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**Master's Programme in Finance**

# Regime-investing sector model performance in benchmark tilting; evidence in the US

Thesis produced in collaboration with Mutual Pension Insurance Company Elo

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**Master’s thesis**
**2024**

Aalto-yliopisto
Aalto-universitetet
Aalto University

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**Title of thesis** Regime-investing sector model performance in benchmark tilting; evidence in the US

**Programme** MSc in Economics and Business Administration

**Major** Finance

**Thesis supervisor** Associate Professor Peter Nyberg

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**Collaborative partner** Elo Mutual Pension Insurance Company

**Date** 07.05.2024 **Number of pages** 93 + 6 **Language** English

**Abstract**

It is generally accepted that business cycles phases have tendencies, allowing for a level of predictability. In addition, it is widely noted that differing assets, including equity sectors, exhibit differing characteristics through these cycle phases. This paper attempts to study whether benchmark-tilting investors could potentially utilize quantitative sector rotation to exploit these observations. This is done by first analysing sectoral behaviour through the cycle, and second by constructing a model, in which probabilities for the upcoming business cycle phase are formed, which in turn are used to dynamically optimise and reallocate sectors in a portfolio based on the sectors' previous characteristics in the business cycle phases. The study is done from the perspective of institutional investors, attempting to cover practical issues related to the strategy. Business cycle probabilities are formed utilising the OECD CLI, a well-established composite leading indicator of economic activity. The study is conducted utilising the S&P 500 index and its sector indexes, with robustness added through similar analysis with European data.

The results obtained in the paper point to business cycle-based sectoral rotation being a potentially useful additional tool for enhanced indexes. Clear behavioural differences between sectors were observed through the business cycle, and although no fully countercyclical sector was found, sectors exhibited cyclical and defensive characteristics. Regime optimised models managed to improve performance over both, the benchmark, as well as non-regime optimised portfolios. Performance improvements when taking into account transaction costs were significant in the US, over 100 basis points annually for the best performing models, with slightly weaker improvements in Europe. The overperformance mostly arrived through contractionary periods, with no clear improvement observed otherwise. The model also proved potentially useful, being robust to smaller delays in reallocation, and exhibiting a level of flexibility. Some practical concerns do remain, due to periods of poor sustained performance.

**Keywords** business cycle, regime model, sector rotation, CLI, enhanced indexing

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|---|---|
| **Tekijä** Theo Auer | |
| **Työn nimi** Regiimisijoittamis-sektorirotaatiomallin suoriutuminen benchmark-indeksin tilttaamisessa; todisteita Yhdysvalloissa | |
| **Koulutusohjelma** MSc in Economics and Business Administration | |
| **Pääaine** Finance | |
| **Vastuuopettaja/valvoja** Apulaisprofessori Peter Nyberg | |
| **Työn ohjaaja(t)** Samu Breite, Mikko Jakovlev | |
| **Yhteistyötaho** Keskinäinen Työeläkeyhtiä Elo | |
| **Päivämäärä** 07.05.2024 **Sivumäärä** 93 + 6 | **Kieli** Englanti |

**Tiivistelmä**

On yleisesti hyväksyttyä että taloussykleillä on taipumuksia, mahdollistaen jonkinasteisen ennustettavuuden. Lisäksi on laajalti havaittu, että erilaiset omaisuuserät, mukaan lukien osakesektorit, omaavat vaihtelevia ominaisuuksia näiden syklien vaiheden läpi. Tämä tutkimus pyrkii tutkimaan mikäli benchmark-tilting sijoittajat voisivat hyödyntää kvantitatiivista sektorirotaatiota näiden huomioiden hyödyntämiseksi. Tämä toteutetaan ensin analysoimalla sektoreiden käyttäytymistä syklin läpi, ja toiseksi rakentamalla malli, jossa muodostetaan todennäköisyysjakauma tulevalle taloussyklien vaiheelle, ja joita lopulta käytetään dynaamiseen sektoreiden optimointiin ja allokointiin portfoliossa perustuen sektoreiden havaittuun käyttäytymiseen syklin vaiheissa. Tutkimus toteutetaan institutionaalisten sijoittajien näkökulmasta, pyrkien käsittelemään strategiaan liittyviä käytännöllisiä asioita. Taloussyklien todennäköisyyksien muodostamiseen käytetään OECD:n CLI:tä, tunnettua sykliä johtavaa taloudellisen toiminnan komposiitti-indikaattoria. Tutkimuksessa käytetään S&P 500 indeksiä ja sen sektori-indeksejä, sekä tutkimuksen tulosten vankistamiseksi myös Eurooppalaista dataa.

Tutkimuksen tulokset viittaavat taloussyklipohjaisen sektorirotaation potentiaalisesti olevan hyödyllinen lisätyökalu enhanced-indekseille. Sektoreiden välillä ilmeni vahvoja käyttäytymiseroja taloussyklin läpi, ja vaikka täysin syklin vastaista sektoria ei löytynyt, selkeästi defensiivisiä ja syklisiä sektoreita ilmeni. Regiimioptimoidut mallit paransivat portfolion suoriutumista yli sekä benchmarkin, että ei-regiimioptimoitujen portfolioiden. Portfolion tuoton parannukset ovat Yhdysvalloissa merkittäviä, parhaiten suoriutuville malleille yli prosentin vuodessa kaupankäyntikulut huomioiden, ja hieman pienempiä Euroopassa. Ylituotot muodostuvat pääasiassa taantuvissa olosuhteissa, eikä merkittävää parannusta muulloin havaita. Malli osoittautuu potentiaalisesti käyttökelpoiseksi, sietäen pienempiä viiveitä uudelleenallokoimisessa, ja osoittaen joustavuutta. Käytännön huolia kuitenkin vielä jää; huonon suoriutumisen jaksoja on havaittavissa.

**Avainsanat** taloussykli, regiimimalli, sektorirotaatio, CLI, enhanced-indeksointi

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# Preface and acknowledgements

I want to thank the whole investments team at Elo and especially Niko Syrjänen for allowing me the opportunity of this project. I particularly extend my gratitude to Samu Breite, Mikko Jakovlev, and Miikka Paavola for their sustained assistance and guidance throughout, in addition to frankly being pleasant colleagues.

I also want to thank my thesis advisor and supervisor, Associate Professor Peter Nyberg, for his guidance and insights.

Finally, I, from the bottom of my heart, want to thank my parents, my sister, and a multitude of friends for their support in the many forms it was presented.

Helsinki, 6.5.2024
Theo Auer

# 1 Introduction

Business cycles have been a prominent element within the economy, and the associated capital markets for practically all their history. The current theory on business cycles was heavily formed in the 20th century, with a surge of ever-deepening research on the topic, with much of the early, still in use basis formed through a series of studies by Burns & Mitchell, released for example in 1938, 1946, 1954, and 1969. For example, the currently standard definition of business cycle as fluctuations in aggregate economic activity, and business cycle phases as aggregate expansions and contractions in multiple economic variables was introduced by Burns & Mitchell (1946). Since then, the theory around economic cycles has managed form an increasingly robust framework. Included in this is the widely accepted stance that economic cycles have certain tendencies, albeit not completely reliable ones, and these tendencies lead to a level of predictability. This tendency of certain variables to lead cycle phases was also already noted by Burns & Mitchell (1938), as they tested various economic indicators against cyclical revivals, and found multiple indicators that tended to lead these revivals.

Despite the very difficult to foresee-nature of economic cycles, as exclaimed for example by Harding and Pagan (2010) who highlight the criticism received by economists for widely failing to see the 2007-2008 financial crisis before it happened, analysts and various models are widely utilized in attempts to predict the business cycle. On the quantitative side, these approaches greatly vary in scope and sophistication, but the general idea is to utilize various economic indicators which have been observed to somehow relate to the business cycle with a lead. The approach may then attempt to either identify the upcoming phase of the cycle, or form probabilities for what would happen next. Despite some common failures, which include for example identifying the 1990 recession, decent success of such models has been observed, as noted by Stock and Watson (1991). One approach to forecasting cycles is composite leading indicators, which combine multiple indicators to form an index, quantifying the cyclical strength of the economy, and thus the soon-to-be phase of the cycle. Perhaps the most established such index is the Composite Leading Indicator by OECD, launched in the 1970's, combining various indicators in an area-specific mix to quantify the strength of the economy in the area by a designed lead of few months. The OECD CLI has generally been viewed as successful, with for example Dueker (2002) finding the indicator capable of forecasting recessions a few months early.

In addition to the wide acceptance of business cycles' inclination to have repeating tendencies, distinctions in behaviour of different assets through these cycle phases is generally acknowledged. Although assets in general move cyclically with the business cycle, certain asset classes (as noted by Claessens, Kose, and Terrarones (2011)), asset subclasses (as noted by Hsu and Feifei (2009)), and even individual assets have presented differing characteristics through the cycle. This also holds for equity sectors; sectors are often categorized into cyclical, defensive, and somewhere in between based on their sensitivity to the business cycle. Perhaps the earliest established framework was provided by Stovall (1996), who offered a framework for relative sector over-, and underperformance through the business cycle, highlighting which sectors are typically high and low performers in which phases of the cycle. This poses an inviting challenge; theoretically, investors who beat the market in estimating business cycle phases could rotate sectors accordingly (or other assets with differing cyclical characteristics) and outperform the market.

This observation ties into regime investing models, which are quantitative investing models, where asset allocation is dynamical and based on the identified regimes. Regime investing models exist in a multitude of different forms, utilizing different methods, with the basic idea, just previously detailed, grouping them under the definition. These models may be built around macroeconomic regimes to divide between expansionary and contractionary business cycle phases, or with a more granular regime split. In a macroeconomic context, identifying the regime, or regime probabilities may be formed through various approaches, much as with predicting business cycle phases, and the model may either attempt to identify the then prevailing regime, or attempt to forecast the upcoming regime. Macroeconomic regime investing models have only been somewhat studied so far, with mixed, but mostly positive results observed. For example, Benoit and Raffinot (2002) utilized machine learning-based GDP growth regimes to dynamically allocate between equity, cash and bonds, improving risk-adjusted returns significantly. As a subcategory of the macroeconomic regime models, sector-based regime investing models have a very limited literary history, which this paper attempts to add to. Some of the main existing literature on the topic includes Conover et. al. (2008), who used monetary policy-based regimes to allocate between cyclical and defensive sectors and found the resulting portfolios to beat benchmarks and any individual sectors. Sauer (2019) observed similar results with dynamical sector allocation based on macro-regimes formed through machine learning forecasting of GDP growth. Dampening the success observed in these papers is a recent paper by Molchanov and Stangl (2023), who challenge the whole concept of sector rotation providing enhanced returns, as they highlight only marginal differences between sector behaviour through different business cycle phases.

This paper, utilizing a macro-based regime-probability model and equity sectors, attempts to combine and exploit the tendencies of business cycles allowing for a level of predictability, with the differing behavioural tendencies of assets and asset classes within business cycle phases. This translates to forming probabilities for the different business cycle phases, i.e. regimes, utilizing the CLI by OECD, and then utilizing these probabilities to dynamically allocate between sectors based on their observed characteristics through these regimes. The allocation is done based on a benchmark index, with the portfolio then tilted away from the benchmark as explained to potentially offer enhanced performance over the benchmark. As far as the author is aware, no such approach has been made utilizing composite leading indicators to rotate sectors dynamically, and this paper attempts to cover some of that ground. This paper also attempts to provide slightly more than just a theoretical framework, by analysing the applicability and feasibility of the strategy for a typical institutional investor attempting to beat a benchmark index. This is done for example by including estimated transaction costs and providing analysis of model performance.

## 1.1 Objectives and research questions

The objective of this paper is to analyse the viability of quantitative sector rotation model investing based on modelled economic regime probabilities, utilizing leading data. This paper focuses on the viability of such a strategy from the perspective of a semi-active investor, performing benchmark tilting to enhance performance. The main research question of the paper is whether a regime-investing sector rotation model utilizing leading macro-data, such as the OECD CLI, can provide a useful tool to sustainably beat the benchmark and improve performance on a risk-adjusted basis. Usefulness is categorized as 1) realistic and possible to implement efficiently, and 2) providing something that other conventional quantitative methods, such as factor investing, do not already do.

Additional research questions include whether significant behavioural differences can be found between sectors through regimes. In addition, this paper aims to study how the modelled portfolios behave, when might they provide relevant performance enhancements, and find potential room for future improvement to enhance model performance.

Based on previous literature, the hypothesis for this study is as follows. First, meaningful differences in sector performance through the business cycle are expected to be observable. Second, enriching portfolio optimisation with regime-based performance metrics for sectors and OECD CLI-based regime probabilities is expected to improve performance of the portfolio over the benchmark, as well as non-regime optimised portfolios. Third, the methodology is expected to provide a new and potentially useful tool for institutional quantitative investors performing enhanced indexing, with usefulness defined as previously in this section.

## 1.2 Limitations of the study

This paper covers a somewhat wide topic and is thus unable to dive into all the aspects in detail. This leaves uncovered ground and does limit the impact of the study. Especially from the perspective of semi-active investors, the usability of the model does require additional analysis. Among these, for example, factor exposure of the model and the created portfolios is tested very briefly utilising only some of the most established factors. Also, analysis of the composition of portfolio performance is mostly done on monthly returns, where daily returns might allow for a more comprehensive view on portfolio characteristics and behaviour. In addition, this paper only utilizes one regime indicator, and thus results are somewhat reliant on the performance of the indicator in question, OECD CLI. The indicator in question is a successful and established one, but other similar leading composite indicators, such as the one produced by The Conference Board, could be tested to potentially find better fits for the sector rotation model.

Practical limitations also exist in the study. First of all, there is a slight timing limitation, despite using the historically available data for each month. This is because the utilised regime-benchmark, OECD CLI is not necessarily released on the first day of a month, but often a few days afterwards. This may introduce a slight skew to results and a cause for concern, but this is addressed in Section 4.3.1, where it is found that the first few days of the month do not disproportionally contribute to performance. Second, the availability of historical OECD CLI data only from 2001 onwards does limit the sample size, especially as mostly monthly data is utilised, and the first couple years are required to calculate initial sector characteristics for optimisation. This is partially addressed by robustness checks utilising European data. Third, the probability model is very simple, and primarily conveys the strength of regime expectations, leaving room for improvement through a more sophisticated model.

Fourth, the paper only utilizes Large Cap equities, which are generally thought of as more stable, excluding Mid-, and Small Cap equities completely from analysis, which might potentially exhibit larger cyclical swings, and thus more room for potential performance improvements. Fifth, only the top-level GICS-sector split is used, which leaves more granular sector splits, and their potentially more amplified behavioural differences uncovered.

## 1.3 Structure of thesis

The thesis is structured as follows. In Chapter 2, the literature related to economic cycles, cycle forecasting and modelling, benchmark tilt-investing, and regime- and sector rotation model investing is broadly and briefly overviewed. In Chapter 3, the data utilized in this paper, and the accompanying methodology is covered. Some methodological tweaks relevant to additional analysis are not covered here, but instead briefly covered in the relevant results section of the additional analysis. Chapter 4 presents and discusses the results of the study. Chapter 6 summarizes the results of the paper, discussing the implications regarding the research questions of this paper. The reference list and all appendices are then contained in the section after.

## 1.4 Overview of results

The results overall point to business cycle-based sectoral rotation potentially offering a useful additional tool for enhanced indexing, with a caveat. Sectoral differences in cyclicality of behaviour, especially in returns, are clearly present in both of the studied regions, US and Europe. No truly countercyclical sectors can be identified, meaning returns inverted with the business cycle, but identified sectoral differences are large enough to warrant reallocation through regimes.

Regime-based models manage to improve on the benchmark through multiple performance metrics, with somewhat larger improvements observed in the US than in Europe. Portfolio returns are on average increased over the benchmark by over a whole percentage point annually in the US with Sharpe- and return-optimised portfolios. Similar, albeit smaller, excess returns are observed with European data. Minimum variance-optimised portfolios seem unfavourable, given their volatility decreases that are unable to justify the weakened returns. As an important metric for enhanced indexing, portfolios overall offer information ratios around 0.5, which can generally be considered good. Utilizing regime-based dynamic covariance in optimisation improves on static covariance models by negligible margins, with regime-based returns clearly driving portfolio optimisation.

The observed overperformance of regime portfolios mostly arrives in contractionary periods, and especially Downturns, which is consistent with previous literature. Despite large sectoral differences in the Recovery-regime, the model is unable to translate this successfully, and thus the regime is the only one with sustained underperformance against the benchmark. On the practical side, no real issues arise in relation to model usability. Active risk limits are fairly linear with portfolio performance, offering flexibility. Small timing delays to regime identification or portfolio reallocation are not critical, as no significant differences in excess returns through different periods of a month are found. In addition, model portfolio excess returns are not contained within the most common factors, thus offering something new. Biggest concerns of the strategy centre around consistency of portfolios. Yearly excess returns, despite being positive most years, and also larger in winning years than the underperformance in losing years, vary heavily. Perhaps most worrisome is the observed sustained period of slight under-, or neutral performance in the US between 2012 and 2019, which could naturally happen again. Still, overall, the provided model and results offer a solid framework for improvements to be built on, with on average an already relevant enhancement over the benchmark.

# 2 Literature review

In this section, the background literature related to the study is covered. As this paper is somewhat broad in the theory it relates to, the literature review covers a wide area of the related literature briefly. The general literature of economic cycles is discussed first, followed by studies on asset behaviour through the cycle, and then literature on business cycle forecasting methodology and indicators. Afterwards, benchmark tilting as a concept is briefly covered. Finally, previous studies on regime investing models are discussed. As very limited studies with a markedly similar approach can be found, the regime model section attempts to highlight studies most related to the one in this paper.

### 2.1.1 Economic cycles – brief overview

The economy inherently goes through phases of expansions and slowdowns of varying degrees, and the economic cycle can be defined as the circular movement of the economy through these phases as claimed by Skare and Stepanjovic (2015). They also note that economic cycles have been an integral part of the global economy for a long time, with identified cycles in the early 18th century. Burns and Mitchell (1938) state that each cycle is unique in some features despite sharing a lot of characteristics. These cycles seem to happen everywhere, but they are more pronounced in emerging economies than in developed ones, as found by Neumayer and Fabrizio (2005).

Grinin, Korotayev, and Tausch (2016) note that an economic cycle depends heavily on the observed time frame. A mid-term cycle and a long-term cycle can also coexist at the same time. This means that the economy can for example be in a state of expansion if we observe a time frame of a few years, but looking at a longer time frame could highlight a period of relatively slow economic growth. In this paper, when discussing economic cycles, we are discussing mainly the business cycle, which tends to last between 3-7 years, as stated by Forrester (1976), or shorter-term fluctuations.

The phases of an economic cycle can be classified in a variety of ways, with just phases of relatively high activity and low activity categorized, or it can be more granular. A common framework is splitting the cycle into four stages. Burns (1969) uses a classification based on the level of economic activity, and the momentum of the activity, splitting the cycle into stages of expansion, downturn, contraction (slowdown), and upturn. Then, the turning points are called the peak and the trough. The terms used to describe these are diverse, but they are generally discussing the same stages, as Burns (1969) notes.

Identifying the business cycle and its stages is not completely objective. Fisher (1925) slightly questions whether business should be thought of going through comprehensive cycles. He notes that underlying aspects of business can signal very different things, which means that aggregating the info into a single stage loses a lot of information on the development of many factors. Burns and Mitchell (1946) however find that, in general, many economic activities experience expansion simultaneously. Same is true for recessions, contractions, and revivals. Thus, economic cycles and stages should be understood as an aggregate of various economic activities. Burns and Mitchell (1938) state that identifying the exact moment where the stage changes is very cloudy due to varying levels of change in the various underlying economic activities, but finding an approximate date can be useful for other analysis. Similarly, they state that using a mean of various activities is a very useful tool for further studies.

As Burns (1969) notes, various changes in economic activity happen during business cycles. During expansions, production and employment is generally up, as well as consumption, whereas they all tend to fall during contractions. However, the magnitude of swings differs significantly. For example, industrial production endures large swings, but total output is much less volatile due to many stable activities, such as services and governmental work. Also, these changes are not absolute; Barnichon (2010) finds, that since the mid-1980s in the US, unemployment and productivity have been positively correlated due to cycles spurred by technology shocks.

Availability of money is another aspect that tends to move with business cycles, as Asea and Blomberg (1998) find that during periods of expansion, banks seem to participate in overlending, and then during contractions lending is curbed, especially through increased loan charges. Overall, the changes are not definite, and the magnitudes vary between periods and activities, as discussed here. In addition, the timing generally varies for different activities, with some, for example, retail sales, wages, and interest rates, lagging the general cycle, as showcased by Burns (1954).

Economic cycles and financial assets are heavily interconnected, but the relationship is not completely clear. The International Monetary Fund (2000) finds that financial markets have a tendency for similar movements around typical business cycle frequencies of 3-10 years. They also note that asset prices have tended to lead economic output cycles. Backus, Routledge and Zin (2007) also find this same lead with equity assets. They state that equity prices tend to move in the same direction as GDP, but the prices lead changes in the business cycle as defined by GDP by a quarter or two, meanwhile the growth of investments, employment, and consumption tend to generally move synchronized with GDP. This lead may be explained at least partially by the findings of Bansal and Yaron (2004), who show that news about future consumption, giving a predictable dimension to future business and dividend growth, can justify big swings in the equity premium and thus asset prices, which implies that investors are somewhat forward-looking regarding business cycles. The relationship of business cycles causing financial swings is natural due to the changes in consumption affecting business growth, as stated by Burns (1969) and Campbell (2001). On the other hand, Gilchrist and Zakrajsek (2008) argue that swings in the financial sector affect the real economy through means such as increased or reduced lending activity increasing the cost of capital for companies.

### 2.1.2 Assets in economic cycles

As stated in the previous section, financial markets are in aggregate connected with business cycles, with movements in similar directions observed, albeit differences existing in the magnitude and timing. Differences on the cyclical nature exist, however, throughout different asset classes and assets. As an example by IMF (2000), equity prices have swung stronger along the output gap than property prices, and have led the gap, whereas property prices have moved more in line in regards to timing. Claessens, Kose, and Terrones (2011) also note that across the world, equity swings tend to be a lot stronger than swings in the housing or credit markets. Interestingly, before the globalization period (pre-1985), credit and housing swings were stronger than today, whereas the opposite is true for equity.

