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Navn:	Didrik Pedersen Haraldstad og Fredrik Kristoffer Nilssen

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- Dynamic Factor Strategies:

Navigating Business Cycle Adaptation With Factor Timing -

Fredrik Kristoffer Nilssen

Didrik Pedersen Haraldstad

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Abstract

In this study, we explore the time-series variation in factor premia and its dependence on business cycle stages. Utilizing this observed variation, we devise a dynamic factor timing strategy that aligns with shifts in the business cycle. Our method involves identifying these business cycle regimes based on leading economic indicators and global risk appetite. The application of this framework yields a strategy that consistently delivers excess returns over static multifactor implementations and the market at large. Our findings reveal that the proposed framework is robust and statistically significant, underlining its practical viability across diverse market conditions and regions. This suggests that our dynamic approach offers significant potential for improved investment outcomes.

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Contents

1 Introduction

In the past few decades, the field of investment management has significantly evolved, demonstrating a growing interest in factor investing. The pioneering work of Sharpe (1964), Lintner (1965), and Treynor (1961) on the Capital Asset Pricing Model (CAPM) introduced the concept of beta - the sensitivity of a security's returns to market returns. This seminal research sparked an era of factor investing, where Fama & French (1993), among others, identified additional factors that explained a security's risk and return.

The five factors, size, quality, value, momentum, and low volatility, are widely accepted in academic literature as a method for explaining asset returns. Each factor represents different characteristics that investors believe can explain differences in expected returns. However, the performance of these factors is not constant; they fluctuate over time and across economic conditions. This has led to a burgeoning interest in strategies that dynamically adjust the exposure to different factors depending on the stage of the business cycle. In essence, the aim is to "rotate" between factors to optimize portfolio performance.

Despite the body of research around factor investing, the current literature mostly focuses on a narrow set of stocks. In particular, large-cap stocks in developed markets have been studied extensively, while small and mid-cap stocks generally receive less attention. Additionally, we find limited research investigating the sensitivity of factor portfolios to aggregate cash flow news, which represents an opportunity for further investigation. Moreover, existing studies mostly employ static, rather than dynamic, factor strategies, which overlooks the potential benefits of a rotation strategy.

The motivation for this research is twofold. Firstly, we aim to fill the gaps identified in the existing literature by testing a factor rotation strategy on a broader set of stocks, including small and mid-cap stocks. This expansion introduces valuable insight into the diversity and robustness of previous research. Secondly, our study incorporates an established, but relatively unexplored component − the sensitivity of factor portfolios to aggregate cash flow news - to make informed decisions on factor exposure through the business cycle. Campbell & Shiller (1988) and Campbell & Perron (1991) introduced a return decomposition framework to back out cash flow news. This is based on the understanding that corporate cash flows are critical drivers of company value, and any news or forecasts about a company's future cash flows can significantly affect its stock price. Consequently, integrating this variable into a factor rotation strategy could potentially enhance its performance and effectiveness. Further, by expanding the scope of the research to a broader set of stocks, we can better understand the generalizability of the bottom-up portfolio construction outlined in Russell (2017a). This, in turn, provides valuable insights for portfolio managers and individual investors who aim to implement these strategies in their investment decisions. This framework could offer a way for investors to better manage their portfolios and reduce risk, particularly during periods of economic uncertainty. Lastly, our research contributes to the broader academic discourse around factor investing and market dynamics.

Our research is aimed at an in-depth investigation of a dynamic factor strategy, seeking to explore its performance across a diverse investment universe rather than being confined to a single index's constituents. The first objective is to estimate the sensitivity of factor portfolios to cash flow news. This necessitates a robust methodology for accurately measuring sensitivity, thereby clarifying how different factors respond to variations in cash flow news. After establishing factor sensitivities, the study aims to forecast subsequent periods of the business cycle. Developing a reliable predictive model will enable a more informed execution of the factor rotation strategy. Following this, the research focuses on implementing a dynamic factor rotation, utilizing the variation in factor sensitivities to optimally adjust portfolio holdings according to each business cycle stage. A primary goal is to outperform both the market index and an equally weighted static multifactor portfolio; therefore, a comprehensive performance evaluation will be conducted to compare the proposed strategy's efficacy. An essential part of this research is to generalize the findings, discerning whether the results are specific to the investment universe or universally applicable across any stock universe. This involves analyzing the results and discussing their broader implications. Lastly, the research will examine the strategy's resilience during high market uncertainty by extending the time-series to include a period of notable market volatility. By focusing on these objectives our research offers an opportunity to generalize the results of previous studies, consolidate the explanation and results of the strategy in a singular comprehensive document, and evaluate the strategy's performance under extreme market conditions. We also highlight the importance of correctly tilting towards the desired target exposure through the business cycle. Following these research objectives, our main research question is formulated as follows:

How do factor premiums vary across business cycles and what implications does this have for factor rotation strategies?

The analysis of cash flow sensitivities across different portfolios revealed interesting patterns. Specifically, we observe that portfolios based on value and size factors exhibited relatively more significant cash flow sensitivities compared to portfolios constructed using low volatility and quality factors. Additionally, the momentum factor exhibited a more extensive cash flow beta during expansionary periods while displaying a reduced beta during contractionary periods.

By exploiting the time-series variation in different factor premiums, we developed a factor-rotating strategy that adapts to the business cycle. The performance evaluation of this strategy yields promising results. Our factor-rotating strategy consistently outperformed both the value-weighted benchmark index and the static multifactor implementation. These findings indicate the effectiveness of the approach in capturing the dynamics of factor premiums throughout different stages of the business cycle.

The remainder of the paper is organized as follows. We provide an overview and summarize the relevant literature in section 2. Section 3 examines the theory behind our factors and the relationship between cash flow news and business cycle regimes. Section 4 describes the data and methodology used to conduct the research. In section 5 we summarize and discuss our main results, while in section 6 we outline our conclusions.

2 Litterature review

2.1 Factor premiums

The concept of characteristic- or style-based factor models took hold in financial academia with the works of Fama & French (1992) Fama & French (1993), who described the cross-section of US stock returns through their factors value and size in addition to the pattern already explained by the Capital Asset Pricing Model of Sharpe (1964) and Lintner (1965). Among now an extensive list, financial researchers have later defined additional factors namely momentum, as documented by Jegadeesh & Titman (1993) and C. S. Asness (1995) and a low-volatility anomaly documented by Haugen & Heins (1975) and also by Baker et al. (2011). While these are probably the most documented and researched factors, it is also worth mentioning that there are today hundreds of different ones to watch both individually and in combination with one another.

The value factor focuses on investing in relatively undervalued assets and capitalizing on their potential for future price appreciation. Research on the value factor has examined the relationship between fundamental valuation metrics and investment returns. The value factor, characterized as the book-to-market effect, is first evident in Stattman (1980). The paper challenged the CAPM, suggesting book-to-market as a driver of stock returns in addition to systematic risk. Fama & French (1993) later included the value factor as part of their three-factor model, highlighting the significance of the price-to-book ratio in explaining cross-sectional variations in stock returns. C. S. Asness et al. (2013) later conducted a comprehensive analysis of the value factor to suggest that relatively cheap assets tend to outperform expensive assets emphasizing benefits from value-based investing. The existence of the value premium is, though, a topic of debate. Explanations of behavioral biases among investors, such as extrapolation of growth trends or delayed overreaction to information (see Lakonishok et al. (1994), Barberis et al. (1998) and Daniel et al. (1998)), as well as risk-based explanations like value stocks showing greater default risk (Fama & French (1992), Fama & French (1993) and Campbell et al. (2008)).

The size factor, or the small-cap effect, suggests that smaller companies tend to outperform larger companies over the long term. Extensive research has examined the relationship between firm size and investment returns. Banz (1981) conducted a seminal study on the small-cap effect and documented the phenomenon where small-cap stocks consistently outperformed their large-cap counterparts. His research contributed to the understanding of the size factor. Fama & French (1992) expanded the analysis by incorporating the size factor into their 3-factor model. Their study concludes the size factor to be a significant determinant of asset returns, emphasizing the importance of considering firm size in portfolio construction.

The quality factor focuses on selecting assets with superior fundamental qualities, such as high profitability, stable earnings growth, and low financial leverage. Previous literature on the quality factor has demonstrated its ability to generate risk-adjusted returns and enhance portfolio performance. The investment effect is first evident in Fairfield et al. (2003), explaining that low-accrual firms are likely to earn high returns relative to their high-accrual counterpart. The profitability effect is first documented in Haugen & Heins (1975), where the authors find that stocks with higher profitability measures tend to have higher returns. Though the importance of investing in profitable and stable stocks is commonly discussed in financial literature, the quality factor does not date that long back in time. Novy-Marx (2013) conducted a comprehensive analysis of the quality factor and identified gross profitability as a robust measure of quality. The study showed that stocks with higher profitability outperformed those with lower profitability, even after controlling for traditional risk factors. C. Asness et al. (2017) extended the analysis to a global context and found that quality is generally not fully priced, leaving high future returns to quality investors. Their research also finds significant time variation in the quality premia showing an economic intuition consistent pattern.

The momentum factor represents the anomaly that assets that have exhibited positive recent performance tend to continue performing well relative to their not-so-strongly performing counterpart. Both the efficacy and the implications of the momentum factor are widely discussed in financial literature. Jegadeesh & Titman (1993) conducted an influential study on momentum which documented significant positive returns from buying recent winners and selling recent losers. Subsequent research and literature build on the foundation of this study. Moskowitz et al. (2012) investigated global applications of the momentum factor and found the anomaly to be persistent across markets and asset classes.

