Analyzing Market Dynamics: A Comprehensive Model Using Macroeconomic, Sentiment and Fundamental Data for Regime Detection and Asset Allocation

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Abstract

This dissertation examines the development and application of a comprehensive financial indicator that incorporates macroeconomic, sentiment, and fundamental data. It is demonstrated that various market features, such as high mean returns and low volatility periods, can be clustered into regimes using well-known models like the Two-State Markov Switching Model and Principal Component Analysis. Important discoveries are obtained by combining the findings in a Combined Indicator. For example, both the Dotcom Bubble and the Global Economic Crisis provided early signals of a downturn based on the classification of regimes. However, when applying these models to investment strategies, further results from the out-of-sample dataset suggest that, despite the potential of certain individual models to improve market timing and achieve greater risk-adjusted returns in the training set, these cannot be replicated consistently. Realistic market conditions, such as the inclusion of a time lag due to signaling and the introduction of transaction fees, thus limit the viability of an effective investment strategy. Nevertheless, the results of the dissertation and the prediction of the Combined Indicator itself can be useful and serve as support for asset allocation.

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Resumo

A presente dissertação examina o desenvolvimento e a aplicação de um indicador financeiro abrangente que incorpora dados macroeconómicos, de sentimento e fundamentais. É demonstrado que várias características do mercado, tais como retornos médios elevados e períodos de reduzida volatilidade, podem ser agrupadas em regimes utilizando modelos conhecidos como o Modelo de Two-State Switching de Markov e a Análise de Componentes Principais. Descobertas importantes são obtidas ao combinar resultados num Indicador Combinado. Por exemplo, tanto a bolha das Dotcom como a crise económica mundial proporcionaram sinais precoces de uma recessão com base na classificação dos regimes. No entanto, ao aplicar estes modelos a estratégias de investimento, outros resultados do conjunto de dados excluídos da amostra sugerem que, apesar do potencial de determinados modelos individuais para melhorar o timing de mercado e obter retornos ajustados ao risco superiores no conjunto de teste, estes não podem ser replicados de forma consistente. Condições de mercado realistas, como a inclusão de um desfasamento temporal devido à sinalização e a introdução de comissões de transação, limitam assim a viabilidade de uma estratégia de investimento eficaz. Não obstante, os resultados da dissertação e a previsão do próprio Indicador Combinado podem ser úteis e servir de apoio à alocação de ativos.

Título: Análise de dinâmicas de mercado: Um modelo abrangente que utiliza dados macroeconómicos, de sentimento e fundamentais para a deteção de regimes e a alocação de ativos

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Palavras-chave: Deteção de regimes, Modelo de Two-State Switching de Markov, Análise de Componentes Principais, indicador financeiro

Table of Contents

List of Figures

List of Tables

1. Introduction

Undoubtedly, the economy and financial markets have been significantly transformed in recent years by technological breakthroughs, the rise of social media and the increase of individual investors. Indeed, there are instances such as the GameStop short squeeze of 2021 that could be seen as a turning point for retail investors to invest (Umar et al., 2021).

Additionally, the rise in popularity of commission-free brokerages like Robinhood Markets Inc. throughout the last years has drawn a sizable number of perhaps less experienced investors and had a substantial effect on the state of the stock market. Retail investors now tend to focus on inexpensive, visually appealing companies, which has increased turnover rates (van der Beck & Jaunin, 2021). Some academics counter that particular aspects of the Robinhood app could promote herding behavior, affecting market dynamics. (Barber et al., 2022).

Shefrin noted decades ago that the psychology background has grown even more important and provides a more in-depth understanding of the dynamics of the market and speculative bubbles (Shefrin, 2002). Moreover, Campbell and Shiller investigated the psychological and emotional components of investing. They discovered that these characteristics may lead to speculative bubbles in the financial markets, which can have a big effect on the dynamics of the market and stock values. This emphasizes how mood influences regime shifts and market timing techniques as well as asset price (Campbell & Shiller, 1988).

With the development of financial markets, the amount and complexity of data available for analysis has increased, requiring increasingly complex techniques to understand market dynamics (Khadjeh Nassirtoussi et al., 2014). A huge amount of information from different sources now needs to be integrated into financial market forecasting. These changes make it necessary to easily assess and evaluate the stock market based on data-driven analysis. For example, CNN Money created a Fear and Greed Index for the US stock market back in 2012, which uses seven data factors to measure the market dynamics of the stock market.

This dissertation is also dedicated to this topic and pursues two objectives: First, to construct a financial indicator formed from key financial and economic data in order to obtain a quick estimate of market dynamics. Secondly, an investment strategy is to be derived from the indicator. This gives rise to the following research questions:

1. Can different models improve market timing and outperform risk-adjusted returns compared to a buy-and-hold strategy?
2. Does the integration of different types of data such as macroeconomic, sentiment and fundamental data improve the formulation of investment strategies, while also taking into account their respective time horizons?
3. Is it possible to develop a customized investment strategy using this combined indicator approach?

A comprehensive analytical framework combining macroeconomic, sentimental, and fundamental data is presented in this research to enhance the development of investment strategies. Making strategic investment decisions that capture the complexity of the modern financial world is the aim of this integrated approach. This information is essential to assist in customizing asset allocation plans to take advantage of intended changes in anticipated returns at various stages of the business cycle, therefore strengthening investment frameworks in a variety of economic environments (Chordia & Shivakumar, 2002).

2. Literature Review

Research on market timing strategies and stock market indicators has been discussed for decades. With successful strategies, a private or institutional investor could regularly outperform the market in terms of risk-adjusted returns if they could accurately predict market behavior. Therefore, the most common goal is to predict the direction of the market. The field of stock market forecasting is widely regarded as one of the most important and at the same time most difficult tasks in financial research (Huang et al., 2005).

While some research shows that some methods are able to accurately predict stock returns, others claim that these models are unable to beat the market on a regular basis. They claim that stock returns are inherently erratic. The Efficient Market Hypothesis (EMH) would consequently be violated if an investor could regularly achieve a higher risk-adjusted return than the market. Prices therefore adjust in response to new information. This results in unpredictability, so that a more adaptable and clearer method of market analysis is required. The EMH distinguishes between three groups of market efficiency: weak-form, semi-strong-form, and strong-form efficiency (Fama, 1991).