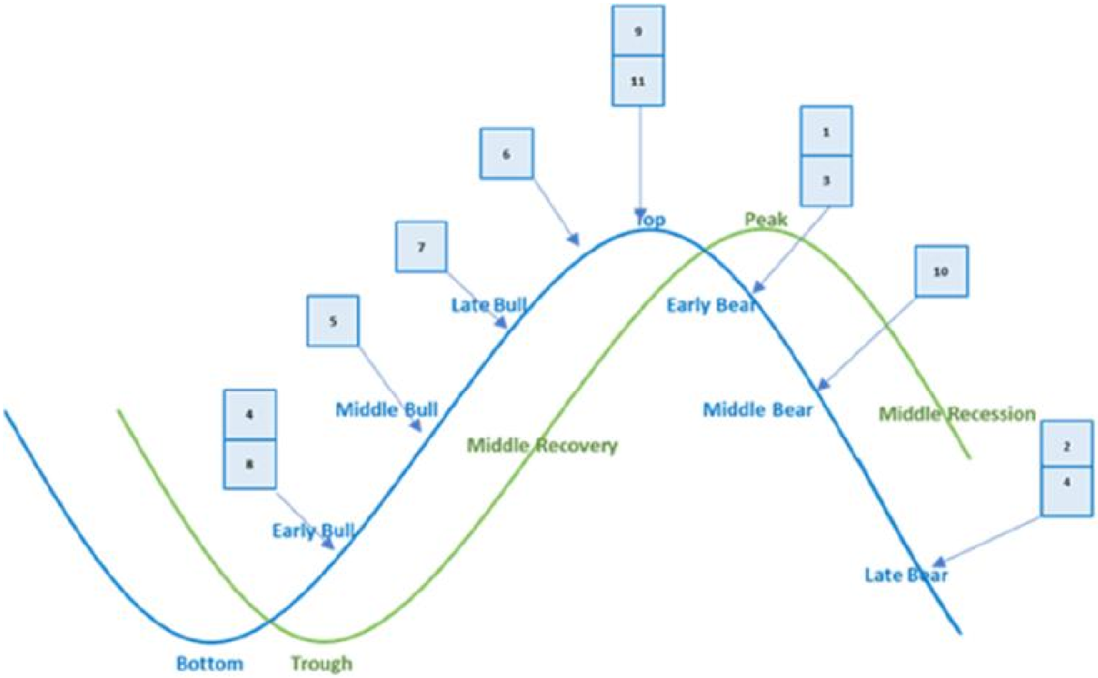
Differences in cyclical behaviour continue inside asset classes. Hsu and Feifei (2009) show that U.S. equities and international equities differ in their returns and volatility through cycles. U.S. equities are slightly more cyclical through bull- and bear markets, but their returns and volatility swing less through economic expansions and recessions than international equities do. Ielpo (2012) shows also, that small cap stocks tend to outperform large cap stocks during good periods and underperform during bad ones. Similarly, he finds that high-yield credit returns are more exposed to cyclical fluctuations than returns for investment grade credit.

Within equities, different sectors tend to also have different characteristics regarding their behaviour through economical and financial cycles. The author here notes, that academic literature on analysing the cyclicality of different equity sectors is thin, but the precedent for cyclical and defensive sectors and equities is strong. For example, MSCI (2014) defines their sectors into a cyclical index and a defensive index. Some academic background does also exist, as Stovall (1996, as referenced by Molchanov and Stangl, 2023) created perhaps the earliest comprehensive framework for sector performance through the business cycle. Different asset classes perform in different intermittent phases of the business cycle with a level of lead, as investors anticipate the changes slightly ahead of time. Figure 1 shows the optimal sectors for various stages in the typical business cycle and highlights the general accompanying financial cycle.

Ross et. al (2018, as referenced by Ishak and Jiun (2021)) also find that sectors can be classified into more cyclical and less cyclical (defensive) sectors based on their fluctuations with the business cycle. MSCI uses the following split: cyclicals include Consumer Discretionary, Financials,

Industrials, IT, and Materials, and defensives includes Consumer Staples, Healthcare, Energy, Telecom, and Utilities. Conover et.al. (2008) have similar findings, as they classify sectors into cyclical and defensive based on their movements along with monetary policy. Sectors identified in their study as cyclical were cyclical consumer goods (consumer discretionary), cyclical services, general industrials, IT, financials, and basic industries. Noncyclical sectors were resources, noncyclical consumer goods (consumer staples), noncyclical services, and utilities.
Chong et.al. (2015) use a sector classification by Morningstar in their sector rotation study, classifying consumer discretionary, financials, and materials as cyclical, consumer staples, health care, and utilities as defensive, and industrials, energy, and technology as somewhere in the middle.

This behaviour is not completely definite however, with Longin and Solnik (2001) finding that the co-movement of equities has a habit of changing, as equity market correlation increases in bear markets, but don't find the same significant effect for bull markets. Molchanov and Stangl (2023) also challenge this, noting that the sector performance differences between cycle phases are mostly negligible.

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|---|---|---|---|---|---|
| 1 | Consumer Non-Cyclicals | 5 | Technology | 9 | Energy |
| 2 | Consumer Cyclicals | 6 | Basic Industry | 10 | Utilities |
| 3 | Health Care | 7 | Capital Goods | 11 | Precious Metals |
| 4 | Financials | 8 | Transportation | | |

*Figure 1: Stovalls framework for best-performing sectors through the business cycle. Source: Molchanov and Stangl, 2023*

The varying behaviour of different assets and asset classes through business cycles implies that optimal asset allocation depends on the state and phase of the economy. Hsu and Feifei (2009) use a Markov-switching model to differentiate between bull- and bear markets to allocate assets optimally and find that an optimised portfolio would shift risk-levels down in bear markets, and vice-versa for bull markets. They suggest that the optimal portfolio depends partially on observed macro variables.

Ang and Bekaert (2002) also study the implications to asset allocation by using a Markov-switching model to differentiate between a normal economical state and a bear state. They find that an optimised portfolio would actually be less internationally diversified (and more US focused) during bear markets, due to the lower volatility of US equities and the increased correlation of international assets during bear markets. In addition, allocation to risk-free assets during bear markets can be very beneficial to risk-adjusted returns. Ang and Bekaert (2004) find a similar effects in their later study, with optimal investors moving to cash during bear markets, and also decreasing their international diversification in favour of US. However, none of the studies mentioned here incorporate transaction costs, meaning that they may slightly overemphasize the return of dynamic asset allocation, but they illustrate the dynamic dependencies of asset allocation through economic phases.

### 2.1.3 Nowcasting and forecasting economic cycles

Forecasting economic cycles, and especially trying to identify the next recession has had a lot of attention, also in academia, as the economic implications of such events are huge. Still, forecasting economic cycles has proven to be an extremely tough task. As Harding and Pagan (2010) note, economists have been widely criticized for failing to realize the 2007-2008 financial crisis before it happened in full swing. They also note that predictions using simple models struggle to predict negative economic growth up until the recession is already happening and find identifying major turning points in the economy extremely difficult.

Forecasting models have been proposed with relatively good success, but also issues do persist. Most, even very good models, are far from foolproof, and big failures pop up. For example, as noted by Stock and Watson (1993), the 1990 recession was very difficult for models to predict, with most indicators performing very poorly. This is somewhat to be expected, as economic developments can happen for a multitude of reasons, some of which can be very hard to identify beforehand, as noted by Marcellino (2006).

Various methods to forecast economic activity have been attempted. Regarding quantitative forecasting, mainly three approaches have been used separately and together. First, using autoregressive (or otherwise based on past values and fluctuations) methods of estimating future activity, for example GPD, by itself or through auto regressing underlying variables, e.g., manufacturing activity. Second, by using other variables (indicators) that have been noted to generally move in patterns with the predicted economic activity, such as the yield curve, confidence surveys, or manufacturing activity, to estimate further economic developments. Third, by utilizing composite indicators, which are basically composite forms of data fitting into the other two categories. The most common composite indicators used are ones offered by The Conference Board and the OECD. We will later on focus on individual indicators more, but first let's briefly go through the general literature on forecasting models.

The foundation for quantitative business cycle forecasting was laid by Burns and Mitchell (1938) and Burns and Mitchell (1946). In the first study they analysed a comprehensive list of various potential indicators for cyclical revivals and found that numerous variables had a tendency to lead revivals. In the later study they built upon the previous work, studying how different time-series and their combinations conformed to various stages in the business cycle. They found that multiple time-series, including combined ones, were strongly aligned with changes in the business cycle. Importantly, they also note that using annual data wipes most of the relevance, with more frequent time-series being much more useful in picturing the cycle.

Since the foundational work of Burns and Mitchell, various takes on the subject have sprung. Recent models using indicators usually combine a set of them to improve performance (some exceptions exist, for example recessions have been widely predicted by using yield curve data, which will be covered later under individual indicators). Camba-Mendez et.al. (1999) construct a dynamic factor model to predict in four European countries GDP using a range of variables, including financial data, surveys, interest rates, and other macroeconomic variables highlighting the level of economic activity. They find that many of these models outperform autoregressive methods, but many also fail. It is important to note, that they tested a huge number of different models, somewhat blurring the line of chance in the study. They also raise the important question on when old data points should not be used anymore for forecast parametrisation, as economies have a tendency to change.

Nyber (2010) uses a dynamic factor model to predict US and German recession probabilities with relative success. The variables used are term spreads, stock market returns, and the interest rate difference between the US and Germany. He finds that the dynamic models outperform static factor models and are generally good at recession predicting. In addition, adding an autoregressive component improved performance.

Berge (2013) tests a variety of models utilizing macroeconomic variables to predict recessions. Multiple models achieve good levels of success, but the important point of the study is that different macroeconomic variables seem to perform well at different time-horizons. Bond markets, especially the yield curve, are the best long-term predictor, whereas real indicators, such as industrial production perform best in the near-term.

As mentioned, autoregressive methods have been typical and somewhat successful in business cycle forecasting, as a component, but also individually. Some examples are listed here. Holden and Broomhead (1990) test various autoregressive models against models based on indicative economic variables to predict macroeconomic variables and find that while some autoregressive models had good performance, the economic models did outperform. Sims (1993) showcases a complex Bayesian vector autoregressive model with time-varying parameters which uses 9 macroeconomic variables, including GDP, to forecast each other and themselves. He finds that the model outperforms stationary autoregressive models and naive predictions, but this comes at the cost of significantly increased complexity. More recently, Maccarone, Morelli and Spadaccini (2021) utilize machine-learning algorithms to forecast U.S. GDP autoregressively, and further include other variables to see whether predictive power increases. They find that GDP is a good predictor of itself one quarter ahead, but for longer horizons added variables, especially the yield curve, are a big help.

In addition to the models, multiple composite indicators have been created and have been offered, which attempt to highlight economic strength through a single number formed by a combination of various macroeconomic indicators. Dueker (2002) uses one such indicator, the Composite Leading Index (CLI) by OECD to attempt to forecast the 1990 and 2001 recessions based on probabilities and exceeding a probability threshold. He finds that forecasting recessions a few months ahead based on the used composite indicators is possible, but also that the 1990 recession was peculiar and a difficult one to detect out of sample. Birchenhall et.al. (2003) also use a similar composite indicator, the CLI by the Conference Board, to forecast between regimes of economical US expansion and contraction using machine learning models They find decent success, with the CLI beating composite coincident indicators out-of-sample. Hamilton and Perez-Quiros (1996) also find the CLI useful for GDP predictions about one quarter ahead. They also note, that the CLI broadly leads GDP by a quarter.

As earlier mentioned, even identifying the current economic phase as it happens can be difficult. A good example of this is the 1990-1991 recession, which was only publicly recognized by the NBER in April of 1991, a month after the recession was already over (Hamilton, 2011). These difficulties are exacerbated by the lagging availability of data, as for example GDP-data is not generally available in real-time, thus requiring a level of prediction to estimate.

This real-time predicting of macroeconomic variables and the economic phase is generally referred to as nowcasting in economics, as defined by Banbura, Giannone, and Reichlin (2010, p.4) *“We define nowcasting as the prediction of the present, the very near future and the very recent past”*. The main difference between nowcasting and forecasting is that within nowcasting, there is the component of utilizing timely variables, for example industrial production to sort of construct another variable, for example GDP. Forecasting methods may also sometimes apply and include similar approaches to form time-series used for forecasting. They utilize the developments of various macroeconomic indicators, such as manufacturing activity, confidence surveys, employment, and equity index data to nowcast GDP growth in the EU-area, which is only released quarterly as an estimate at the end of each quarter. The New York Fed Staff Nowcast is used to project GDP fairly successfully in a similar fashion from other microdata ((Bok, B., Caratelli, D., Giannone, D., Sbordone, A., and Tambalotti, A. (2018). Chauvet and Hamilton (2006) attempted to recognize expansions and recessions in real-time by first using an only GDP-based model, and then adding other indicators on top to model probabilities for being in a recession. They found that using only GDP was mostly on par at timing turning points with NBER, but a multivariate model using sales, income, employment, and industrial production was faster at recognizing turning points.

Now, let's briefly go through literature regarding some of the more established variables utilized in quantitative business cycle forecasting. As previously mentioned, multiple indicators have been used to predict various business activities, and patterns along with other macroeconomic variables have been widely observed.

<u>Survey data</u>

Forward-looking survey data has been used to bring anticipatory qualitative data to forecasting economic events and are a typical component of predicting economic developments. Generally, survey data is viewed as a weak independent predictor compared to financial and economic variables, but valuable for enriching model data. Survey data can be produced for both the business side, and the consumer side. Surveys generally contain questions aimed to categorize the views of respondents as optimistic, pessimistic or neutral regarding current and future developments, or collecting their estimated figures.

Öller (1990) utilized quarterly survey data of the Finnish forestry industry businesses. He finds that survey data by itself does not match the production data it is trying to forecast particularly well. He also finds that incorporating survey data into univariate models of previous production has a relevant effect on the timely identification of turning points, but otherwise the difference in performance is minimal. Batchelor (1982) has very similar results using business survey data from four European countries to assess growth and inflation. He notes that while survey data did outperform naive models, survey models were bad at estimating the magnitude of variables and lost to more complex moving-average predictors. As with the mentioned study from Öller, survey data was however useful in identifying turning points. Hansson, Jansson and Löf (2005) find that a dynamic factor model utilizing Swedish business survey data manages to outperform simple macro-based vector autoregression models in predicting GDP growth in the upcoming two quarters, but expectedly loses out in the longer term.

On the demand side, Pain and Weale (2001) observe household consumer confidence surveys (including questions about issues around their expected spending and financial situation, and the economic situation) in the UK and US. They find that the surveys hold valuable information on the current expenditure of consumers but are significant leading predictors only in the US. Mueller (2001) also finds similar results with US consumer attitude surveys. When combined with consumer financial and employment data, the attitude surveys offer significant and mostly consistent additional predictive power regarding fluctuations in consumer discretionary goods spending, even if future income levels were known.

Interest rates

Information contained by interest rates has been a common indicator used to forecast economic cycles. The effect of interest rates themselves is slightly contested, but empirical evidence seems to signal that they lead the economy countercyclically. King and Watson (1996) note, that in the US, high real and nominal interest rates predict a downshift in economic activity within the next two to four quarters. Neumayer and Fabrizio (2005) find a similar effect in emerging economies, with real interest rates being countercyclical and leading the economy. However, Mendoza (1991) and Correia, Neves and Rebelo (1995) contrarily find, by building a model of a small open economy, that shocks to global interest rates only affect the economy very marginally, and the rates are cyclical. Partly in agreement, Blankenau, Kose, and Yi (2001) find using a small open economy model that interest rates move cyclically with output, but they find the effect of interest rate shocks major.

Within interest rates, especially the yield curve has been held in high value as a recession predictor. Howard (1989) notes, that classically the yield curve has been seen as a capable predictor of inflation, but he finds that the yield curve has historically been a reliable predictor of business cycle turning points in the US. He also argues contrarily that the yield curve should not be used as a standalone indicator of business activity, but more so as a signal of economic strength or weakness. Wright (2006) finds, that historically in the US, an inverted yield curve (where the longer maturity bonds have a lower yield than shorter maturity bonds), along with a high federal rate has been the best yield curve predictor of recessions. In addition, Haubrich and Dombrosky (1996) show the yield curve to be a strong predictor of US GDP development overall, not just recessions, with the 10-year, 3-month spread beating traditional leading indicators and GDP-based forecasts. They did find, however, that the performance varied very strongly through different periods, with the yield curve being a poor predictor between 1985-1995.

Credit spreads, meaning the differences between yields of similar bonds with differing credit quality, have been shown to work as a predictor of various variables. Philippon (2009) finds, that credit spreads predict corporate investments significantly better than the markets do. Gilchrist and Zakrajsek (2012) show using secondary US market prices of outstanding bonds, that high credit spreads are associated with a lagged decrease in economic activity and declines in the stock market. They argue that this predictive power comes mainly from re-pricing of default risk, rather than the risk of default itself, due to a lessened capability of risk-taking in the financial sector. Interestingly, Krishnamurthy and Muir (2017) find a somewhat contrary effect, with low credit spreads observed before major financial downturns. However, consistent with the earlier findings, the transitions into crises begin first with the credit spread shooting up, with the severity of the crisis being able to be forecasted by these changes in the spread relative to before.

Equity lead signals

Equity prices are generally considered to lead economic developments, as prices are formed through forward-looking investor estimates. Chauvet (1999) argues, that equity prices reflect the perception of the strength and future developments of the economy, as investors choose their positions based on their expectations. This leads to investors incorporating news of economic developments as fast as possible. Through empirical evidence, he finds that the stock market generally contracts and expands a few months before a corresponding recession or recovery in the business cycle, and thus argues that the stock market is a useful real-time predictor of economic developments.

Fischer and Merton (1984) are in agreement, as they find that stock returns were at the time the best single predictor of real GDP growth. They argue that this effect arises from the market attempting to forecast future earnings. They also argue that stock prices as predictors convey more than only act as an aggregate of other leading variables. On the other hand, Estrella and Mishkin (1998) do also find stock prices to be a useful and independently solid predictor of recessions, but only in 1-2 quarter horizons, and bond market variables tend to outperform.

Chatelais, Stalla-Bourdillon and Chinn (2023) split US equities into sectors and then utilize the sector-based returns in a factor-model to predict US industrial production growth. They find that this way, the predictive power of equities is significantly higher, as different sectors are linked to the business cycles in different magnitudes. They note unsurprisingly that equities in upstream sectors, such as Oil & Gas, Industrial Materials, are heavily linked with economic developments. Generally, sectors with smaller companies and more value-heavy sectors were also more linked to economic developments.

### Labour-related

Overall, the relationship between labour-related figures, such as employment, hours worked, and salaries seem to have an unclear relationship with business cycles, which can partially be explained by labour market frictions. Generally, though, they do move procyclically. Ohanian and Raffo (2012) note, that employment by itself is not a good proxy for labour input, as in downturns, also hours worked per employee drop correspondingly. Also, McGuckin, Ozyildrim and Zarnowitz (2003) state that businesses tend to adjust hours before turning to firings and hirings. Ohanian and Raffo (2012) continue, that labour input is much more procyclical with output in the US, UK, and Canada than in Europe. Similarly, these adjustments happen more in line with the cycle in the US, whereas in Europe different leads and lags can be observed. They claim that these results could partially be explained by more the rigid labour markets in Europe. Abraham and Haltiwanger (1995) note that real wages are generally procyclical, but the relationship between the business cycle and wages does not seem constantly contemporaneous, with wages even leading production in some moments in the past.

The cyclicality of employment also differs between areas of the economy. Leamer (2007) notes that generally employment has only been volatile and heavily procyclical within manufacturing and construction, and elsewhere job loss even in recessions is comparatively small. He also notes that employment (along with interest rates) seems to be the main driver of durable good consumption.

All in all, labour-related statistics are conventionally not used as an independent predictor of business cycles, but more so thought of as an integral part of the different phases. They are, however, often incorporated into multivariate models to spot early signs of weakening labour markets and production, or for nowcasting GDP. Banbura et. al. (2013) note, that employment can be used to nowcast real GDP despite having typically long publication lags. Previously mentioned models by Chauvet and Hamilton (2006), and Bok, B., Caratelli, D., Giannone, D., Sbordone, A., and Tambalotti, A. (2018) have incorporated employment-based factors with relevant success.

### Housing

Residential real-estate is considered to be one of the strongest leading indicators of business cycles, and for example the 2007-2008 financial crisis was initially kicked off by the residential real-estate sector collapsing (Leamer, 2007). Leamer (2007) argues that residential real-estate is the single best indicator of upcoming recessions, as it seems to react before consumer demand. Even though residential investments account for only a small portion of the US GDP growth (4.6% since 1947), Leamer notes that residential investments are very significant for recessions and recoveries. All of the observed US recessions have been preceded by downturns in housing apart from 1953 and 2001. He finds that within residential real estate, housing starts and changes in housing starts are the best predictors of recessions, and he notes that the housing cycle is based more on volume than price.

Davis and Heathcote (2003) show that residential investment co-moves with GDP, and that residential is much more volatile than other investments. They also note that residential investments precede the business cycle, while other investments lags. Fisher (2007) notes the same regarding housing investments leading the cycle. Interestingly, models tend to have different estimations than what the empirical data shows, with for example models by Benhabib, Rogerson and Wright (1991), and Greenwood and Hercowitz (1991) both predicting that housing investment would lag the business cycle and other investments.

### Sales and orders

Another indicator used to forecast and nowcast business cycles is demand, but it can also be understood as an outcome of the phases themselves. Demand shocks are correlated with lagged supply, as noted by Blanchard and Watson (1986). They also note that changes to demand seem to affect output, whereas supply changes affect prices more in the near future. Massimiliano (2006) states that sales in the manufacturing, wholesale and retail sectors are often used as a variable defining the cycle phase itself, or as a coincident indicator for nowcasting, but that sales have also been used as leading indicators.

In general, new orders seems to be the most common forward-looking demand-indicator used. Orders by manufacturers as a leading indicator is also identified by Massimiliano. McGuckin, Ozyildrim and Zarnowitz (2003) discuss the Leading U.S. Index produced by The Conference Board and note that new manufacturers' orders for consumer goods and materials, and new orders for nondefense capital goods are both used as leading indicators. They note that new orders can be viewed as an investment commitment. Kauffmann (2006) finds, that on the NAPM Report on Business, new orders tend to lead the Purchasing Managers' Index by two months and is also the most reliable predictor of the index.

### Inflation

How inflation and economic output interact is partially unclear. Gali (2002) notes that the various models that have been presented for output and inflation differ in that in some models inflation leads output and in others output leads inflation. Empirical data seems to support the latter more. They also note that generally inflation is positively correlated with output. On the other hand, King and Watson (1996) find that price inflation tends to lead output countercyclically, with higher prices suggesting a drop in output in the shorter term. In the long term, output and prices are positively correlated, however. Also, Faria and Carneiro (2001) found, when studying inflation in Brazil, that high levels of inflation did not affect output in the long term, but it did have a negative effect on output in the shorter term. Lagos and Rocheteau (2005) argue that inflation could have a positive effect on output when the inflation rates are low, but a negative effect when the inflation is already high.

## 2.2 Benchmark tilting

Benchmark tilting is the strategy of following a benchmark, which could for example be an index or fund, and tilting it in some way as desired by the investors, with the general goal to outperform the benchmark. Frino, Gallagher, and Oetomo (2005) call funds that do this enhanced indexes. They note that the goal of the strategy is to be index-oriented, thus allowing for relatively low risk and costs, but to also allow the manager to participate in limited active strategies to enhance returns. Thus, portfolio tilting can be considered a combination of passive and active investing, as the majority of the portfolio is passively linked to the benchmark, but active management is also performed. Tilting the benchmark can include either just adjusting the weights of the equities within the benchmark and perhaps excluding certain equities, or sometimes even adding equities outside of the benchmark.

Portfolio tilting is extremely common in institutional investing, as noted by Browne (1999), and for example the S&P 500 is a very common target and benchmark to beat. Space for outperformance has been observed, as Grinold (1992) finds, by testing the S&P 500, DAX, ALLORDS, TOPIX, and FTA, that simple factor-tilts using the factors value, momentum, volatility, and size can allow investors to achieve portfolios more efficient than the benchmark. Ahmed and Nanda (2005) find that mutual funds' portfolios tilted qualitatively tend to underperform their benchmark, quantitatively tilted portfolios have mixed results, and a combination seems to outperform the benchmark.

