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MULTI-FACTOR ALLOCATION: BNP PARIBAS ASSET MANAGEMENT'S PRINCIPLES FOR REDESIGNING TACTICAL ASSET ALLOCATION

BNP PARIBAS
ASSET MANAGEMENT

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ABSTRACT

Asset managers publish tactical asset allocation views regularly. The implementation of such (usually qualitative) views, in portfolios is often over-simplistic. We propose a robust framework to industrialize the construction of tailored portfolios consistent with the views. First, an unconstrained unique tactical portfolio is created by relating the conviction in each view to the allocation of risk budget to the assets underlying the view. Second, the tailored portfolios with investor-specific constraints and targets are constructed using robust portfolio optimization based on implied active returns derived from the unique unconstrained tactical portfolio. The implied returns are derived from reverse optimization using the same robust approach. Robust optimization is the core engine for the industrialization process. It produces portfolios consistent with the views while complying with constraints without requiring human intervention. Finally, a factor-based risk model endows the framework with transparency, by allowing for comparison of risk-factor exposures in portfolios with those in the original views' exposures.

KEY TAKEAWAYS:

- **The authors propose a robust framework to implement the tailor-made active tilts derived from asset allocation views in investor portfolios. The framework is based on an innovative approach to using robust portfolio optimization.**
- **Through empirical examples, the authors show that robust portfolio optimization produces allocations that are consistent with views while fulfilling constraints, avoiding the well-known weaknesses of mean-variance optimization. This robustness simplifies the industrialization of the construction of customized portfolios.**
- **The adoption of statistical factor-based risk model is key to ensuring transparency. Comparison of risk-factor exposures in portfolios with those in the original views allows investors to gauge whether the framework manages to retain the risk-factor exposures contained in views.**

Multi-asset teams in the asset management industry manage not only many active benchmarked funds but also customized mandates for hundreds or even thousands of institutional investors. Moreover, the arrival of Fintech in the asset manager industry with the development of Robo Advisory is creating an increasing demand for the ability to industrialize asset allocation advisory for thousands, if not millions, of individual investors. And all this is happening at a time when the industry is experiencing significant changes, with pressure towards greater transparency and competition for operational efficiency. In this context, having an efficient and robust framework to implement investment views in portfolios on a large industrial scale is critical.

In most asset management companies, the investment committee (IC) is the source of the tactical active allocation views used in the investment process of multi-asset investment teams. This committee, usually composed of portfolio managers, macro-economists, market strategists and dedicated research professionals, meets regularly to decide about the asset allocation views on selected asset classes. A view typically has two components: direction and conviction[2]. Direction reflects the expected trend in assets' prices, upward or downward and is expressed with words like "overweight" or "positive", "underweight" or "negative" and "neutral" or mathematical signs such as "+", "-" and "0". The conviction expresses how much risk the IC is willing to take on a given view and is formulated either with abstract scores such as "+++", "++", "--" or with words like "very strong" or "low". Through these views, an IC aims at adding value by timing the trends in assets' prices and exploiting the temporary divergence of assets' valuations from equilibrium levels. Investment teams implement these views in investors' portfolios as part of the tactical asset allocation (TAA) process. According to Arnott and Fabozzi [1988], TAA is an active strategy that seeks to enhance the performance by dynamically deviating from the strategic asset allocation (SAA) based on investment views. In the industry, this deviation, measured in risk, is capped by the maximum tracking error (Max TE) or the active risk budget.

Active managers devote significant resources to the formulation of these views, which are regularly updated and communicated by their IC. However, they are usually much less transparent with regard to the process used to transform the IC views, formulated with qualitative scores, into portfolios. The seminal work of Black and Litterman [1992] constitutes a theoretically elegant solution to the implementation of views. However, as pointed out by Da Silva et al. [2009] and Leote de Carvalho et al. [2014], the original Black-Litterman (BL) model yields mean-variance optimal portfolios in the space of absolute returns and volatility. The optimal level of tracking error is itself a result of the optimization controlled by the parameter Tau[3] (O'Toole [2017]). This feature is not in line with the industry's reality in multi-asset active management (Da Silva et al. [2009]). In practice, the Max TE is often an exogenous input set by investors. Industrializing in a transparent and robust manner the implementation of IC views in hundreds or even thousands of portfolios, each with customized constraints and Max TE, remains one of the biggest challenges the industry faces when conducting the TAA exercise.

In this context, we propose a framework to address this industrialization challenge, based on three steps:

1. Construct a unique unconstrained active portfolio using an active risk budgeting approach that fully reflects the IC views at a given level of Max TE kept constant over time.
2. Calculate the implied active returns that render this unconstrained active portfolio optimal under robust portfolio optimization (RPO) and a factor-based risk model by reversing the optimization problem.
3. Run a RPO with the implied active returns and the factor-based risk model as inputs, and adding portfolio specific investor constraints, the benchmark, the universe of financial instruments authorized by the end investor and the specific Max TE tolerated by the investor.

2 Exhibit 15 in the Appendix provides a summary of how some major asset management firms formulate their views.
3 Tau quantifies the level of confidence between the investment views and the equilibrium expected returns.

Transforming IC views into a unique unconstrained active portfolio facilitates the monitoring of performance and encourages the assessment of whether the IC produces timely and accurate TAA views. Along with these two benefits, we list below three key innovations that are crucial for the proposed framework to achieve the industrialized implementation of IC views in customized investors' multi-asset portfolios with the transparency that is required if no human intervention is a target.

First, the active risk budgeting approach in step 1 establishes the relationship between conviction of IC views and the consumption of risk, fully captured in a unique unconstrained active portfolio and in line with the expectations of the IC. The latter is thus assumed to be the optimal representation of IC views in terms of portfolio tactical allocation.

Another innovation is the use of RPO instead of traditional mean-variance optimization (MVO) for both the calculation of implied active returns from the unique unconstrained portfolio representing the IC views, and for the portfolio optimization of tailored investors' portfolios with specific constraints, benchmarks and Max TE. RPO has already been applied in various areas of finance (Fabozzi et al. [2010] and Kim et al. [2018]), including the SAA with the work of ASL and Etula [2012]. However, the traditional approaches to TAA, including the BL model, still rely on MVO. Originally introduced by Markowitz [1952, 1959], MVO has been criticized for its high sensitivity to inputs and its propensity to maximize the estimation errors (Best and Grauer [1991], Chopra and Ziemba [1993] and Michaud [1998]). In particular, we show in our first empirical example that if we used MVO instead of RPO, the presence of constraints exacerbates the MVO problem mentioned above, as it tends to create extreme active positions on assets even when there are no views on them. This is the case for constrained portfolios even when optimizing from implied returns derived from the unique unconstrained portfolio assumed to be optimal. A host of solutions has been proposed to mitigate this drawback without changing the utility function of the MVO, but no consensus has yet been established (Michaud [1998], Jagannathan and MA [2003] and DeMiguel et al. [2009]). However, by accounting for the uncertainty in expected returns directly in the objective function, RPO overcomes this undesirable property of the MVO to overplay arbitrages among highly correlated assets. By ensuring better consistency with IC views even under constraints, the RPO can be used in the industrialization of portfolio construction process even for highly customized portfolios. We follow the recent work of Yin et al. [2020] with regards the practical use and calibration of RPO, which plays a key role in making the approach useful for practitioners.

Finally, there is the question of transparency in investment processes and being able to explain why a given portfolio was proposed. Both academics and practitioners are increasing their emphasis of this issue. In TAA, transparency means that investors should be able to assess easily the impact of constraints on tactical tilts and to gauge the extent to which their constrained portfolios reflect the IC views. Inspired by the recent industry trend, with works by Bass et al. [2017], Martellini and Milhau [2017], Bergeron et al. [2018] and Bender et al. [2019], to reshape asset allocation and multi-asset portfolio analytics from a factor-based perspective, the proposed framework adopts a statistical factor-based risk model to ensure the transparency in each step and demonstrate consistency. Both the unique unconstrained active portfolio and the customized constrained portfolios can be decomposed in terms of their exposures to systematic risk factors and their idiosyncratic risks. This decomposition provides the means to compare portfolios and judge the success of implementation of IC views in the customized portfolios: it is expected that the risk factor exposures of the unique unconstrained portfolio representing IC views are passed on to the customized investor portfolios. In addition, information about the breakdown of tracking error of the customized investor portfolios in terms of systematic risks and idiosyncratic risks (Qian et al. [2007]) as well as the sources of idiosyncratic risks can also be checked, as shown in our second empirical example.

In the remainder of the article, we first detail each of the three steps of the proposed framework. We then present two examples with practical applications. The first aims at highlighting the importance of using RPO instead of MVO in the framework with an application where the IC views are implemented in a portfolio benchmarked against a 50/50 equity and bond benchmark, and using varying IC views. The second example aims at illustrating the implementation of the framework while providing a factor-based risk analysis to break down the impact of each constraint on the risk exposures of the final portfolio.

