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Comparative analysis of static and dynamic approaches to constructing factor investment strategies

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***Abstract*— *The article compares static and dynamic approaches to constructing factor investment strategies, focusing on performance, risks, and practical implementation. The aim of the study is to formalize criteria for selecting a factor portfolio architecture that accounts for the cyclicality of premia, liquidity constraints, and transaction costs, and to clarify under which conditions a more complex dynamic specification is justified relative to fixed rules. The relevance of the work is driven by the widespread adoption of factor investing and, simultaneously, by mounting doubts regarding the persistence of premia and the out-of-sample transportability of factor-timing results. The scientific contribution lies in a comprehensive typology of static and dynamic schemes (exposure timing, volatility scaling, regime filters), an explicit treatment of premium degradation channels via costs, capacity, and model risk, and the rationale for a hybrid design with a robust static core and a minimally parametric dynamic risk-management layer. The main findings indicate that static strategies are superior in terms of interpretability and robustness to overfitting, whereas dynamic constructions can increase return density per unit of risk at the cost of greater sensitivity to estimation errors and to the structure of trading frictions. The article is intended for portfolio managers, risk managers, and researchers engaged in developing and testing factor strategies.*

Keywords*— factor investing, static factor strategies, dynamic factor strategies, factor timing, volatility scaling

I. INTRODUCTION

Factor investing is a portfolio construction method in which the selection and weights of securities are determined by formalized rules designed to harvest persistent risk premia associated with measurable asset characteristics. In the applied literature, this approach is often implemented through long–short portfolios constructed on the basis of characteristics that are empirically related to expected returns (Kagkadis et al., 2023). In the broader context of capital management, factor premia are viewed as an autonomous layer of exposures that can be overlaid on a baseline equity and bond portfolio in order to increase the likelihood of achieving long-term objectives and to smooth the trajectory of wealth. This idea is formalized in studies that analyze factor exposures as a strategic complement to traditional asset allocation, including assessments of the impact of extreme adverse episodes (Cavaglia et al., 2022).

The value of factor investing stems from its discipline and reproducibility. The investor obtains a transparent language of risk, since exposures are described by a limited set of systematic drivers rather than by a list of individual issuers and narratives. At the same time, vulnerability arises from the cyclicality of premia and shifts in the market environment. Survey studies on factor premia in adjacent segments, including government bonds, emphasize that the evidence for factors depends on samples, methods, and observation windows, and therefore the question of premium persistence is methodologically central (Bektić et al., 2020). This provides a practical motivation for comparing strategy-construction architectures, since the same factors may exhibit different returns and risks depending on how the procedure for forming and maintaining exposure is specified.

The problem of choosing an approach to constructing factor strategies centers on the dilemma between rule invariance and market-state adaptation. Static constructions fix the method of measuring signals and the rebalancing frequency, making their properties easier to interpret and to control. Dynamic constructions allow factor weights or trading intensity to vary in response to changing conditions, relying on the notion of time-varying expected premia. Recent research on factor timing shows that the predictability of factor-portfolio returns can be economically meaningful, and models that exploit information contained in portfolio characteristics, in one empirical design, explain about 67% of the variation in factor-portfolio returns and deliver an annual Sharpe ratio of approximately 0.73 for the corresponding trading rules (Kagkadis et al., 2023). These results simultaneously strengthen interest in dynamic methods and sharpen the question of their reliability and out-of-sample robustness, which sets the stage for the subsequent comparative analysis.

II. MATERIALS AND METHODOLOGY

The research material is based on a corpus of academic studies on factor premia and their time-series stability, as well as on practices for constructing long–short and long-only portfolios. To formulate the problem and operationalize factors, the study draws on evidence regarding reproducible premia over long horizons and across different samples, including a global examination of a broad set of premia (Baltussen et al., 2021) and a survey of factor approaches in related asset classes, which underscores the dependence of conclusions on test design and observation period (Bektić et al., 2020). To establish the context of portfolio applications of factors as an exposure layer in multi-asset portfolios, the analysis incorporates results on the role of factors in strategic asset allocation and on sensitivity to extreme adverse episodes (Cavaglia et al., 2022).