The low volatility factor, or the low-risk anomaly, suggests that stocks showing lower historical volatility tend to generate higher risk-adjusted returns than higher-risk stocks. Baker et al. (2011) carried out an in-depth analysis of the low-volatility factor and found that low-volatility stocks consistently outperformed high-volatility stocks. The study also highlights its potential for providing downside protection and enhancing risk-adjusted returns. Blitz & Van Vliet (2007) investigated the low-volatility effect in international equity markets and found similar results suggesting the global persistence of the low-volatility effect.

2.2 Time-series variation in factor premia

The time-series variation in factor premia refers to the observation that factor premiums can vary over different time periods. This variability presents challenges and opportunities for factor investors seeking to exploit the premia. Campbell & Shiller (1988) executed influential research on the time-series variation in stock market returns. Their work, documenting the time-series variation in the established market risk premium, paved the way for investigation also into the time-series variation in factor premia. Their study challenges traditional rational expectations theory and suggests that time-varying risk premia plays a crucial role in explaining important asset price dynamics. C. S. Asness et al. (2000) find time-series variation in the value premia, documenting mean-reverting patterns in the relative price ratio of value and growth stocks. Hodges et al. (2017) investigate the time-series variation in factor returns and document significant fluctuations in factor premia. Their findings suggest that it's possible to predict factor premiums to some extent, but the authors also note that the task is challenging. Specifically, they find that predictability is generally low and varies significantly across different factors. The study highlights the importance of considering the time-varying nature of factor exposures in factor strategies. Moskowitz et al. (2012) examined the time-series variation in factor premia across global markets, revealing that factor returns exhibit pronounced time-varying patterns and are subject to market conditions.

2.3 The influence of the business cycle

One important finding in recent literature is that different financial assets show different sensitivity to the business cycle. Campbell & Vuolteenaho (2004) show that the cash flow beta of small-cap and value stocks exhibits more extensive cash flow beta than their large and growth counterparts. Cochrane & Piazzesi (2002) shows that bonds of different maturities show different exposure to an aggregate cash flow variable and argues that their findings are also applicable to specific stock characteristics.

Polk et al. (2006) investigate the relationship between aggregate investment-to-capital ratio and expected stock returns and suggests that different stocks may show different exposure to aggregate investment news, which has major implications for cash flow news. Lettau & Wachter (2007) and Campbell et al. (2010) found that value and growth stocks react differently to aggregate cash flow news. Campbell et al. (2018) also document similar results when introducing beta to news about future market volatility. Lastly, Polk et al. (2019) documents differences in cash flow beta among size, value, quality, momentum, and low volatility factors for US large-cap stocks, proposing a framework to exploit this time-series variation for the purpose of dynamic factor strategies. Recent studies have explored the influence of the business cycle across a broader set of equity factors Hodges et al. (2017) and Varsani & Jain (2018), providing a descriptive analysis of historical factor performance conditional on economic regimes.

3 Theory and hypotheses

3.1 Factor construction

Researchers differ in their view of how to access the factor premia most efficiently. The traditional way, as famously proposed by Fama & French (1992) selects a given proportion of the selected investment universe according to their rankings on the chosen factor and goes long/short on the top/bottom proportions respectively. Rather than employing this approach to portfolio construction, one can utilize a bottom-up approach by defining a scoring function to obtain individual factor scores for every stock and utilize this to "tilt" away from initial market capitalization weights towards the target exposure following the approach outlined in Russell (2017a). By doing so, one should be able to obtain similar exposure to target factors. The result of this is long-only portfolios with relatively larger weights in stocks with higher scores on the target raw factor characterization. Simple transformations can be performed on the weights to create long-short strategies.

3.2 Cash flow news

From gaining knowledge of the time-series variation on the market risk premia, Campbell & Shiller (1988) also derive a crucial differentiation of the components of market returns. They found that market returns are made up of two elements, the dividend expectation and discount rates applied to the expected dividends. The log-linear present value model, as proposed by Campbell and Shiller, provides a mechanism to enable this distinction. More specifically, subsequent to the foundational works, Campbell & Perron (1991) further clarified a mathematical decomposition of the unexpected log returns on an asset:

$$r_{t+1} - E_t r_{t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j \Delta r_{t+1+j} = N_{CF,t+1} - N_{DR,t+1} \quad (1)$$

where $N_{CF,t+1}$ denotes the innovations to cash flows and $N_{DR,t+1}$ denotes the innovations to discount rates.

This decomposition is widely exploited in financial research for the purpose of explaining how different types of stocks load differently on the two components. Campbell & Vuolteenaho (2004) proposes a model to explain that investors care more about permanent cash flow-driven movements than they care about the more temporary changes in the applied discount rates. They present a model where they decompose the CAPM beta into separate betas for permanent cash flow innovations and for discount rate innovations. Importantly, the study introduces the cash flow beta, which corresponds to the sensitivity of a stock to news about future cash flows. In other words, the cash flow beta quantifies the responsiveness of the stock to changes in the expected future profit of the company.

The evident heterogeneity in cyclical properties and performance across economic regimes among factors is an important motivation for a factor-rotating strategy. Any factor strategy that exhibits a large cash flow beta should perform relatively well in periods of good market fundamentals and relatively worse in periods of worse market fundamentals. Consequently, we expect that tilting towards high cash flow beta factor strategies when signals are positive and vice versa when signals are negative, should improve the strategy performance relative to both single factor strategies and static multifactor strategies.

3.3 Forecasting business cycle

An important consideration for a rotating factor strategy is how to classify the stages of the business cycle. The business cycle is usually defined in four distinct regimes that are recovery, expansion, slowdown, and contraction, where the regimes are characterized by combinations of the level and directional change in production growth. By the application of a consistent framework to forecast economic regimes in subsequent periods, we expect to be able to rebalance our portfolio to target the most promising factors.

The US leading economic index (US LEI) is an indicator of significant economic turning points and is designed to forecast near-term economic activity. When US LEI rises, this typically indicates strong future economic conditions and vice versa for decreasing US LEI. The global risk appetite indicator (GRAI) measures the willingness of investors to engage in riskier investments. When GRAI is high, it would suggest that investors are confident in the global economy. On the contrary, when low, the risk appetite suggests a lack of confidence in the global markets, indicative of an upcoming slowdown or contraction. Financial markets, functioning in a real-time environment, continuously integrate incoming information. This process culminates in market participants forming expectations of future economic activity, consequently making these markets a promising mechanism for forecasting future trends. This concept aligns well with the variance decomposition of stock returns, emphasizing that continuously updating information and expectations play a fundamental role in determining asset prices, thereby fostering a dynamic, forward-looking financial environment (Polk et al., 2019).

Therefore, the US leading economic indicator is indicative of whether the level of growth is expected to be above or below trend, and GRAI should be an indication of its expected directional change. The relevance of both indicators and their combinations are recognized in financial literature and we thus believe combinations of these as able to forecast subsequent economic regimes. Basu et al. (2021) found that risk premia are likely to be predictive of up- and downturns in the economy. Campbell & Perron (1991) and later Lochstoer (2009) documents that risk premia are typically negatively correlated with the business cycle showing high levels in recessions and low levels in expansion. Black (1976) and Christie (1982) also documents similar results for risk aversion. Thus, we assume fluctuations in global risk premia to be able to forecast subsequent fluctuations in economic risk and future risk premia.

3.4 Contribution to literature

The presented study contributes to the existing literature by building upon the research conducted by Polk et al. (2019) and further expanding our understanding of multifactor strategies through the business cycles. While both studies aim to explore the effectiveness of multifactor models and the time-series variation in factor premia, several key differences exist in terms of data and time horizon. We also differ in desired factor exposure through the business cycle, where we argue for increased performance through downside protection in economic downturns.

Firstly, unlike Polk et al. (2019), who utilized the Russell universe as their data source, our study incorporates the CRSP Common Stock file, which provides a broader scope and allows for a more comprehensive analysis of the multifactor strategy. Rather than looking only at large-cap stocks we also incorporate small and medium-cap stocks in our data. However, it is important to note that due to the large number of individual stocks included in our dataset, the investibility of our findings is limited, thereby emphasizing the theoretical implications of our research, rather than the practical ones. Further, an important contribution of our research lies in the utilization of an extended time series. By extending the sample period, our study accounts for recent significant fluctuations in the macroeconomic indicators and financial markets, enabling a more robust analysis of the multifactor strategy's performance across various market conditions.

In addition to the shared methodology for factor construction and market return decomposition, our study also aligns in terms of constructing business cycle regimes. We follow the methodology proposed by Polk et al. (2019) to identify distinct economic phases, allowing us to capture the impact of different business conditions on multifactor strategy performance. We do, however, measure risk appetite slightly differently. In our study, risk appetite is assessed using a combination of indicators, namely the US Swap spread, the CBOE Volatility Index (VIX), the Emerging Markets Bond Index Plus (EMBI+), and a trade-weighted Swiss Franc basket. This nuanced approach to measuring risk appetite enables a more comprehensive assessment of market sentiment and its influence on the performance of the multifactor strategy. By employing a consistent methodology in factor construction and market return decomposition, and by leveraging the insights of renowned researchers in the field, our applied framework aligns with Polk et al. (2019) while we argue that differences in investment universe and time horizon, build to the understanding of the framework.

4 Empirical method

4.1 Data

In our study, we primarily rely on three primary data sources: The Center for Research in Security Prices (CRSP), Compustat, and Global Financial Data. To construct our factor portfolios, we extracted monthly returns for all firms listed on the NYSE, AMEX, and NASDAQ exchanges from the CRSP Common Stock file. The result is a dataset comprising more than 20,000 different stocks, both active and inactive, spanning the period from January 1975 to December 2022. The data does not include financial firms and internationally listed stocks unless cross-listed. For our purpose, also some simple additional screening is necessary. We consider any return below negative 100% to be insufficient data, which we exclude. Also, every return showing absolute values of z-scores higher than 10 standard deviations from the mean will be considered insufficient data and excluded following Russell (2023).

