Integrating Fundamentals and Technicals: A Multi-Strategy Approach to Dynamic Asset Allocation

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ABSTRACT

This study proposes a systematic multi-strategy approach for dynamic asset allocation strategies by integrating macroeconomic and technical signals within a layered framework, illustrated with a multi-asset sample over the period of 1990 to 2023. The strategy employs mean variance optimization with views generated from macroeconomic regime signals to construct the portfolio and fine-tune the weight by applying a rule-based scoring system from value, momentum and sentiment signals. Out-of-sample analysis shows the dynamic portfolio outperforms static benchmarks and provides diversification benefits. The results have practical implications for pure-macro strategies to add value by incorporating technical signal and economic-regime-derived asset covariance estimates in portfolio optimization.

Keywords: dynamic asset allocation, economic regime, technical signal, portfolio optimization

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INTRODUCTION

The asset allocation decision is well-recognized to account for approximately 90% of the return variation in a typical portfolio[1]. Traditional portfolio construction methods such as Markowitz's mean-variance framework (1952), in practice, often rely on the assumption of constant asset returns and covariance inputs, exposing static portfolios to a real-world environment of time-varying risks and returns[2]. This discrepancy has given rise to tactical asset allocation, a strategy designed to exploit these time-varying dynamics, as numerous studies have found significant levels of predictable variation in asset returns[3]. Furthermore, asset correlations can differ substantially during periods of high market volatility[4], posing a notable challenge on the diversification power of a static portfolio[5] and urging the need for a dynamic portfolio strategy.

Despite the well-known challenge of market timing as suggested by Fama's Efficient Market Hypothesis (1970), academics and practitioners have continually sought the "holy grail" of investing, by exploiting the universe of asset-return predictors, including macroeconomic variables (eg. growth, inflation), firm characteristics (eg. size, value), valuations (eg. price-earnings ratio, book-market ratio) and technical factors (eg. momentum, volatility). Although each strategy has been widely documented in the literature, the optimal strategy remains a topic of debate[6]. Given this ongoing discussion, it raises a pertinent question: "Could a multi-strategy dynamic asset allocation approach, by integrating different dimensions of factors, lead to enhanced performance?". As Rapach, Strauss and Zhou (2010) have pointed out, model uncertainty and instability impair the forecasting ability of individual predictive models, and combining different models delivers significant out-of-sample gains over time.

[1] See Singer & Beebower (1991) and Ibbotson & Kaplan (2000)
[2] Harvey (1991) finds the covariance matrix of returns, from which the portfolio frontier is formed, is time varying.
[3] See, for example, Campbell & Yogo (2006) and McLean & Pontiff (2016)
[4] Loretan & English (2000) evaluate the correlation breakdowns during periods of market volatility
[5] Chua, Kritzman & Page (2009) prove that diversification based on unconditional covariances is largely a myth.
[6] Goyal and Welch (2008) find that no academic-proposed factors could consistently predict the equity premium.

This study proposes a multi-strategy dynamic asset allocation framework based on a combination of macroeconomic, value, momentum and sentiment factors, which aims to enhance out-of-sample risk-adjusted returns relative to the static approach and single-strategy approach. This is essentially a global macro strategy as it invests in global multi-asset markets and is fundamentally based on macroeconomic dynamics (defined as "Fundamental Macro") but also exploits the value/momentum/sentiment aspects of asset returns (defined as "Technical Macro"). Specifically, following the methodology proposed by Blitz & Vliet (2011)[7], a regime model using the "Fundamental Macro" indicators (growth, inflation and monetary policy) is first constructed to identify different economic regimes. The time-varying return/risk properties of assets are then incorporated as mean and variance inputs for the Markowitz (1952) model to construct a portfolio that tilts exposures toward favorable assets according to the economic regimes. Having the initial portfolio weights, a rule-based scoring system using the "Technical Macro" indicators (value, momentum and sentiment) is applied for final adjustments. For example, an equity index will be assigned more weight in an economic expansion regime given its higher expected return but the weight will be ungraded if that equity market is experiencing high valuation, high sentiment and low momentum.

This "Fundamental-Technical Macro" multi-strategy approach was motivated by the fact that asset prices are ultimately driven by macroeconomic fundamentals[8], as Harvey and Dahlquist (2001) suggest that a dynamic asset allocation process could add value over static weights due to the predictability of returns using economic factors. Macro strategy is also attractive given its ability to generate strong risk-adjusted returns across a variety of market

[7] Instead of using statistical properties of the assets for regime definitions , Blitz & Vliet (2011) propose a more fundamental approach which uses the level and change of economic data to identify different regimes. This approach was motivated by the work of Weiser (2003) and Vrugt (2003).

[8] See, for instance, Fama & French (1989), Siegel (1991) and Balvers, Cosimano & McDonald (1990)

environments, especially during market drawdowns[9]. However, the asset market tends to overreact to fundamental news (De Bondt and Thaler, 1985)[10] and thus sometimes deviates substantially from predicted values based on fundamentals (Claessens and Kose, 2017). This causes the mean-reverting behavior of asset prices (Poterba and Summers, 1988) thus creating opportunities for the non-fundamental "Technical Macro" strategy. Furthermore, multi-strategy approaches that combine different models are found to have better risk-adjusted returns and less systematic market exposures to a variety of common factors (Qian, Sorensen and Hua, 2009).

This study extends the literature on macro-based tactical asset allocation strategies in several ways. First, in contrast to Kritzman et al. (2012)[11], Jurczenko and Teiletche (2018)[12] and Kim and Kwon (2023)[13] which only utilize fundamental economic variables, this multi-strategy approach also incorporates well-examined technical factors[14] of macro assets such as value, momentum and sentiment, by developing a layered framework that combines the two dimensions. Second, instead of using historical averages to measure the covariance in the mean-variance optimization model, this study estimates the time-varying covariance matrices observed in different economic regimes, enhancing the diversification power as well as the risk-adjusted return. Third, Markowitz mean-variance optimization (MVO) approach is known to be highly sensitive to estimation error in risk-return estimates. While several studies[15] use the Black and Litterman (1992) model to avoid the limitations of traditional MVO, others only address this problem by imposing portfolio weight constraints. By applying the resampling technique, first

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9 As an example, during the Global Financial Crisis, the S&P 500 realized a drawdown of 69% from May 2007 - Feb 2009, while the Dow Jones Credit Suisse Global Macro Index had a positive return of 3.3%.

10 De Bondt and Thaler (1985) find that most people tend to overreact to unexpected and dramatic news events.

11 Kritzman, Page & Turkington (2012) show how to apply Markov-switching models to forecast regimes in market turbulence, inflation, and economic growth. They found that a dynamic process outperformed static asset allocation.

12 Jurczenko and Teiletche (2018) apply the Black-Litterman approach on top of a risk-based portfolio using views generated from economic regime signals, which outperforms passive risk-based strategies and Max-Sharpe strategy.

13 Kim and Kwon (2023) construct a regime-based dynamic strategy that shifts exposures across assets according to growth/inflation economic regimes. The strategy generates a higher risk-adjusted return than the static approach.

14 See, for example, Jegadeesh & Titman (1993), Campbell & Shiller (2001) and Baker & Wurgler (2006)

15 See, for example, Haesen et al. (2017), Jurczenko & Teiletche (2018) and Kim & Kwon (2023)

presented in Michaud (1998)[16], this study is able to generate a more smoothed time-varying MVO portfolio and enhance out-of-sample performance.