According to Fama, the weak form argues that technical analysis cannot predict future price changes because all historical price data is already reflected in the current stock price. The semi-strong version of this concept argues that stock prices are a reflection of all publicly available information, including information unique to a firm, political happenings, and state of the economy. This removes any potential for exploiting such knowledge to outperform buy-and-hold or other passive investment methods. Finally, the robust version of EMH holds that since stock prices consider all information - public and private, including insider information - it is impossible for an investor to routinely beat the market (Fama, 1991).

The rational pricing of assets has been a subject of increasing examination towards the EMH, as noted by researchers such as Daniel et al. (1998). The EMH has been put to the test by behavioral finance, which has shown more and more evidence of how psychological biases affect markets. Research on market overreactions, momentum and reversals by De Bondt & Thaler (1985) and others shows notable departures from the EMH, especially in its weak form. Thus, there has been a shift toward incorporating behavioral insights into financial models due to the prevalence of these anomalies. As a result of this change, Lo (2004) developed the

Adaptive Markets Hypothesis (AMH), which combines classical financial theories with behavioral finance to explain market dynamics and anomalies.

It is now clear that genuine stock markets always have residual inefficiencies and that the concept of market efficiency is only an idealization (Giglio et al., 2008). Consequently, the effectiveness of traditional investment strategies including technical analysis, fundamental analysis and macroeconomic analysis has been a topic of intense debate within the financial industry for a long time. This encourages the development of precise models for stock market prediction through the application of data analysis with computational intelligence techniques. In fact, a large amount of research has been published that aims to create advanced forecasting models or algorithms in order to accurately predict stock markets (Kumbure et al., 2022).

In the framework of stock market analysis, precisely recognizing market regimes - bear and bull phases in particular - is rather important. This method depends critically on an understanding of the fundamental macroeconomic and economic mechanisms causing stock fluctuations (Hamilton & Lin, 1996). Goodwin examined into how business cycles in eight industrialized market economies might be analyzed using the Hamilton Markov-Switching Model. Though its forecasting performance is only somewhat better than that of normal linear autoregressive models, the model can forecast business cycle turning points with remarkable accuracy, nearly matching the signals produced by traditional techniques (Goodwin, 1993). Furthermore, regime switching models are essential for controlling the dynamics of the equity market, particularly in times of volatility when correlations between global markets rise and might potentially undermine the advantages of diversification (Ang & Bekaert, 2002). Another model introduced by Maheu and McCurdy to distinguish between low-return volatile states (bear markets) and high-return stable states (bull markets) in stock returns, detects significant declines in the stock market and discovers that bull markets show declining hazard functions, whereas bear markets show increasing volatility with time, resulting in volatility clustering (Maheu & McCurdy, 2000).

Others argue that since two regimes cannot sufficiently capture the complexity of the market, the conventional Two-State Markov Switching Regression (MSR) model is less helpful in detecting trading regimes. Pomorski's work thus presents a multi-stage method that combines an adaptive moving average with the two-stage MSR to consider volatility and market trends. This increases trading performance and offers a more precise market condition segmentation for more comprehensive financial system forecasts (Pomorski Piotrand Gorse, 2023).

In order to examine stock price and business cycles in the US, Adam and Merkel developed a model that combines investor sentiment, macroeconomic data and fundamental analysis. The core of their strategy is extrapolative belief formation, which enhances boom-bust cycles in asset markets by influencing investor expectations through historical price trends, especially during low risk-free interest rate times. This model offers insights for regime detection and asset allocation strategies by showing how such cycles skew capital allocation and investment decisions, which in turn affects the real economy (Adam & Merkel, 2019). Similarly, technical indicators, macroeconomic variables and financial factors have been found to be among the variables that research has identified as having the greatest impact on stock price changes (Tsai & Hsiao, 2010).

One may combine the earlier observations to show how several factors work together to affect the dynamics of stock prices. This gives more study into the ways in which these elements affect investor behavior in various market conditions a foundation. According to research, in bull markets investors usually allocate a higher proportion of their portfolios to riskier assets, irrespective of their risk tolerance. This suggests that investing choices are greatly influenced by market conditions (Sotomayor & Cadenillas, 2009). For this reason, understanding market dynamics and guiding investment decisions need the use of macroeconomic statistics (Resnick & Shoesmith, 2002).

Thoroughly examining fundamental data is necessary to provide strategic insights for asset allocation and to dive into the complexities of market dynamics when building a sophisticated market analysis model. These indicators are more than just financial measures. They are essential in determining stock returns and forming investor confidence. Forecasts of business development and profitability are especially important because they show the potential for future earnings and consequently market value (Welch & Goyal, 2008). Fundamental data therefore not only reflects the economic situation in a particular country, but also has a significant impact on global markets. This connectivity underlines the significant relationship that exists between fundamental data and global economic cycles, highlighting the value of this data in spotting changes in market regimes (Rapach et al., 2013).

All things considered, adding macroeconomic analysis, sentiment data and fundamental data to financial models facilitates the prediction of market movements and the ability to make strategic investment decisions that adapt to investor sentiment and market conditions. A comprehensive strategy is required to maximize asset allocation and negotiate the complexity of the financial markets of today.

3. Dataset Review

The entire data set for this paper spans from January 1, 1997 to December 31, 2023. The Federal Reserve Economic Data (FRED), the Center for Research in Security Prices (CRSP) and Kenneth R. French Data Library are three of the databases from which the data was collected:

Table 1: Input Data Overview

Name	Type	Frequency	Description	Model	Source
S&P 500	Market	Daily	Daily close price of S&P 500 Index	All	Compustat
CBOE Volatility Index	Market	Daily	Implied volatility of the S&P500 derived from option prices	Markov Switching Regression	Chicago Board Options Exchange
Corporate Bond Spread	Macro-economic	Daily	ICE BofA US Corporate Index Option-Adjusted Spread	Three-State Markov Switching Model	ICE Data Indices
Term Spread	Macro-economic	Daily	10-Year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity	PCA	Federal Reserve Bank of St. Louis
10-Year Real Interest Rate	Macro-economic	Monthly	10Y Treasury Yield minus Inflation Prediction	PCA	Federal Reserve Bank of Cleveland
US Money Supply M2	Macro-economic	Monthly	M2 Money Supply that includes cash, checking deposits, and other deposits	PCA	Board of Governors of the Federal Reserve System
US Unemployment Rate	Macro-economic	Monthly	Number of unemployed as a percentage of the labor force	PCA	U.S. Bureau of Labor Statistics
Risk-Free Rate	Macro-economic	Daily	Benchmark return on theoretically risk-free investment	All	Kenneth R. French - Data Library

University of Michigan: Inflation Expectation	Sentiment	Monthly	Median expected price change next 12 months, Surveys of Consumers	PCA	University of Michigan
University of Michigan: Consumer Sentiment	Sentiment	Monthly	Surveys of Consumers Confidence	PCA	University of Michigan
S&P 500 Earnings	Fundamental	Monthly	12MM basic earnings per share for S&P 500 Index	PCA	Compustat

Note: The data consists of daily and monthly data sets. Nevertheless, the calculated P/E Ratio also fluctuates daily as a result of price changes in the S&P 500. The daily data for the other key figures is generated from the last available date in order to ensure consistency.

