its affiliates trade as principal in connection with making markets in fixed income securities, commodities and other investment instruments discussed in research reports.

Other Disclosures

J.P. Morgan ("JPM") is the global brand name for J.P. Morgan Securities LLC ("JPMS") and its affiliates worldwide. J.P. Morgan Cazenove is a marketing name for the U.K. investment banking businesses and EMEA cash equities and equity research businesses of JPMorgan Chase & Co. and its subsidiaries.

All research reports made available to clients are simultaneously available on our client website, J.P. Morgan Markets. Not all research content is redistributed, e-mailed or made available to third-party aggregators. For all research reports available on a particular stock, please contact your sales representative.

Options related research: If the information contained herein regards options related research, such information is available only to persons who have received the proper option risk disclosure documents. For a copy of the Option Clearing Corporation's Characteristics and Risks of Standardized Options, please contact your J.P. Morgan Representative or visit the OCC's website at http://www.optionsclearing.com/publications/risks/riskstoc.pdf

Legal Entities Disclosures
U.S.: JPMS is a member of NYSE, FINRA, SIPC and the NFA. JPMorgan Chase Bank, N.A. is a member of FDIC. **U.K**.: JPMorgan Chase N.A., London Branch, is authorised by the Prudential Regulation Authority and is subject to regulation by the Financial Conduct Authority and to limited regulation by the Prudential Regulation Authority. Details about the extent of our regulation by the Prudential Regulation Authority are available from J.P. Morgan on request. J.P. Morgan Securities plc (JPMS plc) is a member of the London Stock Exchange and is authorised by the Prudential Regulation Authority and regulated by the Financial Conduct Authority and the Prudential Regulation Authority. Registered in England & Wales No. 2711006. Registered Office 25 Bank Street, London, E14 5JP. **South Africa**: J.P. Morgan Equities South Africa Proprietary Limited is a member of the Johannesburg Securities Exchange and is regulated by the Financial Services Board. **Hong Kong**: J.P. Morgan Securities (Asia Pacific) Limited (CE number AAJ321) is regulated by the Hong Kong Monetary Authority and the Securities and Futures Commission in Hong Kong. **Korea**: J.P. Morgan Securities (Far East) Ltd, Seoul Branch, is regulated by the Korea Financial Supervisory Service. **Australia**: J.P. Morgan Australia Limited (JPMAL) (ABN 52 002 888 011/AFS Licence No: 238188) is regulated by ASIC and J.P. Morgan Securities Australia Limited (JPMSAL) (ABN 61 003 245 234/AFS Licence No: 238066) is regulated by ASIC and is a Market, Clearing and Settlement Participant of ASX Limited and CHI-X. **Taiwan**: J.P.Morgan Securities (Taiwan) Limited is a participant of the Taiwan Stock Exchange (company-type) and regulated by the Taiwan Securities and Futures Bureau. **India**: J.P. Morgan India Private Limited, having its registered office at J.P. Morgan Tower, Off. C.S.T. Road, Kalina, Santacruz East, Mumbai - 400098, is a member of the National Stock Exchange of India Limited (SEBI Registration Number - INB 230675231/INF 230675231/INE 230675231) and Bombay Stock Exchange Limited (SEBI Registration Number - INB 010675237/INF 010675237) and is regulated by Securities and Exchange Board of India. **Thailand**: JPMorgan Securities (Thailand) Limited is a member of the Stock Exchange of Thailand and is regulated by the Ministry of Finance and the Securities and Exchange Commission. **Indonesia**: PT J.P. Morgan Securities Indonesia is a member of the Indonesia Stock Exchange and is regulated by the BAPEPAM LK. **Philippines**: J.P. Morgan Securities Philippines Inc. is a Trading Participant of the Philippine Stock Exchange and a member of the Securities Clearing Corporation of the Philippines and the Securities Investor Protection Fund. It is regulated by the Securities and Exchange Commission. **Brazil**: Banco J.P. Morgan S.A. is regulated by the Comissao de Valores Mobiliarios (CVM) and by the Central Bank of Brazil. **Mexico**: J.P. Morgan Casa de Bolsa, S.A. de C.V., J.P. Morgan Grupo Financiero is a member of the Mexican Stock Exchange and authorized to act as a broker dealer by the National Banking and Securities Exchange Commission. **Singapore**: This material is issued and distributed in Singapore by J.P. Morgan Securities Singapore Private Limited (JPMSS) [MIC (P) 049/04/2013 and Co. Reg. No.: 199405335R] which is a member of the Singapore Exchange Securities Trading Limited and is regulated by the Monetary Authority of Singapore (MAS) and/or JPMorgan Chase Bank, N.A., Singapore branch (JPMCB Singapore) which is regulated by the MAS. **Japan**: JPMorgan Securities Japan Co., Ltd. is regulated by the Financial Services Agency in Japan. **Malaysia**: This material is issued and distributed in Malaysia by JPMorgan Securities (Malaysia) Sdn Bhd (18146-X) which is a Participating Organization of Bursa Malaysia Berhad and a holder of Capital Markets Services License issued by the Securities Commission in Malaysia. **Pakistan**: J. P. Morgan Pakistan Broking (Pvt.) Ltd is a member of the Karachi Stock Exchange and regulated by the Securities and Exchange Commission of Pakistan. **Saudi Arabia**: J.P. Morgan Saudi Arabia Ltd. is authorized by the Capital Market Authority of the Kingdom of Saudi Arabia (CMA) to carry out dealing as an agent, arranging, advising and custody, with respect to securities business under licence number 35-07079 and its registered address is at 8th Floor, Al-Faisaliyah Tower, King Fahad Road, P.O. Box 51907, Riyadh 11553, Kingdom of Saudi Arabia. **Dubai**: JPMorgan Chase Bank, N.A., Dubai Branch is regulated by the Dubai Financial Services Authority (DFSA) and its registered address is Dubai International Financial Centre - Building 3, Level 7, PO Box 506551, Dubai, UAE.

