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Factor Premia and Business Cycle Dynamics in European Equity Markets

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Declaration on Honour

I, the undersigned, Louis De Proft, on the 2nd of August 2025, hereby declare that the attached work complies with the source referencing rules set forth in the academic regulations signed upon my registration at ICHEC (including adherence to APA standards for in-text citations, bibliographic references, etc.); that this work is the product of an entirely personal effort; and that it contains no content generated by artificial intelligence without explicit acknowledgment. By signing this declaration, I certify on my honor that I have read and understood the aforementioned regulations, and that the submitted work is original and free from any uncredited use of third-party material.

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Contents

Part I

Introduction

What drives returns in financial markets? This fundamental question has guided both academic research and investment strategies for decades. While early models, such as the Capital Asset Pricing Model (CAPM), suggested that market risk alone could explain stock returns, further studies have shown that other common characteristics—known as *factors*—can also help understand why some stocks outperform others.

Among these, five key factors have been widely documented in the literature: Value, Size, Quality, Momentum, and Low Volatility. Each represents a different dimension of risk or behavior that investors may reward over time. Strategies that focus on these factors—so-called *factor investing*—have grown significantly, both in academic interest and real-world application.

More recently, researchers have observed that factor performance is not constant over time. Instead, certain factors tend to perform better during specific phases of the business cycle. For example, Value and Size often outperform during economic recoveries, while Quality and Low Volatility tend to hold up better during downturns. This insight has led to a new approach: *dynamic multifactor investing*, where factor exposures are adjusted based on economic conditions.

Inspired by this idea, asset managers such as Invesco have launched products like the Russell 1000® Dynamic Multifactor ETF, which applies a dynamic factor strategy to U.S. equities. The aim of this thesis is to explore whether a similar approach can be successfully applied to European equity markets.

To test this, we construct a *Dynamic Multifactor Portfolio* that invests in European stocks and adjusts its exposure to the five main factors according to the anticipated phase of the economic cycle. The business cycle is identified using the OECD's Composite Leading Indicator (CLI), which provides early signals about changes in economic activity.

This thesis is organized into three main parts:

- **Part I — Literature Review**: This section introduces the five factors and explains how they are traditionally used to understand stock returns. It also explores the idea that factor performance can change over time, especially in connection with the business cycle.
- **Part II — Methodology**: Here, we describe how the portfolio is constructed—from collecting data to calculating factor scores, identifying economic regimes, and building both static and dynamic versions of the portfolio.
- **Part III — Results**: In the final part, we evaluate the performance of the Dynamic Multifactor Portfolio. We compare it to benchmarks like the STOXX Europe 600 and a static multifactor portfolio, looking at returns, risk, and portfolio characteristics to assess whether this strategy can offer an advantage in European markets.

Through this analysis, this thesis aims to apply a contemporary dynamic investing framework to the European equity universe and provide insights into how macroeconomic information can improve multifactor strategies.

Part II

Literature Review

Chapter 1

Cross-sectional Variations in Average Returns – A Factor's View

1.1 Introduction

In a research project entitled *"Construction of a Dynamic Multifactor Portfolio Based on European Equities"*, two words are likely to spark curiosity: multifactor and dynamic. While the dynamic nature of the strategy will be explored in the next chapter, the present one aims to demystify the multifactor concept. More specifically, this chapter will delve into the origins and empirical development of factor investing. What is a factor? Why do certain variables consistently explain asset returns better than others? And how has the academic community come to formalize these insights over time?

To answer these questions, the chapter adopts a chronological and pedagogical approach, tracing how the factor-based framework has evolved in response to theoretical advances and empirical anomalies. To guide the reader through this evolution, the chapter is organized into six sections.

- **Section 1** begins with an introduction to the Capital Asset Pricing Model (CAPM), which formalized beta as the first risk factor and laid the theoretical foundation for later multifactor approaches.
- **Section 2** examines how this single-factor framework was challenged by the emergence of the Value factor, notably through the Price-to-Earnings and Book-to-Price anomalies, and introduces the longstanding debate between model misspecification and market inefficiencies.
- **Section 3** presents the Size effect, showing how firm size contributes to cross-sectional return differences and how its interaction with value metrics led to the development of the Fama-French Three-Factor Model.
- **Section 4** turns to the Quality factor, emphasizing firm fundamentals such as profitability and financial robustness, and distinguishing between the profitability and leverage effects.
- **Section 5** addresses the Momentum effect, the empirical observation that past

winners tend to outperform in the near term—a pattern that challenged traditional theory and found a place in models like Carhart's.

- Finally, **Section 6** focuses on the Low Volatility anomaly, a counterintuitive phenomenon whereby low-risk stocks consistently outperform, and introduces the Betting Against Beta framework as a theoretical explanation.

While the factors examined in this chapter are often used to build multifactor models in the tradition of Fama and French, this thesis takes a different path. The aim here is not to estimate risk premia or propose a new pricing model, but rather to lay the intellectual foundation for constructing a multifactor portfolio.

Importantly, this portfolio will not be static. Its composition will evolve in response to macroeconomic signals—a concept that will be fully developed in the next chapter, where the dynamic aspect of the strategy comes into focus.

Ultimately, this chapter serves as both an analytical review and a conceptual springboard. By clarifying what a factor is and how the multifactor logic has emerged, we prepare the ground for a more ambitious and adaptive portfolio construction process. Let us now begin by exploring the theoretical roots of factor investing: the Capital Asset Pricing Model.

1.2 The Capital Asset Pricing Model: A Single-factor model

1.2.1 A first approach to price assets

Before the early 1960s, accurately pricing financial assets was a major challenge for both academics and practitioners. The absence of a unified theoretical framework made it difficult to understand what determined asset prices and why certain investments yielded higher returns than others. This changed with the development of the Capital Asset Pricing Model (CAPM), introduced by Sharpe (1964), elaborated by Lintner (1965), and later extended by Black (1972). These models marked a turning point in financial theory by proposing a simple yet powerful idea: the expected return of a financial asset is linearly related to its exposure to market risk, captured by a measure known as beta. This linear relationship, mathematically represented by the equation (1) of Sharpe and Lintner, is graphically represented by the Security Market Line (Exhibit 1). For the first time, the CAPM provided a groundbreaking, coherent, and empirically testable framework that fundamentally reshaped how economists and investors understand the relationship between risk and return. This fundamental relationship is formalized by the following equation:

$$\mathbb{E}(r_i) = r_f + \beta_i \left[\mathbb{E}(r_m) - r_f\right] \tag{1}$$

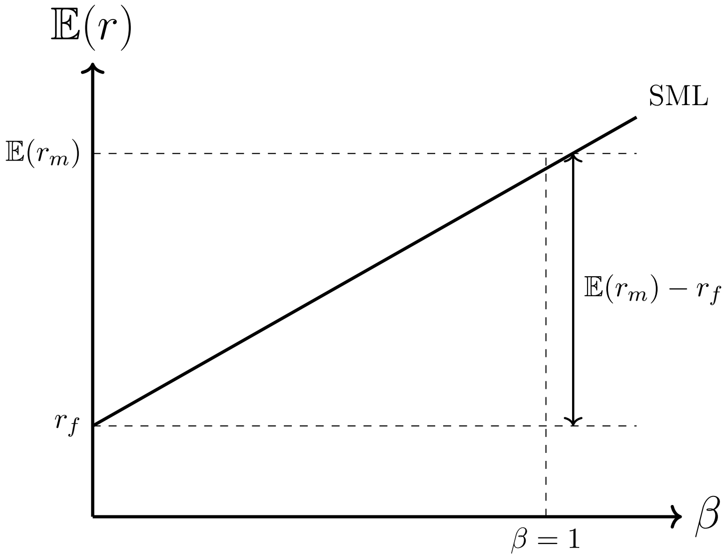
where:

- $\mathbb{E}(r_i)$ is the expected return on asset i,

- r_f is the risk-free rate,
- β_i is the asset's sensitivity to market movements,
- $\mathbb{E}(r_m)$ is the expected return of the market portfolio.

The CAPM provided, for the first time, a coherent and testable model linking risk and return. In this chapter, we begin by exploring the foundations of the CAPM and its empirical validation. We then examine how empirical anomalies such as the value and size effects challenged its assumptions and motivated the emergence of multi-factor asset pricing models.

Exhibit 1 – Security Market Line (SML) under the CAPM framework.



1.2.2 Empirical evidences

The foundational work of Sharpe and Lintner generated significant interest among both academics and market practitioners. Their efforts laid the groundwork for empirical tests of the Capital Asset Pricing Model (CAPM), which quickly became a cornerstone of modern asset pricing theory.

Several key empirical studies emerged in the following years, including those by Jensen et al. (1972), Miller and Scholes (1972), Blume and Friend (1973), and Fama and MacBeth (1973). These contributions sought to validate the CAPM by testing three fundamental predictions derived from its theoretical structure:

1. Expected returns across all assets are solely and linearly determined by their exposure to market risk, as measured by their respective betas. No other variables should add explanatory power.

2. The beta premium is strictly positive: assets with higher sensitivity to market fluctuations should, on average, offer higher expected returns.

3. In the Sharpe-Lintner version of the model:

- Assets with zero market correlation should yield an expected return equal to the risk-free rate:
$$\text{If } \beta_i = 0 \Rightarrow \mathbb{E}(r_i) = r_f$$

- The market risk premium is defined as:
$$\mathbb{E}(r_m) - r_f$$

Among the different formulations of the CAPM, the version proposed by Black (1972) stands out for its empirical robustness. This alternative model relaxes the assumption that investors can borrow at the risk-free rate and introduces the notion of a zero-beta asset. The corresponding equation is expressed as:

$$\mathbb{E}(r_i) = r_z + \beta_i \left[\mathbb{E}(r_m) - r_z\right] \tag{2}$$

Here, r_z denotes the return of a zero-beta portfolio—a portfolio uncorrelated with the market—and the quantity $\mathbb{E}(r_m) - r_z$ represents the zero-beta premium.

With the risk-free rate assumption relaxed, the empirical evaluations of Black's formulation confirmed two essential implications of the CAPM:

- Market beta remains a sufficient statistic to explain cross-sectional differences in expected returns;
- The beta premium consistently exhibits a positive sign.

These findings contributed to solidifying the CAPM's status as a foundational model in financial economics, with Black's version offering a more realistic representation of market conditions where borrowing constraints exist.

1.2.3 A single-factor model

Let us now focus on the first core implication of the CAPM and attempt to reinterpret it from a conceptual standpoint.

In financial theory, beta is referred to as a *factor*—a quantitative characteristic that helps explain variations in asset returns. More broadly, a *factor* captures a common source of risk or return behavior across different assets. The term itself originates from the Latin word *facere*, meaning "to do" or "to make", which is particularly apt: factors are considered to be the underlying forces that "make" or drive asset returns in financial markets.

Within the CAPM framework, beta is the only relevant *factor*. It encapsulates an asset's sensitivity to systematic market risk and is, by construction, sufficient to explain differences in expected returns across individual securities. This exclusive reliance on beta as the sole explanatory variable is what defines the CAPM as a *single-factor model*.

1.3 Beyond Beta: The Rise of Value as a Challenge to the Single-Factor Paradigm

As discussed in the previous sections, the Capital Asset Pricing Model (CAPM) introduced a groundbreaking framework for asset pricing based on a single explanatory quantitative characteristic—a *factor*—namely, beta.

However, over the decades, a growing body of empirical evidence has challenged the sufficiency of beta as the sole determinant of expected returns. Beginning in the 1960s, researchers uncovered persistent pricing anomalies linked to firm-specific value characteristics, particularly the price-to-earnings (P/E) ratio effect and the book-to-market (B/M) effect.

These findings raise several important questions:

1. What exactly are the P/E and book-to-market effects?
2. Who first identified these value-related anomalies, and under what circumstances were they discovered?
3. Most crucially, can these characteristics be interpreted as distinct pricing factors—capable of explaining asset returns independently of, or even more effectively than, beta?

This section aims to address these questions by tracing the historical and empirical emergence of the *Value* factor. We begin with early investment philosophies that emphasized valuation-based decision-making and proceed to formal empirical studies that ultimately posed a direct challenge to the CAPM's single-factor paradigm.

1.3.1 The price-earnings ratio effect

The price-to-earnings (P/E) ratio, defined as the market price of a stock divided by its earnings per share, is a widely used valuation metric indicating how much investors are willing to pay for one unit of a company's earnings. This measure gained prominence through the investment philosophy of Graham and Dodd (1934) who, in their seminal book *Security Analysis*, advocated for investing in undervalued securities, particularly those with relatively low P/E ratios compared to the broader market or their industry peers.

Although Graham's approach was influential, it remained largely philosophical and lacked formal empirical validation. The first study addressing what is now known as the P/E effect was conducted by Nicholson (1960), who analyzed 100 common stocks over the 1939–1959 period. Contrary to the prevailing belief that low P/E stocks were suitable only for income generation, Nicholson found that they also exhibited stronger capital appreciation. A similar study by Drexel & Co. (1963) further illustrated this effect: a $10,000 investment in the ten lowest P/E stocks from the Dow Jones Industrial Average in June 1936 would have grown to $66,866 by June 1962, compared to only $25,347 for the ten highest P/E stocks.

Although these papers represented a transition from philosophy to analytical studies, they still lacked rigorous statistical testing. The first formal empirical investigations came in 1966 with McWilliams (1966) and P. F. Miller and Widmann (1966), whose findings reinforced previous observations but with greater methodological robustness. Breen (1968) added further support by documenting that low P/E stocks tended to outperform the market, especially when compared to their industry peers.

However, these early findings did not explicitly contradict the CAPM, as they failed to adjust for differences in risk. According to the CAPM framework, higher returns are justified only if they reflect greater risk exposure—thus, the superior performance of low P/E stocks could still align with the model if such stocks carried higher risk. It was not until Basu (1977) that a significant challenge emerged: his empirical analysis showed that portfolios composed of low P/E stocks consistently outperformed, even after controlling for systematic risk.

Following Basu's study, a fundamental question arose: what explains the persistence of the P/E effect? A theoretical decomposition of the P/E ratio, based on the Gordon Growth Model (Gordon (1959)) and formalized by Brealey and Myers, provides useful insights.

The forward P/E ratio is defined as:

$$\text{Forward P/E} = \frac{P_0}{\text{EPS}_1} \tag{3}$$

According to the Gordon Growth Model, the price of a stock is:

$$P_0 = \frac{D_1}{r - g} \tag{4}$$

where:

- D_1 is the expected dividend next year,
- r is the required rate of return,
- g is the expected dividend growth rate.

Substituting this into the P/E definition gives:

$$\frac{P_0}{\text{EPS}_1} = \left(\frac{D_1}{\text{EPS}_1}\right) \cdot \left(\frac{1}{r - g}\right) \tag{5}$$

This decomposition identifies two key economic components:

- The dividend payout ratio $\left(\frac{D_1}{\text{EPS}_1}\right)$, reflecting the firm's distribution policy.
- The valuation multiple $\left(\frac{1}{r-g}\right)$, capturing the investor's required return and growth expectations.

If the required return r is incorrectly estimated—possibly due to an incomplete or flawed asset pricing model such as the CAPM—then observed P/E ratios may systematically deviate from levels justified by risk fundamentals. Alternatively, if investors overestimate g, particularly for high-P/E stocks, market prices may rise above intrinsic values, leading to underperformance.

In either scenario, the persistence of abnormal returns associated with P/E ratios could reflect model misspecification, behavioral biases, or both. These explanations will be further explored after the analysis of another value-based anomaly: the book-to-price effect.

1.3.2 The book-to-price effect

The book-to-price (B/P) ratio is defined as the ratio of a firm's book value of equity—computed as total assets minus total liabilities—to its market capitalization. While practitioners today often use the inverse price-to-book ratio for stock screening, we retain the B/P convention here to align with foundational academic literature from the 1980s and 1990s.

A high B/P ratio indicates that a stock is trading at a low market price relative to its accounting value, often interpreted as a sign of undervaluation. As noted by Stattman (1980), "there is a belief that the historical accounting data embodied in the book value is a more accurate appraisal of the actual value of a company's stock than is the market price." In other words, the book value can be seen as a conservative estimate—or lower bound—of a firm's intrinsic worth.

In his influential paper *Book Values and Stock Returns*, Stattman found a significant relationship between the B/P ratio and risk-adjusted returns. Using a chi-square test, he rejected the null hypothesis of independence, showing that portfolios sorted on B/P exhibited systematic variations in performance.

Rosenberg et al. (1985) later proposed a simple yet powerful investment strategy: go long on stocks with high B/P ratios and short those with low B/P ratios. Their approach yielded a t-statistic of 3.57, providing statistically significant evidence against the Efficient Market Hypothesis (EMH). According to the semi-strong form of the EMH, all publicly available information—such as book value—should be already reflected in stock prices. Thus, no strategy based solely on public data should generate persistent abnormal returns.

Further supporting evidence came from L. K. C. Chan et al. (1991), who found that the book-to-market ratio was also highly predictive of average returns among Japanese stocks.

Just as with the P/E effect, it remains to be explored whether the underperformance of low B/P stocks relative to high B/P ones reflects overly optimistic earnings projections by investors, or rather stems from a misspecification or incompleteness in the CAPM framework. It is now time to turn to this question.

1.3.3 Is the model wrong, or are the markets ?

Testing market efficiency inherently entails simultaneously evaluating both the efficiency of the market itself and the validity of the asset pricing model used to define expected returns. This dual assessment is known as a joint hypothesis test, as any rejection of market efficiency may result either from actual inefficiencies or from flaws in the underlying model. Consequently, if either assumption—or both—is violated, the hypothesis of market efficiency cannot be sustained. Hence, as previously mentioned, the price-to-earnings (P/E) effect and the book-to-price effect can be interpreted through two distinct yet interrelated lenses:

- These effects may reflect market inefficiencies, wherein asset prices fail to fully and instantaneously incorporate all available information, thereby allowing for the persistence of predictable return patterns.
- Alternatively, these effects may arise from the misspecification of the asset pricing model, particularly the two-parameter equilibrium model (CAPM), which may inadequately capture the true risk-return relationship in financial markets.

It is widely acknowledged that testing market efficiency is inherently challenging due to the difficulty of jointly accounting for both market inefficiencies and the validity of the asset pricing model. Criticising the underlying asset pricing model while assuming comprehensive control over all market inefficiencies is a particularly delicate task—especially during the period when behavioral finance, which identified numerous market inefficiencies stemming from behavioral biases, was gaining prominence, and the well-known Capital Asset Pricing Model (CAPM) was becoming more sophisticated. Consequently, researchers who identified anomalies in market efficiency tests initially tended to attribute these findings to informational inefficiencies in capital markets rather than to misspecification of the CAPM.

For instance, Basu (1977), after controlling for the price-to-earnings (P/E) ratio by adjusting for risk, attributed the outperformance of low P/E firms to market inefficiencies, particularly those arising from imperfect information processing. Similarly, Dreman (1982) argued that the P/E effect anomaly is better explained by the mispricing of securities. According to him, this mispricing largely stems from biased market expectations regarding earnings and earnings growth (g) for low and high P/E firms, as previously illustrated in the P/E decomposition by Brealey and Myers.

Among the earliest studies challenging the notion that market inefficiencies alone explain observed anomalies, rather than flaws in the asset pricing models themselves, is the work of Breen and Savage (1968). They demonstrated a fundamental inconsistency between the Markowitz model—that is, the mean-variance optimized portfolio—and the empirical probability distribution of portfolio returns. Their analysis showed that the true distribution of returns is leptokurtic, exhibiting fatter tails, and negatively skewed, with a longer left tail. This implies that the variance is not a fully effective measure of risk, as it would be if returns were normally distributed, thereby challenging the Capital Asset Pricing Model (CAPM), since the single-factor model's expected return depends on beta, a portion of the total variance.

Also notably, Ball (1978) conjectured that the earnings-to-price ratio (E/P)—which is simply the inverse of the more familiar price-to-earnings ratio (P/E), also named earnings yield—can be understood as a type of yield, similar to the yield on a bond. In his paper, Ball puts forward the simple yet elegant assumption that, since the earnings-to-price (E/P) represents a measure of yield, it is likely correlated with the 'true' yields or expected returns on common stock. Hence, he suggested that stocks with high E/P ratios (or equivalently, low P/E ratios) tend to earn higher returns not because they are undervalued or mispriced by the market, but because they carry higher risk that the CAPM's single-factor beta does not fully capture.

Basu (1983) test for earnings information effects supported Ball's earlier conjectures, concluding that the so-called earnings yield anomaly—or equivalently, the price-to-earnings (P/E) effect—is more convincingly explained by a misspecification of the traditional two-parameter equilibrium model, the CAPM, than by failures in the information efficiency of capital markets. In other words, the P/E effect reflects limitations in the model's ability to fully capture relevant risk factors, rather than evidence of persistent mispricing or informational inefficiencies in the market.

A similar conclusion can be drawn for the book-to-price (B/P) effect, which, like the price-to-earnings (P/E) ratio, represents a scaled version of a firm's stock price (Keim (1988)). Although both ratios capture value-related characteristics, Fama and French (1992) will later demonstrate that the book-to-price ratio plays a more significant role than the P/E effect in explaining cross-sectional variations in expected returns, ultimately retaining only this variable—among value-related measures—in their three- and five-factor models to avoid redundancy.

1.3.4 Value as a second factor

The examination of the aforementioned empirical anomalies—specifically, the price-to-earnings (P/E) ratio effect and the book-to-price (B/P) effect—raised critical concerns about the sufficiency of beta as the sole explanatory factor. Through the analysis of these effects, this section has demonstrated that such anomalies are not merely reflections of market inefficiencies, but rather indicators of a misspecification within the CAPM framework itself.

The cumulative evidence points toward the necessity of incorporating an additional factor—Value—to account for persistent cross-sectional variations in returns. When combined with beta, this leads to a two-factor model of the form:

$$\mathbb{E}(r_i) = \beta_1(R_m - r_f) + \beta_2 \cdot \mathrm{HML} \tag{6}$$

where $(R_m - r_f)$ captures the market risk premium, and HML (High Minus Low) represents the value premium—measuring the return spread between high book-to-price (value) stocks and low book-to-price (growth) stocks. Parallely, stocks with high book-to-price ratios typically exhibit higher β_2 loadings than those with lower ratios, which contributes to their superior average returns.

This two-factor model represents a simplified version of a six-factor framework, in the spirit of Fama and French, which will be progressively developed in the following sections of this chapter to facilitate the visualization of the factors considered in this thesis.

1.4 Size: A Third Candidate To Explain Cross-Sectional Variations in Returns

A major implication of the discoveries related to value-based characteristics—or the value factor—is that they revealed the inherent incompleteness of the single-factor CAPM. As a result, the search for additional explanatory variables intensified, prompting both academics and practitioners to identify new factors capable of accounting for cross-sectional variations in expected returns. This section aims to address the following key questions:

1. What is the size effect?
2. What underlying mechanisms or narratives have been proposed to explain it?
3. How is the size effect related to the previously discussed P/E and B/P effects?
4. And finally, does the size effect represent a third relevant factor to be added to our previously introduced two-factor model?

1.4.1 The size-effect

Given that both the E/P (or P/E) and B/P ratios have demonstrated explanatory power for cross-sectional variations in expected returns—and that both share market value (P) as a common denominator—Reinganum (1980) sought to assess the robustness of the E/P effect by explicitly controlling for firm size, i.e., market capitalization.

In his study, he constructed ten equally weighted NYSE-AMEX portfolios, ranked in ascending order of average median P/E, each containing varying proportions of small- and large-cap firms. His goal was to determine whether the abnormal returns associated with high E/P ratios could be attributed to size effects. He finds that the portfolio with the highest abnormal return consists predominantly of AMEX-listed stocks, which tend to be smaller firms. This indicates that the E/P anomaly may partly reflect an exchange-related size bias. Further analysis shows that high E/P ratios are strongly concentrated among small-cap stocks, and once firm size is accounted for, the significance of the E/P effect diminishes considerably. This suggests that the anomaly is driven more by firm size than by valuation alone, thereby underscoring a key limitation of the CAPM and supporting the relevance of size, rather than value, in explaining return differentials.

A few months later, Banz (1981) offered a key explanation for the higher risk-adjusted returns observed among small firms. He argued that these firms—typically characterized by limited public information, lower investor attention, and reduced liquidity—are less in demand, prompting investors to require additional compensation for holding them. This phenomenon, which he termed the *size effect*, provides a reinterpretation of earlier anomalies: like Reinganum, Banz concluded that the earnings yield effect is not an independent source of abnormal returns, but rather a proxy for firm size.

1.4.2 The Basu confrontation: reassessing size and E/P effects

In response to the conclusions drawn by Reinganum and Banz, Basu (1983) expresses skepticism, especially in light of the aformentioned Ball's (1978) suggestion that earnings yields (E/P ratios) are likely to be corrolated with “true yields”. This theoretical link motivates Basu to re-examine the role of E/P ratios while controlling for firm size. Through his empirical investigation, he finds that company size appears to exert an indirect influence on risk-adjusted returns, such that the explanatory power of E/P ratios tends to diminish as firm size increases. In particular, for larger NYSE-listed firms, the E/P effect becomes statistically negligible or only weakly significant. Nevertheless, Basu does not interpret this as evidence that the E/P effect is simply a proxy for firm size. Instead, he proposes that firm size *moderates* the strength of the E/P effect without fully accounting for it. Therefore, rather than being entirely driven by size, earnings yield remains a relevant variable—especially among smaller companies. This interpretation stands in contrast to the view that valuation-based anomalies lose their significance once size is included, reinforcing the idea that both effects may operate simultaneously in explaining return patterns. Basu thus concluded that the relationship between earnings yield, firm size, and expected returns is considerably more complicated than earlier studies had suggested. This complexity was later clarified by the seminal contribution of Fama and French (1992), who introduced a three-factor model that formally incorporated both size and value as key determinants of stock returns.

1.4.3 The birth of investment style: Introducing the Fama-French three-factor model

We have seen that, in prior literature, variables and anomalies such as firm size, the earnings-to-price (E/P) effect, and the book-to-price (B/P) effect were frequently identified as significant predictors of expected stock returns. However, as Ball (1978) and Keim (1988) emphasized, these variables were all scaled transformations of a firm’s stock price, raising concerns about potential redundancy. Since each of these measures reflected different ways of extracting information from market prices, it was plausible that not all contributed independently to explaining the cross-sectional variation in returns.

In this context, Fama and French (1992) aimed to investigate the joint roles of market beta, firm size, earnings-to-price, book-to-price, and leverage—which we will explore later—in explaining the average returns on stocks listed on the NYSE, AMEX, and NASDAQ. Their objective was to determine which combination of these characteristics best accounted for observed differences in returns across stocks.

Their empirical analysis led to two central findings:

- First, echoing earlier observations by Reinganum (1980) and Lakonishok and Shapiro (1986), they confirmed that although a positive relationship between market beta and average returns existed during the 1926–1968 period, this relationship disappeared in the more recent 1963–1990 sample.

- Second, and more importantly, their results showed that firm size and book-to-price ratio jointly explained most of the cross-sectional variation in average returns that had previously been attributed to E/P ratios and firm size individually. In other words, size and B/P emerged as the most robust and parsimonious explanatory factors.