The next section introduces the methodology of the multi-strategy global macro tactical asset allocation approach, starting with the sample data and a description of the indicators, followed by the out-of-sample portfolio construction process. The final section presents the empirical results and robustness check, before a brief discussion of the findings and limitations.

DATA AND METHODOLOGY

This study proposes a multi-strategy global macro tactical asset allocation approach to build a dynamic portfolio based on Fundamental Macro signals and Technical Macro signals, by developing a layered framework to integrate the two macro dimensions. This section first introduces the sample data, then describes the signal construction process for Fundamental Macro and Technical Macro, and finally presents how these two signals are combined and transformed into dynamic portfolio allocation in an out-of-sample backtesting setting.

Data

The sample covers the period from January 1990 to December 2023 and consider ten asset classes[17]: US large-cap equities (USLC), US small-cap equities (USSC), Non-US equities (WorldxUS), US long-term treasuries (LTG), US short-term treasuries (STG), US Investment-Grade bonds (IG), US High-Yield bonds (HY), commodities (GSCI), gold (Gold) and REITs

[16] Michaud (1998) introduces Monte Carlo resampling methods into mean-variance optimization to reflect the uncertainty in investment information, resulting in more stable and investment effective MV optimized portfolios.

[17] The ten asset classes are measured by: S&P 500 Total Return Index (US large-cap equities), S&P 600 SmallCap Total Return Index (US small-cap equities), Global Financial Data Indices World x/USA Stock Return Index (Non-US equities), Bloomberg US Long Treasury Total Return Index (US long-term treasuries), Bloomberg US Treasury Bills 1-3 Month Total Return Index (US short-term treasuries), Bloomberg US Corporate Total Return Index (US Investment-Grade bonds), Bloomberg US Corporate High Yield Total Return Index (US High-Yield bonds), S&P GSCI Commodity Total Return Index (commodities), XAU/USD (gold), FTSE Nareit Equity REITs Index (REITs)

(REIT). The indicators for constructing the Macro signals are described in the following sections. All data are retrieved at a monthly frequency from Bloomberg, Global Financial Data, The Federal Reserve System and The Commodity Futures Trading Commission. Table 1 describes the asset return and risk characteristics of the entire sample.

Table 1. Asset Risk and Return Characteristics

	USLC	USSC	WorldxUS	LTG	STG	IG	HY	GSCI	Gold	REIT
Panel A: Descriptive Statistics										
Annualized Return	11.4%	12.6%	6.1%	6.8%	2.7%	6.1%	8.1%	4.1%	6.1%	11.7%
Annualized Volatility	14.9%	19.1%	17.2%	10.8%	0.7%	5.9%	8.7%	21.6%	15.2%	18.8%
Sharpe Ratio	0.63	0.56	0.24	0.44	1.07	0.70	0.70	0.10	0.27	0.51
Panel B: Correlation Matrix										
USLC	1.00									
USSC	0.82	1.00								
WorldxUS	0.77	0.68	1.00							
LTG	-0.03	-0.12	-0.04	1.00						
STG	-0.00	-0.05	-0.06	0.08	1.00					
IG	0.39	0.30	0.37	0.69	0.08	1.00				
HY	0.65	0.66	0.60	0.02	-0.03	0.58	1.00			
GSCI	0.24	0.29	0.31	-0.22	0.03	0.09	0.26	1.00		
Gold	0.01	0.01	0.14	0.20	-0.05	0.26	0.12	0.20	1.00	
REIT	0.61	0.67	0.54	0.12	-0.03	0.44	0.62	0.18	0.11	1.00

Fundamental Macro Signals

To model the effect of macroeconomic forces on asset returns, an economic regime-based approach has proven effective (Ang and Bekaert, 2004)[18]. In this approach, asset performance is analyzed conditional on the prevailing macroeconomic regime and portfolios are constructed considering regime-dependent return and risk characteristics. Markov-switching model[19] is a popular econometric method to detect regime shifts. However, the parameter estimation involved in the process frequently yields a poor out-of-sample robustness. Instead,

[18] Ang & Bekaert (2004) find that high volatility and high correlation regime tends to coincide with a bear market. They develop a regime-switching strategy that dominates static strategies out-of-sample for a global all-equities portfolio, and that the model proposes to switch primarily to cash in a persistent high-volatile market.

[19] Used by, for example, Bulla et al. (2011) and Kritzman, Page & Turkington (2012)

this study adopts a more fundamentally-intuitive[20], data-driven method using the direction of growth and inflation indicators. Vliet and Blitz (2011), Ilmanen et al. (2014) and Jurczenko and Teiletche (2018) use a similar approach to identifying economic regimes, which enables researchers to derive transparent regime-based asset allocation strategies.

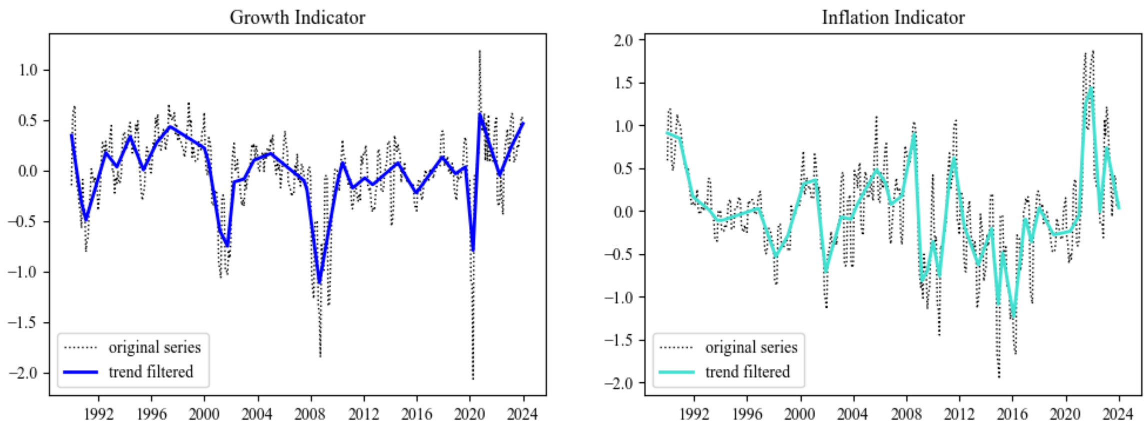
To delineate economic regimes, the growth indicator and inflation indicator are first constructed using the Chicago Fed National Activity Indicator (CFNAI)[21] and US headline CPI inflation rate from January 1990 to December 2023 respectively, and are calculated by averaging with data surprise (measured by actual GDP and CPI relative to the forecasts from the Fed Survey of Professional Forecasters) before normalizing through z-scores. The inclusion of economic surprise mitigates the problem of backward-looking data and also captures the optimism/pessimism about the state of the economy (Scotti, 2016). Next, the widely-used $\ell 1$ trend filtering method developed by Kim et al. (2009) is applied to extract momentum changes in growth and inflation indicators, as shown in Figure 1. In the $\ell 1$ trend filter, the trend estimate (x_t) is chosen as the minimizer of the following objective function:

$$\min_{x_t} \left(\frac{1}{2}\right) \sum_{t=1}^{n} (y_t - x_t)^2 + \lambda \sum_{t=2}^{n-1} |x_{t-1} - 2x_t + x_{t+1}|$$

where y_t is the underlying indicator and λ[22] is a regularization parameter that controls the trade-off between the size of the residual $(y_t - x_t)$ and smoothness of the estimated trend. The $\ell 1$ trend filter is designed in a way that the kink points correspond to changes in the slope of the estimated trend and can be interpreted as changes in the dynamics of the original data.