Country and Region Specific Disclosures
U.K. and European Economic Area (EEA): Unless specified to the contrary, issued and approved for distribution in the U.K. and the EEA by JPMS plc. Investment research issued by JPMS plc has been prepared in accordance with JPMS plc's policies for managing conflicts of interest arising as a result of publication and distribution of investment research. Many European regulators require a firm to establish, implement and maintain such a policy. This report has been issued in the U.K. only to persons of a kind described in Article 19 (5), 38, 47 and 49 of the Financial Services and Markets Act 2000 (Financial Promotion) Order 2005 (all such persons being referred to as "relevant persons"). This document must not be acted on or relied on by persons

who are not relevant persons. Any investment or investment activity to which this document relates is only available to relevant persons and will be engaged in only with relevant persons. In other EEA countries, the report has been issued to persons regarded as professional investors (or equivalent) in their home jurisdiction. **Australia:** This material is issued and distributed by JPMSAL in Australia to "wholesale clients" only. This material does not take into account the specific investment objectives, financial situation or particular needs of the recipient. The recipient of this material must not distribute it to any third party or outside Australia without the prior written consent of JPMSAL. For the purposes of this paragraph the term "wholesale client" has the meaning given in section 761G of the Corporations Act 2001. **Germany:** This material is distributed in Germany by J.P. Morgan Securities plc, Frankfurt Branch and J.P.Morgan Chase Bank, N.A., Frankfurt Branch which are regulated by the Bundesanstalt für Finanzdienstleistungsaufsicht. **Hong Kong:** The 1% ownership disclosure as of the previous month end satisfies the requirements under Paragraph 16.5(a) of the Hong Kong Code of Conduct for Persons Licensed by or Registered with the Securities and Futures Commission. (For research published within the first ten days of the month, the disclosure may be based on the month end data from two months prior.) J.P. Morgan Broking (Hong Kong) Limited is the liquidity provider/market maker for derivative warrants, callable bull bear contracts and stock options listed on the Stock Exchange of Hong Kong Limited. An updated list can be found on HKEx website: http://www.hkex.com.hk. **Japan:** There is a risk that a loss may occur due to a change in the price of the shares in the case of share trading, and that a loss may occur due to the exchange rate in the case of foreign share trading. In the case of share trading, JPMorgan Securities Japan Co., Ltd., will be receiving a brokerage fee and consumption tax (shouhizei) calculated by multiplying the executed price by the commission rate which was individually agreed between JPMorgan Securities Japan Co., Ltd., and the customer in advance. Financial Instruments Firms: JPMorgan Securities Japan Co., Ltd., Kanto Local Finance Bureau (kinsho) No. 82 Participating Association / Japan Securities Dealers Association, The Financial Futures Association of Japan, Type II Financial Instruments Firms Association and Japan Investment Advisers Association. **Korea:** This report may have been edited or contributed to from time to time by affiliates of J.P. Morgan Securities (Far East) Ltd, Seoul Branch. **Singapore:** JPMSS and/or its affiliates may have a holding in any of the securities discussed in this report; for securities where the holding is 1% or greater, the specific holding is disclosed in the Important Disclosures section above. **India:** For private circulation only, not for sale. **Pakistan:** For private circulation only, not for sale. **New Zealand:** This material