3.1. Market Data

Investors often estimate price trends using market indicators, which are derived from historical asset values. The market's estimate of 30-day forward-looking volatility produced from S&P 500 index options is represented by the Volatility Index (VIX), which is obtained from the FRED database. According to Gu, Kelly and Xiu among the most effective predictors are factors that quantify volatility (Gu et al., 2020). In addition, the importance of changing investor knowledge and risk perception as important predictors of market turbulence is evidenced by stock market volatility, suggesting that changes in investor attitudes have a strong impact on market dynamics (Turner et al., 1989).

3.2. Macroeconomic Data

Macroeconomic variables, which are mostly long-term indicators of market fluctuations, were included as a collection of predictors to assess the entire market cycle. Studies highlight the fact that a number of macroeconomic indicators, most notably yield curve spreads and inflation rates, have proven to be useful in predicting bear markets. These macroeconomic indicators offer important insights into the larger economic conditions that may cause stock market downturns (Hamilton & Lin, 1996). Moreover, it is widely acknowledged that broad economic indices like inflation rates and interest rate variations have a substantial impact on the general market environment and long-term projections (Fama & French, 1989). Therefore, the 10-Year

Real Interest Rate is the first indicator derived from FRED. It assesses both the inflation risk premium and the real interest rate itself in a single variable.

Computed as the difference between the 10-Year Treasury Constant Maturity and the 3-Month Treasury Constant Maturity, the term spread is another significant economic indicator and predictor of the most recent economic recessions. Although a flattening or inverted curve may indicate recessions or economic slowdowns, a steepening curve frequently indicates hopeful forecasts for future economic expansion (Resnick & Shoesmith, 2002). These results will be helpful to investors aiming to boost returns by market timing strategies and policymakers trying to reduce economic downturns. This improves our understanding of financial economics and gives practical instruments for making investment decisions (Chen, 2009). Furthermore, through changes in credit spreads and term premiums, even little changes in short-term interest rates have a big impact on loan costs, which emphasizes the need for sophisticated monetary transmission models to better forecast economic results (Gertler & Karadi, 2015).

US Money Supply M2 is determined by the Federal Reserve Board's monetary policy, which changes depending on the state of the economy. Changes in the money supply growth rate and stock returns seem to be correlated in both directions. Specifically, changes in the money supply caused by FED policies directly affect market returns (Rogalski & Vinso, 1977). Other studies show, that the relationship between money supply and share prices is characterized by a feedback system, whereby the money supply causes part of the observed fluctuations in share prices and vice versa (Hashemzadeh & Taylor, 1988).

Bond spreads are important proxies for both economic confidence and credit risk. Therefore, the ICE BofA US Corporate Index Option-Adjusted Spread was derived from FRED Database. Wider spreads have historically been linked to greater risk premiums and have the ability to forecast economic downturns (Keim & Stambaugh, 1986). In addition, research has found that turning points in the economic cycle are characterized by high volatility and highly time-variable term premiums (Boudoukh et al., 1999).

Given that increasing unemployment has been demonstrated to have a favorable impact on stock returns during times of economic expansion and a negative impact on the market during times of economic contraction, employment data was added as a potential predictor (Boyd et al., 2005).

In addition, the Risk-Free Interest Rate is derived from the Kenneth R. French Data Library in order to incorporate it into the investment strategies at the end of the paper, assuming that it earns interest at a risk-free rate (Fama & French, 2004).

3.3. Sentiment Data

Research has shown that, in line with recent discoveries in the US, mood is a good predictor of below-average global stock market results in all countries. Rising sentiment and future stock returns are inversely related (Schmeling, 2009). Other studies show that times of more optimism are frequently correlated with higher market performance, highlighting the important role that investor confidence plays in influencing returns on equity investments (Barberis et al., 1998). Therefore, the Inflation Expectation and Consumer Sentiment data from the University of Michigan were used as the data basis.

3.4. Fundamental Data

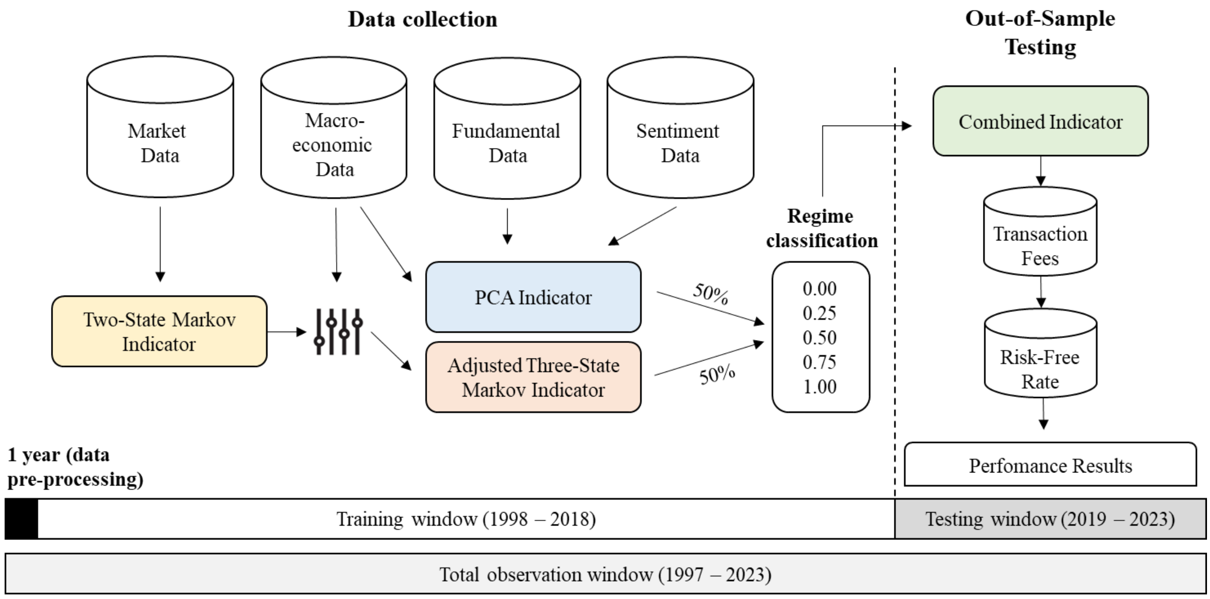
Important component of the dataset used in this study is the Price-to-Earnings (P/E) Ratio, which is computed using earnings data and S&P 500 index prices. The earnings data, which includes comprehensive details on the profits of S&P 500 companies. Risk premiums are well predicted by the P/E Ratio, as has been shown in the past. Lower frequency returns can be forecasted with some success using P/E Ratios, which measure variations in expected returns over time (Lewellen, 2004). The relationship previously shown emphasizes the importance of the P/E Ratio in predicting future market performance, particularly in identifying long-lasting trends and potential turning points in market sentiment (Campbell & Shiller, 1988).