This insight led them to propose a new empirical asset pricing framework: the Fama-

French Three-Factor Model, represented by the following equation:

$$\mathbb{E}(r_i) = \beta_1(R_m - r_f) + \beta_2 \cdot \text{SMB} + \beta_3 \cdot \text{HML} \tag{7}$$

Here, expected returns are determined by exposures to the market premium, the size premium (SMB, or Small Minus Big), and the aforementioned value premium (HML, or High Minus Low). By capturing the joint explanatory power of these key characteristics, the model represented a significant improvement over the single-factor CAPM and laid the foundation for the multifactor approaches to asset pricing that are at the core of this thesis.

1.5 Quality: A Fourth Factor in the Expanding Landscape of Asset Pricing

Following the introduction of the Fama-French Three-Factor Model and the rise of investment style frameworks, there was a renewed impetus within the asset pricing literature to identify additional sources of return that could account for the persistent cross-sectional variations in expected returns. This period marked a significant shift, as researchers and practitioners alike began to explore a broader set of firm-specific characteristics that extended beyond the traditional factors.

Among these, a particular focus emerged around firm quality-based characteristics, which were believed to hold explanatory power in capturing differences in risk-adjusted performance across firms. This line of inquiry led to a wide and heterogeneous body of research, reflecting the many dimensions through which a firm's "quality" could be assessed—ranging from profitability and earnings stability to balance sheet strength and capital efficiency.

In order to bring clarity to this vast literature, this thesis proposes a simplified framework that distinguishes between two primary effects: the profitability effect and the leverage effect.

- The *profitability effect* refers to a firm's ability to generate consistent and sustainable earnings, and it encompasses several related dimensions, including direct measures of core profitability, indicators of asset utilization efficiency, and the level of accruals.
- The *leverage effect*, in contrast, relates to the firm's capital structure and financial resilience, focusing on how debt levels influence return patterns and risk exposure.

As will be discussed later in this section, the convergence of these research efforts ultimately led to the formal emergence of a new asset pricing anomaly—now widely referred to as the Quality factor. By the end of this chapter, the following questions will hopefully have been addressed:

1. What does the term "quality" refer to in the context of asset pricing ?
2. How is the profitability effect defined, and what mechanisms underpin its explanatory power ?

3. What does core profitability mean and how do we measure it ?
4. In what way does a firm's level of accruals relate to its future performance ?
5. What is the relationship between asset utilization efficiency and profitability ?
6. What is meant by the leverage effect, and how does it interact with profitability ?
7. Finally, does the literature offer a more comprehensive model beyond the traditional Fama-French Three-Factor Model that better captures quality-based firm characteristics?

1.5.1 Unpacking Quality: metrics, interpretation, and relevance

In the context of asset pricing, quality refers to a set of firm characteristics that have been shown to predict higher expected returns, even after controlling for traditional factors such as size and value. According to Asness et al. (2013) in their paper "Quality Minus Junk", quality stocks are defined as those that are profitable, growing, and safe.

- Profitability is defined as the level of profits relative to book value.
- Growth refers to the five-year historical growth in profitability metrics. Sustained improvement in fundamentals is seen as a sign of operational strength and efficiency.
- Safety captures financial stability, including low beta, low volatility of profitability, low leverage, and low credit risk.

Beyond its intuitive appeal, the definition of quality provided by Asness et al. (2013) can also be grounded in a theoretical valuation framework. As in many previous studies exploring the relationship between quality and expected returns, the authors draw directly on the Gordon Growth Model—previously discussed in the section on the Value factor—as a theoretical foundation for their analysis.

As explained in previous equation (4), the value of a stock according to Gordon's model is given by:

$$P = \frac{D}{r - g}$$

Dividends can be expressed as a function of earnings and the firm's payout policy. Specifically, if π denotes the payout ratio and E represents earnings, then

$$D = \pi \cdot E \tag{8}$$

Earnings, in turn, can be written as the product of return on equity and the book value of equity: $E = ROE \cdot B$, where ROE is the return on equity and B is the book value. Substituting these expressions into the original Gordon formula yields:

$$P = \frac{\pi \cdot ROE \cdot B}{r - g} \tag{9}$$

Dividing both sides by B allows us to isolate the price-to-book ratio:

$$\frac{P}{B} = \frac{\pi \cdot ROE}{r - g} \tag{10}$$

This decomposition shows that the price-to-book ratio is jointly determined by three fundamental forces: profitability (captured by ROE), the payout policy (through π), and valuation parameters (the required return r and growth rate g). It can be summarized in the following compact form:

$$\frac{P}{B} = \frac{\text{profitability} \times \text{payout ratio}}{\text{required return} - \text{growth}} \tag{11}$$

Equation (11) shows that, all else equal, firms with higher profitability, lower discount rates or risk levels (reflected in r) and higher relative to growth (g) should trade at higher valuations. It reinforces the idea that quality—defined through profitability, growth, and safety—has a direct influence on expected returns and valuation multiples. It is also worth noting that the payout ratio provides no informational value in this context. In a frictionless market where the Modigliani and Miller (1958) theorem holds, the proportion of earnings distributed to shareholders—i.e., the payout ratio—does not influence the firm's valuation. This is because, under such assumptions, whether earnings are retained or paid out as dividends has no bearing on the overall value of the firm (Asness et al., 2013)

In contrast to the Value factor, which focused on identifying undervalued stocks based on low market prices relative to accounting fundamentals (such as book value), the Quality factor emphasizes the intrinsic strength of firms. While Value seeks mispricing through depressed valuations, Quality targets firms with superior fundamentals, regardless of whether those firms are cheap or expensive. In this sense, Quality is less about how much one pays and more about what one buys. Thus, unlike Gordon's (1959) growth model—which assumes that key variables such as profitability, discount rate, and growth remain constant over time—Asness et al. introduce a framework that allows for time variation in both firm characteristics and valuations. Their empirical model accommodates the reality that price-to-book ratios and quality dimensions evolve across firms and over time.

Consistent with market efficiency, they found that although higher-quality firms exhibit higher prices on average, they also tend to maintain their quality status over extended periods—five to ten years into the future. As a result, these firms continue to exhibit robust fundamentals, which translate into sustained profitability, future price appreciation, and ultimately higher expected returns that are not fully reflected in current prices. It is then crucial to capture the time variations in quality-based firms' characteristics to understand the essence of the Quality factor.

With this conceptual foundation in place, we now turn to a more detailed examination of the Quality factor by decomposing it into two underlying effects: the profitability effect and the leverage effect. This breakdown will allow us to better understand the specific mechanisms through which quality characteristics influence return patterns.

1.5.2 The profitability-effect

Profitability is best captured by the sustainable portion of *earnings* relative to book value, once adjusted for *accrual*-based distortions. Moreover, when improvements in profitability stem from enhanced operating efficiency or more *effective asset utilization*, they are more likely to be durable and thus indicative of a firm's underlying quality. Let's dive into these 3 dimensions.

Core profitability

Over time, a number of accounting ratios scaled essentially on book values have been proposed as candidates to represent the first component of the profitability effect—what we will refer to throughout this thesis as core profitability.

Early empirical evidence was provided by Fama and French (2004), who found that earnings display explanatory power in explaining cross-sectional differences in returns. But 2 years later, Fama and French (2008) noted that even though higher profitability tends to be associated with abnormally high returns, there is little evidence that unprofitable firms have unusually low returns, giving less credit to their previous finding.

However, this view was challenged by Novy-Marx (2013), who argued that the limited power of profitability observed in Fama and French's studies is largely due to the use of current earnings as a simple proxy for future profitability. According to him, current earnings are often distorted by investments that are immediately expensed under accounting rules—such as R&D and advertising—even though these expenditures are typically associated with higher future economic profits, as found by L. K. C. Chan et al. (2001). For this reason, Novy-Marx advocates for a dynamic approach, focusing on the time variation in earnings or cash flows rather than relying on static measures. This perspective aligns closely with the inherently dynamic nature of the Quality factor, as previously emphasized.

Hence, because time variation in earnings has long been, and continues to be, considered as a direct proxy for core profitability, the most commonly used relative measure among analysts remains Return on Equity (ROE)—defined as earnings divided by the book value of equity. ROE is often employed as a standardised benchmark across firms and industries. From an accounting standpoint, ROE includes components such as interest income and cash holdings (Damodaran (2007)). Yet, its use is not without pitfalls. As Haldane (2012) notes, performance targets tied to ROE may incentivize firms to increase leverage or expand aggressively through mergers and acquisitions (M&A), particularly during periods of low interest rates—practices observed, for example, in the banking sector in the late 1990s.

Another commonly used measure is Return on Invested Capital (ROIC), which captures a broader notion of profitability. ROIC is calculated as operating income after taxes relative to the book value of invested capital. This ratio reflects not only the return to equity holders but also incorporates the cost of debt through interest expenses, thus taking into account the firm's overall capital structure. Nonetheless, a key limitation of ROIC lies in its sensitivity to accounting definitions of invested capital and operating income, which can vary significantly across firms and industries.

A further candidate is the Profit Margin (PM), defined as net income (or operating income) over total sales. It reflects a firm's ability to exert pricing power, often associated with product innovation, brand strength, or strategic positioning Soliman (2008). PM has been widely used, particularly due to its prominence in the DuPont decomposition of ROE, a framework developed over a century ago by F. Donaldson Brown while at DuPont.

The DuPont model breaks down ROE into three core components: operating efficiency (profit margin), asset efficiency (asset turnover), and financial leverage. However, a notable limitation of the profit margin is that industries with high profit margins often attract new competitors, which tends to erode profitability over time through increased competition.

In this thesis, we adopt Return on Assets (ROA) as our preferred measure of core profitability. As highlighted by the FTSE in "FTSE Global Factor Index Series" (2023), ROA is defined as net income for the current fiscal year divided by the average total assets across the current and prior year. ROA has the advantage of encompassing the entire capital structure of the firm, unlike ROE, which can be inflated through leverage. All else being equal, a firm relying heavily on debt or aggressive acquisitions to boost earnings will display a lower ROA than ROE, making ROA a more neutral and reliable indicator of true operating profitability.

Accruals

While core profitability offers valuable insight into a firm's earnings-generating ability, it does not always reflect the true sustainability of those earnings. As it is well-known, accounting profits can be influenced by non-cash items that do not correspond to actual economic performance.

An alternative perspective on quality, therefore, comes from examining these non-cash balance sheet elements, commonly referred to as accruals. According to Sloan (1996), earnings can be decomposed into a stable component—cash flows—and a transitory one—accruals. Because accruals may artificially inflate or deflate reported profitability, adjusting for them is essential in isolating the portion of earnings that is truly persistent and indicative of quality.

There exists an extensive body of literature dedicated to the study of accruals and their relationship with future firm performance. The key insight across these studies is remarkably consistent: accruals are negatively related to future profitability, and firms with higher accruals tend to deliver lower future stock returns. This suggests that the transitory nature of accruals leads to an overstatement of current earnings, which the market does not fully correct in the short term—resulting in predictable return patterns.

To better understand how accruals affect perceived profitability, we follow the comprehensive framework established by Richardson et al. (2004) that divides total accruals into three main components, each capturing a distinct dimension of balance sheet activity:

- Changes in working capital
- Changes in non-current operating assets
- Changes in net financial assets

The **working capital** component of total accruals is largely influenced by changes in accounts receivable and inventories. These items reflect anticipated future benefits that have not yet been realized in cash terms and whose actual economic value may be lower than their current accounting valuation.

As a result, two firms reporting identical earnings may differ significantly in the quality of those earnings if one displays a larger increase in working capital relative to the other. When this change is scaled by total assets, it provides a measurable indicator of the magnitude of non-cash adjustments embedded in reported earnings. A large variation implies lower earnings quality, as the reported profitability is less likely to be sustained in the future.

The second component of accruals stems from **net non-current operating assets**, calculated as the change in non-current operating assets minus the change in non-current operating liabilities. This category mainly includes Property, Plant, and Equipment (PP&E) as well as intangibles, such as capitalized R&D or internally developed software.

Although these investments are expected to yield long-term benefits, they do not generate immediate cash flows. As such, they can temporarily boost earnings and obscure the firm's true operating performance. For example, a firm engaging in large-scale capital expenditures may appear more profitable in accounting terms, even though the corresponding cash flows will only materialize over time—if at all. This can make current profitability look inflated relative to the firm's economic reality.

Moreover, in opaque contexts, particularly in firms with high R&D intensity, managerial discretion further complicates interpretation. As highlighted by Polk and Sapienza (2004) and Polk and Sapienza (2009), such firms may choose to capitalize or expense intangible investments strategically—capitalizing in weak quarters to preserve earnings, and expensing in strong ones to smooth volatility. These practices reduce the reliability of reported earnings as a signal of sustainable performance. In both cases—whether driven by aggressive investment or accounting discretion—high non-current accruals often indicate a larger gap between reported profitability and cash-based performance, thus lowering earnings quality.

The third component of accruals relates to **net financial assets**, defined as the change in short-term investments and long-term investments minus the change in financial liabilities.

Although short-term investments are highly liquid and reliably measured, they are still included in accruals because they can generate interest income or capital gains without stemming from core operating activities. Their variation may thus inflate earnings in a way that weakens the link with sustainable profitability.

Long-term investments are more heterogeneous. On one hand, government bonds or listed securities are generally reliable. On the other hand, illiquid items such as long-term receivables are often difficult to value and can be subject to accounting discretion or earnings management, making them a less reliable component of earnings. Financial liabilities, including debt and preferred stock, are typically measured with high precision, as accounting rules prevent firms from anticipating non-payment of their obligations.

Change in asset turnover

Having established that core profitability must be adjusted for accruals to reflect the sustainable component of earnings, we now turn to another crucial dimension of the profitability effect: the efficiency with which firms use their assets to generate revenue.

While core profitability captures the magnitude of earnings, and accruals help distinguish between transitory and persistent components, asset turnover (ATO) reflects the operational efficiency behind those earnings. Specifically, it measures how effectively a company converts its asset base into sales. Improvements in ATO indicate that a firm is generating more output from the same resources, which reinforces the quality of its profits.

According to Soliman (2008), positive changes in ATO are strong predictors of future profitability, even after controlling for profit margins and the initial level of ATO. This highlights that firms improving asset efficiency are not only more operationally sound, but also more likely to sustain superior performance over time.

Therefore, in the context of the quality factor, an upward trend in asset turnover serves as a meaningful signal of increasingly durable profitability, complementing both core earnings and their accrual-adjusted assessment.

1.5.3 The leverage-effect

The second dimension of the Quality factor, alongside the profitability-effect, is the leverage-effect. While the previous section highlighted how sustainable earnings define high-quality firms, it is equally important to consider the firm's financial structure, as future earnings tend to be inversely related to leverage Nissim and Penman (2001). In other words, more profitable firms generally maintain lower levels of debt, whereas highly leveraged firms are often associated with weaker earnings quality and higher financial risk.

Traditionally, leverage has been measured using the ratio of total debt to total assets, a metric long used in corporate finance to assess financial risk. However, Rajan and Zingales (1995) challenged this conventional approach by arguing that total assets do not provide a consistent or meaningful base for leverage calculations. They highlight that certain liabilities—such as accounts payable or obligations tied to pension assets—should not influence a firm's capital structure assessment, as they are not related to financial debt per se.

Further complicating this issue, M. Baker and Wurgler (2002) demonstrate that firms adjust their capital structure in response to market valuations. Their findings show that low-leverage firms tend to issue equity when their market price-to-book ratios are high, while high-leverage or financially distressed firms are more likely to raise funds when valuations are depressed. This market timing behavior suggests that leverage ratios based on book assets may be distorted by factors unrelated to fundamental risk or financial discipline.

Building on this, Nassim and Penman (2003) provide evidence that financial leverage is negatively related to future earnings performance. They show that increases in leverage are often followed by weaker profitability, and suggest that highly profitable firms typically generate sufficient free cash flow, which they use to repay debt or accumulate financial assets, thereby maintaining more conservative balance sheets.

Given these findings, more relevant measures of leverage in the context of quality investing focus on the firm's ability to meet its debt obligations through internal resources. One such measure is the ratio of operating cash flow to total debt (OPCFD). This ratio captures how much of a firm's debt burden is covered by its core cash-generating activities. Low levels of OPCFD have been shown to be associated with higher default risk (Fiedler, 1971) and, consequently, with higher required rates of return. From this perspective, higher cash flow coverage of debt reflects stronger financial discipline and a lower risk profile, which are consistent with the characteristics of high-quality firms.

1.5.4 Fama French five-factor model: Adding Quality to the equation

The increasing recognition of profitability as a key determinant of expected returns led Fama and French (2015) to extend their classic three-factor model into a more comprehensive Five-Factor Model. This new specification includes two additional factors: one capturing profitability, the other investment behavior.

$$\mathbb{E}(r_i) = \beta_1(R_m - r_f) + \beta_2 \cdot \mathrm{SMB}_t + \beta_3 \cdot \mathrm{HML}_t + \beta_4 \cdot \mathrm{RMW}_t + \beta_5 \cdot \mathrm{CMA}_t \tag{12}$$

The profitability factor, called Robust Minus Weak (RMW), captures the average return spread between firms with strong and weak profitability. Fama and French define profitability as revenues minus cost of goods sold, interest expense, and SG&A expenses, scaled by book equity at fiscal year-end — though, as we have examined, relying on book equity to measure core profitability has important limitations.

In addition to profitability, the model includes an Investment factor, labelled Conservative Minus Aggressive (CMA). Several studies offer explanations for the negative relation between high investment and future stock returns. For instance, Haugen and Baker (1996) argue that overvalued firms attract excessive capital, leading to overinvestment and eventual underperformance as expectations correct. Cohen et al. (2002) suggest that investors become overly optimistic about future cash flows, which are later revised downward along with discount rate adjustments. Fairfield et al. (2001) propose that as firms invest more, profitable opportunities become scarcer, reducing future profitability. Titman et al. (2004) link high investment to empire building, where managers pursue growth for personal or organizational power rather than shareholder value.

Although the investment effect is treated as a separate dimension in the Five-Factor Model, part of its influence is already embedded in our own framework. Specifically, our use of Return on Assets (ROA) incorporates total assets into the definition of profitability, and our focus on asset turnover directly reflects how efficiently those assets are utilized—both concepts indirectly capturing aspects of the firm's investment intensity.

In this sense, while Fama and French treat investment and profitability as separate factors, our quality-oriented approach—rooted in the framework proposed by the FTSE in "FTSE Global Factor Index Series" (2023) and applied in the work of Polk et al. (2020), which serves as the primary inspiration for this thesis—integrates these dimensions more holistically into a broader understanding of high, sustainable and operationally efficient profitability, as well as a leverage effect. Hence, our 4 factor model, enhanced with the Quality Factor has the following equation:

$$\mathbb{E}(r_i) = \beta_1(R_m - r_f) + \beta_2 \cdot \text{SMB}_t + \beta_3 \cdot \text{HML}_t + \beta_4 \cdot \text{QMJ}_t \tag{13}$$

Where β_4 measures the sensitivity of asset i to the Quality factor or Quality Minus Junk (QMJ). Quality Minus Junk refers directly to the work of Asness et al. (2017), and the quantitative characteristics composing this factor are those adopted in the theoretical framework of this section, in alignment with the FTSE's definition of Quality (Sandford, 2025).

1.6 Momentum: Beyond Fundamentals, Toward Return Dynamics

The momentum factor is built on a simple yet powerful empirical observation: stocks that have performed well in the recent past tend to continue performing well in the short to medium term, while poorly performing stocks tend to underperform. This persistence in relative performance, typically measured over horizons of 6 to 12 months, challenges the foundations of traditional finance theory.

More specifically, momentum stands in direct contradiction with the random walk hypothesis (Fama (1965)), which assumes that asset prices follow an unpredictable path and that past returns contain no exploitable information about future performance. In this context, momentum appears to violate even the weak form of market efficiency, which posits that all information contained in past prices is already reflected in current prices.

Among all the commonly studied asset pricing anomalies, momentum is arguably the most intuitive and accessible to investors exploring factor-based strategies. It is no surprise, then, that a wide range of market participants—from retail traders to professional asset managers—have long relied on technical analysis, which seeks to identify and exploit trends in past price movements without reference to fundamental valuation. Its apparent simplicity makes momentum especially striking, and at times even provocative, as it directly challenges one of the most deeply held assumptions in financial economics—that markets are informationally efficient, even in their weakest form. This chapter aims to explore the momentum effect in depth by addressing the following questions:

1. What is the momentum effect, and how is it defined empirically?
2. Is it better to buy past losers (contrarian strategy) or past winners (momentum strategy) ?
3. What are the theoretical explanations—both rational and behavioral—that have been proposed to account for it ?
4. And lastly, does momentum constitute a distinct and robust factor worthy of inclusion alongside the other components of a multi-factor asset pricing model ?

1.6.1 Challenging the random walk: First empirical researches and limitations

One of the earliest empirical investigations into the predictability of returns and the validity of the random walk hypothesis was conducted by Levy (1967). His study analyzed return patterns across sequential time intervals, during a period in which the Capital Asset Pricing Model (CAPM) was gaining prominence. He observed that stocks with above-average past returns tended to exhibit significantly positive future returns, suggesting a departure from purely random price behavior.

However, Levy did not interpret these results as a definitive violation of the random walk hypothesis. He emphasized that such a violation would only hold if predictable return patterns could not be attributed to higher risk. Yet measuring that risk accurately remains problematic. For instance, a stock that experiences a sharp short-term rise in returns may also display greater variability in those returns. This is reflected in a rising coefficient of variation—defined as the ratio of the standard deviation to the mean return—which signals increased dispersion relative to average performance. Such behavior complicates the assessment of whether excess returns result from inefficiency or from a risk premium.

Moreover, Levy acknowledged that the overlapping nature of the return intervals led to autocorrelated returns, thereby violating the assumption of independence required for standard statistical inference. This limitation rendered traditional variance estimates unreliable and called for caution in interpreting the persistence of returns. Three years later, Jensen and Bennington (1970) raised doubts about Levy's conclusions, noting that his findings were based on results obtained after testing a large number of different strategies. They argued that this approach reduced the credibility of his results. When they re-evaluated his findings on a different and extended time period—mostly outside the original sample—they found no significant outperformance of stocks with above-average past returns compared to a simple buy-and-hold strategy, suggesting that the observed effect might have been due to a selection bias than a persistent phenomenon.

1.6.2 Contrarian versus Momentum strategies

Contrarian strategies

A key behavioral explanation for return patterns in financial markets lies in the tendency of investors to overreact to new information. This concept is central to the work of Bondt and Thaler (1985), who investigated how individuals update their beliefs when faced with new data. In their study, they define a "normative" reaction as one that aligns with Bayes' rule—a statistical principle that prescribes how to rationally revise probabilities when new evidence becomes available. According to Bayes' rule, the updated belief should proportionally reflect both the prior probability and the strength of the new signal.

However, as shown by Kahneman and Tversky (1982), individuals often fail to update beliefs in line with this normative model. In practice, people tend to overweight recent or salient information and underweight base rates or prior probabilities, leading to systematic overreaction.

Building on this psychological insight, De Bondt and Thaler hypothesized that if investors overreact to recent poor or strong performance, stock prices may deviate from fundamental values. Consequently, a portfolio strategy that buys past losers and sells past winners should yield abnormal returns once prices revert. Their empirical analysis confirmed this hypothesis: over three- to five-year horizons, stocks that had underperformed in the past tended to outperform those that had previously performed well. Further evidence of this pattern was provided by Jegadeesh (1990) and Lehmann (1990), who found that even over shorter horizons—such as one week or one month—return reversals persist. Their findings show that stocks with extreme recent performance often reverse direction shortly afterward, again implying that investor overreaction plays a role. This behavior forms the basis of a contrarian strategy, which aims to exploit market overreactions by betting on reversals in relative performance.

Limitations and criticisms of Contrarian strategies

Despite the apparent success of contrarian strategies in capturing return reversals, several studies have questioned whether their profitability truly reflects investor overreaction or simply compensation for systematic risk. For instance, K. C. Chan (1988), Ball and Kothari (1989), and Zarowin (1990) suggest that the superior performance of past losers may be attributed to their exposure to higher risk or to firm characteristics such as size. Specifically, smaller firms tend to exhibit greater return volatility and are more likely to fall into the "loser" category; thus, the abnormal returns could reflect a size effect rather than a behavioral anomaly.

Moreover, the findings of De Bondt and Thaler (1985) lose some of their generality when analyzed through a seasonal lens. Their strategy only significantly outperforms during the month of January, a pattern that aligns with the well-known January effect, which refers to the historical tendency to outperform during the first month of the year (Thaler (1987)).

When it comes to shorter-term contrarian strategies, such as the aforementioned strategies proposed by Jegadeesh (1990) and Lehmann (1990), further scrutiny has revealed additional concerns. Jegadeesh (1991) show that much of the profitability from short-term reversals is linked to market frictions, particularly bid-ask bounce, which can generate artificial return patterns. Lo and MacKinlay (1990) add to this critique by arguing that a significant portion of these apparent profits is due to delayed reactions to common risk factors, rather than to investor overreaction itself.

The emergence of Momentum strategies

Given these criticisms, Jegadeesh and Titman (1993) proposed a different approach to return continuation, known as relative strength or momentum strategies. Instead of betting on reversals, these strategies buy stocks that have recently performed well and sell those that have performed poorly, effectively taking the opposite stance to contrarian models.

In their seminal study, the authors ranked stocks based on their past six-month returns, formed portfolios accordingly, and held them for the following six months. Over the period from 1965 to 1989, this approach yielded an average annualized excess return of 12.01%, highlighting the systematic and robust nature of momentum in the cross-section of stock returns.

One possible interpretation of their results is that traders who chase past winners and avoid losers create temporary price pressures, pushing prices away from their long-run equilibrium. These patterns can be amplified by "positive feedback traders", a term introduced by De Long et al. (1990) to describe investors who reinforce trends by buying after prices rise and selling after they fall. Such behavior may induce short- to medium-term momentum, even if long-run mean reversion eventually corrects mispricing, typically after a period of two years according to Jegadeesh and Titman.

1.6.3 Carhart's four-factor model: Adding Momentum

In response to the mounting empirical evidence on return continuation documented by Jegadeesh and Titman (1993), Carhart (1997) extended the traditional three-factor model developed by Fama and French (1993) by incorporating a momentum factor. This fourth factor, often referred to as "PR1YR," captures the excess returns earned by a strategy that goes long on past winners and short on past losers over a 12-month formation period, excluding the most recent month to mitigate short-term reversal effects. The resulting model—now commonly known as the Carhart four-factor model—includes market, size, value, and momentum components, thereby offering a more comprehensive framework for explaining cross-sectional variations in stock returns.

$$\mathbb{E}(r_i) = \beta_1(R_m - r_f) + \beta_2 \cdot \mathrm{SMB}_t + \beta_3 \cdot \mathrm{HML}_t + \beta_4 \cdot \mathrm{WML}_t \tag{14}$$

Where β_4 measures the sensitivity of asset i to the Momentum factor or Winners Minus Losers (WML).

By adding the momentum factor, Carhart was able to account for patterns in return persistence that the Fama-French model could not fully explain. One particularly relevant phenomenon in this context is the so-called "hot hands" effect, as described by Hendricks et al. (1993). Drawing from an analogy in sports, where players are perceived to be "on a streak" after successive successful actions, the authors analyzed mutual fund performance and found that funds with strong recent returns tended to continue outperforming in the near future. This short-term persistence in performance challenges the notion of purely random outcomes and suggests a degree of predictability in returns. The momentum factor introduced by Carhart provides a plausible mechanism for explaining this effect. It captures the empirical tendency for assets that have performed well over the past year to continue doing so in the near term—a pattern consistent with the "hot hands" phenomenon observed among mutual funds.