is issued and distributed by JPMSAL in New Zealand only to persons whose principal business is the investment of money or who, in the course of and for the purposes of their business, habitually invest money. JPMSAL does not issue or distribute this material to members of "the public" as determined in accordance with section 3 of the Securities Act 1978. The recipient of this material must not distribute it to any third party or outside New Zealand without the prior written consent of JPMSAL. **Canada:** The information contained herein is not, and under no circumstances is to be construed as, a prospectus, an advertisement, a public offering, an offer to sell securities described herein, or solicitation of an offer to buy securities described herein, in Canada or any province or territory thereof. Any offer or sale of the securities described herein in Canada will be made only under an exemption from the requirements to file a prospectus with the relevant Canadian securities regulators and only by a dealer properly registered under applicable securities laws or, alternatively, pursuant to an exemption from the dealer registration requirement in the relevant province or territory of Canada in which such offer or sale is made. The information contained herein is under no circumstances to be construed as investment advice in any province or territory of Canada and is not tailored to the needs of the recipient. To the extent that the information contained herein references securities of an issuer incorporated, formed or created under the laws of Canada or a province or territory of Canada, any trades in such securities must be conducted through a dealer registered in Canada. No securities commission or similar regulatory authority in Canada has reviewed or in any way passed judgment upon these materials, the information contained herein or the merits of the securities described herein, and any representation to the contrary is an offence. **Dubai:** This report has been issued to persons regarded as professional clients as defined under the DFSA rules. **Brazil**: Ombudsman J.P. Morgan: 0800-7700847 / ouvidoria.jp.morgan@jpmorgan.com.

General: Additional information is available upon request. Information has been obtained from sources believed to be reliable but JPMorgan Chase & Co. or its affiliates and/or subsidiaries (collectively J.P. Morgan) do not warrant its completeness or accuracy except with respect to any disclosures relative to JPMS and/or its affiliates and the analyst's involvement with the issuer that is the subject of the research. All pricing is as of the close of market for the securities discussed, unless otherwise stated. Opinions and estimates constitute our judgment as of the date of this material and are subject to change without notice. Past performance is not indicative of future results. This material is not intended as an offer or solicitation for the purchase or sale of any financial instrument. The opinions and recommendations herein do not take into account individual client circumstances, objectives, or needs and are not intended as recommendations of particular securities, financial instruments or strategies to particular clients. The recipient of this report must make its own independent decisions regarding any securities or financial instruments mentioned herein. JPMS distributes in the U.S. research published by non-U.S. affiliates and accepts responsibility for its contents. Periodic updates may be provided on companies/industries based on company specific developments or announcements, market conditions or any other publicly available information. Clients should contact analysts and execute transactions through a J.P. Morgan subsidiary or affiliate in their home jurisdiction unless governing law permits otherwise.

"Other Disclosures" last revised December 7, 2013.