Implementing Systematic Risk Premia, Factor-Based Strategies, and Sector Rotation with ETFs

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Abstract
This article presents a simple methodology for implementing systematic investment strategies using exchange-traded funds (ETFs) for long-only investors, suitable family offices and wealth managers, who manage portfolios relative to a benchmark. The approach integrates views on risk premia, style factors, and sector trends, allowing portfolio managers to tilt their portfolios toward selected premia, factors or style while controlling their risk relative to their benchmark. The methodology does not require expected return forecasts and can be applied using a variety of settings. To illustrate the approach, we provide three case studies: (i) portfolio manager Bob, who is tracking the S&P 500 Index while integrating beliefs about the technology sector; (ii) portfolio manager Alice, who is tracking the Bloomberg Barclays U.S. Aggregate Bond Index while incorporating beliefs about short-term Treasury and corporate bond ETFs; and (iii) portfolio manager Charlie, who is tracking the S&P 500 Index while incorporating positive belief about the technology sector, and negative belief on the value factor. The methodology described in this article is available as a service on the Aisot AI Insights Platform.

Keywords: Active management; Asset management; Exchange-traded fund (ETF); Factor-investing; Family offices; Long-only investing; Optimization; Portfolio allocation; Risk parity; Sector rotation; Systematic strategies; Tracking error; Wealth management

Introduction

Institutional investors have a long history of incorporating risk premia, factor and style tilts, and sector trends into their investment portfolios. By employing these systematic strategies, portfolio managers can boost returns, convey their market views, and adjust portfolios to match prevailing market conditions. This aligns with the broader shift toward factor-based and systematic investing, which has been widely adopted by institutional investors, including pension funds, endowments, and large asset managers. They adjust portfolios by "tilting" toward factors such as value, momentum, size, and volatility (Fama and French, 1992; Cochrane, 1999), as well as sectors (Froot and Teo, 2008; Alexiou and Tyagi, 2020), with the goal of outperforming the broader market. These systematic strategies have become a fundamental aspect of modern institutional investment management (Kolanovic and Wei, 2013; Maeso and Martellini, 2017; Reid and Van Der Zwan, 2019; DiMaggio et al., 2024).

While institutional investors typically have the resources and infrastructure to trade complex portfolios – including derivatives and custom strategies – family offices, wealth managers, and retail investors may face limitations. In particular, these investors may lack the capability to execute sophisticated strategies and must rely on simpler, more accessible approaches. One effective solution is the use of exchange-traded funds (ETFs), which offer a cost-effective and efficient way to implement risk premia, factor strategies, and sector rotation. ETFs enable these investors to express their views and construct diversified portfolios without the complexities of direct asset selection, shorting or derivatives, while effectively managing risk and simplifying implementation.

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To implement risk premia, factor strategies, and sector rotation, investors today can choose from a variety of ETFs that provide targeted exposure to specific factors, sectors, and other investment themes. Factor ETFs, such as those focused on value, momentum, or size, allow investors to express views on factors like undervalued stocks or those with strong recent performance. Sector and industry ETFs provide exposures to specific sectors like technology, healthcare, or financials, while thematic ETFs focus on trends such as clean energy or artificial intelligence. Dividend ETFs target companies with stable earnings, and smart beta ETFs blend passive and active factor-based strategies. Additionally, bond ETFs enable investors to express views on fixed income risk premia, such as term and credit premia, across different bond market segments.

ETFs offer a range of benefits that make them an attractive investment vehicle for both institutional and smaller investors. One major advantage is liquidity, as ETFs can be bought and sold on exchanges throughout the trading day, just like individual stocks, allowing for great flexibility and real-time execution. They also have low costs, with lower expense ratios compared to actively managed funds, which makes them cost-effective for investors looking to implement factor strategies or sector tilts without incurring high fees. Additionally, ETFs provide transparency, as their holdings are typically disclosed on a daily basis, giving investors a clear view of the underlying assets. Another key benefit is tax efficiency, as the in-kind creation and redemption process helps avoid frequent sales of securities within the ETF and limits taxable distributions, thereby minimizing capital gains taxes and making them a highly tax-efficient investment vehicle. Moreover, ETFs facilitate diversification by providing exposure to a broad range of assets, sectors, or factors, thereby helping to mitigate the risk of concentrated positions.