The factor construction process incorporates several fundamental components specific to each stock. First, the value factor is created as an equally weighted composite of earnings yield, cash flow yield, and price to sales for each firm. The quality factor is an equally weighted composite of profitability and leverage ratio, where the profitability part is a composite of return on assets, change in asset turnover, and accruals. Further, the size factor is the inverse of the full market capitalization index weights. The Low Volatility factor is the standard deviation of five years of monthly returns. Finally, the momentum factor is constructed using the 12-month cumulative return excluding the 12th period. The data for the fundamental variables for value and quality are obtained from Compustat and the data for size, low volatility, and momentum is from CRSP. To include a stock in our dataset, we require all necessary components for factor construction to be available and verified through the unique ID assigned to each firm. The formation period for the volatility factor is 60 months, while the momentum factor takes 12 months to form. Hence, the first five years of data are excluded in our final single-factor portfolios as these correspond to the formation periods. The sample period for our regression results for the single factor exposure to aggregated cash-flow news is therefore from May 1980 to December 2022. After constructing all the factors, our multifactor portfolio is based on the period from March 1989 to December 2022. The data length is shorted due to the availability of components to construct our business cycle regimes, which is not available before 1989. The number of stocks in the different portfolios varies based on the number of listed stocks at each point in time along with data available in the different factor characteristics components. Please refer to Table A3 in Appendix A for a full overview.

To construct our business cycle regimes, we sourced the Leading Economic Indicator (LEI) directly from the Federal Reserve of Economic Data (FRED) on a monthly basis. The indicator is normalized for the United States and seasonally adjusted. Our Global Risk Cycle Indicator is constructed based on four different variables namely the U.S Swap Spread, Chicago Board Options Exchange Volatility Index (VIX), Emerging Market Bond Index Plus (EMBI+) and finally a trade-weighted Swiss Franc Basket. This data is sourced from Global Financial Data and variables are further explained in our methodology part. The resulting sample period is dictated by data availability and goes from March 1989 to December 2022.

As a benchmark, we employ the CRSP Value-Weighted Index. This index is constructed based on all listed companies on the respective exchanges with valid prices and shares outstanding in both the current and the previous periods. For the risk-free rate, we utilized the 1-month US Treasury bill data from CRSP Treasuries. Our cash flow news estimator specified by a VAR model includes six state variables. The first is the log real return on the market, by the CRSP Value-Weighted Index minus the consumer price index (CPI). The second is the expected market variance made by taking the within-month realized variance of daily returns on the CRSP Value-Weighted Index. The third variable is the Shiller price-to-earnings ratio which is the log ratio of the S&P500 price index to a ten-year moving average of S&P500 earnings, in line with Shiller (2000). The fourth is the term yield (TERM), computed as the difference in log yield on the 10-year US Constant Maturity Bond (IGUSA10D) and the 3-month US Treasury Bill (ITUSA3D), fetched from Global Financial Data. The fifth variable is the Default Spread (DEF), fetched from Global Financial Data defined as the difference in log yield between Moody's BAA and AAA bonds. The sixth and final variable is the small-stock value spread from Kenneth French's website. The data is constructed on six elementary equity portfolios formed on size and book- to market. The final dataset for our VAR model extends from June 1927 to December 2022.

4.2 Factor construction

Since Fama & French (1992) published one of the most influential and frequently referenced papers on expected stock returns, investors have consistently pursued capturing value, size, and quality premiums. Previous literature reveals that these three factors have demonstrated both strengths and weaknesses across different economic cycles, which may lead to underperformance relative to the benchmark in specific periods. Through the adoption of smart beta strategies, as discussed by Jiang et al. (2021), we aim to exploit the unique benefits of each factor. Specifically, the value factor can help capture exposure to stocks with good fundamentals relative to their market price. The size factor can potentially capture the excess returns of smaller companies. Further, the quality factor can capture the future excess return related companies that consistently tend to perform well, as quality is rarely fully priced in financial markets. Furthermore, the low volatility strategy is implemented as a risk management tool to protect against potential downside risk, while the momentum strategy is employed to generate alpha as suggested by Russell (2017b). For a more comprehensive understanding of these factors and their purposes, please refer to Table 1.

	Value	**Size**	**Quality**	**Low Volatility**	**Momentum**
Premium	Stocks that appear cheap tend to perform better than stocks that appear expensive.	Smaller companies tend to demonstrate higher performance than larger companies.	Higher quality companies tend to demonstrate higher performance than lower-quality companies.	Stocks that exhibit low volatility tend to perform better than stocks with higher volatility.	Stock performance tends to persist, either continuing to rise or fall.
Exposure	Can help capture exposures at a reasonable price relative to their fundamentals.	Can help capture excess returns of smaller companies relative to their larger counterparts.	Can help capture companies with the ability to consistently generate strong future cash flows, while limiting exposures to stocks that are unprofitable or highly leveraged.	Can help capture companies with a historically lower risk profile relative to higher risk counterparts. The value factor helps to mitigate the risk of overpaying for stocks.	Can lead to the selection of companies with strong recent performance, with the expectation that this will continue to produce short-term excess returns in the future.
Definition	Equally weighted composite of cash-flow yield, earnings yield, and price-to-sales ratio.	Inverse of full market capitalization index	Composite of profitability, efficiency, earnings quality, and leverage.	Standard deviation of 5 years of monthly local total returns.	Cumulative 12-month return, skipping the 12th period.
Data Source	Compustat	CRSP	Compustat	CRSP	CRSP

Table 1: Factor Characteristics. Source: Russell (2017b)

To create the mentioned factor-based portfolios, we follow the methodology described in this section, to take on exposure to the factors in line with Russell (2017a), Russell (2017b), and Russell (2023) approach and utilize the underlying factor characteristics.

Specifically, we depart from market capitalization weights ($\hat{w}_i$) that we multiply with a set of factor scores, before normalizing the resulting weights. For the factor scores, we first calculate the raw factor scores (f_i) for each individual stock $i = 1, \ldots, N$, based on the factor fundamentals. Then, to overcome problems related to differences in ranges and units, we perform a simple z-scoring procedure to rescale such that each stock is represented by the z-score:

$$Z_i = \frac{f_i - \mu}{\sigma} \tag{2}$$

Where μ and σ represent the cross-sectional mean and standard deviation across all listed firms. Outliers are then windsorized so that none of the observations exceeds three standard deviations from the mean by truncating the z-scores on the interval $[-3, 3]$. We then recalculate the z-scores iteratively, until every z-score is within the given interval. The result of this treatment is that we limit the influence of extreme cases and rare events.

To obtain positive real numbers to represent the weights, we map the z-scores using the cumulative normal distribution function. This functional form is particularly useful under the assumption that the factor returns are normally distributed. The resulting weights are then, for a single factor, to be expressed as:

$$W_i^T = \frac{CN(Z_i) \cdot \hat{w}_i}{\sum_{j=1}^{N} F(Z_j) \cdot \hat{w}_j} \tag{3}$$

Where $CN(Z_i)$ denotes the cumulative normal equivalent of the z-score for stock i and $\hat{w}_i$ is the market capitalization weight, so that W_i^T is the final normalized weight of stock i in the portfolio.

By acknowledging that we can tilt away from the set of weights formed by the underlying index, we also acknowledge the natural extension that this new set of weights is just another set of weights that we can tilt away from. This realization is neat for the idea of multiple factor-tilting with the sequential application of factor scores. The weights of each stock i in a multiple-factor portfolio are obtained from iteratively applying the tilting procedure and are expressed in the form:

$$W_i^T = \frac{F_1(Z_{1,i}) \cdot \ldots \cdot F_n(Z_{n,i}) \cdot \hat{w}_i}{\sum_{j=1}^{N} F_1(Z_{1,j}) \cdot \ldots \cdot F_n(Z_{n,j}) \cdot \hat{w}_j} \tag{4}$$

where $Z_{n,i}$ is the z-score of the nth factor for the ith stock.

	Return	St.dev	Excess Return	Sharpe Ratio	IR	Max DD	Skewness
Value	15.64	15.63	4.58	0.76	0.29	-45.66	-0.74
Size	14.94	15.50	3.88	0.72	0.25	-47.26	-0.79
Quality	14.88	15.55	3.81	0.72	0.24	-47.11	-0.79
Low Volatility	13.98	14.38	2.92	0.71	0.20	-46.05	-0.83
Momentum	15.10	15.92	4.04	0.71	0.25	-46.97	-0.82
Benchmark	11.06	15.57	-	0.47	-	-51.48	-0.70

Table 2: Single Factor performance summary statistics. Sample period from May 1980 to December 2022. Benchmark is the CRSP Value-Weight Index. Returns are annualized and reported in percentage.

Table 2 presents risk and return characteristics for the single-factor portfolios and the benchmark portfolio. Among the factors, the value and size factors exhibit relatively higher Sharpe Ratios of 0.76 and 0.72, respectively, suggesting solid risk-adjusted performance. The quality, low volatility, and momentum factors also display respectable Sharpe ratios, although slightly lower. These results indicate that the value and size factors offer relatively more robust risk-adjusted returns compared to the other factors throughout the full sample period.

As seen from Table 3, there is not a lot of correlation between the factor portfolios, except for the large correlation between the value and size factors. This suggests that the factor portfolios are not moving in tandem through the business cycle. This has implications for the diversification benefits in multifactor implementations and suggests that there is a possible profit from rotating factors relative to economic regimes.