FRAMEWORK

In this section, we present the framework, starting with a discussion of the active risk budgeting exercise to derive the unique unconstrained active portfolio from views. We then introduce the risk model used in this framework and show how the views on assets can be projected on the identified risk factors. Finally, we show that the use of RPO delivers more intuitive and well-diversified portfolios than MVO. It is also important to note that the proposed framework aims at building customized portfolios based on IC views. Therefore, in the absence of views, the final portfolio should be just the best possible replication of the benchmark to the extent constraints allow it.

Constructing the Unique Unconstrained Active Portfolio from Views

In this subsection, we explore the way to use a risk-based approach to form a unique portfolio reflecting the views. As pointed out by Herold [2003] and illustrated by Exhibit 15 in the Appendix, the IC of multi-asset solutions teams do not generate quantitative forecasts in terms of expected returns: they cannot be certain regarding future expected returns. In this context, the IC prefers to represent views on the market outlook for different assets with scores rather than with returns, and to have the scores representing intended deviations from benchmarks for the assets in question. To model this portfolio, the framework adopts the active risk budgeting methodology based on the generic risk-based portfolio proposed by Jurczenko and Teiletche [2018]:

$$\boldsymbol{w}_{RB} = k\boldsymbol{\sigma}^{-1} \tag{1}$$

with $\boldsymbol{\sigma} = (\sigma_1, \cdots, \sigma_n)^T$ the vector of volatilities, n the number of assets in the investment universe, and where k is calibrated to target a predefined level of volatility for the risk-based portfolio. Each IC view is considered as an independent directional strategy that consumes the Max TE of a portfolio. The IC determines the link between the level of conviction on a view and the proportion of Max TE allocated to this view. In this article, we propose that a view with full conviction will consume 100% of Max TE and a view with half conviction will only consume 50% of Max TE. Hence, each view will be allocated a score that reflects the conviction, which determines its Max TE consumption.

Let us note the score of the IC view on asset *i* as S_i, with $-100\% \leq S_i \leq 100\%$. Assume that the Max TE of a portfolio, which represents the risk budget, is RB. The unconstrained risk-based active portfolio derived from views, $\boldsymbol{w}_{active}$ is given by:

$$\boldsymbol{w}_{active} = \boldsymbol{S}^T(RB\boldsymbol{\sigma}^{-1}) \tag{2}$$

with $\boldsymbol{S} = (S_1, \cdots, S_n)^T$ the vector of IC views. $\boldsymbol{S}^T RB$ captures the tracking error of the portfolio that is allocated to the views, based on the convictions and the directions. We observe that Equation (2) is consistent with Equation (1), which represents the generic risk-based portfolio in Jurczenko and Teiletche [2018] where, instead of using tracking error RB, they introduced a constant k representing a predefined level of volatility for the risk-based portfolio.

The IC is not subject to any constraints on the scores to express the views and can set any scores between -100% and +100%. The ex-post tracking error of this unconstrained active portfolio may exceed the prefixed tracking error. The portfolio construction step of the framework, step 3, will ensure that the final constrained portfolio complies with the tracking error set by the investor by imposing a Max TE constraint. By doing so, with the framework, the unconstrained active portfolio can fully capture the information contained in IC views.

In Exhibit 1, we show an example of the construction of the unique unconstrained portfolio that reflects the views, with a Max TE of 5%, using the risk-budgeting approach. The list of relevant assets and the corresponding Bloomberg tickers are in Exhibit 16 of the Appendix. Bloomberg is the source of all net total return data series used in this article. All returns are in local currency. Monthly returns from February 2003 to October 2020 were used. Throughout the article, the volatility of returns was calculated over the entire sample period and annualized with the squared root of frequency.

The performance of the unique unconstrained active portfolio, assumed to be the optimal representation of IC views, can be used to assess the value added of the IC over time.

Risk Model and Factor-Based Analysis of Views

Having presented the construction of the unique unconstrained active portfolio representing IC views, we now introduce the statistical factor-based risk model and show how it can be used to provide transparency by expressing this portfolio in terms of exposures to the systematic risk factors and to the idiosyncratic risks.

Exhibit 1: Unique Unconstrained Active Portfolio representing Qualitative views

	Qualitative View	Score: % of TE consumption	TE Allocated Based on Conviction and Direction	Volatility	Unconstrained Active Portfolio
Bond EUR Sovereign	----	-100.0%	-5.0%	4.0%	-124.8%
Bond EUR Investment Grade	++	50.0%	2.5%	4.0%	63.2%
Bond USD Investment Grade	=	0.0%	0.0%	5.9%	0.0%
Bond USD High Yield	++	50.0%	2.5%	9.2%	27.2%
Bond EMD HC Sov. Global	-	-25.0%	-1.3%	8.7%	-14.4%
Equity Europe EMU	--	-50.0%	-2.5%	16.4%	-15.2%
Equity Europe EMU SC	++	50.0%	2.5%	18.2%	13.8%

Note: '++++' represents a positive directional view (against cash) with full conviction.
'=' represents a neutral view,
'----' represents a negative direction view with full conviction.
'Investment Grade' and 'High Yield' refer to corporate bonds and their common definitions using agency ratings and standard indices
This example is for illustration purposes only and does not reflect any current or past or expected views
The choice of abstract scores to express full conviction is arbitrary and, in practice, can be more granular.

Sources: Bloomberg monthly returns from February 2003 to October 2020& QRG Calculations

Following the methodology proposed by Bass et al. [2017], we use principal component analysis (PCA) to select a set of statistical factors from the correlation matrix constructed using monthly returns in local currency of the 17 global major assets. The list of these 17 assets as well as their Bloomberg tickers is given in Exhibit 16 in the Appendix. We identified six statistical (but interpretable) factors that correspond to the first six eigenvectors of the correlation matrix and explain 88.6% of the variance; this is consistent with the finding of Bass et al. [2017]. The eigenvectors are long-short portfolios of 17 global assets; the six factors are named following our macroeconomic interpretation of these long-short portfolios[4], which are shown in Exhibit 17 in the Appendix: **Market Risk**, **Duration**, **EM/Commodities**, **Corporate Spreads**, **US** and **Asia/Japan**. In Exhibit 2, we describe our interpretation of these statistical factors in macroeconomic terms.

Exhibit 2: Interpretation of Statistical Factors in Macroeconomic Terms

Market Risk	"Risk-on factor", reflecting a portfolio invested in risky assets such as equities and corporate credit, excluding government bonds.
Duration	Factor exposed to interest rate sensitive assets, including government bonds, corporate credit and emerging debt
EM/Commodities	Factor exposed to emerging assets and commodities
Corporate Spreads	Factor mainly exposed to corporate credit vs. government bonds duration.
US	Factor mainly exposed to US related assets
Asia/Japan	Factor tilted towards Asian and Japanese assets

It is important to note that de-noising the covariance matrix by retaining only its first six eigenvectors also contributes to reducing the undesirable sensitivity of portfolio optimization to minor changes in views (Roncalli [2014]).

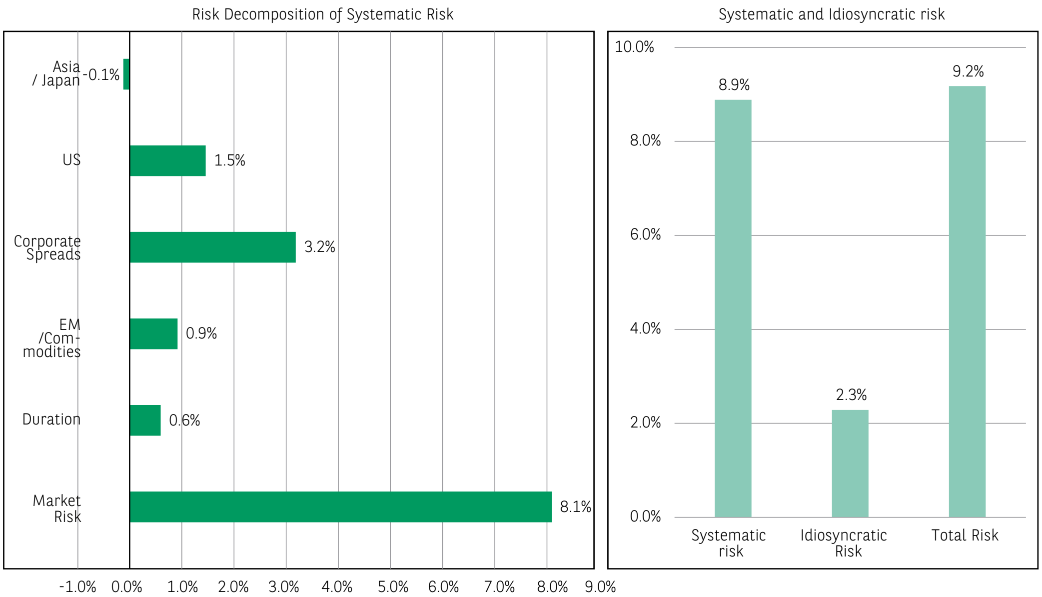
By expanding the variance of the asset i in terms of exposures to the orthogonal eigenvectors, its volatility can be formulated as: $\sigma_i = \sqrt{\sum_{j=1}^{6} \beta_{i,j}^2 \lambda_j + \varepsilon_i^2}$, , where $\beta_{i,j}$ is the factor exposure of asset *i* on factor j, λ_j the eigenvalue of the factor j and ε_i the idiosyncratic risk of the asset *i*. We denote $\beta_{i,j}\sqrt{\lambda_j}$ [5] as the risk decomposition of systematic risk in factor *j*. Taking the squared root of the sum of squared risk decomposition from six statistical factors gives the systematic risk exposure of asset *i*, $\sqrt{\sum_{j=1}^{6} \beta_{i,j}^2 \lambda_j}$. The risk decomposition also sheds light on the implicit directional bets on factors when expressing views on an asset.

