A Century of Macro Factor Investing - Diversified Multi-Asset Multi-Factor Strategies through the Cycles*

Alexander Swade[1,2], Harald Lohre[1,2], Sandra Nolte[1], Mark Shackleton[1] and Laurens Swinkels[2,3]

[1]Lancaster University Management School†
[2]Robeco ‡
[3]Erasmus University Rotterdam §

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Abstract

We diversify an investment portfolio across macroeconomic factors that are mimicked by investable asset classes and style factors. Using a century of global data we analyze the resulting macro factor portfolio's sensitivities to different macroeconomic scenarios and highlight the relevance of navigating time variation in macroeconomic risk premia. Specifically, we adapt the portfolio allocation to align with the identified macro environment as predicted by a forward-looking business cycle model. A Black-Litterman framework is used to thus improve upon a diversified macro factor allocation and to further tap into predictive asset class and style factor signals.

Keywords: Macroeconomic factors, diversification, business cycles, Black-Litterman

JEL Classification: C38, C41, G11, G15

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Corresponding author: Alexander Swade, a.swade@lancaster.ac.uk

†Lancaster University Management School, Bailrigg, Lancaster LA1 4YX, United Kingdom.

‡Robeco Institutional Asset Management B.V., Weena 850, 3014 DA Rotterdam, The Netherlands.

§Erasmus School of Economics, Erasmus University Rotterdam, Burgemeester Oudlaan 50, 3000 DR Rotterdam, The Netherlands.

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Abstract

We diversify an investment portfolio across macroeconomic factors that are mimicked by investable asset classes and style factors. Using a century of global data we analyze the resulting macro factor portfolio's sensitivities to different macroeconomic scenarios and highlight the relevance of navigating time variation in macroeconomic risk premia. Specifically, we adapt the portfolio allocation to align with the identified macro environment as predicted by a forward-looking business cycle model. A Black-Litterman framework is used to thus improve upon a diversified macro factor allocation and to further tap into predictive asset class and style factor signals.

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A guiding principle in the theory and practice of portfolio management is to maximize returns while controlling for associated risks. Besides asset class-specific risks, growth and inflation risks are amongst a few economic risk drivers that crucially drive investment portfolio performances, and a prudent multi-asset investor would look to navigate such risks across asset classes through a diversified portfolio. Such an approach rests on a long investment horizon, which eventually will see alternative investment philosophies or styles performing better over shorter horizons. However, the underlying risk premia are rewarded throughout different economic environments, and, therefore, portfolios targeting such cross-sectional risks come with more balanced risk-return profiles and are expected to be more resilient.

One way to harvest the long-term risk premia across asset classes and exploit their medium-term cyclicality is to dynamically allocate to specific risk premia based on macroeconomic indicators, e.g., gross domestic product (GDP), consumer price index (CPI), unemployment rates, default-, or term spreads. Such indicators are deemed relevant not only theoretically but also empirically for explaining time-variation in asset class returns (e.g., Chen, Roll, and Ross, 1986, Estrella and Hardouvelis, 1991, Gilchrist and Zakrajšek, 2012, or Boons, 2016), but less so for explaining the variation of asset class specific style factor returns (Ilmanen, Israel, Moskowitz, Thapar, and Lee, 2021, Baltussen, Swinkels, and Van Vliet, 2021, or Baltussen, Swinkels, Vliet, and Vliet, 2023). It is thus a challenge to conceive a multi-asset portfolio allocation that allows investors to diversify across salient macro risk factors while simultaneously exploiting time variation in asset class as well as style factor returns.

Alternatively, the literature analyzes key drivers of asset class and style factor returns by decomposing the given investment universe via statistical techniques (e.g., Greenberg, Babu, and Ang, 2016 or Bass, Gladstone, and Ang, 2017). The resulting statistical factors are then linked to macroeconomic risks such as economic growth and inflation, prompting to label them 'macro factors'. The underlying principle is to pin down the inherent variation in the returns of different asset classes and style factors rather than targeting pure macroeconomic indicators that could inform about an economic state. In this paper, we emphasize the use of such macro factors for portfolio construction and analyze the robustness of diversified macro factor investing throughout different economic cycles over a 100-year sample period. For augmenting such diversified macro allocation, we investigate a dynamic approach that accounts for the impact of these cycles on the performance of different asset classes and style factors. To this end, we develop specific macro factor views that result in macro factor weights based on the identified economic cycle. These macro factor views can readily be transferred into tactical allocation decisions at the asset class or style factor level, and we demonstrate how these signals can be exploited in a Black-Litterman framework.

Our work is related to Amato and Lohre (2020), who analyze macro factor investing based on a broad set of asset classes as well as to Swade et al. (2021) who extend the investment universe to also include the corresponding style factors. However, these works focus on rather short samples, leaving the authors with only few macroeconomic regimes to navigate. In contrast, our study enjoys a considerably increased sample period of 100 years, allowing us to evaluate macro factor investing over multiple economic cycles. Specifically, we construct a dynamic macro factor allocation strategy in the spirit of Scherer and Apel (2020) but we operationalize macro factor views in a Black-Litterman framework. Additionally, we augment this macro-sensitive strategy by individual asset class and style factor views such as time-series factor momentum (Gupta and Kelly, 2019).

We contribute to the literature in several ways. First, we extend the macro factor investing evidence by constructing and analyzing multi-asset multi-factor portfolios over a 100-year period. This comprehensive sample period enables a better mapping of asset classes and style factors onto macro factors as well as a larger number of economic cycles to navigate and evaluate to gauge the efficacy of tactical timing models. Specifically, we can account for different economic regimes and analyze their impact on the robustness of the constructed portfolios. Second, we adapt models used in the business cycle literature to pair the construction process of macro factor portfolios with identified macroeconomic cycles. The resulting dynamic macro factor allocation enables capturing the cyclicality of macro factors, asset classes, and style factors alike while mitigating salient macroeconomic risks. Third, we incorporate these macro factor views in a classic Black-Litterman framework by transforming them into investable style factor and asset class views. The resulting setup can readily be augmented by further individual style factor views, offering a highly versatile strategic and tactical macro allocation framework.

Our results confirm the medium-term cyclicality of macro-based portfolios and their sensitivity to different economic regimes and periods of distress. We build diversified macro factor mimicking portfolios that retain the genuine macro characteristic but prove to be more robust over the last century than the underlying macroeconomic factor by virtue of diversification effects. Exploiting their time variation a tactical allocation overlay yields an information ratio of 0.49 out-of-sample compared to a diversified macro factor risk parity portfolio. Combining the latter with time-series momentum signals increases the information ratio to 1.73. The outperformance varies across specific economic regimes, with recovery periods benefiting the most. Please note however that the primary objective of this paper is to present a framework for macro-sensitive multi-asset multi-factor allocation. Our empirical results serve to illustrate the potential of such an approach, but do not aim to represent directly replicable real-life investment strategies.

The remainder of this paper is structured as follows. Section 2 reviews factor modeling and investing as well as the challenges associated with investing through different economic cycles. It also explains how to back out macro factor-mimicking portfolio weights based on the orthogonalization technique of Meucci, Santangelo, and Deguest (2015). Section 3 navigates a sample of 100 years through the lens of a macro factor investor by constructing robust macro factor-mimicking portfolios based on asset classes and style factors and testing for their diversification properties in different macroeconomic regimes. Following this strategic allocation approach, Section 4 emphasizes the use of a dynamic business cycle model to navigate macro factor premia more effectively. The resulting portfolios are complemented by predictive style factor and asset class tilts. Section 5 concludes.