	Value	Size	Quality	Low Volatility	Momentum
Value	1.00	0.86	0.19	0.29	0.55
Size	0.86	1.00	0.16	0.42	0.44
Quality	0.19	0.16	1.00	-0.13	-0.08
Low Volatility	0.29	0.42	-0.13	1.00	-0.01
Momentum	0.55	0.44	-0.08	-0.01	1.00

Table 3: Excess factor returns correlations. Sample period from May 1980 to December 2022.

We include all available stocks in every period to avoid survivorship bias which refers to the phenomenon of only focusing on successful stocks. Survivorship bias often leads to a skewed understanding of the investment landscape, falsely representing performance as it overlooks delisted or acquired stocks. Even though this wide-ranging inclusion of all US common stock may limit the practical investibility of the strategy, as managing such a diverse portfolio may prove difficult and expensive, it is necessary for a robust and comprehensive analysis. Small-cap stocks often receive less attention from investors and analysts, primarily because they tend not to provide immediate significant returns and they carry higher risks. However, their inclusion is critical in our research, as they might exhibit unique trends and opportunities, and can offer valuable insights into the overall behavior and efficacy of the factors.

The execution of an investment strategy also involves transaction costs. These costs, which can significantly impact net returns, typically include brokerage fees, bid-ask spreads, and potential market impacts. However, due to the lack of exact data, and the changing nature of these costs, obtaining the precise historical transaction costs of the strategy is close to impossible. We approximate these transaction costs by calculating the turnover of the portfolio. Turnover, in this context, measures the extent to which the portfolio's holdings change over time. Since our investment strategy involves regular rebalancing by adjusting the weights of each stock in the portfolio every period, the turnover calculation becomes especially relevant.

To compute turnover, we sum the absolute values of the change in weight for each stock in the portfolio for each period. This process involves subtracting the initial weight from the final weight for each stock, taking the absolute value of the difference, and summing these values across all stocks in the portfolio. This provides an indication of how much the portfolio has been 'turned over' or altered during a given period. Once we have the turnover, we then estimate the effect of transaction costs on our returns. Petajisto (2011) found transaction costs in US large-cap stocks to be in the range of 21-28 bps and in US small and mid-cap stocks to be between 38-77 bps annually. Since our investment universe consists of all US common stock, we assume transaction cost to be 50 basis points per 100% of portfolio turnover and deduct this from the total return of the portfolio. This deduction represents our estimate of the transaction cost per unit of turnover. This methodology gives us an approximate measure of the net returns of our investment strategy after considering transaction costs. However, it's worth noting that this approach is a simplification. The actual transaction costs can depend on a wide range of factors, and they can vary over time and across different market environments. As such, the accuracy of our net return estimate depends largely on how closely our assumed transaction cost per unit of turnover aligns with the actual costs we would incur in practice.

4.3 Benchmarks

To ensure robust and meaningful conclusions, it is crucial to establish a benchmark for comparison in our analysis. In this thesis, we use the CRSP Value-Weighted Index as a benchmark. This is a value-weighted portfolio built each year using all issues listed on NYSE, AMEX, and NASDAQ, providing a comprehensive reference point for evaluating investment strategies.

In addition to the benchmark index, we have constructed our own Static Factor Index using the data derived from our research dataset. This index serves as a key component in our analysis, enabling us to draw insightful comparisons between our Dynamic Multifactor strategy and an equally tilted factor portfolio. The Static Factor Index is designed to capture the performance of a portfolio with a constant and equal tilt towards each of the five factors across all business regimes. This approach allows us to evaluate the relative performance of our Dynamic Multifactor strategy against a portfolio that maintains a consistent allocation to each factor. The inclusion of a benchmark and the construction of the Static Factor Index strengthens the rigor and validity of our findings.

4.4 Innovations to cash flow

We use the methodology of Campbell et al. (2018) to derive the cash flow news series. We consider six state variables in the VAR specification with monthly observations from 1927 to 2022. As our proxy for the aggregate wealth, we base our first variable on the log real return on the market, r_m, for which we use the difference between the log return on the Center for Research in Security Prices (CRSP) Value-Weighted stock index and the log return on the Consumer Price Index (CPI). The second variable is the expected market variance (EVAR) capturing the variance, σ^2, of market returns conditional on information available at time t. EVAR is constructed from a series of within-month realized variance of market returns, RVAR, where a first-step vector autoregressive model on lagged values of RVAR and the other five state variables creates a series of predicted RVAR which becomes the EVAR, so that $EVAR \equiv R\hat{V}AR_{t+1}$. To capture investor sentiment and expectations regarding future earnings growth, our third variable is the log price-to-smoothed earnings ratio (PE).

The fourth element in the VAR specification is the term yield spread (TERM), the difference in yield between the log yield on the 10-year US constant maturity bond and the log yield on the 3-month treasury bill. It reflects market expectations of future economic conditions. A wider spread indicates that investors expect stronger economic growth, which can positively impact cash flows. A narrower spread, on the other hand, may suggest expectations of weaker economic growth and potentially negative cash flow news Diebold & Li (2006). The fifth element is the default spread (DEF), where we look at the spread between the log yield on Moody's BAA and AAA bonds. A wider default spread indicates higher perceived credit risk and potential financial stress in the economy. This can be associated with negative cash flow news as it suggests a higher likelihood of defaults and deteriorating financial conditions Altman (1984). The last element is the small-stock value spread (VS). The small stock value spread captures the performance differential between small-cap stocks and value stocks. Including this variable allows us to assess the market sentiment towards smaller, potentially riskier companies compared to value-oriented companies. A wider spread suggests a preference for value stocks, which may indicate concerns about the cash flows and profitability of small-cap companies C. S. Asness et al. (2013).

We follow the approach outlined in Campbell et al. (2018) to derive cash flow innovations. Specifically, consistent with existing literature, we assume that the economy follows a first-order vector autoregressive (VAR) model:

$$x_{t+1} = \bar{x} + \Gamma(x_t - \bar{x}) + \sigma_t u_{t+1} \tag{5}$$

Where x_{t+1} is a 6×1 vector of the state variables as follows:

$$x_{t+1} = [r_{M,t+1} \; EVAR_{t+1} \; PE_{t+1} \; r_{TBill,t+1} \; DEF_{t+1} \; VS_{t+1}] \tag{6}$$

So that the real market return is the first element. $\bar{x}$ is a 6×1 vector of the means of the state variables, and Γ is a 6×6 matrix of constant parameters. u_{t+1} is the 6×1 vector of innovations with the constant variance-covariance matrix Σ, where Σ_{11} is equal to 1. To pick out only the unexpected market returns component, we also define e_1, a 6×1 vector with all elements being zero except for the very first unit element. I is the 6×6 identity matrix. Discount rate innovations and cash flow innovations are then calculated as follows:

$$N_{DR,t+1} = e_1' \rho \Gamma (I - \rho \Gamma)^{-1} \sigma_t u_{t+1} \tag{7}$$

$$N_{CF,t+1} = \left(e_1' + e_1' \rho \Gamma (I - \rho \Gamma)^{-1}\right) \sigma_t u_{t+1} \tag{8}$$

In line with existing literature (see Campbell & Vuolteenaho (2004)), we set $\rho = 0.95^{1/12}$, to correspond with an average dividend-price ratio of 5.2 percent. ρ can be related to either the average dividend yield or the average consumption wealth ratio. An annualized ρ of 0.95 corresponds to an average dividend-price or consumption-wealth ratio of 5.2 percent, where wealth is measured after subtracting consumption.

By acknowledging that market returns are comprised of two components that both have their volatility and that show small correlations, Campbell & Vuolteenaho (2004) define the separate betas as follows:

$$\beta_{i,CF} = \frac{\mathrm{Cov}(r_{i,t}, N_{CF,t})}{\mathrm{Var}(r^e_{M,t}, E_{t-1} r^e_{M,t})} \tag{9}$$

$$\beta_{i,DR} = \frac{\mathrm{Cov}(r_{i,t}, -N_{DR,t})}{\mathrm{Var}(r^e_{M,t}, E_{t-1} r^e_{M,t})} \tag{10}$$

Where $\beta_{i,CF}$ and $\beta_{i,DR}$ denote the cash flow beta and discount rate beta, respectively. As the focus of our research relates to the business cycle, we will focus only on the cash flow betas of the factor portfolios. To examine the sensitivity of the factor portfolios to the business cycle, we run regressions of their respective monthly returns on the cash flow news variable. To adjust for nonsynchronous data and for a better reflection of the true responsiveness to cash flow innovations, we introduce one- and two-lagged betas, in line with academic literature Scholes & Williams (1977), Dimson (1979). The estimated regression is on the form:

$$R_{p,t+1} = \alpha + \sum_{k=0}^{2} \beta_p N_{CF,t+1-k} + \epsilon_{p,t+1} \tag{11}$$

So that the reported cash flow beta is the sum of the zero-to-two lagged betas. It is worth noticing that this regression form assumes temporal decay of the effect of past innovations, though this assumption might be a simplification of the real world. In order to examine the significance of the exposure, we also report the t-statistics. We include, for reference, the market portfolio proxied for by the Value-Weighted Index and the Static Factor Portfolio. In Table 4, we summarize the resulting single-factor exposure to aggregate cash flow news.