For illustration, the left panels in Exhibits 3 and 4 show the risk decomposition of Bond USD High Yield and Equity Europe EMU, two of the assets on which the IC expresses views in Exhibit 1. Exhibit 3 shows that the **Market Risk** and **Corporate Spreads** factors are the two main risk drivers for Bond USD High Yield. This is not surprising because high yield represents the riskiest of fixed income assets and they tend to be highly correlated with equities. The right panel of Exhibit 3 breaks down the total risk of Bond USD High Yield into systematic risk, $\sqrt{\sum_{j=1}^{6} \beta_{i,j}^2 \lambda_j}$, and the idiosyncratic risk, ε_i. We can calculate its volatility of 9.2% using $\sigma_i = \sqrt{\sum_{j=1}^{6} \beta_{i,j}^2 \lambda_j + \varepsilon_i^2}$. Exhibit 4 shows the risk decomposition of Equity Europe EMU; it is clear that the latter has a large positive exposure in **Market Risk** while it is exposed negatively to **Duration**, **Corporate spreads** and **EM/Commodities**. These exposures are consistent with economic intuition about the relationship between equity and fixed-income assets. From the right panel of Exhibit 4, the volatility of Equity Europe EMU, 16.4%, can again be calculated by combining its systematic risk with the idiosyncratic risk components.

4 Note that we have computed the statistical factors (eigenvectors) from the correlation matrix. Each eigenvector can be interpreted as a long-short portfolio built in risk budget. The latter is defined as the product of weight and volatility.

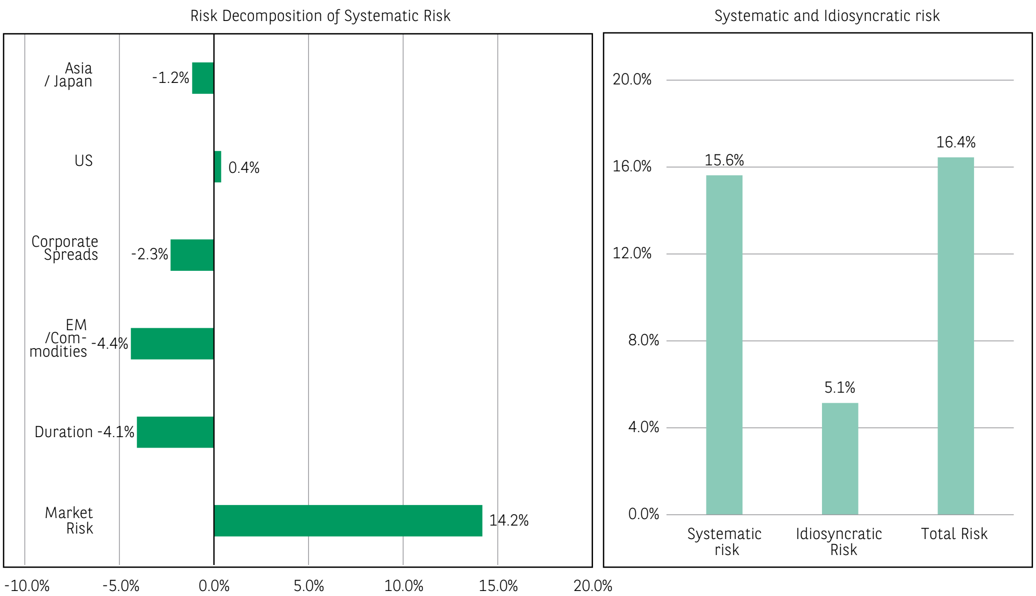
5 We denote $\beta_{i,j}\sqrt{\lambda_j}$ as the risk decomposition of systematic risk in factor j. The risk (total risk, systematic risk or idiosyncratic risk) here is measured in units of annualized volatility. This definition of risk is valid for the rest of the article.

Exhibit 3: Risk Decomposition of Bond USD High Yield



Sources: Bloomberg monthly returns from February 2003 to October 2020 & QRG Calculations

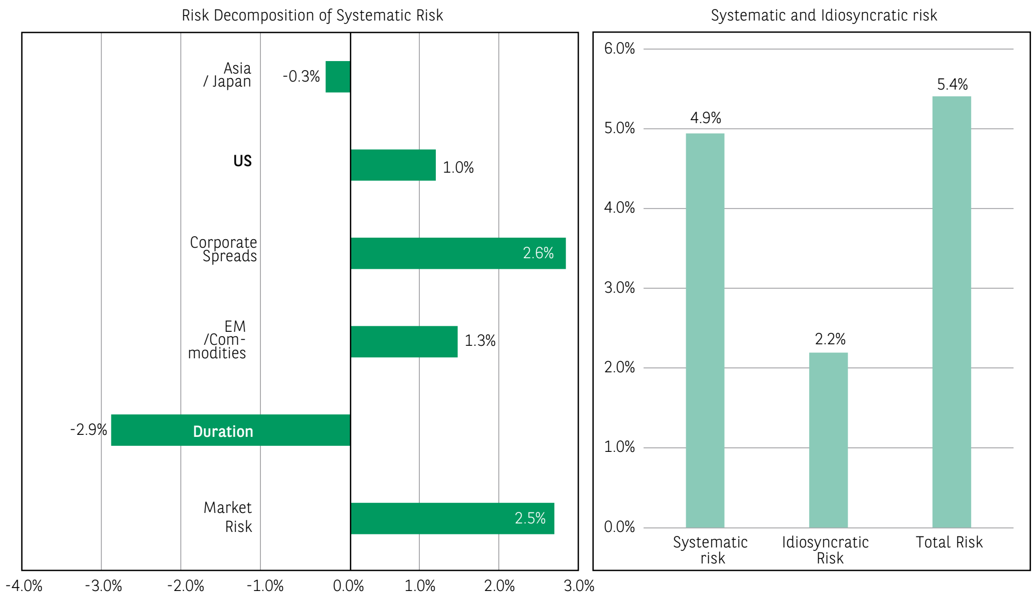
Exhibit 4: Risk Decomposition of Equity Europe EMU



Sources: Bloomberg monthly returns from February 2003 to October 2020 & QRG Calculations

Given a set of views, one can easily derive the projection of the unique unconstrained active portfolio reflecting these views on this set of factors. The factor-based risk analysis sheds light on valuable and practical guidelines for IC when formulating views. For instance, IC members can judge whether the views, combined together, are consistent with the underlying economic and financial rationales. Moreover, the distinction between systematic risk and idiosyncratic risk also provides the IC with information regarding the extent to which the views can be implemented in a holistic way.

Exhibit 5: Risk Decomposition of the Unique Unconstrained Active Portfolio in Exhibit 1



Sources: Bloomberg monthly returns from February 2003 to October 2020 & QRG Calculations

The left panel of Exhibit 5 shows the statistical factor exposures of the unique unconstrained active portfolio derived from IC views in Exhibit 1. The set of IC views has strong positive exposure to the **Market risk** and **Corporate Spreads** factors while expressing a negative outlook on **Duration**. From Exhibit 3, one can observe that both **Market Risk** and **Corporate Spreads** are the main risk drivers of Bond USD High Yield. A positive view with rather strong conviction on the latter induces optimism regarding these two factors. The large negative exposure on **Duration** can be attributed to the negative view on Bond EUR Sovereign with full conviction as well as the negative view on Bond EMD HC Sov Global. We also observe from Exhibit 5 that the total risk of this portfolio is 5.4%, which is higher than the 5% set initially. This is because the portfolio is unconstrained and there is strong conviction in some of these IC views. The systematic risk of the portfolio is 4.9%, with an idiosyncratic risk of 2.2%. It is worth noting that almost half of the idiosyncratic risk comes from the combination of a negative view on Equity Europe EMU and a positive view on Equity Europe EMU SC, as shown in Exhibit 18 in the Appendix. These views, by construction, neutralize exposure to the **Market Risk** factor and keep an idiosyncratic risk component. We will show how the framework reacts to the constraints like Max TE, long-only or constraints on the authorized investment universe in the second example.