This article presents a simple methodology for implementing systematic strategies with ETFs for long-only investors, including family offices and wealth managers, who manage their portfolios relative to a benchmark. While the approach adapts easily to blended or customized benchmarks, we focus on equity and fixed-income benchmarks such as the S&P 500 Index and the Bloomberg Barclays U.S. Aggregate Bond Index. The core idea is simple: Combine the manager's beliefs into a *view portfolio* and then *tilt* their existing portfolio toward it ensuring that any tracking error or other investment constraints are met. The methodology does not require expected return forecasts but assumes access to a risk model that provides a daily covariance matrix of returns of the ETFs to generate reasonable portfolio variance forecasts. We emphasize that the view portfolio can be constructed a number of ways, from ad-hoc methods to more quantitative approaches like risk parity portfolios, tailored to meet the needs of family offices, wealth managers, and other investors.

After introducing the methodology, we present a few case studies to illustrate its application. In the case studies, we focus on equity and fixed-income ETFs from the SPDR Portfolio family for the U.S. market (see Table 1), managed by State Street Global Advisors under the SPDR (Standard & Poor's Depositary Receipts) brand. These ETFs cover a broad range of sectors, investment styles, and fixed-income securities. Other ETF families or ETFs can be used depending on the investors' needs. The portfolio analyzer, risk model, and optimizer described in this article are available as a service to aisot customers [1].

Methodology

We first assume the manager's benchmark is tradable, such as the S&P 500 Index, which can be accessed through the SPY ETF. The manager is allowed to make active bets relative to the benchmark, provided their portfolio stays within a specified tracking error (TE). The portfolio manager believes that a specific sector or style factor (e.g., the technology sector or value stocks) will outperform over a given time horizon. Although the manager does not have an estimate of the expected return, they simply wish to reallocate a portion of the portfolio to the view portfolio, creating a weighted combination of the benchmark and the view portfolio.

Equipped with the covariance matrix of ETF returns, the manager determines the allocation between the benchmark and view portfolios to maximize exposure to the view portfolio, while

[1] https://aisot.com/products

Name	Symbol	No. of Assets	ER (bps)	AUM (Million USD)
Sector ETFs				
Energy Select Sector Fund	XLE	23	9	39,000
The Materials Select Sector Fund	XLB	28	9	5,650
Industrial Select Sector Fund	XLI	78	10	15,600
Consumer Discretionary Select Sector Fund	XLY	52	9	19,586
The Consumer Staples Select Sector Fund	XLP	38	9	14,284
The Health Care Select Sector Fund	XLV	64	9	38,006
Financial Select Sector Fund	XLF	76	10	36,346
Communication Services Select Sector	XLC	22	9	17,780
Utilities Select Sector	XLU	31	9	13,675
Real Estate Select Sector	XLRE	31	9	5,772
Technology Select Sector	XLK	65	9	64,646
Equity Style ETFs				
Portfolio S&P 500 Value ETF	SPYV	402	4	20,850
Portfolio S&P 500 Growth	SPYG	208	4	25,599
S&P 400 Mid Cap Value ETF	MDYV	299	15	2,430
S&P 400 Mid Cap Growth	MDYG	246	15	3,057
S&P 600 Small Cap Value ETF	SLYV	461	15	3,750
S&P 600 Small Cap Growth	SLYG	346	15	3,241
SSGA US Large Cap Low Volatility Index	LGLV	162	12	710
SSGA US Small Cap Low Volatility Index	SMLV	421	12	184
S&P 1500 Momentum Tilt ETF	MMTM	1503	12	94
S&P 1500 Value Tilt	VLU	1480	12	356
Portfolio S&P 500 High Dividend	SPYD	78	7	7,035
Fixed Income ETFs				
Portfolio Aggregate Bond	SPAB	7683	3	8,080
Portfolio Short Term Corporate Bond	SPSB	1466	4	7,711
Portfolio Intermediate Term Corporate Bond	SPIB	4709	4	8,621
Portfolio Long Term Corporate Bond	SPLB	2890	4	860
Portfolio Corporate Bond	SPBO	5062	3	1,500
Portfolio Short Term Treasury	SPTS	96	3	4,500
Portfolio Intermediate Term Treasury	SPTI	115	3	5,880
Portfolio Long Term Treasury	SPTL	91	3	10,000
Portfolio Mortgage Backed Bond	SPMB	2443	4	5,280