1.6.4 Behavioral and economic explanations of momentum

The momentum premium has been attributed to a combination of behavioral biases and structural market dynamics. On the behavioral side, several studies argue that investors tend to underreact to new information, causing prices to adjust gradually rather than instantaneously. This slow diffusion of information leads to return continuation, as initially underpriced assets continue to rise until prices fully reflect fundamentals (Barberis et al. (1998); Hong and Stein (1999)). Moreover, cognitive biases such as conservatism and representativeness heuristics contribute to delayed belief updating and excessive extrapolation of past trends (Tversky and Kahneman (1974)), reinforcing the momentum effect. Finally, the previously mentioned trend-following behavior exhibited by "positive feedback traders"—who buy following price increases and sell after declines—underscores a significant form of herding among market participants.

From an economic standpoint, some researchers propose that the momentum anomaly may reflect compensation for exposure to specific risks not captured by traditional factors. For instance, momentum strategies often experience sharp and clustered losses during market regime shifts, suggesting that they carry crash risk (Daniel and Moskowitz (2016)). Furthermore, the existence of arbitrage limits—such as short-selling constraints, transaction costs, and career concerns faced by fund managers—prevents the full exploitation of momentum profits, allowing the anomaly to persist (Shleifer and Vishny (1997)). Combined, these behavioral and structural explanations offer a richer understanding of why momentum continues to deliver abnormal returns, and why it remains a vital component in multifactor asset pricing models like Carhart's.

1.6.5 Fama French about Momentum : Not a candidate

Despite the strong empirical evidence supporting momentum as a persistent and robust anomaly in cross-sectional returns, Fama and French (2015) notably excluded it from their influential five-factor model. While the momentum effect demonstrates significant explanatory power, especially in the short- to medium-term, it is not considered a viable risk factor by Fama and French for inclusion alongside market, size, value, profitability, and investment. The authors justify their decision on both conceptual and empirical grounds.

First, they argue that momentum is largely incompatible with their framework, which is grounded in rational asset pricing theory and long-term investment fundamentals. In their view, momentum lacks a clear economic rationale linked to firm characteristics such as profitability or investment behavior, making it difficult to interpret as a risk-based factor.

Second, and perhaps more crucially, Fama and French highlight the instability and inconsistency of momentum returns when interacting with their five-factor model. Specifically, they observe that the momentum factor generates negative intercepts for many value-oriented portfolios, and that its performance is highly sensitive to market conditions and time horizons—features that contrast sharply with the relative robustness of the five chosen factors.

Nevertheless, in line with the empirical framework developed by Polk et al. (2020), this thesis adopts a more pragmatic and dynamic perspective. From a portfolio construction standpoint—especially one that adapts to different phases of the business cycle—the contribution of momentum cannot be overlooked. Accordingly, we augment our initial asset pricing framework—building on the spirit of the Fama-French methodology—by introducing momentum as a fifth explanatory factor. The resulting extended multifactor model is specified as follows:

$$\mathbb{E}(r_i) = \beta_1(R_m - r_f) + \beta_2 \cdot \mathrm{SMB}_t + \beta_3 \cdot \mathrm{HML}_t + \beta_4 \cdot \mathrm{QMJ}_t + \beta_5 \cdot \mathrm{WML}_t \tag{15}$$

Where, as explained in equation (14), β_5 measures the sensitivity of asset i to the Momentum factor or Winners Minus Losers (WML).

1.7 Low Volatility: When Less Risk Delivers More Return

The final factor considered in this analysis is Low Volatility, a phenomenon that has garnered increasing attention in empirical asset pricing research. Contrary to the predictions of traditional financial theory, the low volatility effect suggests that stocks with lower historical volatility or market beta tend to deliver higher risk-adjusted returns than their more volatile counterparts.

This counterintuitive pattern, often referred to as the low-risk anomaly, has proven remarkably persistent across different time periods, asset classes, and geographical markets. Its growing popularity among practitioners and academics alike has spurred numerous attempts to explain its existence, ranging from structural market frictions to behavioral biases and institutional constraints. This section aims to shed light on the low volatility effect by addressing the following key questions:

1. How is the low volatility factor defined and measured empirically?
2. Why does it appear to contradict standard asset pricing theory?
3. What rational and behavioral explanations have been proposed to account for its persistence?
4. Finally, should low volatility be considered a standalone factor within a multi-factor investment strategy?

1.7.1 Early empirical foundations: Black (1972)

One of the earliest and most influential investigations into the relationship between risk and return—particularly in the context of volatility—can be traced back to Black (1972). At a time when the Capital Asset Pricing Model (CAPM) was becoming a dominant paradigm in financial economics, Black sought to understand how asset returns behaved under real-world market conditions, especially when certain theoretical assumptions were relaxed.

In the standard CAPM framework, whose equation (2) has been explored in the first section, investors are assumed to be able to borrow and lend unlimited amounts at the risk-free rate. Under such conditions, all investors would construct their optimal portfolios by combining the risk-free asset with the market portfolio, leading to a linear and positive relationship between beta and expected returns. However, Black questioned the realism of this assumption—particularly the idea that investors can easily take on leverage.

By developing the zero-beta CAPM, Black introduced a setting in which borrowing constraints exist, meaning that investors cannot always achieve their desired exposure to the market portfolio through leverage. In this more constrained environment, investors who are unable to borrow are forced to allocate more capital to high-beta assets in order to increase their portfolio's expected return. This behavior results in excess demand for high-beta stocks, inflating their prices and thereby reducing their future returns.

Conversely, low-beta stocks become relatively underpriced, as they are less attractive to constrained investors seeking higher returns. This imbalance leads to a flattening—or even an inversion—of the risk-return relationship, whereby low-beta stocks may offer comparable or even superior risk-adjusted returns compared to high-beta stocks.

1.7.2 Institutional constraints and investor behavior

Following Black's foundational work, several empirical and theoretical studies have explored why the low volatility anomaly persists. These investigations have largely focused on the behavior of institutional investors, the structural constraints they face, and the psychological biases that influence market pricing.

A notable contribution comes from M. P. Baker et al. (2010), who argue that investor preferences and structural frictions can systematically distort asset pricing. They suggest that high-beta stocks are perceived as "lottery tickets" by many investors: because these stocks offer the potential for large gains in rising markets, they tend to be overpriced—especially by investors who are unable or unwilling to take on leverage. As a result, low-beta and low-volatility stocks become relatively undervalued, leading to superior risk-adjusted returns. This perspective aligns closely with the skewness preference hypothesis, originally developed by Kahneman and Tversky (1982). According to this view, investors exhibit a behavioral bias toward assets with, again, lottery-like payoffs—that is, assets with a small probability of very high returns. Since high-volatility stocks often display such skewed return distributions, they attract disproportionate demand and become overvalued.

This mispricing is further exacerbated by the popularity of benchmark-relative investing. In line with this, Blitz and van Vliet (2007) highlight the role of benchmark constraints faced by institutional investors such as mutual funds, pension funds, or insurance companies. These investors are often evaluated relative to a market index, which encourages them to maintain a portfolio beta close to one. In an effort to outperform their benchmarks, they tend to tilt toward high-beta, high-volatility stocks, which offer greater short-term upside potential. This behavior contributes to persistent demand for risky stocks, thereby depressing their future returns and reinforcing the low-volatility anomaly. These benchmark pressures also give rise to agency problems, as highlighted by Falkenstein (1996) and L. K. C. Chan et al. (2003). In seeking to outperform peers or benchmarks, managers may prioritize their own career incentives or visibility, favoring volatile and attention-grabbing stocks—even when such positions are misaligned with long-term, risk-adjusted client interests.

1.7.3 From anomaly to factor: The emergence of Betting Against Beta

In light of these institutional frictions and behavioral tendencies, it became increasingly clear that the low volatility effect was not merely a statistical curiosity, but a systematic anomaly with potential to be formalized as a distinct factor. This transformation was notably achieved in the work of Frazzini and Pedersen (2014), who introduced the *Betting Against Beta (BAB)* factor as a practical and theoretically grounded approach to capturing the mispricing implied by the traditional risk-return paradigm.

Their central insight builds on Black's earlier intuition: if leverage constraints prevent investors from scaling up low-risk positions, they will naturally gravitate toward high-beta assets, driving up their prices and lowering their expected returns. To exploit this distortion, the BAB strategy takes a leveraged long position in low-beta stocks and a short position in high-beta stocks, thereby betting against the linearity of beta in pricing returns.

Using global equity data, Frazzini and Pedersen show that the BAB factor produces significant positive alphas that are not explained by standard risk factors, including market, size, value, or even momentum. More importantly, they demonstrate that these returns are not the result of hidden risks, but rather stem from the mispricing generated by institutional constraints and benchmarking pressures.

The BAB framework offers a powerful reinterpretation of the low volatility anomaly: rather than violating risk-based models, it reflects the inefficiencies induced by real-world constraints and investor behavior. In this sense, low volatility emerges not only as an empirical regularity, but also as a theoretically motivated factor that deserves explicit modeling in asset pricing frameworks.

1.7.4 Why Low Volatility is not in the Fama-French Model—And why we include it

As with the momentum factor, low volatility is notably absent from the Fama-French five-factor model (Fama and French, 2015), despite the growing empirical evidence of its explanatory power. In the concluding sections of their 2015 paper, Fama and French explicitly address the exclusion of low volatility.

In particular, the low volatility factor is deemed redundant in their framework. According to Fama and French, much of the cross-sectional variation captured by low volatility overlaps with exposures already embedded in their existing factors. For instance, low-volatility portfolios often have tilts toward large-cap, profitable, and conservative investment firms, which correspond respectively to the negative SMB (size), positive RMW (robust profitability), and positive CMA (conservative investment) exposures. As a result, the alpha of the low volatility factor becomes statistically insignificant in regressions that include the five Fama-French factors, leading them to conclude that it does not represent an independent source of risk premia.

However, this view—while defensible in the context of static, cross-sectional asset pricing models—may not fully account for the dynamics of portfolio construction in a changing macroeconomic environment. In this thesis, aligning with Polk et al. (2020), low volatility remains a valuable and distinct factor, particularly in the context of a dynamic portfolio strategy that adapts to business cycle phases. Accordingly, the final specification of our asset pricing model if we were to present it in a Fama-French's style, would be the following:

$$\mathbb{E}(r_i) = \beta_1(R_m - r_f) + \beta_2 \cdot \mathrm{SMB}_t + \beta_3 \cdot \mathrm{HML}_t + \beta_4 \cdot \mathrm{QMJ}_t + \beta_5 \cdot \mathrm{WML}_t + \beta_6 \cdot \mathrm{BAB}_t \quad (16)$$

Where β_6 measures the sensitivity of asset i to the Low Volatility factor or Betting Against Beta (BAB).

1.8 Conclusion

This first chapter has served as a foundational step in this thesis by clarifying what a factor is in the context of asset pricing. A factor refers to a quantitative characteristic that explains the cross-sectional variations in asset returns across securities. In its simplest form, a factor captures a systematic source of risk or performance that investors can be exposed to through portfolio construction.

We have examined the evolution of the Capital Asset Pricing Model (CAPM), which introduced beta as the sole explanatory variable in what became known as a single-factor model. While the CAPM was a major theoretical breakthrough, its empirical limitations gave rise to multi-factor extensions, most notably those of Fama and French, who formalized the role of size, value, and later, profitability and investment. These models laid the groundwork for further refinements such as Carhart's inclusion of momentum and Frazzini and Pedersen's Betting Against Beta framework for low volatility. Beyond these core factors, a wide array of additional characteristics—such as liquidity, investment growth, or yield—have been proposed in the literature, giving rise to a diverse set of models collectively referred to under the umbrella of factor style investing. Harvey et al. (2015) compiled a list of 316 anomalies that have been suggested as potential explanatory factors in asset pricing models.

Although the goal of this thesis is not to develop a new multi-factor model to explain the performance of financial assets, this chapter offers a comprehensive visualization of the five core factors that will underpin the remainder of the analysis: Value, Size, Quality, Momentum, and Low Volatility. While several key questions remain—particularly regarding the cyclicality of these factors (i.e., their varying performance across business cycle phases) and the construction of a dynamic multi-factor portfolio—this introductory analysis has provided a necessary first step by clarifying the economic and behavioral rationales underlying each factor.

The **Value** factor emerged from the consistent outperformance of undervalued stocks and is supported by two central effects: the *price-to-earnings (P/E) effect*, where low P/E stocks deliver superior returns, and the *book-to-price (B/P) effect*, which captures valuation misalignments between market price and accounting value. These effects are often attributed to mispricing due to investor over-optimism about growth (g) or to model misspecifications that fail to capture all relevant risks related to the value factor.

The **Size** factor builds on the *size effect*, whereby small-cap firms tend to outperform large firms on a risk-adjusted basis. This phenomenon is often explained by liquidity constraints, information asymmetries, and limited analyst coverage, which collectively make small firms riskier and therefore associated with higher expected returns.

The **Quality** factor is underpinned by two key dimensions: the *profitability effect*, which emphasizes sustainable earnings as captured by measures like ROA, accruals, and asset turnover, and the *leverage effect*, which penalizes financially fragile firms. Quality firms are defined as profitable, stable, and conservatively financed—characteristics that tend to persist and predict stronger long-term performance.

The **Momentum** factor is associated with the *momentum effect*—the empirical finding that past winners often continue to outperform. This effect challenges the random walk hypothesis and is grounded in behavioral explanations such as underreaction, herding, and overconfidence, as well as structural limits to arbitrage. Carhart's (1997) four-factor model incorporates this dimension to better explain short-term performance persistence.

The **Low Volatility** factor contradicts traditional finance theory by showing that less risky stocks can outperform their more volatile peers. This *low-volatility effect* is captured empirically by the Betting Against Beta (BAB) strategy, which exploits mispricing driven by leverage constraints, benchmarking behavior, and skewness preference. Although Fama and French (2015) exclude this factor due to perceived redundancy with others, its inclusion remains compelling in a macro-sensitive and dynamic allocation framework.

While models such as those of Fama and French, Carhart, or Pedersen generally assume static factor exposures, a growing body of evidence indicates that factor performance fluctuates with macroeconomic conditions. This chapter has shown that understanding the theoretical and empirical foundations of each factor is crucial—but not sufficient. For example, it remains unclear whether the Value factor truly compensates investors for bearing additional risk. Similarly, it is difficult to assume that all factors perform uniformly over time: small-cap stocks, for instance, may suffer more during economic downturns, while the opposite is true for low-volatility stocks.

To properly evaluate the role of factors in portfolio construction, one must account for the *time-varying nature of risk premia*. The next chapter therefore introduces a more dynamic modeling framework aimed at better capturing the underlying time variations in factor risk premia—variations that are often overlooked in static approaches. Recent research has highlighted the potential link between these time-varying exposures and business cycle dynamics, offering new insights that will serve as a foundation for the construction of a factor-based portfolio with adaptive, cycle-aware allocations.

Exhibit 2: Summary of the five factors.

Factor	**Brief Definition**	**Associated Effect**
Value	Stocks perceived as undervalued based on fundamentals tend to outperform those considered expensive.	Price-to-Earnings effect Book-to-Price effect
Size	Smaller firms, in terms of market capitalization, tend to achieve higher returns than larger ones.	Size effect
Quality	Companies with strong profitability and solid financial health tend to deliver better performance than lower-quality firms.	Profitability effect Leverage effect
Momentum	Stocks with rising or falling prices tend to keep moving in the same direction over short periods.	Momentum effect
Low Volatility	Stocks with lower price volatility generally provide superior risk-adjusted returns compared to more volatile stocks.	Low-volatility effect

Chapter 2

Time-series Variation in Factor Premia and Business Cycle Dynamics: From Theory to Strategy

2.1 Introduction

Having demystified the notion of *multifactor* investing in the previous chapter—by tracing the origins, theoretical foundations, and empirical validations of the main cross-sectional factors—this second chapter now turns to the other central concept of this thesis: dynamism. In the context of the project titled *"Construction of a Dynamic Multifactor Portfolio Based on European Equities"*, understanding what makes a portfolio truly dynamic is just as crucial as selecting the right factors. Specifically, this chapter explores how the explanatory power of factor premia evolves over time, and how these variations can be linked to macroeconomic conditions, most notably the business cycle. By introducing the concept of time-varying expected returns and reviewing empirical evidence on the cyclicality of factor performance, we set the stage for a portfolio construction methodology that adapts to economic regimes rather than remaining static.

To that end, **Section 2** introduces the limitations of the static CAPM framework and motivates the use of intertemporal models like Merton's ICAPM; **Section 3** presents the dual-beta decomposition proposed by Campbell and Vuolteenaho, distinguishing between cash-flow and discount-rate risk; **Section 4** discusses how these two risk components explain the risk premia observed across factors. In **Section 5**, we shift to the empirical observation that factor returns exhibit cyclicality, a theme further developed in Section 6 through evidence from recent empirical studies. Finally, **Section 6** introduces a dynamic factor allocation strategy that leverages the time-varying nature of factor exposures.

2.2 Limitations of the Static CAPM and the Rise of Intertemporal Models

The CAPM, as introduced in the previous chapter, provided a foundational framework linking expected returns to an asset's sensitivity to market-wide risk. However, the

CAPM—like the Fama-French multi-factor models that extend it—rests on the assumption of static investment opportunities. That is, it presumes investors operate in a fixed economic environment where risk premia and asset characteristics remain constant over time. This overlooks the fact that financial markets are inherently dynamic, and that investors regularly revise their expectations in response to evolving macroeconomic conditions.

To address this limitation, Merton (1973) developed the Intertemporal Capital Asset Pricing Model (ICAPM). In contrast to the static CAPM, the ICAPM incorporates a forward-looking perspective in which investors not only care about current consumption but also about the future state of the investment opportunity set. Expected returns, therefore, depend on an asset's exposure to both market risk and to innovations in state variables—such as interest rates or economic growth—that influence future investment conditions:

$$\mathbb{E}[R_i - R_f] = \beta_{i,M} \cdot \lambda_M + \sum_{k=1}^{K} \beta_{i,k} \cdot \lambda_k \tag{17}$$

Where:

- $\beta_{i,k}$ represents asset i's sensitivity to the k-th macroeconomic factor or state variable,
- λ_k is the risk premium (price of risk) associated with factor k,
- λ_M is the market risk premium,
- $\beta_{i,M}$ is the sensitivity of asset i to the market factor.

To operationalize this model empirically, Campbell (1991), building on Campbell and Shiller (1988) log-linear approximation of asset prices, demonstrates that unexpected returns can be decomposed into two conceptually distinct components: cash-flow news, which reflects revisions in expected future earnings, and discount-rate news, which captures changes in the rate at which those cash flows are discounted:

$$\begin{aligned} r_{t+1} - \mathbb{E}_t[r_{t+1}] = & \underbrace{(\mathbb{E}_{t+1} - \mathbb{E}_t)\left[\sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j}\right]}_{\text{Cash-flow news}} \\ & - \underbrace{(\mathbb{E}_{t+1} - \mathbb{E}_t)\left[\sum_{j=1}^{\infty} \rho^{j-1} r_{t+j}\right]}_{\text{Discount-rate news}} \end{aligned} \tag{18}$$

Where:

- r_{t+1} is the log return from period t to $t+1$,

- Δd_{t+j} is the log dividend growth at horizon j,
- $\rho \in (0, 1)$ is a constant discount factor close to 1.

The discount factor ρ reflects the present value of future variables. It is used to discount both future dividend growth and future expected returns, effectively capturing the total value of an asset as the sum of capital appreciation and dividend income.

This decomposition highlights that return shocks can arise either from revisions in expectations about future cash flows (which reflect changes in firm fundamentals) or from changes in the discount rate (which reflect shifts in required returns due to varying economic risk). While cash-flow shocks are generally persistent and affect intrinsic value, discount-rate shocks tend to be transitory and reflect time-varying risk aversion or macro uncertainty. This distinction between permanent and transitory components has important implications for how we interpret risk. Specifically, it allows us to decompose the total variance of returns into parts attributable to either long-lasting changes in fundamentals or short-term fluctuations in discount rates.

Consequently, if a stock exhibits a higher proportion of its return variance driven by cash-flow news, it is considered fundamentally more exposed to permanent shocks. Holding total variance constant, such a stock would be riskier than another whose variance is largely attributable to discount-rate news, as the latter reflects reversible changes in investor sentiment or market conditions rather than enduring shifts in the firm's economic value. Therefore, greater exposure to cash-flow risk justifies a higher required risk premium, all else being equal.

This distinction lays the groundwork for the next section, where we explore how this decomposition can be used to better understand the nature of risk in equity factors through the lens of "bad" and "good" beta exposures.

2.3 Bad Beta, Good Beta – A Dual Risk Channel Framework

Building on the decomposition of unexpected returns into cash-flow and discount-rate news, Campbell and Vuolteenaho (2004) proposed a refined view of equity risk that distinguishes between two fundamentally different types of beta. In their model, a stock's total exposure to market risk—traditionally measured by a single beta—can be separated into a cash-flow beta and a discount-rate beta, each capturing distinct economic risks.

Formally, they posit that a stock's total market beta can be expressed as the sum of two components:

$$\beta = \beta^{\mathrm{CF}} + \beta^{\mathrm{DR}} \tag{19}$$

Where:

$$\beta^{\mathrm{CF}} = \frac{\mathrm{Cov}(\mathrm{CF}_i, \mathrm{CF}_m)}{\mathrm{Var}(r_m)} \quad \text{and} \quad \beta^{\mathrm{DR}} = \frac{\mathrm{Cov}(\mathrm{DR}_i, \mathrm{DR}_m)}{\mathrm{Var}(r_m)}$$

With:

- β^{CF} denoting the cash-flow beta, i.e., the stock's sensitivity to innovations in market-wide cash-flow news,
- β^{DR} denoting the discount-rate beta, i.e., the stock's sensitivity to innovations in discount-rate news,
- CF_i and CF_m: unexpected cash-flow news for firm i and the market,
- DR_i and DR_m: unexpected discount-rate news for firm i and the market,
- $\mathrm{Var}(r_m)$: variance of market returns.

The cash-flow beta—referred to as "bad beta"—measures how sensitive a stock is to changes in expectations about future earnings or dividends. If bad news arrives suggesting that a firm's future profits will be permanently lower—for example, because it lost a major client or faces stronger competition—its cash-flow beta will reflect that. As we mentioned, these shocks are persistent, and they reduce the intrinsic value of the firm. Investors strongly dislike this kind of risk because it represents permanent loss. For this reason, stocks with high cash-flow betas are considered more dangerous and require higher compensation, in the form of a higher risk premium.

The discount-rate beta, on the other hand, captures how sensitive a stock is to fluctuations in the required rate of return. For example, if interest rates temporarily rise, or if investors become more risk-averse for a short time, all future cash flows are discounted more heavily, and prices fall. However, this kind of shock is usually transitory—market conditions normalize, and valuation levels recover. Because it does not reflect fundamental damage to the firm's profitability, investors view it as less severe, and thus the discount-rate beta earns a smaller risk premium.

2.4 Factor Risk Premia through the Lens of Dual Betas

This decomposition offers a compelling explanation for some of the empirical anomalies observed in asset pricing—particularly the strong performance of *value stocks*. The authors found that these firms, typically characterized by low prices relative to fundamentals (such as low price-to-book ratios), tend to exhibit high exposure to "bad" cash-flow beta. This implies that their returns are especially sensitive to persistent negative shocks affecting firm fundamentals—possibly due to their positioning in mature industries, exposure to structural economic shifts, or lower profitability.

These results are consistent with prior research by Cohen et al. (2002), who found that value stocks exhibit higher return-on-equity betas compared to growth stocks. They also align with findings from Liew and Vassalou (2000), who showed that value stock returns are positively correlated with shocks to GDP growth—highlighting their greater exposure to macroeconomic risks, particularly those that impact the cash-flow component of stock returns. Because these cash-flow shocks represent permanent losses in expected future earnings, investors perceive them as highly undesirable and therefore demand a higher risk premium to hold such assets. Interestingly, value stocks also tend to have relatively low discount-rate betas, making them less reactive to transitory changes in the cost of capital. This asymmetry in risk exposure helps explain why value stocks often generate positive alpha under the CAPM, which fails to capture the deeper nature of their risk.

In contrast, *growth stocks* tend to have elevated betas with respect to the market portfolio, yet these betas mainly reflect their exposure to "good" discount-rate risk, which is associated with relatively low risk premia. These stocks are particularly sensitive to fluctuations in discount rates because a large portion of their valuation depends on cash flows expected far into the future. This makes them behave similarly to long-duration bonds, which are more responsive to interest rate movements than bonds with shorter maturities (Cornell (1999)). However, since discount-rate shocks are generally transitory and less damaging from a fundamental standpoint, the CAPM tends to overestimate the actual risk of growth stocks. As a result, they often exhibit negative alphas under the CAPM, since their true risk exposure is lower than what is implied by their high market beta.

In the case of the *size anomaly*, the gap in cash-flow beta between small-cap and large-cap stocks has narrowed over time, suggesting that their exposure to permanent cash-flow shocks is now more comparable. However, small firms continue to display much higher discount-rate betas than their larger counterparts. This indicates that they are more sensitive to temporary changes in financing conditions or investor sentiment, rather than to long-term fundamentals. A likely explanation is that small companies tend to depend more heavily on external capital, making them more exposed to fluctuations in equity market conditions and broader financial variables (Ng et al. (1992); Perez-Quiros and Timmermann (2000)).

Although the price of discount-rate risk is relatively low compared to cash-flow risk, the magnitude of the difference in exposure between small and large firms is substantial. This large spread in discount-rate beta is therefore sufficient to explain a significant portion of the size premium observed in empirical asset returns.

This analytical framework has significantly deepened our understanding of factor-related risks and returns by clarifying the distinction between cash-flow risk and discount-rate risk. It suggests that the elevated average returns observed for value and small-cap stocks are better interpreted as rational compensation for their greater exposure to fundamental, persistent risks, rather than as anomalies or calls for systematic overexposure to these styles.

In the next section, we build on this decomposition to examine how separating factors into their cash-flow and discount-rate components can be used to construct smart beta strategies—strategies that deliberately allocate capital toward specific sources of risk in order to enhance return potential while managing exposure more precisely.

2.5 The Business Cycle as a Source of Time-Variation in Factor Premia

The previous chapter provided a conceptual foundation for understanding factor risk by decomposing total systematic variance into two economically distinct components: cash-flow risk and discount-rate risk. This decomposition revealed that not all risk is equally priced and that exposure to persistent shocks—namely, those that impact long-term firm fundamentals—commands a higher premium. From an asset allocation perspective, this distinction opens the door to more refined portfolio construction, where exposures can be tilted not only according to a factor's average return, but also in light of which type of risk drives its performance.

Building on this framework, a large body of empirical research has documented that factor premia are not stable over time. In other words, the excess returns delivered by systematic factor strategies—such as value, size, quality, or momentum—exhibit significant time variation, which cannot be fully explained by static models like the CAPM or even multi-factor extensions.

Early evidence of this phenomenon comes from Cohen et al. (2003), who show that the profitability of value strategies fluctuates over time in response to changes in the value spread, defined as the cross-sectional dispersion in book-to-market ratios between value and growth stocks.