4. Methodology

Four distinct data groups make up the total input for developing the Combined Indicator, as was covered in the previous chapter: market, macroeconomic, sentiment and fundamental data. Training window data was gathered between January 1, 1997, and December 31, 2018. By including relevant financial events such as the World Economic Crisis and the Dotcom Bubble, this window provided a large sample.

Market data is first utilized to record short-term variations in volatility and S&P 500 returns. Two states - high and low volatility - were captured in a Two-Stage Markov Switching Model using the logarithmic returns and volatility of the S&P 500. The Corporate Bond Spread was the third variable added to the two-state regime in the next stage with the introduction of another macroeconomic component. Furthermore, macroeconomic, fundamental and sentiment data were gathered in order to build an indicator using dimensionality reduction with Principal Component Analysis (PCA). The ultimate regimes were finally established by integrating both indicators and consolidated in the Combined Indicator. In the final stage, the investment strategies were tested by introducing a risk-free rate and transaction fees. The model was then evaluated using out-of-sample data, gradually increasing the testing window.

Figure 1: Flowchart of Methodology



Note: The illustration of the flowchart provides an overview of the subsequent stages of the process of creating the Combined Indicator.

4.1. Two-State Markov-Switching Model

As a first step towards creating a comprehensive indicator, the dissertation aimed to analyze short-term stock market fluctuations. The aim is to identify periods of high and low volatility and to be invested in low volatility periods wherever possible. In the past, phases with low volatility and steady returns have proven to be bull markets, while rising volatility could be classified as bear markets with low returns (Maheu & McCurdy, 2000).

These concepts of regime transitions and volatility are applied in financial analysis to understand market dynamics with the introduction of the Markov Switching Model by Hamilton (1989). To increase forecasting accuracy, Stock and Watson, for instance, propose that an approximate factor model employ the whole collection of economic data and propose this method as a suitable one, which means using Markov Switching Models (MSM) to recognize and adjust to various market regimes (Stock & Watson, 2002). Furthermore, Nelson, Turner and Startz developed a Markov Model to help understand stock market volatility. The results showed that in addition to market mechanics, investor attitudes and information can significantly affect market volatility over time (Turner et al., 1989).

Since it can identify regimes via examining market phases of volatility and return, a Markov Switching Model is quite useful in the financial markets. Assessing on the stochastic characteristics of Markov chains, Markov Switching Models enable a financial time series to be regime-dependent, or behave differently, with the parameters of the model changing according to the current state, or regime (Stock & Watson, 2002).

Markov Switching Models represent a time series that varies between multiple states with a few distinctive statistical characteristics. The state equation and the observation equation form the foundation of this framework (Hamilton, 1989). A key component of the Markov Switching Model, the state equation is based on the transition probability matrix P and expresses the likelihood that an anticipated shift from one regime to another will take place:

$$P = \begin{bmatrix} P11 & P12 \\ P21 & P22 \end{bmatrix}$$

Each element *Pij* in the matrix represents the probability of moving from regime *i* to regime *j*. Specifically:

- $P11$ is the probability of staying in regime 1,

- $P12$ is the probability of moving from regime 1 to regime 2,
- $P21$ is the probability of moving from regime 2 to regime 1,
- $P22$ is the probability of staying in regime 2.

The likelihood that the process will be in one of the possible states at the next time point is limited such that the total number of rows adds up to one.

The observation equation of a Markov Switching Model relates the observable data series to the hidden states that the model infers. Because it creates a connection between the theoretical constructs of the model - the latent states - and the actual data that analysts and researchers can see and measure, this equation is crucial. The following is how financial applications might represent this relationship:

$$yt = \mu St + \epsilon t, \epsilon t \sim N(0, \sigma_{St}^2)$$

In this expression:

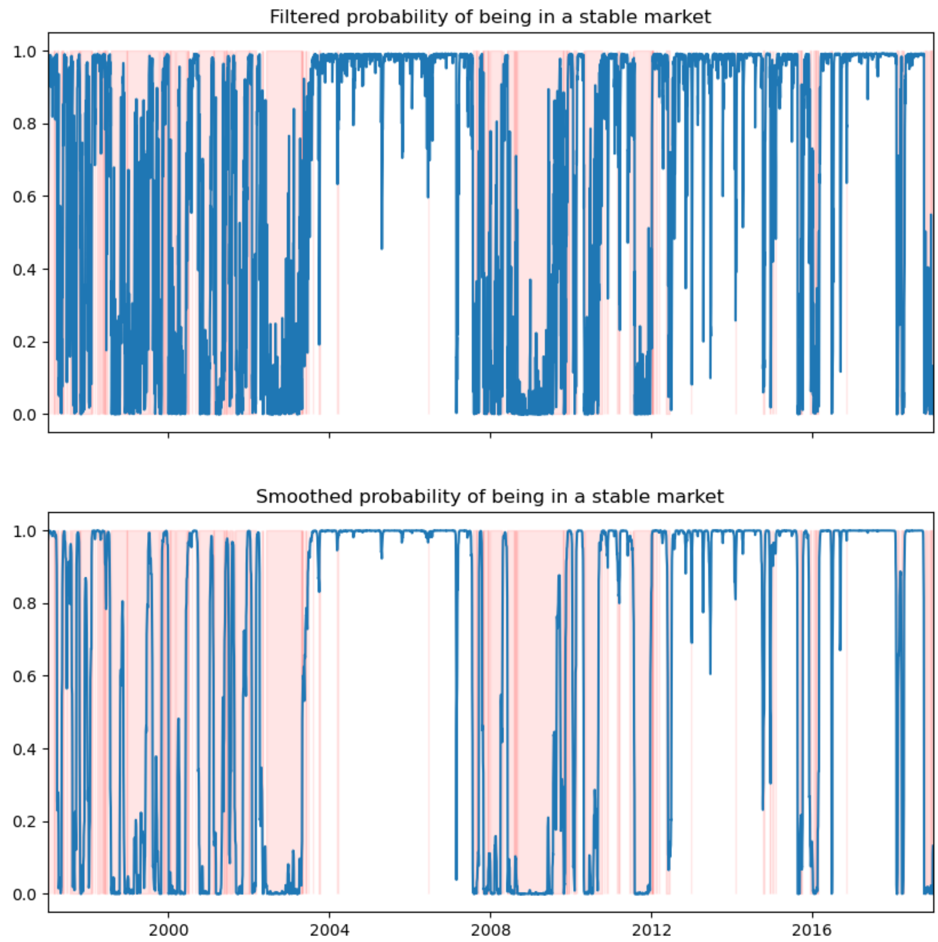
- yt represents the observed data at time t, such as the log returns of a stock index.
- μSt indicates the mean of the log returns conditional on the state St at time t. Every state might be suitable for various market circumstances, such as bull or bear markets, which are usually linked to distinct return profiles.
- ϵt is the error term, assumed to be normally distributed with a mean of zero and a state-dependent variance σ_{St}^2 The variance component enables the model to accommodate fluctuations in volatility, a defining characteristic of financial time series data.