2 Macro factors and mimicking portfolios

2.1 Reviewing macro and style factor research

Ever since the introduction of the seminal capital asset pricing model (CAPM)[1] and Ross's (1976) arbitrage pricing theory (APT), a variety of factor models have been put forward to explain asset returns. Although these models differ in the choice of explanatory factors, they all follow the same intuition. For instance, under APT, the returns $\boldsymbol{R} \in \mathbb{R}^{N \times 1}$ of N risky assets follow a factor intensity structure expressed as:

$$\boldsymbol{R} = \boldsymbol{B} \cdot \boldsymbol{F} + \boldsymbol{\varepsilon}, \tag{1}$$

where $\boldsymbol{F} \in \mathbb{R}^{K \times 1}$ represents the returns of K systematic factors with respective factor loadings $\boldsymbol{B} \in \mathbb{R}^{N \times K}$ and asset-specific idiosyncratic risks $\boldsymbol{\varepsilon} \in \mathbb{R}^{N \times 1}$, which are assumed to be uncorrelated across assets and factors and have zero mean.

Following APT, many different factor models have been developed to determine asset prices (see, for example, Fama and French (1993, 2015); or Hou, Xue, and Zhang (2015) in the realm of equity factor models). Most factor models deal with asset-specific factors, i.e., factors that are constructed by sorting on asset class-specific characteristics. Notwithstanding, various studies have shown macroeconomic variables to be relevant in explaining individual asset prices and even emphasized that asset prices are not only sensitive to economic news but also find the related risks being priced, see, e.g., Chen, Roll, and Ross (1986), Fama and French (1989), Pontiff and Schall (1998), or Ilmanen, Maloney, and Ross (2014). Macroeconomic variables, such as industrial production, inflation shocks, or more financial market-related ones like the term spread, have not only been tested for their effect on as-

[1]See Sharpe (1964), Lintner (1965), Mossin (1966) and Treynor (1961).

set class returns but also on individual style factors. For example, Chordia and Shivakumar (2002) suggest that profits of momentum strategies can be explained by a set of lagged macro variables, and adjusting for such variables significantly curbs momentum profits.

In a similar vein, Cooper, Mitrache, and Priestley (2022) as well as Kirby (2019) document significant explanatory power of macroeconomic variables for value and momentum factors. They highlight the time-dependency of different style factor returns with respect to macroeconomic regimes and structural breaks. Yet, although Ilmanen et al. (2021) confirm this significant time variation in risk-adjusted style factor returns over a century of historic data, they deem them hard to forecast based on macroeconomic variables. This is in line with Baltussen, Swinkels, and Van Vliet (2021) who also do not find significant explanatory power of macro variables to forecast style factors using a spanning analysis covering about two centuries.

These seemingly contradictory findings might be rationalized through structural breaks that separate different economic regimes. Specific style factors might come with differentiated performance patterns for individual regimes but seem fairly unaffected by macro changes over the whole sample period. In this context, Ang and Bekaert (2004) propose a regime-switching model characterizing different market regimes in terms of expected returns and conditional volatility. They emphasize the strong performance of regime-shifting investment strategies compared to static allocations. Such evidence is substantiated by various researchers in the context of factor timing strategies based on different regime classifications (see, e.g., Polk, Haghbin, and De Longis, 2020; Chousakos and Giamouridis, 2020). To this end, Markov-switching models are frequently used, see, e.g., Kritzman, Page, and Turkington (2012) who forecast regimes in market turbulence, inflation, and economic growth. An alternative approach for navigating different regimes has been put forward by Jurczenko and Teiletche (2018). They propose an alternative to the framework of Black and Litterman (1991, 1992) and ultimately use views generated by macroeconomic regime signals to construct a linear combination of a passive risk-based portfolio and a mean-variance optimized portfolio.

Another strand of the style factor timing literature deals with slower-moving models based on economic regimes. These models typically come with fewer changes between the different regimes, i.e., the necessary criteria to pinpoint a regime switch are more restrictive. For instance, Blin, Ielpo, Lee, and Teiletche (2021) use a nowcasting procedure to identify business cycles; Van Vliet and Blitz (2011) and Scherer and Apel (2020) use classic financial market variables to classify different cycles. All these papers document significant exposure of some style factor strategies to different economic regimes, which at the very least suggests some room for profitable timing of style factors.

2.2 Constructing macro factor-mimicking portfolios

Macro factors directly follow the factor representation in equation (1) and the implications of APT; however, there is no preferred macro factor model which leaves a few choices to the researcher. Besides the choice of factors, there is an important challenge in dealing with macro factors instead of asset class-specific style factors: Macro factors lack direct investability. Whilst style factors are usually represented by long-short portfolios created from an investable universe, macro factors call for mapping them to tradable instruments. Therefore, investors typically resort to mimicking portfolios that consist of tradable assets but have similar properties as the given macro factor.

Addressing the said challenges of macro factor investing we resort to a specific set of macro factors. Ideally, the chosen macro factor representation would consist of uncorrelated factors to speed the construction of diversified macro factor portfolios (Swade et al., 2021). Given that macroeconomic factors need to be mimicked by investable assets anyways, one might as well resort to orthogonal factor versions instead as suggested by Meucci, Santangelo, and Deguest (2015). Given a K-factor model, with factor returns $\boldsymbol{F} \in \mathbb{R}^{K \times 1}$, their approach expresses portfolio returns $\boldsymbol{R^w}$ of a weighted portfolio with portfolio weights $\boldsymbol{w} \in \mathbb{R}^{N \times 1}$ for

N investable assets in terms of uncorrelated factors $\boldsymbol{F}_{\text{orth}}$:

$$\boldsymbol{R}^{\boldsymbol{w}} = \boldsymbol{w}^{\intercal}\boldsymbol{R} = \boldsymbol{b}^{\intercal}\boldsymbol{F} = \boldsymbol{b}_{\text{orth}}^{\intercal}\boldsymbol{F}_{\text{orth}}, \tag{2}$$

where $\boldsymbol{b}$, $\boldsymbol{b}_{\text{orth}} \in \mathbb{R}^{K\times 1}$ denote the factor loadings of the related factors $\boldsymbol{F}$, $\boldsymbol{F}_{\text{orth}} \in \mathbb{R}^{K\times 1}$. A key component is the minimum torsion matrix $\boldsymbol{t}_{\text{orth}}$ to transform the original factors into uncorrelated ones such that $\boldsymbol{F}_{\text{orth}} = \boldsymbol{t}_{\text{orth}}\boldsymbol{F}$. We follow Meucci, Santangelo, and Deguest (2015) and choose the minimum torsion matrix $\boldsymbol{t}_{\text{orth}}$, which minimizes the tracking error to the original factors as:

$$\mathbf{t}_{\text{orth}} = \underset{\text{Cor}(\mathbf{tF})=\mathbf{Id}_K}{\arg\min} \sqrt{\frac{1}{K}\sum_{k=1}^{K} \text{Var}\left(\frac{(\boldsymbol{t}\mathbf{F})_k - \mathbf{F}_k}{\sigma_k^F}\right)}, \tag{3}$$

where $\boldsymbol{t} \in \mathbb{R}^{K\times K}$, $\boldsymbol{Id}_K$ represents the K-dimensional identity matrix, and $\sigma_k^F \in \mathbb{R}$ denotes the volatility of factor $\boldsymbol{F}_k$. To arrive at investable factor portfolios, we can compute macro factor-mimicking portfolio (MFMP) weights as $\boldsymbol{t}_{\text{orth}}\boldsymbol{B}^{-1}$, and their returns are given by:

$$\boldsymbol{R}_{MFMP} = \boldsymbol{t}_{\text{orth}}\boldsymbol{B}^{-1}\boldsymbol{R}, \tag{4}$$

where $\boldsymbol{B}^{-1} \in \mathbb{R}^{K\times N}$ is the Moore-Penrose inverse of the original factor loadings matrix $\boldsymbol{B}$.[2] In the following, we leverage this framework and build out investable MFMPs as core building blocks of a macro factor allocation strategy.