More recently, Campbell et al. (2010) and Campbell et al. (2018) have deepened this line of inquiry by linking exposure to aggregate "bad" cash-flow news with firm-level characteristics commonly associated with smart beta strategies—such as profitability and leverage. For instance, firms with higher profitability or lower leverage tend to exhibit lower sensitivity to adverse cash-flow shocks, suggesting that these characteristics may serve as proxies for resilience to macroeconomic risk.

This apparent heterogeneity in how firms respond to fundamental economic shocks laid the groundwork for dynamic factor allocation approaches, often referred to as smart beta timing strategies. These strategies are based on the premise that factor exposures can be optimized over time by anticipating changes in the nature of risk that will be rewarded in the future. The idea is straightforward:

- When future fundamentals are expected to improve, investors should tilt towards factors with high cash-flow betas, as these are most likely to benefit from stronger earnings revisions.
- Conversely, when the outlook is deteriorating, it is more prudent to favor factors with low exposure to cash-flow risk, offering more stability in adverse conditions.

This framework moves beyond the traditional diversification logic behind static multifactor portfolios, which combine lowly correlated factor returns (Exhibit 3) to improve the risk-return profile.

Exhibit 3: Factor excess return correlations (07/1980 – 09/2018).

	Size	Value	Low Vol.	Quality	Mom.
Size	1				
Value	0.32	1			
Low Vol.	-0.42	0.30	1		
Quality	-0.27	-0.55	-0.06	1	
Momentum	-0.05	-0.44	-0.15	0.29	1

Source: FTSE Russell and FactSet as of 9/30/18

While this approach provides diversification benefits—as seen in the correlation matrix of factor returns—it does not account for predictable fluctuations in the components of expected return. As recent research suggests, exploiting the time-variation in the risk premia associated with these factors can offer incremental performance over static implementations. In other words, although we understand how different factors contribute to performance, we lack a systematic framework to determine when each factor should be emphasized.

This line of thinking is central to the approach proposed by Polk et al. (2020), whose work served as the primary source of inspiration for this thesis. Their objective is to address precisely the missing "when" dimension by linking the evolution of factor premia to the business cycle. Their intuition stems from two empirical observations:

1. Factor returns exhibit heterogeneous performance across different time periods, as can be seen in annual return rankings of factors—where some consistently outperform in expansions, while others dominate in downturns.

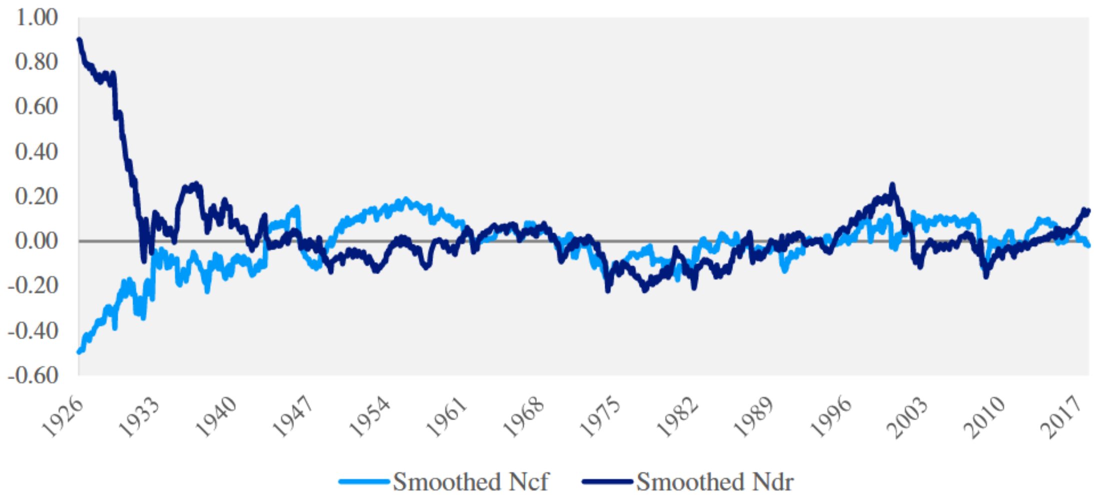
2. The low correlation between factor returns supports their potential use in combination, but also raises the question of when each factor should be emphasized.

2.6 Empirical Evidence of Factor Cyclicality

Their research begins with the idea that if factor returns are not only time-varying but also follow systematic patterns, then macroeconomic signals—particularly those reflecting the state of economic fundamentals—can be used to anticipate which factors are likely to be rewarded at different points in time. The hypothesis is that certain factors are inherently more exposed to variations in cash-flow expectations, and that this exposure can be identified and exploited.

As discussed in the previous section, returns can be decomposed into two distinct sources: cash-flow news and discount-rate news. This decomposition, grounded in the variance framework developed by Campbell and Shiller (1988) and later operationalized by Campbell (1991), allows us to identify how different types of shocks contribute to asset and factor returns. Importantly, cash-flow news reflects persistent information about future fundamentals, and is more closely linked to the economic cycle.

Exhibit 4: Smoothed components of aggregate returns (07/1926 - 06/2018).



Source: Polk et al. (2020).

To illustrate this, Polk compute the aggregate cash-flow (Ncf) and discount-rate news (Ndr) series for the Russell 1000 Index. When observing the graph of these two components (Exhibit 4), one can clearly see that the contribution of cash-flow news aligns with major economic turning points. For example, negative cash-flow shocks dominate during well-known periods of economic distress such as the Great Depression, the 1973–1975 recession, and the 2007–2009 Global Financial Crisis. These periods correspond to strong and persistent downward revisions in earnings expectations, confirming that cash-flow risk is a key driver of long-term return dynamics.

Building on this insight, the authors propose that if macroeconomic fundamentals can be forecasted, then factor exposures should be adjusted accordingly:

- When economic signals are positive, tilting towards factors with high exposure to cash-flow news is likely to be rewarded.
- When signals deteriorate, shifting towards factors with low cash-flow sensitivity offers more protection against persistent shocks.

To operationalize this concept, the authors regress the monthly excess returns of each factor—Value, Size, Quality, Momentum, and Low Volatility—on the cash-flow news time series derived from the Russell 1000. The estimated coefficients from these regressions represent each factor's sensitivity to innovations in aggregate cash-flow expectations, i.e., their cash-flow betas. The regression takes the following form:

$$R_{p,t+1} = a + \sum_{k=0}^{2} \beta_p NCF_{t+1-k} + \epsilon_{p,t+1} \tag{20}$$

where:

- $R_{p,t+1}$ is the return of portfolio p at time $t+1$,
- β_p is the sensitivity of portfolio p to the aggregate cash-flow news NCF_{t+1-k}
- a is the intercept term, and $\epsilon_{p,t+1}$ is the error term.

The empirical results reveal meaningful heterogeneity across factors. Size and, to a lesser extent, Value exhibit positive and significant cash-flow betas of 1.16 and 0.99 respectively, confirming their pro-cyclical nature. These factors tend to benefit most during periods of improving fundamentals.

In contrast, Quality and especially Low Volatility have low or even negative cash-flow betas of respectively 0.94 and 0.75, suggesting that they are more resilient during downturns—hence, counter-cyclical.

Momentum shows a moderate and unstable cash-flow sensitivity, with results varying across time and market conditions. This variability is consistent with the inherently transient nature of the momentum signal, which does not reflect persistent firm characteristics but rather exploits short-term trends.

These findings confirm that factor returns are cyclically sensitive in different ways, and that cash-flow beta serves as a reliable indicator of how a factor will perform across the phases of the business cycle. Moreover, the clear dispersion in factor sensitivities opens the door to tactical allocation strategies, where exposure is shifted toward or away from certain factors based on the anticipated direction of macroeconomic fundamentals. In the next section, we explore how this cyclical behavior can be directly integrated into a dynamic smart beta strategy, using macroeconomic indicators as signals to adapt factor exposure.

2.7 Smart Beta Strategy Based on Business Cycle Signals

Polk et al. (2020) propose a dynamic factor allocation framework that directly incorporates macroeconomic information to systematically tilt exposures across equity factors. Their strategy is motivated by the observation that different factors exhibit heterogeneous sensitivities to aggregate cash-flow news, and that this heterogeneity can be leveraged when forecasting fundamental economic conditions.

The authors construct a macro regime model based on two complementary signals:

1. A U.S. Leading Economic Indicator (LEI), which assesses whether economic growth is likely to be above or below its long-term trend;
2. A Global Risk Appetite Cycle Indicator (GRACI), which captures changes in investor risk tolerance based on realized returns and volatility across global financial assets.

By combining these two dimensions—level of economic growth and direction of risk appetite—they define four distinct business cycle regimes (Exhibit 5):

- **Recovery**: growth is below trend and accelerating;
- **Expansion**: growth is above trend and accelerating;
- **Slowdown**: growth is above trend but decelerating;

Exhibit 5: Business cycle regimes.

GRACI Accelerating	**Recovery**	**Expansion**
GRACI Decelerating	**Contraction**	**Slowdown**
	US LEI below Long-Term Trend	US LEI above Long-Term Trend

Source: Polk et al. (2020).

- **Contraction**: growth is below trend and decelerating.

Having defined these regimes, the authors exploit the aforementioned cash-flow betas of each factor to allocate exposure dynamically. For example, Size and Value—factors with high sensitivity to cash-flow news—are overweighted in Recovery and Expansion phases.

In contrast, Quality and Low Volatility—characterized by lower cash-flow betas—are favored in Slowdown and Contraction periods. Momentum, due to the transitory nature of its signal, plays a more nuanced role, often performing well at late-stage regime transitions.

The portfolio construction is guided by a regime-specific tilt matrix (Exhibit 6), in which multiplicative tilts are applied to factor scores on a stock-based level—a mechanism whose exact formulation, implementation and calculation will be outlined in the methodology section of this thesis. These tilts are adjusted according to both the prevailing macroeconomic regime and the factor's sensitivity to economic fundamentals.

For instance, in periods of expected economic recovery, factors with high exposure to cash-flow news—such as Value and Size—are assigned a tilt of 2, meaning their factor scores are applied twice, thereby increasing their relative weight within the portfolio. In contrast, more defensive factors—such as Low Volatility and Quality—receive either no tilt or a reduced weighting, as their performance tends to benefit less from an environment of accelerating economic growth.

The LEI is constructed using a panel of forward-looking macroeconomic indicators, normalized and detrended using a z-scoring procedure. GRACI, in turn, measures the excess return per unit of risk across a diversified basket of global equities, sovereign and corporate bonds, and serves as a proxy for the market's current willingness to bear risk. Notably, this measure is shown to be strongly correlated with global business cycle proxies and to lead macroeconomic turning points (Campbell and Cochrane (1999) ; Christie (1982)).

2.8 Conclusion

Whereas Chapter 1 provided a foundation for understanding the cross-sectional variation in expected returns, highlighting how certain firm characteristics—such as value, size, quality, momentum, or volatility—give rise to return premia, this second chapter shifted focus to the temporal dimension of those premia. The first chapter helped uncover the existence of persistent anomalies or exposures that were either linked to systematic sources of priced risk or reflective of market inefficiencies. In contrast, this chapter sought to understand how and when these factor premia evolve over time, progressing from theory to strategy.

The chapter began by addressing the limitations of the static CAPM and introducing intertemporal models, such as Merton's ICAPM, which allow risk to be decomposed along multiple state variables. From there, we explored the distinction proposed by Campbell and Vuolteenaho between cash-flow beta and discount-rate beta—a dual-channel framework that separates risk into persistent and transitory components. This decomposition was then applied to the Value and Size factors to explain their differing average returns, underscoring the fact that these factors are fundamentally exposed to distinct sources of risk—namely, variations in cash-flow news for Value and discount-rate news for Size.

We then extended this reasoning into the time-series domain, showing that factor premia vary cyclically, and that this variation is not random but predictable based on macroeconomic indicators. Empirical studies revealed that cash-flow sensitivity can serve as a useful proxy for the cyclical nature of a factor, and that this information can be used to guide tactical allocation. Finally, we examined the dynamic smart beta strategy developed by Polk, Haghbin, and de Longis (2020), which integrates leading economic indicators and market-based signals to classify regimes and adapt factor exposures accordingly. Their regime-switching approach outperforms static benchmarks both in absolute and risk-adjusted terms, providing a compelling framework for time-varying multifactor investing.

In sum, Chapters 1 and 2 jointly provide a comprehensive set of theoretical tools and empirical insights to understand both the cross-sectional and time-series dimensions of factor premia. This dual perspective is essential for the construction of a dynamic multifactor portfolio—one that not only captures structural sources of return but also responds flexibly to shifting macroeconomic conditions. In light of these conclusions, the following part of this thesis will be dedicated to the methodological implementation of this dynamic framework, through the construction of a dynamic multifactor portfolio built on

Exhibit 6: Factor tilts through the business cycle.

	Low Volatility	Size	Value	Momentum	Quality
Recovery	0	2	2	0	0
Expansion	0	1	1	2	0
Slowdown	2	0	0	0	2
Contraction	2	0	0	2	2

Source: Polk et al. (2020).

an investment universe distinct from that used by Polk, Haghbin, and de Longis.

Part III

Methodology

Introduction

This methodology is designed to support the achievement of the central objective of this thesis, which is to construct a *Dynamic Multifactor Portfolio* made of European stocks that adjusts its exposures based on the prevailing phase of the business cycle. This design directly echoes the aforementioned approach proposed by Polk et al. (2020), whose work demonstrated that factor premia exhibit significant time-series variation driven by macroeconomic regimes. Rather than maintaining static exposures to individual factors, the aim is to systematically tilt the portfolio toward those factors most likely to outperform in the current and expected economic environment.

Building such a portfolio, however, involves a dual challenge. First, it requires a forward-looking model capable of detecting and anticipating shifts in the business cycle using timely and predictive macroeconomic signals. Second, it entails a comprehensive bottom-up process of computing accurate factor scores for a broad cross-section of securities. This in turn depends on the collection and processing of a large volume of firm-level fundamental and historical price data for hundreds of European equities. The methodology developed in the next sections is designed to tackle both aspects—top-down regime identification and bottom-up factor scoring—in a coherent and repeatable framework.

To guide the reader through this process, the following methodological structure is adopted:

- **Section 2** outlines the *data collection and processing* framework, and defines both the *investment universe* and the *time horizon.*
- **Section 3** focuses on the *construction of factor scores*, detailing the underlying fundamental ratios and metrics, the statistical standardization used to compute comparable Z-scores across stocks, and the transformation of these Z-scores into final factor scores.
- **Section 4** outlines how these factor scores are *transformed into portfolio weights*, following a bottom-up "tilt" methodology that preserves exposure to multiple desired factors, and tackle the construction of a *Comprehensive Multifactor Portfolio.*
- **Section 5** introduces the *dynamic top-down overlay*, in which factor exposures are adapted in response to macroeconomic regime signals derived from a leading indicator, as well as the construction of a *Dynamic Multifactor Portfolio.*

This methodology will ultimately allow us to build a business-cycle-aware portfolio, whose empirical performance will be evaluated in the next part of this thesis, dedicated to results and backtesting.

In order to enhance the transparency and pedagogical clarity of this methodology, the reader will find in Appendix A the computation of factor scores, while Appendix B and C illustrate how these scores are transformed into portfolio weights using a step-by-step evolution of two selected stocks. This complementary analysis aims to illustrate how the methods described in the main sections are applied concretely to securities within our investment universe.

Chapter 3

Calculating Factor Score

3.1 Setting the Stage: Data, Investment Universe, and Horizon

3.1.1 Data collection and processing

All data used throughout this thesis were sourced from Bloomberg and collected between April and July 2025. The Bloomberg terminal employed was one of the seven made available on campus in Louvain-la-Neuve. Without access to these institutional resources, the completion of this thesis would have been infeasible, given the extensive dataset involved—more than 440,000 fundamental data points and approximately 4.1 million price observations were retrieved. It is worth noting, however, that the Bloomberg terminals were subject to monthly download limits, which, while renewable, made the data collection process particularly time-consuming and logistically constrained.

The data collected fall into two main categories: fundamental data and price data. Regarding the former, the list of STOXX Europe 600 constituents was retrieved on May 1st of each year. Although using quarterly or semi-annual financial reports would have provided a more dynamic and granular view of firms' fundamentals, such an approach posed standardization challenges. Not all firms disclose earnings at the same frequency—some report quarterly, others semi-annually—but all are required to publish full-year audited statements. Due to the significant variability in reporting dates—ranging from early January to mid-April—it was decided to collect financial statements on May 1st of each year. This approach ensures that all annual reports for the preceding fiscal year have been published. It is consistent with the requirements of the ESMA (2004) Transparency Directive, which stipulates that issuers must publish their annual financial reports no later than four months after the end of each financial year and ensure their public availability for a minimum of ten years. This design choice mitigates the risk of *look-ahead bias*, which would otherwise result from using data not yet available at the time of portfolio formation. A limitation of this timing is that by May 1st, unexpected cash-flow news may have already been incorporated into stock prices, potentially amplified by momentum-driven feedback effects (as discussed in Chapter 1). As a result, some companies may already exhibit significantly higher market capitalization by the time factor scores are computed.

Price data were collected for every component of the STOXX 600 as of May 1st of each year. For each stock, a five-year backward-looking price history was downloaded in order to compute trailing volatility (used for the Low Volatility factor) and twelve-month price trends (used in the Momentum factor). Additionally, forward-looking one-year price histories were retrieved to evaluate out-of-sample performance and backtest portfolio strategies.

Due to the large volume of raw data and the complexity of the operations required—including iterative normalization, percentile transformations, and truncation procedures—a powerful data processing and visualization environment was necessary. For this purpose, Python was selected. All financial data presented in the methodology section and corresponding appendices were first exported from Bloomberg into Excel format, then structured and transformed into Python DataFrames. From there, the data were cleaned, processed, and visualized using customized scripts tailored to each step of the portfolio construction framework. For reference, Appendix D includes Python scripts employed during the data processing and portfolio construction stages

3.1.2 Investment universe: Why the STOXX Europe 600?

In contrast to the original study by Polk et al. (2020), which focused on the Russell 1000—a U.S.-centric index composed of the largest American companies by market capitalization—this thesis adapts the framework to the European market by selecting the STOXX Europe 600 as its investment universe. The choice of this index is motivated by both practical and conceptual considerations.

In this thesis, the investment universe is strictly defined as the set of constituents included in the STOXX Europe 600 index. This implies that the portfolio can only be composed of stocks that are part of this index—no external securities are considered. However, while the STOXX Europe 600 is a market-cap-weighted index, the portfolio constructed in this study will use the same set of 600 European equities but assign dynamic, factor-driven weights to each constituent. In doing so, we retain the breadth and diversity of the index while introducing a valuation- and macro-sensitive structure tailored to business cycle dynamics.

The STOXX Europe 600, according to STOXX's website (STOXX (n.d.)), is a broad pan-European equity index that captures approximately 90% of the market capitalization of the European stock market. It comprises 600 publicly traded companies across 17 countries, including not only the Eurozone but also the United Kingdom, Switzerland, and the Nordics. Importantly, it includes large-, mid-, and small-cap firms, thereby offering a richer and more heterogeneous sample than narrower indices.

This stands in stark contrast to indices such as the STOXX Europe 50, which only includes the 50 largest and most liquid companies from the STOXX 600, selected based on free-float market capitalization. While the STOXX 50 is often used as a benchmark for blue-chip exposure in Europe, its heavy concentration in a small number of sectors and geographies makes it less suitable for a multifactor approach. In such a restricted universe, the potential to diversify factor exposures across firms is severely limited, and many firm-specific characteristics—especially those relating to size, quality, or volatility—tend to be highly correlated.

The STOXX 600, by contrast, provides a much more fertile ground for factor-based analysis. With a broader cross-section of companies varying in market capitalization, sectoral orientation, and country affiliation, the index allows for greater dispersion in factor scores. This heterogeneity is critical for the effective implementation of a multifactor strategy, as it facilitates the identification of meaningful differences in firm characteristics—such as valuation multiples, profitability, or risk levels—and enables better diversification within each factor.

Furthermore, applying a business-cycle-driven methodology to European equities introduces both challenges and opportunities. While Europe has experienced macroeconomic phases that parallel those of the United States—such as the 2000 dot-com crash, the 2008 global financial crisis, or the 2020 COVID-19 pandemic—it has also undergone region-specific shocks, most notably the *sovereign debt crisis* in the early 2010s. These additional dynamics may lead to asynchronous recovery patterns and differences in factor behavior across regimes, making Europe an ideal setting to test the dynamic multifactor framework. The presence of multiple, distinct economic phases strengthens the case for a dynamic portfolio approach—since in a world with only one economic regime, such adaptability would have little added value.

In summary, the STOXX Europe 600 offers:

- A wide cross-sectional representation of the European equity market
- Inclusion of multiple market-cap segments (large, mid, small)
- Sufficient dispersion in factor characteristics across securities
- Exposure to diverse business cycle dynamics across countries

3.1.3 Time horizon: Capturing economic cycles in a European context

In the original study by Polk et al. (2020), the analysis covers a period from January 1989 to September 2018. This long time frame allows for the observation of multiple business cycle regimes and macroeconomic turning points in the U.S. equity market.

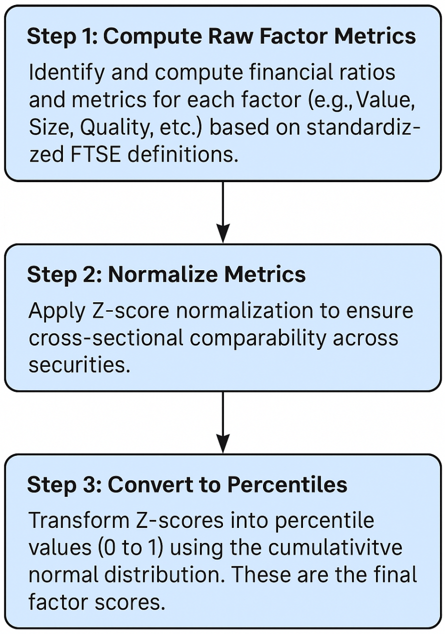
In the present study, we consider a time horizon that spans from May 2002 to December 2024. While the STOXX Europe 600 index was officially introduced in 1998, the complete and consistent list of its historical constituents—as retrievable via Bloomberg—only becomes available starting in 2002. This limitation determines the practical starting point of our analysis.

Although our sample period is slightly shorter than that of Polk et al., it still offers a sufficiently long window to observe several distinct macroeconomic regimes within the European context. These include the aftermath of the dot-com bubble, the 2008 global financial crisis, the Eurozone sovereign debt crisis, the COVID-19 pandemic, and the recent inflationary shock following geopolitical tensions. As such, the time horizon remains adequate to assess the effectiveness of a dynamic factor allocation strategy and to test whether such an approach adds value over static multifactor exposure in European markets.

3.2 Scoring the Fundamentals

The construction of a multifactor portfolio begins with the computation of **factor scores** at the individual stock level. These scores quantify the exposure of each security to the targeted style factors: Value, Size, Quality, Momentum, and Low Volatility. The process involves three main steps.

Exhibit 7: From raw factor metrics to factor scores.



First, for each factor, we identify and compute the relevant financial ratios and metrics that capture its core characteristics. These ratios and metrics are not arbitrarily chosen; they are based on the standardized definitions provided in the *FTSE Global Factor Index Series Methodology* (Sandford (2025)), ensuring consistency with institutional practices and academic rigor. Each ratio is precisely defined and mathematically formulated to enable transparent and replicable signal extraction.

Second, once these raw factor metrics are computed for all securities in the investment universe, a normalization procedure is applied to transform them into standardized Z-scores. This step ensures cross-sectional comparability and allows for a consistent ranking of stocks within each factor dimension.

Lastly, the standardized Z-scores are converted into percentile values using the cumulative distribution function of the standard normal distribution. These percentile values between 0 and 1 constitute the *final factor scores*, which serve as direct inputs for portfolio construction.

Let us now begin by examining the normalization procedure, as a first step, in order to better understand how the factor scores are calculated according to the FTSE (2025) methodology.

3.2.1 Z-score and Factor Score Normalization Procedure

Before factor scores can be used for portfolio construction, the raw financial ratios and metrics associated with each factor must be standardized to allow for cross-sectional comparison. This is achieved through a Z-score normalization, which transforms each raw metric into a standardized value reflecting how far it deviates from the mean of the distribution within the investment universe.

For each stock i and factor-related variable F, the Z-score is computed as:

$$Z_{F,i} = \frac{F_i - \mu_F}{\sigma_F} \tag{21}$$

Where:

- F_i is the raw value of the variable for stock i
- μ_F is the cross-sectional mean of F across all stocks in the universe
- σ_F is the cross-sectional standard deviation of F

This transformation rescales all variables to a common statistical format with mean zero and unit variance, thus allowing different financial ratios and metrics to be aggregated meaningfully within composite factor scores.

Truncation and iterative renormalization

To limit the influence of extreme outliers, Z-scores are truncated to lie within the range of $[-3, +3]$. That is:

$$Z_{F,i} = \begin{cases} +3 & \text{if } Z_{F,i} > 3 \\ -3 & \text{if } Z_{F,i} < -3 \\ Z_{F,i} & \text{otherwise} \end{cases} \tag{22}$$

After truncation, the normalization process is repeated iteratively: the full set of Z-scores is recomputed based on the truncated distribution until all values lie within the acceptable range and convergence is achieved. This approach follows the methodology outlined by FTSE Russell (2025) and ensures stability in the factor construction process.

Handling missing data

If a company lacks data for a given ratio or metric, it is excluded from the mean and standard deviation calculations for that variable. For composite factors (e.g., Value or Quality), the final Z-score is computed as the average of the available Z-scores. In rare cases where data is entirely missing, a neutral score of zero is assigned.

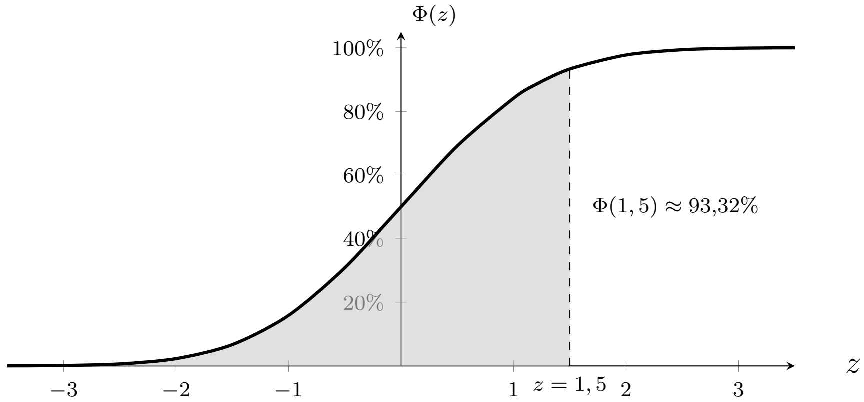
Conversion to percentile-based factor scores

Once the Z-scores have been truncated and stabilized, they are transformed into percentiles using the cumulative distribution function (CDF) of the standard normal distribution. This transformation converts each Z-score into a percentile rank between 0 and 1, reflecting the asset's relative standing in the cross-sectional distribution of the factor.

Formally, for a given asset i, the percentile score is defined as:

$$\mathrm{S}_{F,i} = \Phi(Z_{F,i}) \tag{23}$$

where $\Phi(\cdot)$ denotes the standard normal cumulative distribution function, and $Z_{F,i}$ is the normalized and truncated Z-score for factor F.



These percentile values represent the final **factor scores** used in portfolio construction. Higher values indicate stronger exposure to the desired factor characteristics (e.g., cheaper valuation for Value, higher profitability for Quality), while lower values indicate weaker exposure.