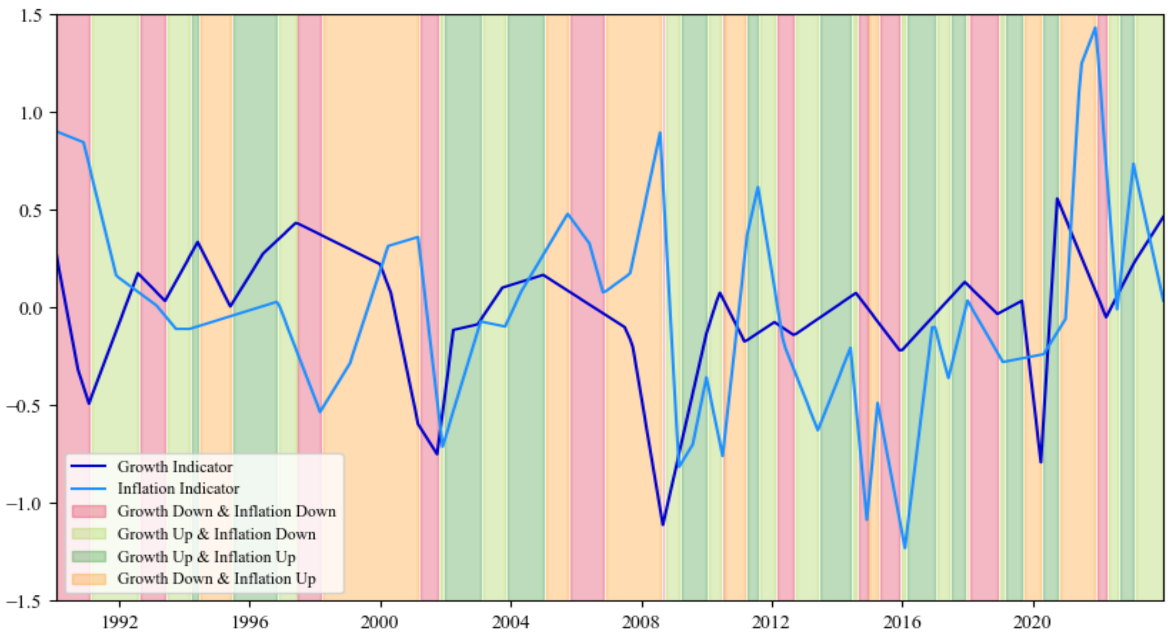
[20] The rationale behind this framework by Merrill Lynch (2004) is that economies cyclically deviate from their sustainable growth path and policy makers use tools to correct the path. An economy running below potential will suffer deflationary pressure and central banks cut rates to stimulate the economy. On the other hand, an economy consistently above its potential output will generate disruptive inflation, pushing growth back to its long-run path.
[21] Ilmanen et al. (2014) and Jurczenko and Teiletche (2018) both use CFNAI to represent growth indicator.
[22] The regularization parameter λ is set to 0.3, similar to Kim and Kwon (2023), to capture sufficient short-term momentum changes in growth and inflation. Different values of λ will be considered in sensitivity analysis.

Figure 1. Trend-Filtered Growth and Inflation Indicators



Having the trend-filtered indicators, economic regimes can be identified, in Figure 2, by a combination of rising/falling growth and inflation—specifically, (1)Growth Down & Inflation Down, (2)Growth Up & Inflation Down, (3)Growth Up & Inflation Up, and (4)Growth Down & Inflation Up. The risk-return characteristics of different assets within each regime can be calculated to derive regime-based dynamic asset allocation views. These views are then utilized as input for the Markowitz portfolio optimization model.

Figure 2. Growth/Inflation Economic Regimes



The idea of Markowitz mean-variance portfolio (Markowitz, 1952) is to find a trade-off between the expected return and the risk of a portfolio with the following objective function:

$$\max_{w} \; w^T\mu - \lambda\, w^T \Sigma w.$$

$$s.t. \; 1^T w = 1 \;\; (w \geq 0)$$

where w is the weight vector of each asset in the portfolio, μ is the vector of expected returns for i assets, $\sum$ is the covariance matrix and λ is a parameter that measures risk-aversion. Typically, investors pursue the maximum Sharpe ratio portfolio, $\max_{w} \frac{w^T\mu - r_f}{\sqrt{w^T \Sigma w}}$, along the Markowitz's Pareto-optimal efficient frontier (Sharpe, 1966). However, to align the volatility of this strategy with the traditional 60/40 stock-bond benchmark, this portfolio is designed to maximize return with a given volatility level (α). Moreoever, to build a strategy with lower traditional market beta, the portfolio releases the long-only constraint by setting -50% and 50% as the lower and upper bounds[23] of asset weights. Thus the optimization problem becomes:

$$\max_{w} \; w^T\mu$$

$$s.t. \; w^T \Sigma w \leq \alpha, \;\; 1^T w = 1 \;\; (-0.5 \leq w \leq 0.5)$$

Technical Macro Signals

The Technical Macro signal comprises three components: a value signal, a momentum signal and a sentiment signal. Initially processed as z-scores derived from their underlying indicators, these signals are then transformed into categorical variables with values of -1, 0, or 1. These categorical variables are subsequently employed using a rule-based approach to adjust portfolio weights in line with the signals generated by value, momentum and sentiment indicators. While using an indicator's statistical forecasting power is appealing theoretically, it

[23] The traditional long-only constraint will be considered in sensitivity analysis.

often works poorly in reality[24]. Alternatively, Schnetzer (2020) shows a simple combination approach based on percentile scores of standard indicators, such as valuation and risk, can improve investment performance, providing support for the design of Technical Macro Signals.

Value strategies are found to deliver positive returns in almost all global asset classes (Asness, Moskowitz and Pedersen, 2013), thereby improving portfolio performance. In this study[25], value is assessed through six-month cumulative price returns for all assets relative to historical averages, as several papers have discussed the use of price movement in determining value[26]. The process involves assigning signal scores based on the readings of the value indicator. When the value indicator surpasses one standard deviation, indicating over-valuation, a signal score of -1 is assigned. Conversely, when the indicator falls below one standard deviation, suggesting under-valuation, a signal score of +1 is assigned.

Momentum effects are well-documented in existing research[27]. The momentum indicator of this study is measured by the sign of 12-month price return for each asset. Assets with positive momentum tend to sustain their upward trends and thus are assigned with a signal score of +1. Assets that are trending down over the past 12 months, on the other hand, are more likely to keep underperforming and are assigned with a signal score of -1.