[2] We refer to Swade et al. (2021) for more details on the construction and attributes of orthogonal factors.

3 A century of macro factor investing

3.1 Data

In implementing a macro factor-based investment approach, we work with a global set of assets, style factors, and macro factors. Our sample is based on Baltussen, Swinkels, and Van Vliet (2021) and considers 104 years of monthly data from 31 January 1918 through 31 December 2021. The data set is constructed using financial market prices and macroeconomic series from Bloomberg, Datastream, and the OECD. These series are combined with data from Global Financial Data as well as monthly commodity future data from Chicago Board of Trade annual reports.[3] All returns are in excess of local risk-free rates and expressed in U.S. dollars.

Our final set of investable assets features one global index instrument for each of the three asset classes equities, bonds, and commodities as well as four style factors within each of these asset classes and within currencies. The four style factors are betting against beta (BAB), carry, momentum, and value. These style factors are defined as follows: Carry is defined as the implied yield on each instrument, i.e., futures implied excess dividend yield for equities, the interest rate differential for currencies, excess bond yield plus rolling curve for bonds, and futures implied convenience yield for commodities. Value is the dividend yield for equities, the real yield for bonds, a five-year reversal in spot prices for commodities, and absolute and relative purchasing power parity for currencies. Momentum is the 12-month–1-month excess return. BAB is defined as low beta assets minus high beta assets with positions neutralized for the ex-ante beta, where beta is measured relative to the global asset class portfolio.

Table 1 gives the descriptive statistics of the described investment universe. For equities, we consider a global equity index that yielded 9.41% return at 15.07% volatility annualized

[3] For a detailed overview of how the individual time series are constructed, we refer the reader to Baltussen, Swinkels, and Van Vliet (2021) as well as the corresponding online appendix.

over the sample period from January 31, 1918, to December 31, 2021. The equity style factors exhibit annualized returns ranging from 2.17% (Value) to 7.11% (Momentum) with volatilities around 10.30%. As for fixed income, the utilized global bond index yields 5.06% return at 3.94% volatility, and the corresponding four style factors show annualized returns ranging from 0.76% (BAB) to 6.50% (Carry) and come at 8.16% (BAB) to 11.35% (Carry) volatility. Commodities are the most volatile asset (18.57%) and have an annualized return of 2.69%. The corresponding style factors have returns between 1.27% (BAB) and 5.70% (Momentum). Lastly, we consider four currency factors with annual returns ranging from 0.32% (Value) to 3.35% (Carry). Overall, 15 out of these 20 style factor strategies have Sharpe ratios significantly greater than zero as indicated by their t-statistics in Table 1.

[Table 1 about here.]

Next, we turn to the choice of macro factors. Ideally, macro factors are representative of investors' concerns and exogenous shocks across regions and asset classes. Specifically, we choose a parsimonious set of three macro factors to describe, model, and navigate distinct economic regimes. The three factors are Growth, Inflation, and Defensive. Growth and Inflation directly address investors' core concerns about expected future cash flows. Whilst the growth factor determines future cash flows, inflation crucially impacts their present value. The third factor, Defensive, is expected to do well when the other two factors perform poorly. Swade et al. (2021) rationalize this choice of macro factors by statistical clustering of a broad multi-asset multi-factor universe. Similar to Lohre, Hixon, et al. (2020), they build corresponding macro factor-mimicking portfolios to investigate their efficacy in macro factor completion strategies.

Before constructing diversified and robust mimicking portfolios for these three macro factors, we need to select relevant time series proxies for these three macro dimensions. Specifically, we choose representative global indices as approximations of the genuine macro factors, i.e., global equities (Growth), commodities (Inflation) as well as global treasuries (Defensive). Next, we mimic these proxies using the whole set of asset classes and style factors to create highly diversified macro factor portfolios. Of course, the choice of macro factors and their representative proxy can be altered based on investor preference without any loss of generality of our proposed macro factor investing framework. For instance, a naive approach would simply define the three said asset class indices as macro factor portfolios. However, one would thus forego the key virtue of the proposed MFMP construction which is to bring diversification within and across the various MFMPs.

Our choice is in line with alternatives that look to identify the most dominant components of asset return variation in a given portfolio (see, for example, Bass, Gladstone, and Ang, 2017). While the authors end up using seven macro factors that account for over 95% of the comovement of asset class returns, our choice of macro factors resonates with their first three principal components that account for 85% of the cross-asset movements. However, instead of resorting to such statistical factors, we choose macro factors close to investable assets by characterizing macro factors as proxies of global asset baskets. As a consequence, we give up some statistical relevance but we benefit from an increase in economic relevance and robustness of the resulting MFMPs.

3.2 Constructing robust MFMPs

Given the set of macro factors and investable assets, we aim to construct robust portfolios clearly mimicking the orthogonalized macro factors throughout various economic cycles. We calculate these MFMPs as stated in Equation (4). In addition to the three individual MFMPs we also construct the macro factor risk parity (MFRP) portfolio, that targets equal risk contribution of the orthogonalized MFMPs. The individual factor contributions $\boldsymbol{\rho} \in \mathbb{R}^{K\times 1}$ to the overall portfolio variance can be derived as:

$$\boldsymbol{\rho} = \frac{\boldsymbol{w}_{\mathrm{orth}}^2 \odot \boldsymbol{\sigma}_{\mathrm{orth}}^2}{Var\left(\boldsymbol{R}^w\right)}, \tag{5}$$

where $\odot$ is the Hadamard product.[4] To gauge the mimicking portfolios' ability to measure the targeted macro factor exposure we compute the *effective number of uncorrelated bets* based on Meucci's (2009) measure of portfolio diversification:

$$\mathcal{N}_{\text{Ent}} = \exp\left(-\boldsymbol{\rho}^{\intercal}\ln\left(\boldsymbol{\rho}\right)\right). \tag{6}$$

The effective number of uncorrelated bets will range from 1 (where the portfolio is entirely driven by a single macro factor, i.e., $\rho_k = 1$ and $\rho_j = 0$ for $j \neq k$) to K (for a portfolio with equal factor risk contributions, i.e., $\rho_k = \frac{1}{K}$ for all k).

Our empirical analysis builds on an expanding window with an initial window size of 48 months allowing for out-of-sample observations starting in January 1922. To mitigate adverse effects from potential estimation biases, we run a constrained mean-variance optimization that targets the unconstrained MFMP in light of a quadratic transaction cost (TC) penalty:

$$\max_{\boldsymbol{w}} \boldsymbol{w}'\boldsymbol{\mu} - \frac{\gamma}{2}\boldsymbol{w}'\boldsymbol{\Sigma}\boldsymbol{w} - \lambda_{TC}\boldsymbol{\Gamma}'|\Delta\boldsymbol{w}|^2, \tag{7}$$

where $\boldsymbol{\Gamma} \in \mathbb{R}^{N\times 1}$ and $\lambda_{TC} \in \mathbb{R}$ are the asset-specific transaction cost vector and its scaling parameter; $\Delta\boldsymbol{w} = \boldsymbol{w} - \boldsymbol{w}_0$ is the difference between target weights, $\boldsymbol{w}$, and initial portfolio holdings, $\boldsymbol{w_0}$. For targeting the specified MFMP, the optimization is fed with expected returns $\boldsymbol{\mu} = \gamma\boldsymbol{\Sigma}\boldsymbol{w}^*$, where $\gamma \in \mathbb{R}$ is the risk aversion coefficient, $\boldsymbol{\Sigma} \in \mathbb{R}^{N\times N}$ is the asset covariance matrix, and $\boldsymbol{w}^* \in \mathbb{R}^{N\times 1}$ is the weights vector of the targeted macro portfolio. Following Dichtl, Drobetz, Lohre, and Rother (2021) and Swade et al. (2021), we set $\lambda_{TC} = 0.3$, $\gamma = 5$, and assume $\boldsymbol{\Gamma}$ is linear in the diagonal of the variance-covariance matrix. Note that all means and covariance matrices in this paper are calculated using sample means and covariance estimators based on the corresponding analysis period.