This representation offers several advantages: it enables intuitive interpretation as relative rankings, ensures comparability across heterogeneous factor distributions, and mitigates the disproportionate influence of extreme observations—even after truncation—by bounding the factor scores within a well-defined and positive range. As such, these percentile-based scores serve as the standardized inputs for weighting schemes in the dynamic portfolio model.

Now that these procedures have been clearly established, we turn to the computation of factor scores for each dimension—starting from the raw financial data collected from Bloomberg and ending with the final, standardized factor scores used in portfolio construction. As aforementioned, each factor is accompanied by a concrete example in Appendix A, based on the year 2024, comparing two companies from the investment universe—Ackermans & Van Haaren and Siemens—to illustrate how raw inputs are transformed into factor scores.

3.2.2 Value Factor

The Value factor aims to identify stocks that are relatively undervalued with respect to their fundamentals. According to the FTSE (2025), Value is defined as a composite of three widely used valuation ratios:

- Cash-Flow Yield

- Earnings Yield
- Sales-to-Price Ratio

This structure also reflects the academic insights discussed in the litterature part of this thesis. In particular, Ball (1978) emphasized the relevance of the *earnings yield*—the inverse of the popular price-to-earnings (P/E) ratio—as a robust valuation signal, arguing that it may proxy for a stock's true expected return. In a similar spirit, the *cash-flow yield* captures actual liquidity generation, while the *sales-to-price* ratio offers a top-line perspective, less sensitive to accounting decisions. Together, these three measures form a comprehensive picture of relative valuation, covering earnings, cash, and revenues.

$$\text{Cash-Flow Yield}_i = \frac{\text{Operating Cash Flow}_i}{\text{Market Capitalization}_i} \tag{24}$$

$$\text{Earnings Yield}_i = \frac{\text{Net Income}_i}{\text{Market Capitalization}_i} \tag{25}$$

$$\text{Sales-to-Price}_i = \frac{\text{Annual Sales}_i}{\text{Market Capitalization}_i} \tag{26}$$

Composite Value Score

Once each of these three ratios is calculated, they are standardized using the Z-score normalization procedure detailed in the last section. The Composite Value Z-Score for stock i is then defined as:

$$\text{Composite Value Z-score}_i = \frac{1}{3}\left(Z_{\text{CFY},i} + Z_{\text{EY},i} + Z_{\text{SP},i}\right) \tag{27}$$

Where:

- $Z_{\text{CFY},i}$ = Z-score of the cash-flow yield
- $Z_{\text{EY},i}$ = Z-score of the earnings yield
- $Z_{\text{SP},i}$ = Z-score of the sales-to-price ratio

Finally, the Composite Value Z-score is rescaled using the standardization procedure described earlier, which maps it to a percentile-based factor score bounded between 0 and 1. A higher Value score indicates that the stock appears more attractively priced across multiple dimensions of valuation.

3.2.3 Size Factor

As discussed earlier, the Size factor reflects the empirical finding that smaller firms tend to yield higher average returns than their larger counterparts, a phenomenon known as the *size effect* (Banz, 1981).

In accordance with the FTSE (2025), the Size factor is operationalized through the negative logarithm of a company's market capitalization:

$$\text{Size}_i = -\log\left(\text{Market Capitalization}_i\right) \tag{28}$$

The use of the negative sign ensures that smaller companies receive higher raw scores, in line with the theoretical premise that they are expected to outperform larger firms

Once the raw Size values are calculated for all stocks in the universe, they are transformed into standardized Z-scores using the normalization procedure described previously. These standardized Z-scores are then mapped through the standard normal cumulative distribution function to obtain final factor scores bounded between 0 and 1. A higher Size score thus corresponds to a smaller company in relative terms, and a lower score indicates a larger, more established firm.

3.2.4 Quality Factor

The Quality factor seeks to identify firms with strong and sustainable fundamentals—typically characterized by high profitability and low financial leverage. In the FTSE Russell Methodology (2025), Quality is modeled as a composite of two dimensions:

- **Profitability**, based on operating and accounting performance
- **Leverage**, capturing the firm's ability to service its debt

Each dimension is computed using a set of financial ratios, which are standardized via Z-scores and averaged to obtain a final Quality score.

Profitability

Profitability reflects the firm's ability to generate returns on its assets in a consistent and sustainable manner. It is constructed from three sub-indicators, the rationale for which was discussed earlier:

1. Return on Assets (ROA)
2. Change in Asset Turnover
3. Accruals (with sign reversal)

$$\text{ROA}_i = \frac{\text{Net Income}_i}{\text{Average Total Assets}_i} \tag{29}$$

Average total assets are computed over the current and previous fiscal years. As mentioned, ROA has the advantage of encompassing the entire capital structure of the firm, unlike ROE, which can be inflated through leverage or aggressive acquisitions.

$$\Delta\text{Asset Turnover}_i = \left(\frac{\text{Sales}_t}{\text{Total Assets}_t}\right) - \left(\frac{\text{Sales}_{t-1}}{\text{Total Assets}_{t-1}}\right) \tag{30}$$

This metric captures changes in efficiency of resource utilization. We previously mentioned that positive changes in ATO are strong predictors of future profitability (Soliman, 2008).

$$\text{Accruals}_i = -\frac{\Delta WC_i + \Delta NCO_i + \Delta FIN_i}{\text{Average Total Assets}_i} \tag{31}$$

Where:

- ΔWC: change in working capital
- ΔNCO: change in net non-current operating assets
- ΔFIN: change in net financial assets

This decomposition, which was examined earlier in the litterature part, follows the framework studied by Richardson et al. (2004). Accruals are sign-inverted to reflect that higher accruals imply lower earnings quality.

Finally, each of the three profitability sub-indicators is normalized via Z-scores, then averaged to obtain a Composite Profitability Z-score, which is itself normalized again after aggregation.

$$\text{Composite Profitability Z-score}_i = \frac{1}{3}\left(Z_{\text{ROA},i} + Z_{\Delta\text{ATO},i} + Z_{\text{Accruals},i}\right) \tag{32}$$

Leverage

Leverage is measured using the ratio of operating cash flow to total debt:

$$\text{Leverage Ratio}_i = \frac{\text{Operating Cash Flow}_i}{\text{Total Debt}_i} \tag{33}$$

It was also shown in Chapter 1 that financial leverage is negatively related to future earnings performance (Nissim and Penman, 2003). This measure is also normalized via Z-score across the investment universe.

Composite Quality Score

The final Composite Quality Z-score for stock i is computed as the average of the profitability and leverage Z-scores:

$$\text{Quality}_i = \frac{1}{2}\left(Z_{\text{Profitability},i} + Z_{\text{Leverage},i}\right) \tag{34}$$

The Quality Composite Z-Score is normalized a last time and then mapped through the standard normal cumulative distribution function to obtain a final Quality score bounded between 0 and 1. A higher Quality score indicates that the stock exhibits stronger fundamental characteristics across multiple dimensions of financial quality.

For securities classified under financials and real estate (ICB industry code 30 and 35), Return on Assets (ROA) is used as the sole indicator of quality. This is because certain quality metrics—such as operating cash flow and accruals—are either not applicable or cannot be reliably calculated for companies in these sectors (FTSE, 2025).

3.2.5 Momentum Factor

The Momentum factor captures the tendency of stocks that have performed well in the recent past to continue outperforming in the short to medium term—a phenomenon we have explored through the paper of Jegadeesh and Titman (1993).

In the FTSE Global Factor Index Series Methodology (FTSE, 2025), Momentum is calculated as the cumulative total return over an 11-month period, excluding the most recent month. This exclusion helps mitigate short-term mean-reversion effects and is standard practice in momentum strategies. Accordingly, we compute momentum using the stock's total return over the past 52 weeks, ending 4 weeks prior to the calculation date.

$$\text{Momentum}_i = \sum_{t=-52}^{-4} R_{i,t} \tag{35}$$

Where:

- $R_{i,t}$ is the total local return of stock i in week t
- The summation excludes weeks -4 to -1 (i.e., the most recent full month)

A full 12-month return history (excluding the last month) is required for the calculation. Securities lacking sufficient price history are excluded from the Momentum factor computation for that period.

The raw cumulative return is then standardized using the Z-score normalization procedure described earlier. Finally, the final Z-scores are mapped through the standard normal cumulative distribution function to obtain a Momentum score bounded between 0 and 1. A higher Momentum score corresponds to a stock with strong recent price performance.

3.2.6 Low Volatility Factor

The Low Volatility factor is based on the empirical anomaly that stocks with lower historical price volatility tend to generate higher risk-adjusted returns than their more volatile counterparts—a phenomenon often referred to *low-risk anomaly* (Black, 1972; Frazzini and Pedersen, 2014), as we explored earlier.

In the FTSE methodology (2025), Low Volatility is defined as the inverse of a stock's historical return volatility, computed over a five-year window using weekly returns.

$$\text{Volatility}_i = \text{Standard Deviation of Weekly Total Returns (over 5 years)} \tag{36}$$

A minimum of 52 weekly return observations is required for a valid calculation. Formally, for a given stock i, let $x \in \mathbb{N} \cap [52, 260]$ denote the number of available weekly observations. Then, the volatility is computed as:

$$\sigma_i = \max_{x \in \mathbb{N} \cap [52,260]} \left(\sigma_i^{(x)} \right) \tag{37}$$

where $\sigma_i^{(x)}$ is the standard deviation of weekly returns over the past x weeks. If $x < 52$, the stock is excluded from the computation.

To ensure consistency with other factors (where higher scores are better), the raw volatility is multiplied by -1 before standardization:

$$\text{LowVol}_i = -\sigma_i \tag{38}$$

The transformed Low Volatility value is then standardized using the now well-known Z-score normalization procedure, and mapped through the standard normal cumulative distribution function to obtain a Low Volatility score bounded between 0 and 1. A higher Low Volatility score therefore corresponds to a stock with relatively stable historical returns.

Exhibit 8: FTSE Russell Factor Definitions

Factor	**FTSE Russell Factor Definition**
Value	Equally weighted composite of cash-flow yield, earnings yield, and price-to-sales ratio.
Quality	Equally weighted composite of profitability (return on assets, change in asset turnover, accruals) and leverage ratio.
Size	Inverse of full market capitalization index weights.
Low Volatility	Standard deviation of five years of weekly total returns.
Momentum	Cumulative 11-month return (last 12 months excluding the most recent month).

Source: Polk et al. (2020) and FTSE (2025)

Chapter 4

From Scores to Weights

Once factor scores have been computed for each stock across the five dimensions—Value, Size, Quality, Momentum, and Low Volatility—these scores must be translated into portfolio weights. This transformation is a crucial step: it bridges the gap between factor signal extraction and actual portfolio implementation.

This subsection details the procedure used to construct what Polk et al. (2020) refer to as the *Comprehensive Multifactor Portfolio*. This portfolio aims to provide a neutral, equally-exposed allocation to the five factors and does not adjust to the business cycle. In that sense, it serves as a static benchmark against which the performance of our dynamic, cycle-sensitive portfolio will later be evaluated.

Before describing the technical steps involved in this construction, it is useful to briefly distinguish between two major approaches to combining factors: the *Top-Down* (composite index) method and the *Bottom-Up* (tilt-tilt) method, which underlies the FTSE Russell approach adopted in this thesis ("Multi-factor indexes: The power of tilting" (2017)).

4.1 The Factor Combination Process: Top-Down vs. Bottom-Up Construction

As emphasized in the FTSE Global Factor Index Series methodology (FTSE, 2025), combining exposure to multiple factors can be achieved through different portfolio construction philosophies:

4.1.1 Composite index (top-down approach)

This approach consists in constructing separate single-factor portfolios—referred to as *single-factor indices*—and then combining them through fixed-weight aggregation. A single-factor index is a portfolio that isolates exposure to a specific characteristic, such as Value, Quality, or Size, by allocating higher weights to stocks with high scores on that particular factor and lower weights to those with poor scores.

A Value index, for example, could be formed by assigning weights to each stock proportionally to its Value score (see example in Appendix A):

$$w_{i,t}^{\text{Value}} = \frac{S_{i,t}^{\text{Value}}}{\sum_{j\in\mathcal{U}_t} S_{j,t}^{\text{Value}}} \tag{39}$$

where $\mathcal{U}_t$ denotes our investment universe at time t, i refers to the specific stock whose portfolio weight is being calculated, and j indexes all stocks within $\mathcal{U}_t$. $S_{i,t}^{\text{Value}}$ represents the Value factor score of stock i at time t.This ensures that stocks with the strongest valuation metrics receive the highest exposure in the Value index. The same procedure can be independently applied to create single-factor indices for Size, Quality, Momentum, and Low Volatility.

The composite index is then built by allocating a fixed proportion of capital to each of these single-factor portfolios. For instance, an investor could form a multi-factor exposure by allocating one-third of total capital to each of three indices:

$$w_{i,t}^{\text{composite}} = \frac{1}{3}w_{i,t}^{\text{Value}} + \frac{1}{3}w_{i,t}^{\text{Quality}} + \frac{1}{3}w_{i,t}^{\text{Size}} \tag{40}$$

While straightforward and modular, this method comes with structural drawbacks. Because each single-factor index is constructed independently, overlapping positions may cancel out. For example, a stock with strong Value characteristics but weak Quality may be overweighted in the Value index and underweighted in the Quality index. In the composite portfolio, these opposing effects dilute the intended exposure.

This issue is particularly pronounced when combining negatively correlated factors—such as Value and Quality. The averaging process reduces the presence of stocks that exhibit strong tilts along only one axis, thereby weakening the composite's factor profile. In short, while intuitive, the Top-Down method may blur the precision of targeted multi-factor exposures by treating each factor in isolation rather than considering their joint distribution across stocks.

4.1.2 Tilt-tilt Index (bottom-up approach)

In contrast to the Top-Down method, the Bottom-Up or "tilt-tilt" approach constructs the multi-factor portfolio directly at the stock level, without relying on independent single-factor indices. This method—advocated by FTSE Russell and implemented in this thesis—applies sequential tilts to each stock's base weight based on its factor scores across multiple dimensions.

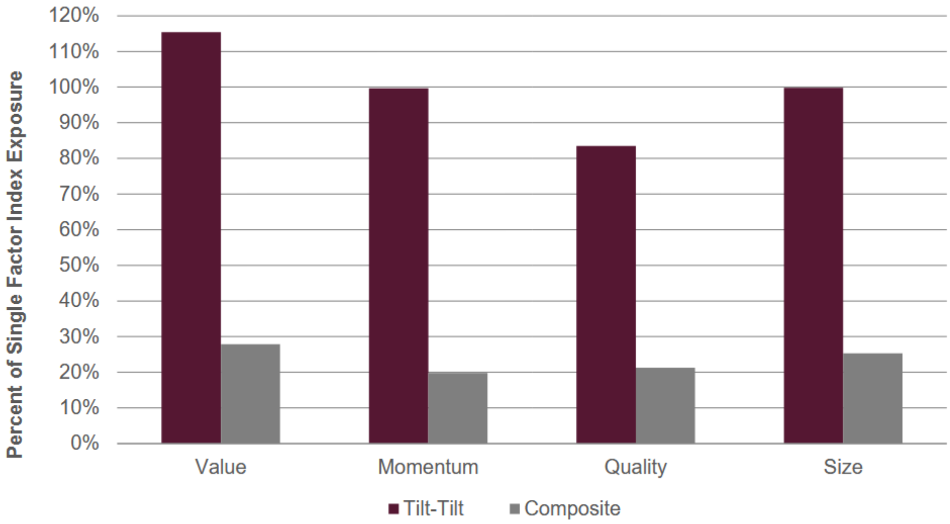
The logic is as follows: instead of building separate portfolios for Value, Size, or Quality, we begin with a neutral baseline allocation—such as the market capitalization weight—and adjust it using the factor scores calculated in earlier sections. These scores, normalized to lie between 0 and 1, reflect the stock's relative exposure to each factor. For a given stock i, its raw multifactor weight is defined as:

$$w_{i,t}^{\text{raw}} = w_{i,t}^{\text{mkt}} \times \prod_{f=1}^{n} S_{i,t}^{(f)} \tag{41}$$

This multiplicative structure ensures that stocks scoring highly across all dimensions are strongly overweighted, while those with weak or mixed signals are naturally down-weighted. Unlike the composite index approach, this method preserves the full intensity of factor exposure and allows for meaningful interactions across factors.

For instance, consider a stock with a very high Value score but weak Quality and Momentum. Under the Top-Down method, its presence would be reduced by averaging it with indices in which it is underrepresented. In the Bottom-Up method, this contrast is resolved internally: the weak scores directly downscale the weight applied to the Value tilt, resulting in a smoother and more integrated weighting outcome.

Exhibit 9: Comparison of Top-Down vs. Bottom-Up exposure.



Source: FTSE Russel (2017).

Now that the distinction between Top-Down and Bottom-Up approaches is clear, we proceed to implement the latter in constructing what we refer to as the *Comprehensive Multifactor Portfolio*. This portfolio is built using the bottom-up methodology described above, where each stock's weight is derived by sequentially tilting its market capitalization weight according to its factor scores across Value, Size, Quality, Momentum, and Low Volatility. The following subsection provides an overview of this construction; a detailed explanation, along with a concrete example illustrating the mechanics of the process, is provided in Appendix B.

4.2 Comprehensive Multifactor Portfolio

4.2.1 Purpose

The Comprehensive Multifactor Portfolio aims to provide a neutral, equally-exposed allocation to the five factors and does not adjust to the business cycle. In that sense, the creation of this portfolio serves three key purposes.

First, it offers a practical and intuitive framework to understand how sequential tilts are applied to factor scores in order to determine a stock's final weight within a multifactor strategy. By following the construction step-by-step, we can observe how a stock's exposure to Value, Size, Quality, Momentum, and Low Volatility influences its allocation relative to its initial market capitalization.

Second, it provides a relevant benchmark—both conceptually and empirically. On one hand, it allows us to assess whether an equally-weighted exposure to factor premia outperforms a market-capitalization approach that ignores factor signals altogether. In this construction, portfolio weights are derived from market-capitalization weights and adjusted up or down depending on each stock's relative factor scores. The resulting portfolio thus embodies a balanced, rules-based multi-factor exposure grounded in economic intuition.

On the other hand, this benchmark will serve to evaluate the added value of dynamic allocation. Since the *Comprehensive Multifactor Portfolio* applies constant tilts and does not adapt to changing macroeconomic conditions, it will enable a direct comparison with the *Dynamic Multifactor Portfolio* developed in the next section. This comparison will help determine whether a dynamic, cycle-aware tilt strategy offers superior performance relative to a static, cycle-agnostic approach.

4.2.2 Construction

The methodology used for constructing the portfolio is based on the work of Polk et al. (2020). The starting point is the market capitalization weight $w_{i,t}^{\text{mkt}}$ of each stock i. This weight is then sequentially tilted by the stock's percentile-based factor scores $S_{i,t}^{(f)} \in [0, 1]$ for each factor $f \in \{1, \dots, n\}$. The raw (unnormalized) multifactor weight is defined as:

$$w_{i,t}^{\text{raw}} = w_{i,t}^{\text{mkt}} \times \prod_{f=1}^{n} S_{i,t}^{(f)} \tag{42}$$

Finally, the raw weights are normalized across all eligible stocks to ensure full capital allocation:

$$\tilde{w}_{i,t} = \frac{w_{i,t}^{\text{raw}}}{\sum_{j \in \mathcal{U}_t} w_{j,t}^{\text{raw}}} \tag{43}$$

The notation is the same as in equation (40), i.e. $\mathcal{U}_t$ denotes our investment universe at time t, i refers to the specific stock whose portfolio weight is being calculated, and j indexes all stocks within $\mathcal{U}_t$. This approach ensures that stocks with higher factor exposures receive greater weight, while maintaining total portfolio exposure at 100%.

4.3 Adapting to the Cycle: Dynamic Allocation through Macro Regimes

In contrast to the static benchmark previously discussed, the construction of a *Dynamic Multifactor Portfolio* requires a more methodical approach. While the *Comprehensive Multifactor Portfolio* assumed a constant and balanced exposure to factors throughout the investment horizon, the dynamic version allows these exposures to vary over time. Specifically, they will adjust based on monthly signals, the origin and construction of which must first be explained

To achieve this, we proceed in two steps. First, we define a set of distinct macroeconomic regimes—expansion, slowdown, contraction, and recovery—using a forward-looking indicator of economic activity. Second, we describe how these regimes are used to dynamically reweight stocks in the *Dynamic Multifactor Portfolio*, based on the relative attractiveness of each factor within the prevailing economic context.

4.3.1 Identifying Macro Regimes

The role of the OECD Composite Leading Indicator (CLI)

In their 2020 study, Polk et al. (2020) propose a dynamic asset allocation framework that adjusts portfolio factor exposures based on macroeconomic conditions. Their methodology relies in part on a leading indicator constructed from a set of U.S. economic variables. However, given that the investment universe in this thesis is European, we adapt that leading indicator to a more geographically relevant context by selecting a regional macroeconomic proxy.

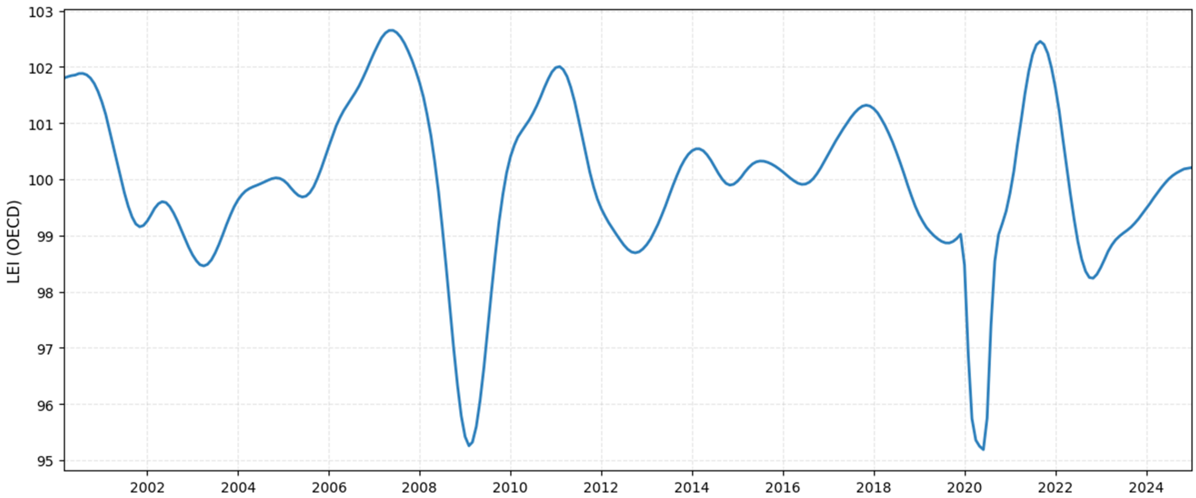
To capture the cyclical dynamics of the European economy, we employ the OECD "Composite Leading Indicator (CLI)" (n.d.) for the "Major Four European Countries." This indicator aggregates forward-looking economic signals for France, Germany, Italy, and the United Kingdom—countries which together represent approximately 60% of the total market capitalization of the STOXX Europe 600 Index. Although the STOXX 600 includes firms from 17 countries, these four core economies exert significant influence on regional dynamics. Moreover, the remaining countries are part of the broader European region and are therefore likely to exhibit similar cyclical patterns.

The OECD Composite Leading Indicator is designed to anticipate turning points in economic activity relative to trend. It is constructed from a weighted combination of variables that typically change direction before the economy as a whole. These components include:

- **Average weekly hours** in manufacturing, capturing early shifts in labor demand;
- **New orders**, reflecting changes in future production activity;
- **Consumer expectations**, which often foreshadow consumption trends;
- **Housing permits**, a proxy for anticipated construction and investment;
- **Stock prices**, which embed forward-looking assessments of economic prospects;
- **Interest rate spreads** (e.g., 10-year minus 3-month), which signal monetary policy stance and credit conditions.

These variables are considered "leading" because they tend to move ahead of coincident indicators such as GDP or industrial production, often by a margin of 6 to 9 months. As such, the CLI provides a timely and interpretable signal of future economic conditions. By tracking the direction and magnitude of changes in this composite index, we

Exhibit 10: OECD Composite Leading Indicator (CLI)



Source: Data retrieved from OECD (2025).

can define macroeconomic regimes—such as expansions, slowdowns, contractions, and recoveries—and adjust factor exposures accordingly in the construction of our dynamic portfolio.

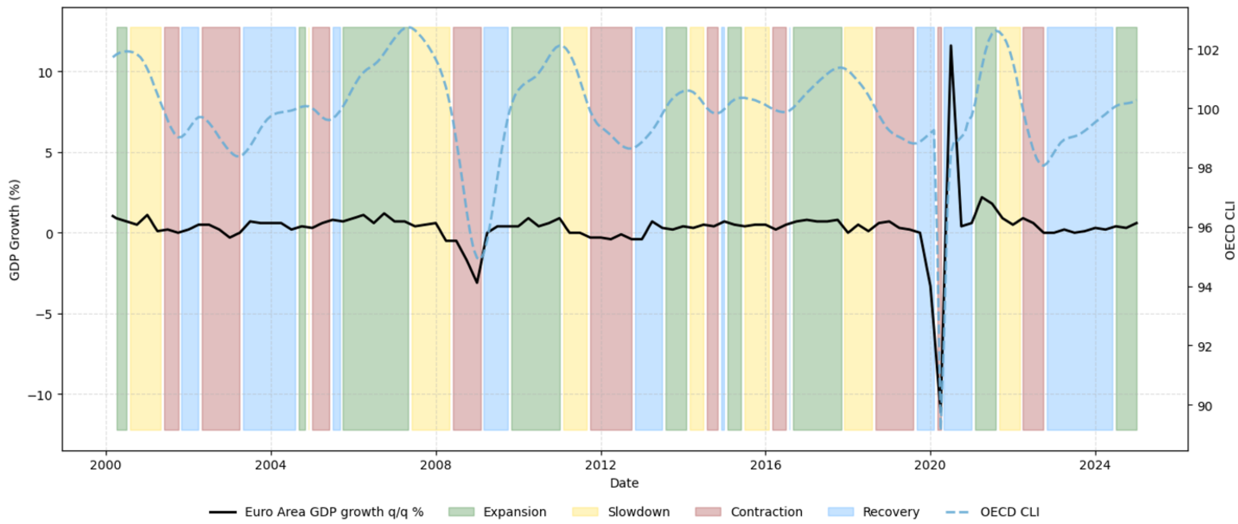
The CLI is a normalized index with a long-term trend value set at 100. A reading above 100 suggests that future GDP levels are expected to be above trend, while a reading below 100 indicates GDP levels are expected to be below trend. In addition, the month-on-month change in the CLI provides information about the expected pace of growth. A rising CLI typically signals improving economic momentum, whereas a falling CLI suggests deceleration.

Building on the OECD framework, we define the four macroeconomic regimes as follows:

- **Expansion**: CLI $>$ 100 and increasing month-on-month $\rightarrow$ Real GDP is expected to remain above trend, with the GDP gap widening and growth momentum accelerating.
- **Slowdown**: CLI $>$ 100 but decreasing month-on-month $\rightarrow$ GDP remains above trend, but the pace of growth is expected to moderate.
- **Contraction**: CLI $<$ 100 and decreasing month-on-month $\rightarrow$ GDP is expected to remain below trend, with the negative GDP gap widening and economic activity weakening.
- **Recovery**: CLI $<$ 100 but increasing month-on-month $\rightarrow$ GDP is below trend, but momentum is improving and the GDP gap is expected to narrow.