Investment sentiment is demonstrated to have a systematic impact on asset price fluctuations in the finance literature[28]. Brown and Cliff (2005) show that excessive optimism leads to periods of market overvaluation and high current sentiment is followed by low cumulative long-run returns. The sentiment index is constructed, following Baker and Wurgler

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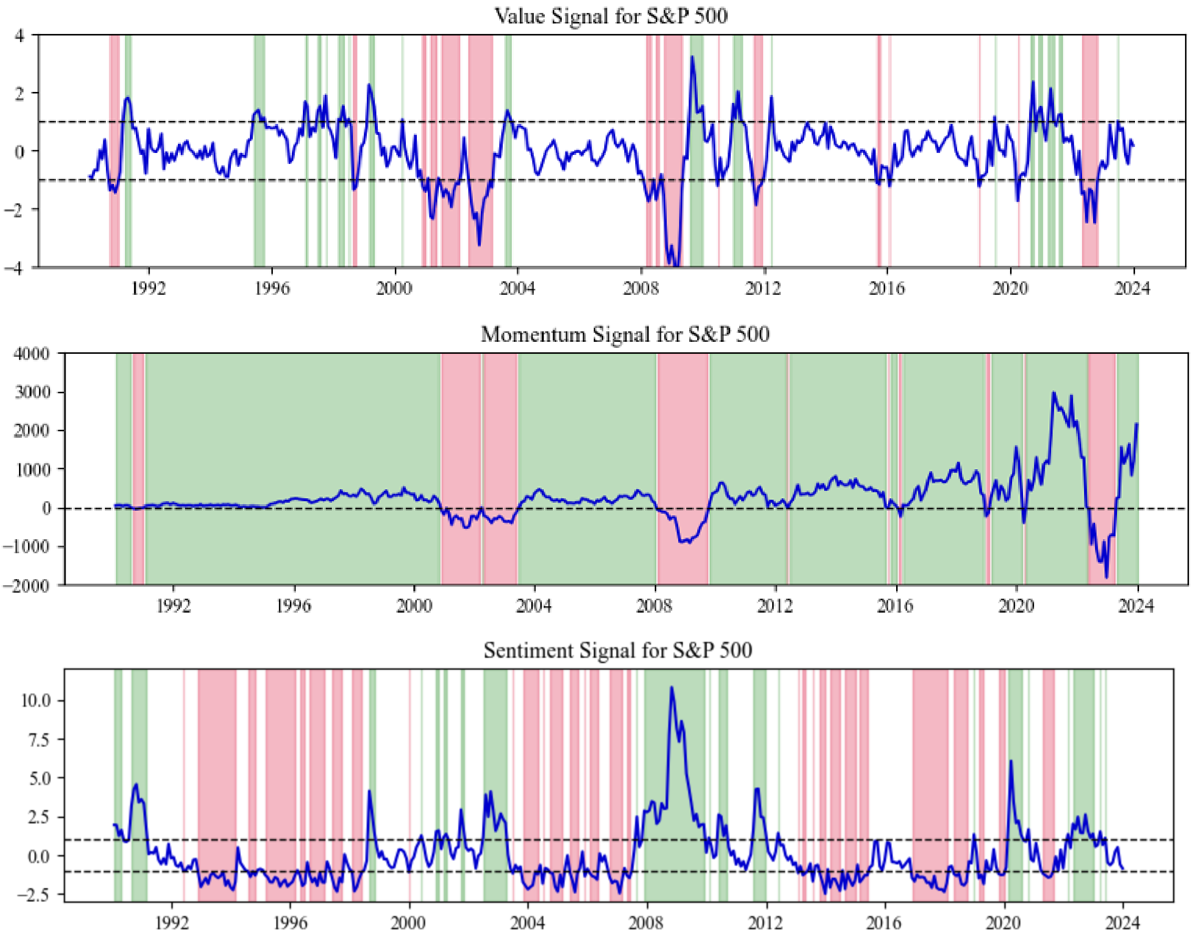
[24] For example, Stock & Watson (2003) point out that good forecasting performance by an indicator in one period seems to be unrelated to whether it is a useful indicator in a later period.
[25] While traditional valuation metrics such as price-earnings ratio (for equities), real yields (for treasury bonds) and credit spreads (for non-treasury bonds) are more widely used, they are found to deliver less ideal out-of-sample performance and therefore are not incorporated in the strategy of this study.
[26] See, for example, Shiller (1988), Asness, Moskowitz & Pedersen (2013) and Madhogarhia & Lam (2015)
[27] See, for example, Jegadeesh & Titman (1993), Fama and French (1996), Moskowitz, Ooi & Pedersen (2012)
[28] See, for example, De Long et al. (1990), Kothari & Shanken (1997) and Neal & Wheatley (1998))

(2006)'s approach, based on the first principal component of nine indicators[29] that are examined in previous research or widely-adopted among practitioners, including market-based metrics such as VIX index and survey-based metrics such as AAII Investor Sentiment Survey. Readings above one standard deviation are considered "over-optimistic" and assigned a signal score of -1 for risky assets (equities, credits, commodities and REITs) and +1 for safe assets (treasuries and gold). On the contrary, readings below one standard deviation are considered "over-pessimistic" and assigned a signal score of +1 for risky assets and -1 for safe assets.

Figure 3. Technical Signals: Take S&P 500 For Example



[29] The nine indicators include: AAII Investor Sentiment Survey: Bullish-Bearish Spread, AAII Investor Sentiment Survey: Cash Level, (see De Bondt, 1993), High-Yield Credit Spread (see Fama and French, 1989), University of Michigan Consumer Confidence Index (see Qiu and Welch, 2006), NYSE 52 Week High-Low Index (see Huddart, Lang & Yetman, 2009), Equity Market Uncertainty Index (see Baker, Bloom & Davis, 2016), Chicago Fed's National Financial Conditions Index – Risk (see Brave, Cole & Fogarty, 2020), CBOE VIX Index (see Kaplanski & Levy, 2010) and Yen + Gold CFTC non-commercial futures net positions (see Han, 2008)

Out-Of-Sample Portfolio Construction Method

The proposed asset allocation strategy integrates Fundamental Macro signals and Technical Macro signals within a structured framework. Initially, Fundamental Macro signals are employed to identify the current economic regime, leveraging historical samples to generate expected returns and covariance corresponding to similar economic episodes. These inputs drive mean-variance optimization to construct a regime-based optimal portfolio. Next, Technical Macro signals are applied to adjust the initial portfolio through a rule-based scoring system to produce asset-specific overweight/underweight signals, ultimately yielding a final combined-signal optimal portfolio. In the out-of-sample experiment, the first 308 months of the data (Jan. 1990 – Aug. 2015) are used as training sample to initialize the model, and the remaining 100 months (Sep. 2015 – Dec. 2023) of the data are set up for out-of-sample testing. The specific portfolio construction process is described in the following three steps.

First, starting from the last month of the training sample (time t), growth and inflation indicators at time t +1 (first month of the test sample) are estimated using ARIMA forecasting regression from data available at time t. The economic regime at time t+1 is then able to be derived by applying the ℓ1 trend filter to the predicted indicators. Having the forecasted regime, expected returns and covariance of assets can be calculated by taking the historical averages in the corresponding regime, driving the mean-variance optimization model. The regime-dependent parameters are re-estimated every month with an expanding window as new data becomes available. To address the sensitivity to estimation errors in mean-variance models, a Monte Carlo resampling method[30] is applied, by performing portfolio optimization with 1000 iterations, to generate a more stable and efficient mean-variance optimized portfolio.

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[30]The Resampled Efficiency optimal portfolios, proposed by Michaud (1998), are constructed as follows: (1)sample a mean vector and covariance matrix of returns from a distribution of both centered at the original values normally used in MV optimization, (2)calculate mean-variance efficient frontier based on these sampled risk and return

In the second step, the regime-based optimal portfolio weight is adjusted based on the overweight/underweight signals generated from the value, momentum and sentiment indicators. Every month (from time t+1), each technical indicator from the previous period (time t) is assigned with a signal score of -1, 0 or 1 to each asset according to the extreme values relative to historical median, measured by ±1 or ±2 standard deviations. The sum of the three signal scores is then applied for the final portfolio weight adjustment (time t+1), with a 30% adjusting factor γ[31] for each signal score. For example, the regime-based mean variance optimal weight for US large-cap equities was 20% at time t+n. If US large-cap equities had signal scores of +1 (value), +1 (momentum) and 0 (sentiment) in the prior month, the final weight would be 32%[32].