The empirical motivation for comparing static and dynamic architectures relies on evidence of the predictability of factor-portfolio returns through portfolio characteristics and on the potential economic significance of factor timing (Kagkadis et al., 2023), as well as on the literature concerning the time-variation of premia and the fragility of gains once execution frictions are taken into account (Haddad et al., 2020).

The methodology implements a comparative analysis of two classes of factor-strategy construction and focuses on differences in mechanisms for maintaining exposures, sources of risk, and channels through which results may deteriorate. The static approach is interpreted as a fixed algorithm for measuring signals and calendar-based rebalancing, contrasted with dynamic rules that permit time-varying factor weights, risk scaling, and regime filters (Lioui & Tarelli, 2020), including the impact of sector neutrality as a structural parameter of implementation (Ehsani et al., 2023).

For dynamic constructions, three applied directions are distinguished, which serve as objects of comparison at the level of decision logic and feasible trade-offs: factor-exposure timing (Kagkadis et al., 2023), volatility-based scaling (Nucera & Uhl, 2022), and regime schemes tied to inflation and macroeconomic states (Baltussen et al., 2023), with separate consideration of the role of transaction costs and rebalancing-boundary optimization as sources of differences between architectures (El Bernoussi & Rockinger, 2022; Bai et al., 2025).

III. RESULTS AND DISCUSSION

In modern asset-pricing theory, factor premia are understood as the average excess returns of portfolios formed on the basis of ex-ante characteristics that are persistently related to subsequent returns and risk. In practical constructions, such characteristics are grouped into several families (Baltussen et al., 2021). These include value characteristics that reflect the relative cheapness of a firm based on accounting and market metrics; momentum characteristics that capture the continuation of recent return trends; size characteristics that separate small-capitalization companies from large ones; quality characteristics that proxy for profitability, robustness of outcomes, and the issuer’s investment discipline; and low-volatility characteristics that select securities with more subdued price dynamics.

In empirical surveys based on extensive historical data, factors are treated as reproducible sorting rules applicable across asset classes, and dozens of premia are shown to retain economic meaning under uniform out-of-sample verification. Across a global universe of markets, the analysis of 24 premia over a 217-year horizon shows that most survive out-of-sample testing without pronounced degradation in average effect (Baltussen et al., 2021).

Explanations for the existence of factor premia typically revolve around two families of mechanisms. Risk-based arguments relate the premium to compensation for systematic risks that intensify in adverse states of the economy and financial markets, so that the expected premium co-moves with the price of risk. Behavioral arguments attribute the premium to persistent expectation errors and to limits to arbitrage, which cause over- and underpricing to be corrected slowly and generate predictability. For both lines of reasoning, the temporal stability of the premium is critical, since it distinguishes a structural effect from a statistical accident.

Studies of the dynamics of factor returns reveal considerable time-variation in expected premia and simultaneously demonstrate that the benefits of attempts at systematic timing often prove fragile due to statistical uncertainty and execution frictions (Haddad et al., 2020). The problem of cyclicality manifests in the ability of individual factors to enter prolonged periods of weak premium realization and to experience rare but severe loss episodes (Dierkes & Krupski, 2022). For momentum strategies, a characteristic pattern of sharp performance deterioration has been documented in reversal phases after market downturns.