The following chart (Exhibit 11) illustrates the identification of macroeconomic regimes based on the OECD framework and compares them with the actual quarter-over-quarter annualized GDP growth of the Euro Area. Monthly values between quarterly observations have been linearly interpolated to smooth the GDP growth curve.

Exhibit 11: Business cycle phases identification vs. current GDP growth.



Source: Data retrieved from Eurostat and OECD.

The figure confirms that the regime classification derived from the CLI is broadly consistent with contemporaneous and subsequent GDP dynamics. In particular, the CLI anticipates major inflection points in economic activity, reinforcing its role as a reliable forward-looking indicator. Naturally, no model-based signal can foresee abrupt exogenous shocks—so-called "black swan" events—such as the COVID-19 pandemic. However, the indicator does capture more structural, endogenous slowdowns with notable accuracy.

For example, the economic deceleration associated with rising interest rates prior to the burst of the early-2000s dot-com bubble is clearly visible in the form of a prolonged slowdown regime. A similar pattern is observed in the lead-up to the 2008 global financial crisis, where the CLI shows a gradual deterioration in economic conditions well before GDP contractions materialize. This sequence aligns with macroeconomic narratives emphasizing the delayed consequences of loose monetary policy and speculative excess—criticisms that were notably raised in the U.S. context at the time (Polleit (2007)).

The European sovereign debt crisis that began in 2010 is also well captured, with the CLI reflecting a progressive slowdown in activity consistent with rising financial instability in the region.

More recently, the CLI captures the global deceleration associated with inflationary pressures linked to the Russo-Ukrainian conflict and related energy shocks.

These examples illustrate the relevance of the CLI-based regime framework for capturing both cyclical turning points and broader macro-financial trends. Beyond its ability to flag directional shifts in activity, the CLI offers a structured lens through which economic momentum can be interpreted in real time. By smoothing out short-term volatility and transitory noise, it enables a clearer reading of the underlying trajectory of the economy, and provides a valuable signal of long-term trend deviations that are likely to influence asset returns.

Limitations: The lack of a global risk appetite indicator

While the use of a leading macroeconomic indicator such as the OECD Composite Leading Indicator (CLI) provides a structured and anticipatory framework for regime classification, it represents only one dimension of the drivers of asset returns. Specifically, the model implemented in this thesis captures macroeconomic momentum but does not explicitly incorporate investor sentiment or risk appetite—factors that can significantly influence market behavior, particularly over shorter horizons (Campbell and Cochrane (1999)).

Global risk appetite refers to investors' willingness to bear risk and is often proxied by measures such as credit spreads, the VIX or VSTOXX index, or cross-asset flows into risk-on versus risk-off assets. During periods of heightened risk aversion, for instance, even an improving macroeconomic backdrop may not translate into stronger equity returns, as investors may remain reluctant to reallocate toward risky assets. Conversely, in periods of exuberant sentiment, risk assets may perform well even in the absence of robust macro fundamentals.

It is important to clarify that the exclusion of a sentiment-based signal in the present framework—unlike in the model developed by Polk et al. (2020)—is not a deliberate modeling choice, but rather a reflection of the complexity involved in constructing a robust and reliable risk appetite indicator. Building such a composite requires access to high-frequency market data, dynamic weighting schemes, and advanced filtering techniques that fall outside the scope of this thesis. Preliminary attempts conducted in the context of this thesis yielded sentiment-based indicators that exhibited excessive noise and lacked coherence when combined with the OECD leading indicator. Moreover, smoothing such a signal—e.g., using a moving average—tends to introduce a lag that undermines its purpose as a leading indicator, further complicating its effective integration into a dynamic macro-financial framework.

Nonetheless, it is worth noting that certain elements of investor sentiment are partially embedded within the CLI itself. Specifically, one of its components is the stock market return of the Euro STOXX 600, which acts as a proxy for expectations about future economic and financial conditions. As such, while not explicitly modeled, aspects of risk appetite and market confidence are indirectly reflected in the macroeconomic signal used in this study.

4.3.2 From Macroeconomics Signals to Factor Tilts

Now that macroeconomic regimes have been clearly identified using the OECD Composite Leading Indicator, the next step is to translate these signals into actionable portfolio adjustments. More specifically, we aim to conditionally tilt factor exposures based on the anticipated phase of the business cycle that we identify, thus aligning the portfolio with the most relevant sources of return in each macroeconomic environment.

As discussed in the literature review—particularly in the chapter on time-series variations in factor premia—factor returns are not stable over time, but instead exhibit strong cyclical patterns. Some factors are pro-cyclical, meaning they tend to perform better during expansions (e.g., Value and Size), while others are more defensive or acyclical (e.g., Quality or Low Volatility), offering resilience in downturns. These dynamics are driven in part by differences in each factor's sensitivity to persistent cash-flow shocks, as captured by their respective "bad beta" exposures (Campbell and Vuolteenaho, 2004). The table below summarizes the cyclical behavior of each factor, as outlined in Chapter 2:

Exhibit 12: Cyclicality and cash-flow sensitivity of equity factors.

Factor	**Cyclicality**	**Cash-flow Beta**
Value	Pro-cyclical	High
Size	Pro-cyclical	Very High
Momentum	Late-cycle sensitive	Moderate
Quality	Defensive / Acyclical	Low
Low Volatility	Defensive / Acyclical	Very Low

To incorporate these patterns into the portfolio, we adopt the previously mentioned tilt framework inspired by the conditional allocation model of Polk et al. (2020). The approach adjusts factor exposures in response to macroeconomic regimes by differentially weighting the factor scores of each stock.

Exhibit 13: Factor tilts through the business cycle.

Factor Tilts for Given Regime					
	Low Volatility	Size	Value	Momentum	Quality
Recovery	0	2	2	0	0
Expansion	0	1	1	2	0
Slowdown	2	0	0	0	2
Contraction	2	0	0	2	2

Source: Polk et al. (2020).

As shown in Exhibit 13, factor scores are amplified or dampened depending on the phase of the cycle. For instance, during expansions, greater emphasis is placed on pro-cyclical factors such as Value and Size, while defensive factors like Quality and Low Volatility receive no attention. Momentum is also emphasized during expansions and contractions, as these phases often exhibit strong and persistent market trends that momentum strategies are designed to exploit. In contrast, during transitions such as slowdowns and recoveries—where market direction is less clear—momentum tends to be de-emphasized. Defensive exposures are tilted up in contractions, while pro-cyclical exposures are muted.

Concretely, this is operationalized by applying a multiplicative tilt to each stock's factor score. If a given factor is favored in the current regime, its score is scaled up by a factor of 2; if it is not favored, its score is not targeted. This yields the following adjustment:

$$\tilde{S}_{i,t}^{(f)} = \begin{cases} 2 \text{ or } 1 \times S_{i,t}^{(f)} & \text{if factor } f \text{ is favored in regime } R_t \\ 0 \times S_{i,t}^{(f)} & \text{otherwise} \end{cases} \tag{44}$$

These adjusted scores $\tilde{S}_{i,t}^{(f)}$ are then used in the same bottom-up, sequential tilt process described in the previous section. Stocks that score highly on factors emphasized in the current macro regime will therefore receive proportionally larger weights, making the portfolio dynamically responsive to evolving economic conditions.

4.4 Summary

The second part of this thesis has outlined the complete framework for building a dynamic multifactor investment strategy tailored to the European equity market. The methodology began by clearly defining the investment universe, namely the STOXX Europe 600 index. This choice offers a broad and diversified pool of European equities, covering a range of sectors, countries, and firm sizes, while ensuring sufficient dispersion in fundamental characteristics for effective factor modeling.

We then introduced a three-step factor construction pipeline. First, raw financial indicators were computed for each stock in accordance with the FTSE Russell Global Factor Index definitions. These included standard metrics such as earnings yield, operating cash flow, asset turnover, and volatility. Second, these variables were standardized using a Z-score normalization procedure—truncated and iteratively renormalized to ensure robustness. Finally, Z-scores were converted into percentile-based factor scores using the cumulative distribution function of the standard normal distribution. These bounded scores between 0 and 1 serve as the foundation for portfolio weighting.

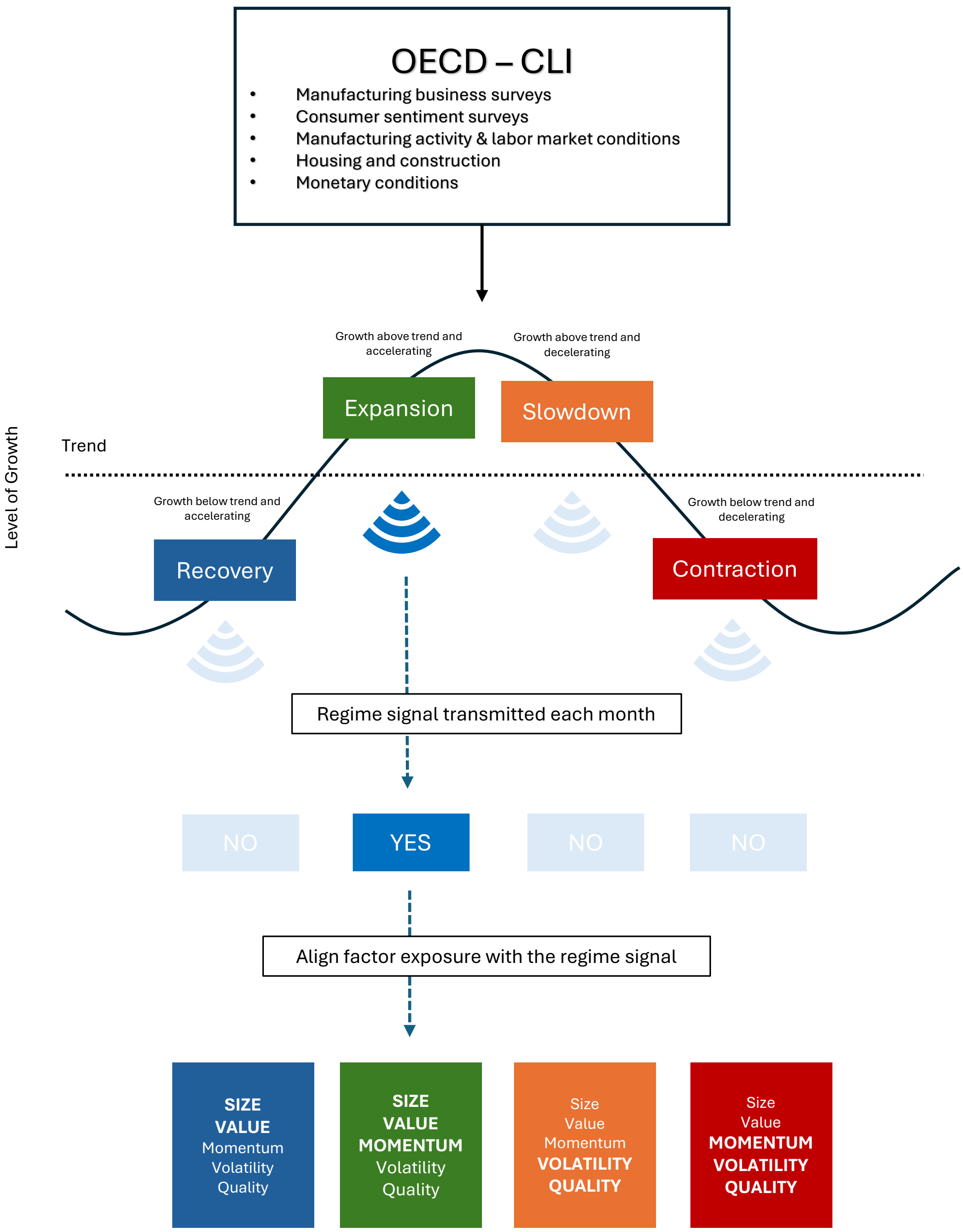
Two types of portfolios were then constructed. The first is the Comprehensive Multifactor Portfolio, a static benchmark that applies sequential, bottom-up tilts to market-capitalization weights using all five factor scores equally—regardless of the economic environment. This portfolio not only provides a useful benchmark for evaluating the value-added of dynamic allocation, but also serves as a pedagogical example for understanding how raw scores are transformed into investable weights.

The second portfolio—the Dynamic Multifactor Portfolio—incorporates a top-down overlay based on macroeconomic regime signals. These signals are derived from the OECD Composite Leading Indicator (CLI) for the Major Four European countries. Using this forward-looking index, we identified four business cycle regimes: expansion, slowdown, contraction, and recovery. Each regime implies a different set of favored factors based on empirical findings about their cyclical behavior. During expansions, for example, Value, Size, and Momentum are emphasized, while in contractions, Quality and Low Volatility are prioritized.

In the dynamic portfolio, each stock's factor scores are tilted according to these regime-specific priorities. Favored scores can be squared (to enhance selectivity) or dropped (to remove irrelevant exposure), and the resulting effective scores are used to recompute portfolio weights monthly, in line with the latest macroeconomic signal. This design allows the portfolio to continuously align itself with the most relevant risk premia, as determined by the evolving macroeconomic environment.

It is now time to evaluate whether this added complexity translates into better performance. The next part of this thesis presents the empirical results and backtests, comparing the dynamic strategy against both static and market-cap-weighted benchmarks.

Exhibit 14: Factor tilts and regime signals.



Part IV

Results

Introduction

Building on the methodological framework developed in the previous section, this part presents the empirical results of the multifactor strategies constructed throughout the thesis. The primary goal is to evaluate the performance and robustness of the proposed Dynamic Multifactor Portfolio and to assess whether incorporating macroeconomic signals into factor allocation leads to superior investment outcomes compared to static or market-cap-weighted benchmarks.

This analysis is particularly relevant in the European context, where academic literature and institutional applications of dynamic multifactor strategies remain relatively limited. By testing the strategy on the STOXX Europe 600 over a multi-decade horizon, we aim to determine whether a macro-regime-aware portfolio can generate higher risk-adjusted returns, improved downside protection, or greater consistency across market environments.

To navigate the performance results, the following analytical structure is used:

- **Section 2** presents the set of portfolios under comparison, including the Market-Capitalization Weighted Portfolio, the static Comprehensive Multifactor Portfolio, the Dynamic Multifactor Portfolio, and the STOXX Europe 600 index.
- **Section 3** reports the main results across four analytical dimensions: raw return performance (cumulative and annualized returns), risk metrics (volatility, beta, drawdowns, and skewness), risk-adjusted returns (Sharpe and Information Ratios), and statistical significance of returns.
- **Section 4** compares the Static (Comprehensive) and Dynamic Multifactor Portfolios to isolate the added value of macro-regime-based tilting, and examines the performance of individual style factors across business cycle phases to assess whether the observed behavior justifies the regime-specific tilt strategy.
- **Section 5** takes a closer look at the Dynamic Multifactor Portfolio by analyzing its turnover profile, the potential impact of transaction costs, its sector allocation characteristics, and its exposures through a Fama-French-style factor regression.

Through this structured analysis, we aim to assess whether integrating macroeconomic information into multifactor allocation can provide a material advantage in constructing more adaptive and resilient investment portfolios in the European equity space. Let us first revisit the portfolios and the index previously introduced, as a foundation for the upcoming performance evaluation.

Chapter 5

Portfolio Definitions and Testing Framework

As stated in the Methodology, the empirical evaluation spans from May 2002 to December 2024 and includes four portfolios:

- The **Market-Capitalization Weighted Portfolio**, composed of the same securities as the multifactor portfolios but weighted strictly by market capitalization;
- The **STOXX Europe 600 Index**, a dynamic benchmark representing the broader European equity market;
- The **Comprehensive Multifactor Portfolio**, a static strategy applying equal exposure to all five factors across time;
- The **Dynamic Multifactor Portfolio**, which adjusts its factor exposures monthly according to macroeconomic regime signals.

While the STOXX Europe 600 serves as the standard market benchmark, its composition changes quarterly. In contrast, the portfolios constructed in this thesis are reconstituted annually—specifically, on May 1st of each year—based on the constituents of the STOXX 600 at that date. As a result, discrepancies can arise between our portfolios and the official index: stocks may exit the STOXX 600 during the year due to market cap deterioration or corporate actions, but remain in our investment universe until the next rebalancing date.

This mismatch makes direct comparison with the live STOXX 600 index imperfect. For instance, if a company experiences a rapid collapse—such as Wirecard following its accounting scandal in June 2020—it is removed from the index almost immediately but continues to be held in our portfolios until May of the following year.

To address these practical discrepancies, we include a **Market-Capitalization Weighted Portfolio** that uses exactly the same set of securities as the Comprehensive and Dynamic Multifactor Portfolios. This makes it a particularly relevant benchmark, as it isolates the effect of factor-based tilting from differences in universe composition.

As previously discussed in the Methodology section, the Comprehensive Multifactor Portfolio applies equal exposure to the five style factors using a bottom-up tilting process. It serves a dual purpose in this analysis: first, to evaluate whether multifactor exposure can improve upon traditional market-cap-weighted approaches—by comparing it to both the Market-Cap Replicated Portfolio and the STOXX 600 Index; and second, to act as a static benchmark against which the performance of the Dynamic Multifactor Portfolio can be assessed.

Overall, this framework allows for a consistent comparison between passive, static multifactor, and dynamically tilted strategies, while acknowledging the constraints and lags involved in academic backtesting relative to real-time index management.

Exhibit 15: Summary of portfolio characteristics.

Portfolio	Weights	Rebalance	Universe
STOXX 600	Mkt Cap	Quarterly	Index-driven
Market Cap (Replicated)	Mkt Cap	Yearly	STOXX 600 (May)
Comprehensive Multifactor	Factor Tilt	Yearly	STOXX 600 (May)
Dynamic Multifactor	Factor + Macro Tilt	Monthly	STOXX 600 (May)

Chapter 6

Performance and Risk Analysis

To evaluate the effectiveness of the multifactor strategies under consideration, we adopt a comprehensive set of performance indicators that capture different aspects of portfolio behavior.

First, we report **return-based metrics**, including cumulative returns and annualized returns, which provide an overall sense of growth and long-term effectiveness.

Second, we evaluate **risk characteristics**, such as annualized volatility, market beta, maximum drawdown, skewness and kurtosis. These indicators help assess the downside exposure and the distribution of returns under various market conditions.

Third, we compute **risk-adjusted performance measures**, notably the Sharpe Ratio and the Information Ratio. These capture the efficiency of return generation per unit of risk, relative to both the risk-free rate and benchmark performance.

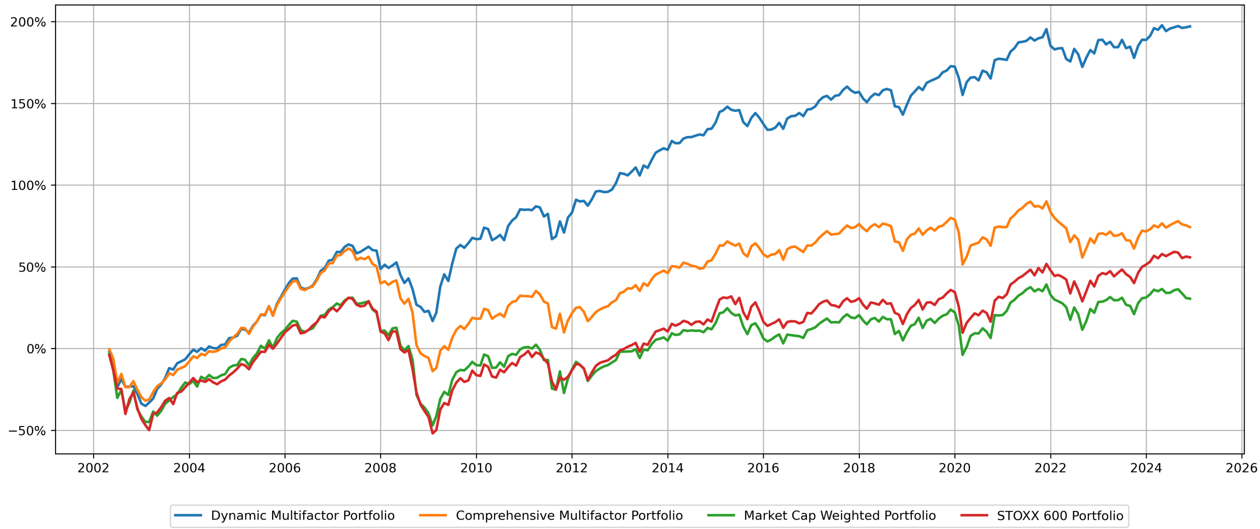
Finally, we conduct **statistical significance tests**, focusing on the t-statistic of the average monthly returns. This allows us to evaluate whether the observed excess returns are statistically distinguishable from zero and, therefore, potentially exploitable by investors.

6.1 Return-Based Metrics

6.1.1 Cumulative and annuzalized returns

Exhibit 16 illustrates the cumulative performance of the four portfolios from May 2002 to December 2024. The Dynamic Multifactor Portfolio (in blue) demonstrates a clear and persistent outperformance relative to all other strategies.

Exhibit 16: Cumulative log returns (May 2002 to December 2024).



The quantitative summary in Exhibit 17 confirms this visual evidence. Over the full period, the Dynamic Multifactor Portfolio achieved a cumulative log return of **197.09%**, far ahead of the Comprehensive Multifactor Portfolio (**74.26%**), the STOXX Europe 600 Index (**55.76%**), and the replicated Market-Cap Weighted Portfolio (**30.49%**).

In terms of annualized compounded returns before transaction costs, the Dynamic strategy generated **9.08%** per year, compared to **3.33%** for the static multifactor strategy and **2.49%** for the STOXX 600 Index. The Market-Cap Weighted Portfolio—built on the same universe of stocks—delivered the lowest performance with an average annual return of only **1.35%**.

Exhibit 17: Return-based metrics (May 2002 – Dec 2024).

Metric	**Mkt. Cap**	**Comp. MF**	**STOXX 600**	**Dyn. MF**
Cum. Log Return	30.49%	74.26%	55.76%	**197.09%**
Ann. Return	1.35%	3.33%	2.49%	**9.08%**

For context, the S&P 500 Index delivered a compounded annual return of approximately **7.79%** over the same period, significantly outperforming the relatively weak performance of the STOXX 600. Similarly, the orignal study of Polk et al. (2020) reported an annualized compounded return of **15.23%** for their multifactor strategy, compared to **10.71%** for the Russell 1000 between January 1989 and September 2018—further highlighting the historical outperformance of U.S. equities and the success of a dynamic strategy.

6.1.2 Interpretation

The performance gap is particularly informative when examined chronologically. From May 2002 to mid-2003, the Dynamic Multifactor Portfolio's outperformance stems from the CLI's signal of an anticipated contraction regime, which triggered tilts toward defensive factors such as Quality and Low Volatility. As European markets experienced significant declines during that period, the portfolio's defensive orientation allowed it to cushion drawdowns and preserve capital more effectively.

Between 2003 and 2007, all four portfolios—Dynamic, Comprehensive, STOXX, and Market-Cap Weighted—deliver similar performance. This period was marked by a prolonged expansion in Europe, characterized by low volatility and robust earnings growth. However, while the CLI showed month-over-month improvement, it remained below the 100 threshold, thus formally classifying the regime as Recovery rather than Expansion. As a result, the Dynamic Portfolio did not increase its exposure to pro-cyclical factors (such as Momentum, Size, or Value) as aggressively as it might have, had an explicit risk appetite indicator been incorporated into the regime model. Although the recovery tilt supported a strong rebound from the earlier downturn, the lack of a transition to an Expansion signal likely limited the Dynamic Multifactor Portfolio's potential outperformance during this bullish phase.

However, from mid-2007 onward, the CLI began emitting Slowdown and subsequently Contraction signals that enabled the Dynamic Multifactor Portfolio to meaningfully shift toward defensive exposures. This positioning helped cushion losses during the Global Financial Crisis of 2008, limiting the drawdown relative to the other portfolios. More importantly, the CLI identified a Recovery phase relatively early, allowing the portfolio to reorient toward more cyclical factors just as markets began to rebound. This timely rotation significantly shortened the recovery time from the crisis-induced drawdown and widened the performance gap between the dynamic strategy and its static counterparts.

Between 2011 and 2014, a similar sequence unfolded during the Eurozone sovereign debt crisis. The CLI correctly anticipated a period of macroeconomic weakness, followed by an eventual rebound.

From 2014 to 2017, macroeconomic signals became shorter and more erratic, reflecting a period of economic stagnation in Europe. Growth in GDP hovered around 0% to 1%, and inflation remained persistently low. During this phase, the CLI struggled to maintain persistent directional signals, and this ambiguity translated into a more muted edge for the dynamic strategy. Nevertheless, the portfolio maintained relative stability.

From 2017 to mid-2018, the CLI began to signal a shift toward Recovery and Expansion, accurately capturing the rebound in European economic activity, with GDP growth approaching the 2% mark. This led the Dynamic Portfolio to gradually tilt toward pro-cyclical factors—namely Momentum, Size, and Value—enabling a new period of outperformance.

Between mid-2018 and mid-2019, signals of Slowdown and Contraction emerged in response to growing concerns around trade tensions, a softening global manufacturing cycle, and Brexit-related uncertainty. The Dynamic Portfolio's defensive tilt during this phase helped shield it from market corrections that affected cyclically exposed strategies.

From early 2020 to 2022, the Dynamic Multifactor Portfolio underperformed the STOXX 600. In the months leading up to the COVID-19 crisis, the CLI continued to indicate a Recovery phase, prompting the portfolio to tilt toward pro-cyclical factors, notably Value and especially Size, which proved highly vulnerable during the sudden market collapse. This episode underscores a key limitation of dynamic strategies: in the face of unanticipated exogenous shocks, such portfolios can suffer disproportionate losses if positioned toward growth-sensitive exposures at the time of impact.

Between 2022 and 2023, signals of Slowdown and eventually Contraction reappeared, reflecting the macroeconomic impact of the Russia-Ukraine conflict, soaring energy prices, and monetary tightening. Once again, the Dynamic Portfolio effectively reduced cyclical exposure in favor of Quality and Low Volatility, helping to contain losses during a volatile period for European equities and outperforming all portfolios.

Since early 2023, the CLI has transitioned from recovery to expansion—crossing the 100 threshold in May 2024—with consistent month-over-month improvements. In turn, the Dynamic Portfolio increased its exposure to pro-cyclical factors, leading to progressive outperformance relative to the three benchmark portfolios over the final months of the backtest.

While this overall outperformance makes the Dynamic Multifactor Portfolio appear attractive, no definitive conclusion can be drawn without jointly considering returns and associated risks. The following subsection therefore turns to a comparative analysis of the portfolios from a risk perspective.

6.2 Risk Characteristics

To complement the analysis of raw and risk-adjusted returns, this section assesses the volatility and downside risk profile of the four portfolios. The metrics considered include monthly and annualized standard deviation, beta relative to the STOXX 600, skewness and kurtosis of return distributions, and maximum drawdown. Exhibit 18 presents a comparative summary of these risk indicators over the period May 2002 to December 2024.

Exihbit 18: Risk metrics of the four portfolios (May 2002 - December 2024).