Factor	**Constant**	**Cash Flow News Sensitivity**	**R-squared**
Value	0.01 (41.62)	1.04 (147.36)	0.98
Size	0.01 (45.21)	1.04 (167.58)	0.98
Quality	0.01 (41.36)	0.99 (153.21)	0.98
Low Volatility	0.01 (24.13)	0.91 (86.95)	0.95
Momentum	0.01 (32.26)	1.07 (122.36)	0.97
Market	0.01 (44.54)	1.06 (224.62)	0.99
Factor equal weight	0.01 (29.50)	0.95 (99.49)	0.95

Table 4: Single Factor Exposure to aggregate Cash-Flow News. T-statistics is reported in parentheses. Sample period from May 1980 to December 2022.

From Table 4, we see that the portfolios exhibit varying levels of sensitivity to aggregate cash-flow news. Momentum reveals the most significant beta of 1.07, followed by size and value with betas of 1.04. This indicates that these portfolios are highly responsive to changes in cash-flow news. Low-volatility, with a sensitivity of 0.91, is the least responsive to such changes, while quality shows only a moderate beta of 0.99.

4.5 Business cycle forecast

We aim to distinguish four distinct business cycle regimes in our time series analysis, based on an economic growth indicator. These regimes are categorized as recovery, expansion, slowdown, and contraction. To better visualize these stylized business cycle regimes, we have created a plot that represents the changes in economic growth. Please refer to Exhibit 5 for a visual representation of the plot.

Business Cycle Regimes Visualization

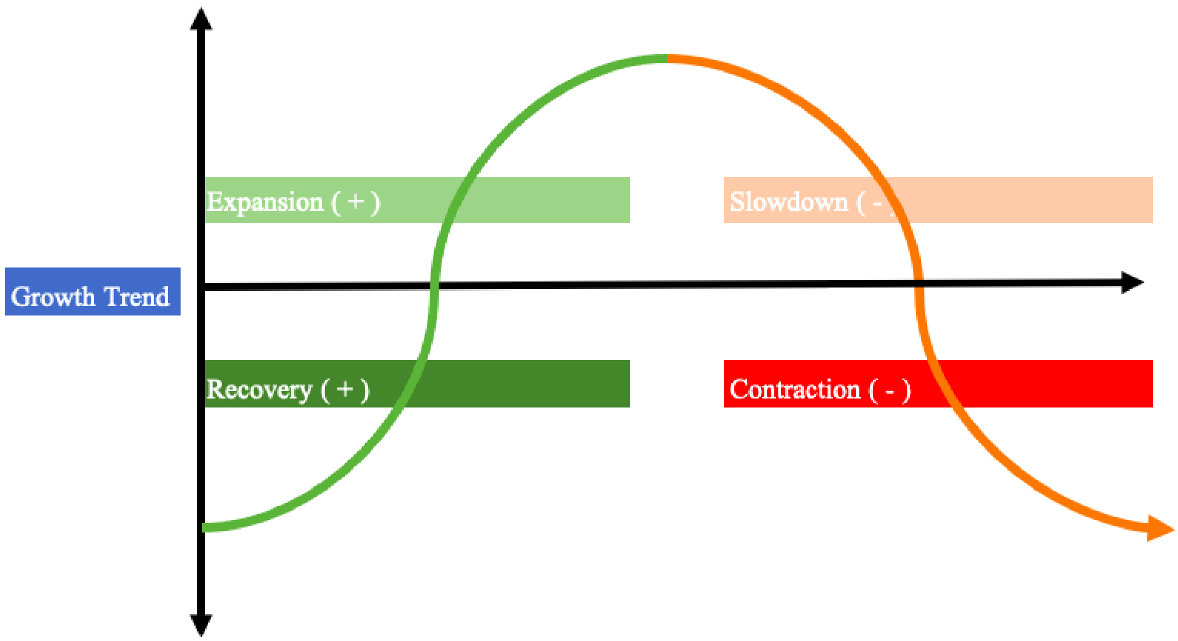

Figure 1: Source: The figure is created by to authors to visualize the general business cycle regimes.

We define four distinct economic regimes based on the level and the directional change of economic growth in a similar fashion to Polk et al. (2019). We specifically define economic regimes based on 1) if the economic growth is above or below its long-term trend, and 2) if the economic growth is accelerating or decelerating. To define these, we combine interactions of binary variables of the US leading economic indicator and the global risk appetite indicator with the following rules:

$$\begin{aligned}
\text{Recovery}_{t+1}: &\quad \text{US LEI}_t < \text{LT US LEI trend}_t \quad \& \quad \text{GRAI}_t \geq \text{MA (GRAI)}_t \\
\text{Expansion}_{t+1}: &\quad \text{US LEI}_t \geq \text{LT US LEI trend}_t \quad \& \quad \text{GRAI}_t \geq \text{MA (GRAI)}_t \\
\text{Slowdown}_{t+1}: &\quad \text{US LEI}_t \geq \text{LT US LEI trend}_t \quad \& \quad \text{GRAI}_t < \text{MA (GRAI)}_t \\
\text{Contraction}_{t+1}: &\quad \text{US LEI}_t < \text{LT US LEI trend}_t \quad \& \quad \text{GRAI}_t < \text{MA (GRAI)}_t
\end{aligned}$$

where LT US LEI trend_t is the long-term trend of the US leading economic indicators at time t and MA $(\text{GRAI})_t$ is the short-term moving average of the global risk appetite indicator at time t.

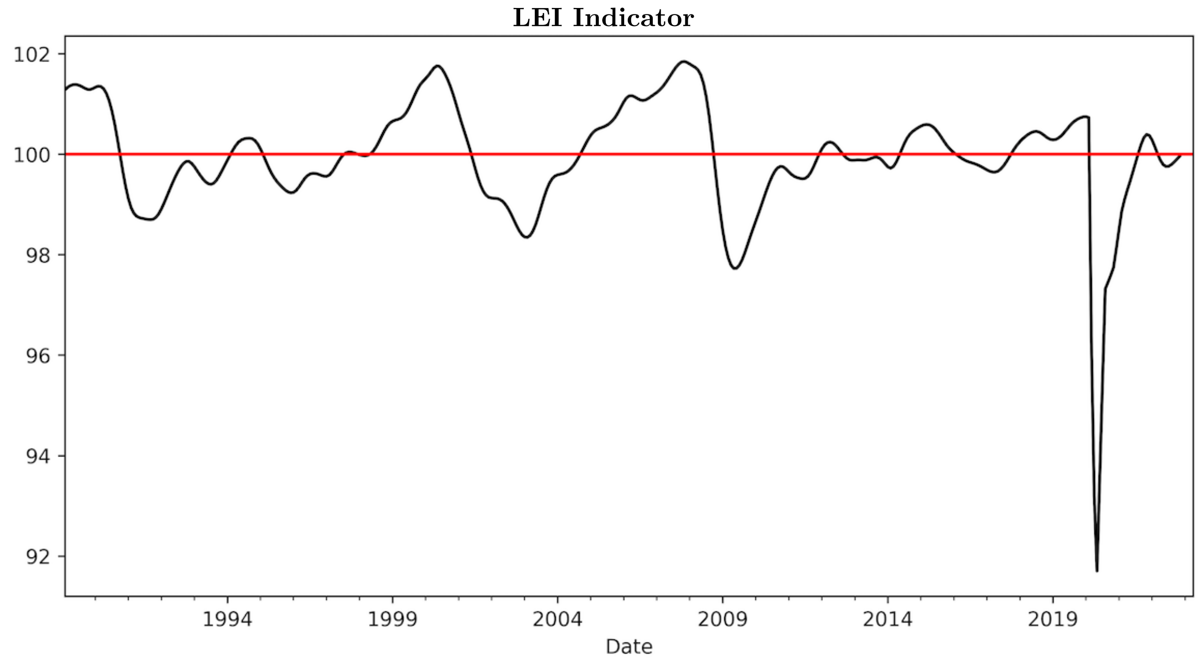

Figure 2: Source: The plot is created by the authors to visualize the LEI Indicator. Sample period from 1989-2023.

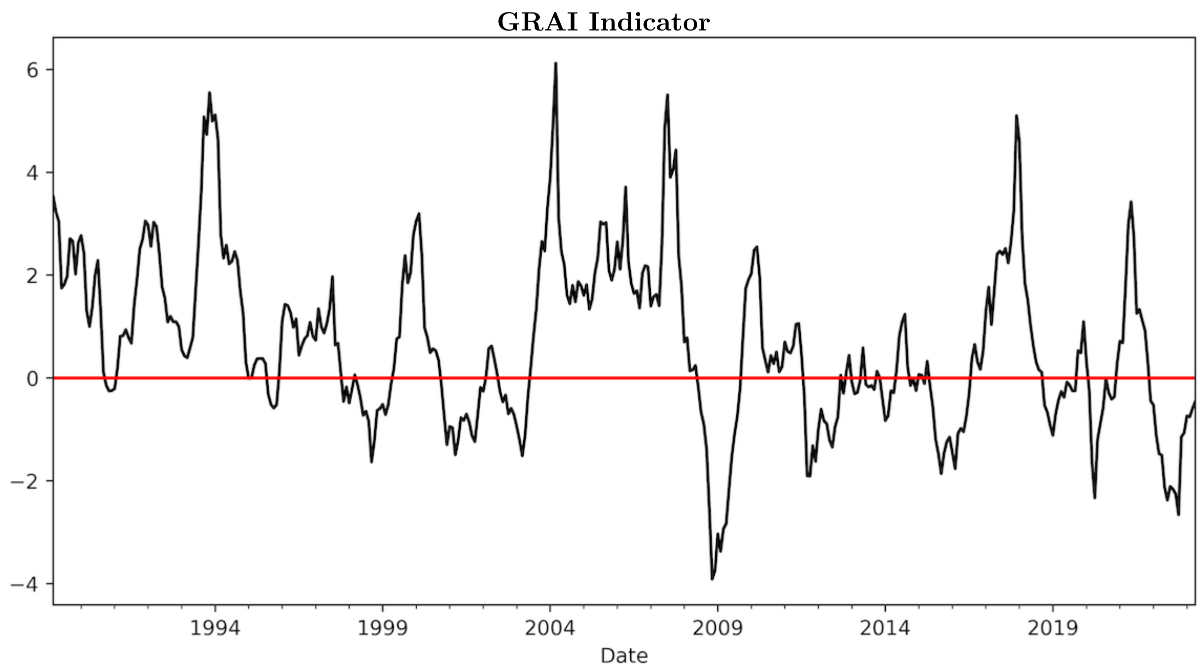

Figure 3: Source: The plot is created by the authors to visualize the GRAI Indicator. Sample period from 1989-2023.