Static approaches in factor strategies rely on a prespecified algorithm for forming exposures, in which the set of characteristics, the rules for ranking securities, and the rebalancing calendar are determined before live implementation and change very little thereafter. Within such a framework, the researcher or manager chooses a metric for each characteristic and specifies a procedure for constructing portfolios from sorted groups of securities, which is then repeated at regular intervals. A canonical example is a construction in which stocks are sorted by size and a second characteristic, and long–short portfolios are then formed from several groups with constant shares in sub-portfolios. This logic is standard for empirical factor portfolios and serves as a baseline for discussing what is forfeited when fixed weights ignore time variation in premia and market exposures (Lioui & Tarelli, 2020).

A typical implementation of static design begins by partitioning the universe into quantiles or deciles along the chosen characteristic, after which portfolios are formed with long positions in the upper groups and, where permitted, short positions in the lower groups. A long-only variant is usually constructed as a tilt toward the top group, subject to concentration and risk constraints. The long–short variant is often supplemented by requirements for neutrality to market risk and to sector tilts to approximate a pure factor exposure and reduce dependence on sectoral conditions. At the same time, sector neutrality is a structural parameter that affects the efficacy of long–short and long-only implementations differently. In one empirical study, it is shown that preserving the sector component more often improves the properties of long-only strategies, whereas sector-neutralization more often enhances the performance of long–short portfolios (Ehsani et al., 2023). More flexible static constructions replace coarse partitioning at fixed thresholds with the construction of characteristic portfolios, in which the aggregation of signals and asset weights is estimated more parsimoniously from the data and allows for explicit limits on individual positions (McGee & Olmo, 2022).

The main strength of static approaches lies in their transparency and reproducibility. They are easier to verify, to explain, and to monitor, since strategy behavior follows from a small set of rules and does not require continual recalibration. An additional practical advantage is the predictability of turnover and rebalancing costs, which is important under limited liquidity and explicit cost control. Theoretical–empirical analysis of rebalancing with transaction costs shows that fixed-weight restoration can preserve attractive risk–return trade-offs at realistic cost levels, although dominance depends on the structure of autocorrelations and cross-correlations among assets (El Bernoussi & Rockinger, 2022).

A key limitation of static design manifests as extended adverse cycles of factor premia, which create the risk of prolonged drawdowns and the erosion of investor confidence. For the value premium, a multi-year period of weak performance has been documented, where, as of mid-2020, a drawdown on the order of 55% relative to growth stocks is discussed, illustrating the phenomenon of factor winters and raising the question of how long it is acceptable to wait for premium recovery under invariant rules (Arnott et al., 2021). Static Factor Strategy Implementation is shown in Figure 1.

Fig. 1. Static Factor Strategy Implementation

A factor strategy becomes dynamic when it incorporates rules that adjust exposures in response to the market's observed state or to internal indicators of the strategy. In a static construction, a signal generates a portfolio according to a fixed scheme and is then maintained on a calendar basis. In a dynamic construction, a management layer is superimposed on the signal, allowing for reconfiguration of factor weights, risk scaling, switching of constraint sets, and changes in trading speed. Such an architecture presumes that expected factor premia and their risks follow their own dynamics and that these dynamics can be measured through variables observable at the decision time. Empirical results on the timing of factor portfolios show that characteristics aggregated at the factor-portfolio level contain information about future returns and permit the construction of strategies that systematically differ from fixed-weight schemes in their realized performance trajectories (Kagkadis et al., 2023).

The most widely used class of dynamics concerns factor-exposure timing, in which factor weights change in response to predictors reflecting valuation, momentum, sentiment, and other features of the market environment. A second class is associated with volatility targeting and risk scaling, whereby exposures are increased in tranquil periods and reduced in turbulent periods. Studies devoted to volatility scaling for factor portfolios document improved predictability of factor returns and substantial time-variation in performance characteristics, while translating this predictability into robust factor rotation remains limited and sensitive to portfolio-construction methodology (Nucera & Uhl, 2022). A more applied branch of this approach develops volatility-targeting mechanisms that incorporate transaction costs via rebalancing bands, where optimization aims to reduce costs without losing risk control, and shows that even the simple introduction of a no-trade zone alters the performance profile of the dynamic mechanism (Bai et al., 2025).