Metric	**Market Cap**	**Comprehensive**	**STOXX 600**	**Dynamic**
Monthly Std. Dev.	4.60%	4.18%	4.35%	4.16%
Annualized Std. Dev.	15.94%	14.48%	15.06%	14.41%
Beta (vs STOXX 600)	0.96	0.92	1.00	0.86
Skewness	-1.15	-1.35	-0.74	-0.53
Kurtosis	0.18	0.03	-0.03	-0.43
Max Drawdown	-54.26%	-52.80 %	-56.41%	-46.87%

6.2.1 Total and systematic risk

The Dynamic Multifactor Portfolio exhibits the lowest risk profile across multiple dimensions. Its annualized volatility, at 14.41%, is the lowest among the portfolios considered, indicating a smoother performance trajectory over time. However, given that the portfolio comprises approximately 600 stocks and is broadly diversified, it is appropriate to assess its systematic risk exposure.

Notably, the portfolio's relatively low beta indicates weaker co-movement with the benchmark index, suggesting reduced sensitivity to systematic market fluctuations. Crucially, the combination of this low beta with previously observed superior returns aligns with the notion of capturing alternative sources of return beyond traditional market exposure, such as factor premia.

This observation prompts a central question in asset pricing: does the excess return relative to the benchmark-adjusted risk reflect genuine alpha, or is it more accurately attributed to exposures to non-market sources of systematic risk not accounted for within the CAPM framework? To address this issue, further empirical investigation—such as a regression analysis using a Fama-French-style multifactor model—is necessary and will be undertaken in a subsequent section.

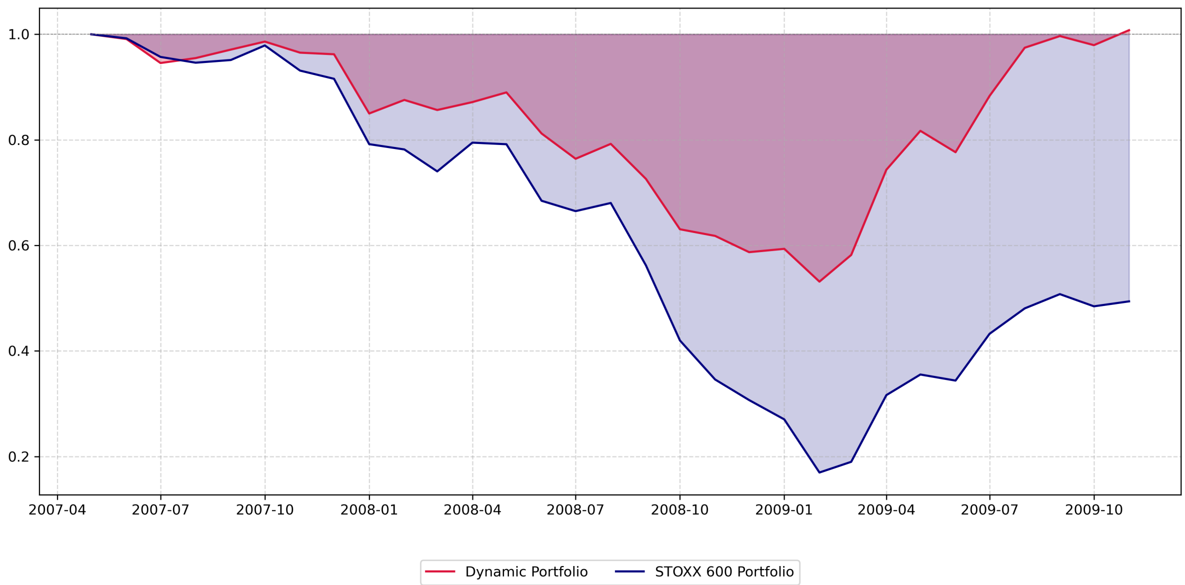
6.2.2 Maximum drawdown

An important measure of downside risk in portfolio management is the *maximum drawdown* (MDD), which quantifies the largest observed loss from a peak to a trough before a new peak is attained. Formally, for a portfolio value process $P(t)$ over a time horizon $[0, T]$, the maximum drawdown is defined as:

$$\text{MDD} = \max_{t \in [0,T]} \left(\frac{\max_{\tau \in [0,t]} P(\tau) - P(t)}{\max_{\tau \in [0,t]} P(\tau)} \right) \tag{45}$$

It captures the worst cumulative loss experienced by an investor who bought at the highest point prior to a downturn and sold at the lowest point of the same period.

Exhibit 19: Dynamic vs. STOXX - Maximum drawdown and time to recovery.



Applied to the portfolios under consideration, the *Dynamic Multifactor Portfolio* exhibits the lowest maximum drawdown at –46.87%. This drawdown was recorded during the financial crisis period spanning from May 2007 to October 2009, which includes the sharp downturn in global equity markets associated with the Global Financial Crisis.

In comparison, the *Comprehensive Multifactor Portfolio* and the *Market-Cap Portfolio* experienced more severe drawdowns of –56.41% and –52.80%, respectively. These results highlight the effectiveness of the dynamic allocation strategy during periods of market distress. In particular, the portfolio's timely tilt toward defensive factors during the downturn contributed to a significantly more moderate loss compared to the STOXX 600, as illustrated in Exhibit 19. Moreover, the subsequent recovery signal enabled the Dynamic Portfolio to rebound more rapidly, resulting in a substantially shorter time-to-recovery than that of the benchmark index. Notably, the chart displays cumulative returns scaled to a common starting value of 1 at the onset of the drawdown period, allowing for a direct and normalized comparison of the recovery paths across portfolios.

6.2.3 Skewness and kurtosis

Skewness and *kurtosis* provide complementary insights into downside risk. While skewness measures the asymmetry of returns—indicating whether extreme losses are more likely than extreme gains—kurtosis captures the overall propensity for extreme deviations from the mean, regardless of direction.

Formally, skewness is defined as:

$$\text{Skewness} = \frac{E\left[(R-\mu)^3\right]}{\sigma^3} \tag{46}$$

and kurtosis (excess) as:

$$\text{Kurtosis} = \frac{E\left[(R-\mu)^4\right]}{\sigma^4} - 3 \tag{47}$$

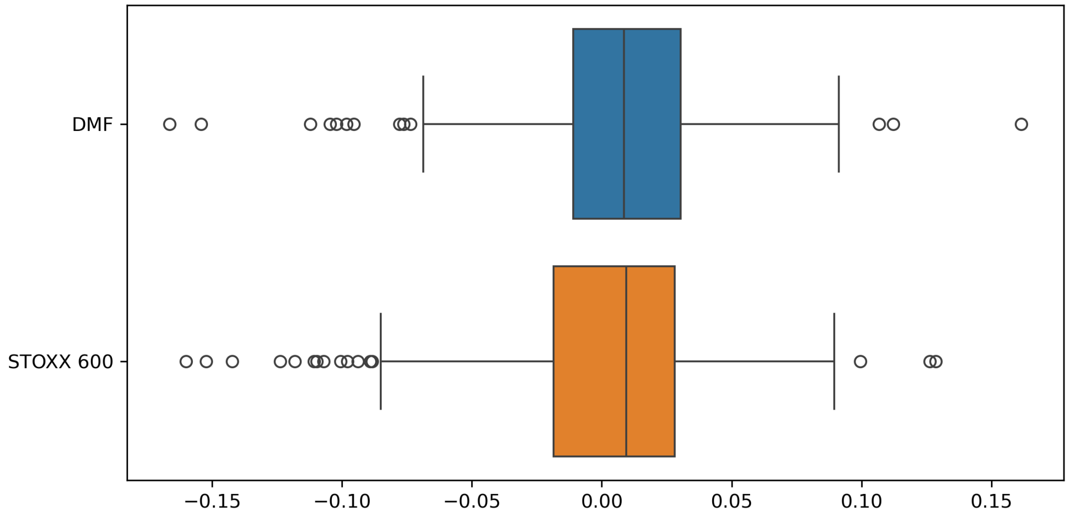
where R denotes returns, μ the mean, and σ the standard deviation. Note that we subtract 3 because we are referring to excess kurtosis, which measures deviation from the normal distribution's kurtosis (3).

All portfolios exhibit negative skewness, consistent with the *true* distribution of financial returns (Breen and Savage, 1968). However, the Dynamic Multifactor Portfolio shows the least negative skewness (–0.530), compared to –1.346 for the Comprehensive Portfolio and –0.736 for the STOXX 600. This suggests that it is less prone to severe left-tail events, offering a more balanced return distribution.

At the same time, the Dynamic Multifactor Portfolio also has the lowest kurtosis (–0.426), versus –0.026 for the STOXX 600 and 0.029 for the Comprehensive Portfolio, implying fewer extreme outliers overall and a more stable pattern of returns. Together, these characteristics signal a more favorable downside risk profile: the Dynamic Multifactor Portfolio not only reduces the likelihood of extreme losses, but also smooths out volatility relative to its benchmark.

As shown in Exhibit 20, the return distribution of the Dynamic Multifactor Portfolio is visibly less skewed and more concentrated. Nonetheless, it has experienced two notable loss events—–16.64% in July 2002 and –15.43% in August 2011—-highlighting that tail risk, though reduced, remains present.

Exhibit 20: Monthly returns distribution - Dynamic Multifactor and STOXX.



6.3 Risk-adjusted Returns and Statistical Tests

While raw returns offer an initial view of portfolio performance, they must be evaluated in light of the risks taken to achieve them. This section presents a comparative analysis of risk-adjusted returns across the three main strategies—Comprehensive Multifactor, STOXX 600, and Dynamic Multifactor—focusing on both Sharpe and Information Ratios. The goal is to assess whether higher returns are simply a compensation for higher volatility, or if they reflect true excess performance.

Exhibit 21: Risk-adjusted performance metrics (annualized).

Metric	Comprehensive	STOXX 600	Dynamic
Sharpe Ratio Inputs			
Mean Return (%)	4.40	3.64	10.21
Mean 1M EURIBOR (%)	1.20	1.20	1.20
Volatility (%)	14.48	15.06	14.41
Sharpe Ratio	**0.22**	**0.16**	**0.62**
Information Ratio Inputs			
Mean Excess Return vs. STOXX (%)	0.73	0.00	6.36
Tracking Error (%)	6.95	0.00	8.44
Information Ratio	**0.10**	**0.00**	**0.75**

6.3.1 Sharpe Ratio: return per unit of total risk

The Sharpe ratio is a widely used metric in finance that measures the risk-adjusted return of a portfolio. It quantifies how much excess return a strategy delivers per unit of total volatility, thus providing a standardized way to compare different portfolios regardless of their absolute performance. Mathematically, it is computed as the difference between the portfolio's return and the risk-free rate, divided by the standard deviation of returns:

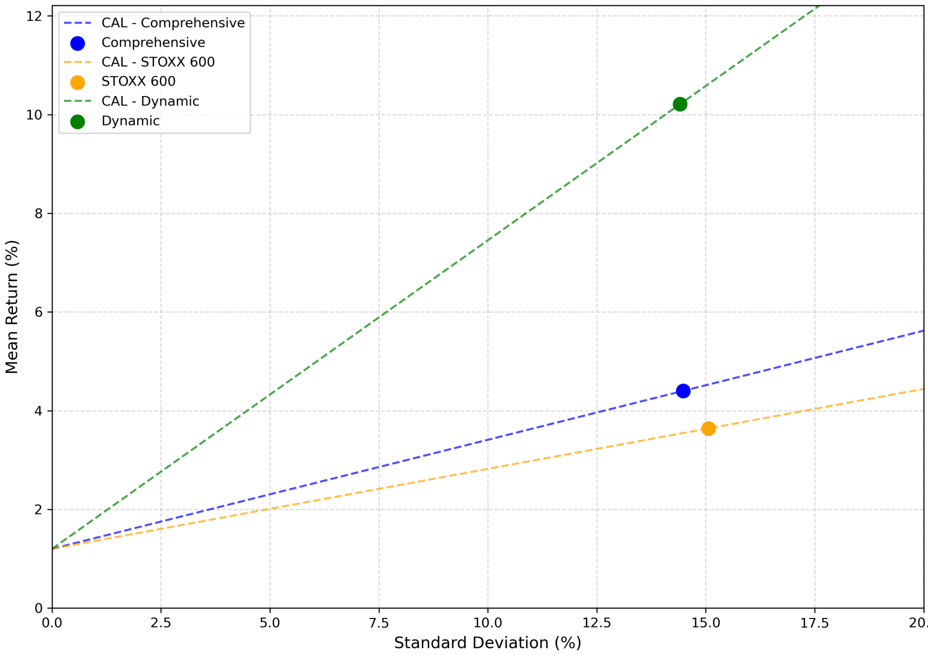
$$\text{Sharpe Ratio} = \frac{E[R_p] - R_f}{\sigma_p} \tag{48}$$

where $E[R_p]$ is the expected portfolio return, R_f is the risk-free rate (here proxied by the 1-month EURIBOR), and σ_p is the portfolio's volatility.

As shown in Exhibit 21, the Dynamic Multifactor Portfolio achieves the highest Sharpe ratio at 0.62, significantly outperforming both the STOXX 600 (0.16) and the static Comprehensive Multifactor Portfolio (0.22). This result suggests that the dynamic strategy delivers the most favorable trade-off between return and risk, outperforming not just in absolute terms, but also in terms of efficiency.

This superior efficiency is visually illustrated in Exhibit 22, which presents the *Capital Allocation Line* (CAL) for each portfolio. The CAL represents the set of achievable portfolios when combining a given one of our four portfolios with the risk-free asset. The slope of each CAL corresponds precisely to the Sharpe ratio: the steeper the line, the better the risk-return trade-off.

Exhibit 22: Capital Allocation Line (CAL) - Sharpe Ratio illustration.



6.3.2 Information Ratios: Benchmark-relative excess performance

While the Sharpe Ratio captures absolute risk-adjusted performance relative to a risk-free asset, the *Information Ratio* (IR) evaluates a strategy's consistency in outperforming a benchmark. It is computed as:

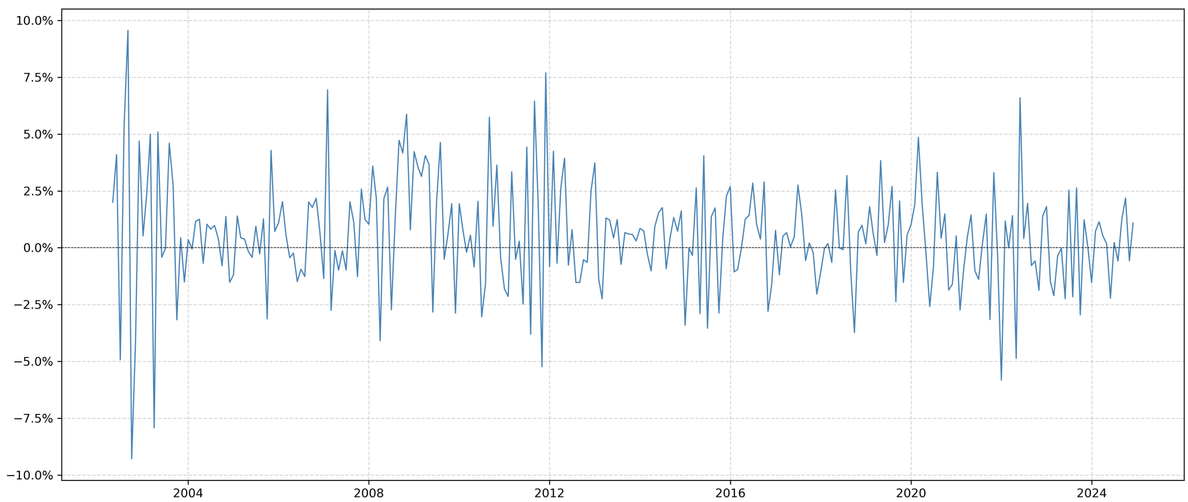
$$\text{Information Ratio} = \frac{E[R_p - R_b]}{\sigma_{p-b}} \tag{49}$$

where $E[R_p - R_b]$ is the annualized excess return of the portfolio over the benchmark (here, the STOXX 600), and σ_{p-b} is the annualized standard deviation of that excess return, commonly referred to as the tracking error.

The Dynamic Multifactor Portfolio achieves a notably high Information Ratio of 0.75, highlighting not only its strong outperformance over the STOXX 600 but also the stability of that excess return. In contrast, the Comprehensive Portfolio records a much lower IR of 0.10, reflecting weaker and less consistent relative gains. Naturally, the STOXX 600, used as the benchmark, has an IR of zero by construction.

These findings reinforce the superiority of the dynamic strategy, demonstrating its consistent ability to generate alpha as defined by the single-factor CAPM framework, and to do so persistently over time. A high Information Ratio suggests that the excess performance is not driven by a few outlier months, but rather by a structurally sound allocation process aligned with changing macroeconomic regimes. Interestingly, the dynamic portfolio constructed by Polk et Al. (2020) achieved an information ratio of 0.78, further supporting the robustness of a well-designed dynamic multifactor strategy when applied to the European market.

Exhibit 23: Excess return of the Dynamic Portfolio relative to the STOXX 600.



6.3.3 Statistical significance of returns

To complement the analysis of absolute and risk-adjusted performance, this section evaluates the statistical robustness of the observed portfolio returns through a series of t-tests. These tests assess whether the performance differentials reported in previous sections are likely to be attributable to genuine alpha or simply to random variation.

Three statistical tests are presented:

- **Test 1 – Monthly Return Different from Zero:** This test assesses whether the average monthly return of each portfolio is statistically different from zero.
- **Test 2 – Excess Return over STOXX 600:** This test compares each portfolio's performance to that of the STOXX 600, serving as the main market benchmark.

- **Test 3 – Excess Return over Market-Capitalization Weighted Portfolio:** This test isolates the added value of factor-based construction relative to a baseline portfolio holding identical securities with market weights.

Exhibit 24: Statistical significance of portfolio performance.

Portfolio	Mean Monthly Return	t-stat
Equal Weighted Portfolio	0.11%	0.40
STOXX 600 (Market)	0.21%	0.78
Comprehensive Portfolio	0.27%	1.08
Dynamic Portfolio	0.72%	2.87

Exhibit 25: Excess returns over STOXX 600.

Comparison	Excess Return	t-stat
Comprehensive vs STOXX 600	0.07%	0.19
Dynamic vs STOXX 600	0.52%	1.41

Exhibit 26: Excess returns over Market-Cap Weighted Portfolio.

Comparison	Excess Return	t-stat
Comprehensive vs Equal Weighted	0.16%	1.91
Dynamic vs Equal Weighted	0.61%	4.87

The results confirm the robustness of the Dynamic Multifactor Portfolio's performance. Not only does it exhibit the highest average return, but it is also the only strategy for which the null hypothesis of zero monthly return can be rejected at conventional confidence levels (t = 2.87). Moreover, the t-statistics of 4.87 and 1.41 in comparisons against the equal-weighted and STOXX 600 benchmarks, respectively, lend further support to the value added by the dynamic, cycle-aware tilting methodology. In contrast, the Comprehensive Portfolio's excess returns fail to reach statistical significance across most comparisons, highlighting the incremental value of dynamic macro-based allocation.

Chapter 7

Evaluating the Value of Dynamic Tilts Across the Cycle

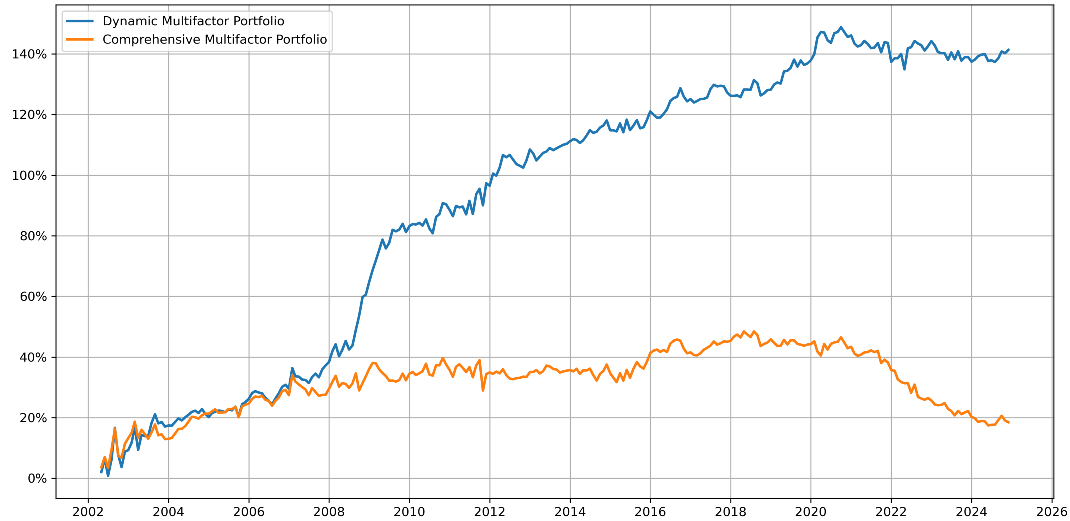
While the Comprehensive Multifactor Portfolio initially appears attractive relative to the STOXX 600—thanks to its superior cumulative returns and slightly lower volatility—a closer analysis reveals structural weaknesses. Specifically, the Comprehensive Portfolio exhibits more pronounced downside risks, with a significantly more negative skewness and higher excess kurtosis than the STOXX 600. These distributional asymmetries suggest greater exposure to tail risk and more frequent extreme deviations from the mean, which are not immediately visible from standard deviation measures alone.

Moreover, although the Sharpe ratio of the Comprehensive Portfolio is slightly above that of the STOXX 600 (0.22 vs. 0.16), the Information Ratio paints a more nuanced picture. The relatively modest mean excess return, combined with a non-negligible tracking error, suggests that the observed outperformance is not consistently delivered, but may rather be attributed to a handful of positive outliers. This interpretation is supported by statistical tests, which fail to reject the null hypothesis that the Comprehensive Portfolio's average return is significantly different from zero, or that its excess return over the benchmark is reliably positive. Furthermore, Exhibit 27 indicates that the excess return of the Comprehensive Multifactor Portfolio has been steadily declining since 2018.

Still, the Comprehensive Portfolio does outperform the Market Cap Weighted Portfolio on all dimensions, reinforcing the notion that equal, diversified exposure to style factors yields superior outcomes relative to the cap-weighted benchmark. By addressing some of the limitations of this study through the use of more advanced tools—such as improving the frequency of fundamental data, incorporating precise tracking of index inclusions and exclusions, and aligning factor score calculations more closely with the actual earnings release dates of individual securities—the performance of the Comprehensive Portfolio could be significantly enhanced.

By contrast, the Dynamic Multifactor Portfolio not only achieves a markedly higher annualized return, but also exhibits superior downside risk metrics—less negative skewness, lower kurtosis, and a smaller maximum drawdown. These characteristics point to a more stable return distribution and improved downside protection compared to a static strategy. On the risk-adjusted front, the Dynamic Portfolio boasts a Sharpe ratio nearly three times higher than that of the static alternative, as well as an Information Ratio of 0.75, indicating both magnitude and consistency of outperformance. Notably, a t-test confirms that the Dynamic Portfolio's average monthly excess return over the Comprehensive Multifactor Portfolio is statistically significant at 0.45%, with a t-statistic of 4.28. Its statistically significant average return, as well as its robust excess return over both the STOXX 600 and Market Cap Weighted Portfolio, emphasize the superiority of a dynamic allocation strategy relative to a static approach.

Exhibit 27: Excess return over STOXX 600: Dynamic vs. Static strategy.



These results support the central hypothesis of this thesis: factor premia exhibit cyclical behavior, and dynamically adjusting portfolio exposures in response to macroeconomic conditions can improve performance in European equity markets. To validate this assertion, we now examine the behavior of individual style factors across phases of the business cycle.

Five single-factor portfolios were constructed, each representing a pure exposure to one of the five styles: Value, Size, Quality, Momentum, and Low Volatility. The average monthly return of each factor was calculated for each phase of the business cycle. The corresponding heatmap is presented in Exhibit 28, where each return cell also includes, in parentheses, the tilt level assigned by the Polk et al. (2020) framework: 0 (no tilt), 1 (moderate tilt), or 2 (strong tilt).

Exhibit 28: Single-factor portfolios performance during business cycle phases.

The results show a strong alignment between the observed factor performance and the recommended tilts. Pro-cyclical factors such as Size and Value deliver the highest returns in Recovery and Expansion phases. Conversely, defensive factors like Low Volatility and Quality perform best during Slowdowns and Contractions, justifying their overweight in those periods. Lastly, the cyclical nature of factor returns is further supported by Fama-French European data. Exhibit 29 presents the historical correlation matrix of the factors from Fama-French's most recent model over the portfolio's investment horizon (May 2002 to December 2024). The low pairwise correlations—especially the strong negative correlation between Value and Quality (–0.70)—underscore the complementary behavior of these styles, enabling the success of a rotation-based approach.

Exhibit 29: Factor correlation matrix (May 2002 - December 2024)

Source: Data from Fama-French website

Chapter 8

Dynamic Portfolio Characteristics

8.1 Factor Decomposition: Alpha or Beta-Driven Returns?

Having established the outperformance of the Dynamic Multifactor Portfolio relative to both static and benchmark portfolios, we now turn our attention to the underlying source of this performance: is it attributable to well-compensated factor exposures (*beta*), or does it reflect an idiosyncratic excess return, i.e., *alpha*?

To answer this question, we adopt an extended factor model inspired by the most comprehensive framework available in empirical asset pricing. Specifically, we use the already introduced five-factor model of Fama and French (2015), augmented with the momentum factor, as formalized by Carhart (1997). This model captures the primary systematic risk premia documented in the literature: size (SMB), value (HML), profitability (RMW), investment (CMA), market risk premium (MRP), and momentum (WML). The regression specification is as follows:

$$\begin{aligned} r_t^{\text{dyn}} = \alpha &+ \beta_{\text{MRP}} \cdot \text{MRP}_t + \beta_{\text{SMB}} \cdot \text{SMB}_t + \beta_{\text{HML}} \cdot \text{HML}_t \\ &+ \beta_{\text{RMW}} \cdot \text{RMW}_t + \beta_{\text{CMA}} \cdot \text{CMA}_t + \beta_{\text{WML}} \cdot \text{WML}_t + \varepsilon_t \end{aligned} \tag{50}$$

The full regression output is presented in Exhibit 30:

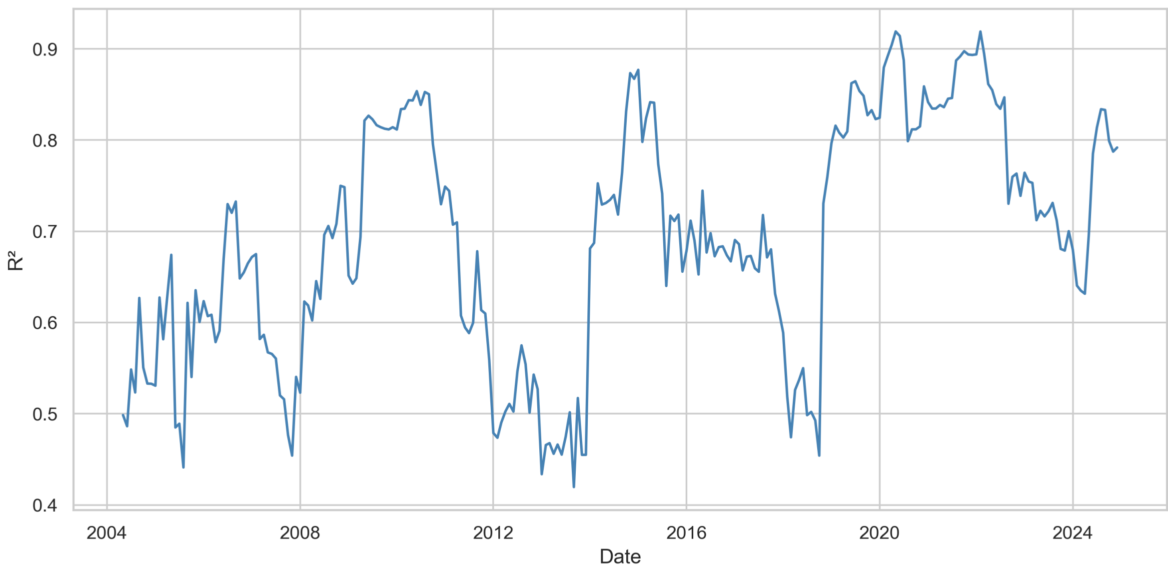
Among the factor loadings, only the market beta (β_{MRP}) is statistically significant at the 1% level. In contrast, the other factor betas are not statistically different from zero, indicating that their contributions to the portfolio's returns are likely negligible or not reliably estimated. More notably, the regression yields a statistically significant alpha of 0.37% per month ($t = 2.06$), indicating a positive intercept unexplained by exposure to these factors. However, the overall explanatory power of the model remains modest, with an R^2 of 0.56. This suggests that while systematic exposures explain part of the Dynamic Portfolio's performance, a substantial portion remains unaccounted for by static factor models.