When tilting a benchmark, portfolio performance is usually not only compared based on stand-alone metrics, such as the CAPM alpha, Sharpe ratio and other risk-adjusted returns, but through relative terms against the benchmark. As stated by Jorion (2002), measuring the performance of a portfolio in comparison to its benchmark is commonly measured using methods such as the information ratio and tracking error. Li, Sun and Bao (2011) call enhanced indexing a dual-optimisation problem, as the investor aims to find a balance in the trade-off between enhancing returns and keeping the tracking error low. Goodwin (1998) notes that the information ratio is used to quantify the performance of managers' active investing and argues that it is the best one-figure measure of the performance of an actively managed portfolio. The information ratio compares the excess return produced over the benchmark with the excess volatility, i.e., tracking error.

## 2.3 Regime models and macro-based asset allocation

Traditionally, portfolio optimisation has mostly been a static endeavour, with historical and expected asset performance used to optimise a portfolio per the investor's requirements. Many newer approaches build on top of this, by including a dynamic element to the optimisation. This includes regime models, which attempt to split the economical or financial environment into distinct separate regimes. Various methods of doing this have been attempted, with the formed regimes and the method of application differing.

The popularization of regime models in the economics context can mainly be traced back to Hamilton's seminar in 1989 (Bulla et.al., 2011). Hamilton (1989) applied Markov-switching models to economics to highlight that there seems to be two distinct regimes of GDP growth, and to produce time-varying transitory probabilities for the regimes. He found the model to potentially explain business cycles better than autoregressive models.

Regime-models were introduced to asset allocation later, with Ang and Bekaert publishing one of the earliest studies in 2002. Overall, studies indicate that market timing is possible, and that the differences in asset performance through regimes can be exploited. Ang and Bekaert (2002) studied international diversification benefits through bull- and bear-regimes and found that diversification benefits exist in both situations. Ang and Bekaert (2004) extended on this by studying dynamic asset allocation based on transitory probabilities of bull and bear markets. The regimes here are defined by the behaviour of the financial markets themselves. They find that dynamic allocation outperforms a static one, both when allocating between international equities and especially when allocating between equity, bonds, and a risk-free asset. Graflund and Nilsson (2003) have similar results with monthly reallocation of assets utilizing Markov-probabilities for financial market-based two-regime and three-regime models. They find that optimal asset allocation is heavily dependent on the regime, and ignoring regimes when reallocating assets is costly in the long run, with the results being true across the US, UK, Japan and Germany. Interestingly, when forming the regimes, they were able to define three distinct regimes from U.K. stock data, but only two in the US, Japan, and Germany. The latter three had the typical bull- and bear- split and lacked a more neutral but also less volatile one, which was observed in the UK. Guidolin and Timmermann (2004) had very similar results when allocating between equity, bonds and T-bills in the UK.

Nowadays, multiple regime-based asset allocation studies have been conducted with success and implications for a more dynamic asset balancing approach. For example, Wang, Lin, and Mikhelson (2020) use a Markov-switching model based on S&P 500 data to distinguish between different market regimes, and then switched between different factor models to price assets based on the models' performance in the regimes. They split the market regimes into three distinct regimes: a bull market, a bear market, and a neutral market. They found the dynamic model to outperform all of the used factor models themselves, with a higher Sharpe-ratio, higher information ratio, higher returns, and smaller maximum drawdowns. Kim, Jeong, and Lee (2019) achieved similar results of overperformance with a Markov-switching model, when allocating between different asset classes based on asset class specific regimes. Hess (2006) did a similar study with a Markov-switching model and bull- and bear regimes based on Swiss stock data to rebalance sectors in a portfolio dynamically. Out-of-sample overperformance against the benchmark was very slight however, but Hess still argues for regime switching as an important timing signal for asset allocation and rebalancing.

One of the issues regarding practicality with the mentioned studies is that they ignore transaction costs, which can play a big role in total returns when rebalancing is routine. Bulla et.al. (2011) attempt to address this gap by using a fairly typical Markov-switching model to dynamically allocate assets between an index and cash, while also introducing transaction costs. They also introduced transaction thresholds so that the portfolio would better avoid overtrading and inducing high transaction costs when regimes are uncertain. They found that the dynamic strategies outperformed all benchmark indexes, both reducing volatility and increasing annual returns.

The previously mentioned studies define financial market-based regimes themselves based on financial market data to identify regimes as they happen, and don't utilize external macro data. The literature on macro-based asset allocation models is much less comprehensive, but examples do exist. Blin et.al. (2020) utilize macroeconomic indicators to construct macro regimes and combine this with sentiment and valuation indicators to dynamically allocate between equities. They used the OECD Composite Leading Indicator to construct four regimes of economic growth based on the level and momentum of growth: High-Up, High-Down, Low-Down, and Low-Up. These correspond to expansion, slowdown, downturn (or recession) and recovery phases. They managed to achieve improved performance through individual and combined indicators and note that market-timing through macroeconomic indicators was helpful, especially in downturns. Importantly, the use of macro-indicators limited maximum drawdowns significantly. Dichtl et.al. (2019) incorporate a variety of macroeconomic indicators along with technical variables into factor-timing and factor tilting and overall manage to improve performance over the benchmark. However, the role of the macroeconomic variables in the improved performance is unclear.

Benoit and Raffinot (2019) used machine-learning algorithms to nowcast GDP growth and identify turning points using business surveys and financial data, including yield curves, asset volatilities, stock returns, and bond yields. They divided the forecasted GDP growth into two regimes, slowdown and acceleration, based on the nowcasted momentum of GDP growth. Ultimately, this was used to dynamically allocate assets between equity and cash or equity and bonds. They found the various machine-learning algorithms successful in identifying turning points, and the investment strategies built on them provided excellent risk-adjusted returns.

Regime-based sector rotation is a widely noted investment strategy, but the literature on it is somewhat incomprehensive. These strategies employed in studies do, however, seem mostly beneficial. Conover et.al. (2008) used monetary policy-based phases of expansive and restrictive periods to allocate between cyclical and defensive sectors. They identify sector cyclicality based on their movements with monetary policy. The sector-rotation portfolio outperformed equal-weight and index benchmarks, and the best individually performing sectors. They also note that the biggest difference in performance was generated in periods of restrictive policy, as during them, the portfolio had higher returns than the benchmark, while also carrying less risk.

Chong and Phillips (2015) use sectors' sensitivity to macro factors to allocate between sectors based on the macro factors to dynamically optimise performance through expansions and contractions. They utilize a sector classification by Morningstar to classify sectors into cyclical, defensive, and somewhere in between. The results were positive, with sector-rotated portfolios outperforming benchmarks. A minimum-variance sector-rotation portfolio was the best performer on a risk-ratio basis.

Sauer (2019) nowcasts GDP through various machine-learning algorithms and simpler regression methods to identify business cycle phases and dynamically allocate between sectors. He identifies sectors as cyclical or defensive based on their betas to industrial production. Sauer classifies the economic cycle into four phases based on the level of growth of GDP and the momentum of the growth. Level of growth is divided into High and Low, based on whether GDP growth is higher or lower than the long-term trend. Similarly, momentum of growth is divided into Rising and Falling, based on whether the growth is accelerating or slowing down. The sector rotation strategy was able to achieve improved results and significantly reduced drawdowns over an equal-weight benchmark. The majority of outperformance generated in Low Falling (downturn) regimes through tilting away from cyclical sectors, whereas performance in High Rising (expansion) regimes was worse than the benchmark. Sauer notes that significant results can be sustained by tilting the portfolio in under a quarter of periods by preparing for large negative shifts.

However, despite the overall success in the mentioned studies, Molchanov and Stangl (2023) challenge the previous literature, claiming that business cycle sector rotation does not seem able to generate practical and beneficial returns. They find that even with perfect foresight of business cycles as identified by NBER, the potential overperformance is marginal and dissipates once transaction costs are implemented. They also note that simply switching to cash when recessions begin outperforms sector rotation significantly. Additionally, they find that sector performance differences in various business cycle stages are not as pronounced as generally expected.

# 3 Research material and methods

## 3.1 Data

### 3.1.1 Benchmark (S&P 500 & MSCI Europe Large Cap)

The selected benchmark is the S&P 500, launched initially in 1957, and generally considered one of the leading indices of large-cap U.S. equities and is one of the most common benchmarks used by funds (Browne, 1999). The S&P 500 is weighted by the float-adjusted market cap. The S&P 500 consists of 500 major US companies and covers approximately 80% of available US equities market capitalization. The index currently on 24.11.2023 contains 503 stocks due to companies with dual stocks. S&P 500 operates on a selection basis, with the list of constituents being updated regularly, to measure the performance of US large-cap equities. The index holds multiple criteria for stock selection based on US status, market cap, public float, earnings performance, liquidity, and sector representation. The S&P 500 is rebalanced quarterly in March, June, September, and December. (S&P Global, 2023).

Even though the S&P 500 is considered one of the leading indices in the US, some criticism of it as a benchmark for US equities has been presented through characteristics that partially skew the index from an objective representation. Siegel (2003) covers two of these claims. First, the S&P 500 is arguably partially active itself, as the committee has selection criterion for stocks, excluding stocks they view as not of high enough quality. Second, the historic good performance of the S&P 500 has been partially attributed to momentum, which has been used as evidence for the index itself distorting the markets to a degree. Siegel does however rebut, as the active management of S&P 500 does not seem to be of particularly high investing quality, and also studies on the distortional effects on S&P 500 show no evidence of significant distortions from the index. Another skewing aspect of the index is that the S&P 500 does not cover small-cap equities at all, which, albeit by design, leaves out a big portion of equities on a quantity basis. One last issue with the S&P 500 is its very top-heavy nature, with the top 10 constituents covering around 34% of the index, as can be seen in Table 1, but this in general is an issue with market cap weighted US indices. All considering, this paper still uses the S&P 500 as the benchmark due to its status as by far the most used equity benchmark in the US (Siegel, 2003) and it's convenient and well-established categorization of different sectors.

As mentioned before, the S&P 500 is a large-cap index, excluding smaller equities, but it is still extremely top-heavy. As of 31.10.2023, the largest market cap of the constituents in the index is 2,669,857.80 million USD, while the median is 74,414.59 million USD and the median 28,913.93 million USD. The smallest market cap in the index is 4,024.10 million USD.

A summary of the float-adjusted market cap weight distribution of the top constituents of the S&P 500 index on 05.04.2024 is visible in Table 1.

*Table 1: Top constituents of S&P 500 index as of 05.04.2024. Source: LSEG Datastream*

| Company | Ticker | M. Cap (USD bn) | Index weight % |
|---|---|---|---|
| Microsoft Corp. | MSFT | 3 105.0 | 6.81 % |
| Apple Inc. | AAPL | 2 606.9 | 5.72 % |
| Nvidia Corp. | NVDA | 2 147.6 | 4.71 % |
| Alphabet Inc | GOOGL | 1 879.5 | 4.12 % |
| Amazon.com Inc | AMZN | 1 869.7 | 4.10 % |
| Meta Platforms Inc A | META | 1 302.5 | 2.86 % |
| Berkshire Hathaway B | BRK.B | 898.6 | 1.97 % |
| Eli Lilly and Co | LLY | 730.3 | 1.60 % |
| Broadcom Inc | AVGO | 610.6 | 1.34 % |
| JPMorgan Chase & Co | JPM | 563.6 | 1.24 % |
| TOTAL | - | 15 741.4 | 34.46 % |

The S&P 500 is also split into sectors based on the first level split of GICS sectors. Separate SP indexes exist for all the sectors. These separate indexes are used for sector returns in this paper. The sector split of the S&P 500 is visible in Table 2.

*Table 2: Sector split of the S&P 500 index as of 31.10.2023. Rounded to nearest 10$^{th}$ of a percent. Source: S&P Global 2023*

| Sector | Index weight % |
|---|---|
| Information Technology | 28.1% |
| Health Care | 13.1% |
| Financials | 12.8% |
| Consumer Discretionary | 10.6% |
| Communication Services | 8.7% |
| Industrials | 8.3% |
| Consumer Staples | 6.6% |
| Energy | 4.5% |
| Utilities | 2.5% |
| Materials | 2.4% |
| Real Estate | 2.4% |

As an additional robustness check, we also perform tests with European data. In Europe, we use the MSCI Europe Large Cap Index as the benchmark. The index includes large cap stocks across 15 countries in Europe classified as developed markets. The countries included are Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the UK. The index covers approximately 70% of the free-float -adjusted market capitalization within the included countries. (MSCI, 2023)

The index has 199 constituents as of November 2023. The top 10 constituents of the index account for approximately 26% of the index. A summary of the float-adjusted market cap weight distribution of the top constituents of the MSCI Europe Large Cap on 30.11.2023 is visible in table Table 3, and the sector split in table Table 4.

*Table 3: Top constituents of MSCI Europe Large Cap index as of 30.11.2023. Source: MSCI, 2023*

| Company | Ticker | M. Cap (EUR bn) | Index weight % |
|---|---|---|---|
| Novo Nordisk B | NOVO B | 304.4 | 3.90 % |
| Nestle | NESN | 279.6 | 3.58 % |
| ASML HLDG | ASML | 251.2 | 3.22 % |
| Shell | SHEL | 199.1 | 2.55 % |
| LVMH Moet Hennessy | LVMH | 194.0 | 2.49 % |
| Novartis | NVS | 183.9 | 2.36 % |
| AstraZeneca | AZN | 182.1 | 2.33 % |
| Roche Holding Genuss | ROG | 174.8 | 2.24 % |
| SAP | SAP | 151.9 | 1.95 % |
| Total Energies | TTE | 140.0 | 1.79 % |
| TOTAL | - | 2,061.0 | 26.41 % |

The MSCI Europe Large Cap Index uses the same GICS sector split as S&P uses in their index. They also provide first level sector-based indexes, which are used to track sector returns. The sector split of the index differs from the S&P 500, with especially Information Technology being much less prevalent.

*Table 4: Sector split of the MSCI Europe Large Cap Index as of 30.11.2023. Rounded to nearest 10th of a percent. Source: MSCI, 2023*

| Sector | Index weight % |
|---|---|
| Financials | 17.9% |
| Health Care | 17.2% |
| Industrials | 13.8% |
| Consumer Staples | 13.2% |
| Consumer Discretionary | 10.4% |
| Information Technology | 7.5% |
| Energy | 6.7% |
| Materials | 6.0% |
| Utilities | 4.4% |
| Communication Services | 2.6% |
| Real Estate | 0.24% |

The MSCI Large Cap Index was only formed in 2008. To cover years between 2001 and 2008, the 2008 constituents are used for the sectors over the period to simulate the index before it's conception. Returns and would-be weights are calculated based on the constituent returns over the period. This does include a small issue of survivor bias, but as the constituents are large cap, and we are not investing into singular constituents, but whole sectors, the bias should not significantly alter results.

### 3.1.2 Regime Data

For regime data, we use both GDP and the OECD Composite Leading Indicator. The OECD Composite Leading Indicator (CLI) is a composite indicator time-series designed to predict turning points and fluctuations in the business cycles of countries. The CLI by OECD is provided currently for the G20 countries plus Spain, and also regional CLIs are calculated. The OECD CLI is one of the most prevalent composite business cycle indicators, with perhaps the Conference Board Leading Economic Indicator being the other best-known such indicator. It has prevalence for use in institutions, as multiple institutions have employed the CLI or similar indicators for business cycle identification purposes, and it has been incorporated in quantitative investing models before. In addition, it is even included in the OECD Main Economic Indicators dataset policy makers utilize in economic decisions. Some research also exists on the merits of CLI by OECD and other parties, which is covered later in this section.

The CLI was originally created in the 1970's with the purpose of identifying turning points in economic activity by acting as an early signal. The CLI is constructed with the goal of forecasting cycles in a reference series used as a proxy for economic activity by using a selection of components. Previously the reference series was industrial production, but GDP has been used since 2012.

The CLI is designed to highlight the developments economic activity against the long-term trend (or long-term potential). It works as an index moving around the level of 100, where values over 100 reflect the expectation that the economy will grow faster than the long-term trend, and values under 100 reflect an expectation of the opposite. Monthly changes in the CLI on the other hand reflect changes in expectation and can be construed as the momentum of economic activity. Negative changes signal the expectation that economic growth will slow down, and vice versa for positive changes. The CLI is not designed around highlighting the level of economic activity but is more concentrated on changes and turning points.

The components, being other economic time-series, are selected on a country-basis. There is a set of both economical and practical rationale for selecting components from a wider set of possible short-term indicators. Selection is done based on what components tend to have similar but leading fluctuations as the reference series. The components are also required to be economically justifiable, so observed co-movement with the reference series is not by itself sufficient. Also, series covering a wider area of the economy are preferred to more limited ones. Practical requirements include preferences for monthly data, data not subjected to significant revisions, data that is available fast after the fact, and time-series with long history and few breaks or missing data points. (OECD, 2012)

Components are subjected to filtering, removing seasonal alternations and mitigating outlier values. Significant outliers are replaced by estimated values, to mitigate the effects of sudden shocks, for example strikes. If quarterly data is used, it is transformed into a monthly time-series through interpolation. After this, data is smoothed and de-trended using a Hodrick-Prescott filter to separate cyclical behaviour from noise and long-term developments. After this, data is subject to normalisation to make different indicators comparable. The data is normalized by demeaning the time-series, dividing values by the mean absolute deviation, and finally by adding 100 to each value. (OECD, 2012)

After components have been selected and modified for the CLI, construction is fairly straightforward as an aggregation of the individual component growth rates. The CLI uses equal weighting for all the modified components (albeit a type of weighting done in the modification phase through the mean absolute deviation of the time-series'), meaning that optimisation is mainly done in the selection phase. As different indicators tend to lead the reference series at different lengths, some indicators are lagged to match the timing of others. Finally, the data is aggregated once at least 60% of the selected indicators are available. (OECD, 2012)

The version of CLI used in this paper is amplitude-adjusted CLI. This means, that as both the components and the reference series have been de-trended and smoothed, the CLI is rescaled to match the amplitude of the reference series. As stated by OECD, “This form allows for output-gap type interpretations”. (OECD, 2012)

As by design, the CLI tends to lead its reference series, which is currently GDP. The US amplitude adjusted CLI and US quarterly seasonally adjusted GDP growth can be seen in Figure 2 and German CLI and quarterly seasonally adjusted GDP growth can be seen in Figure 3. As designed, CLI is not primarily optimised to forecast level of GDP, but rather forecast the direction of GDP, and thus whether the growth is positive or negative.

As an established leading index of economic strength, the OECD CLI has been tested independently, and also utilized in other studies, albeit very recent studies are somewhat lacking. OECD itself has naturally analysed the performance of its own indicator. In a paper by OECD, Nilsson and Guidetti (2007) analyse revisions to OECD CLI and find that the composite indicator generally has worked well. Drawing concrete conclusions from one-month changes had a somewhat unreliable effect in some countries especially, but the index was still found to reliably give early signals of turning points in the business cycle. Smoothing of the index and its components was also found to reduce revisions, improving performance of the indicator. The one-month revisions (i.e. the second estimate) were overall on the smaller side, with both USA and Germany only undergoing minor adjustments. With both countries, the direction of the CLI changed after the 1-month revision under 4% of the time. Overall, the indicator was found to have been improved over time through its development. In another OECD study, Astolfi et. al. (2016) study CLI forecasting of the Great Recession and find that the indicators were successful in anticipating the recession with a lead of a few months, albeit being unable to indicate the depth of the crisis.

External studies have also been done on the performance of OECDs indicators. Camacho and Palmieri (2020) analyse the full OECD MEI dataset for 32 countries, including the CLI. Utilizing machine-learning models, they find that the full dataset exhibits very good performance in forecasting business cycles, but that the CLI independently also has accurate performance, over one-component indicators, perhaps due to the composite nature of the CLI reducing volatility. This overperformance does diminish leads, and some one-component indicators, especially financial, do overtake the CLI. In other words, while the CLI perform very accurately, they don’t maximize their signal for turning points at leads. Ojo, Aguira-Conraria and Soares (2023) analyse the performance of the OECD CLI in 16 countries and found it to be a legitimate leading indicator of business cycles, when measured by industrial production; GDP-based cycle prediction was much less consistent. Blin et. al. (2020) were able to successfully incorporate the OECD CLI into a dynamic regime model, improving results. They constructed four regimes based on the CLI based on the level and momentum of the indicator and managed to improve portfolio performance through dynamically altering utilized risk premia based on the regime in portfolio construction.