A third class of dynamics is based on regime filters that use indicators of inflation, macroeconomic phase, liquidity, and market volatility to select factor tilts that are more appropriate for current conditions. These filters are motivated by the observation that factors behave differently across deflationary, high-inflation, and stagflation regimes, as well as across regimes with different trend persistence and different costs of capital. Empirical analysis of premia on assets and factors across inflation regimes shows that regime comparisons provide a meaningful foundation for conditional exposure management and help formalize the risk of adverse cycles that, in a static strategy, are perceived as protracted factor winters (Baltussen et al., 2023).

A fourth class of dynamics is associated with adaptive selection thresholds and rebalancing frequency, in which the strategy varies the intensity of intervention to maintain a compromise between deviations from target weights and trading costs. The risks of dynamics are concentrated in regime-classification errors, in the accumulation of estimation error, and in the latent dependence of outcomes on execution costs. As a result, every source of added return in a dynamic construction simultaneously constitutes a channel of model risk (Nuriyev et al., 2024). Figure 2 illustrates Dynamic Factor Strategies.

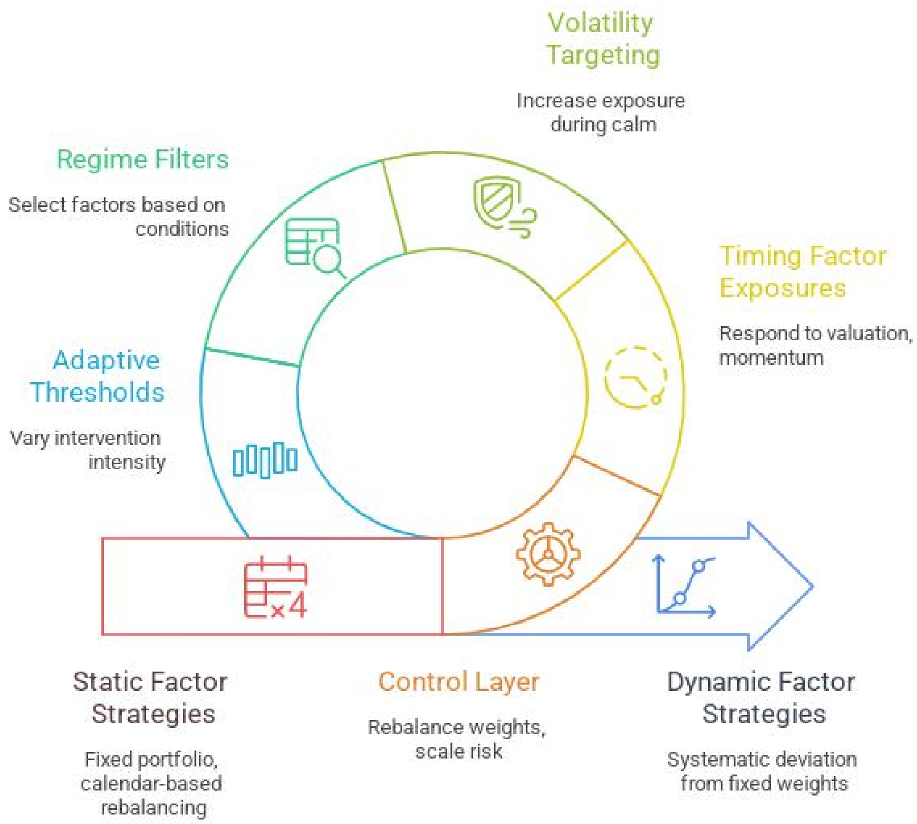

Fig. 2. Dynamic Factor Strategies

The comparison of static and dynamic approaches to expected return begins with the observation that, in both cases, the source of performance is the same: compensation for systematic exposures. The difference lies in how the strategy attempts to transform the conditional variability of premia into realized returns. A static construction treats the premium as a long-horizon quantity and seeks to accumulate it through continuous exposure. This mechanism is advantageous when the premium materializes slowly and is relatively evenly distributed over time.