Figure 1 depicts the resulting asset class and style-factor portfolio weights (left column) as well as the risk decomposition in terms of macro factor risk (right column). The first three

[4] See Swade et al. (2021) for details on computing risk contributions of single orthogonal factors.

rows show single MFMPs whilst the last row shows the long-only macro factor risk-parity (MFRP) portfolio. All three single MFMPs display asset return loadings similar to that of the pure (unorthogonalized) factors, with clear and mostly stable style factor exposures through time. The defensive and inflation MFMPs faithfully mimic their underlying factor, exhibiting almost pure factor risk exposures to the targeted macro factor. While the growth MFMP exhibits some non-growth macro factor exposure in the early sample, it is also meaningfully tracking growth risk through time. Lastly, we turn to the diversified risk parity strategy along the three MFMPs, labeled MFRP portfolio (last row).[5] Despite constraints, this portfolio maintains equal risk contributions of all underlying macro factors over time. Also, the corresponding asset weights are fairly stable over time without unduly high turnover or leverage.

[Figure 1 about here.]

3.3 MFMPs through the cycles

We next explore the MFMPs' sensitivity to different macroeconomic market cycles and we leverage 100 years of data covering multiple economic and market regimes, including several bear markets and recessions. To classify market states as regimes, we consider the following approaches. First, we differentiate between 'good' and 'bad' market states as characterized by positive or negative global equity returns. Specifically, bull and bear market periods are classified based on calendar year returns of the global equity return series, and we thus pinpoint 22 bear and 78 bull market years in the out-of-sample period. Second, we determine recessionary versus expansionary periods. A given calendar year is classified as recessionary when it is considered recessionary at least six months by the NBER; otherwise, it is classified as expansionary. The out-of-sample period has 15 recessionary and 85 expansionary years. Lastly, we analyze the MFMPs' performance in distinct growth-inflation regimes.

[5]Early applications of diversified risk parity strategies based on PCA-based factor portfolios can be found in Lohre, Opfer, and Ország (2014) for multi-asset investing and in Lohre, Neugebauer, and Zimmer (2012) for equity portfolios selection.

Specifically, we divide the out-of-sample period into four regimes, based on the annual return of the simple growth factor and end-of-year realized inflation. The resulting regimes are characterized by positive (negative) annual growth returns in combination with positive (negative) inflation. Our out-of-sample data comprises 6 (2) years of positive (negative) growth and negative inflation as well as 72 (20) years with positive (negative) growth and positive inflation.

Table 2 highlights the performance of the three original macro factors (Panel A) as well as the orthogonal MFMPs and the diversified risk parity portfolio (MFRP, Panel B). The full sample statistics (first column) illustrate that the growth factor as well as its associated MFMP are the most profitable in terms of absolute returns, yielding annualized historical returns of 10.69% and 19.88%, respectively, followed by the defensive factor with 5.08% and 13.25%, respectively. On a risk-adjusted basis, the latter MFMP is most appealing with a Sharpe ratio of 1.56 compared to 0.98 for the growth MFMP. The inflation MFMP has an annualized return of 10.34% and a Sharpe ratio of 0.37.

[Table 2 about here.]

Focusing on the different 'good' and 'bad' states, we clearly see the risks associated with investing in risky assets. Whilst the growth MFMP has extraordinary annualized returns in positive regimes like bull markets (27.93%) or expansionary regimes (23.93%), its performance lags in 'bad' states (-8.65%) or recessionary periods (-3.06%). The most robust MFMP is the defensive one, which has the highest Sharpe ratios throughout bear versus bull markets (1.61 vs 1.39) as well as recessionary versus expansionary regimes (1.87 vs 1.49).

These observations also hold across the four distinct growth/inflation regimes. Here, the defensive MFMP has the highest Sharpe ratios for the majority of considered macro regimes, i.e., positive growth paired with negative inflation (1.65 for 6 years) or negative growth paired with positive (1.49 for 20 years) or negative inflation (0.38 for 2 years), respectively. However, the growth MFMP performs best with a Sharpe ratio of 1.66 in positive growth and inflation regimes which was the prevailing regime (72 years) in our sample period. The inflation MFMP performs best in the positive growth and inflation regime (0.58) but still lags behind the other two portfolios.

Overall, we see diversification taking effect, with all MFMPs experiencing larger risk-adjusted performance than the original factors. Yet, we still observe relevant mimicking properties, and the MFMPs' behavior is consistent with that of the original macro factors in specific regimes. Naturally, the single portfolios perform best in their targeted regime, but the single MFMPs are more robust across various macroeconomic states.

Maximizing diversification, we next build the MFRP portfolio across the three individual MFMPs. The diversified MFRP portfolio benefits from macro diversification effects curbing the downside associated with poor macroeconomic conditions while only giving up a small portion of the upside. Importantly, the MFRP portfolio has the highest Sharpe ratios for the majority of considered macro regimes, i.e., bull markets (1.74), expansionary periods (1.56) as well as positive growth/inflation regimes (1.77). Still, the MFRP lacks the defensive MFMP in a few periods, e.g., bear markets (0.29 vs. 1.39) or recessionary periods (0.59 vs. 1.87). Naturally, this suggests room for improving portfolio performance through dynamic portfolio allocation which we investigate subsequently.

4 Dynamic macro factor investing

4.1 Combining macro and style factor views via Black-Litterman

The previous section suggests that a dynamic macro factor allocation correctly anticipating macro factor cyclicality can outperform the diversified MFRP portfolio. To this end, we investigate tactical allocation signals by complementing strategic portfolio allocations in the Black-Litterman (BL) (1991, 1992) framework. In particular, we generate macro factor views as well as asset class and style factor views to refine the expected returns in the mean-variance optimization (7). Using the standard master BL formula for refining return and covariance estimates, the return inputs result from:

$$\boldsymbol{\mu}_{BL} = \left[(\tau\boldsymbol{\Sigma})^{-1} + \boldsymbol{P}^T\boldsymbol{\Omega}^{-1}\boldsymbol{P}\right]^{-1}\left[(\tau\boldsymbol{\Sigma})^{-1}\boldsymbol{\Pi} + \boldsymbol{P}^T\boldsymbol{\Omega}^{-1}\boldsymbol{Q}\right], \tag{8}$$

with $\boldsymbol{\Sigma}$ referring to the variance-covariance matrix of all assets and style factors as well as $\tau \in \mathbb{R}$ being a scaling constant. $\boldsymbol{\Omega} \in \mathbb{R}^{L\times L}$ represents the view uncertainty by a diagonal covariance matrix of error terms from the expressed views. $\boldsymbol{P} \in \mathbb{R}^{L\times N}$ identifies the asset classes and style factors subject to views, i.e., it is a projection matrix loading on affected asset classes and style factors. The equilibrium views are given by matrix $\boldsymbol{\Pi} \in \mathbb{R}^{N\times 1}$ and are extracted from the strategic benchmark (bm) allocation: $\boldsymbol{\Pi} = \gamma\boldsymbol{\Sigma}\boldsymbol{w}_{bm}$. In our case, $\boldsymbol{w}_{bm}$ corresponds to the portfolio weights of the MFRP allocation. The timing signals are collected in the vector $\boldsymbol{Q} \in \mathbb{R}^{L\times 1}$. In our empirical application, we follow Dichtl, Drobetz, Lohre, and Rother (2021) and use a prudent specification of $\boldsymbol{\Omega}$ and τ such that $\boldsymbol{\Omega} = \text{diag}(\boldsymbol{\Sigma})$, $\tau = 0.015$. The variance-covariance matrix in equation (7) is also adjusted according to the classic Black-Litterman formula:

$$\boldsymbol{\Sigma}_{BL} = \boldsymbol{\Sigma} + \left[(\tau\boldsymbol{\Sigma})^{-1} + \boldsymbol{P}^{\intercal}\boldsymbol{\Omega}^{-1}\boldsymbol{P}\right]^{-1} \tag{9}$$