Using the Markov Switching Model, specifically with respect to the log returns of the S&P 500, the dynamic changes in the behavior of financial markets were attempted to be understood. Recording changes that matched to different phases of return measures and market volatility was the first regime identification objective of this study. The model was built from 5,500 daily data points collected between January 1, 1997, and December 31, 2018. The logarithmic returns of the S&P 500 are the dependent variable in this model. The volatility index (VIX) is one of the exogenous variables in the model that helps it forecast changes in the dependent variable under different market situations. Typical of financial time series data, this variance component allows the model to adapt to changes in volatility.

Two different regimes were described for the Markov Switching Model to represent different market states: Regime 1 may indicate a less erratic market environment with comparatively constant returns, while Regime 0 may be an indication of a more erratic market state where returns fluctuate more. Taking the above data into account, the probability of remaining in the less volatile Regime 1 from one day to the next is 0.988, which is quite high and indicates that stable market conditions, if they occur, will last for a long time. On the other hand, the probability of changing from unstable Regime 0 to stable Regime 1 is comparatively low at 0.0227, which underlines how rarely states with high volatility change to stability. This underpins the classification into bull and bear markets.

Presenting the Markov-Switching Model, Hamilton (1989) showed that the unobserved regime develops as a first-order Markov process with time. Nevertheless, the regime is undetectable so one has to deduce which regime existed at each time period. Thus, what is now known as the filtered probabilities was created by Hamilton and enables to iteratively infer the likelihood of the regime at each moment in time. A few years later, Kim (1994) introduced the smoothed probabilities, a backwards recursive filter that enables inference on the regime at each point in time using the whole sample of observations.

Figure 2: Filtered and smoothed probability being in a stable market during Training Window



Note: Filtered probabilities indicate the probability of being in a regime based on data up to that point, whereas smoothed probabilities utilize all available data. Consequently, filtered probabilities are utilized in forecasting because they are predicated on data up to the time of the prediction.

Accordingly, upon transforming the time index for a more accurate representation, two types of probabilities, filtered and smoothed probabilities, are visualized. These probabilities indicate that the market is in a stable, less volatile state. It should be noted that the smoothed probabilities cannot be incorporated into the model, as the smoothing method employs forward-looking data and the calculations are dependent on all observations, including those from the future (Kim, 1994).

However, there is significant noise and volatility when using the filtered probability of being in a stable market. As such, the information was separated into two values: 0 (volatile market) or 1 (stable market). Setting a threshold, which was optimized with the output of the summary statistics: Regime 1 should have as many days as is practical with a low standard deviation and high mean returns. The analysis revealed that the optimal outcome is obtained at the threshold value of 0.4, meaning that a regime is categorized as 1 if its probability of being in a stable market is higher than 0.4.

Table 2: Summary Statistics of Two-State MSM Regimes during Training Window

	Days	Mean	Std	Min.	Median	Max.	Skew.	Kurt.
0	1639	0.000006	0.018985	-0.09035	0.000782	0.115800	0.01403	2.697928
1	3644	0.000363	0.007000	-0.02370	0.000489	0.022235	-0.16462	0.513035

Note: Extreme value events and increased volatility are indicated by Regime 0, which has a mean return of nearly zero, a larger standard deviation, and a higher kurtosis. By contrast, regime 1 is in a more stable and less volatile environment with a greater mean return, smaller standard deviation, and kurtosis.

The characteristics of the regimes presented above show a successful division of both regimes. The result also confirms the characteristics of bull and bear markets, which entails greater uncertainty and higher risk with more pronounced price fluctuations in Regime 0 (Maheu & McCurdy, 2000).

4.2. Three-State Model Development considering Corporate Bond Spread

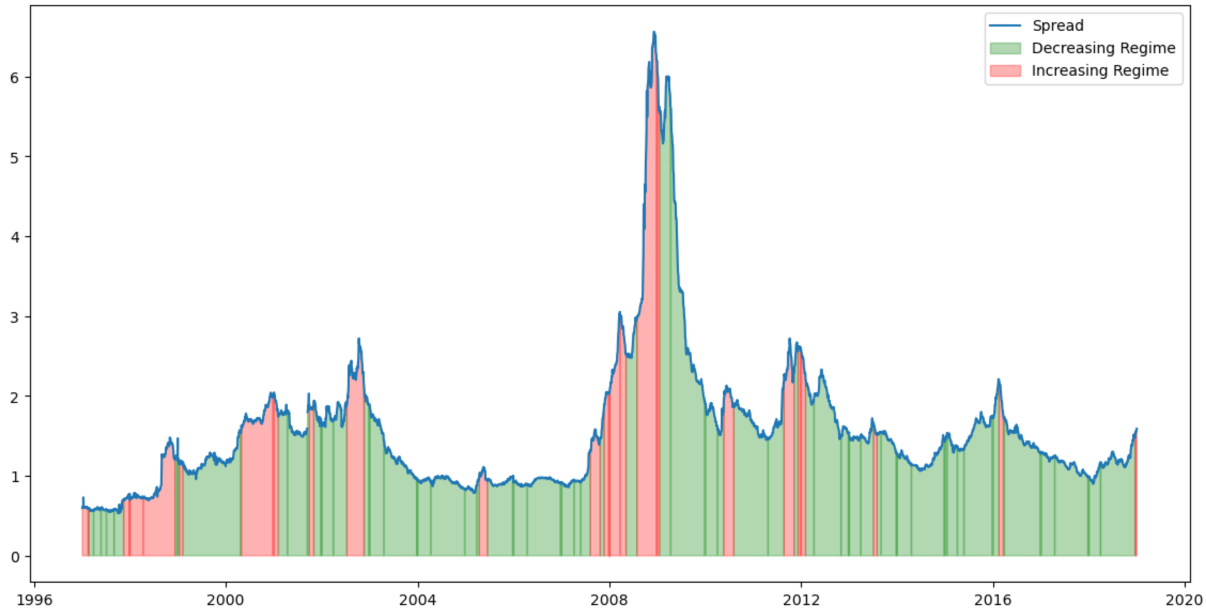
The aim of the following chapter of the dissertation was to create a Three-State Model integrating Corporate Bond Spread and a neutral regime to improve and smoothen the regime detection obtained from the Two-State Markov Switching Model.