Table 1. The SPDR Portfolio ETFs covering U.S. equity and fixed income used in the examples. Other ETFs and families can be substituted depending on the specific needs and preferences of the investor. Symbol, No. of Assets, ER (bps), and AUM (Million USD) represent the ticker symbol, the number of assets in the portfolio, the expense ratio in basis points, and the assets under management in millions of US dollars.

ensuring the tracking error stays within the specified limit. This is achieved through a simple optimization (see Appendix), which is often solvable in closed form.

We observe that sector and style factor ETFs often have a high correlation with the SPY ETF. However, because the weight in the view portfolio is determined through the tracking error optimization above, the *effective tilt* towards the manager's view remains *uncorrelated* with the benchmark. This enables the portfolio manager to express their conviction while managing risk relative to the benchmark.

By combining *multiple views* in the view portfolio, the manager can potentially further enhance his risk-adjusted returns while maintaining the same tracking error to the benchmark. In this situation, they can add each view one at a time using the process outlined above. Alternatively, the manager may opt to create a single view portfolio that combines all their views. For example, they could use an ad-hoc method or a suitable quantitative approach, such as a risk parity portfolio (see Appendix), tailored to their specific needs. We illustrate this approach in Case study II.

When the benchmark is not directly tradable, the manager first constructs a portfolio of ETFs that tracks the benchmark. This tracking portfolio can then serve as a substitute for the benchmark. Using a tracking portfolio is especially useful when a manager wants to reduce exposure to certain styles or sectors. By adjusting the exposures within the tracking portfolio, the manager can lower their allocation to these styles or sectors without the need for short positions in ETFs.

Finally, we note that incorporating more complex risk or trading constraints into the methodology described above is straightforward.

Case study I – Portfolio manager Bob with a long-only equity mandate

Portfolio manager Bob manages an equity mandate with the goal of outperforming the S&P 500 while maintaining a tracking error of 400 bps. He has been closely monitoring AI within the technology sector and believes it will be the next major growth opportunity.

To express his view on AI/technology and manage his portfolio relative to the S&P 500, he constructs a portfolio consisting of the SPY and XLK ETFs, applying the portfolio tilt methodology.[2] Figure 1 shows Bob's profit and loss (PnL) and portfolio holdings over the past four years of implementing this strategy. We observe that Bob consistently maintains exposure to SPY, ranging from 52% to 65%, with its weight fluctuating based on market volatility and the correlation between SPY and XLK, while the remainder is allocated to the XLK tilt portfolio. Bob's strategy benefits from XLK's outperformance, all while successfully fulfilling his mandate to track the S&P 500 Index with the desired tracking error.