Implied Active Returns and Robust Portfolio Optimization

Having built the unique unconstrained active portfolio representing views, we now focus on the calculation of its implied active returns. In the absence of any constraints, the final active portfolio obtained from portfolio optimization from the implied active return used as input must be the same as the unique unconstrained active portfolio. To satisfy this requirement, the calculation of the implied active returns from the unique unconstrained active portfolio must be based on reversing the portfolio optimization problem using the same portfolio optimization approach that will be used afterwards to add customization, e.g. constraints.

Recall that the MVO finds the best tradeoff between maximizing return and reducing variance when seeking the most efficient portfolio, which satisfies:

$$\boldsymbol{w}_{mvo} = argmax\left(\overline{\boldsymbol{\mu}}^t \boldsymbol{w} - \frac{\lambda}{2}\boldsymbol{w}^t \boldsymbol{\Sigma} \boldsymbol{w}\right) \tag{4}$$

with $\boldsymbol{w}$ the vector of weights, $\overline{\boldsymbol{\mu}}$ the estimated expected returns of the portfolio, $\boldsymbol{\Sigma}$ the variance-covariance matrix of returns (in this case constructed with the factor-based risk model) and λ the investor risk aversion parameter.

RPO modifies the utility function of MVO to account for uncertainty in expected returns. Fabozzi *et al*. [2007 a, b] identified three important choices in RPO: the form of the uncertainty set, the uncertainty matrix $\boldsymbol{\Omega}$ and the aversion to uncertainty $\boldsymbol{\kappa}$. Following the argument of Fabozzi *et al*. [2007 a] and the arguments and methodology proposed by Yin et al. [2020], the RPO problem can be best formulated using a quadratic uncertainty set as follows:

$$\mathbf{w}_{rob} = argmax\left(\overline{\boldsymbol{\mu}}^t \mathbf{w} - \kappa\sqrt{\mathbf{w}^t \boldsymbol{\Omega} \mathbf{w}} - \frac{\lambda}{2}\mathbf{w}^t \boldsymbol{\Sigma} \mathbf{w}\right) \tag{5}$$

where $\boldsymbol{\Omega}$ is proportional to the diagonal matrix with variances on the diagonal, and $\boldsymbol{\kappa}$ is set to be half the average of Sharpe ratios of assets in the investment universe. As shown by Yin *et al*. [2020], the RPO, calibrated with such way, leads to more diversified and balanced portfolios. In this framework, we use RPO to optimize in terms of active risk (tracking error) and active returns.

Once the choices behind the robust portfolio optimization are set, the implied active returns $\overline{\boldsymbol{\mu}}_I$ can be calculated by reversing the robust optimization problem starting from the unique unconstrained active portfolio reflecting the IC views. By definition, the vector of implied active returns is the set of expected returns that renders the unconstrained active portfolio efficient:

$$\overline{\boldsymbol{\mu}}_I = \frac{\kappa \boldsymbol{\Omega} \boldsymbol{w}_{active}}{\sqrt{\boldsymbol{w}_{active}{}^T \boldsymbol{\Omega} \boldsymbol{w}_{active}}} + \lambda \boldsymbol{\Sigma} \boldsymbol{w}_{active} \tag{6}$$

where $\boldsymbol{w}_{active}$ is the unique unconstrained active portfolio derived from Equation (2). The implied active returns translate at individual asset level the information contained in the views. Note that the reverse robust optimization implies a holistic way for the views' transmission. A view on an asset will bring about expected returns revisions in other assets that are in line with the correlations of returns.

Customization of investor portfolios with specific constraints at portfolio level can be addressed using a constrained robust optimization in terms of active weights, using the implied active returns as inputs and optimizing in terms of tracking error risk. With $\boldsymbol{\kappa}$ linear constraints $p_i, 1 \leq i \leq k$, the RPO in Equation (5) can be rewritten as:

$$\boldsymbol{\gamma}_{rob} = argmax\left(\overline{\boldsymbol{\mu}}_I{}^T \boldsymbol{\gamma} - \kappa\sqrt{\boldsymbol{\gamma}^T \boldsymbol{\Omega} \boldsymbol{\gamma}} - \frac{\lambda}{2}\boldsymbol{\gamma}^t \boldsymbol{\Sigma} \boldsymbol{\gamma}\right) \text{ u.c. } p_i^T(\boldsymbol{w}_{benchmark} + \boldsymbol{\gamma}) \geq q_{\boldsymbol{i}} \tag{7}$$

where $\boldsymbol{\gamma}$ is the vector of active weights and is equal to $\boldsymbol{w} - \boldsymbol{w}_{benchmark}$. We deliberately adopted a different notation from that used for the unique unconstrained active portfolio $\boldsymbol{w}_{active}$ and the robust optimal constrained active weights $\boldsymbol{\gamma}_{rob}$. The RPO can handle not only linear constraints but also quadratic constraints, for example a Max TE constraint.

EXAMPLES

We now illustrate the application of this robust framework with two concrete multi-asset tactical asset allocation problems. The first seeks to show that by integrating uncertainty into the utility function, the RPO adds robustness to the framework and tends to produce constrained portfolios that are more in line with IC views. The second presents the framework from views to final customized portfolios, with a particular focus on the analysis of risk exposures of the unique unconstrained portfolio reflecting views compared with those of the final constrained portfolio. The objective is to show the transparency and holistic features of the proposed framework.

Gains in robustness and consistency from using RPO instead of MVO

In this framework, choosing between MVO and RPO is irrelevant when the portfolio has no constraints, because both will generate the same starting unique unconstrained active portfolio in such a case. The choice of optimization approach becomes vital when constraints are introduced in the final step. To illustrate how the RPO produces more diversified and intuitive portfolios than MVO in the presence of constraints, we constructed a simple example with four assets in a EUR-based portfolio, with all assets hedged against EUR.

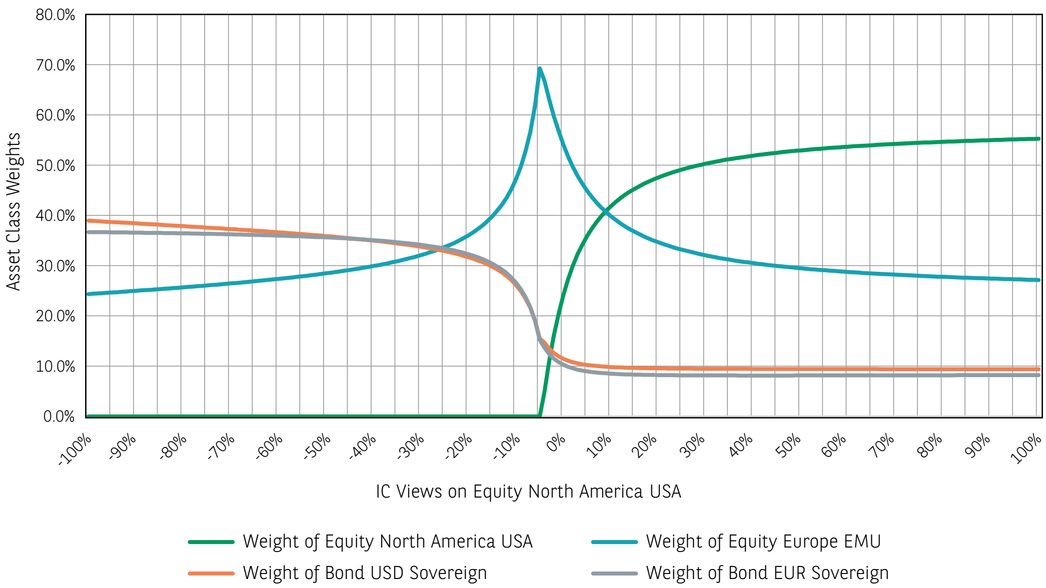
Exhibit 6: 50/50 Benchmark, Volatilities and Correlations

			Correlation			
	Benchmark Weights	Volatility	Equity North America USA	Equity Europe EMU	Bond USD Sovereign	Bond EUR Sovereign
Equity North America USA	25.0%	14.3%	100.0%			
Equity Europe EMU	25.0%	16.4%	82.1%	100.0%		
Bond USD Sovereign	25.0%	4.3%	-28.5%	-34.4%	100.0%	
Bond EUR Sovereign	25.0%	4.0%	-6.0%	-1.7%	58.9%	100.0%