4.2 Macro factor views

In order to time the three macro factor portfolios, we consider a business cycle model to identify changes in the macroeconomic environment. Business cycle models are used to forecast the global economic environment by combining various macroeconomic indicators. There is extensive literature about different models and variable choices, and we adapt the approaches of Van Vliet and Blitz (2011) and Scherer and Apel (2020) to our needs. Specifically, we build an aggregated indicator of multiple individual macroeconomic variables to classify the economic state. In order to construct a forward-looking business cycle model we incorporate a combination of market-based indicators as well as output and consumption related ones. Whilst we invest in global assets and factors, we focus on U.S. indicators to enable covering our deep sample.[6]

The nature of the used indicators is threefold. First, we consider two market-based indicators, the price-earnings ratio of the S&P 500 and the AAA–BAA US spread. A high P/E ratio or a small absolute credit spread indicate a growing economy whilst a low P/E ratio or a large absolute credit spread indicate a shrinking one. Second, we use logarithmic changes in production led by 1 month as output related measure. Last, we consider two consumption-related indicators, expected and unexpected inflation, measured as the fitted values and residuals of a full sample regression of inflation data on 12 months of lagged inflation, respectively.[7] All these macroeconomic timing indicators are standardized. The resulting Z-scores are winsorized at three standard deviations using an expanding window, in line with our portfolio construction methodology. The aggregate macroeconomic timing indicator results as the equal-weighted combination of the Z-scores.

Next, we explain how to forecast economic regimes based on the aggregated Z-score. While the state of the economy is captured by the sign of the indicator, the economic trend can be gauged via the sign of the annual change of levels. Combining these two dimensions results in four possible economic regimes which we classify in line with the related literature as Expansion (positive and increasing Z-score), Peak (positive but decreasing Z-score), Recession (negative and decreasing Z-score), as well as Recovery (negative but increasing Z-score). To limit the number of regime switches and related turnover, we either demand two consecutive periods of uniform changes or a significant one-time move that deviates more than one standard deviation from its mean to mark a regime switch.

Figure 2 depicts the development of the aggregate Z-score and resulting business cycle classifications for our sample period from January 1924 to May 2021. Shaded areas indicate NBER recession periods. At first glance, the model timely forecasts most of the recession

[6]Rapach, Strauss, and Zhou (2013) show that U.S. data are also predictive for other developed countries' stock market returns.

[7]See Chen, Roll, and Ross (1986) for a detailed description of the production and inflation measures.

periods and indicates a recovery of a thriving economy otherwise. The model reflects the most extreme shocks during the Great Depression in the 1930s, the early 1980s recession, the Global Financial Crisis in 2008 and 2009, as well as the COVID-19 lockdown in early 2020. These recessionary periods were characterized by extreme stock market turmoil and sell-off. However, the model does not capture all NBER recession periods equally well, especially milder and/or shorter ones. For instance, the recessions of 1960/1961, 1969/1970, and the burst of the dot-com bubble in 2001 went unnoticed by the macroeconomic indicator.

[Figure 2 about here.]

Overall, the business cycle model classifies most of the 1,157 sample period months as Expansion (567 months), followed by Peak periods (395 months), see Table 3. There are only few periods classified as Recovery (48 months). The average duration of a given regime is 7.85 months, with Expansion periods lasting the longest (9.78 months) and Recovery periods the shortest (3.69 months). In terms of NBER recessions, there is an overlap of 53% to recession periods in our business cycle model. Some 21% of the Peak periods in our model are (later) categorized as an NBER recession, resonating with the slight delay of our market-based indicators compared to the ex-post classification of NBER.

[Table 3 about here.]

Panel B of Table 3 depicts the transition matrix for the four regimes. Regime classifications are highly persistent, with probabilities of staying in the previous month's regime ranging from 73% (Recovery), 85% (Recession) to about 90% (Expansion). Conversely, extreme jumps "skipping" one regime in the business cycle have a lower single-digit probability, where the highest probability applies to jumping from a recessionary straight into an expansionary period (6%).

Next, we look to turn the regime classifications of the business cycle model into actionable expected return forecasts for the targeted asset classes and style factors. To this end, we define macro factor view portfolios to inform the BL framework. Specifically, a given macro factor view portfolio is designed to navigate the predicted macro regime well. Note that we do not present optimized macro factor view portfolios but rather choose simple, intuitive view portfolio weights, emphasizing that the efficacy of macro factor timing will be crucially dependent on the accuracy of regime forecasts and much less on the specified view portfolio.

Specifically, Panel D of Table 3 shows the four macro factor view portfolios for each of the four regimes. In expansions, the macro factor view portfolio is solely invested in the Growth MFMP. In peak regimes, one is also putting a high weight on the Growth MFMP (80%), but also bringing in defensiveness via the Defensive MFMP (20%) is considered prudent. The recessionary view portfolio should be more diversified with the strongest weight on the Defensive MFMP (120%) and a short position in the Inflation MFMP (-100%); the smallest weight is in the Growth MFMP (80%). Lastly, the recovery view portfolio maintains the negative position in the Inflation (-100%) but goes all in w.r.t. the Growth MFMP (200%).

Given these macro view portfolio weights we can back out the corresponding asset class and style factor weights using equation (4). In turn, we populate the view vector Q and projection matrix P for the macro factor view case based on the predicted regime and thus operationalize a dynamic macro timing allocation.

4.3 Asset class and style factor views

In addition to macro factor views, we also look to harvest views at the level of individual asset classes or style factors. To this end, we focus on time-series factor momentum, noting that our framework can be extended to accommodate any other view. Moskowitz, Ooi, and Pedersen (2012) demonstrate timing financial instruments or whole asset classes based on their past performance, given the strong autoregressive structure in the underlying return series. We follow Gupta and Kelly (2019) in constructing a time-series momentum (TSM) strategy to generate asset class and style factor views. The individual TSM return for an individual style factor or asset i with a one-month holding period is given as:

$$\begin{aligned} f_{i,j,k,t}^{TSM} &= s_{i,j,k,t-1} \times f_{i,t}, \\ \text{where} \quad s_{i,j,k,t-1} &= \min\left\{\max\left\{\frac{1}{\sigma_{i,t-1}}\sum_{\tau=k}^{j} f_{i,t-\tau-1}, -2\right\}, 2\right\} \end{aligned} \tag{10}$$

Equation (10) scales the actual factor return $f_{i,t}$ of factor i at time t by the scaling term $s_{i,j,k,t-1}$. That is, the factor is dynamically scaled by the factor's return standardized by its annualized volatility $\sigma_{i,j,t-1}$ over the formation period j and after an initial exclusion period k. We choose the formation and exclusion periods in line with the literature and focus on the short-term phenomenon of time series momentum, i.e., $j = 1$ and $k = 0$. The annualized factor volatility $\sigma_{i,t-1}$ is calculated over the previous 36 months. The resulting Z-scores are capped at ± 2.