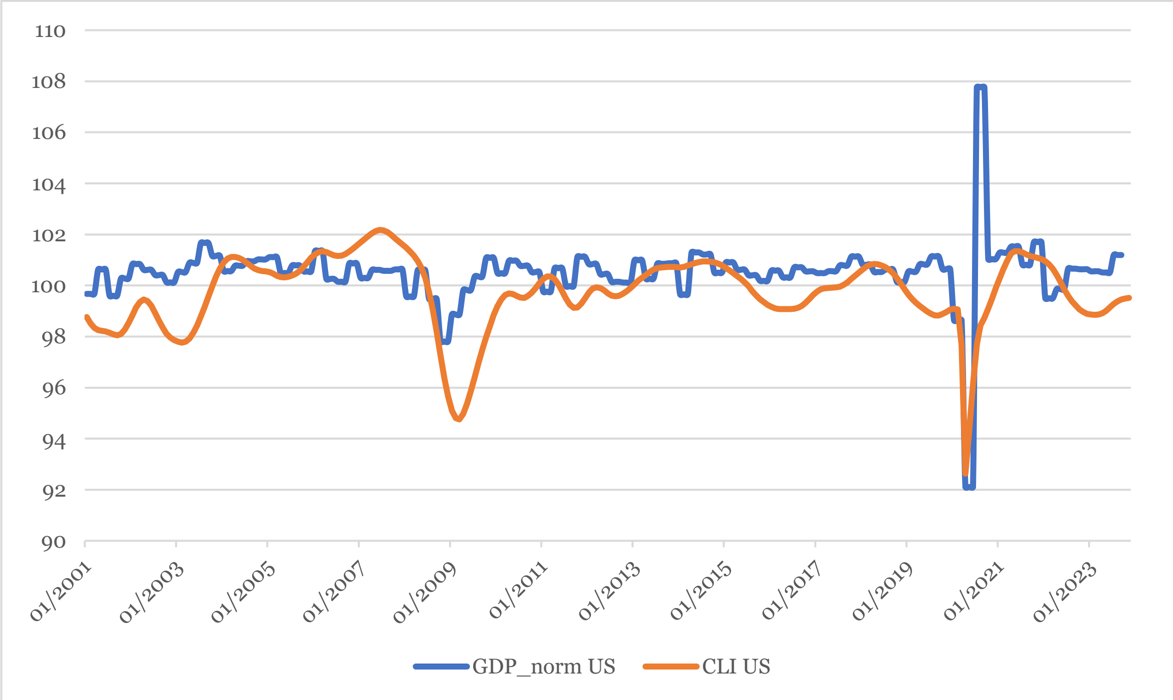


*Figure 2: US amplitude adjusted current CLI and quarterly seasonally adjusted GDP growth. CLI source: OECD on 3.1.2024; GDP source: OECD on 3.1.2024*

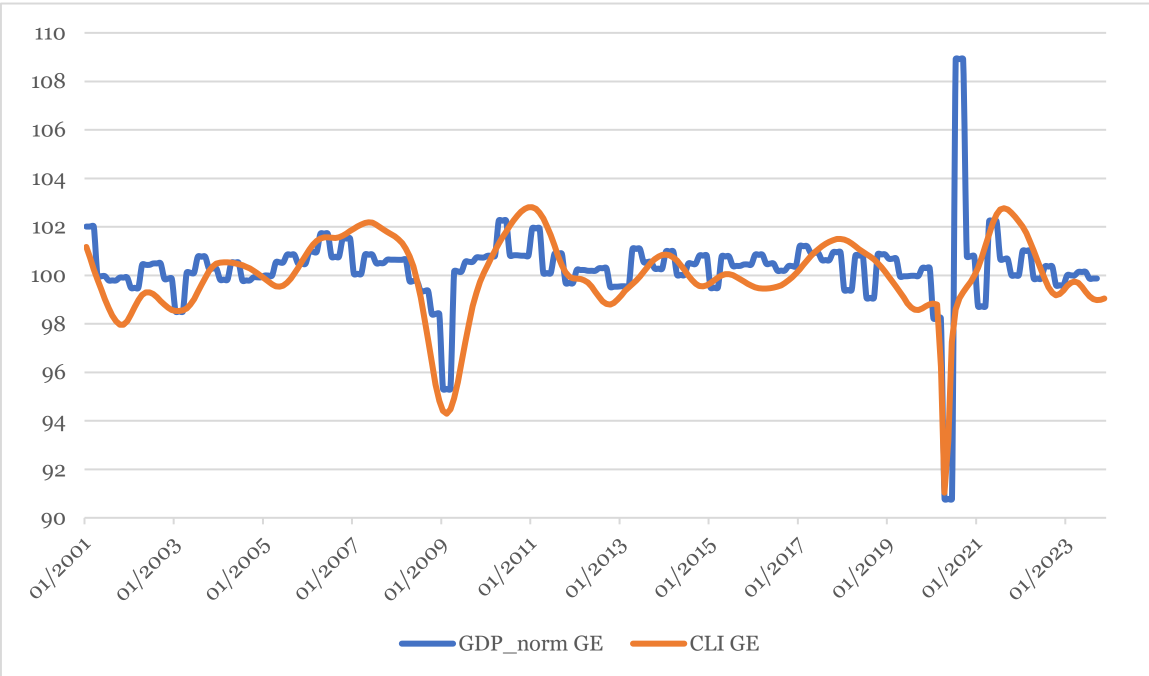


*Figure 3: Germany amplitude adjusted current CLI and quarterly seasonally adjusted GDP growth. CLI source: OECD on 3.1.2024; GDP source: OECD on 3.1.2024*

## 3.2 Methodology

### 3.2.1 CLI data formation

Regime probabilities and regimes are formed using CLI. CLI is designed to incorporate various aspects of the economy to give a more comprehensive picture of the forecasted regime. In addition, as financial markets generally are forward-looking, as pointed out by Chauvet (1999), the forward-looking nature of the CLI fits the purpose really well. The level of CLI (which moves around 100) corresponds to a high or low regime. When the CLI is over 100, the regime is understood as high, and when the CLI is under 100, the regime is understood as low. The reasoning for this is that the level 100 is designed to correspond to the economy growing in line with the long-term trend, values under or over signal deviations from neutral, or long-term potential, economic growth. Monthly changes in CLI on the other hand represent momentum shifts in the economy. A positive change from one month to another corresponds to a rising regime, and a negative change corresponds to a falling regime. When these two classifications are combined, the four previously mentioned regimes are formed.

The regime probabilities are constructed from the CLI based on the monthly variation of the CLI itself and its monthly changes. Historical CLI values, instead of the current revised ones, are used to ensure that the data availability conforms to reality. Unrevised CLI data is only available from 2001 onwards, limiting how far analysis can reach back in history. Revised values exist for much further into history, but this would skew the results, as the data was not available at the time. For each month, we utilise the CLI value that was the most recent available one. As CLI is generally published with a slight lag which has somewhat varied (1-3 months), this means that the CLI value for a month is actually one that has been calculated for a previous month. A few individual months in the data are also missing, and in these scenarios, we use the same level and change as in the previous month.

Revised CLI values are subjected to smoothing to get rid of noise and make the indicator more stable. As is visible in Figure 4, the revised CLI values are significantly more stable than the historical values. In this paper this is replicated by smoothing the historical CLI values with a Hodrick-Prescott filter at a low frequency, which is also used by OECD to smooth the components of CLI. The Hodrick-Prescott filter is a very common method of separating cycles and trends especially in economics, as stated by Hodrick and Prescott (1997), but the filter is also used to get rid of random noise in data, as done for example by Sauer (2019) with quarterly GDP data.

The Hodrick-Prescott filter, which primarily decomposes a time-series into a trend-component $g_t$ and a cycle-component $c_t$, as presented by Hodrick and Prescott (1997) is defined as the solution to the following optimisation formulas.

$$y_t = g_t + c_t$$
$$Min_{\{g_t\}_{t=-1}^{T}} \left\{ \sum_{t=1}^{T} c_t^2 + \lambda \sum_{t=1}^{T} [(g_t - g_{t-1}) - (g_{t-1} - g_{t-2})]^2 \right\}$$
$$Where\ g_t = growth\ component, c_t = cyclical\ component,$$
$$and\ \lambda = smoothing\ frequency$$

As explained by Sauer (2019), the frequency is responsible for the trade-off between smoothness and fit. In this case, as the smoothing is done to remove noise, and not separate trend from the cycle, a low frequency is used. Choosing the frequency for noise removal is somewhat arbitrary, but as done by Sauer (2019), is chosen here through inspection. A frequency of 10 is used to smooth the CLI, as it removes most of the noise, but also allows for the series to not differ too much from the original one. Importantly, the behaviour of the CLI is not majorly altered by smaller, especially positive, changes to the frequency. A graph of the unsmoothed historical US CLI and smoothed historical CLIs can be seen in Figure 5.

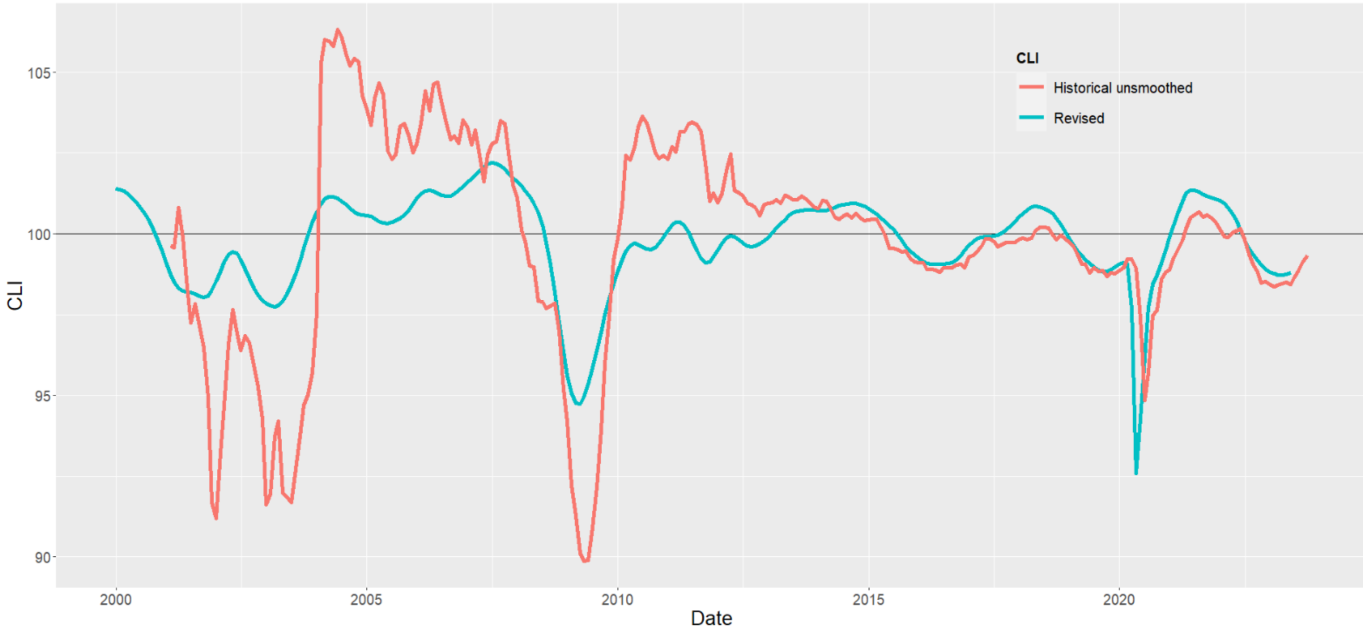


*Figure 4: Amplitude-adjusted historical US CLI and revised values between 2001-2023 as of 31.10.2023.*

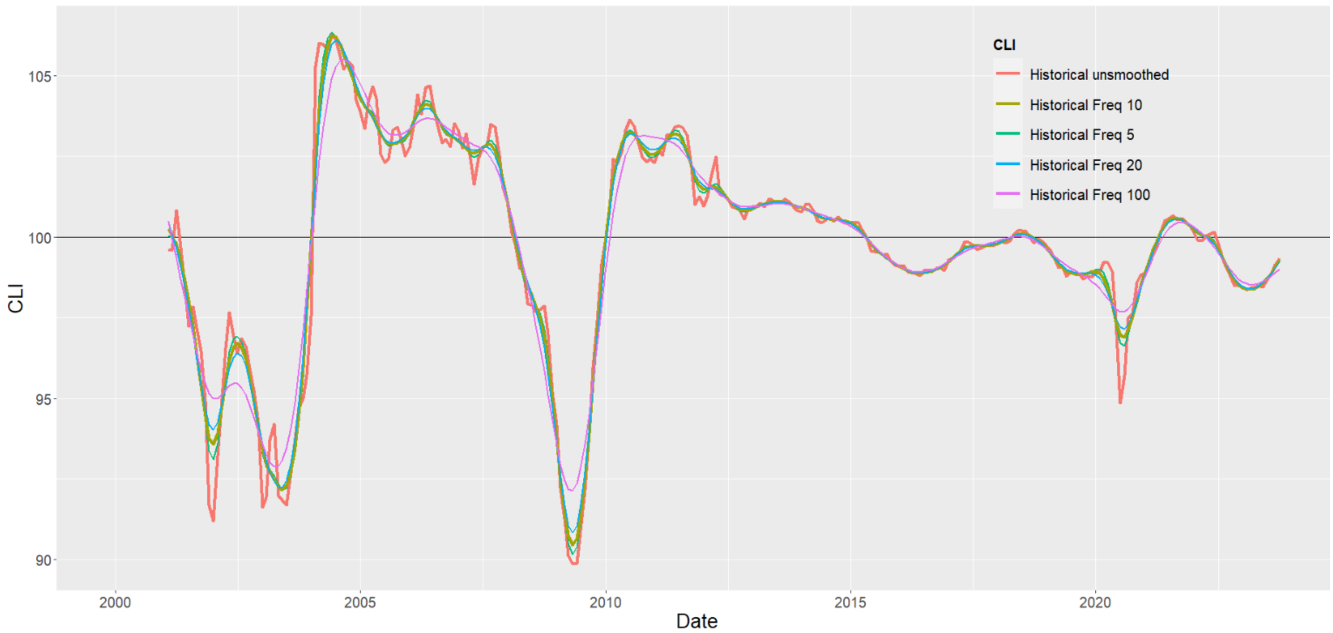


*Figure 4: Amplitude-adjusted historical US CLI unsmoothed and smoothed at various frequencies between 2001-2023. Frequency 10 used for model.*

### 3.2.2 Regime identification and probability model

As previously mentioned, historical CLI values are used to form probabilities for regimes and differentiate between the different regimes. In this paper, the business cycle is split into four regimes. The four regimes are Expansion, Slowdown, Downturn, and Recovery. Regime formation is straightforward. First distinction utilizes the level of economic growth. If economic growth is above the long-term trend, economic growth is deemed high, and if economic growth is below the long-term trend, economic growth is deemed low. Second, the momentum of economic growth distinguishes between expansionary and contractionary conditions. If economic growth is accelerating, conditions are expansionary, and if economic growth is slowing down, conditions are deemed contractionary. These two definitions are then used to form the four regimes. High and accelerating economic growth corresponds to an Expansion regime, high and slowing economic growth to a Slowdown regime, low and slowing economic growth to a Downturn regime, and low and accelerating economic growth to a Recovery regime.

Similar splits have been used by Sauer (2019) and Blin et. al. (2020), who both utilize a four-way regime split based on economic growth and its momentum. Sauer (2019), for example, splits regimes based on GDP growth into High-Rising, High-Falling, Low-Falling, and Low Rising. Here High-Rising corresponds to Expansion, High Falling to Slowdown, Low Falling to Downturn, and Low Rising to Recovery. Blin et. al. (2020) utilize a very similar split based on the OECD CLI.

Multiple studies, such as Chong et. al. (2015) and Benoit and Raffinot (2019) instead utilize a two-way regime split. They both split the business cycle into just expansionary and contractionary regimes. In this paper, a four-way split is used to hopefully capitalize on the more detailed differences between sector performance in the different stages of the cycle. Stovall (1996, as referenced by Molchanov and Stangl, 2023) argued that different sectors perform through the different intermittent phases of the business cycle, and thus there is potential to capture this better with a more granular approach. On the other hand, dividing the cycle into more than four phases becomes increasingly difficult to do efficiently.

CLI is used to differentiate between the regimes, and due to its characteristics, the transformation into regimes is very intuitive. As explained before, CLI values convey the expectation of stronger or weaker economic growth in relation to the long-term trend, where a CLI value of 100 is a neutral position. Similarly, monthly changes in CLI can be understood as positive or negative momentum for the growth rate. Thus, the four-way split is constructed by simply combining whether the level of CLI is above or below neutral levels, and whether the CLI is undergoing a positive or negative monthly change. So, just to state the logic explicitly, CLI over 100 with a positive change signals an Expansion, CLI over 100 with a negative change signals a Slowdown, CLI under 100 with a negative change signals a Downturn, and CLI under 100 with a positive change signals a Recovery. A graph of the US historical amplitude adjusted CLI, and the signalled regimes is visible in Figure 6, and the same graph with German CLI is visible in Figure 7. The 2001 and 2008 economic crashes, as well as the 2020 crash and later rebound are clearly visible in the regimes.

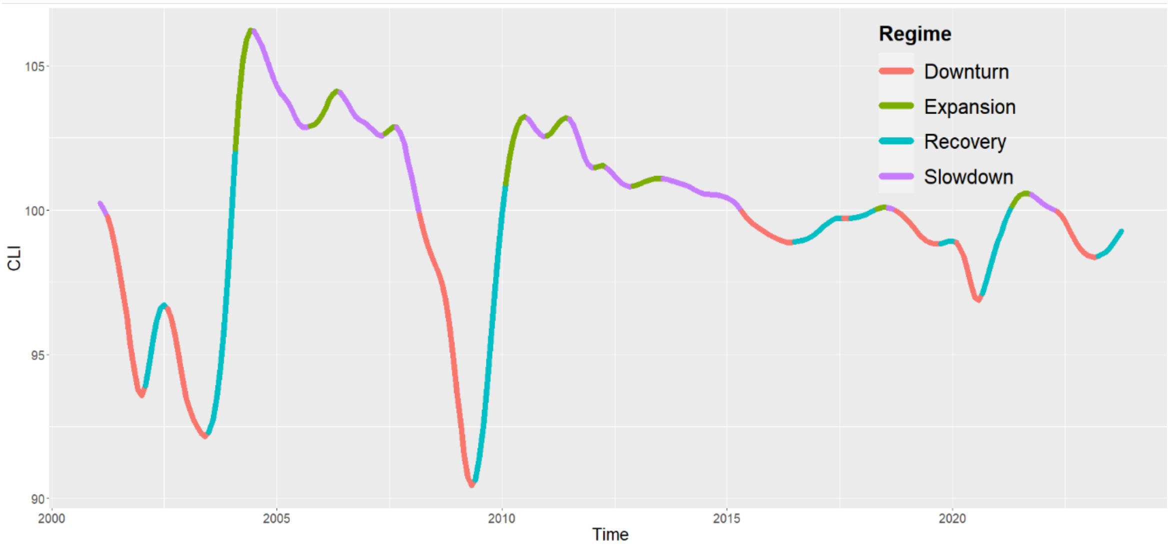


*Figure 5: Amplitude-adjusted historical US CLI and defined regimes between 01/2001 and 09/2023.*

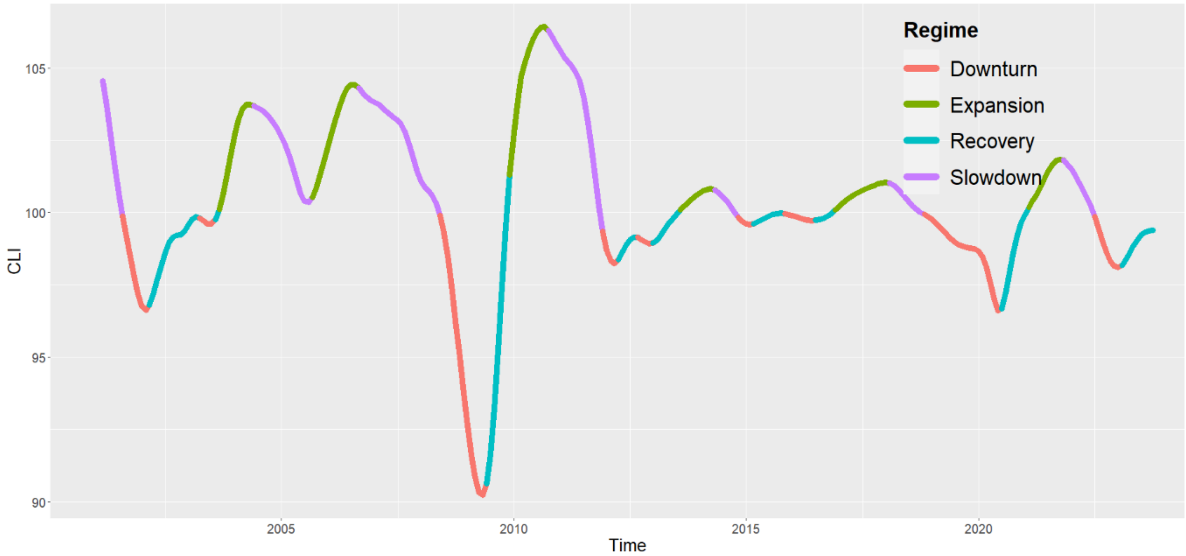


*Figure 6: Amplitude-adjusted historical German CLI and defined regimes between 02/2001 and 09/2023.*

Regime probabilities are calculated based on the values of CLI itself, and the chance that the regime indicated by CLI becomes something completely different in the following month. The probabilities are calculated based on the historical variance of CLI, and the variance of monthly changes in CLI. This should not necessarily be understood just as the chance that the underlying economic situation actually swings that much, but additionally as the chance that the initial CLI was wrong, and revision to the values changes the perceived situation dramatically. This is especially true for the CLI when there are large swings in opposite directions in consequent months. This is also why just the monthly change is not simply used to calculate probabilities for the CLI itself.

To form the probabilities for the separate regimes, a percentage for the level of CLI and the monthly change of CLI to be above the neutral level for the next month are calculated. For the level, the probability that the CLI will be above 100 is calculated, and for the change, the probability that the monthly change of CLI is positive is calculated. This basically boils down to calculating the probability for the forecasted economic growth to be high (above the neutral level), and the probability for forecasted momentum of economic growth to be positive.

The logic in both calculations is the same. The value of CLI or the monthly change is taken as the baseline value. First, the distance in standard deviations between the baseline value and the neutral value, which is 100 for the level and 0 for the monthly change of CLI, is calculated. Next, the normal density function is used to calculate the probability that the CLI or its monthly change will be at or above the neutral value using the normal distribution formula. For all periods, the standard deviation used to calculate the probabilities, only historical past values of CLI and the monthly change of CLI are used.

The formula used to calculate the percentages is as follows:

$$CLI_p = \frac{1}{\sqrt{2 * \pi}} * \int_{\frac{Value_{CLI} - 100}{(\sigma_{CLI})}}^{\infty} e^{\frac{-x^2}{2}}$$

$Where\ CLI_p = the\ probability\ that\ CLI\ will\ be \geq 100,$
$Value_{CLI} = the\ CLI\ value\ for\ which\ probability\ is\ calculated,$
$\sigma_{CLI} = the\ historical\ standard\ deviation\ of\ CLI$

$$CLI\_Change_p = \frac{1}{\sqrt{2 * \pi}} * \int_{\frac{Value_{CLI\_Change} - 100}{(\sigma_{CLI\_Change})}}^{\infty} e^{\frac{-x^2}{2}}$$

$Where\ CLI\_Change_p = the\ probability\ that\ monthly\ change\ will\ be \geq 0,$
$Value_{CLI\_Change} = the\ monthly\ \ change\ for\ which\ probability\ is\ calculated,$
$\sigma_{CLI\_Change} = the\ historical\ standard\ deviation\ of\ the\ CLI\ monthly\ change$

Once these values are calculated for a period, calculating the probability split for the regimes is straightforward. The probability of CLI being above or at 100 and the monthly change of CLI being above or at 0 are combined based on the regime classifications. The exact formulas for the regime probabilities are listed below:

$Expansion_p = CLI_p * CLI\_Change_p$
$Slowdown_p = CLI_p * (1 - CLI\_Change_p)$
$Downturn_p = (1 - CLI_p) * (1 - CLI\_Change_p)$
$Recovery_p = (1 - CLI_p) * CLI\_Change_p$

The result is a probability split of all four regimes which naturally adds up to a hundred percent. The probability split basically conveys the expected development of the economy in the forthcoming months. As per the calculations, the further away the CLI or its monthly change is from the baseline, the heavier will the probability tilt be towards some of the regimes. If the CLI and monthly change are at their neutral values, 100 and 0 respectively, the regime probabilities will be split evenly. The probability split time-series based on US historical amplitude-adjusted CLI is visible in Figure 8 and the same graph based on German values is visible in Figure 9.