Even though it is often used to capture regime shifts in financial markets, the conventional Two-State Markov Switching Model frequently fails to capture the complex dynamics of financial markets. Usually, the model just distinguishes between two different volatility states: high and low. The dynamic patterns of low-volatility expansion and abrupt high-volatility contractions seen in market cycles are not entirely captured by this simplification. The two-state technique may be too constrained to capture meaningful shifts in asset returns, variances, and correlations that can significantly influence trading strategies, according to historical data and theoretical extensions (Pomorski Piotrand Gorse, 2023).

Another variable was included, which is also related to economic cycle turning points, so as to prevent generating an isolated observation of market phases dependent on volatility (Boudoukh et al., 1999). The US Corporate Bond Spread offered another proxy for credit risk and economic confidence. Historically, wider spreads have been associated with higher risk premiums and the capacity to predict economic downturns (Keim & Stambaugh, 1986). The additional variable therefore helps to provide a medium-term economic outlook. A rising spread for US corporate bonds is therefore seen as a higher risk premium and can be seen as an indicator of an economic downturn or weakening of the economy. Conversely, a falling spread is seen as a low-risk premium or economic recovery.

These two phases could be distinguished as follows: The additional model calculated the percentage change of the US Corporate Bond Spread over a rolling 20-day window. Regime detection was defined using a predetermined threshold of +0.8% and -0.5% for rising and falling spread trends, respectively. The model calculated a rolling value of the spread movements within the window, which was smoothed at the end of the regime. The above variables and thresholds were calculated to optimize the summary statistics - namely mean returns and standard deviations - of the respective regimes. Higher thresholds ensured that transitions only occurred when there was a tangible change in market dynamics.

Figure 3: Corporate Bond Spread with Regime Classification during Training Window



Note: The figure shows the US corporate bond spread, broken down into rising spread (red) and falling spread (green). The aim is to identify the regimes with a falling spread in order to participate in a possible recovery.

The introduction of the generally medium-term variable prevented the Two-State Markov Model from switching too frequently. Furthermore, downturns or upturns were identified through the increase or decrease of the US Corporate Spread.

The implementation of US Corporate Bond Spread regimes in a Three-State Model was carried out to optimize the Two-State Markov Switching Model and limit its application when both regimes showed opposite regime detection. Consequently, the introduced Three-State Model only switched to Regime 1 or Regime 0 when the two models had the same regime classifications. This also led to the introduction of the Corporate Bond Spread regimes as an additional validator of the regimes of the Two-State Markov Model. A neutral regime was thus introduced for corresponding opposing regimes as follows:

$$Markov\ x\ Spread\ Indicator$$
$$= \begin{cases} 0\ if\ Markov\ Indicator = 0\ \wedge Spread\ Indicator = 0 \\ 0.5\ if\ Markov\ Indicator = 1\ \wedge Spread\ Indicator = 0 \\ 0.5\ if\ Markov\ Indicator = 0\ \wedge Spread\ Indicator = 1 \\ 1\ if\ Markov\ Indicator = 1\ \wedge Spread\ Indicator = 1 \end{cases}$$

Both models were combined to generate the Markov x Spread Indicator. By introducing the third regime, a neutral position was achieved. The change in the differentiation of the regimes can be observed in the following summary statistics:

Table 3: Summary Statistics of Adjusted Three-State MSM Regimes during Training Window

	Days	Mean	Std	Min.	Median	Max.	Skew.	Kurt.
0	671	0.000115	0.021602	-0.09035	0.000534	0.115800	0.08357	3.312309
0.5	1387	0.000128	0.014762	-0.06663	0.000853	0.070758	-0.13765	1.508222
1	3225	0.000335	0.006918	-0.02370	0.000468	0.022224	-0.16124	0.558457

Note: The several regimes are classified properly in the table. The volatility is therefore arranged in descending order and the mean returns upward. Kurtosis and declining minimum values indicate that regimes 0.5 and 1 are less extreme.

4.3. Principal Component Analysis of Financial and Economic Variables

Adding fundamental valuation and general macroeconomic and market sentiment was the last stage in the development of the Combined Indicator. It is crucial and somewhat difficult to predict the regimes and identify economic and financial downturns in the world of financial markets. Variables that interact in complex ways affect stock market fluctuations. Market dynamics are influenced by basic factors like P/E Ratio and economic factors like interest rates and money supply as well as psychological factors like investor expectations and consumer sentiment (Enke & Thawornwong, 2005).

A comprehensive and efficient data mining process was introduced to predict macroeconomic data, fundamental data and sentiment data in order to identify medium to long-term developments in the S&P 500 Index. The aim was to utilize seven financial and economic variables through Principal Component Analysis (PCA). These variables included Term Spread, 10-Year Real Interest Rate, US Money Supply M2, US Unemployment Rate, Inflation Expectation, Consumer Sentiment and P/E Ratio.

A statistical technique called Principal Component Analysis (PCA) condenses a large number of data into a smaller set that preserves most of the information in the larger set, hence reducing the dimensionality of huge data sets. The transformation is designed such that, provided each component is orthogonal to the one before it, the variance of the first principal component and each consecutive component is maximized. The eigenvectors and eigenvalues of the data covariance matrix are computed in the mathematical representation of Principal Component Analysis to identify the main components (Pearson, 1901).