Exhibit 30: Results of the multifactor regression.

	WML	CMA	RMW	HML	SMB	MRP	α
$\hat{\beta}$	-0,08	-0,20	0,23	0,05	0,06	**0,56**	**0,37**
$\|t - stats\|$	(1,42)	(1,28)	(1,52)	(0,44)	(0,59)	**(11,06)**	**(2,06)**
$\widehat{\text{S.E.}}$	0,05	0,15	0,14	0,11	0,09	0,04	0,18
$R^2/\hat{\sigma}_y$	**0,56**	2,78	–	–	–	–	–
F/d.f.	57	**265**	–	–	–	–	–
$\text{SS}_{\text{reg}}/\text{SS}_{\text{resid}}$	2637	2056	–	–	–	–	–

Importantly, such a regression represents a static snapshot and does not fully reflect the dynamic nature of our portfolio, which adapts factor exposures monthly in response to anticipated business cycle shifts. To better capture this time-varying structure, we perform a rolling 24-month window regression of the same model. While traditional studies often employ windows of 36 to 60 months, we opt for a shorter 24-month horizon to better align with the average cycle length observed in our dataset—approximately 8 months—with occasional extremes ranging from 1 to 20 months. As shown in Exhibit 31, the rolling R^2 fluctuates substantially over time.

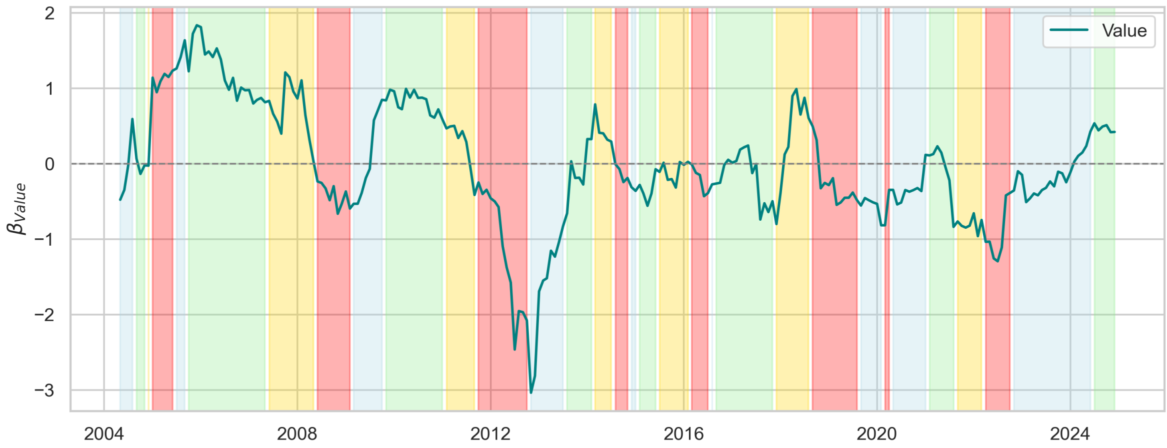
Exhibit 31: R^2 - Rolling 24-month.



This volatility in model fit is not only expected but also conceptually consistent with the time-varying nature of factor premia, as discussed previously. Unlike the static factor loadings assumed in traditional Fama-French frameworks, our approach adjusts exposures in anticipation of macroeconomic turning points. At times, exposures to certain factors are deliberately set to zero, and rapidly reallocated when regimes change. This strategic tilting causes rolling betas to fluctuate significantly.

For example, Exhibit 32 displays the rolling β_{HML} (Value factor) over time.

Exhibit 32: Value factor exposure - Rolling 24-month.



The time-variation aligns closely with macroeconomic conditions: heightened exposure to the Value factor occurs during recovery phases—such as the post-2008 financial crisis, post-2013 eurozone stabilization, post-COVID recovery, and the resurgence following the 2022 energy shock. In these windows, the R^2 of the model naturally increases due to alignment with well-specified factor premia (e.g., Size, Value, Momentum).

Conversely, during periods of slowdown and contraction, our portfolio tilts toward defensive factors—namely, Low Volatility and Quality—which are either excluded from the factor model (in the case of Low Volatility) or constructed differently (Fama-French split Profitability and Investment, whereas this thesis defines a distinct Quality factor). As a result, the model underfits during these phases, underestimating the role of these protective tilts.

Consequently, the observed monthly alpha of 0.37% may partially result from omitted variables or model misspecification, rather than reflecting true abnormal performance. A more precise modeling framework would ideally account for time-varying risk premia in line with Merton's Intertemporal Capital Asset Pricing Model (1973). In addition, as proposed by Vuolteenaho (2002), a decomposition of firm-level return variance would allow a more nuanced understanding of the extent to which firm betas are genuinely exposed to shifts in the business cycle. While such an approach would undoubtedly provide deeper insights, it exceeds both the methodological scope and technical capacity of this thesis.

Nevertheless, it is important to note that the Quality factor, as defined in this thesis, is not universally recognized as a priced risk factor in the asset pricing literature. This implies that excess returns generated during downturn phases—when Quality tends to dominate portfolio exposure—are more likely to reflect genuine alpha rather than compensation for systematic risk. This observation supports the relatively high alpha estimated in the regression analysis, and aligns with the portfolio's particularly strong excess returns over the STOXX 600 during periods of economic slowdown and contraction.

8.2 Sector Allocation and Cyclical Exposure

Although the portfolio construction methodology is not explicitly sector-driven, examining sector weights provides meaningful insight into the macroeconomic alignment of the strategy. In particular, it is useful to assess whether the Dynamic Multifactor Portfolio tilts toward pro-cyclical industries during economic upswings—such as recoveries and expansions—and conversely, shifts toward more defensive sectors during downturns.

To investigate this, we isolate the sector allocation of the Dynamic Portfolio as of May 2024. At that point, the OECD Composite Leading Indicator (CLI) had just surpassed the 100 threshold and was exhibiting a month-over-month increase, signaling the onset of a new expansion phase. Given the model's tilt rules, this period triggered an overweight in pro-cyclical factors—specifically *Value*, *Size* and *Momentum* (although the latter is more transitory). As a result, we would expect the portfolio to exhibit greater exposure to sectors that are empirically classified as cyclical.

But how should sector cyclicality be defined? Major classification providers offer diverging taxonomies: MSCI, in "MSCI Cyclical / Defensive Indexes" (2023), distinguishes between "cyclical" and "defensive" sectors, while Morningstar, in "Stock Sector Structure" (2011), identifies three "super sectors," including a "sensitive" category positioned between the two. For instance, Information Technology, Communication Services, and Industrials are classified as cyclical by MSCI, yet as sensitive by Morningstar. Conversely, Energy is labeled defensive by MSCI and sensitive by Morningstar. These discrepancies highlight the challenge in categorizing sector cyclicality using traditional industry labels.

To address this ambiguity, Longis et al. (2022) propose a more systematic approach by estimating sector cyclicality through regression on a Cyclical Factor Portfolio—long in Value and Size, and short in Quality and Low Volatility, which they interpret as proxies for high versus low cash-flow beta. This approach, perfectly in line with the theme of this thesis, allows the derivation of a continuous "cyclical exposure score" for each sector, thereby quantifying the share of each sector that behaves cyclically.

Exhibit 33: Sector exposures and cyclicality - Dynamic Portfolio vs STOXX 600.

Industry	**STOXX 600 (%)**	**Dynamic Portfolio (%)**	**% Cyclical**
Technology	7.67	2.85	28%
Telecommunications	2.77	1.10	0%
Healthcare	14.70	3.07	0%
Financials	16.56	35.54	100%
Real Estate	1.35	1.23	50%
Consumer Discretionary	17.55	13.07	92%
Consumer Staples	9.31	4.63	0%
Industrials	16.31	26.44	100%
Basic Materials	5.11	4.31	100%
Energy	4.32	5.14	43%
Utilities	4.36	2.63	29%

As shown in Exhibit 33, as of May 2024, the Dynamic Portfolio allocates substantially more weight to the most cyclical—and correspondingly largest in terms of market capitalization—sectors, namely Industrials and Financials, than the STOXX 600, while significantly underweighting less cyclical sectors. This logic extends to the full investment horizon as illustrated in Exhibit 34, which shows the sector allocation of the Dynamic Portfolio over time. A clear inverse relationship is observable between the relative exposure to cyclical sectors such as Financials and Industrials and more defensive sectors such as Healthcare and Consumer Staples, further reflecting regime-aware allocation behavior. Note that the "Undefined" sector represented in the graph between 2002 and 2007 is due to the fact that Bloomberg did not report the ICB classification of certain securities during that period.

This alignment reflects the top-down macroeconomic signal of expansion and the resulting tilt toward pro-cyclical style factors. It further supports the idea that macro-regime-sensitive factor allocation naturally results in sector-level tilts consistent with economic expectations, despite sector neutrality in the portfolio's construction methodology.

Hence, another way to interpret the portfolio is to view it as a sector rotation strategy—yet with the added advantage of being driven by a bottom-up stock-level approach, where portfolio weights are determined not only by sector cyclicality but also by each stock's underlying fundamentals.

Exhibit 34: Dynamic Portfolio – Sector allocation (May 2024).

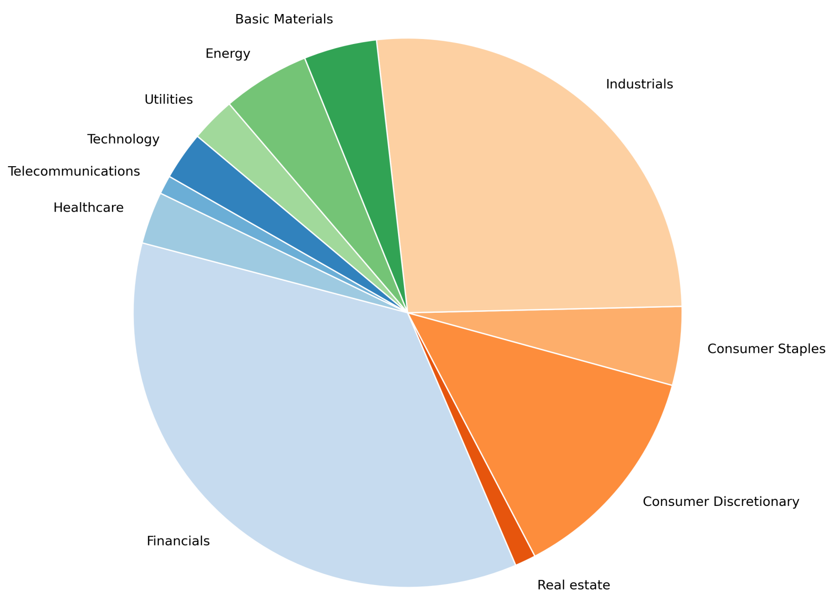
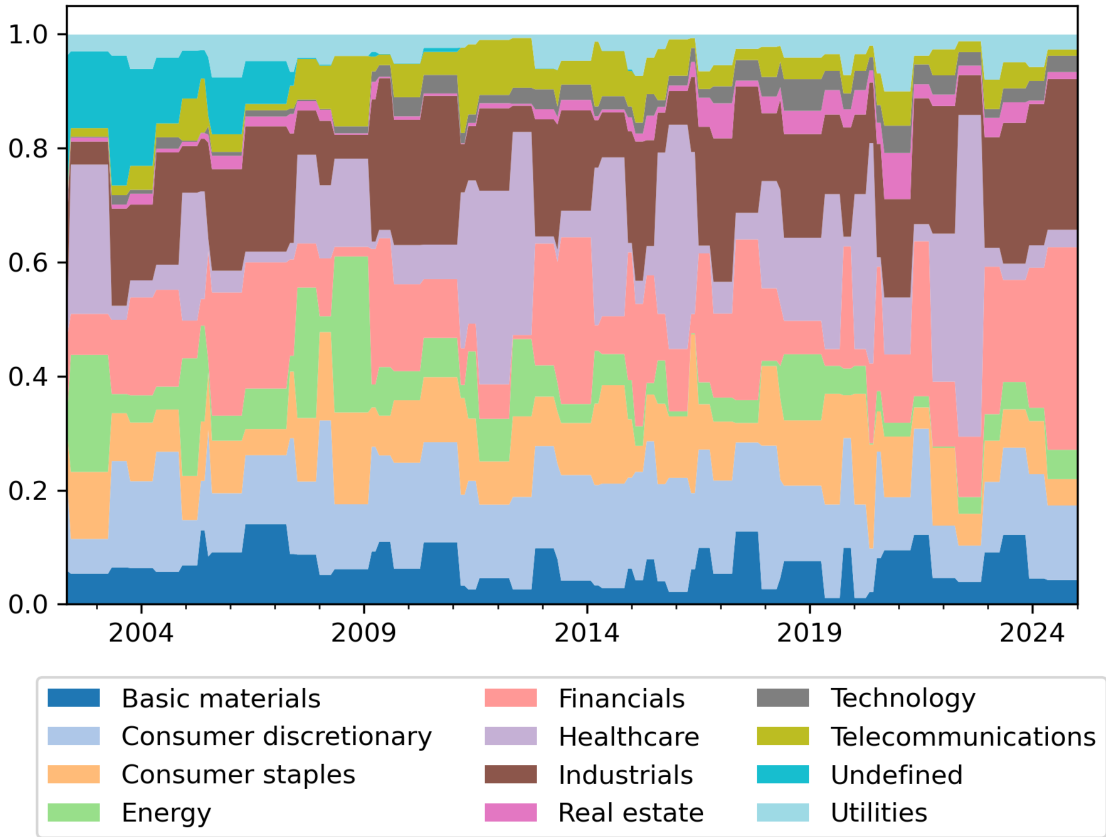


Exhibit 35: Dynamic Portfolio – Sector allocation (May 2002 - December 2024).



8.3 Turnover and Transaction Costs

In order to assess the practical viability of the Dynamic Multifactor Portfolio, it is essential to evaluate not only its raw and risk-adjusted performance, but also its implementation costs. A key metric in this regard is the portfolio turnover rate, which measures the proportion of the portfolio that is replaced over a given time period. High turnover typically implies more frequent trading and, consequently, higher transaction costs. Understanding this dynamic helps contextualize whether the strategy's excess returns are eroded by trading frictions.

Exhibit 36: Dynamic Portfolio - One-way annual turnover.

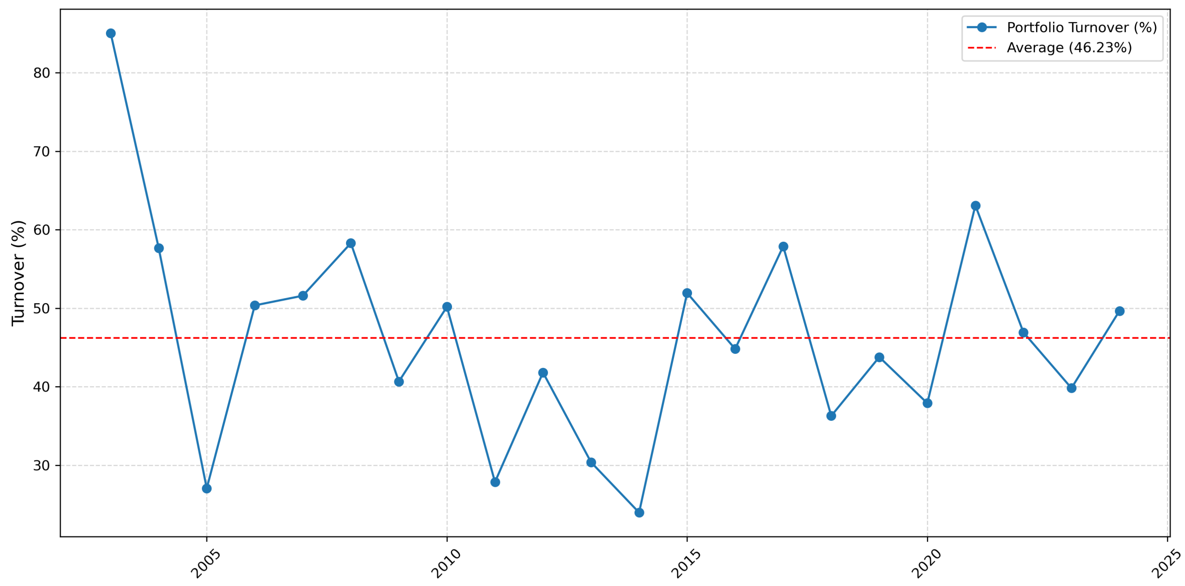


Exhibit 36 presents the one-way annual turnover of the Dynamic Multifactor Portfolio. Over the full sample period, the average turnover stands at 46.23%, which implies that approximately half of the portfolio's capital is reallocated each year. This level of activity is consistent with the estimate of Frazzini et al. (2018), who report an annual turnover of 57% for a strategy combining Value, Size, and Momentum factors.

To assess the financial impact of this turnover, we apply widely accepted academic estimates of trading costs in European equity markets. Following Novy-Marx and Velikov (2016) and Frazzini et al. (2018), we assume a cost of 30 basis points (bps) per 100% annual turnover. By that logic, the average turnover of 46.23% corresponds to an annual transaction cost of:

$$\text{Cost} = 0.4623 \times 30 \text{ bps} = 13.87 \text{ bps/year} \approx 1.16 \text{ bps/month}.$$

After adjusting for this friction, the Dynamic Portfolio's excess return over the STOXX 600 remains statistically significant at the 10% threshold, confirming the robustness of the result.

However, transaction costs are influenced by a variety of market microstructure and implementation factors, and assigning an arbitrary value—such as 30 basis points per 100% annual turnover—may lack rigor. It is therefore insightful to identify the precise threshold of transaction costs beyond which the strategy would no longer deliver statistically significant excess returns.

We define this break-even transaction cost as the cost level (in basis points per 100% annual turnover) at which the null hypothesis—stating that the excess return is not significantly greater than zero—fails to be rejected at a confidence level of 10%. Mathematically, we denote this threshold as:

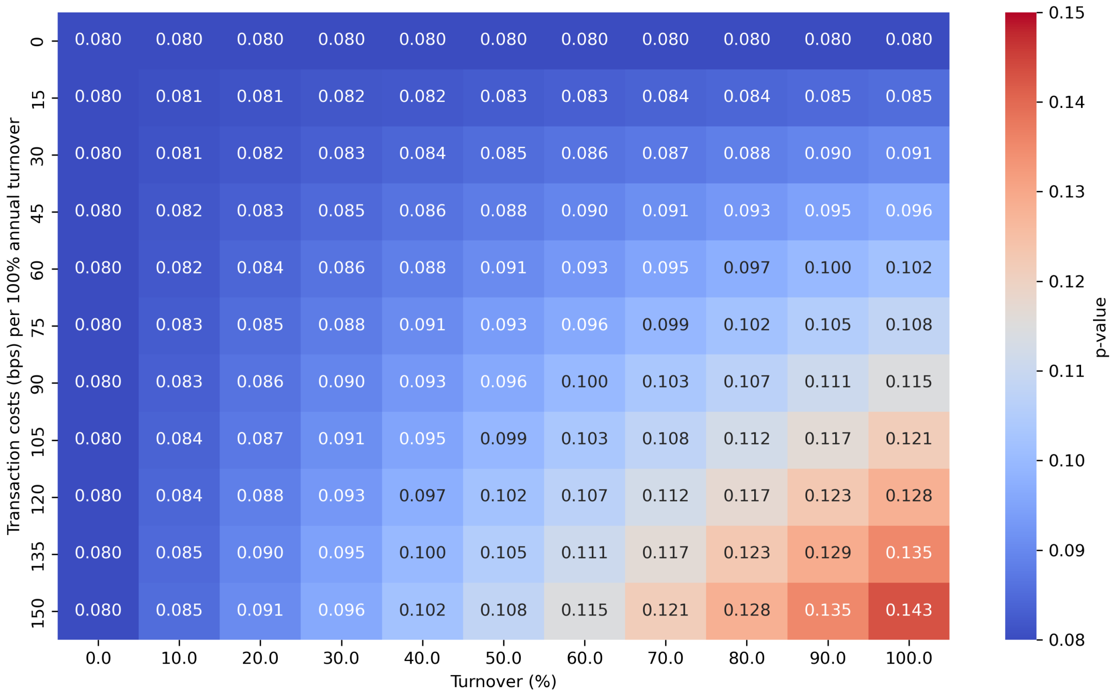
$$\text{TC}^* = \min\left\{\text{TC} \in \mathbb{R}_+ \mid \text{p-value}\left(\bar{r}_{\text{dyn}} - \bar{r}_{\text{stoxx}} - \text{TC}\right) \geq \alpha\right\}, \quad \text{with } \alpha = 10\% \tag{51}$$

Numerical simulations yield a threshold of 118.18 bps per 100% annual turnover, equivalent to a transaction cost of 4.56 bps per month for a turnover of 46.23%. Beyond this level, the dynamic strategy's net excess return can no longer be considered statistically different from zero at the chosen confidence level.

The Sensitivity Analysis presented in Exhibit 37 further illustrates the interaction between turnover rates and transaction costs. It highlights the various combinations for which the hypothesis that the excess return is significantly greater than zero is no longer supported at the 10% confidence level. This provides a more nuanced view of the conditions under which the strategy's outperformance remains robust to implementation frictions. Note that, as calculated earlier, the p-value for the Dynamic Strategy's excess return over the STOXX 600, without accounting for transaction costs, is 8.01%.

These findings reinforce the portfolio's robustness even after implementation costs, confirming that its superior performance is not simply an artifact of unrealistic trading assumptions.

Exhibit 37: Sensitivity Analysis – p-value vs Turnover and Cost.



Part V

Conclusion

This thesis set out to assess whether a dynamic multifactor investment strategy, guided by macroeconomic signals, could outperform both static multifactor strategies and traditional benchmarks in the European equity market. Building on the growing academic consensus that factor premia are time-varying and influenced by the business cycle, we constructed a Dynamic Multifactor Portfolio that adapts its exposure to five style factors—Value, Size, Quality, Momentum, and Low Volatility—according to macroeconomic regimes identified by the OECD's Composite Leading Indicator (CLI).

The first part of the thesis established the conceptual and empirical foundations for the project. We discussed the evolution from single-factor models to multifactor approaches, and presented evidence of cyclical behavior in factor returns. Notably, prior research demonstrated that certain factors (such as Value and Size) tend to outperform during economic expansions, while others (like Quality and Low Volatility) are more resilient in downturns. This cyclical behavior justified the hypothesis that factor timing could enhance portfolio performance.

The second part outlined the methodology used to construct both static and dynamic multifactor portfolios. Financial and price data for over 600 European equities were retrieved from Bloomberg, normalized through a multi-step process, and aggregated into factor scores. The static portfolio applies equal exposure to all five factors without adjusting to macroeconomic conditions, while the dynamic strategy adjusts these exposures monthly based on CLI-determined business cycle phases.

The final part presented the empirical findings. The Dynamic Multifactor Portfolio consistently outperformed the STOXX Europe 600, the Market Capitalization Weighted Portfolio, and the static Comprehensive Multifactor Portfolio across a range of performance metrics. In addition to delivering the highest cumulative and annualized returns, the dynamic strategy also exhibited more favorable risk characteristics—lower volatility, lower drawdowns, and less negative and kurtosis. Risk-adjusted returns, as captured by Sharpe and Information Ratios, further validated the superiority of the dynamic approach. Factor regressions revealed a statistically significant monthly alpha of 0.37%, although the relatively low R^2 and the absence of significance for most factor betas suggested that static models (such as the Fama-French model) may not fully capture the portfolio's dynamics. Furthermore, we have shown that, although sector exposures are not an explicit input in the portfolio design, they emerge naturally from factor tilts and align closely with macroeconomic regimes—shifting toward cyclical sectors during expansions and toward defensive ones in contractions. Finally, the sensitivity analysis indicates that the strategy's outperformance remains statistically significant under a broad range of transaction cost assumptions; only relatively high turnover rates or elevated trading costs would be sufficient to eliminate significance at the 10% level.

Despite these promising results, several limitations must be acknowledged:

- **Single macro signal.** The CLI, while well-constructed, captures only one dimension of the macroeconomic environment. It does not reflect investor sentiment, liquidity conditions, or geopolitical risk—all of which can significantly affect factor performance and asset prices.

- **Static factor modeling.** The regression framework used to assess alpha is inherently static and fails to account for the time-varying nature of factor exposures. As emphasized by Merton's ICAPM and the work of Vuolteenaho (2002), a dynamic model with state variables and variance decomposition would better disentangle the role of factor risk versus true alpha.

- **Data frequency and scope.** Factor scores and portfolio compositions were updated annually based on company data collected each May. While this approach avoids look-ahead bias, it may underreact to earnings surprises already priced in by the market. A more granular point-in-time data approach—along with dynamic tracking of STOXX 600 membership—could improve responsiveness and real-time accuracy.

- **Implementation complexity.** While transaction costs remained moderate given the turnover profile, the operational burden of monthly rebalancing and multi-factor signal management should not be overlooked for practitioners.

Several avenues for future research naturally emerge from this study. First, the methodology developed in this thesis could be extended to incorporate an ESG (Environmental, Social, and Governance) dimension. Since the current portfolio construction process relies on normalized factor scores scaled between 0 and 1, an ESG score could be seamlessly integrated as an additional multiplicative tilt in the weighting formula. This would allow for the construction of a multifactor portfolio that not only captures rewarded style premia, but also aligns with sustainability objectives—paving the way for responsible factor investing. Second, the integration of machine learning techniques could enhance the responsiveness and precision of regime identification. For instance, supervised learning algorithms could be trained to detect latent economic regimes based on a richer set of inputs—combining macroeconomic data, investor sentiment indicators, and risk appetite proxies. These models could then be used to optimize factor tilt intensity or determine the relative importance of each factor under different conditions.

This thesis contributes to the literature by providing empirical support for macro-aware dynamic factor investing in European equity markets. The results demonstrate that adapting to the business cycle—not only through factor selection, but also through timing—can enhance returns and mitigate risk. In an era of increased market volatility and economic uncertainty, such adaptive strategies may prove particularly valuable for investors seeking resilient and responsive portfolio solutions.

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