We apply the framework of Polk et al. (2019) in forecasting the economic state, though we measure risk appetite slightly differently. We develop a Global Risk Appetite Index (GRAI) utilizing a composite of four variables. Initially, we represent liquidity risk via the U.S. swap spread, an established indicator of perceived credit risk in the interbank market. Second, equity market risk is captured through the Chicago Board Options Exchange Volatility Index (VIX). Thereafter, we consider the emerging market's credit risk, by the incremental return per unit of risk over a one-year period, as characterized by the rolling Sharpe ratio on the J.P. Morgan EMBI+ (Emerging Market Bond Index Plus) exchange-traded fund. Finally, currency market risk appetite is encapsulated using a trade-weighted Swiss Franc basket, providing a comprehensive view of currency market dynamics.

We ensure the normalization of these components and aggregate them with equal weighting to derive the GRAI. The final form GRAI index is positively correlated with investors' risk appetite, suggesting an increased willingness to take on risk as the index value escalates. This measure of global risk appetite offers, in combination with the raw form LEI indicator, a tool to forecast business cycle regimes in the subsequent period.

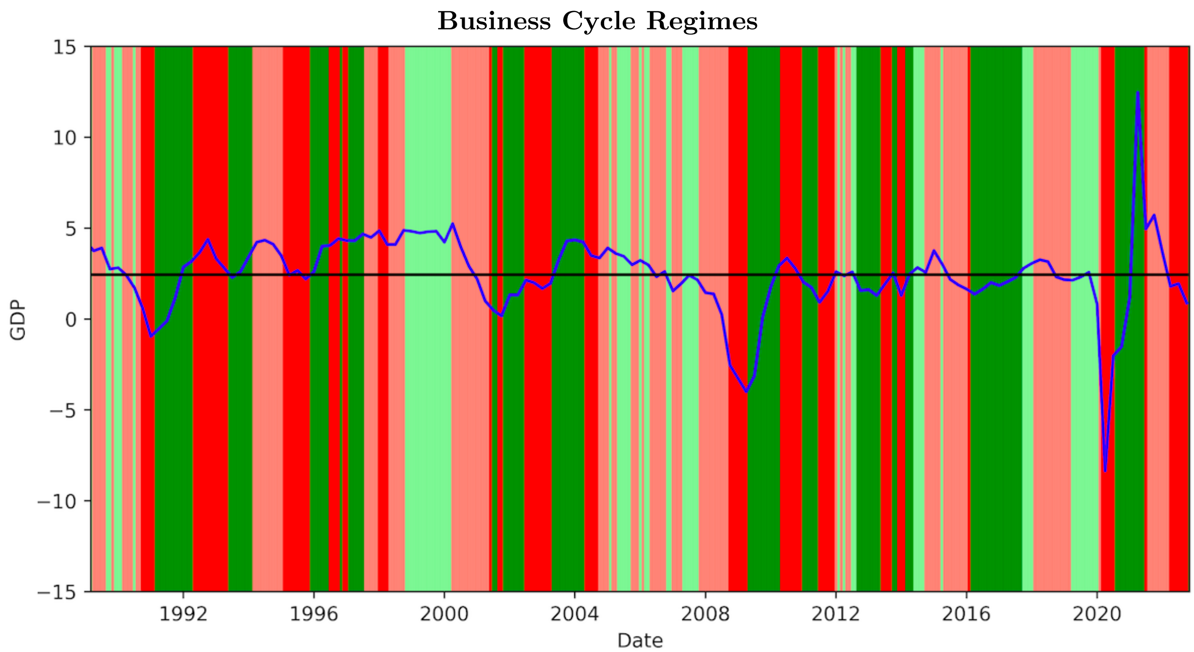

Figure 4: Business Cycle Regimes. **Green** = Recovery, **Light Green** = Expansion, **Light Red** = Slowdown, **Red** = Contraction. The **Blue** line represents the year-on-year growth in GDP, expressed in percentage terms. Constructed using the GRAI and LEI Indicators. Sample period from March 1989 to December 2022.

Figure 4 presents a visual comparison of our forecasted macro-regimes and the actual evolution of the GDP through time. The forecast model seems to work well when GDP grows steadily. However, in unstable times, characterized by steep fluctuations in GDP growth, it seems our model might be late in forecasting the subsequent period.

4.6 Tilting towards a Dynamic Multifactor Strategy

Based on the predicted business cycle regimes displayed in Figure 4 and considering the impact of cash flow news on factor returns as presented in Table 4, we have developed distinct portfolios for each regime. These portfolios are designed to align with the prevailing economic conditions during each phase of the business cycle. Consistent with the literature and considering our analysis we anticipate that size and value will exhibit a strong pro-cyclical behavior, meaning they are expected to perform well during periods of economic recovery and expansion. Consequently, we have constructed portfolios that emphasize investments in companies with smaller market capitalization and those exhibiting value characteristics during these phases. On the other hand, we anticipate that factors such as quality and low volatility will load less on the business cycle, making them more attractive in downturns. Therefore, our portfolios for these phases focus on selecting investments with low volatility and strong quality metrics. By tailoring our portfolios to align with the specific characteristics of each business cycle regime, we aim to optimize performance and capture opportunities that arise from different market conditions.

The momentum factor sets itself apart from the other four. While size, value, quality, and low volatility rely on persistent fundamental characteristics like leverage and profitability, momentum operates on a different premise. It capitalizes on behavioral principles that indicate the continuation of recent price trends. However, it's crucial to note that momentum signals have a relatively short lifespan. Our expectations align with the observed behavior of momentum. We anticipate that momentum will exhibit stronger performance during the late stages of a cyclical upturn (expansion) and the late stages of a downturn (contraction). This is because, at these points, the momentum strategy benefits from the continuation of existing price trends. Conversely, during the recovery and slowdown phases, we expect momentum to underperform. During these periods, relative price trends are prone to change, reducing the effectiveness of the momentum strategy (Polk et al., 2019).

	Constant	**Cash Flow News Sensitivity**	**R-squared**
Recovery portfolio	0.00 (0.47	-0.03 (-1.47)	0.02
Expansion portfolio	0.00 (0.88)	0.09 (1.72)	0.05
Slowdown portfolio	0.00 (0.54)	0.04 (1.77)	0.03
Contraction portfolio	0.00 (1.01)	-0.04 (-2.83)	0.08
All regimes	0.00 (0.25)	0.00 (-0.11)	0.00

Table 5: Momentum portfolio performance conditional cash flow sensitivity (1980-2022). Source: Table created by authors. T-statistic are reported in parentheses. Sample period dictated by data availability in business cycle forecasting.

In Table 5 we present the conditional cash flow sensitivity of the momentum portfolio, in the different business cycle regimes. Interestingly, and in line with previous literature and economic intuition, we see that the portfolio exhibits the largest cash flow beta in expansion (0.09) and the lowest cash flow beta in contraction (-0.04). The pro-cyclicality in expansion and counter-cyclicality in contraction suggests that we load on momentum in both of the late stages of the economic up- and downturns.

To ensure that these patterns are not mere reflections of broader market trends, we validate them by measuring the sensitivities of these factors relative to a benchmark index. Since the business cycle regime can transition from one month to the next, and considering that momentum signals have a short-lived nature, we focus on measuring contemporaneous sensitivities. By considering these cyclical patterns and sensitivities, we gain a deeper understanding of how different factors behave within the context of the business cycle.

Taking advantage of the underlying characteristics and the estimated exposure of our five factors to our forecasted business cycle, we can construct a dynamic multifactor strategy. Following Russell (2017a) approach, we utilize a “Tilt-Tilt” method. The factor tilts represent the number of tilts towards the target factor exposure we want on the underlying index and are used when constructing our dynamic multifactor strategy.

Tilt Matrix

Regimes	**Low Volatility**	**Size**	**Value**	**Momentum**	**Quality**
Recovery	0	2	2	0	0
Expansion	0	1	1	2	0
Slowdown	3	0	0	0	1
Contraction	3	1	1	3	1
Benchmark	0	0	0	0	0
Static	1	1	1	1	1

Table 6: Tilt Matrix: Numerical magnitude of tilts assigned to each factor in each business cycle regime.

The Tilt Matrix presents a dynamic investment strategy that adapts to different business cycle stages. In a recovery phase, we lean towards size and value, reflecting an expectation that smaller, undervalued firms will benefit from the improving economy. During an expansion, we tilt stronger towards momentum, capitalizing on continued upward trends, and moderate our tilt towards size and value. As growth begins to slow, the strategy favors low-volatility and quality, given their resilience in uncertain times indicated by weaker cash flow sensitivity. During a contraction, the portfolio maintains a strong tilt towards Low Volatility for stability and momentum for potential benefits from downward trends, while also tilting towards the static portfolio which shows low cash flow sensitivity. this dynamic approach aims to leverage the cyclicality of factor returns to optimize the strategy performance across different regimes.