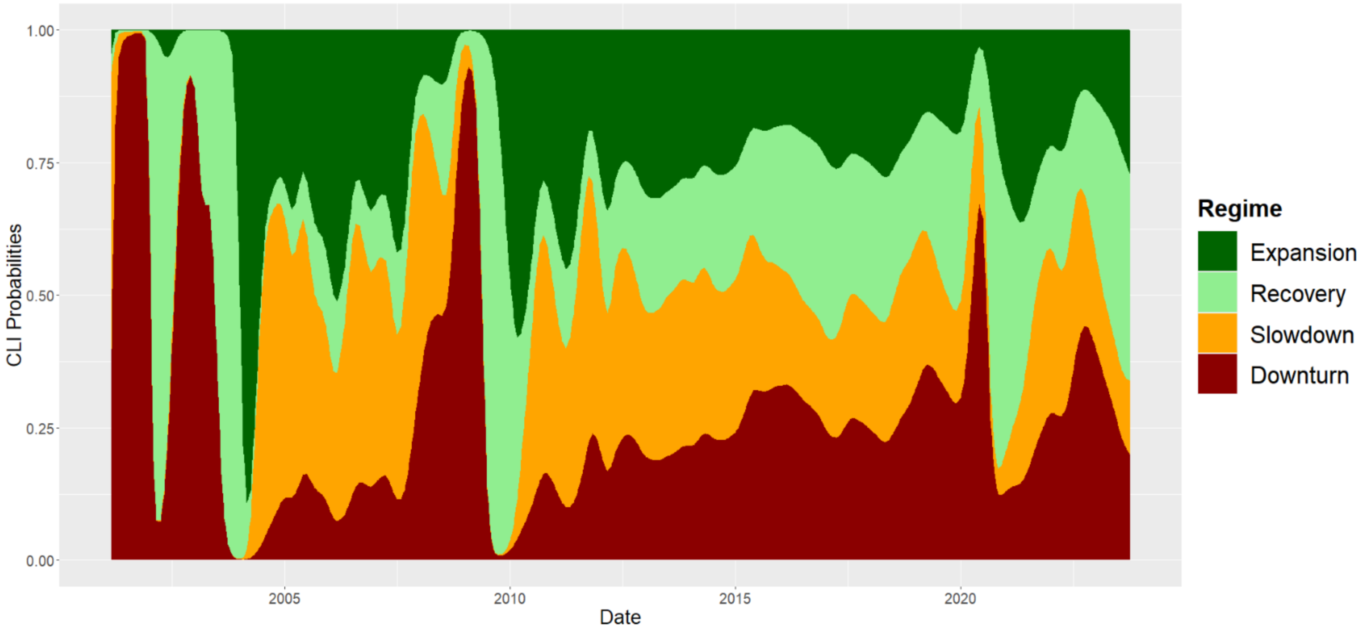


*Figure 7: US monthly regime probabilities based on historical amplitude adjusted CLI between 02/2001 and 09/2023.*

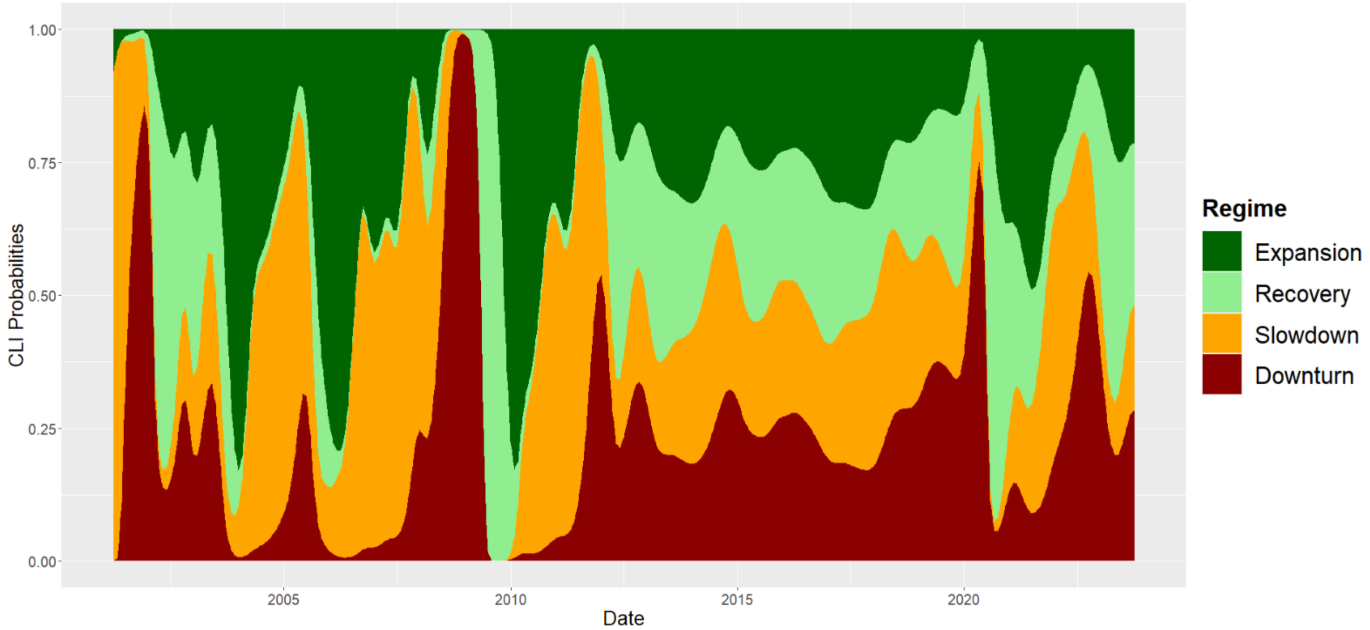


*Figure 9: Germany monthly regime probabilities based on historical amplitude adjusted CLI between 02/2001 and 09/2023.*

### 3.2.3 Sector characteristics through regimes

Sector performance through different regimes is 1) studied to understand the sector-specific behaviour through different regimes, and 2) used as an integral part of portfolio optimisation in the model. Various characteristics can be calculated for the sectors using the identified regimes and sector returns in a straightforward fashion. Monthly data is utilized, as the regime-data is also updated monthly.

The most significant measure is sector returns through regimes. This is simply calculated as the average monthly return of a sector when a certain regime is underway. Sector variance and covariance are also studied through regimes. Variance for a sector in a certain regime is simply calculated as the variance of the sector's monthly returns in periods when the regime in point is underway. Covariance between sectors is calculated following the same logic.

### 3.2.4 Portfolio optimisation

Portfolio optimisation is done based on traditional optimisation methods and metrics but utilizing the added information from regime probabilities and observed sector performance in the regimes. Each of the sectors is treated as a separate asset. This means that the optimisation is done by allocating weight to the separate sectors, and that the characteristics which are utilized in optimisation, for example returns and variance, are sector-level. This treatment of sectors as assets is similar in approach to the regime models by Sauer (2019), Chong et. al. (2015), and Stangl and Molchanov (2023). Optimisation is based on monthly values, as optimisation and reallocation are also done monthly when new regime data becomes available. Picking the optimal portfolio is finalised by choosing the best portfolio from a list of portfolios that have been optimised at varying risk tolerance levels.

Regime probabilities are used in the model to optimise the portfolio instead of the strictly defined regimes. This has a couple advantages. First, this allows the model to not make a strict decision on the direction of the economy, something that is often considered hard to forecast. Thus, it somewhat restricts the downsides of wrong regime predictions on portfolio performance. Second, the probability spread automatically means that the optimisation takes into account how strong the regime sentiment is, weighting the portfolio more towards a certain regime if the regime seems more certain. The potential downside of the probability split is that it does "soften" the portfolio optimisation, and in cases where the upcoming regime is the one directly predicted by CLI, the optimisation is not fully optimised towards it.

The optimisation is performed based on the expected independent performance and co-movement of sectors. The main performance metric used for portfolio optimisation is the expected performance of sectors. The expected performance for a period is calculated from the CLI-based regime probabilities, and the historical returns of sectors in the identified CLI-based regimes. In practice, each sector has a calculated historical return in each regime, meaning a separate average return for the Expansion, Slowdown, Downturn, and Recovery regimes. A sector's expected return for a period is then calculated as a simple weighted average, weighting each of these returns by the probability of the corresponding regime for the period as follows:

$$R_s = Exp_p * R_{es} + Slo_p * R_{ss} + Dow_p * R_{ds} + Rec_p * R_{rs}$$
$$Where\ R_s = Sector\ expected\ return$$

Here the probability of Expansion $Exp_p$ is multiplied by the sector's historical return in expansions, the probability of Slowdown $Slo_p$ is multiplied by the sector's historical return in slowdowns, and so forth. These values are all added together to receive the expected return for the sector for the period, which is the upcoming month.

Another metric that is used in the model is sector variance and covariance to quantify risk. The model can either use a static version, which is simply the historic variance and covariance of the sectors, or a dynamic version, where regime-specific historic variance and covariance is utilised. Variance and covariance are calculated separately for each period based on the past returns at that point in time. Dynamic variance and covariance, much like the expected return, are weighted based on the regime probabilities. This is done as follows by utilizing the law of total covariance:

$$Cov(X,Y) = E[Cov(X,Y|Z)] + Cov(E[X,Y|Z])$$

X and Y are random variables, whose values are dependent on Z. When adapted to the model, the formula looks as follows:

$$Cov(S_1,S_2) = E[Cov(S_1,S_2|R_t)] + Cov(E[S_1,S_2|R_t])$$

Where $S_1$ and $S_2$ are two sector returns, and $R_t$ is the regimes at period $t$. The first part is the expected covariance between the two sectors, calculated as a weighted average of the sector covariance in different regimes weighted by the regime probabilities in period $t$:

$$E[Cov(S_1,S_2|R_t)] = Exp_p * Cov(S_1,S_2)_{Exp} + Slo_p * Cov(S_1,S_2)_{Slo} + Dow_p * Cov(S_1,S_2)_{Dow} + Rec_p * Cov(S_1,S_2)_{Rec}$$

$Exp_p$ is the probability of Expansion at period t, $Cov(S_1,S_2)_{Exp}$ is the covariance of the two sectors in expansions, $Slo_p$ is the probability of Slowdown at period t, $Cov(S_1,S_2)_{Slo}$ is the covariance of the two sectors in slowdowns, and so forth for the last two regimes.

The second part in the equation is covariance of the expected returns of the two sectors through different regimes. Further explained, there are four previously calculated expected returns for both sectors, one for each regime, and the returns in each of the regimes act as pairs. Thus, the covariance is calculated from four pair observations, as visible below:

$$Cov(E[S_1,S_2|R_t]) = Cov\begin{pmatrix} R^{s1}_{Exp} & R^{s1}_{Slo} & R^{s1}_{Dow} & R^{s1}_{Rec} \\ R^{s2}_{Exp} & R^{s2}_{Slo} & R^{s2}_{Dow} & R^{s2}_{Rec} \end{pmatrix}$$

Where $R^{s1}_{Exp}$ stands for the expected return of sector 1 in the expansion regime, $R^{s2}_{Slo}$stands for the expected return of sector 2 in the slowdown regime, and so forth.

The sector variances are calculated using the same logic, but all of the formulas simply utilize the same sector twice, instead of having the two sectors. These calculated covariances and variances form a covariance matrix for all the sectors which is used in portfolio optimization. When creating the matrix in R, the values are not exact values, but approximations. This may in some cases lead to a situation where the covariance matrix has a negative eigenvalue. In these cases, R is used to find the nearest covariance matrix with a positive eigenvalue. These changes are minimal and do not affect optimisation in actuality, but it is a necessity, as negative eigenvalue matrices are not compatible with the optimization solver.

Once the necessary optimisation parameters have been calculated, they are used to optimise the portfolio. The calculation of an optimal portfolio is done using R, and the convex optimisation package CVXR. The optimisation tool in CVXR is an iterating optimising solver, which means that it iterates through a huge number of possibilities and then returns the optimal solution. The solver is a very typical iterating solver, in that it accepts an objective, which is the function it is trying to optimise, and a list of constraints within which it has to find a solution. As the output, the solver produces an optimal portfolio in the form of a list of the optimised sector weights. The objective function that is optimised the portfolio is formed as follows:

$$Objective = R_p - \sigma_p^2 * G$$

$Where\ R_p = Portfolio\ expected\ return,$
$\sigma_p^2 = Portfolio\ expected\ variance, and\ G = risk\ multiplier$

The risk multiplier, G, is used to create portfolios for differing risk tolerance levels. To incorporate transaction costs, they can be added to the objective function by subtracting them from the expected return.

Constraints used limit the portfolio's total weight to a 100%, limit sector weights to be positive, and contain various active risk constraints. A default set of risk constraints is used, as listed here. Active risk here should be understood as the deviation from neutral, i.e. benchmark, weights. Total active risk is capped at 40%, meaning that the sum of the absolute deviations from the benchmark cannot exceed 40%. Sectors deviations are capped through a two-fold constraint. First, absolute deviation of a sector is capped at 5% by default. Second, a relative constraint is used based on the weight of the sector in the benchmark. The relative constraint is 40% of the sector's benchmark weight, meaning that a sector with 10% weight can deviate in the portfolio between 6% and 14%. The stricter of the absolute and relative constraints are applied. These two constraints are utilized so that the overall structure of the benchmark is not completely mangled through for example either doing all of the tilting through one large sector (avoided by the absolute constraints) or tilting by removing the smaller-weighted sectors from the portfolio (avoided by the relative constraint). This set of constraints is used as the default in all of the portfolio tests unless otherwise specified.

Optimisation for a certain period is performed utilizing Markowitz' (1952) efficient portfolio theory, commonly called the efficient frontier, which highlights that for every risk-level, there is an optimal portfolio, maximizing the expected return for the corresponding risk level. When optimising a portfolio for a certain period, the optimiser is iterated through multiple times at differing risk levels to create a list of risk-return optimal portfolios. Out of these risk-return optimised portfolios, the best portfolio is chosen based on the desired outcome. The portfolio with the highest expected return, highest expected Sharpe-ratio, or lowest expected variance can be for example chosen. One notable mention here is that the Real Estate sector index is not among the investable universe in the US until October 2016, as it was only then added to S&P 500 as a separate sector.

### 3.2.5 Performance metrics

Various performance metrics are utilized to characterise and compare the performance of the modelled portfolios, of which some require additional defining. These are defined in this section, as extensively as required, and include information ratio, Sharpe-ratio, and drawdowns.

Sharpe-ratio is simply calculated as the return of the portfolio divided by standard deviation to quantify the risk-adjusted returns of a portfolio. In this paper it is calculated based on the average monthly return and average monthly standard deviation of the portfolio.

Drawdowns are also calculated based on monthly returns. Drawdowns are categorized periods, where the portfolio falls below its peak. Only the depth of the drawdown is quantified in the performance metrics, and the depth is calculated as the lowest point from the previous peak as a percentage return. When calculating average drawdowns, simply the average maximum depth of all drawdowns over the period is considered, without any weighting.

The information ratio is perhaps the best one-figure measure of performance for active investing against a benchmark, as argued by Goodwin (1998). Information ratios are always calculated against the benchmark and quantify the enhancement of returns over the benchmark against excess volatility of the portfolio. The general definition, and the definition used by Goodwin, is as follows:

$$IR = \frac{\overline{ER}}{\sigma_{ER}}, where$$

$$\overline{ER} = \ arithmetic\ mean\ of\ the\ returns\ of\ the\ portfolio\ over\ the\ benchmark$$

$$\sigma_{ER} = standard\ deviation\ of\ the\ return\ over\ the\ benchmark$$

The ratio can be calculated from various periods and then annualized. In this paper, information ratio is calculated based on weekly returns of the portfolio and the benchmark, using averages of weekly excess returns and the volatility of these excess returns. For the purposes of this paper, annualization of returns is performed simply by multiplying the average excess return by 52, the number of weeks in a year. Volatility is annualised by multiplying the weekly volatility by the square root of 52. As a benchmark for the levels of information ratios, Goodwin (1998) states that 0.5 is generally considered a good information ratio for an active manager, and anything over 1.0 is considered exceptional. Realistically, ratios over 1.0 are almost unachievable, as empirically they have been shown to be extraordinarily rare.

# 4 Results

## 4.1 Sector performance

Sector performance is categorized through the previously mentioned characteristics, which include returns, volatility, covariance. These combined give a good view of how sector returns may be affected by changes in the business cycle. As sector returns are mainly tracked on a monthly basis, and portfolio allocation is also performed on the same schedule, sector performance metrics are also on a monthly basis.

As CLI is forward-looking by a few months, forecasting future business cycle developments, sector performance is not analysed strictly in relation to the real business cycle changes. Instead, sector performance is analysed in relation to changes in the sentiment of the economy, which is portrayed by changes in CLI. The regimes used for sector performance are defined as explained in the previous section.

Sector returns are the main characteristic used to differentiate sector performance in the various regimes. For the model to have a realistic chance of working, sectors must exhibit returns that differ through the regimes relative to each other. For it to be able to potentially give an advantage in practicality, these differences must be able to justify potential reallocation costs. Without these costs, even very slight differences would give a slight theoretical edge, but as the costs are forcibly accrued, larger differences are required. The regime-based sector returns in the US are shown in Table 5, where, as stated before, S&P sector indices portray sector returns. In the sample, no significance of the regimes on returns should be interpreted as more or less acyclical, or at the very least inconsistent behaviour in the corresponding regime compared to significant regime returns.

*Table 5: US S&P sector index monthly returns by US CLI-defined regimes. Sector/regime significance levels calculated based on demeaned returns to capture whether regime deviates sector returns from sector average. EQ W stands for a sectorally equal-weighted portfolio.*

*Significance levels indicated as follows: '***' 0.001, '**' 0.01, '*' 0.05, '^' 0.1*

| | Downturn | Expansion | Recovery | Slowdown | Overall |
|---|---|---|---|---|---|
| Enrg | -0.013* | 0.015^ | 0.018* | 0.018* | 0.009 |
| Mtrls | -0.005^ | 0.013 | 0.019* | 0.010 | 0.008 |
| Indu | -0.007* | 0.015* | 0.023** | 0.008^ | 0.008 |
| ConsD | -0.002 | 0.015 | 0.019^ | 0.010 | 0.009 |
| ConsS | 0.001 | 0.010 | 0.011 | 0.011 | 0.008 |
| Hlth | -0.004* | 0.011' | 0.016* | 0.012* | 0.008 |
| Fncl | -0.016** | 0.014* | 0.027*** | 0.004^ | 0.005 |
| IT | 0.002 | 0.012 | 0.030* | 0.009 | 0.012 |
| Comms | -0.002 | 0.011 | 0.015^ | 0.007 | 0.007 |
| Util | -0.001^ | 0.003 | 0.01 | 0.017** | 0.008 |
| ReEst | -0.008^ | 0.012 | 0.011 | 0.012^ | 0.006 |
| EQ W | -0.005 | 0.012 | 0.018 | 0.011 | 0.008 |

As is visible in Table 5, relatively large differences can be identified in regime returns, both through the regimes, and overall. As expected, the worst performance overall is observed through the Downturn regime, whereas the best performance is observed in Recoveries, where the economy is bouncing back from downturns. One interesting observation is that return differences are most pronounced in the Downturn-regime, despite equities generally exhibiting stronger correlation in bear-markets, as per Longin and Solnik (2001). Somewhat surprisingly, Expansion and Slowdown seem to be fairly aligned in terms of returns, but there is more dispersion between sectors in Slowdown-regimes. Sector returns mostly follow the overall trend. In fact, not a single sector performs better in the Downturn-regime than in any one of the other regimes. Thus, no truly countercyclical regimes can be identified. As with Sauer (2019), however, some sectors clearly follow a cyclical pattern more strongly than others.

As expected, based on the study by Conover et.al. (2008), the sectors Financials, IT, and Industrials can be observed to behave cyclically relative to other sectors. They all exhibit large differences between regimes. Financials vary the most between the regimes, showcasing very strong returns in the Expansion-, and Recovery-regimes, and the weakest returns in the Downturn-regime. Even though IT has very strong relative returns in the Downturn-regime, it's returns are still very cyclical, having the second-largest difference between returns in the Recovery-, and Downturn-regimes, after Financials.

In line with Conover et.al. (2008), some of the observably less cyclical sectors are Consumer Staples, Utilities, and Communication Services. Rest of the sectors fall somewhere in between, with a couple surprises in contrast with previous categorizations. Even though exhibiting stronger regime-based differences in returns than Consumer Staples, Consumer Discretionary is relatively stable as a sector, despite generally considered one of the most cyclical sectors, as per Conover et.al. (2008) and Chong et.al (2015). Energy on the other hand exhibits heavy movements through regimes, despite a defensive classification by Conover et. al. (2008). This comes with a caveat; Energy differs from the rest of the sectors in that it performs very well in the Slowdown-regime.

Reasons for sectors not falling expectedly on the defensive-cyclical spectrum are hard to pin-point. It may be due to the regime-classification used in this paper, the reference series for cyclicality in previous papers (for example Conover et. al. (2008) and the Morningstar classification use different references for cyclicality and end up with slightly differing sector classifications in cyclicality), or perhaps due to market-timing factors in investors anticipating cycle developments.

Unlike what is proclaimed by Molchanov and Stangl (2023), significant performance differences are visible within many sectors, even without their more granular sector-split. This could be explained by the difference in regime timing, as they observe sector-specific returns at the time of business cycle phase, whereas the CLI-regimes used in this paper automatically incorporate a level of lead. It should be expected that investors would adjust according to expectations and with a lead, and thus a large portion of returns could already be baked into returns once the regime hits. This is consistent with the sector performance framework of Stovall (1996, as referenced by Molchanov and Stangl, 2023), and the fact that overall sector rotation portfolio performance improves slightly in the study of Molchanov and Stangl when a lead of 1-2 months is incorporated.

Regime differences can also be observed in the volatility of sectors. Very expectedly, Downturn-regimes exhibit the highest volatility, which is true for all 11 sectors. Expansion-regimes on the other hand generally exhibit the most stable returns. Sector volatilities don't exhibit as strong variability through the regimes in relation to each other, as the more stable sectors are generally more stable throughout regimes, and vice versa for the more volatile sectors. The most stable sectors are Consumer Staples and Health Care, and the most volatile sectors are Energy and Real Estate. The US sector volatilities through US CLI-based regimes are visible in Table 6.

*Table 6: US S&P sector index monthly return standard deviation by US CLI-defined regimes.*

| | Downturn | Expansion | Recovery | Slowdown | Overall |
|---|---|---|---|---|---|
| Enrg | 0.102 | 0.051 | 0.073 | 0.060 | 0.075 |
| Mtrls | 0.081 | 0.043 | 0.044 | 0.050 | 0.058 |
| Indu | 0.077 | 0.035 | 0.043 | 0.042 | 0.053 |
| ConsD | 0.083 | 0.037 | 0.035 | 0.043 | 0.054 |
| ConsS | 0.043 | 0.026 | 0.035 | 0.029 | 0.034 |
| Hlth | 0.051 | 0.030 | 0.036 | 0.034 | 0.039 |
| Fncl | 0.093 | 0.043 | 0.056 | 0.042 | 0.063 |
| IT | 0.074 | 0.040 | 0.042 | 0.049 | 0.055 |
| Comms | 0.066 | 0.039 | 0.048 | 0.039 | 0.049 |
| Util | 0.051 | 0.035 | 0.040 | 0.034 | 0.041 |
| ReEst | 0.097 | 0.050 | 0.042 | 0.051 | 0.065 |

The CAPM-beta of sectors to their benchmark (S&P 500) was calculated based on monthly returns. Sector betas are visible in Table 7. Sector betas are on average highest in Downturns, which is consistent with Longing and Solnik (2001) finding that asset correlations tend to go up in bear markets. Lowest average betas on the other hand are observed in Slowdowns. Four sectors appear as clearly less cyclical with benchmark returns: Utilities, Consumer Staples, Health Care, and Communication Services. As with earlier analysis, no sector appears as truly countercyclical. Financials, unsurprisingly, appears as the sector with the highest market exposure.

Some differences in sector betas do exist between regimes, but drawing concrete conclusions is difficult due to the somewhat limited number of months in each regime, and no extraordinary swings existing. Generally, with regime-betas, it would be preferable to have a low beta in the Downturn-regime, and a high beta in the Recovery regime, as the market tends to have low and high returns respectively. Perhaps the most notable difference in sector betas is Energy, as it has a really high beta in Recoveries, but a low one in Slowdowns. Real Estate exhibits some slightly unfavourable characteristics, as it has a high beta in Downturns, and a fairly low one in Recoveries. An additional observation concerns Utilities, which generally bear low beta, but in Recoveries drop to a beta of just 0.15.