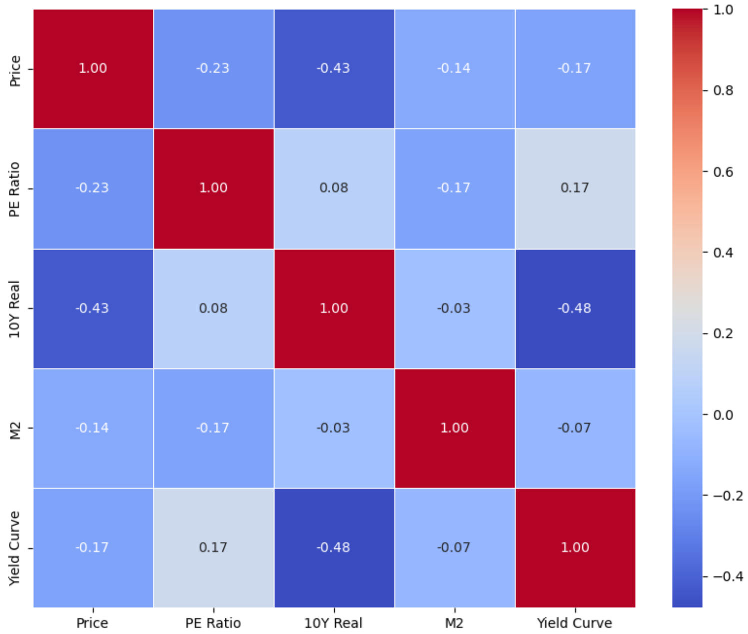
In specifics, every primary component, on a scale from 0 to 1, represents a percentage of the overall variation. Components that together account for a sizable percentage of the data variability are chosen for practical use. This simplified method improves the accuracy and efficiency of financial assessments (Tsai & Hsiao, 2010).

Nevertheless, PCA has its limits, especially when dealing with complicated nonlinear data. Many statistical approaches, like PCA, can be severely impacted by the presence of noisy data, especially outliers. A further challenge to data analysis is dealing with missing values, inaccurate data and inconsistencies between various data sources. Thus, ensuring that classification algorithms avoid wasting time handling outliers and enhancing the robustness of PCA and accuracy requires effective data preparation. A large number of outliers in a dataset makes it unlikely to be symmetric or normal, which might impair classification performance.

To improve the performance of the PCA model, careful pre-processing of the data was carried out. Notably, the Term Spread was integrated into the model, as there is evidence that it is also a strong signal of future macroeconomic fluctuations. Further study, which is already expanding on the previous point, indicates that one may create plans to take use of the forecasts' benefits considering the yield spread's predictive capacity. The research shows that, with an eight-month lag between the yield spread and the stock market, it can assist forecast high-probability turning periods in the business cycle (Resnick & Shoesmith, 2002). According to previous studies, the Term Spread is helpful for predicting production growth, particularly for timeframes of six to twelve months, and it remains helpful even when other factors, such as monetary policy measures, are included to the forecasting model (Wheelock & Wohar, 2009). Consequently, this discovery led to a 120 trading day shift of the Term Spread data used in this work in order to alter the implied leading times for the recession-predicting signals. For the modeling objective, the adjustment is crucial since it enables the PCA model to include the relevant and current economic activity factors.

Moreover, the remaining data were computed as they were obtained, and US Money Supply M2 was expanded over months to reflect changes from the prior point. Still, more examination of the correlation matrix and Principal Component Analysis showed that the Unemployment Rate, Inflation Forecast and Consumer Sentiment did not improve output, therefore they were left out of the analysis. This choice acted as a prompt for the need to choose the best features for the PCA, which improved the procedure's final interpretation and increased its efficiency. The final input of the PCA model was the correlation matrix shown below:

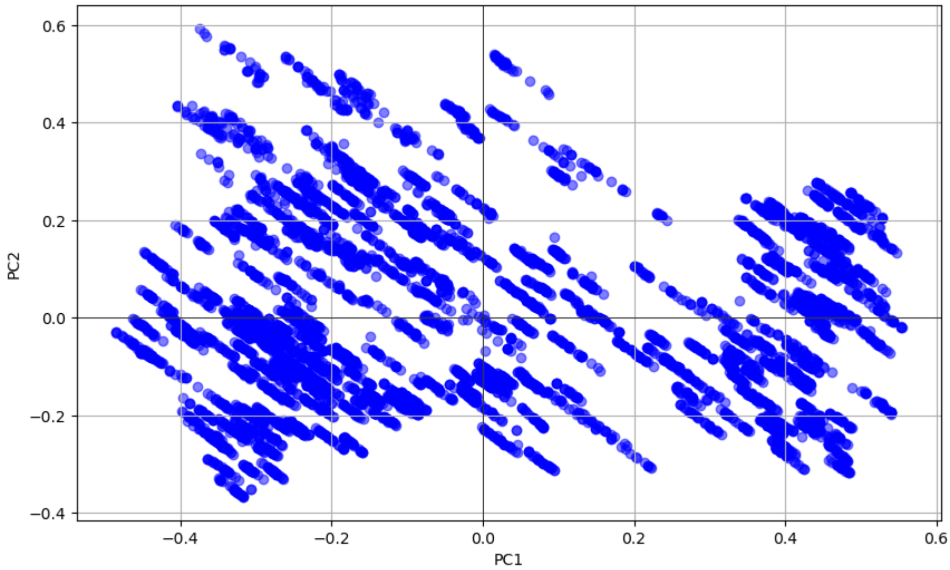
Figure 4: Correlation Matrix of Input Data for PCA Model



Note: The correlation matrix indicates that there is a negative correlation between Price and all other variables. The strongest negative correlation is with the 10-Year Real Interest Rate (-0.43), which suggests that as long-term real interest rates increase, the S&P 500 tends to decrease.

In dimension reduction with PCA, the characteristics that maximize the variance are determined. If a feature dominates the direction of the principal components if it differs from the others solely in relation to their respective scales. Therefore, normalization of the data is essential prior to PCA. The scatter plot shows the distribution of the PCA components, as well as how each feature contributes to the main components after normalization.

Figure 5: Scatter Plot of PCA Components



Note: The scatter plot illustrates the alignment of the data points along a number of diagonal lines. The tendency of alignment suggests that the data set may contain multiple subgroups with similar traits.