Sources: Bloomberg monthly returns from February 2003 to October 2020 & QRG Calculations

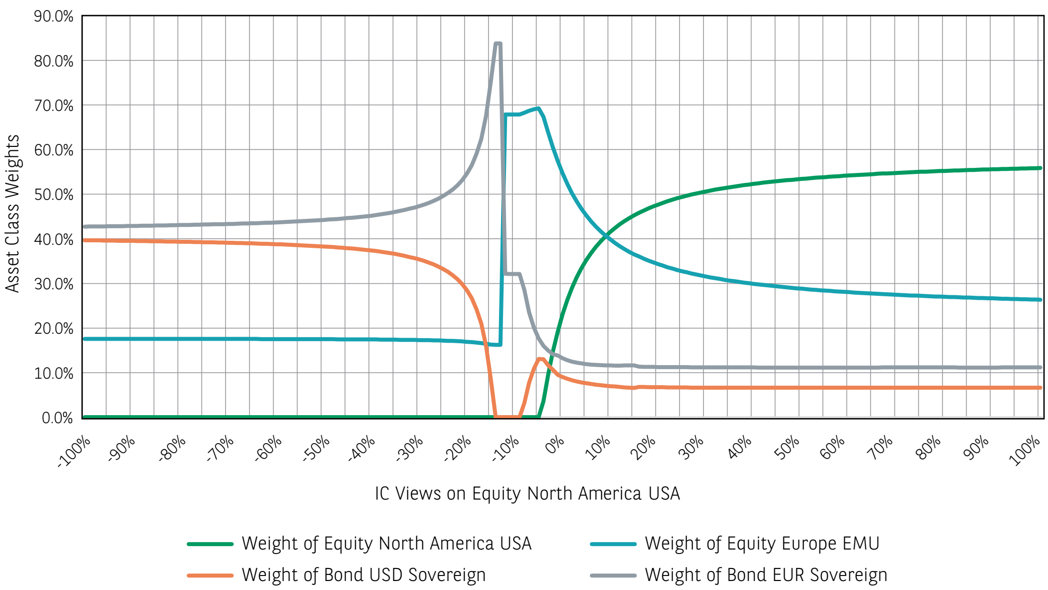
Exhibit 6 shows the volatilities and the correlations of the assets in a traditional 50/50 benchmark allocating equally to equities and bonds. Assume that the Max TE of this portfolio is 5% and that the IC has a positive view on "Equity Europe EMU" with a low conviction that allocates 10% of the tracking error to this view. We introduce no-short sale and full investment constraints. These two standard constraints are common in investors' portfolios. All else being equal, we vary the view on "Equity North America USA" from -100% to 100% by steps of 1% each time. For each view, we compute the MVO and the RPO portfolios using the proposed framework. We set the aversion to risk parameter λ to one.

Exhibit 7: RPO Constrained Portfolio with +10% Views on Equity Europe EMU and Varying Views on Equity North America USA



Sources: Bloomberg monthly returns from February 2003 to October 2020 & QRG Calculations

Exhibit 8: MVO Constrained Portfolio with +10% Views on Equity Europe EMU and Varying Views on Equity North America USA



Sources: Bloomberg monthly returns from February 2003 to October 2020 & QRG Calculations

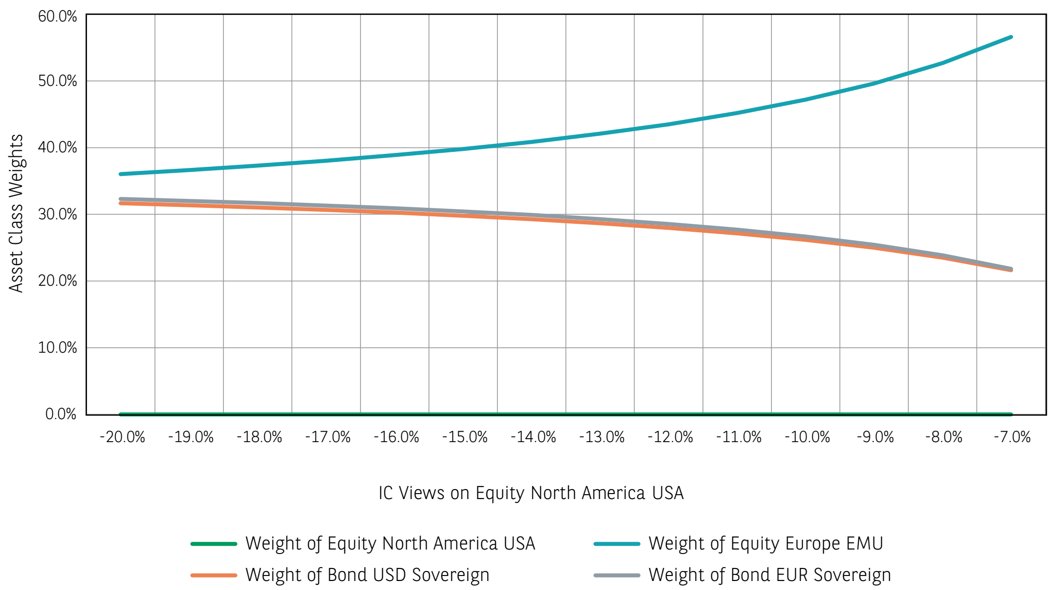
From Exhibits 7 and 8, one can see that the RPO portfolios evolve gradually according to the changes in conviction on the views, while for MVO, the sensitivity of portfolios on the same changes in views is much higher and some abrupt changes in weights can occur. Moreover, in the MVO portfolios, the two fixed-income assets can experience significant changes in weights despite the fact that no views were explicitly formulated on them. When the views on "Equity North America USA" are strong enough, the portfolios produced by MVO and the RPO converge.

However, when the views "Equity North America USA" are in the range between -20% and -7%, the MVO and the RPO behave rather differently.

In Exhibit 10, we zoom in on the MVO portfolios in this range of views. The jumps in weights are striking, with the weight of Equity Europe EMU surging from 16.2% to 67.9% when the view on Equity North America USA only increases from -13% to -12% and the view on itself remains unchanged. The other two fixed-income assets also witness high turnover. The weight of "Bond EUR Sovereign" increases from 54.6% to 83.8% before engaging in a sharp fall from 83.8% to 32.1%, while the weight of "Bond USD Sovereign" also experiences a large swing. It first falls from 26.7% to 0% and then increases to 7.8%. These big jumps in weights with small changes in views are not intuitive since there are no IC views on them. On the contrary, Exhibit 9 shows that when the conviction in the view on Equity North America USA increases, the weight of Equity Europe EMU increases gradually RPO portfolios. The behavior of the weight allocated to the two sovereign bonds is more intuitive. Under RPO, the weight of the Bond USD Sovereign stays close to that allocated to the Bond EUR Sovereign, which makes sense because of their high positive correlation. They both decrease smoothly without any unexpected large jumps as the conviction on the view on Equity North America USA increases.

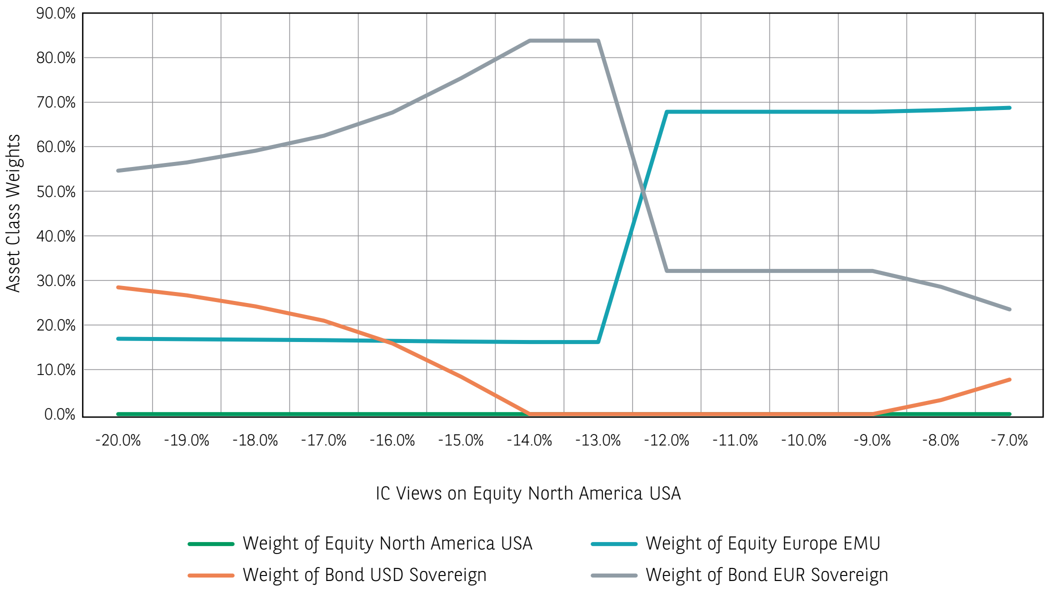
This range of views is interesting because in this case the IC is expressing two views with similar convictions but opposite signs on two assets that are highly correlated. The high correlation tends to create small eigenvalues in the covariance matrix. The solution to MVO requires the inversion of this matrix and thus, this solution is dominated by those small eigenvalues leading to the significant weights arbitraging among highly correlated assets. However, RPO includes two additional parameters in the utility function, namely the uncertainty matrix and the uncertainty parameter. As shown by Yin *and al*. [2020], when the uncertainty matrix equals the diagonal matrix of sample variances, it effectively shrinks the small eigenvalues towards zero, while the uncertainty parameters reduce the expected returns associated with the eigenvectors associated with those small eigenvalues. It is through these two mechanisms that the RPO overcomes the drawbacks of MVO and introduces an extra layer of robustness.