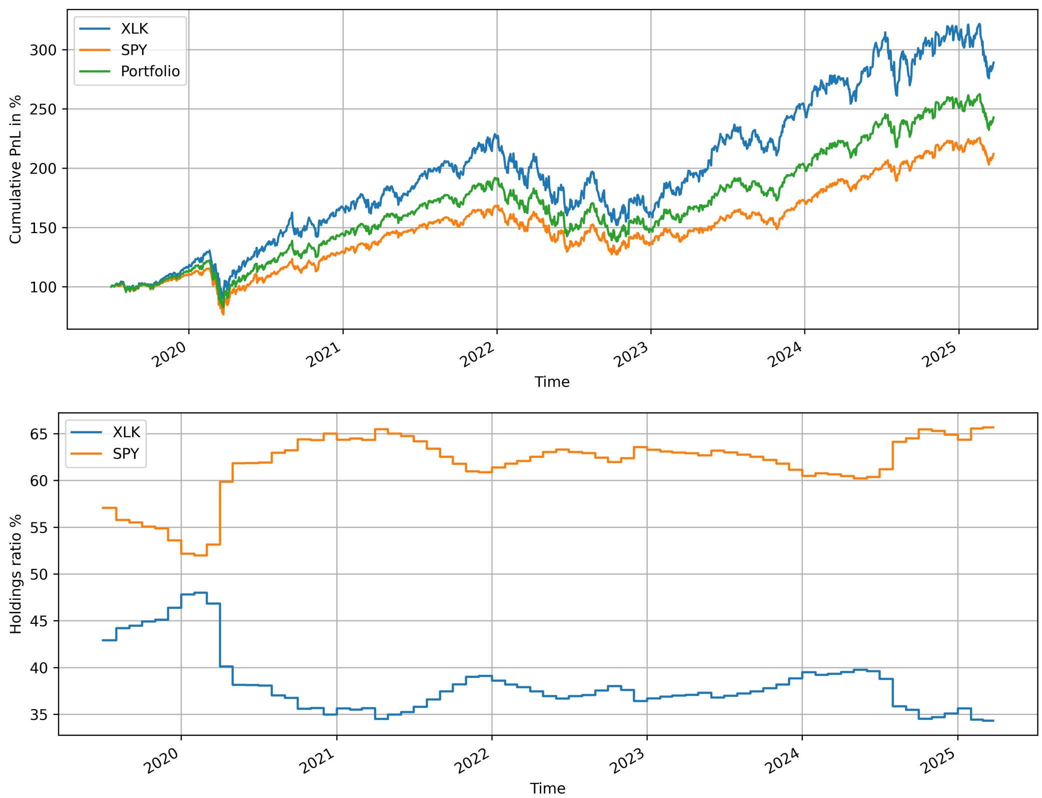

Figure 1. Portfolio manager Bob's PnL (top panel, x-axis: years, y-axis: cumulative PnL) and holdings (bottom panel, x-axis: years, y-axis: holdings ratio). Bob is tilting his portfolio towards XLK while maintaining a 400 bps annual tracking error relative to his benchmark, the S&P 500 Index.

Case study II – Portfolio manager Alice with a long-only fixed income mandate

Portfolio manager Alice manages a fixed-income mandate relative to the Bloomberg Barclays U.S. Aggregate Bond Index, which is closely tracked by the SPAB ETF. Alice believes that short-

[2]The SPDR S&P 500 ETF (SPY) tracks the performance of the S&P 500 Index, providing broad exposure to the U.S. equity market. The Technology Select Sector SPDR ETF (XLK) focuses on the technology sector of the S&P 500 Index, investing in a diversified portfolio of technology companies such as AI, software, hardware, semiconductors, and other IT services.

Figure 2. Portfolio manager Alice's PnL (top panel, x-axis: years, y-axis: cumulative PnL) and holdings (bottom panel, x-axis: years, y-axis: holdings ratio). Alice is tilting her portfolio towards the risk parity portfolio pair (SPTS, SPSB) while maintaining a 300 bps annual tracking error relative to her benchmark, the Bloomberg Barclays U.S. Aggregate Bond Index, through 2021. From 2022 onwards, she increased her tracking error to 400 bps.

term Treasuries and corporates will outperform her benchmark and decides to express this view through the SPTS and SPSB ETFs.[3]

Before 2021, Alice held a long position in the SPAB aggregate bond market index. At the start of 2021, she decided to incorporate her view on short-term Treasuries and corporates by using the SPTS and SPSB ETFs. First, she constructs a view portfolio consisting of these two ETFs, applying a risk parity approach (see Appendix) to ensure each ETF contributes an equal amount of risk. Then, she uses the portfolio tilt methodology to combine the risk-parity portfolio (SPTS, SPSB) with SPAB, allowing for a 300 bps tracking error. Starting in 2022, Alice was authorized to increase the tracking error to 400 bps, offering greater flexibility for portfolio adjustments.