Finally, the procedure is repeated sequentially by including observations in the Fundamental Macro and Technical Macro signals one at a time throughout the out-of-sample period, thereby generating a dynamic portfolio on a monthly basis. However, rebalancing every month might not be an optimal choice. Financial markets tend to underreact to economic news and only slowly adjust to changes in fundamentals[33], making it reasonable to prolong the rebalancing period. Thus, considering signal noises as well as transaction costs, the dynamic portfolio is designed to be rebalanced every six months, consistent with previous findings[34].

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estimates, (3)repeat steps 1 and 2 until enough observations are available for convergence, (4)average the portfolio weights from step 2 to form the Resampled Efficiency optimal portfolio.

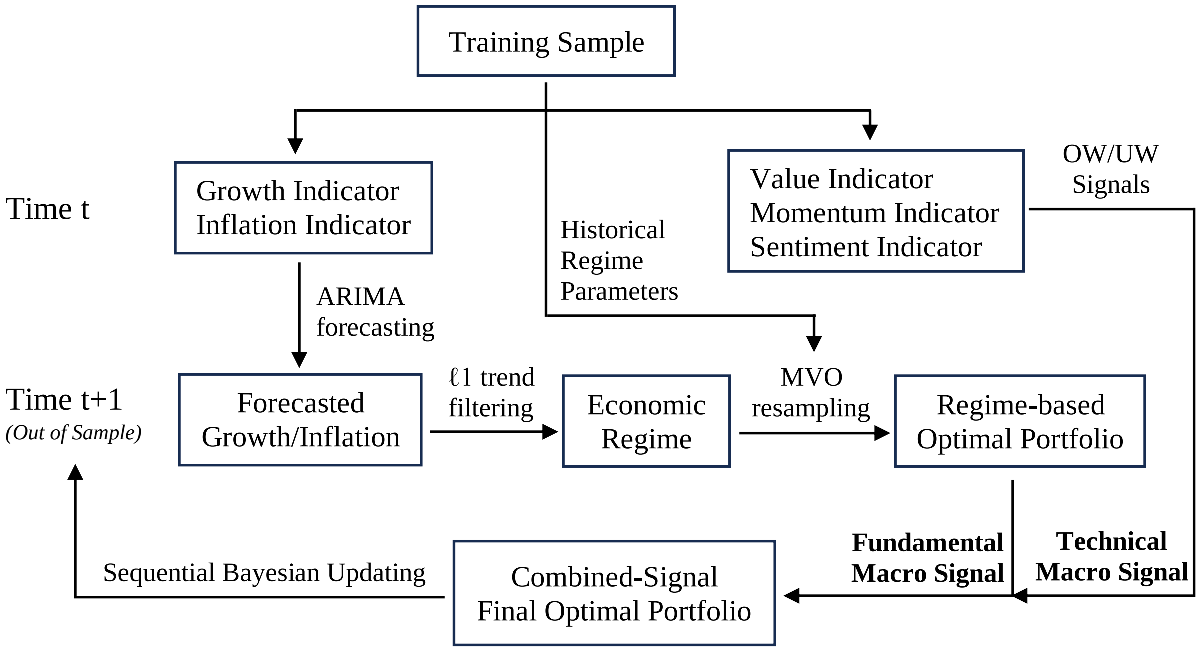
[31] Different values of the adjusting factor γ will be considered in sensitivity analysis.

[32] 32% = 20% * (1 + 30% * 2), where 20% is the regime-based mean variance optimal weight, 30% is the signal score adjusting factor and 2 is the sum of signal scores.

[33] Chan, Jegadeesh & Lakonishok (1996), Frazzini (2006), and Sinha (2016) focus on underreaction to news in individual stocks, while Bhojraj & Swaminathan (2006) and Brooks, Katz, & Lustig (2018) extends this empirical evidence to international equity indices and fixed income markets.

[34] Larsen & Resnick (2001) study portfolio optimization/holding period frequency intervals and find that using a 6-month interval dominates that of 3-month and 12-month. Chong and Phillips (2014) show that six-month forecasting horizon is optimal for their macro-based tactical asset allocation model.

Figure 3. Out-of-Sample Portfolio Construction Process



EMPIRICAL RESULTS

This section begins by analyzing the impact of Fundamental Macro and Technical Macro regimes on asset class relative performance and their implications for the multi-strategy dynamic asset allocation. Then, the out-of-sample performance results will be reported comparing to different benchmarks. Finally, the robustness of the results with respect to changes in key inputs and parameters used in the out-of-sample experiment will be examined.

Asset Class Relative Performance Under Different Macro Regimes

Table 2 contrasts the performance of assets across economic regimes[35]. In line with theories, asset classes behave differently in varying economic environments. For example, the best environment for equities, especially small-cap stocks, is the combination of rising growth and rising inflation. While treasury bonds are less desirable under this scenario, they provide

[35] The annualized returns are normalized by the individual full-sample volatility to facilitate comparisons.

more stable less correlated returns across all economic regimes. Non-traditional financial assets also have their roles. Commodities deliver strong returns in the “Growth Down & Inflation Up” economy, while REITs are good investments when both growth and inflation are trending down. Although the economic regime-derived returns are generally not statistically different from their unconditional means, the signals are relatively persistent with an average hit rate[36] of 64.2%, supporting the potential benefits of economic regime-based dynamic strategy.

Table 2. Asset Risk and Return Characteristics by Economic Regime[37]

	USLC	USSC	World	LTG	STG	IG	HY	GSCI	Gold	REIT
Panel A: Annualized Return										
Growth ↓ Inflation ↓	8.5%	6.9%	-2.4%	6.6%	3.0%*	5.7%	2.9%*	-7.2%	-0.7%	17.3%
Growth ↑ Inflation ↓	7.5%	8.8%	0.9%	6.8%	2.7%	4.8%	8.6%	-15.3%**	3.6%	3.5%
Growth ↑ Inflation ↑	19.2%	24.0%	19.4%	5.4%	2.2%***	8.8%	15.6%*	26.8%**	13.0%	24.7%
Growth ↓ Inflation ↑	10.8%	10.7%	9.1%	8.7%	3.5%***	5.5%	4.8%	14.9%	6.9%	6.4%
Panel B: Annualized Volatility										
Growth ↓ Inflation ↓	13.5%	17.1%	19.2%	8.9%	0.8%	4.5%	7.0%	22.3%	13.8%	14.9%
Growth ↑ Inflation ↓	17.1%	21.7%	19.8%	13.5%	0.7%	7.7%	11.7%	21.1%	16.8%	24.3%
Growth ↑ Inflation ↑	13.8%	17.5%	14.4%	10.8%	0.5%	5.9%	8.0%	17.1%	15.6%	17.6%
Growth ↓ Inflation ↑	15.1%	19.7%	15.6%	9.3%	0.7%	4.9%	7.3%	24.0%	14.1%	17.1%
Panel C: Sharpe Ratio										
Growth ↓ Inflation ↓	0.42	0.24	-0.25	0.39	1.74	0.52	0.05	-0.42	-0.19	0.78
Growth ↑ Inflation ↓	0.38	0.37	-0.05	0.48	0.84	0.56	0.82	-0.80	0.12	0.10
Growth ↑ Inflation ↑	1.14	1.15	0.98	0.32	-0.52	1.17	1.54	1.12	0.73	1.20
Growth ↓ Inflation ↑	0.59	0.46	0.40	0.60	2.15	0.53	0.28	0.61	0.32	0.22