The combined TSM strategy then combines all individual factor time-series momentum signals into a single long-short portfolio (with formation window j and exclusion window k) as:

$$TSM_{j,k,t} = \underbrace{\frac{\sum_i 1_{\{s_{i,j,k,t-1}>0\}} f_{i,j,k,t}^{TSFM}}{\sum_i 1_{\{s_{i,j,k,t-1}>0\}} s_{i,j,k,t-1}}}_{TSM^{long}} - \underbrace{\frac{\sum_i 1_{\{s_{i,j,k,t-1}\leq 0\}} f_{i,j,k,t}^{TSM}}{\sum_i 1_{\{s_{i,j,k,t-1}\leq 0\}} s_{i,j,k,t-1}}}_{TSM^{short}} \tag{11}$$

Hence, the long and short legs are rescaled to form a unit leverage TSM portfolio. We use the corresponding portfolio return as well as the long and short positions to populate the view vector Q and projection matrix P of the BL optimization.

4.4 Empirical results

Next, we investigate the efficacy of the tactical overlays based on macro factor views as well as asset class and style factor views. Table 4 depicts net performance characteristics of the MFRP anchor portfolio (Panel A), the MFRP portfolio augmented with a tactical overlay based on either a macro signal (Panel B) or a momentum signal (Panel C), as well as a combination of both signals (Panel D) over the full sample period but also over the four salient economic regimes. All performance figures account for two-way turnover[8] and relative performance figures are measured against the MFRP anchor portfolio.

[Table 4 about here.]

We first analyze the MFRP portfolio. It has an annualized return of 16.04% at 9.17% volatility, resulting in a Sharpe ratio of 1.75 for the out-of-sample period from January 1924 to May 2021. The risk-adjusted performance peaks in expansionary periods (Sharpe ratio 1.75) and is lowest during recessionary periods (1.30). The performance during Recessions comes with lower return and higher volatility compared to Expansions. The differences in performance across different regimes suggests ample room for tactical allocation decisions to improve performance, cf. Cavaglia, Scott, Blay, and Hixon (2022).

Exploring the potential for (macro) factor timing, we first augment the MFRP allocation by macro factor views (Panel B). One can clearly observe an improvement in absolute returns at similar volatility levels for the whole out-of-sample period but also for all individual regimes. The corresponding Sharpe ratios are improved as well, ranging from 1.41 (Recession) to 2.66 (Recovery). The active overlay comes with active returns of 0.72% for the full period at a tracking error of 1.46, corresponding to an IR of 0.49. The different subperiods yield similar results with the Recovery period being the one where the overlay portfolio deviates the most from its benchmark resulting in a regime-specific information ratio of 1.23. All other periods experience information ratios between 0.25 (Expansion) and 0.79 (Recession). Despite these improvements in performance outcomes, the overall hit ratio, i.e., the proportion of outperformance of the overlay compared to its benchmark on a month-to-month basis, is only 48.50% in the full out-of-sample period, suggesting that the outperformance of the tactical allocation overlay is generated in more extreme months rather than uniformly distributed across the sample.

Next, we analyze the performance of the tactical allocation overlay based on momentum

[8]For simplicity, we use trading costs of 10bps for all securities and per trade assuming an efficient execution via futures or similar vehicles.

views. Panel C clearly highlights the strength of the momentum signals which boosts the performance of the MFRP portfolio to 22% annualized returns at a volatility level of 9.27% and thus results in a Sharpe ratio of 2.39. The active performance is 6.06% at a TE of 3.90% relative to the MFRP portfolio, resulting in an information ratio of 1.55. The performance across the four regimes comes with a much smaller amplitude, suggesting that the momentum overlay works similarly well across all regimes. Note that the hit ratio of the momentum signal is 64.59% overall, ranging from 63.14% (Expansion) to 70.21% (Recovery).

Combining macro and momentum views gives even higher risk-adjusted performance, as one is diversifying two distinct timing signals. The full out-of-sample Sharpe ratio increases to 2.50 whilst volatility stays very similar to that of the MFRP (9.30%). The corresponding information ratio is 1.73 at a tracking error of 4.19%. The combined timing strategy adds value in all regimes, but the outperformance is particularly pronounced in recession and recovery periods. Overall, the timing strategy improves upon the MFRP benchmark 71.17% of the time.

All in all, the tactical allocation overlay helps to improve the performance of the MFRP benchmark portfolio. Whilst the momentum signal boosts performance across all regimes, we also find the macro factor signal to help improve performance, especially in recession and recovery periods. As a result, the overall portfolio becomes more robust in periods of economic downswings while missing less upside potential during economic growth periods.

5 Conclusion

To navigate different macroeconomic environments we build macro factor-mimicking portfolios, MFMPs, for Growth, Defensive, and Inflation. These MFMPs are natural building blocks to construct a diversified macro factor risk parity strategy that proves resilient across various economic regimes over a 100-year sample period. Moreover, we explore the possibility of dynamic macro factor allocation using a Back-Litterman framework.

We generate two distinct sets of signals. First, we build macro factor views based on a simple business cycle model to identify the state of the economy. Second, we construct time series momentum signals for the single asset class and style factor instruments that drive the tested multi-asset multi-factor strategies. Both, macro and momentum, signals prove valuable and complementary in a combined dynamic macro factor allocation. Overall, the presented macro factor investing framework is an effective route to structure multi-asset multi-factor investment process for navigating various economic cycles.

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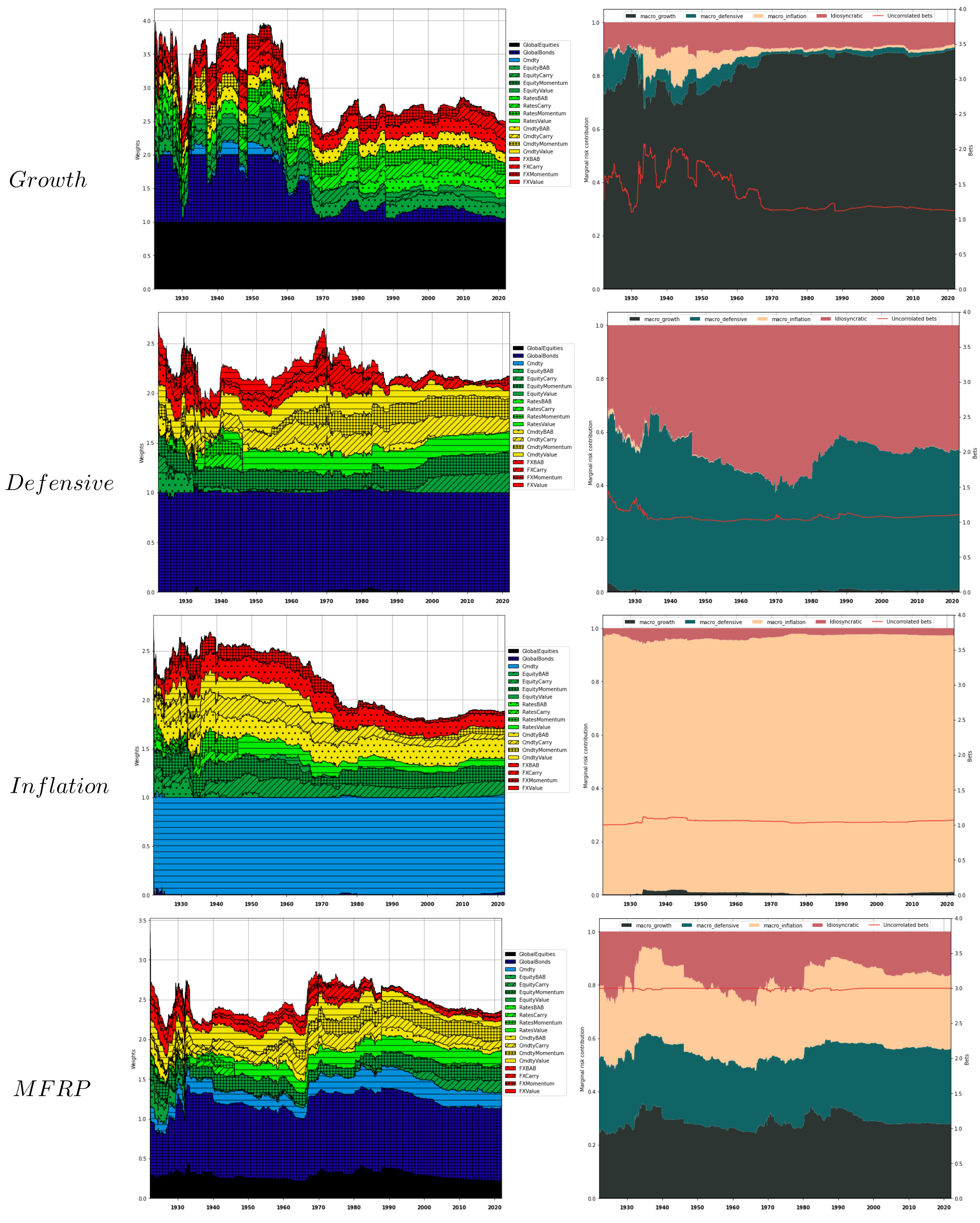
Table 1: Descriptive Statistics