Instead of simply averaging the factor scores, the multifactor strategy employs a more sophisticated approach known as multiplicative tilting. This strategy allows us to selectively overweight assets in our portfolio based on their desirable underlying factor characteristics. To achieve this, we multiply the weights of the underlying market capitalization index by the estimated factor scores. Next, we adjust the weights by grossing them up to ensure they sum to 100%.

To illustrate the concept of multiplicative tilting, Table 7 presents a hypothetical example using three stocks. In this example, both stocks A and B exhibit high scores in both the value and size factors compared to stock C. Consequently, the tilt approach assigns the highest weights to stocks A and B. This example demonstrates that by utilizing the factor scores, we can deviate from the initial market capitalization weight. Notably, stock C, despite having the highest market capitalization weight, receives relatively low scores in both size and value factors and is therefore assigned the lowest finalized weight. By multiplying the tilts, rather than averaging them, we achieve almost the same level of exposure towards the individual factors without the dilution of factor exposures. That is, by multiplication, rather than averaging, of factor exposures, we obtain higher factor exposure for a given level of diversification. The importance of this feature increases with the number of individual factors and tilts on each factor (Russell, 2017a).

	Market Cap weight	**Value score**	**Size score**	**Unadjusted weights**	**Final weights**
Stock A	25%	0.70	0.50	8.8%	37.7%
Stock B	33%	0.50	0.80	13.2%	56.9%
Stock C	42%	0.10	0.30	1.3%	5.4%
	100%			23.2%	100%

Table 7: Hypothetical example of multiplicative tilts

5 Results and discussion

In Table 8 we report the cash-flow sensitivity of the constructed regimes portfolios. The evident cash flow news sensitivities support the idea of the portfolios, where we want to load on the business cycle in good market environments and less in economic downturns. Sensitivities of different portfolios to cash flow news play a crucial role in understanding their performance. Our findings reveal varying degrees of sensitivities among the analyzed portfolios. The recovery portfolio demonstrates a high sensitivity (0.99) to cash flow news, indicating that changes in cash flow information significantly influence its returns. The expansion portfolio exhibits an even higher sensitivity (1.16) to cash flow news, emphasizing the heightened impact of cash flow information on its returns. In contrast, the slowdown portfolio (0.80) and contraction portfolio (0.84) display moderate sensitivities to cash flow news. This aligns with the intuition that we want to load relatively more on the business cycle in economic upturns than in economic downturns.

Regime Portfolio	Constant	Cash Flow News Sensitivity	R-squared
Recovery Portfolio (N=122)	0.01 (22.01)	0.99 (52.64)	0.96
Expansion Portfolio (N=65)	0.02 (6.76)	1.16 (14.01)	0.76
Slowdown Portfolio (N=121)	0.01 (9.33)	0.80 (28.37)	0.87
Contraction Portfolio (N=98)	0.01 (9.16)	0.84 (41.58)	0.95

Table 8: Regression results of cash flow news sensitivities conditional on regime portfolios. T-statistics are reported in parentheses. Sample period from March 1989 to December 2022.

We present the main results in terms of returns in Table 9. The table compares the performance of Dynamic Multifactor, Static Factor Portfolio, and market portfolio strategies, showing mean monthly returns and t-statistics, which are used to assess the statistical significance of the results, for the period 1980-2022.

	Mean Monthly Return	Return over market	Return over Static
Dynamic Multifactor	1.38% (6.67)	0.48% (6.62)	0.17% (2.95)
Static Factor Portfolio	1.20% (6.02)	0.31% (6.47)	
Market portfolio	0.89% (4.09)		

Table 9: Mean Monthly Returns. The table provides results for mean monthly returns and excess of the benchmark portfolio. T-statistics are reported in parentheses. Sample period from March 1989 to December 2022.

The Dynamic Multifactor strategy shows a mean monthly return of 1.38%, with a highly significant t-statistic of 6.67, indicating a statistically robust performance. This strategy also outperforms the market by 0.48% monthly, again with a highly significant t-statistic of 6.62. Compared to the Static Factor Portfolio, the Dynamic Multifactor strategy delivers an excess return of 0.17% per month, with a t-statistic of 2.95, suggesting this difference is also statistically significant. Further, in Figure 5, the cumulative returns of the Dynamic and Static Multifactor strategies are plotted in excess of the benchmark. The figure shows that the dynamic implementation outperforms the static over the sample period.

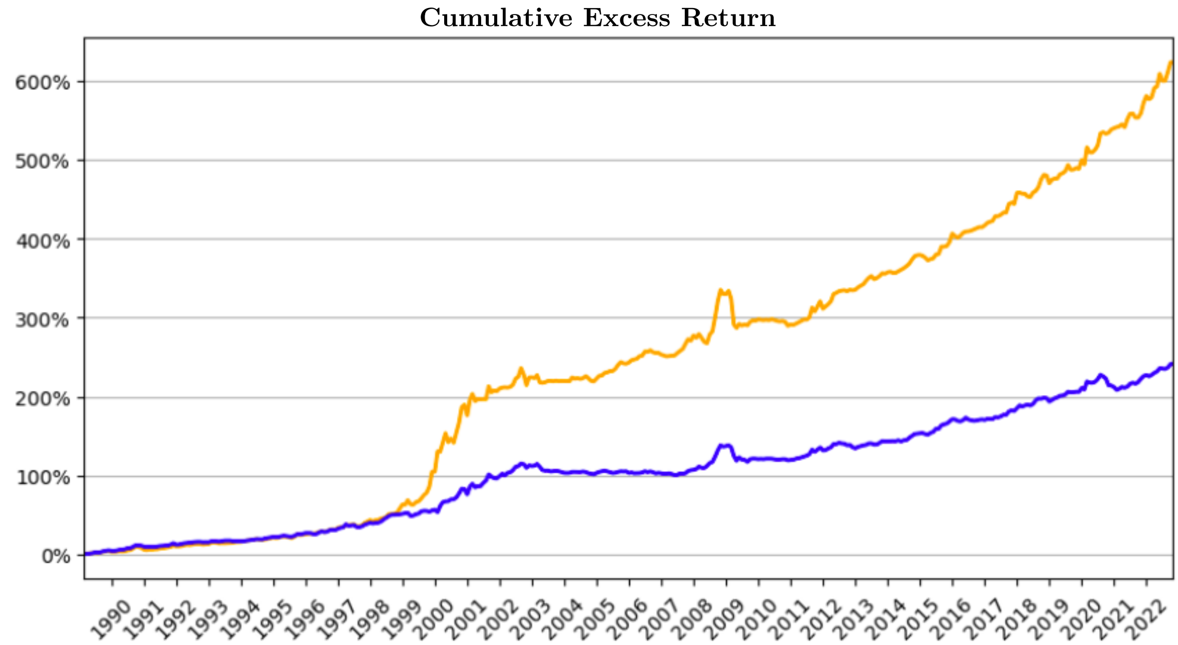

Figure 5: Cumulative Excess Return above the CRSP Value Weighted Index. Orange = Dynamic Multifactor Portfolio, Blue = Static Multifactor Portfolio. Sample period time from March 1989 to December 2022.

Further, Table 10 shows tabulated summary statistics to present an evaluative overview of the broader pre-cost characteristics of the portfolios for the period spanning from 1989 to 2022. The Dynamic Multifactor strategy shows the most considerable annualized return of 16.64%, superseding the Static strategy, which posts an annualized return of 14.32% and significantly outperforms the market at large, which shows an annualized return of 9.98%. Also, the dynamic and the static factor implementations show standard deviations of 14.40% and 13.94%, suggesting potential diversification benefits from factor implementations. Examining excess returns, the Dynamic Multifactor strategy triumphs with 6.66%, outpacing the Static strategy's 4.34%. The Sharpe Ratios reveal the Dynamic Multifactor strategy leading with a ratio of 0.90, thus generating superior risk-adjusted returns compared to the Static (0.76) and market (0.41) strategies.

	Return	**St.dev**	**Excess Return**	**Sharpe Ratio**	**IR**	**Max DD**	**Skewness**
Dynamic	16.64	14.40	6.66	0.90	0.46	-42.99	-0.23
Static	14.32	13.94	4.34	0.76	0.31	-42.03	-0.53
Market	9.98	15.23	-	0.41	-	-51.48	-0.66

Table 10: Performance characteristics. Returns are annualized and given in percent. Sample period March 1989 to December 2022.

The Dynamic Factor strategy shows higher turnover than the static implementation, suggesting that transaction costs might consume the returns that the strategy yields in excess of the static implementation. In Table 11, we present the after-cost comparison of monthly returns, taking into account the

50 bps of transaction cost per 100% turnover. The results suggest that the strategy delivers favorable returns also after accounting for transaction costs.

	Mean Monthly Return	**Return over market**	**Return over Static**
Dynamic Multifactor	1.29% (6.34)	0.39% (5.03)	0.14% (2.35)
Static Factor Portfolio	1.14% (5.73)	0.25% (4.54)	
Market portfolio	0.89% (4.09)		

Table 11: After-Cost Monthly Returns. Transaction cost set to 50bps. Transaction costs not calculated for benchmark. T-statistics are reported in parentheses. Sample period from March 1989 to December 2022.

Finally, Table 12 presents the broader characteristics of the performance of the dynamic and the static implementations after subtracting transaction costs. The Dynamic portfolio achieved a higher return (15.39%) than both the Static (13.42%) and the Market (9.98%). It exhibited an excess return of 5.41% over the market, a Sharpe ratio of 0.82, and an information ratio of 0.38, indicating its ability to consistently generate excess returns relative to the benchmark.