Figure 2 illustrates the PnL of Alice's portfolio. Alice performed monthly rebalancing, and in 2021, the SPAB weight dropped to around 40%. After 2022, with the larger tracking error constraint, the SPAB weight further reduced to below 20%, maintaining compliance with the tracking error constraint while simultaneously increasing exposure to the risk-parity portfolio (SPTS, SPSB).

[3]The Portfolio Short-Term Treasury ETF (SPTS) consists of a diversified portfolio of short-term U.S. Treasury securities, providing low-risk exposure to government debt with maturities typically ranging from one to three years. The Portfolio Short-Term Corporate Bond ETF (SPSB) invests in a diversified portfolio of short-term investment-grade corporate bonds, offering low-risk exposure to corporate debt with similar maturities.

Case study III – Portfolio manager Charlie with a long-only equity mandate and long-short views

Portfolio manager Charlie has a more complex view. Like Bob, he believes technology will outperform and seeks to tilt towards that sector. At the same time, he believes the value factor will underperform. After some analysis, he decides his tilt portfolio will have fixed weights of 2 for XLK and -1 for SPYV.[4] If allowed to short, he could apply the methodology outlined above. However, as he is required to maintain a long-only portfolio, Charlie follows a different approach. First, he constructs a portfolio that tracks the S&P 500 Index, using SPYV and SPYG.[5] The daily return of the resulting tracking portfolio has an average R^2 to that of SPY of about 99.8%. By adjusting the weights in SPYV and SPYG within the tracking portfolio, Charlie can offset the negative exposure to value (through SPYV) by allocating more weight to growth (through SPYG) and technology (through XLK). This approach allows Charlie to tilt the portfolio towards his views (positive on technology, negative on value) without violating the long-only constraint, as he is not directly shorting any assets but instead adjusting the exposures within the tracking portfolio. The result is a portfolio that reflects his beliefs while maintaining an overall exposure that maintains a tracking error of 400 bps to the S&P 500 Index.

Figure 3 illustrates the PnL of Charlie's portfolio. Charlie performed monthly rebalancing with a 400 bps tracking error. He held around 20% of SPYG and approximately 40% of XLK in 2020, gradually reducing his XLK allocation to about 30% from 2021 onward while increasing his SPY holdings from 40% in 2020 to around 55% from 2021. The weights varied depending on SPY's volatility. Overall, Charlie has fulfilled his mandate of tracking SPY with a 400 bps tracking error while improving his performance relative to the benchmark by making appropriate tilts towards XLK and away from SPYV.

Conclusions

This article introduced a simple methodology for implementing systematic investment strategies using exchange-traded funds (ETFs) for long-only investors, particularly family offices and wealth managers managing portfolios relative to a benchmark. By integrating views on risk premia, style factors, and sector trends, the approach enables portfolio managers to tilt their portfolios toward selected premia, factors or sectors while maintaining control over their risk relative to the benchmark. The methodology does not require expected return forecasts and is adaptable to many investment settings.

Through three case studies – (i) portfolio manager Bob, tracking the S&P 500 Index while incorporating views on the technology sector; (ii) portfolio manager Alice, tracking the Bloomberg Barclays U.S. Aggregate Bond Index while incorporating beliefs on short-term treasury and corporate bond ETFs; and (iii) portfolio manager Charlie, tracking the S&P 500 Index while incorporating a positive view on the technology sector and a negative view on the value factor – we demonstrated how the methodology can be practically applied in different scenarios. These case studies highlight the versatility and practicality of the approach in real-world portfolio management.