Exhibit 9: RPO Constrained Portfolio -- Zooming in on the Range between -20% and -7% of View on Equity North America USA



Sources: Bloomberg monthly returns from February 2003 to October 2020 & QRG Calculations

Exhibit 10: MVO Constrained Portfolio -- Zooming in on the Range between -20% and -7% of View on Equity North America USA



Sources: Bloomberg monthly returns from February 2003 to October 2020 & QRG Calculations

This first example shows how the use of RPO adds an extra layer of robustness to the framework by avoiding strong arbitrage positions among correlated assets, in particular when there is high uncertainty in the IC views. The RPO is key for industrializing the implementation of TAA views in the optimization of a large range of funds, as it leads to more intuitive and robust portfolios even with the presence of high uncertainty. In the next application, we will show how the framework handles constraints with a holistic approach.

Implementation with Constraints and Risk Analysis

In this example, we show how the proposed framework handles constraints and how it manages to replicate investments positions with others that bring in similar factor exposures. Finally, we show how a risk analysis can introduce the require levels of transparency to interpret the portfolio choices. In Exhibit 1 and Exhibit 5, we presented unconstrained active portfolios as well as their systematic risk factor decomposition. In this application, we implement the views in Exhibit 1 while widening the investment universe. The Max TE is again 5%. We analyze three portfolios:

- Without constraints,
- With Max TE and a constraint not allowing investments in Bond USD High Yield
- With Max TE, long-only and a constraint not allowing investments in Bond USD High Yield, long-only.

Cash is not available as an asset class in the last two cases. All these portfolios have the same benchmark as in Exhibit 6.

Exhibit 11: Implementing Views from Exhibit 1 in Constrained Portfolios

	Fund Parameters and IC Views			Unconstrained		Max TE + No Bond USD High Yield		Max TE + Long Only + No Bond USD High Yield	
	Volatility	IC Views	Benchmark	Portfolio	Active Portfolio	Portfolio	Active Portfolio	Portfolio	Active Portfolio
Bond EUR Sovereign	4.0%	-100.0%	25.0%	-99.8%	-124.8%	-100.0%	-125.0%	-	-25.0%
Bond EUR Investment Grade	4.0%	50.0%	-	63.2%	63.2%	99.4%	99.4%	37.2%	37.2%
Bond USD Sovereign	4.3%	-	25.0%	25.0%	-	48.8%	23.8%	3.4%	-21.6%
Bond USD Investment Grade	5.9%	-	-	-	-	4.5%	4.5%	0.9%	0.9%
Bond USD High Yield	9.2%	50.0%	-	27.2%	27.2%	-	-	-	-
Bond EMD HC Sov Global	8.7%	-25.0%	-	-14.4%	-14.4%	-11.5%	-11.5%	-	-
Equity Europe EMU	16.4%	-50.0%	25.0%	9.8%	-15.2%	12.3%	-12.7%	19.3%	-5.7%
Equity Europe EMU SC	18.2%	50.0%	-	13.8%	13.8%	16.3%	16.3%	8.7%	8.7%
Equity North America USA	14.3%	-	25.0%	25.0%	-	28.0%	3.0%	28.0%	3.0%
Equity North America USA SC	19.2%	-	-	-	-	2.2%	2.2%	2.5%	2.5%
Risk (volatility for portfolios or TE for active portfolios)				**10.0%**	**5.4%**	**10.1%**	**4.4%**	**9.5%**	**2.9%**

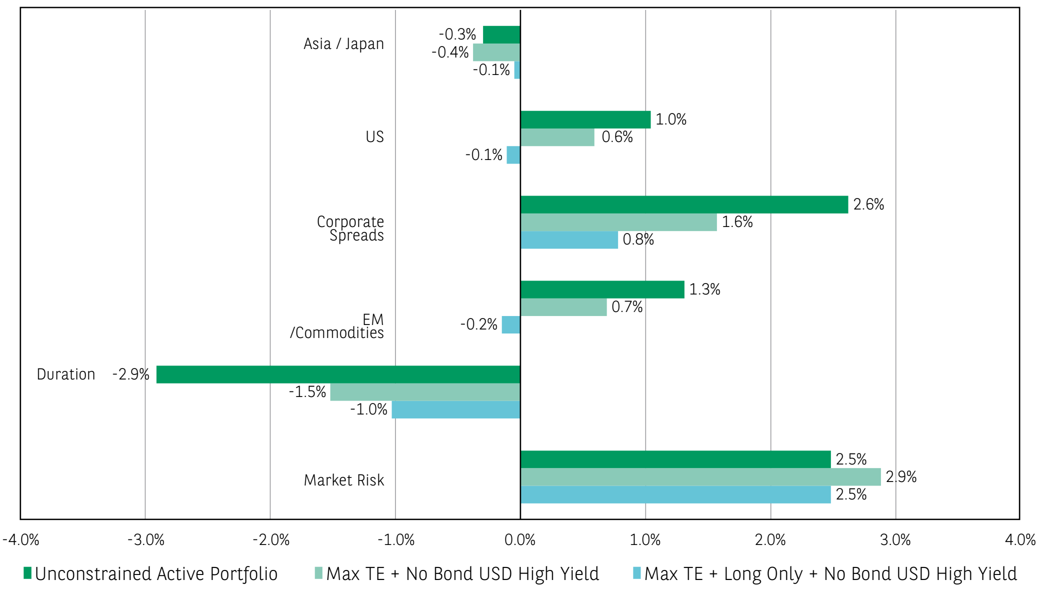
Note: 'Investment Grade' and 'High Yield' refer to corporate bonds and their common definitions using agency ratings and standard indices
Sources: Bloomberg monthly returns from February 2003 to October 2020 & QRG Calculations

Exhibit 11 shows the final portfolio as well as the active portfolios for the unconstrained and the two constrained cases. For each portfolio, we also show the systematic risk decomposition in Exhibit 12, the total systematic risk factor exposures and the specific risk exposure in Exhibit 13, and the decomposition of idiosyncratic risks in Exhibit 14.

From Exhibit 11, the overall opportunity cost of implementation can be easily measured by the fall in the risk (tracking error) of the active portfolios as more constraints are added. In this example, the tracking error is reduced first from 5.4% to 4.4% with the first set of constraints and then from 4.4% to 2.9% by adding more constraints. This cost has two potential sources: 1) the mismatch between the investor's authorized investment universe and the universe for which the IC expresses views; and 2) the investor's specific constraints. It is interesting to highlight the *replication* of Bond USD High Yield in the constrained optimal portfolio. Given that Bond USD High Yield is not in the investment universe of the first constrained portfolio, the long position in Bond USD High Yield is replaced with long positions in US Investment Grade bonds and US equities. Even in the presence of the long only constraint in the second constrained portfolio, the framework manages to recover partially the view expressed on Bond USD High Yield by investing in the three US assets, which is driven by the correlation structure. As our statistical factor-based risk model is constructed from the correlation matrix, a view on Bond USD High yield leads to changes in implied active returns of assets in the investment universe that share the closest factor exposures. When there is a positive view on Bond USD High Yield, which has **Market Risk** as its main risk factor exposure, other assets significantly exposed to the **Market Risk factor** will see their implied active returns revised upwards. Through this mechanism, the framework enables a *replication* in a holistic manner and solves partially for the mismatch in views and investment universes. In reality, a perfect replication of an asset is not possible, as demonstrated by the lower tracking error of the "Max TE + No Bond USD High Yield" portfolio, 4.4% versus the 5.0% Max TE. It means that the constraint of Max TE is not binding and the *replication* of the Bond USD High Yield views is not one by one.