*Table 7: US S&P sector index monthly return CAPM-beta with S&P 500 by US CLI-defined regimes.*

| | Downturn | Expansion | Recovery | Slowdown | Overall |
|---|---|---|---|---|---|
| Enrg | 1.19 | 1.00 | 1.42 | 0.89 | 1.13 |
| Mtrls | 1.18 | 1.20 | 1.17 | 1.26 | 1.19 |
| Indu | 1.17 | 0.98 | 1.23 | 1.13 | 1.15 |
| ConsD | 1.23 | 1.11 | 0.96 | 1.09 | 1.15 |
| ConsS | 0.56 | 0.52 | 0.77 | 0.63 | 0.58 |
| Hlth | 0.66 | 0.70 | 0.94 | 0.78 | 0.72 |
| Fncl | 1.33 | 1.23 | 1.27 | 1.03 | 1.26 |
| IT | 1.12 | 1.18 | 1.02 | 1.24 | 1.14 |
| Comms | 0.84 | 0.71 | 0.89 | 0.66 | 0.79 |
| Util | 0.54 | 0.58 | 0.15 | 0.40 | 0.47 |
| ReEst | 1.22 | 1.18 | 0.79 | 0.96 | 1.10 |

Similar analysis was also performed on European sectors in the different regimes, with MSCI Europe Large Cap sector indices used for sector returns, which can be found below in Table 8. The regime-based volatilities and market betas (with the MSCI Europe Large Cap index) can be found in Appendix 2 and Appendix 3.

With the European data, slightly less significance is observed across the board and overall returns seem to swing slightly less with cycles, perhaps due to the more heterogenous market over the US and the utilization of Germanys CLI-based regimes for the whole European area. Still, as with US data, clear differences are observable in regime performance between sectors. Sectoral cyclicality is mostly in line with US results, especially when looking at betas. A few major differences can be observed especially within regime-based returns, which also go against expectations. IT is weirdly simultaneously defensive, through very strong returns in Downturns, but also cyclical, due to a high market beta. Utilities on the other hand loses its status as a defensive sector, with very weak returns in Downturns, as well as do Communication Services. Energy varies even heavier between regimes than in the US, with the worst Downturn performance out of the sectors, but its best performance is observed in the Slowdown-regime. Real Estate rises as a very cyclical sector, which is somewhat expected.

*Table 8: MSCI Europe Large Cap sector index monthly returns by Germany CLI-defined regimes. Sector/regime significance levels calculated based on demeaned returns to capture whether regime deviates sector returns from sector average. EQ W stands for a sectorally equal-weighted portfolio.*

*Significance levels indicated as follows: '***' 0.001, '**' 0.01, '*' 0.05, '^' 0.1*

| | Downturn | Expansion | Recovery | Slowdown | Overall |
|---|---|---|---|---|---|
| Enrg | -0.013** | 0.016** | 0.007^ | 0.018** | 0.008 |
| Mtrls | -0.006* | 0.019* | 0.008 | 0.013^ | 0.009 |
| Indu | 0.001 | 0.018^ | 0.014 | 0.006 | 0.010 |
| ConsD | 0.005 | 0.017 | 0.013 | 0.005 | 0.010 |
| ConsS | 0.003 | 0.013 | 0.011 | 0.007 | 0.008 |
| Hlth | 0.005 | 0.015 | 0.01 | 0.006 | 0.009 |
| Fncl | -0.008^ | 0.018* | 0.013^ | 0.000 | 0.005 |
| IT | 0.006 | 0.014 | 0.012 | 0.003 | 0.009 |
| Comms | -0.006* | 0.012* | 0.009* | 0.004 | 0.005 |
| Util | -0.004^ | 0.013* | 0.006 | 0.012* | 0.007 |
| ReEst | -0.009* | 0.016* | 0.014* | 0.006 | 0.006 |
| EQ W | -0.002 | 0.015 | 0.011 | 0.007 | 0.008 |

An overview of the results does showcase differences between how sectors behave through the defined regimes. Overall, all of the sectors do exhibit cyclical behaviour in the sense that they all suffer from Downturns and have positive market betas, and thus no truly countercyclical behaviour is observable. Still, some sectors are clearly less cyclical than others, on stronger levels than what was found by Stangl and Molchanov (2023). As mentioned, a good portion of the sectors behave in line with previous frameworks on sector cyclicality, but surprises do exist, with especially the Energy-sector exhibiting strong cyclical behaviour, apart from very strong returns in Slowdowns.

IT seems to be the heavy standout sector in the US, which is not surprising, seeing the massive growth of the sector, and the fact that the sample does miss the 2000 IT bubble market crash. Even though it exhibits large cyclicality, it is still a relatively strong performer even in Downturns. IT does also perform well throughout regimes in Europe, but not nearly at the same level as in the US. The Financials-sector is the major underperformer on the other hand, showcasing low average returns in both regions. It does, however, have redeeming qualities in terms of regime investing, as its high cyclicality leads it to do well in bull-markets.

## 4.2 Optimisation results

### 4.2.1 Portfolio performance

Portfolios are built on varying optimisation targets, constraints, and methods to understand how they affect portfolio performance. Portfolio performance is analysed against the benchmark portfolio, as simply comparing returns from the US strategy to the Europe strategy is not practical due to the differences in characteristics and performance of the markets.

As mentioned earlier, transaction costs are incorporated already in the optimisation and construction of the portfolio. The default transaction cost used is 20 basis points, 0.2%. This number is in line with typical transaction costs for institutional investors. In reality, the costs do vary depending on size of sale, whether it is a buy or sell commission, market, etc., but 20 basis points works as a good, slightly conservative estimate, as shown by Keim and Madhavan (1998), especially with the expectation that institutional transaction costs have gone down over time. Overall, transaction costs have a minuscule effect on returns, as will be shown later, and small adjustments to the transaction cost do not materially change results.

The main version of the model is the Sharpe-ratio optimised model utilizing regime-based covariances, which will be referred to as the default model. In addition, the strategy is tested with multiple versions of the model, with changes consisting of two elements. First, the optimization is done on three different monthly parameters: Sharpe-ratio, maximum return (includes transaction costs already in optimisation), and minimum variance. Second, the models use either dynamic, regime-based covariance, or non-regime-based covariance. Combining these two elements amounts to six different versions of the model. The US models and some of the most important performance metrics are visible beneath, in Table 9.

*Table 9: US model performance between 1.2.2004 and 31.5.2023. Y Denotes annualized values, M denotes monthly values. Excess return defined as average annualized return over the benchmark. Turnover defined as average proportion of portfolio being traded in or out monthly. Drawdown defined as lowest point fall from last peak.*

| Optimisation method | Sharpe | | Return | | Min Var | | S&P 500 |
|---|---|---|---|---|---|---|---|
| Covariance | Static | Dynamic | Static | Dynamic | Static | Dynamic | |
| Avg. return (Y) | 11.36 % | 11.41 % | 11.29 % | 11.37 % | 9.98 % | 10.09 % | 10.35 % |
| Avg. excess ret. (Y) | 1.01 % | 1.07 % | 0.94 % | 1.02 % | -0.37 % | -0.26 % | n.a. |
| St. Dev. (M) | 4.14 % | 4.14 % | 4.24 % | 4.24 % | 4.01 % | 4.01 % | 4.29 % |
| Sharpe Ratio (M) | 0.217 | 0.218 | 0.211 | 0.213 | 0.198 | 0.200 | 0.192 |
| Info Ratio | 0.549 | 0.593 | 0.571 | 0.621 | -0.21 | -0.157 | n.a. |
| Turnover (M) | 4.44 % | 4.27 % | 3.46 % | 3.34 % | 3.75 % | 4.45 % | n.a. |
| Max Drawdown | -46.22 % | -46.15 % | -46.71 % | -46.43 % | -47.34 % | -47.19 % | -50.91 % |
| Avg. Drawdown | -5.84 % | -5.84 % | -6.05 % | -6.22 % | -5.74 % | -5.78 % | -6.41 % |

The default model, Sharpe-optimised model utilising dynamic covariance, improves benchmark performance through multiple metrics, and overall does seem like a significant enough improvement over the benchmark, S&P 500. Monthly Sharpe-ratio improves from 0.192 to 0.218, which is not huge in itself, but represents improvements in both returns, and volatility. On a monthly basis, the excess return improves by just 0.08%, but this amounts to a meaningful improvement annually. Annualized returns improve by over a whole percentage point against the S&P 500.

Monthly standard deviation also experiences a slight decrease, but as is visible, decreasing volatility seems difficult, which is also visible in the minimum variance portfolios. Overall, the portfolio is able to deliver improved risk-adjusted returns. Drawdowns are limited slightly, as the portfolio is able to somewhat prepare for downturns, with the largest downturn (between

2008 and 2009) over the period limited by over 4.5 percentage points, and the average drawdown limited by over 0.5 percentage points.

From the perspective of an enhanced index, or any semi-active manager, the information ratio forms an important benchmark of performance, as deviation from benchmark needs to be compensated. The portfolio has an average weekly information ratio of 0.593, beating the generally considered limit for acceptable trade-off at 0.5. Another important aspect is the monthly turnover, as continuous high turnover may translate to arduous workload on top of the already built-in transaction costs. The portfolio has a reasonable monthly average turnover of 4.27%. With a 20-basis point transaction cost, this translates to average monthly transaction costs (which are built into the other performance metrics) of 0.0085% of the portfolio value, which is fairly negligible.

The portfolio provides significant improvement over the benchmark over the optimisation period, between 1.2.2004-31.5.2023, beating the benchmark by 121 percentage points. The cumulative performance is visible in Figure 10. Performance is not consistent, and the portfolio is naturally very highly correlated with the S&P 500. Overperformance is still persistent, in that the overall performance is not dependent on individual good periods, but outperformance is more so the average behaviour of the portfolio. This is visible in the relevant difference in average annualized returns (which are calculated based on average monthly returns). This nature of the overperformance is also visible in Figure 11, highlighting the annual cumulative performance of the portfolio. A table of the yearly performance of the different models is also visible in Table 10. Yearly results should be taken with a grain of salt, as years are an arbitrary cutoff point, and the observed period only contains a handful of years, 19 years to be exact, but they do contain some information on the consistency of performance.

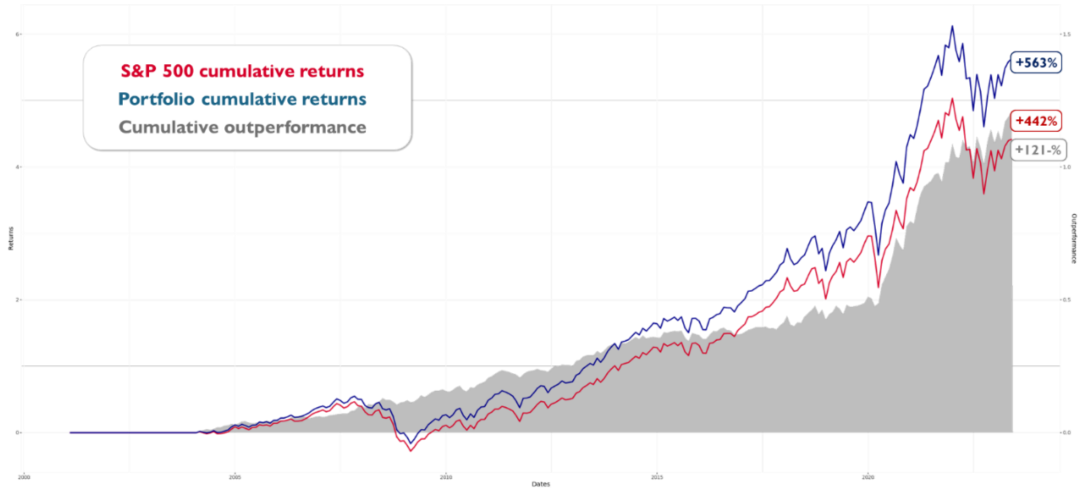


*Figure 10: Cumulative returns of Sharpe-optimised dynamic covariance portfolio, S&P 500 between, and excess cumulative returns between 1.2.2004 and 31.5.2023.*

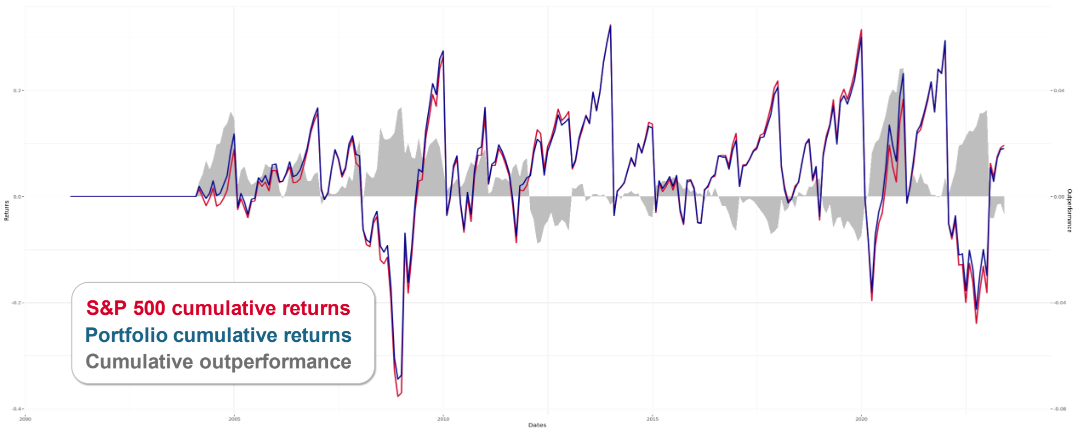


*Figure 11: Yearly cumulative returns of Sharpe-optimised dynamic covariance portfolio, S&P 500, and annual excess cumulative returns between 1.2.2004 and 31.5.2023. Cumulative returns nullified at the start of each year. Outperformance on 5x scale compared to portfolio and benchmark returns.*

*Table 10: US model yearly performance between 2004-2022. Benchmark used is S&P 500. Win ratio denotes the portion of years where portfolio beat the benchmark. Mean win and mean loss denote average return where portfolio beat and lost to benchmark respectively. Excess if BM< 0 denotes average excess return in years where benchmark had negative returns, and Excess if BM > 0 the opposite.*

| Optimisation method | Sharpe | | Return | | Min Var | |
|---|---|---|---|---|---|---|
| Covariance | Static | Dynamic | Static | Dynamic | Static | Dynamic |
| Win ratio | 68 % | 74 % | 68 % | 63 % | 32 % | 37 % |
| Mean excess | 0.97 % | 0.99 % | 0.82 % | 0.87 % | -0.36 % | -0.25 % |
| Median excess | 0.93 % | 1.05 % | 0.75 % | 0.83 % | -0.36 % | -0.36 % |
| Mean win | 1.90 % | 1.80 % | 1.67 % | 1.80 % | 1.72 % | 1.59 % |
| Mean loss | -1.05 % | -1.28 % | -1.03 % | -0.72 % | -1.32 % | -1.32 % |
| Excess if BM < 0 | 2.44 % | 2.34 % | 0.60 % | 1.03 % | 1.66 % | 1.70 % |
| Excess if BM > 0 | 0.69 % | 0.73 % | 0.86 % | 0.84 % | -0.74 % | -0.61 % |

As we can see from the annual performance of the portfolio, the portfolio outperforms the S&P 500 in most years. In addition, when the portfolio wins, it wins by more than what it loses by when it loses. So overall, the performance is fairly reliable in beating the benchmark. One attractive quality of the Sharpe-optimised portfolios is, that their outperformance increases when the benchmark is underperforming, somewhat protecting the portfolio from bear markets. This result is expected, as both Sauer (2019) and Molchanov & Stangl (2023) find sector rotation to perform best during bear markets. This is also visible looking at the yearly cumulative performance, as periods of both the 2009 financial crisis and the Covid crisis in 2020 showcase strong returns for the portfolio.

One clear weakness of the default portfolio (also holds for the other portfolios) is visible when looking at the annual cumulative results, as the portfolio has a poor period between 2012 and 2020, which is certainly a sustained period of poor performance. This does raise some worries on the reliability of sector rotational performance, but somewhat mitigating these worries, the underperformance over the period is small in magnitude when compared to winning periods.

When comparing the models, the impact of utilizing regime-enhanced covariance seems minimal, apart from improvements in information ratios, and thus return data seems to be heavily driving the optimisation after all. This could partially be due to the small number of observations, as monthly data is used, and building regime-specific covariances effectively divides the observations by four (as there are four regimes). In addition, in calculation of regime-based sector characteristics, months which are strongly classified as certain regime are weighted the same as months which are weakly classified. This same limitation also applies to regime return data. To improve on the limitation, weighting in calculation of these metrics could in the future be done based on strength of classification, to create better portrayals of regime-specific characteristics. The impact of regime-based covariance is most pronounced with variance minimizing optimisation, which is natural, as optimisation is then fully based around variance and covariance.

Return-optimised portfolios also outperform the benchmark, and in many ways exhibit very similar performance to the Sharpe-optimised portfolios. The return-optimised portfolios seemingly perform slightly more in line with the benchmark than Sharpe-portfolios. Somewhat surprisingly, returns are weaker, which could be explained by the ability of the Sharpe-optimised portfolio to handle shocks slightly better (visible for example in drawdowns). The Sharpe-ratio is slightly worse, as is the volatility (although volatility is still reduced in comparison to benchmark). The return-optimised portfolios boast the highest information ratios out of the models, with the dynamic covariance version having an information ratio of 0.621. Monthly turnovers are very much in line with the Sharpe-optimised portfolios, albeit slightly decreased.

Minimum variance portfolios perform significantly worse than the other portfolios, and it's hard to perceive the decrease in volatility to compensate for the other, weak metrics. The portfolio returns are below the S&P 500. Sharpe-ratio of the portfolios is still slightly improved over the benchmark, but information ratios are naturally negative, as excess returns are as well. Overall, the weak performance of the min-var portfolios is surprising, as for example Chong et. al. (2015) find the best risk-adjusted performance with min-var optimisation. Contradictory to their findings, in this model, it seems that minimising variance overall does not significantly prepare the portfolio for market downturns and shocks.

On a yearly performance basis, the minimum variance portfolios are once again clearly the worst performers. They do perform well when the benchmark is underperforming, but even in bear market years, Sharpe-optimised portfolios perform generally better. Sharpe-optimised portfolios slightly outperform the return-optimised ones, but they also have slightly worse losing years. The overperformance for return-optimised portfolios is less dependent on the benchmark performance, but this is not necessarily desired, as then the portfolio is less protected against bear markets, compared to the Sharpe-portfolios.

Next, the same performance metrics are observed with European data to potentially provide additional evidence of the model in an alternate setting. Worse performance against the benchmark than in the US would generally be expected, as the regime-data does not cover the whole region. The regime-data is Germany-based, while the benchmark consists of multiple European countries. In contrast, the regime-data used for USA is USA-specific. The main performance metrics with European data are visible in Table 11.

Overall, the European models perform slightly worse than the US ones, but improvements over the benchmark are still clear. The Sharpe-optimised model utilising dynamic covariance outperforms the MSCI Europe Large Cap annually by 0.69%, compared to the 1.07% excess return observed with the S&P 500. The absolute returns are naturally significantly lower than in the US due to the return differences in the benchmarks, with S&P 500 providing higher returns over the observed period. The cumulative performance of the default model and the benchmark, MSCI Europe Large Cap, is visible in Figure 12, where we can see the portfolio beating the benchmark cumulatively by 68 percentage points between 01.09.2003-30.11.2023. During the period, the portfolio and the MSCI index generated returns of approximately 398% and 330% respectively.

*Table 11: Europe model performance between 01.09.2003 and 30.11.2023. Y Denotes annualized values, M denotes monthly values. Excess return defined as average annualized return over the benchmark. Turnover defined as average proportion of portfolio being traded in or out monthly. Drawdown defined as lowest point fall from last peak.*

| Optimisation method | Sharpe | | Return | | Min Var | | MSCI L. Cap Europe |
|---|---|---|---|---|---|---|---|
| Covariance | Static | Dynamic | Static | Dynamic | Static | Dynamic | |
| Avg. return (Y) | 9.39 % | 9.35 % | 9.32 % | 9.45 % | 8.71 % | 8.61 % | 8.66 % |
| Avg. excess ret. (Y) | 0.73 % | 0.69 % | 0.66 % | 0.79 % | 0.05 % | -0.05 % | n.a. |
| St. Dev. (M) | 3.97 % | 3.96 % | 4.02 % | 4.02 % | 3.84 % | 3.83 % | 4.15 % |
| Sharpe Ratio (M) | 0.189 | 0.189 | 0.185 | 0.188 | 0.182 | 0.180 | 0.167 |
| Info Ratio | 0.420 | 0.400 | 0.402 | 0.499 | 0.001 | -0.053 | n.a. |
| Turnover (M) | 4.39 % | 4.35 % | 3.91 % | 3.86 % | 3.78 % | 4.17 % | n.a. |
| Max Drawdown | -48.82 % | -48.65 % | -49.27 % | -48.86 % | -49.09 % | -49.06 % | -53.21 % |
| Avg. Drawdown | -5.82 % | -5.69 % | -6.35 % | -5.97 % | -5.99 % | -6.19 % | -7.17 % |


*Figure 12: Cumulative returns of Sharpe-optimised dynamic covariance portfolio, MSCI Europe L. Cap index, and excess cumulative returns between 01.09.2003 and 30.11.2023.*

Very similar behaviour to the US can be observed despite the worse performance. Sharpe-ratio improvements are very similar in magnitude across the models. The turnover of the models is also very close to what was observed with the US portfolios. The information ratio achieved in Europe is not quite as high, which is expected seeing the lower excess returns. The biggest visible positive compared to the US is the improvement in drawdowns, which is significantly more muted in the US.

Differences between models don't highlight anything peculiar either when compared to the US. Once again, dynamic and static covariance have marginal effects on model performance. Optimisation targets seem to produce a very similar set of differences between performance metrics as in the US, albeit with some small deviations. The return-optimised portfolios are about par on returns with the Sharpe-optimised portfolios, and have slightly higher volatility, leading to very similar Sharpe's as those of the Sharpe-optimised portfolios. Minimum variance portfolios perform about at par with the benchmark, and somewhat reduce volatility, by approximately 0.3% for both the static and dynamic covariance variants, but interestingly are not standouts at reducing drawdowns.

The yearly performance of the European models is visible in Table 12 and the yearly cumulative performance is visible in Figure 13 below. Yearly results in Europe are mostly very similar in nature to what is observed in the US. The model is somewhat less reliable, having lower win ratios. Still, the Sharpe-, and return-optimised portfolios do beat the benchmark on average, and they win by more than what they lose by. In Europe, returns are seemingly even more reliant on bracing against bear markets, with the return of the Sharpe portfolios being negligible when the benchmark has positive returns, and the return-optimised portfolios also giving much smaller excess returns than on average. The European Sharpe-optimised dynamic-covariance portfolio does not have a similar sustained period of poor underperformance, but the good and bad years are much more sporadic. The same strong performance observed in the US during the financial crisis and Covid crisis is observable in Europe as well.