Table 3 compares the annualized returns of assets grouped by technical signals where extreme values exist. Given the contrarian nature of these signals, an overweight (underweight) signal of +1 (-1) may not coincide with positive (negative) returns immediately in the same period. As shown in Panel A, assets with high valuations (signal of -1) tend to continue their outperformance, vice versa. However, returns in the consecutive months generally follow the mean-reversion path. On the other hand, assets react more quickly to momentum and sentiment

[36] Hit rate denotes those where return is consistently positive or negative with respect to their regime-based return.
[37] *, **, and *** denote rejection of the null hypothesis that regime-derived returns and full-sample returns have identical expected values for a two-tailed p-value at the 10%, 5%, and 1% significance levels, respectively.

signals, with much higher expected returns when signals are positive. Overall, these figures, with most statistically significant, support the inclusion of Technical Macro signals in the dynamic portfolio strategy.

Table 3. Asset Returns by Technical Signals[38]

	USLC	USSC	World	LTG	STG	IG	HY	GSCI	Gold	REIT
Panel A: Value Signal										
-1	52.7%***	58.7%***	47.3%***	50.5%***	0.1%***	20.5%***	36.3%***	75.9%***	39.3%***	66.6%***
0	14.7%	13.3%	11.7%	6.1%	2.8%	6.7%	9.0%	3.4%	5.2%	13.5%
1	-25.7%***	-22.7%**	-33.7%***	-13.2%***	4.0%***	-6.6%***	-19.5%***	-41.0%***	-28.8%***	-27.1%**
Panel B: Momentum Signal										
-1	-13.1%***	-5.8%*	-10.7%**	-5.1%***	2.3%**	-2.4%**	-5.3%**	-16.8%***	-10.7%***	-5.4%
1	17.7%	19.7%	16.3%**	10.9%	2.9%	7.7%	11.9%*	23.9%***	19.3%***	17.8%
Panel C: Sentiment Signal										
-1	-14.3%***	-17.6%***	-22.0%***	5.8%	2.8%	6.7%	-0.5%	-9.6%	2.9%	-12.1%**
0	12.8%	14.7%	7.5%	3.6%	2.8%	5.3%	8.8%	7.1%	5.8%	17.8%
1	29.3%***	33.6%***	26.4%***	15.0%	2.6%	6.8%	13.1%***	9.9%	12.0%	21.3%*

Out-of-Sample Performance Results

Based on Fundamental Macro and Technical Macro signals, the proposed asset allocation strategy dynamically adjusts portfolio weights over the out-of-sample period. As shown in Figure 4, the portfolio is rebalanced every six months with the flexibility for short-selling. Despite the capital budget constraint ($1^T w = 1$) in the mean variance portfolio, the technical overweight/underweight signals are applied after the optimization, resulting in a more volatile portfolio allocation. The average portfolio weight across four economic regimes is reported in Table 4. In general, the portfolio fluctuates significantly with changing economic environments compared to static portfolios such as the classic 60/40 stock-bond benchmark.

[38] *, **, and *** denote rejection of the null hypothesis that value signal-derived returns and full-sample returns have identical expected values for a two-tailed p-value at the 10%, 5%, and 1% significance levels, respectively.

Figure 4. Dynamic Portfolio Allocation

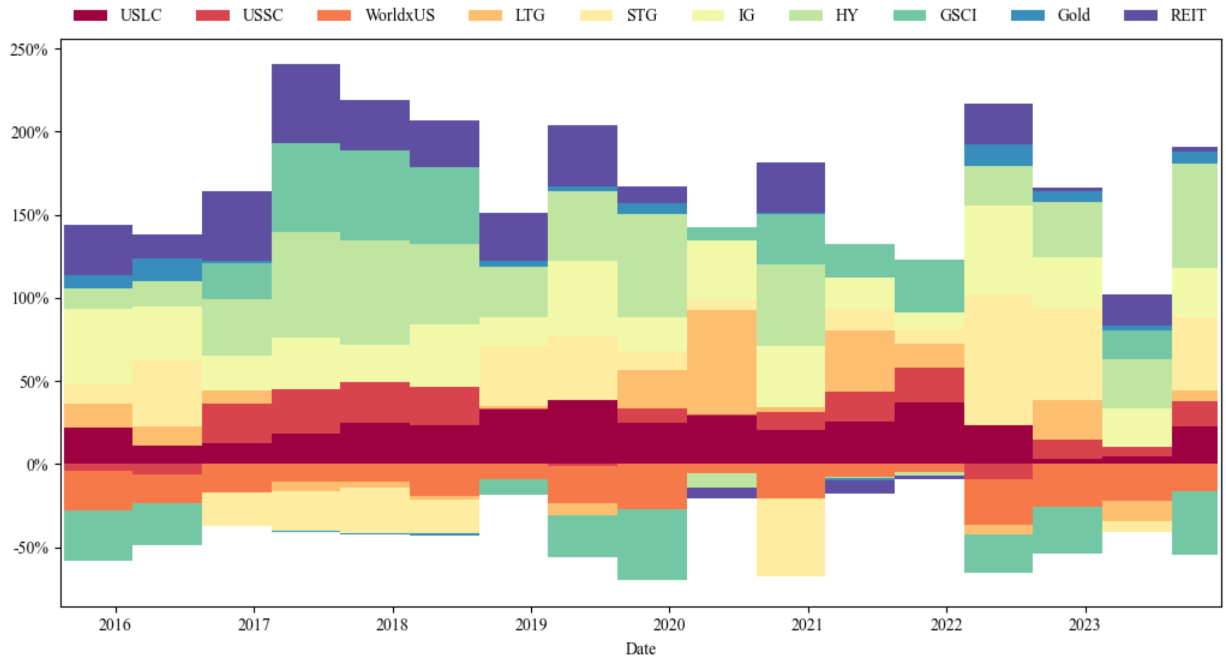


Table 4. Average Portfolio Allocation Across Economic Regimes

	USLC	USSC	World	LTG	STG	IG	HY	GSCI	Gold	REIT
Growth ↓ Inflation ↓	26.9%	13.0%	-15.3%	4.1%	3.4%	29.4%	31.6%	18.9%	2.0%	23.8%
Growth ↑ Inflation ↓	16.9%	7.5%	-19.0%	-0.5%	20.0%	31.9%	37.5%	-1.7%	5.2%	23.8%
Growth ↑ Inflation ↑	20.8%	6.8%	-16.8%	12.6%	17.9%	32.7%	30.1%	-0.4%	4.5%	22.0%
Growth ↓ Inflation ↑	26.1%	13.6%	-15.4%	21.2%	-4.0%	23.6%	30.2%	7.7%	1.5%	8.2%

Performance results are summarized in Table 5. The dynamic portfolio strategy lead to both superior returns and better risk control, with substantially higher risk-adjusted returns of 1.20 Sharpe ratio, compared to all other benchmark portfolios. The dynamic portfolio not only dominates all the relative-performance metrics but also leads to the highest absolute return and the lowest maximum drawdown, as shown in Figure 5. More notably, the dynamic portfolio has an equity beta of only 0.37, compared to 0.68 of the 60/40 portfolio, proven to be a low-correlation but high-yielding strategy. In fact, by adding the market neutral constraint[39] in the mean variance model, the beta can further go down to 0.21 with a still higher Sharpe of 1.04.