A dynamic construction allows the premium to depend on market conditions, valuations, and the uncertainty regime. It aims to amplify exposure during favorable phases and attenuate it during unfavorable ones. The potential benefit is associated with a higher density of return per unit of risk. The potential loss is associated with misclassification of phases and with the possibility that the adaptation process itself destroys the effect owing to lags and trading frictions. Premium robustness in a static scheme rests on the stability of factor definition and on the persistence of its economic rationale. Premium robustness in a dynamic scheme also requires the stability of conditional relationships linking market states to future premia.

Risk criteria highlight the contrast more sharply, since the risk of factor strategies is concentrated in rare episodes when usual relationships break down. Static strategies are characterized by a predictable pattern of volatility and drawdowns, yet they remain vulnerable to extended adverse periods and to abrupt crashes that occur when regimes shift, liquidity spikes, or positions are forcibly unwound by market participants. Dynamic strategies introduce mechanisms to mitigate such episodes by reducing exposure or redistributing risk. When tuned successfully, this reduces drawdown depth and the probability of extreme losses. When tuning is unsuccessful, an additional layer of risk emerges: procyclicality, in which exposure reduction occurs after losses have already accumulated, thereby locking in damage. There is also the risk of frequent switching, which transforms rare events into a sequence of moderate losses. Tail risk in a dynamic architecture arises from a combination of market turbulence and control errors. Tail risk in a static architecture is closer to a pure form of factor risk, with the potential for collapse.

Cross-factor correlations and diversification properties are particularly important in stress periods, when many return sources begin to move in tandem. A static multifactor portfolio typically assumes that different factors will offset one another. However, in stressed phases, correlations may increase, and the expected diversification benefit may weaken. A dynamic approach seeks to account for such shifts and reallocate risk to reduce dependence on generalized market stress. At the same time, precisely in stress periods, statistical estimates of correlations and risks become less reliable.

This leads to the criterion of parameter and estimation-error sensitivity. Static strategies usually feature fewer degrees of freedom and a lower probability of hidden overfitting. Their errors are more often linked to poor choices of characteristics, data biases, and persistent structural changes in the market. Dynamic strategies involve more control parameters. They are more sensitive to the quality of estimates, to indicator stability, and to the choice of observation windows. Consequently, even for the same factor idea, dynamic implementation requires stricter discipline in robustness testing. Otherwise, adaptivity becomes a source of noise-driven decisions that appear plausible in backtests but disintegrate when the environment changes. Fig. 3 compares static and dynamic strategies.

Fig. 3. Comparison of Static and Dynamic Strategies

The implementation of factor strategies begins with portfolio turnover and immediately confronts transaction costs. Even with identical signals, static and dynamic architectures generate different trading profiles, since dynamics amplify the frequency and magnitude of weight changes. Costs arise through bid–ask spreads, market impact, and the limited availability of securities for borrowing on the short side. In the short book, costs become endogenous because borrowing fees rise precisely when demand for short positions clusters. In real-world settings, strategy performance is determined by how closely the expected incremental return matches the total cost of maintaining exposure. In dynamic constructions, an additional cost layer arises associated with regime switches and frequent risk adjustments, making trading speed, rather than just target weights, a central object of control.

Liquidity and capacity constraints delineate the feasible domain of factor premia. A strategy may be effective at a small scale but deteriorate as capital grows, because market impact increases more than linearly and affects precisely those securities where the signal is strongest. This is particularly visible in small-cap segments and in constructions that require short positions in low-signal securities. Capacity depends on the breadth of the universe, permissible deviations from neutrality constraints, and the holding horizon. Dynamic strategies often claim an advantage through more active risk management, yet their capacity may be lower due to the need to move capital more swiftly across factors and segments. As a result, the choice of architecture must be aligned with market depth, instrument availability, and acceptable levels of hidden concentration.