In summary, the model seems to improve portfolio returns throughout the various performance metrics, and even though many of the individual metrics are not improved that much, the overall improvement is noteworthy. Returns are improved by around 1 percentage point in the US, and this improvement is robust, albeit smaller in Europe. The sector rotation model also does not seem to have major drawbacks, apart from the unavoidable portfolio turnover, which is also generally negligible during the observed period. The portfolios are not completely consistent in beating the benchmark, but they do showcase reliable behaviour, in that they beat the benchmark in most years, and winning years win by more than losing years lose by. Importantly, the model provides additional protection against bear markets, outperforming especially in poor years, and limiting drawdowns. The observed period is limited in the number of equity market crises to just two, the financial crisis and the Covid crisis, limiting also the potential to draw strong conclusions, but good performance is observed through both. Thus, the model can be perceived to limit downside risk beyond the straight-forward volatility reduction. A point of worry is the period of poor performance observed in the US between 2012 and 2020, but the observed underperformance is small in magnitude compared to the outperformance in other periods.

*Table 12: Europe model yearly performance between 2004-2022. Benchmark used is MSCI Europe Large Cap index. Win ratio denotes the portion of years where portfolio beat benchmark. Mean win and mean loss denote average return where portfolio beat and lost to benchmark respectively. Excess if BM< 0 denotes average excess return in years where benchmark had negative returns, and Excess if BM > 0 the opposite.*

| Optimisation method | Sharpe | | Return | | Min Var | |
|---|---|---|---|---|---|---|
| Covariance | Static | Dynamic | Static | Dynamic | Static | Dynamic |
| Win ratio | 63 % | 58 % | 68 % | 74 % | 47 % | 47 % |
| Mean excess | 0.67 % | 0.63 % | 0.62 % | 0.78 % | 0.03 % | -0.10 % |
| Median excess | 0.43 % | 0.43 % | 0.64 % | 0.11 % | -0.23 % | -0.60 % |
| Mean win | 1.57 % | 1.65 % | 1.39 % | 1.38 % | 1.74 % | 1.58 % |
| Mean loss | -0.87 % | -0.78 % | -1.04 % | -0.92 % | -1.51 % | -1.61 % |
| Excess if BM < 0 | 2.23 % | 2.30 % | 1.26 % | 1.37 % | 1.93 % | 1.99 % |
| Excess if BM > 0 | 0.11 % | 0.03 % | 0.39 % | 0.57 % | -0.65 % | -0.84 % |

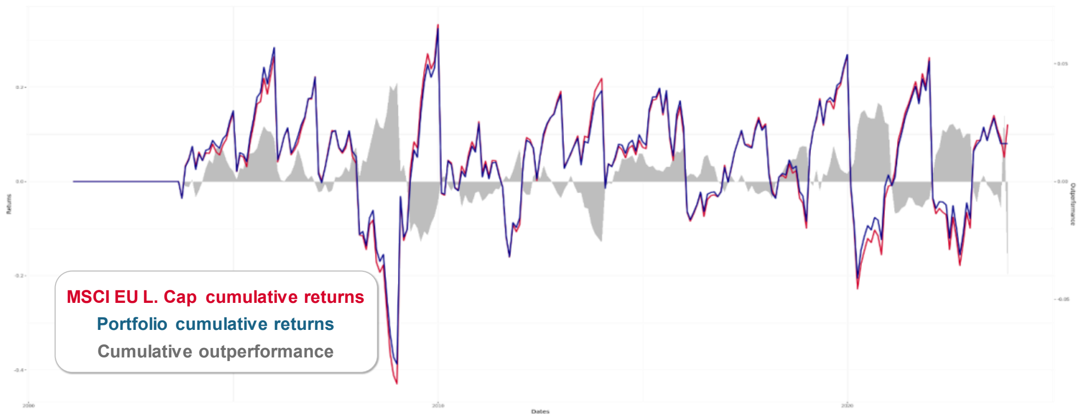


*Figure 13: Yearly cumulative returns of Sharpe-optimised dynamic covariance portfolio, MSCI Europe Large Cap, and annual excess cumulative returns between 2004 and 2022. Cumulative returns nullified at the start of each year. Outperformance on 5x scale compared to portfolio and benchmark returns.*

### 4.2.2 Comparison to non-regime optimisation

As a first robustness check of model performance, the S&P 500 is optimised with the same optimisation metrics and logics as with the regime model, but regime information is excluded from the process. This is to simply make sure that potential performance enhancements observed with the regime model are due to the regime optimisation, and not simply due to Sharpe- or return-optimising the portfolio. As the index itself is not optimised, these optimisations could potentially provide excess performance and improvements on the benchmark itself. Optimisation here is performed based on past returns, as with the regime optimisation, but without regime weighting, i.e., expected return of a sector is simply the average historical return over the observed period.

The performance of the portfolios optimised without the regime-enrichment of sector characteristics is visible below in Table 13. As is visible, the optimised portfolios improve on the benchmark only very slightly. The Min Var-portfolio naturally acts exactly similarly to the static covariance-based regime-model. Both return-optimised and Sharpe-optimised portfolios manage to improve the Sharpe-ratio in comparison to the benchmark, but improvements are very muted. In addition, the Sharpe-optimised portfolio weakens returns in comparison to S&P, whereas the return-optimised portfolio manages annual excess returns of 0.33%, which then also comes with the downside of only very slightly limiting volatility and drawdowns. The information ratio for the return-optimised portfolio is also relatively weak at 0.183. One benefit of the non-regime optimised portfolios is the lower monthly turnover, sitting at 3.36% and 2.26% for the Sharpe- and return-optimised portfolios respectively. Still, as previously discussed, the effect of the turnover on transaction costs is minimal, and as also observable, the lower turnover does not necessarily transfer to higher returns. All in all, it’s safe to say that the enhanced performance of the regime model is not attributable to simply conventionally optimising the S&P 500.

*Table 13: US non-regime optimised model and S&P 500 performance between 1.2.2004 and 31.5.2023.*

| Optimisation method | Sharpe | Return | Min Var | S&P 500 |
|---|---|---|---|---|
| Avg. return (Y) | 10.30 % | 10.67 % | 9.98 % | 10.35 % |
| Avg. excess ret. (Y) | -0.04 % | 0.33 % | -0.37 % | n.a. |
| St. Dev. (M) | 4.11 % | 4.24 % | 4.01 % | 4.29 % |
| Sharpe Ratio (M) | 0.200 | 0.200 | 0.198 | 0.192 |
| Info Ratio | -0.053 | 0.183 | -0.208 | n.a. |
| Turnover (M) | 3.36 % | 2.26 % | 3.75 % | n.a. |
| Max Drawdown | -48.07 % | -48.66 % | -47.34 % | -50.91 % |
| Avg. Drawdown | -5.68 % | -6.05 % | -5.74 % | -6.41 % |

### 4.2.3 Portfolio composition and deviation

The composition of the optimised portfolios is studied to understand how, and through which sectors the model attempts to improve performance. The composition analysis is done in the US, comparing the sectoral deviation to the benchmark overall and through the identified regimes. This is done with all the three optimisation methods, all utilizing dynamic covariance. In addition, the non-regime optimised Sharpe-portfolio is studied to see the impact of enriching optimisation with regime probabilities. The Sharpe-optimised portfolio composition analysis, as in the average sectoral deviation from the benchmark, is visible below, in Table 14. The analysis for the return-, and minimum variance optimised portfolios are visible in the appendix, in Appendix 4 and 5 respectively. The corresponding overall sectoral deviations for the non-regime optimised portfolios are visible as well in Appendix 6 to provide a point of comparison. It's important to note here that the total deviations may not add to 0% due to the deviation for the Real Estate sector calculated only after its introduction to the S&P 500 index, in October 2016.

*Table 14: Average sectoral deviation overall and in the CLI-based regimes of the US Sharpe-optimised portfolio utilizing dynamic covariance. Deviations calculated based on monthly weights against benchmark, S&P 500. Note: total deviations may not sum to 0% due to Real Estate sector deviations only calculated from October 2016 forward.*

| | Expansion | Slowdown | Downturn | Recovery | Overall |
|---|---|---|---|---|---|
| Enrg | 3.65 % | 3.69 % | 2.32 % | 2.20 % | 3.05 % |
| Mtrls | 0.99 % | 1.20 % | 0.67 % | 1.12 % | 1.01 % |
| Indu | 1.36 % | -0.10 % | -3.25 % | -2.92 % | -1.16 % |
| ConsD | -0.41 % | 0.42 % | 2.38 % | 3.37 % | 1.32 % |
| ConsS | 3.89 % | 3.48 % | 3.52 % | 3.52 % | 3.58 % |
| Hlth | -1.48 % | 0.06 % | 4.37 % | 1.71 % | 1.19 % |
| Fncl | -2.20 % | -3.57 % | -4.78 % | -1.97 % | -3.32 % |
| IT | -4.97 % | -4.99 % | -2.53 % | -3.54 % | -4.07 % |
| Comms | -0.98 % | -0.70 % | -2.22 % | -2.11 % | -1.42 % |
| Util | 0.30 % | 0.59 % | 0.09 % | -0.58 % | 0.19 % |
| ReEst | -1.02 % | -1.05 % | -1.12 % | -1.11 % | -1.09 % |

When trying to understand the deviations, a few things are important to keep in mind. First, the fact that Recoveries happen out of Downturns, with high probabilities often coexisting for both, and that the sector performance in both is generally flipped. This same logic of probabilities coexisting does also apply to all the regimes. Second, when, for example in Downturns, the model deviates away from sectors, this has to flow into the others. Thus, even if a sector has poor performance in a certain regime, it may gain weight due to relatively higher returns or lower variance compared to the others. Third, there is an in-built bias to weight away from large sectors and towards small sectors when considering covariance, as this would automatically increase diversification. Similarly, due to the differences in neutral weights of the sectors, a similar deviation may be a relatively small deviation to a large sector, like IT, but a large deviation for a small sector. Additionally, as active risk constraints, sector deviations are capped at 40% of neutral weight, forcing a limit on some sectors.

The weightings mostly follow the logic of the previously observed sectoral performance metrics through the regimes. With the Sharpe-optimised portfolio, overweight sectors are mostly overweight through regimes as well, and the same applies for underweight sectors. This is true for the return-optimised and minimum variance-optimised portfolios as well. Thus, there is a somewhat clear split between which sectors are overall over-, and underweighted, with IT and Financials being the least desirable for the model, and Consumer Staples and Energy being weighted towards the most. Materials seems to be considered a generally good sector to keep, and the ~1% overweight is significant, given its small, nowadays ~2.5%, weight in the benchmark, with the opposite being true for the Real Estate-sector (where the 1% is fairly close to their maximum allowed deviation due to the sectoral relative active risk constraint). Cyclicality in weighting is most pronounced in Health Care and Industrials, where the model places more weight countercyclically into Health Care and cyclically into Industrials. Financials are also clearly curtailed in Downturns, even further from their general underweighting.

The notable anomalies in the composition are IT, Consumer Discretionary. The IT sector is underweighted despite its very strong performance over the period, and it underweighted less in Downturns. The speculative reasoning for this is as follows: firstly, the overall high weight of the sector likely leads the model to deviate away from it as a means of diversification to improve portfolio variance. Secondly, even though the sector acts somewhat cyclically in Downturns, it may be a recipient of the outflows from other sectors due to relatively alright returns. Consumer Discretionary is tilted towards in Downturns (and Recoveries), which is surprising given its cyclical nature. This might perhaps be due to the Downturn/Recovery probability coexistence, as the sectors that generally perform better in Recoveries are also much weaker in Downturns.

The return-optimised and minimum variance-optimised portfolios don't contain any significant surprises in comparison to the Sharpe-optimised one. For both, the sectors they overall over/underweight, they also generally do as well through the regimes. The return-optimised portfolio somewhat increases weights, relative to the Sharpe-portfolio, into some of the more cyclical sectors (Financials, IT, Industrials) to capture their higher returns) and away from some of the defensive sectors (Consumer Staples, Health Care, Utilities). The minimum variance-portfolio on the other hand clearly weights defensive sectors, especially Health Care and Consumer Staples, more heavily throughout regimes, which is expected. The only sector with a beta over 1 that is overweighted is Energy.

Finally, comparing to the non-regime optimised portfolios, the sectors are mostly weighted somewhat close to the overall weightings of corresponding regime-optimised portfolios. This is a natural result, larger differences might be visible through regimes, but this is somewhat redundant as a separate analysis, as the non-regime models don't take the regimes into account.

### 4.2.4 Active risk and portfolio performance

As active risk is an important aspect of enhanced indexing, and institutional investors have varying levels of acceptable active risk, the effects of different active risk levels are tested. This is done through changing the total active risk limit of the portfolio. As previously mentioned, the default parameters are as follows: total active risk (sum of the absolute weigh tilts in the portfolio) is 40%, absolute sector tilt is capped at 5% of portfolio weight, and relative sector tilt is capped at 40% of the weight of the sector in the portfolio. As also previously mentioned, the two-fold sector limiting is done to avoid both tilting purely through tilting larger sectors (through the absolute limit) and avoid completely tilting smaller sector away (through the relative limit). To keep the risk limitations consistent, and avoid concentration into certain sectors, the sector-level tilting parameters are scaled based on the active risk. In other words, if the active-risk limit is decreased by a quarter to 30%, then the relative and absolute sector tilt limits are also decreased by a quarter.

The default model, i.e. Sharpe-optimised model utilising dynamic covariances, is optimised with varying active risk levels, using 5 percentage point increments. The results are visible below in Table 15. As is visible in the table, the performance metrics scale consistently in line with the scaling of the active risk, with slightly larger changes when decreasing active risk. For example, a 10% decrease in active risk from the default level leads to a 0.28% decrease in annualized return, while a 10% increase in active risk leads to a 0.23% increase in annualized return. Information ratios stay mostly consistent through these smaller adjustments, but interestingly the default limit carries the highest information ratio, albeit very slightly. Finding an optimal level of active risk for the model is not a goal in this paper, but it does seem that increasing the active risk comes with somewhat diminishing enhancements. To summarise, the portfolio behaves very much in line with changes to active risk limits, with returns, volatility, drawdowns, and turnover scaling along with limits to tilting. This is an attractive quality showcasing flexibility, as it allows active investors to scale according to their personal active risk preferences.

*Table 15: Active risk and sector rotation portfolio performance. Portfolio is Sharpe-optimised, utilising dynamic covariance, with varying levels of acceptable active risk. Sector tilting limits scaled along with total active risk limit.*

| Model used | Sharpe-optimised, Dynamic Covariance | | | | | S&P 500 |
|---|---|---|---|---|---|---|
| Active risk limit | 30% | 35% | 40% | 45% | 50% | |
| Avg. return (Y) | 11.13 % | 11.28 % | 11.41 % | 11.54 % | 11.64 % | 10.35 % |
| Avg. excess ret. (Y) | 0.79 % | 0.93 % | 1.07 % | 1.19 % | 1.30 % | Na. |
| St. Dev. (M) | 4.18 % | 4.16 % | 4.14 % | 4.13 % | 4.12 % | 4.29 % |
| Sharpe Ratio (M) | 0.211 | 0.215 | 0.218 | 0.221 | 0.224 | 0.192 |
| Info Ratio | 0.582 | 0.589 | 0.593 | 0.584 | 0.574 | Na. |
| Turnover (M) | 3.79 % | 4.02 % | 4.27 % | 4.49 % | 4.77 % | Na. |
| Max Drawdown | -47.33 % | -46.74 % | -46.15 % | -45.54 % | -44.95 % | -50.91 % |
| Avg. Drawdown | -6.12 % | -6.06 % | -5.84 % | -5.79 % | -5.76 % | -6.41 % |

### 4.2.5 Portfolio performance analysis

To understand the characteristics and applicability of the sector rotation model better, its vital to understand what drives the returns of the portfolio, and in what scenarios does it perform. This is analysed through multiple simple analyses, mainly focusing on what variables are found to correlate with the excess return of the portfolio, and what sectors are driving the difference. In addition, how the portfolio behaves over time will be looked at.

First, the behaviour of the model through different regimes, and other variables defining the environment is looked at. The returns and excess returns through the regimes for the models with different optimisation metrics is visible below in Table 16. All of the models here utilize dynamic regime-based covariance.

*Table 16: Regime performance as monthly returns of portfolio and excess returns against benchmark in the US through the regimes. Benchmark used is S&P 500. Regimes defined based on level and change of CLI.*

*Significance levels:* $\wedge = 0.1,\ * = 0.05,\ ** = 0.01,\ *** = 0.001$

| Model | Sharpe, Dyn. | | Return, Dyn. | | Min Var, Dyn. | |
|---|---|---|---|---|---|---|
| | Return | Vs. BM | Return | Vs. BM | Return | Vs. BM |
| Recovery | 2.06 %** | -0.02 %* | 2.12 %** | 0.04 %^ | 1.93 %** | -0.16 %^ |
| Expansion | 1.33 %* | 0.05 % | 1.34 %* | 0.06 % | 1.24 %* | -0.04 % |
| Slowdown | 0.99 %· | 0.10 % | 0.94 %* | 0.05 % | 0.94 %* | 0.05 % |
| Downturn | -0.35 %* | 0.16 %** | -0.34 %* | 0.16 % | -0.50 %* | 0.00 % |

Returns clearly differ between regimes, with returns unsurprisingly being the weakest in Downturn-months and the strongest in Recovery-months. The difference between average returns in Downturns and Recoveries is at least 2.40 % for all the portfolios, which would annually translate to about 33% in return differential between the regimes, a huge difference. At the same time, outperformance of the portfolio is most enhanced in Downturns, except surprisingly for the Min Var portfolio. The Sharpe- and Return-optimised portfolios also outperform in Expansions and Slowdowns, but this outperformance is not significant. The only regime where the Sharpe-portfolio underperforms the S&P 500 is the Recovery regime, whereas the Return-portfolio on average achieves modest outperformance of 0.04 %. Thus, the Return-portfolio actually has positive excess returns in all regimes, but in turn has lower excess returns in Slowdowns compared to the Sharpe-portfolio. Also, the profile of the Return-portfolio outperforms most in Downturns, which is surprising, as expectations would have it geared for more high-returning, but also riskier assets.

The portfolios are clearly geared towards performing relatively better in bear markets, but this is not enough to make these periods desirable. Rather, the portfolio offers some consolation relative to the benchmark for when markets are performing poorly. This is consistent to the results observed with sector rotation by Sauer (2019), Conover et.al. (2008), and Molchanov and Stangl (2023), but also in other regime-based equity allocation strategies, as the study by Blin et. al. (2020), as portfolio improvements were either most pronounced, or even mainly driven by contractionary periods, where the overall market is performing worse.

The weakest performance of the portfolio is observed through Recoveries, which is a slight surprise due to the strong cyclical and countercyclical performance and variation of sector performances observed in the regime, as mentioned in Section 4.1, which would theoretically allow for more potential in optimisation and reallocation. Identifying the exact reasoning for this is difficult, but it could be explained by a two-fold process. First, the assets that outperform in recoveries are very different from the ones to outperform in downturns, in fact asset performances are almost flipped. Second, recoveries happen out of downturns, and the exact timing of the turn is hard. Thus, the probability of a downturn continuing is always relatively high before a recovery. Overall, this means that the model will also often allocate to assets that do not do well in recoveries when recoveries are coming up. In addition, perhaps the generally strong returns of the benchmark in Recoveries also makes it harder to beat, but this is completely speculative.

Next, a few variables are looked into to understand more on the performance of the portfolio, with the results visible in Table 17. The level of CLI and the monthly change of CLI are looked at, as well as the volatility of the benchmark in the previous month and the corresponding month. The rationale for studying volatility is straightforward; in volatile times, the markets are generally either moving to a direction, or uncertainty is increasing. In theory, both of these scenarios could give the model room to improve on the benchmark, especially if the movement of the market is down, as observed with the regime-based returns. In addition, the returns of the benchmark, S&P 500, for the corresponding and previous month are also used as variables. The analysis is done based on a simple linear regression using R, with all the variables analysed separately.

*Table 17: CLI, CLI monthly change, volatility, and benchmark return effects on monthly returns of portfolio and excess returns against benchmark in the US, tested separately. CLI has been normalized by subtracting 100 from all values. Effect is deviation from overall average return and average excess return of portfolio. Benchmark used is S&P 500. Volatility of previous and current month calculated based on daily returns of S&P 500.*

*Significance levels:* $\hat{} = 0.1,\ * = 0.05,\ ** = 0.01,\ *** = 0.001$

| Model | Sharpe, D | | Return, D | | Min Var, D | |
|---|---|---|---|---|---|---|
| | Return | Vs. BM | Return | Vs. BM | Return | Vs. BM |
| CLI | -0.0001 | 0.0000 | -0.0001 | -0.0001 | 0.0002 | 0.0002* |
| CLI Change | 0.0205** | -0.0018** | 0.0208** | -0.0015* | 0.0208** | -0.0015^ |
| Volatility (Prev M) | 2.4822 | 3.6874*** | 2.2232 | 3.4284*** | 0.8578 | 2.0630 |
| Volatility (Cur. M) | -67.4643*** | 6.2092*** | -68.4569*** | 5.2167*** | -68.2096*** | 5.4370*** |
| Benchmark (Prev M) | -0.0128 | -0.0134* | -0.0116 | -0.0122* | -0.0104 | -0.0110 |
| Benchmark (Cur. M) | 0.9633*** | -0.0368*** | 0.9856*** | -0.0144** | 0.9318*** | -0.0682*** |

It’s clear from the results that the level of CLI itself is not a great predictor of model performance. The change of CLI however is significant, and increasing CLI connects to better returns, but also weaker performance relative to the benchmark. Decreases in CLI on the other hand are correlated with outperformance over the benchmark. These results are expected based on the regime-based returns, as the best performing regimes, Slowdowns and Downturns, are both characterized by negative monthly CLI changes, whereas the only underperforming regime, Recovery, is characterized by an increase in CLI.

Higher volatility in the current month decreases returns overall but seems to provide the model possibilities to outperform, and this also holds true for higher observed volatility in the past month. This is interesting, as this might provide a future possibility of utilising past volatility to further aid the model in optimisation or for use-case rulesets. The correlation between the volatility and excess returns may simply be due to higher volatility in bear markets, but it may also partially represent uncertainty in the market and the economy, which then the model may be able to capitalize on. Defining what part the uncertainty plays in the outperformance is challenging, though.

Finally, benchmark returns unsurprisingly explain returns of the portfolios very well, and in addition higher returns of the benchmark seem to correlate with worse excess return performance for the portfolios. This is unsurprising, as the model seemingly on average pivots the portfolio into a slightly more defensive shape, as witnessed by returns in different regimes observed earlier in this paper. Benchmark returns of the previous month are on the other hand not generally linked to portfolio returns or excess returns (apart from the return-optimised portfolio and its excess returns).

#### 4.2.6 One-regime optimisation results

The last analysis to help understand the inner workings of the optimisation is overseeing the returns of portfolios which have been specifically optimised for one of the four regimes. This is done by simply setting the probability of the specific regime to 100% throughout the optimisation period. Optimisation is done utilizing the Sharpe-optimised model with dynamic covariance (i.e., covariance in just the specific regime). The performance of the four regime-specific models through regimes are visible below in Table 18.