[39] It is not technically equity-market neutral but having the sum of asset weights equals to one in the MVO model.

Table 5. Out-of-Sample Portfolio Performance Results

	Dynamic Portfolio	Static MVO Benchmark[40]	60/40 Benchmark[41]	Equal-Weight Benchmark	S&P 500 Benchmark
Annualized Return	14.3%	6.7%	9.8%	6.7%	14.7%
Annualized Volatility	10.2%	12.8%	11.1%	9.7%	16.0%
Sharpe Ratio	1.20	0.37	0.70	0.49	0.79
Maximum Drawdown	-11.1%	-29.7%	-20.6%	-15.8%	-23.9%
Calmar Ratio	1.29	0.23	0.47	0.43	0.62
Information Ratio	0.91	–	0.48	0.00	0.80
Beta to S&P 500	0.37	0.66	0.68	0.54	–

Figure 5. Portfolio Absolute Performance Comparison

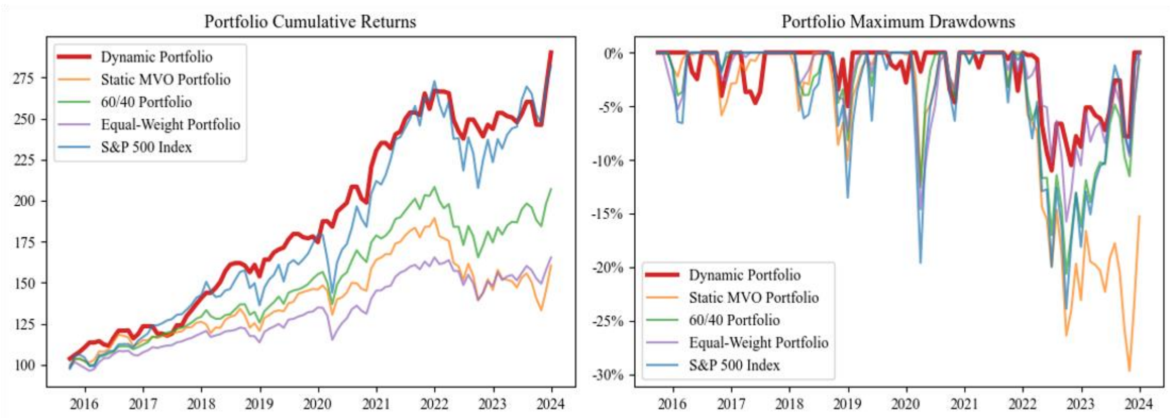


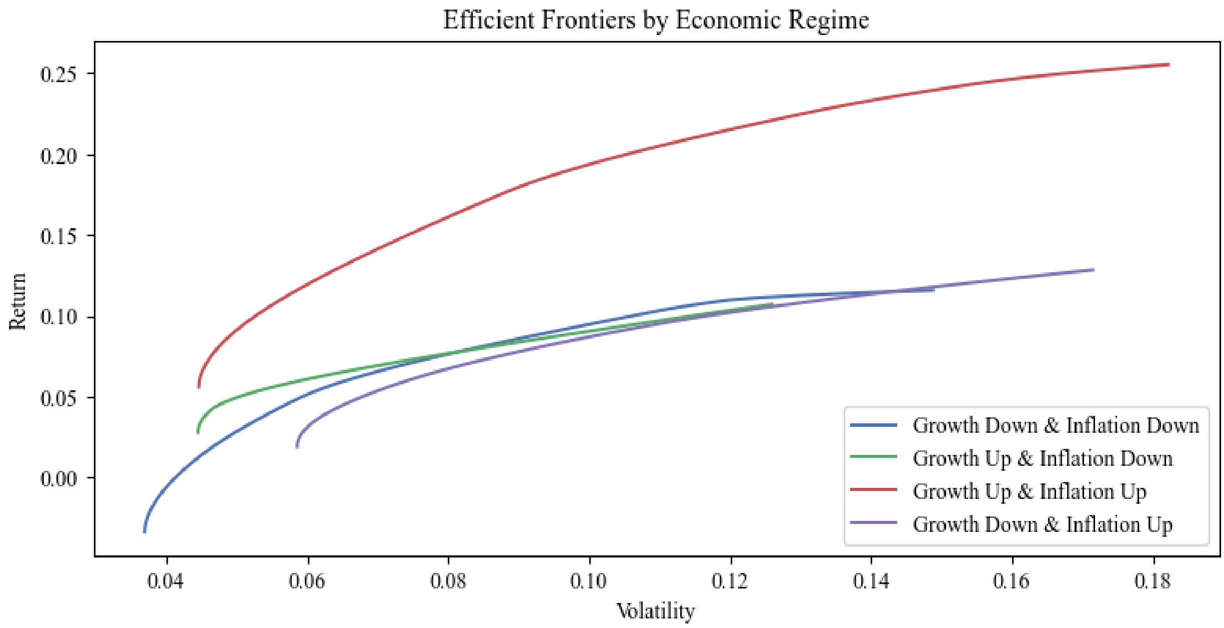
Table 6 further illustrates the diversification power of the dynamic portfolio strategy. It generates an average Sharpe ratio of 2.45 in the "Growth Down & Inflation Down" regime, compared to negative values of three benchmark portfolios. Thus, it is when traditional portfolios need diversification the most that this dynamic strategy provides the most diversification benefit. The efficient frontiers in each economic regime is shown in Figure 6. This also shows that the outperformance is robust to different types of economic environments.

[40] The static MVO portfolio is optimized, maximizing returns given the volatility level of 10%, based on the entire training sample with long-only constraint. The portfolio weight is 37.6% USSC, 43.2% LTG and 19.2% REIT.
[41] The 60% equity is S&P 500; the 40% bond is the simple average of LTG, STG, IG and HY.

Table 6. Dynamic Portfolio Performance by Economic Regime

	Dynamic Portfolio	Static MVO Benchmark	60/40 Benchmark	Equal-Weight Benchmark	S&P 500 Benchmark
Panel A: Annualized Return					
Growth ↓ Inflation ↓	18.3%	-0.7%	2.6%	0.6%	8.3%
Growth ↑ Inflation ↓	5.8%	-0.8%	4.9%	1.8%	5.9%
Growth ↑ Inflation ↑	15.9%	14.7%	17.5%	14.3%	24.6%
Growth ↓ Inflation ↑	18.0%	8.8%	9.1%	5.2%	14.4%
Panel B: Annualized Volatility					
Growth ↓ Inflation ↓	6.7%	10.5%	9.1%	6.8%	13.9%
Growth ↑ Inflation ↓	13.5%	16.3%	13.3%	10.7%	18.1%
Growth ↑ Inflation ↑	8.2%	11.8%	10.4%	8.8%	15.2%
Growth ↓ Inflation ↑	11.7%	11.9%	11.1%	11.8%	17.1%
Panel C: Sharpe Ratio					
Growth ↓ Inflation ↓	2.45	-0.26	0.06	-0.20	0.45
Growth ↑ Inflation ↓	0.28	-0.17	0.21	-0.01	0.22
Growth ↑ Inflation ↑	1.70	1.08	1.50	1.40	1.49
Growth ↓ Inflation ↑	1.37	0.57	0.63	0.28	0.73

Figure 6. Dynamic Portfolio Efficient Frontiers by Economic Regime



Sensitivity Analysis

The design of the dynamic portfolio strategy requires various input choices, including (1)the inclusion of Technical Macro signals, (2)the inclusion of data surprise in the Fundamental Macro indicators, (3)the adoption of economic-regime based covariance, as well as several key parameter settings, such as (1)the regularization parameter λ in the ℓ1 trend filter (2)short-selling flexibility in the mean variance optimization (3)the weight-adjusting factor γ for technical signals (4)portfolio rebalancing period. Overall, sensitivity analysis indicates that the input choices of this study lead to better outcomes. While selecting sub-optimal parameters negatively affects performance, it does not lead to highly inferior results. The main findings largely remain intact, supporting the outperformance of the dynamic strategy.