Model risk and overfitting issues arise from the temptation to turn a dynamic strategy into a set of knobs tuned to past data. The more parameters there are, the easier it is to obtain an impressive historical track record, and the lower the probability that it will repeat once the regime changes. The danger is amplified when regime indicators are employed that are themselves unstable and subject to revision. Macroeconomic time series are revised; inflation and output estimates are updated; liquidity indicators depend on methodology; even market microstructure metrics may change meaning due to regulatory reforms and alterations in trading microstructure.

Distinguishing structure from noise requires a rigorous robustness-testing discipline. A genuine regularity manifests itself across samples, markets, and reasonable parameter variations. Noise disappears under minor changes in the observation window, threshold, or normalization scheme. An additional signal is provided by economic coherence, whereby the mechanism has a clear channel through which it affects risks and participants' expectations.

Proper testing and comparison require a design that mirrors real-time decision-making. In-sample performance is suitable for diagnosing the idea and for an initial filter of hypotheses. Out-of-sample testing assesses viability. Step-ahead evaluation over time reduces the risk of information leakage and forces the model to make decisions under conditions of uncertainty closer to those in practice. The portability of results should be assessed across markets and asset classes, since local regularities often reflect institutional features of a specific venue.

The modeling of costs and constraints must be embedded in the research from the outset, including the dependence of costs on volume and on market conditions. Stress tests and scenario analysis examine how the strategy behaves in regimes where correlations and liquidity change abruptly. Performance attribution decomposes the contribution of timing decisions from that of risk scaling and separates the impact of market direction from the factor premium per se.

On this basis, hybrid solutions are constructed. A stable core sets long-term factor tilts, while a dynamic layer manages risk and constrains drawdown depth. A model committee allocates responsibility across several simple rules, thereby reducing dependence on a single regime classifier. The principle of minimal dynamics calls for a small number of parameters and clear application conditions, so that adaptation remains interpretable and controllable.

Practical recommendations converge on aligning the architecture with the investor's objectives and capabilities. A static approach suits those for whom explainability, compliance, and a long horizon are paramount, as well as those constrained in instruments and execution budget. A dynamic approach suits those who possess appropriate infrastructure, can employ derivative instruments, and prioritize risk management in adverse regimes. The choice can be structured through a set of questions concerning acceptable drawdowns, tolerance for extended periods of weak performance, availability of shorting, turnover limits, and the share of performance that can be entrusted to a model requiring continuous validation and oversight.

IV. CONCLUSION

The comparative analysis of static and dynamic approaches to constructing factor investment strategies shows that in both cases, the core of performance remains the idea of systematic exposures to measurable asset characteristics and the discipline of formalized rules. In static design, the advantage lies in interpretability and reproducibility, as well as in turnover predictability and cost control, which make such an architecture convenient for verification and operation under liquidity and compliance constraints. At the same time, empirical time variation of factor premia and the phenomenon of extended adverse cycles reinforce the importance of robustness, since even economically coherent premia can pass through periods of deep drawdowns, creating the risk of confidence loss and forced strategy unwinding in an unfavorable phase.

Dynamic constructions expand the decision space through exposure timing, volatility targeting, and regime filters, attempting to exploit the conditional variability of premia and convert it into higher returns per unit of risk. Empirical findings point to predictability in factor returns at the portfolio-characteristics level and thus support the motivation for adaptive methods, yet also reveal fragile out-of-sample transportability, sensitivity to methodology, and increased dependence on trading frictions and estimation error. Ultimately, the choice of architecture becomes a problem of aligning investment horizon, infrastructure, and acceptable model risk, while a proper comparison requires a testing design that reflects real-time decision-making and embeds costs, constraints, and stress behavior as coequal elements of evaluation.

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