The distortion caused by constraints can be directly visualized with Exhibit 12. It shows that the IC views are essentially expressing a strong negative perspective on the Duration factor and positive outlooks for the **Market Risk** and **Corporate Spreads factors**. For the second portfolio, "Max TE + No Bond USD High Yield", as Bond USD High Yield is not in the investment universe of the constrained portfolio, the framework manages to implement partially the positive outlook on **Corporate Spreads** with a long position in Bond USD Investment Grade. The framework also recovers almost entirely the exposure on **Market Risk** embedded in the positive view on Bond USD High Yield with a long position in US Equities. The long-only constraint added to the third portfolio is quite binding. The negative exposure on the **Duration factor** is reduced considerably because the portfolio can no longer have short positions in Bond EUR Sovereign. However, the framework still finds its way to expressing the factor outlooks underlying the IC views, especially with regard to the **Market Risk** factor, which maintains a large positive exposure. It is important to note that although we impose a global tracking error constraint, there is no risk management in terms of factor exposures. This explains why sometimes a constrained portfolio would see itself more exposed to a factor than the unconstrained one. In this case, the "Max TE + No Bond USD High Yield" portfolio has higher exposure towards **Market Risk** than the unconstrained active portfolio due to active weights on US equities.

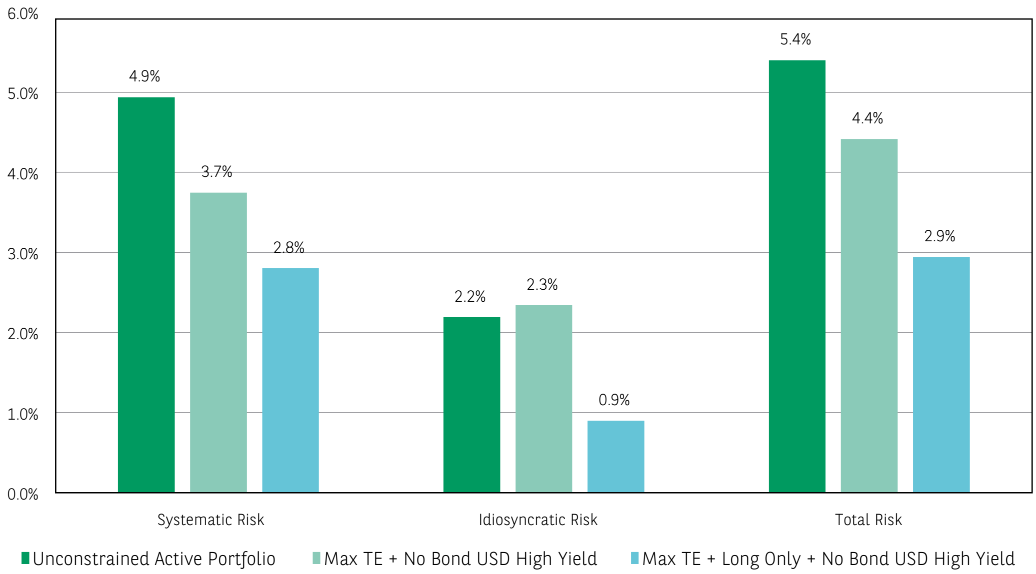
Exhibit 12: Systematic Risk Decomposition of Unconstrained and Constrained Active Portfolios



Sources: Bloomberg monthly returns from February 2003 to October 2020 & QRG Calculations

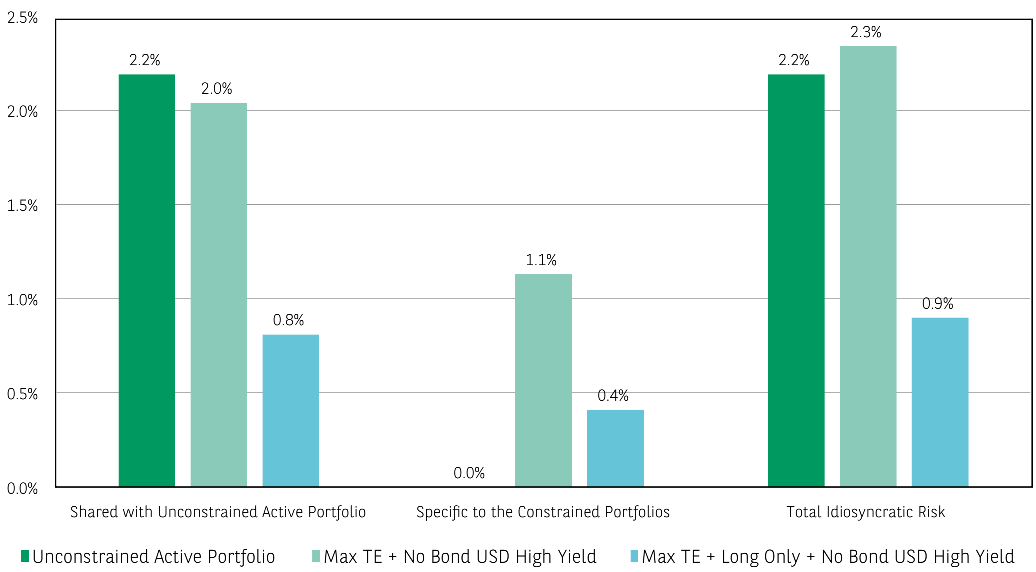
Exhibit 13 shows the breakdown of portfolio active risk in terms of systematic risk and idiosyncratic risk, highlighting the impact of constraints on the implementation of IC views in investors' portfolios. Although the overall active risk of the constrained portfolios is significantly lower than that of the unconstrained active portfolio, this is not the case for idiosyncratic risk, where the "Max TE + No Bond USD High Yield" portfolio generates slightly higher idiosyncratic risk (2.3% against 2.2%). Thus, it is important for investors to understand the sources of idiosyncratic risks in their portfolios. Exhibit 14 provides this useful information by breaking down the idiosyncratic risk into two parts: one inherited from the unconstrained active portfolio and the other specific to the constrained portfolios. All idiosyncratic risk in the unique unconstrained active portfolio comes from the IC views and the risk budgeting approach used to construct it. However, for the two other constrained portfolios this is not always the case. The presence of binding constraints, e.g. not allowing for investments in Bond USD High Yield, introduces idiosyncratic risks that are specific to the constrained portfolios, arising from the need to use different assets to replicate the original systematic factor exposures that were found in the unique unconstrained active portfolio. However, it is important to note that most of idiosyncratic risks of constrained portfolios (about 70%) still have their origins in the unique unconstrained active portfolio.

Exhibit 13: Total Risk Decomposition of Unconstrained and Constrained Active Portfolios into Systematic Risk and Idiosyncratic Risk



Sources: Bloomberg monthly returns from February 2003 to October 2020 & QRG Calculations

Exhibit 14: Idiosyncratic Risk Decomposition of the Unconstrained and Constrained Active Portfolios



Sources: Bloomberg monthly returns from February 2003 to October 2020 & QRG Calculations

This example highlights the transparency introduced by the factor risk analysis of the proposed framework. At each stage of the implementation of views, one can assess the efficiency of the implementation and the loss of information caused by constraints. The IC is able to measure the exposures of its views to systematic risk factors, while the investors also have a clear view of the risk exposures in their customized portfolios along with the alignment of those risk exposures with those in the initial views. This facilitates the evaluation regarding whether portfolios have factor exposures consistent with the views of IC as well as the source of the idiosyncratic risks of their portfolios.

CONCLUSION

Multi-asset teams at asset management companies are being increasingly challenged in terms of their operational efficiency. They manage not only many active benchmark funds but also hundreds, or even thousands, of institutional mandates. At the same time, the arrival of Robo Advisory brings the additional demand of making sure that IC views are properly implemented at an industrial scale and with no delay even in the most customized portfolios. That is part of the asset manager's fiduciary duty towards all of its investors.

The objective of this article is to propose a robust framework that tackles this challenge. Designed for practitioners, the framework allows multi-asset teams to provide tailor-made solutions for each investor without sacrificing operational efficiency by constructing a unique unconstrained active portfolio as the optimal representation of IC views. The skill of the IC can be gauged by monitoring the performance of this portfolio. A clear and direct measurement of IC views' performance also contributes to a more granular and precise performance attribution at the multi-asset team level.

The steps of the proposed framework are designed to efficiently implement the views into customized investor portfolios in a robust manner while complying with risk aversion constraints. The improvement in terms of operational efficiency and automation brought about by this framework significantly reduces the delay between decisions and their implementation across a large scale of portfolios ('time to market') and allows portfolio managers to focus on the core tasks of performance generation for investors. This framework can be also deployed for robo-advisors that aim at adding value with TAA or adapted for types of active investing.