Table 7 considers the results with different input choices in the model. Compared to the baseline case, the dynamic portfolio in Panel B yields less favorable returns when excluding technical signals[41], suggesting the multi-strategy portfolio approach that combines Fundamental Macro and Technical Macro signals is advantageous. Similarly, including data surprise in the growth and inflation indicators generates better performance. Finally, unlike most literature that use the full-sample asset covariance as mean variance model input, this strategy produces a higher Sharpe ratio by deriving the covariance based on the prevailing economic regime.

Table 7. Portfolio Performance with Different Input Choices

Portfolios With Different Input Choices	Annualized Return	Annualized Volatility	Sharpe Ratio
Panel A: Benchmarks			
Dynamic Portfolio	14.3%	10.2%	1.20
Static MVO Benchmark	6.7%	12.8%	0.37
60/40 Benchmark	9.8%	11.1%	0.70
Equal-Weight Benchmark	6.7%	9.7%	0.49
S&P 500 Benchmark	14.7%	16.0%	0.79

[41] Multi-technical signals, combing value, momentum and sentiment factors, also outperform single signals.

Panel B: Inclusion of Technical Signals			
Dynamic Portfolio – Included (baseline)	14.3%	10.2%	1.20
Dynamic Portfolio – Not Included	11.6%	8.8%	1.08
Panel C: Inclusion of Data Surprise			
Dynamic Portfolio – Included (baseline)	14.3%	10.2%	1.20
Dynamic Portfolio – Not Included	11.2%	9.9%	0.93
Panel D: Asset Covariance Measure			
Dynamic Portfolio – Regime-Based Covariance (baseline)	14.3%	10.2%	1.20
Dynamic Portfolio – Full-Sample Covariance	10.9%	9.05%	0.98

Table 8 reports the robustness of the performance results with respect to changes in parameter settings used in the out-of-sample backtest. First, the regularization parameter λ[42] controls the smoothness of the trend function for the macro indicators, where 0.3 is set as baseline to capture sufficient short-term momentum changes in growth and inflation. A smaller (λ=0.1) or bigger (λ=0.5) value leads to slightly lower Sharpe ratio but still outperforms all benchmarks, suggesting that a λ of 0.3 best captures the shifts in economic regimes. Second, the mean variance optimization is set to allow short-selling with a weight bound of -50% – 50% for each asset, in order to build a strategy with lower traditional market beta. Even following the traditional long-only constraint (a weight bound of 0%–100%) as shown in Panel C, the dynamic portfolio still generates a higher risk-adjusted return. Third, the weight-adjusting factor γ determines how much the final portfolio weight will deviate from the regime-optimal portfolio based on the sum of technical signal scores. Different values of γ do not have a meaningful impact on the portfolio performance. Finally, rebalancing period is an important consideration. The baseline is set as six months given investors' underreaction to macroeconomic news and transaction costs. Panel E shows that rebalancing every month is less ideal, consistent with the

[42] The trend-filtered series converges to the original data as the parameter λ goes to zero, whereas it becomes smoother and closer to a straight line as the parameter λ goes to infinity.

theory and previous findings, while rebalancing every twelve months yields better results. Overall, the performance results are robust with different parameter settings.

Table 8. Portfolio Performance with Different Parameter Settings

Portfolios With Different Parameter Settings	Annualized Return	Annualized Volatility	Sharpe Ratio
Panel A: Benchmarks			
Dynamic Portfolio	14.3%	10.2%	1.20
Static MVO Benchmark	6.7%	12.8%	0.37
60/40 Benchmark	9.8%	11.1%	0.71
Equal-Weight Benchmark	6.7%	9.7%	0.49
S&P 500 Benchmark	14.7%	16.0%	0.79
Panel B: Regularization parameter λ of ℓ1 Trend Filter			
Dynamic Portfolio: $\lambda = 0.1$	13.7%	14.1%	0.83
Dynamic Portfolio: $\lambda = 0.3$ (baseline)	14.3%	10.2%	1.20
Dynamic Portfolio: $\lambda = 0.5$	12.8%	10.3%	1.05
Panel C: Mean Variance Asset Weight Constraint			
Dynamic Portfolio: Allow Short-Selling -50% – 50% (baseline)	14.3%	10.2%	1.20
Dynamic Portfolio: Long-Only 0% – 100%	12.0%	10.0%	1.00
Panel D: Technical Signals Weight-Adjusting Factor γ			
Dynamic Portfolio: $\gamma = 10\%$	12.4%	9.1%	1.15
Dynamic Portfolio: $\gamma = 30\%$ (baseline)	14.3%	10.2%	1.20
Dynamic Portfolio: $\gamma = 50\%$	16.0%	12.0%	1.17
Panel E: Portfolio Rebalancing Period			
Dynamic Portfolio: Every Month	7.9%	10.3%	0.57
Dynamic Portfolio: Every 6 Month (baseline)	14.3%	10.2%	1.20
Dynamic Portfolio: Every 12 Month	18.0%	11.7%	1.36

CONCLUSION

This study develops a systematic multi-strategy approach for dynamic asset allocation strategies by integrating macroeconomic signals and technical signals within a layered framework. The strategy employs mean variance optimization with views generated from macroeconomic regime signals to construct the portfolio and apply a rule-based signal scoring system from value, momentum and sentiment signals. Out-of-sample analysis shows that the multi-strategy dynamic portfolio outperforms static benchmark portfolios and provides diversification benefits, with robust results under different input and parameter settings in the model.

The empirical results has two major implications for macro-based dynamic portfolio strategies. First, the inclusion of technical signals within a layered framework adds value to a macroeconomic-based portfolio strategy. The portfolio that incorporates technical signals produces a Sharpe ratio of 1.20, compared to 1.08 of that with only macroeconomic signals, indicating that a combination of different signals captures additional risk premia with superior performance. Second, deriving the asset covariance based on the prevailing economic regime in mean-variance optimization enhances risk-adjusted returns. The traditional full-sample covariance portfolio yields a Sharpe ratio of 0.98, compared to 1.20 of the regime-based covariance portfolio. The suggests that asset correlations also depend on varying economic regimes and a portfolio adopting regime-based covariance can improve diversification thus the out-of-sample performance.

The proposed investment framework could be extended in various directions. The layered approach, which generates portfolio weight using macroeconomic signals first then fine-tune with technical signals, can be operated the other way around. It would be interesting to see how a technical-first, macroeconomic-later strategy performs differently. It also seems worthwhile to incorporate more signals that suit macro assets, such as interest rates, liquidity, volatility, carry, cross-sectional momentum, etc. Moreover, the asset allocation model can be easily applied to dynamic factor allocations to further enhance risk-adjusted returns.

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