	Ret p.a.	Vol p.a.	SR	t-stat	Min	Max	MaxDD
Global Equities	9.41	15.07	0.62	6.37	−34.07	25.43	−70.20
Global Bonds	5.06	3.94	1.28	13.10	−5.87	7.92	−10.71
Commodities	2.69	18.57	0.14	1.48	−21.18	28.55	−93.05
Equity BAB	5.65	10.35	0.55	5.57	−36.01	18.04	−43.57
Equity Carry	5.58	10.28	0.54	5.54	−14.28	12.70	−63.97
Equity Momentum	7.11	10.34	0.69	7.01	−11.50	13.90	−28.47
Equity Value	2.17	10.32	0.21	2.15	−15.31	12.09	−75.20
Rates BAB	0.76	8.16	0.09	0.95	−21.53	19.00	−64.58
Rates Carry	6.50	11.35	0.57	5.84	−55.54	11.09	−62.40
Rates Momentum	1.33	11.22	0.12	1.21	−61.00	12.58	−74.19
Rates Value	3.34	10.97	0.30	3.11	−10.90	55.93	−36.14
Cmdty BAB	1.27	9.95	0.13	1.30	−11.42	17.77	−64.49
Cmdty Carry	3.02	10.47	0.29	2.94	−21.29	19.76	−46.61
Cmdty Momentum	5.70	10.64	0.54	5.46	−11.53	13.60	−54.88
Cmdty Value	3.54	10.50	0.34	3.44	−14.29	12.34	−64.47
FX BAB	0.72	6.62	0.11	1.12	−14.05	29.78	−52.01
FX Carry	3.35	11.39	0.29	3.01	−43.63	14.09	−68.35
FX Momentum	3.05	10.97	0.28	2.84	−44.50	39.20	−52.66
FX Value	0.32	10.78	0.03	0.30	−45.15	19.93	−86.77

The table shows descriptive statistics of excess returns for asset classes and style factors. Min and Max denote the lowest and highest monthly excess return during the sample period. SR is the corresponding Sharpe ratio and t-stat reports the t-statistic for testing the null hypothesis that the SR equals 0. Return, volatility, Min, Max, and Maximum Drawdown (MaxDD) are in percentage terms. The sample period is from January 31, 1918 to December 31, 2021.

Figure 1: MFMP Weights and Risk Decompositions



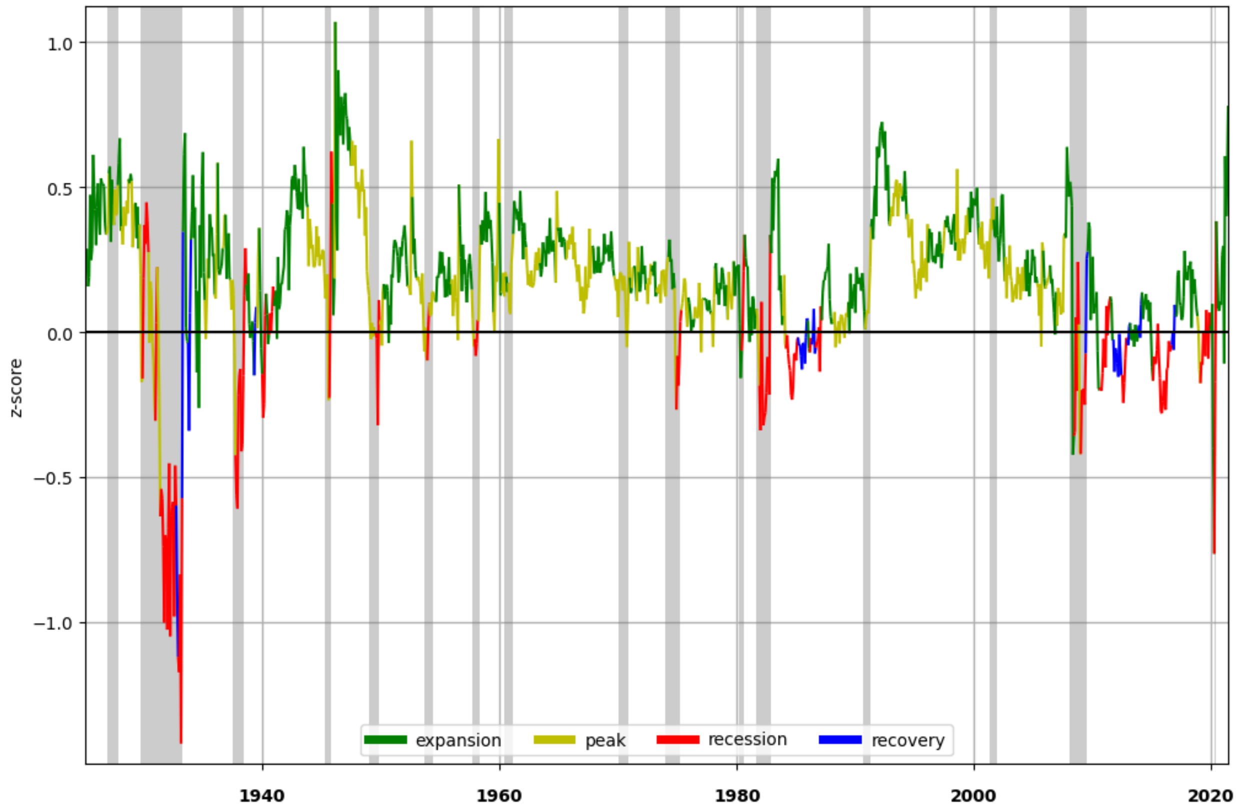
This figure depicts the decomposition of the macro factor-mimicking portfolios (MFMPs) in terms of single asset and factor weights (left-hand column) and macro factor risk contributions (right-hand column) under long-only restrictions. The results build on expanding window estimations using an initial window of 48 months. The sample period is from January 31, 1922 to December 31, 2021.