The methodology's simplicity, adaptability, and ability to use liquid, low-cost ETFs make it an attractive tool for a broad range of investors. It provides a scalable, cost-effective way to express market convictions, implement factor tilts, and manage risk within specified constraints, all without the need for complex derivatives or short positions.

Appendix

In the following, we assume daily access to the covariance matrix of returns for the securities (ETFs) of interest, providing reasonable variance forecasts for all feasible portfolios. These covariance

[4] The SPDR S&P 500 Value ETF (SPYV) tracks the performance of the value stocks in the S&P 500 Index, consisting of companies that are considered undervalued relative to their fundamentals, such as earnings, sales, or book value.

[5] The SPDR S&P 500 Growth ETF (SPYG) focuses on the growth segment of the S&P 500 Index, investing in a diversified portfolio of U.S. companies with above-average growth potential. SPYG targets stocks that exhibit higher earnings growth rates and capital appreciation, typically in sectors like technology, consumer discretionary, and healthcare.

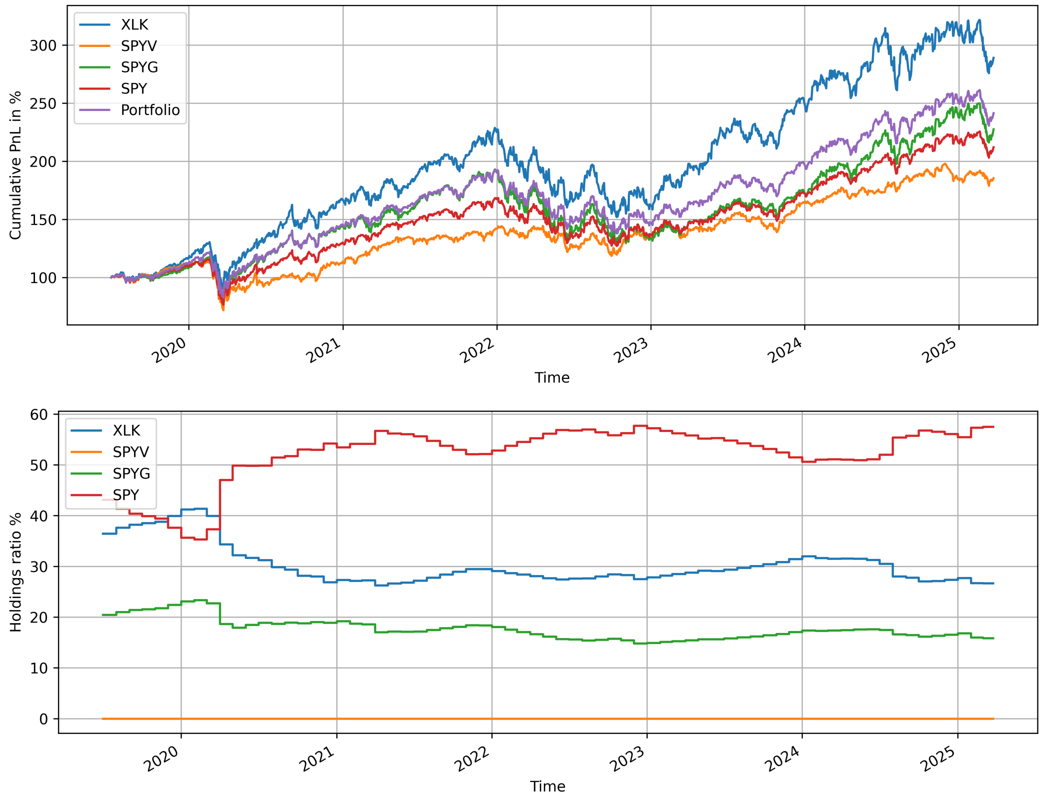

Figure 3. Portfolio manager Charlie's PnL (top panel,x-axis: years, y-axis: cumulative PnL) and holdings (bottom panel, x-axis: years, y-axis: holdings ratio). His tilt portfolio expresses the view that technology (XLK) will outperform while value (SPYV) will underperform. He implements this view using a long-only portfolio of ETFs, achieving negative exposure to SPYV by tracking the S&P 500 Index with long-only holdings in both SPYV and SPYG.

matrices can be obtained, for example, from standard cross-sectional factor models (Rosenberg, 1974; Connor et al., 2010) or by employing covariance estimation techniques, such as shrinkage methods or random matrix theory-based approaches (Ledoit and Wolf, 2022; Bun et al., 2017). We denote the daily covariance matrix by Σ_t (or simply Σ when the specific day is not important).