	Return	**St.dev**	**Excess Return**	**Sharpe Ratio**	**IR**	**Max DD**	**Skewness**
Dynamic	15.39	14.18	5.41	0.82	0.38	-41.26	-0.17
Static	13.42	13.94	3.44	0.69	0.25	-42.03	-0.53
Market	9.98	15.23	-	0.41	-	-51.48	-0.66

Table 12: Performance characteristics after transaction costs. Transaction cost set to 50bps. Transaction costs are not calculated for the benchmark. Returns are annualized and given in percent. Sample period March 1989 to December 2022.

To examine the robustness of our original tilting approach, we implement a final statistical test for a hypothetical strategy that maintains a long position in our dynamic strategy, while simultaneously shorting a strategy where the target exposure is inverted, that is the exposure intended for recovery is employed during contraction and vice versa, and likewise for expansion and slowdown. The alternative tilt matrix, which employs counterintuitive tilts, is provided in Table A1 in Appendix A. The strategy yields significant results, with a mean monthly return of 0.29% and a t-statistic of 2.49. The results suggest that a strategic selection of factor loadings, appropriately tailored to align with different phases of the business cycle, can indeed enhance the performance of the investment strategy.

6 Conclusion

In this thesis, we seek to answer our main research question: *How do factor premiums vary across the business cycle, and what implications does this have for factor rotation strategies?* To do so, we develop a dynamic multifactor strategy that leverages the underlying characteristics of our selected factors and their sensitivity to cash flow news and cyclical performance. We have drawn upon methodologies established in prior literature, mainly inspired by the approach outlined in Polk et al. (2019). We construct long-only portfolios tilted toward the size, value, quality, momentum, and low-volatility factors and look at the sensitivity of these portfolios to aggregate cash flow news. With these sensitivities, supplemented by financial intuition, we tilt towards desired factors through the different business cycle regimes. Finally, by forecasting the subsequent period's business cycle regime, we readjust our factor loadings accordingly. Through the application of the framework on the CRSP Common Stock file, we carry out a strategy that rotates factor exposure through the business cycle to demonstrate significant excess return over both the market and the static multifactor implementation, showing an excess return above the benchmark index of 6.66% on an annual basis. The strategy also provides a Sharpe ratio of 0.90 and an information ratio of 0.46. In comparison, the Static strategy yields an annualized excess return above the benchmark of 4.34%, a Sharpe ratio of 0.76, and an information ratio of 0.31. Also, considering transaction costs, we find that our Dynamic strategy both statistically and economically outperforms the static strategy by 1.97%.

However, it is important to acknowledge the limitations of our research. Firstly, our findings are based on historical data and may not necessarily guarantee similar results in future market conditions. Market dynamics and factor performance can evolve, introducing uncertainties that may impact the efficacy of our multifactor strategy. Additionally, while we have applied rigorous analysis and utilized extensive data, there may still exist unaccounted-for variables or alternative methodologies that could influence the outcomes. As with any research, inherent limitations should be considered when interpreting and generalizing our findings. When considering an investment strategy, investors often consider three variables: risk, return, and investibility. Our results yield significant risk-adjusted returns. However, it's important to note that the investibility aspect of the strategy may present some challenges due to the large set of stocks included. The employed tilts are also based on in-sample regressions and intuition, possibly biasing the true out-of-sample results. Nonetheless, our results hold valuable implications for researchers, providing a consistent framework within the existing literature to implement a multifactor strategy across a broad range of individual stocks. Furthermore, this thesis contributes to the body of knowledge by highlighting the time series variation in individual factors and their performance fluctuations over extended periods. In summary, our research presents a dynamic multifactor strategy that exhibits promising outcomes. Still, it is essential to recognize the limitations inherent in our methodology and the potential for future market dynamics to affect the results.

In conclusion, our study has provided valuable insights into the flexible construction of the tilt matrix and its applications. We have demonstrated the existence of factor-loading approaches, underscoring the adaptability of the tilt matrix. Our methodology incorporates economic principles and existing literature, though with an intuition-based selection process. Future research can focus on optimizing the tilts by investigating factors, variables, and their interactions. By refining the fine-tuning process, researchers can enhance the factor loading effectiveness in achieving specific objectives. Advanced quantitative techniques, like machine learning and optimization algorithms, can also contribute to improving factor loading. Finally, continuously conducting new empirical studies that build upon previous research, will contribute to the enrichment and evolution of the existing body of literature.

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A Appendix A

Cash flow news

Figure A1: Cumulative aggregate cash flow news variable. Sample period from October 1926 - December 2022

RVAR

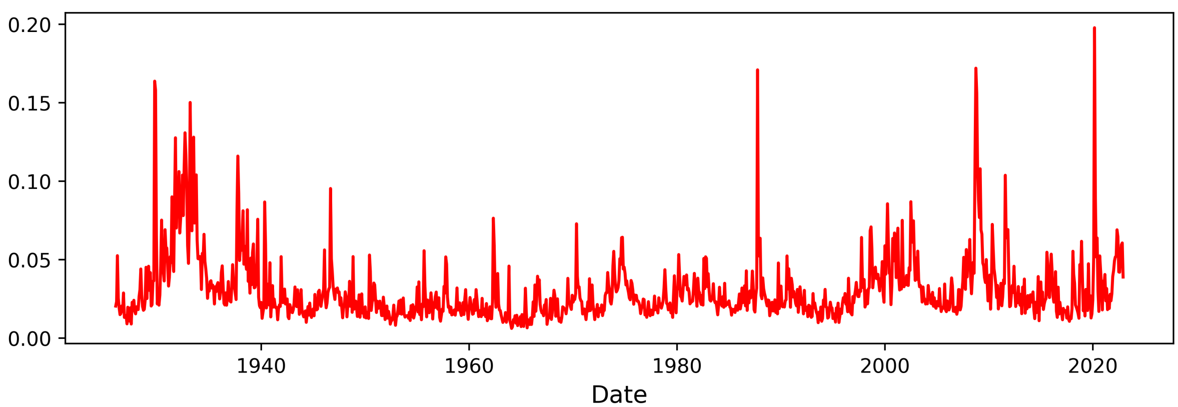

Figure A2: Within month realized standard deviation of daily returns on the CRSP Value Weight Index

Opposite Tilt Matrix

Regimes	Low Volatility	Size	Value	Momentum	Quality
Recovery	3	1	1	3	1
Expansion	3	0	0	0	1
Slowdown	0	1	1	2	0
Contraction	0	2	2	0	0
Benchmark	0	0	0	0	0
Static	1	1	1	1	1

Table A1: Reversed Tilt Matrix from origianl tilting. Exposure intended for recovery is employed during contraction and vice versa, and likewise for expansion and slowdown.

	Return	St.dev	Excess Return	Sharpe Ratio	IR	Max DD	Skewness
Dynamic	12.73	15.55	2.75	0.58	0.18	-43.93	-0.57
Static	14.32	13.94	4.34	0.76	0.31	-42.03	-0.53
Market	9.98	15.23	-	0.41	-	-51.48	-0.66

Table A2: Dynamic Multifactor performance with mirror imaged from estimated cash flow news exposure. Sample period from March 1989 to December 2022.

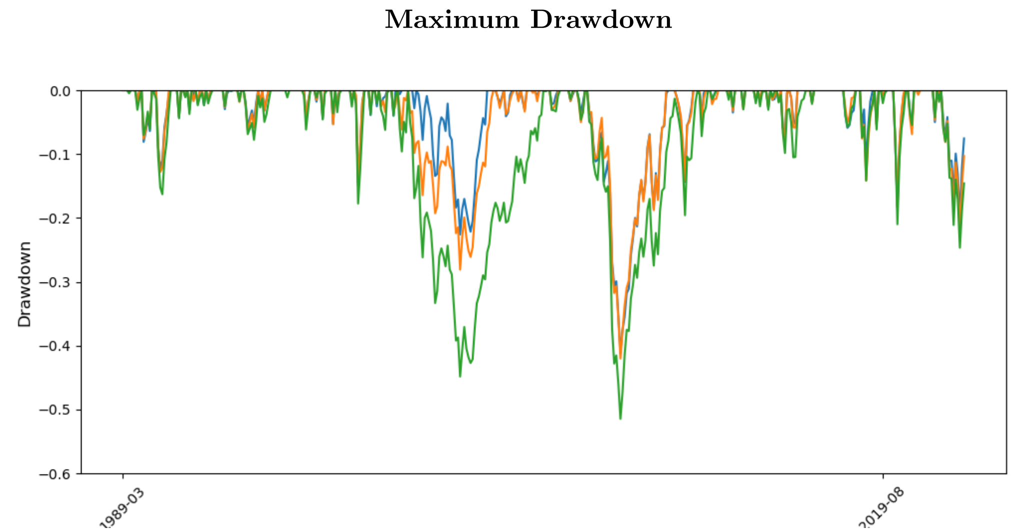

Figure A3: Maximum Drawdown plotted. Blue = Dynamic Multifactor, Orange = Static Portfolio, Green = Value Weighted Index. Sample period from 1989-2022.

	Minimum	Maximum	Average
Volatility Factor	2696	3608	3146
Size Factor	4329	7798	5586
Momentum Factor	3895	6590	4885
Value Factor	3040	6288	4123
Quality Factor	3122	6580	4369
Equal index	2241	3247	2722
Recovery Portfolio	3040	6288	4123
Expanison Portfolio	2952	5715	3933
Slowdown Portfolio	2241	3246	2731
Contraction Portfolio	2240	3245	2721

Table A3: The table presents the number of stocks included in each regression result for the different factors and portfolios. Number of stocks is dictated by availability of components for the construction of the factors and the number of listed stocks. Sample period time is dictated by data availability.