Table 2: Macro Factor Performance in 'Good' and 'Bad' States

Portfolio		Full	Bull/bear		NBER cycle		Growth/inflation regimes			
			Bull	Bear	Rec	Exp	+/-	+/+	-/-	-/+
Panel A: Orthogonal macro factors										
Growth	Ret	10.69	18.01	−15.27	−7.42	13.88	14.16	18.33	−30.12	−13.79
	Std	14.88	13.26	17.67	16.48	14.39	16.63	12.95	17.44	17.67
	Sharpe	0.50	1.12	−1.05	−0.65	0.74	0.66	1.17	−1.91	−0.96
	MaxDD	−58.22	−23.32	−97.76	−83.19	−40.58	−22.32	−23.32	−50.40	−95.74
Defensive	Ret	5.08	5.16	4.83	6.29	4.87	7.74	4.94	−0.62	5.37
	Std	3.91	3.84	4.16	4.36	3.83	3.61	3.85	4.32	4.12
	Sharpe	0.48	0.50	0.39	0.71	0.43	1.25	0.45	−0.89	0.52
	MaxDD	−10.71	−10.18	−12.75	−10.71	−10.18	−1.87	−10.18	−9.98	−5.68
Inflation	Ret	3.39	5.89	−5.49	−11.75	6.06	1.74	6.24	−45.38	−1.50
	Std	18.25	17.68	19.97	20.72	17.68	25.14	16.93	25.32	19.04
	Sharpe	0.01	0.15	−0.44	−0.72	0.16	−0.06	0.18	−1.92	−0.25
	MaxDD	−91.20	−71.26	−82.90	−92.26	−72.60	−60.63	−59.66	−61.30	−66.02
Panel B: Macro factor mimicking portfolios (MFMPs)										
Growth	Ret	19.88	27.93	−8.65	−3.06	23.93	20.24	28.57	−30.88	−6.43
	Std	17.07	15.64	19.26	18.70	16.50	19.90	15.24	19.78	19.13
	Sharpe	0.98	1.58	−0.62	−0.34	1.26	0.86	1.66	−1.72	−0.50
	MaxDD	−58.25	−26.91	−91.02	−74.10	−45.48	−26.91	−26.60	−50.37	−82.49
Defensive	Ret	13.38	13.67	12.34	15.50	13.00	13.62	13.68	5.62	13.01
	Std	6.51	6.50	6.56	6.57	6.49	6.32	6.51	6.28	6.56
	Sharpe	1.56	1.61	1.39	1.87	1.51	1.65	1.61	0.38	1.49
	MaxDD	−11.60	−11.60	−10.59	−7.94	−11.60	−3.94	−11.60	−7.94	−10.59
Inflation	Ret	10.34	13.36	−0.35	−5.05	13.06	8.70	13.75	−42.22	3.84
	Std	19.47	18.97	20.92	21.56	18.99	25.89	18.29	24.42	20.20
	Sharpe	0.37	0.53	−0.17	−0.38	0.52	0.21	0.58	−1.86	0.03
	MaxDD	−85.35	−59.02	−78.15	−86.66	−59.48	−53.07	−51.18	−60.71	−56.47
MFRP	Ret	16.07	18.94	5.91	9.06	17.31	18.26	18.99	−13.69	7.87
	Std	9.22	9.05	9.21	9.93	9.04	10.69	8.91	9.38	9.02
	Sharpe	1.39	1.74	0.29	0.59	1.56	1.41	1.77	−1.80	0.52
	MaxDD	−27.18	−12.90	−38.13	−27.18	−15.46	−9.40	−12.90	−27.18	−17.94
Observations		1,200	936	264	180	1,020	72	864	24	240

This table shows historical performance characteristics of the orthogonal macro factors (Panel A) and long-only MFMPs (Panel B) across various 'good' and 'bad' states based on macroeconomic and market sub-periods based on annual classifications. Return, volatility, and Maximum Drawdown (MaxDD) are in percentage terms. The sample period is from January 31, 1922 to December 31, 2021.

Figure 2: Business cycle model



This figure depicts the development of the Z-score of the aggregated business cycle indicator. Shaded areas indicate NBER recession periods. The sample period is from January 31, 1924 to May 31, 2021.

Table 3: Business cycle model and macro factor view portfolios based on MFMPs

Characteristic	Expansion	Peak	Recession	Recovery	Overall
Panel A: Regime size & NBER overlaps					
Monthly observations	567	395	160	48	1,170
Unique regimes	58	53	25	13	149
Average duration [months]	9.78	7.45	6.40	3.69	7.85
NBER recession overlap [%]	0.06	0.21	0.53	0.19	0.18
Panel B: Transition matrix [%]					
Expansion	89.93	7.95	1.41	0.71	
Peak	10.13	86.58	3.29	0.00	
Recession	6.25	4.38	84.38	5.00	
Recovery	16.67	2.08	8.33	72.92	
Panel C: Annualized return [%]					
Growth	13.92	5.85	6.57	24.85	10.64
Defensive	3.73	5.57	8.50	6.08	5.10
Inflation	7.87	2.96	−10.33	−6.43	3.14
Panel D: Macro view portfolio weights [%]					
Growth	100.00	80.00	80.00	200.00	
Defensive	0.00	20.00	120.00	0.00	
Inflation	0.00	0.00	−100.00	−100.00	

This table shows descriptive statistics of the business cycle model (Panel A), monthly transition probabilities between the different cycles (Panel B), annualized returns of the original macro factors (Panel C), and the resulting macro view portfolio weights (Panel D). The sample period is from January 31, 1924 to May 31, 2021.

Table 4: Net Performances of Macro Factor Portfolios

Characteristic	Overall	Expansion	Peak	Recession	Recovery
Panel A: MFRP anchor portfolios					
Return p.a.	16.04	17.19	14.31	14.83	20.71
Volatility p.a.	9.17	8.76	8.31	11.43	11.79
Sharpe ratio	1.75	1.96	1.72	1.30	1.76
Turnover	2.77	2.34	2.49	4.83	3.32
Panel B: MFRP + macro					
Return p.a.	16.76	17.53	15.05	16.10	23.98
Volatility p.a.	9.18	8.74	8.31	11.39	12.38
Sharpe ratio	1.83	2.01	1.81	1.41	1.94
Active return p.a.	0.72	0.34	0.73	1.27	3.27
Tracking error	1.46	1.35	1.32	1.61	2.66
Information ratio	0.49	0.25	0.55	0.79	1.23
Hit ratio	48.50	46.38	50.89	48.75	53.19
Turnover	22.14	20.12	17.35	32.13	52.79
Panel C: MFRP + momentum					
Return p.a.	22.10	22.19	20.77	23.82	26.33
Volatility p.a.	9.27	9.21	8.00	11.44	11.50
Sharpe ratio	2.39	2.41	2.60	2.08	2.29
Active return p.a.	6.06	4.99	6.46	8.99	5.62
Tracking error	3.90	3.23	4.20	5.24	2.96
Information ratio	1.55	1.55	1.54	1.72	1.90
Hit ratio	64.59	63.14	63.80	70.00	70.21
Turnover	71.60	68.44	69.41	87.74	73.30
Panel D: MFRP + macro + momentum					
Return p.a.	23.29	23.03	21.94	25.20	31.34
Volatility p.a.	9.30	9.20	8.01	11.25	12.58
Sharpe ratio	2.50	2.50	2.74	2.24	2.49
Active return p.a.	7.25	5.84	7.62	10.37	10.63
Tracking error	4.19	3.55	4.43	5.43	3.68
Information ratio	1.73	1.64	1.72	1.91	2.89
Hit ratio	71.17	68.96	71.39	75.62	80.85
Turnover	79.64	76.92	75.91	93.32	97.09

This table shows net performance statistics for macro factor portfolios during different regimes. Relative performance statistics are reported against the MFRP portfolio (Panel A). This anchor portfolio is augmented with business cycle-related macro factor views (+ macro) as well as momentum views (+ momentum). Performances figures account for two-way turnover. The hit ratio measures the relative months in which the portfolio beats its benchmark. All measures but the Sharpe and information ratios are in percentage terms. The sample period is from January 31, 1924 to May 31, 2021.