Risk parity portfolio

A risk parity portfolio is one where each asset contributes equally to the overall portfolio risk, preventing any single asset from dominating the risk profile. To create such a portfolio, we aim to equalize the risk contributions across assets. Let $\mathbf{w} = (w_1, w_2, \ldots, w_n)^\top$ represent the portfolio weights, and Σ denote the covariance matrix of asset returns. The portfolio's total risk is $R(\mathbf{w}) = \sqrt{\mathbf{w}^\top \Sigma \mathbf{w}}$, and the risk contribution of asset i is given by

$$RC_i = w_i \frac{(\Sigma \mathbf{w})_i}{\sqrt{\mathbf{w}^\top \Sigma \mathbf{w}}} .$$

The goal is to minimize the sum of squared deviations from the average risk contribution $\overline{RC} = \frac{1}{n} R(\mathbf{w})$, leading to the optimization problem

$$\min_{\mathbf{w}} \sum_{i=1}^{n} \left(RC_i - \overline{RC} \right)^2 ,$$

subject to $\sum_{i=1}^{n} w_i = 1$ and $w_i \geq 0$ for all i. This formulation ensures balanced risk contributions from each asset, achieving the risk parity objective. The solution with all positive weights is unique (Bai et al., 2016) and can be easily computed using an optimizer.

Incorporating systematic views through portfolio tilts

We employ a simple portfolio tilt approach to integrate systematic views into an existing portfolio managed relative to a benchmark. Specifically, we tilt the benchmarked portfolio toward the chosen view portfolio by reducing its holdings in the benchmark and reallocating those funds to the view portfolio.

To make this concrete, we denote by $\mathbf{w}^{bm} = (w_1^{bm}, \ldots, w_n^{bm})$ the weights of the benchmark portfolio. In this article, we use SPY as the benchmark for the equity portfolio, with $w_{SPY}^{bm} = 1$ and all other weights set to zero, and SPAB for the fixed income portfolio. We let $\mathbf{w}^{v} = (w_1^{v}, \ldots, w_n^{v})$ represent the weights of the view portfolio. If the portfolio manager allocates a proportion $t \in [0, 1]$ of funds to the view portfolio, the weights of the resulting portfolio can be expressed as

$$\mathbf{w} = t\mathbf{w}^{v} + (1 - t)\mathbf{w}^{bm},$$

which is a convex combination of the two portfolios. In addition, the portfolio manager is subject to a tracking error constraint relative to their benchmark, resulting in the optimization problem

$$\begin{array}{ll} \text{maximize} & t \\ \text{subject to} & \mathbf{w} = t\mathbf{w}^{v} + (1 - t)\mathbf{w}^{bm}, \\ & t \in [0, 1], \\ & \sqrt{(\mathbf{w} - \mathbf{w}^{bm})^\top \Sigma (\mathbf{w} - \mathbf{w}^{bm})} \leq TE\,, \end{array}$$

where TE denotes the desired tracking error relative to the benchmark portfolio. More complex risk and trading constraints can be easily incorporated as needed. In the case studies in the main text, the tracking error constraint is always binding, and therefore the optimal value of t can be obtain explicitly by solving a quadratic equation.

Finally, we note that this simple approach can be easily adapted to more general scenarios. For instance, the assumption of a tradable benchmark can be relaxed by constructing a tradable portfolio that tracks the benchmark and then tilting away from it. Case study III illustrates such an example.

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