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DISCLOSURE STATEMENT

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APPENDIX

Exhibit 15: Views Formats of Major Asset Managers

Asset Managers	Directions of Views	Conviction of Views	Source
Amundi	+ / 0 / -	Abstract Scores: ---, --, -, 0, +, ++, +++	https://research-center.amundi.com/page/Article/Amundi-Views/2020/11/Global-Investment-Views-November-2020?search=true
Aviva Investors	Underweight / Neutral / Overweight	Numerical Scores: -2, -1, 0, +1, +2	https://www.avivainvestors.com/en-sg/views/house-view/global-outlook/
Blackrock	Underweight / Neutral / Overweight	Numerical Scores: -2, -1, 0, +1, +2	https://www.blackrock.com/us/individual/insights/blackrock-investment-institute/outlook/asset-class-views#directional-views
Fidelity International	Red / Blue / Green	Shades of the Color	https://professionals.fidelity.co.uk/articles/expert-opinions/2019-02-05-asset-allocation-view-1549368120561
JP Morgan Asset Management	Underweight / Neutral / Overweight	Words: High, Low, Moderate	https://am.jpmorgan.com/us/en/asset-management/gim/adv/insights/portfolio-insights/global-asset-allocation-views
Legal & General Investment Management	Positive / Neutral / Negative	Shades of the Color	https://www.lgim.com/landg-assets/lgim/_document-library/knowledge/thought-leadership-content/asset-allocation/asset-allocation-aug-16-eng.pdf
Neuberger Berman	Underweight / Neutral / Overweight	Abstract Scores: positions on an axis from underweight to overweight	https://www.nb.com/en/global/aac/aac-outlook-2q2019
Nuveen	Positive / Neutral / Negative	Shades of the Color	https://www.nuveen.com/en-us/thinking/asset-allocation-insights/asset-allocation-views
PIMCO	Underweighting / Neutral / Overweighting	Abstract Scores: a heat map of + and -	https://blog.pimco.com/en/2020/02/asset-allocation-views-prolonging-the-expansion
PICTET Asset Management	Underweight / Neutral / Overweight	Abstract Scores: ---, --, -, 0, +, ++, +++	https://www.am.pictet/en/us/global-articles/2020/monthly-market-views/asset-allocation/april#PAM_Section_1
Shroders	Positive / Neutral / Negative	Shades of the Color combined with words like « Maximum positive » or « Maximium negative »	https://www.schroders.com/getfunddocument/?oid=1.9.2436437

Note: the list of asset managers is not exhaustive and their orders are alphabetical

Exhibit 16: Asset Classes and Corresponding Bloomberg Tickers

Asset Class Name	Bloomberg Ticker
Equity Europe EMU	NDDLEURO Index
Equity Europe EMU Small Cap	NCLDEMU Index
Equity Europe UK	NDDLUK Index
Equity North America USA	NDDUUS Index
Equity North America USA Small Cap	RU20INTR Index
Equity Pacific Japan	NDDLJN Index
Equity Emerging Global	NDUEEGF Index
Bond EUR Sovereign	LEATTREU Index
Bond EUR Investment Grade	LECPTREU Index
Bond EUR High Yield	LF88TREU Index
Bond USD Sovereign	LUATTRUU Index
Bond USD Investment Grade	LUACTRUU Index
Bond USD High Yield	LF89TRUU Index
Bond EMD HC Sov Global	JPGCCOMP Index
Bond EMD LC Sov Global	JGENVUUG Index
Diversification Real Estate Pan Europe	TRNHUE Index
Diversification Commodity Global	BCOMXAL Index

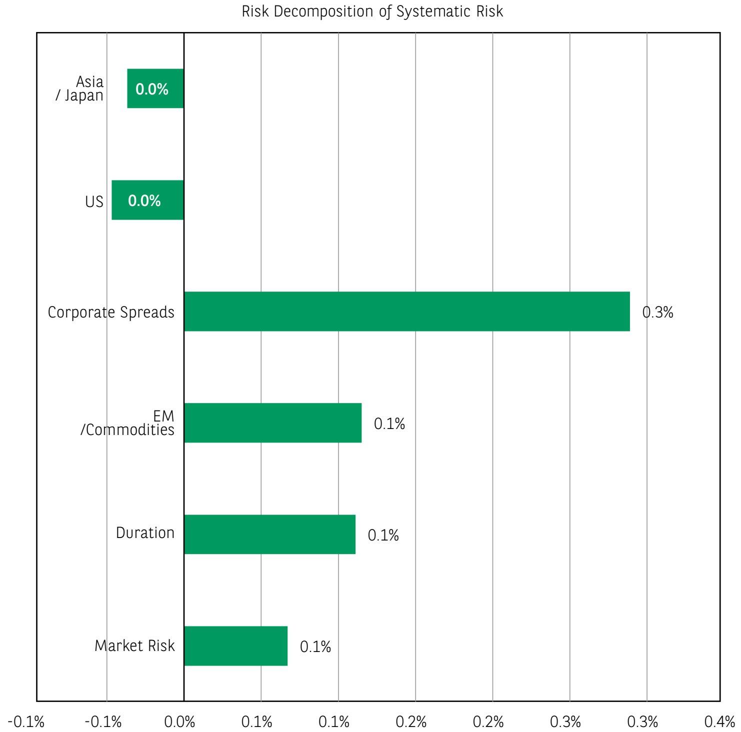
Sources: Bloomberg

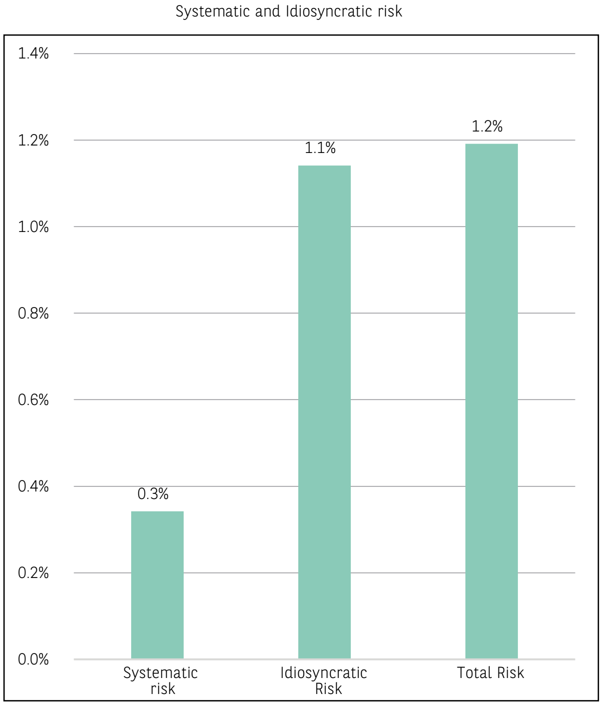
Exhibit 17: Six Statistical Factors

	Market Risk	Duration	EM /Commodities	Corporate Spreads	US	Asia/ Japan
Equity Europe EMU	28.2%	-14.7%	-25.6%	-16.5%	3.1%	-10.3%
Equity Europe EMU SC	29.1%	-12.0%	-21.2%	-2.9%	0.6%	-12.5%
Equity Europe UK	27.5%	-9.3%	-10.1%	-23.2%	-4.1%	-22.1%
Equity North America USA	28.8%	-12.8%	-2.4%	-19.6%	8.1%	-9.4%
Equity North America USA SC	27.0%	-16.7%	-3.3%	-16.8%	12.4%	-15.4%
Equity Pacific Japan	21.8%	-20.9%	-17.4%	-18.2%	-14.9%	79.7%
Equity Emerging Global	28.2%	-5.5%	27.8%	-17.6%	6.6%	14.0%
Bond EUR Sovereign	3.0%	47.8%	-32.5%	-22.9%	-38.4%	10.0%
Bond EUR Investment Grade	21.8%	33.5%	-19.0%	25.6%	-30.6%	9.4%
Bond EUR High Yield	28.3%	2.4%	-2.4%	51.2%	1.9%	8.8%
Bond USD Sovereign	-6.6%	49.6%	7.8%	-39.3%	18.1%	-10.8%
Bond USD Investment Grade	19.5%	42.5%	6.0%	14.3%	12.5%	2.8%
Bond USD High Yield	28.8%	3.8%	9.6%	40.9%	21.1%	-2.0%
Bond EMD HC Sov Global	26.0%	26.4%	19.4%	4.3%	19.2%	5.8%
Bond EMD LC Sov Global	24.4%	13.1%	38.4%	-25.1%	22.8%	15.9%
Diversification Real Estate Pan Europe	25.4%	1.6%	-32.6%	-0.9%	-7.3%	-36.1%
Diversification Commodity Global	17.9%	-8.4%	56.3%	-1.7%	-72.1%	-19.9%

Sources: Bloomberg monthly returns from February 2003 to October 2020 & QRG Calculations

Exhibit 18: Risk Decomposition of the Unconstrained Active Portfolio Derived from Long EU Equity and Short EU Equity SC





Sources: Bloomberg monthly returns from February 2003 to October 2020 & QRG Calculations

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