*Table 18: Monthly returns and excess returns against benchmark through the four regimes of portfolios optimised for specific regimes between 1.2.2004-31.5.2023. Portfolios are Sharpe-optimised and utilize dynamic regime covariance. Benchmark is S&P 500. Regime returns corresponding to the portfolio optimised for marked in bold.*

| Model | Recovery | | Expansion | | Slowdown | | Downturn | |
|---|---|---|---|---|---|---|---|---|
| | Return | Vs. BM | Return | Vs. BM | Return | Vs. BM | Return | Vs. BM |
| Recovery | **2.04 %** | **-0.05 %** | 2.02 % | -0.06 % | 1.91 % | -0.18 % | 2.13 % | 0.05 % |
| Expansion | 1.29 % | 0.01 % | **1.33 %** | **0.04 %** | 1.28 % | 0.00 % | 1.27 % | -0.02 % |
| Slowdown | 0.87 % | -0.02 % | 0.92 % | 0.03 % | **0.96 %** | **0.07 %** | 0.89 % | 0.00 % |
| Downturn | -0.57 % | -0.07 % | -0.49 % | 0.01 % | -0.47 % | 0.03 % | **-0.37 %** | **0.14 %** |
| Overall | 0.79 % | -0.03 % | 0.83 % | 0.01 % | 0.83 % | 0.00 % | 0.87 % | 0.04 % |

Unsurprisingly, none of the regime-specific portfolios manage to achieve outperformance close to the regime optimised portfolios, with only the Downturn-specific portfolio achieving somewhat relevant monthly excess returns of approximately 0.04 %. Overall, the regime-specific portfolios do behave in a very expected fashion apart from the Recovery-portfolio, which actually has very weak returns even in the Recovery-regime. This leads to the conclusion, as previously discussed, that perhaps predicting Recoveries is very difficult, as they come out of Downturns, meaning that the probability of both is likely high. Along with this, as also previously mentioned, the sectors typically performing well in the regimes differ greatly. Lastly, the innate strong returns in Recovery-regimes may simply make it difficult to beat the benchmark, but this is speculative reasoning as well.

## 4.3 Model practicality

### 4.3.1 Time sensitivity of performance

This section studies how sensitive the performance of the portfolio is to delays in either data-availability or portfolio re-allocation, i.e. how fast the information of regime expectations contained in the OECD CLI loses relevance for portfolio optimisation. This is partially studied due to the fact that the monthly OECD CLI is not necessarily always published at the beginning of a month, but a few days after. The return differences to mean excess returns of the US Sharpe-optimised dynamic covariance portfolio based on both day of month, and tercile of month, are visible below in Figure 14 and Figure 15.

As is visible, excess return variation across the month does appear, but this seems to be almost completely explainable by natural variation. The differences in daily excess returns between days and terciles of the month are miniscule, and none of the periods have a significant observable effect on portfolio excess returns. The last tercile of a month does have a negative correlation with excess daily returns, but the observed effect on daily excess returns is under -0.002%. This helps alleviate the practical worry of being able to implement new regime data and reallocate immediately at the beginning of a month, and also alleviates most of the worry regarding the timing issue contained in the OECD CLI.

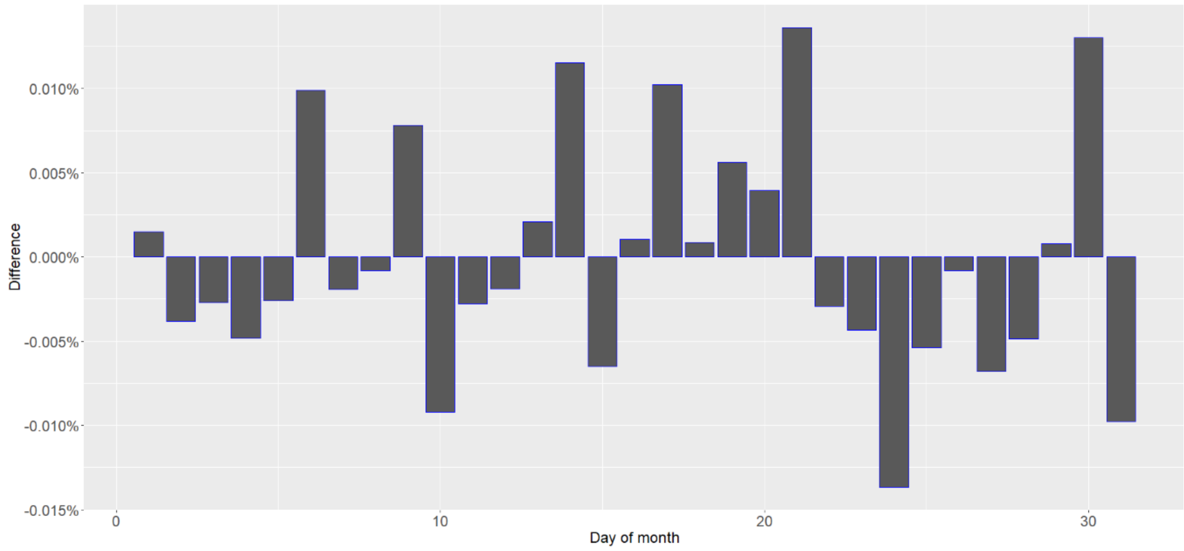


*Figure 8: Effect of day of month on US portfolio daily excess returns (against the S&P 500). Portfolio is Sharpe-optimised and utilizes dynamic covariance. X-axis is day of month, and y-axis is excess returns. Effect calculated as difference from mean excess return.*


*Figure 15: Effect of tercile of month on US portfolio excess returns (against the S&P 500). Portfolio is Sharpe-optimised and utilizes dynamic covariance. X-axis is tercile of month, and y-axis is excess returns. Effect calculated as difference from mean excess return.*

### 4.3.2 Factor exposure

This section aims to briefly examine whether the sector rotation model may provide some additional insight to institutional investors by analysing whether the performance of the portfolio is strongly linked to the more commonly used factors. If the case was such, then implementing a factor model is surely the more robust, flexible, and perhaps even more straightforward method, rendering the regime-based information less useful in actuality. This analysis is performed by simply analysing how well common factor returns explain the returns and excess returns of the model portfolios. The factors tested are Momentum, Quality, Value, Low Risk, Size, and 60-month Beta. The analysis is done utilising US factor returns and the S&P 500 Sharpe-optimised regime model portfolio with dynamic covariance.

The factors are retrieved from Global Factor Data, based on the construction by Jensen, Kelly, and Pedersen (2023). Factor returns are constructed from all US stocks larger than NYSE 20$^{th}$ percentile. The utilized returns are capped and value-weighted, meaning that stocks are value-weighted, but also the largest stocks are capped at market value to the 80$^{th}$ percentile of NYSE. Factors are constructed as high tercile minus low tercile of the observed universe. More in depth explanation of the factor construction is not covered in this paper, but the detailed explanation and formulas are available in the mentioned paper by Jensen, Kelly, and Pedersen (2023).

A brief summary of the utilised factors is contained in this section. As mentioned, all factors are constructed as returns of top tercile minus returns of the bottom tercile over the month unless otherwise specified. Momentum factor is constructed as high momentum versus low momentum, where the split is aggregated based on multiple momentum factors. Quality factor is constructed as high quality companies vs low quality companies, where quality split is aggregated based on multiple quality factors. Size factor is constructed as the smallest companies versus the largest companies, where the size split is aggregated based on multiple factors. Value factor is constructed as high value versus low value, where the value split is aggregated based on multiple value factors. Low Risk is constructed as low risk companies versus high-risk companies, where the split is aggregated based on multiple risk factors. 60-month Beta factor is constructed as lowest Beta over the past 60 months versus highest Beta over the period.

The factor return R2s and Betas in relation to portfolio returns and excess returns for the Sharpe-optimised dynamic covariance model are visible in Table 19 below. It’s important to note that the results visible are static, and in reality, when observing on a rolling basis, the Betas and R2s may look drastically different through different periods. The analysis is based on monthly returns of the model portfolio and the factor portfolios. The R2 for portfolio returns of the combined factors is 0.562, with the Low Risk and 60M Beta factors having by far the highest correlation coefficient. With excess returns, the combined R2 drops to 0.239. Momentum becomes the individual factor with the highest R2. Overall, the combined R2 shows that the majority of portfolio excess returns is not explained by these common factors, and that thus, the model does provide relevant additional information over simple factor models.

*Table 19:Factor Betas and R2s for monthly returns and excess returns of the US Sharpe-optimised portfolio utilizing dynamic covariance.*

| | Returns | | Excess Returns | |
|---|---|---|---|---|
| | Beta | R2 | Beta | R2 |
| Momentum | -0.45 | 0.08 | 0.06 | 0.19 |
| Quality | -0.84 | 0.09 | 0.08 | 0.11 |
| Size | 0.31 | 0.01 | -0.07 | 0.09 |
| Value | -0.04 | 0.00 | -0.03 | 0.04 |
| Low Risk | -1.01 | 0.40 | 0.05 | 0.11 |
| 60M Beta | -0.83 | 0.45 | 0.04 | 0.14 |
| Combined | - | 0.562 | - | 0.239 |

# 5 Conclusion

This paper constructed and studied a sector rotation model, based on monthly values of the OECD Composite Leading Indicator to quantify the expected upcoming economic regime, and utilised these expectations to optimise sector weights based on their historical performance in these regimes. The state of the economy was categorised into four regimes, Downturn, Slowdown, Recovery, and Expansion. Clear differences in regime-based behaviour were found between sectors in the US, and similar results were also obtained in Europe. The hypothesis for the study was to, firstly, identify clear differences among sector cyclicality and regime-based performance. Secondly, for the model to be able to improve on benchmark performance by enriching dynamic optimisation with sectoral regime-based characteristics and regime probabilities based on the CLI. Thirdly, and finally, this approach was expected to provide a potentially useful tool for enhanced indexing, offering something new, feasible, and not fully overlapping with conventional quantitative strategies. The first two hypotheses hold, with the third hypothesis mostly being fulfilled, albeit leaving some concerns, especially regarding consistency of the strategy.

Clear sectoral differences through the regimes were found in both the US and Europe; meaningful behavioural differences seemingly exist, with Recoveries and Downturns unsurprisingly highlighting sectoral differences by far the most clearly (apart from Europe, where larger differences were also found in Expansions). No truly countercyclical sectors, i.e. returns inverted with the cycle, could be identified, but differing levels of cyclicality were clearly present. Overall, the least cyclical sectors identified in the US were Consumer Staples, Utilities, and Healthcare, while the most cyclical sectors were Financials, Materials, Consumer Discretionary, and IT. In Europe results are otherwise similar, but IT is classified as defensive, Utilities is not quite as defensive as in the US, and Real Estate arises as a very cyclical sector.

Regime-based optimisation is observed to improve performance over the benchmark in both US and Europe over the board, at the very least for the optimisation metric in hand. Minimum variance portfolios are able to somewhat limit volatility, but otherwise they offer poor results, underperforming the benchmarks in returns. Performance enhancement is overall more pronounced in the US than Europe, with Sharpe-optimised and return-optimised portfolios both offering significant improvements over the benchmark. In the US, the Sharpe-, and return-based portfolios reach around 1% annual excess returns, whereas in Europe the excess returns hover between 0.65% and 0.80%. Both optimisation methods also manage to lower monthly volatility in both regions. Sharpe-optimised portfolios naturally improve the ratio the most, achieving somewhat small, but still relevant improvements, with return-optimised portfolios also improving on the metric. Overall, the effects of introducing regime-based dynamic covariance to portfolios improves performance, but only very slightly, with regime-based return data clearly driving the performance. The effects of transaction costs are very slight across the board, and don't materially affect annual returns due to limited portfolio turnover.

Information ratios (based on weekly data) achieved in the US for Sharpe-, and return-portfolios reach past 0.5, the generally considered limit for "good" active management performance, with the Sharpe-optimised dynamic covariance portfolio having the highest information ratio at 0.621. In Europe information ratios are more muted, but generally not too far off the 0.5 limit. The performance improvements are also robust against non-regime optimised portfolios in the US, with these portfolios not offering significant overall improvements over the benchmark.

The performance enhancements from introducing regime data are observed to arrive mostly due to bear markets, and especially in Downturns, which is expected based on previous research of such regime models. Only small excess returns are observed in Expansions, and negative excess returns observed in Recoveries, despite strong sectoral differences observed previously in the regime. The reasoning for poor performance in Recoveries seems to mostly be a case of timing and identifying the regime, as Recoveries tend to happen suddenly out of Downturns (where very different sectors perform well). Further highlighting the bear-market overperformance, volatility in the market for the corresponding and previous month, negative CLI growth, and weak benchmark returns all had a significant correlation with higher excess returns.

On the practical side, the strategy generally works well, and seems to potentially be able to provide a useful additional tool for enhanced indexing investors, but some issues and concerns do arise. Portfolio performance is fairly linear with active risk adjustments, allowing for flexibility. Simultaneously, timing issues seem mitigated, as no significant differences in excess returns were found through different periods of a month, not rendering the strategy mute in the face of issues such as immediate data-availability and execution speed of reallocation. In addition, the excess returns of the strategy are not generally well explained by the most common factors, thus potentially offering an additional way of enriching quantitative investing systems. Concerns with the regime model mainly relate to consistency of performance. Despite the modelled portfolios beating the benchmark in most years and beating it by more in winning years than it loses by in losing years, big swings exist in annual excess returns. In addition, there is a long period of stable stock market returns in the US between 2012 and 2019 where overperformance of the regime model does not exist, raising concerns for utilizing the strategy, in fear of a similar sustained period appearing in the future.

Moving forward, the model provides a clear framework to build on. For the purpose of this study, model-based decisions were kept simple and intuitive to avoid overfitting the model for the past returns, especially as sample size is relatively small. This also leaves room for more sophistication and improvement. For example, a more sophisticated method for calculating regime probabilities is a natural next step. Especially concentrating on how identify and better utilize Recovery-regimes is also natural next step due to the observed poor performance in the regime despite large sectoral differences. Finding more reliable indicators of recoveries is a point of further improvement, or perhaps even a more rule-guided approach could be taken, where potential recoveries are treated as some sort of special case. Alternatively, human guidance and insight could potentially prove helpful here to manually alter probabilities in the model.

Naturally, other measures of identifying business cycle regimes could be utilized. Although the OECD CLI is a very established indicator, it could at least potentially be combined with other indicators to further improve performance. In addition, other characteristics of sectors could be utilized, for example skew and kurtosis, to further provide additional tools for optimization. The model could also be translated to be based on daily returns, as it might reveal more intricate behavioural differences between regimes. The added utility of this, however, may be limited, as regime data is unlikely to be available at a higher frequency than monthly, limiting optimisation frequency as well. Another simple potential future avenue would be testing the framework on small-cap and mid-cap equities, as they may behave significantly

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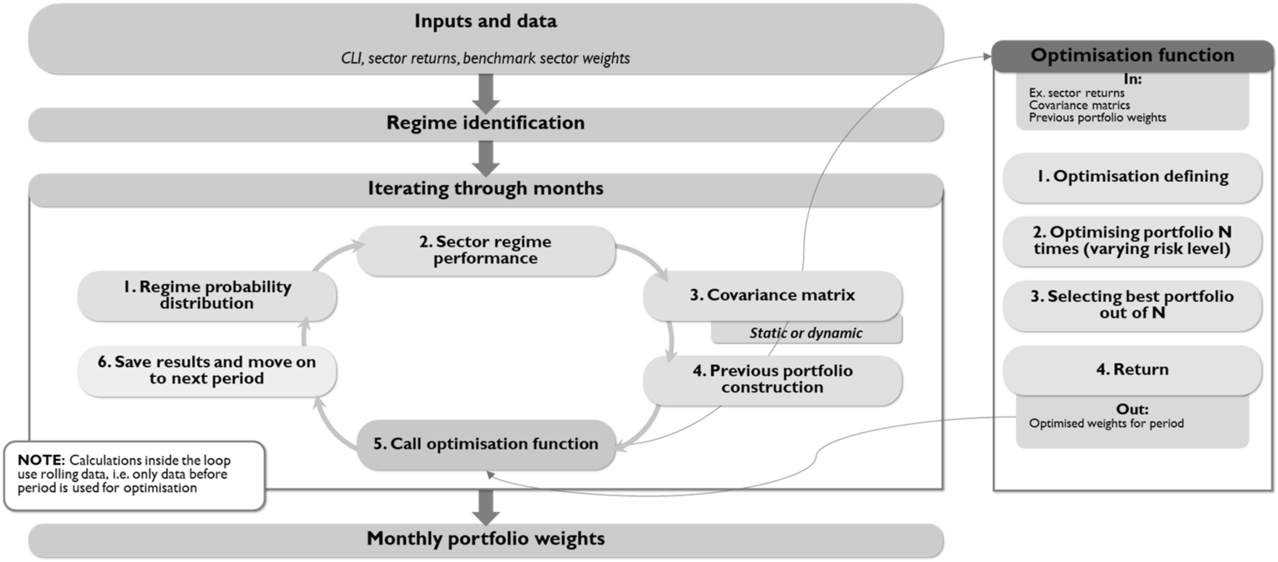
# Appendix

*Appendix 1: Descriptive illustration of model structure utilised in this paper.*



*Appendix 2: MSCI Europe Large Cap sector index monthly standard deviation by Germany CLI-defined regimes.*

| | Downturn | Expansion | Recovery | Slowdown | Overall |
|---|---|---|---|---|---|
| Enrg | 0.063 | 0.047 | 0.071 | 0.053 | 0.059 |
| Mtrls | 0.081 | 0.042 | 0.055 | 0.049 | 0.058 |
| Indu | 0.074 | 0.034 | 0.045 | 0.042 | 0.051 |
| ConsD | 0.075 | 0.036 | 0.055 | 0.049 | 0.055 |
| ConsS | 0.047 | 0.028 | 0.035 | 0.029 | 0.035 |
| Hlth | 0.041 | 0.029 | 0.037 | 0.031 | 0.035 |
| Fncl | 0.088 | 0.039 | 0.070 | 0.047 | 0.063 |
| IT | 0.077 | 0.048 | 0.057 | 0.049 | 0.059 |
| Comms | 0.046 | 0.033 | 0.039 | 0.034 | 0.039 |
| Util | 0.055 | 0.042 | 0.042 | 0.036 | 0.044 |
| ReEst | 0.081 | 0.038 | 0.062 | 0.041 | 0.058 |

*Appendix 3: MSCI Europe Large Cap sector index monthly return CAPM-beta with MSCI Europe Large Cap index by Germany CLI-defined regimes.*

| | Downturn | Expansion | Recovery | Slowdown | Overall |
|---|---|---|---|---|---|
| Enrg | 0.82 | 0.92 | 1.15 | 1.08 | 0.95 |
| Mtrls | 1.26 | 1.24 | 1.14 | 1.18 | 1.22 |
| Indu | 1.25 | 1.11 | 1.04 | 1.15 | 1.17 |
| ConsD | 1.18 | 1.11 | 1.08 | 1.20 | 1.15 |
| ConsS | 0.66 | 0.67 | 0.61 | 0.66 | 0.65 |
| Hlth | 0.53 | 0.56 | 0.61 | 0.55 | 0.55 |
| Fncl | 1.40 | 1.17 | 1.53 | 1.21 | 1.36 |
| IT | 1.24 | 1.27 | 1.03 | 1.15 | 1.17 |
| Comms | 0.63 | 0.90 | 0.81 | 0.76 | 0.74 |
| Util | 0.79 | 1.05 | 0.73 | 0.80 | 0.81 |
| ReEst | 1.23 | 0.95 | 1.08 | 0.76 | 1.09 |

*Appendix 4: Average sectoral deviation overall and in the CLI-based regimes of the US return-optimised portfolio utilizing dynamic covariance. Deviations calculated based on monthly weights against benchmark, S&P 500. Note: total deviations may not sum to 0% due to Real Estate sector deviations only calculated from October 2016 forward.*

| | Expansion | Slowdown | Downturn | Recovery | Overall |
|---|---|---|---|---|---|
| Enrg | 3.50 % | 3.55 % | 1.76 % | 1.82 % | 2.75 % |
| Mtrls | 0.97 % | 1.24 % | 0.94 % | 1.16 % | 1.09 % |
| Indu | 3.13 % | 3.65 % | -0.61 % | -1.05 % | 1.56 % |
| ConsD | -0.46 % | 1.28 % | 2.70 % | 3.49 % | 1.72 % |
| ConsS | 3.06 % | 2.33 % | 3.40 % | 2.70 % | 2.82 % |
| Hlth | -4.22 % | -4.39 % | 0.29 % | -2.10 % | -2.70 % |
| Fncl | -0.80 % | -3.09 % | -4.66 % | -0.42 % | -2.55 % |
| IT | -3.81 % | -4.13 % | -0.08 % | -1.39 % | -2.49 % |
| Comms | -0.98 % | -0.60 % | -2.23 % | -2.11 % | -1.38 % |
| Util | -0.23 % | 0.25 % | -0.91 % | -1.30 % | -0.44 % |
| ReEst | -1.03 % | -1.06 % | -1.13 % | -1.09 % | -1.10 % |

*Appendix 5: Average sectoral deviation overall and in the CLI-based regimes of the US minimum variance-optimised portfolio utilizing dynamic covariance. Deviations calculated based on monthly weights against benchmark, S&P 500. Note: total deviations may not sum to 0% due to Real Estate sector deviations only calculated from October 2016 forward.*

| | Expansion | Slowdown | Downturn | Recovery | Overall |
|---|---|---|---|---|---|
| Enrg | 2.17 % | 3.31 % | 2.89 % | 2.11 % | 2.75 % |
| Mtrls | -1.09 % | -1.11 % | -1.12 % | -0.79 % | -1.05 % |
| Indu | -2.09 % | -2.37 % | -3.04 % | -3.26 % | -2.65 % |
| ConsD | -1.58 % | -2.34 % | -1.76 % | 0.56 % | -1.50 % |
| ConsS | 3.89 % | 3.93 % | 3.55 % | 3.55 % | 3.75 % |
| Hlth | 4.60 % | 4.89 % | 4.97 % | 5.00 % | 4.88 % |
| Fncl | -2.86 % | -3.06 % | -4.05 % | -4.82 % | -3.61 % |
| IT | -5.00 % | -5.00 % | -5.00 % | -5.00 % | -5.00 % |
| Comms | 0.59 % | 0.37 % | 2.02 % | 1.39 % | 1.03 % |
| Util | 1.31 % | 1.30 % | 1.33 % | 1.30 % | 1.31 % |
| ReEst | 0.22 % | 0.57 % | 0.40 % | -0.07 % | 0.22 % |

*Appendix 6: Average sectoral deviation overall and in the CLI-based regimes of the US non-regime optimised portfolios. Deviations calculated based on monthly weights against benchmark, S&P 500. Note: total deviations may not sum to 0% due to Real Estate sector deviations only calculated from October 2016 forward.*

| Optimisation | Sharpe | Return | MinVar |
|---|---|---|---|
| Enrg | 3.10 % | 2.94 % | 3.24 % |
| Mtrls | 0.92 % | 1.21 % | -1.23 % |
| Indu | -3.37 % | -0.41 % | -2.76 % |
| ConsD | 2.56 % | 3.55 % | -2.64 % |
| ConsS | 3.74 % | 3.38 % | 3.76 % |
| Hlth | 1.52 % | -3.28 % | 4.93 % |
| Fncl | -2.94 % | -2.81 % | -3.08 % |
| IT | -4.80 % | -2.27 % | -5.00 % |
| Comms | -1.54 % | -1.80 % | 1.15 % |
| Util | 0.85 % | -0.23 % | 1.31 % |
| ReEst | -0.16 % | -0.84 % | 0.89 % |