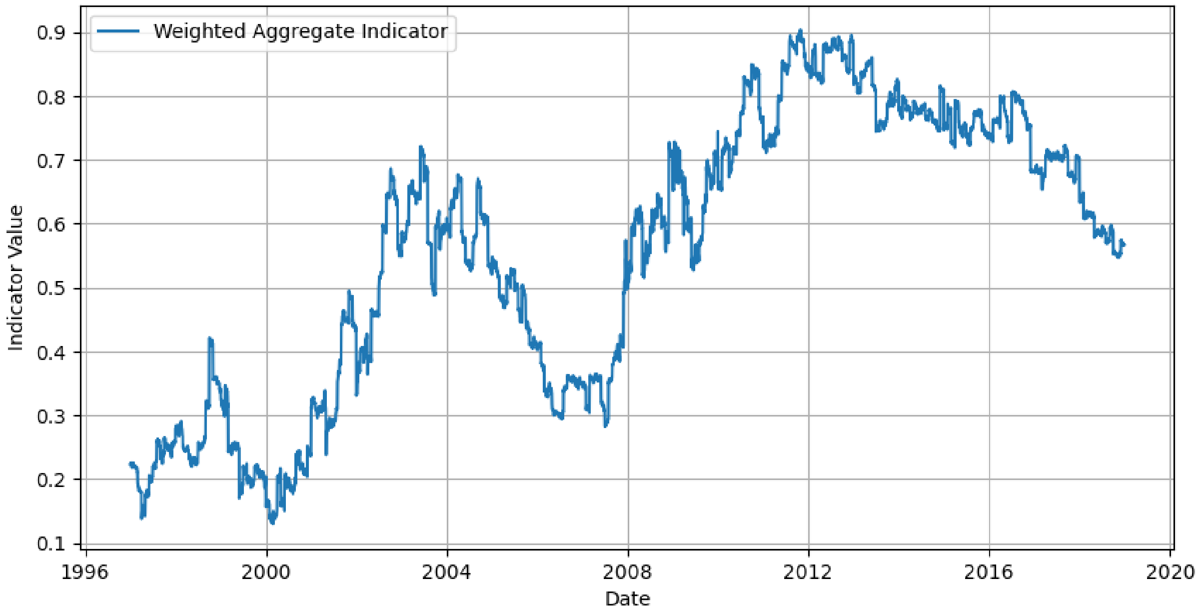
Analyzing the scatter plot, a linear connection between subgroups or clusters may be indicated by the diagonal line. The presence of numerous parallel stripes or clusters may indicate the existence of several internal groupings or categories within the data set that exhibit differences while maintaining a degree of similarity.

PC1 seemed to have documented a higher degree of variation in the initial data set than did PC2. PC1 might thus be associated with the most important underlying component or with a conglomeration of factors influencing the data set's variability. As such, PC1, the first main component, explained 57.67% of the variation, whereas PC2, the second, explained just 20.96%. The goal was to illustrate most of the input components, hence, a weighting strategy was used for the aggregated PCA Indicator. The weightings were established using the corresponding amounts of explainable variance for PC1 and PC2.

$$PCA\ Indicator = PCA\ Indicator\ 1 * \frac{\sigma PC1}{\sigma PC1 + \sigma PC2} + PCA\ Indicator\ 2 * \frac{\sigma PC2}{\sigma PC1 + \sigma PC2}$$

The final PCA Indicator consequently took into consideration both variances but favored PC1 because of its more significant variance. The indicator had to be inverted as a last step in order to optimize the regime classification because the input data and the S&P 500 had a negative correlation. The following output was generated for the PCA Indicator:

Figure 6: Output of PCA Indicator during Training Window



Note: The PCA Indicator fluctuated only slightly over time, which suggests long-term orientation. However, the strong changes shortly after the dotcom bubble and the global economic crisis are striking.

The development of regimes for the PCA Indicator - bearish, neutral and bullish - was the final step to ensure consistency with the other two models. After testing several thresholds to optimize the mean returns and standard deviation of the regimes, the optimal choice appeared to be >0.5 for bullish = 1, <0.3 for bearish = 0 and otherwise neutral = 0.5. Taking these classifications into account, the following summary statistics were calculated for the regimes below:

Table 4: Summary Statistics of PCA Model Regimes during Training Window

	Days	Mean	Std	Min.	Median	Max.	Skew.	Kurt.
0	728	-0.000055	0.012128	-0.06801	-0.000106	0.047639	-0.26354	2.285356
0.5	1053	0.000279	0.010707	-0.04921	0.000566	0.050899	0.13243	2.592916
1	3502	0.000308	0.012436	-0.09035	0.000596	0.115800	-0.03807	9.922095

Note: Mean returns distribution shows to be useful. Still, the standard deviation shows no obvious variations. Furthermore, evident is the extreme distribution shown by the kurtosis being highest in regime 1 of this model.

4.4. Investment Strategy Formulation

While each indicator assessed different factors and investment horizons, it can be difficult to combine the PCA and Markov x Spread indicators into a single Combined Indicator. For example, short- to medium-term conditions such as volatility swings and growing spreads caused by shocks are usually captured by the Markov x Spread Model. Conversely, the input values caused the PCA Indicator to exhibit a long-term oriented horizon. An equal weighted approach is presented as an example since the common indicator aims to represent the overall conditions by taking into consideration the large macroeconomic picture and reacting to specific fluctuations (50% and 50%).

Given this, five distinct allocation regimes - derived from 0%, 25%, 50%, 75% and 100% invested - were created by the combination of the indicators. Bearish signals are indicated by 0%, neutral signals by 50%, and bullish signals by 100%. Values of 25% and 75% function as a transition regime.

The investment strategy and indicator need to be determined before proceeding. In order to develop a feasible strategy, it is crucial that the data utilized as input was accessible at the time of its utilization. Using closing prices as a signal, it is unrealistic to trade on the same day. Hence, it is advisable to presume that the signal is applied with a delay, for instance, by utilizing the closing price of the following trading day (Pedersen, 2019).

To make regime identification feasible, the Combined Indicator has been delayed by one trading day. Then, the daily returns of the S&P 500 were multiplied by the daily regime allocation. Should the regime not be fully invested, the daily risk-free return from the Kenneth French Library was multiplied by the proportion of the uninvested component (Fama & French, 2004). Moreover, transaction fees are a part of every regime shift in real investment environment. Although Frazzini et al. (2012) calculated potential transaction fees of around 0.05-0.1% for professional investors, transaction costs of 0.2% were assumed in this paper to account for the higher fees for retail investors. The fees were deducted from the corresponding returns for regime transitions and are incurred in the amount of the changed share.

4.5. Investment Strategy Optimization

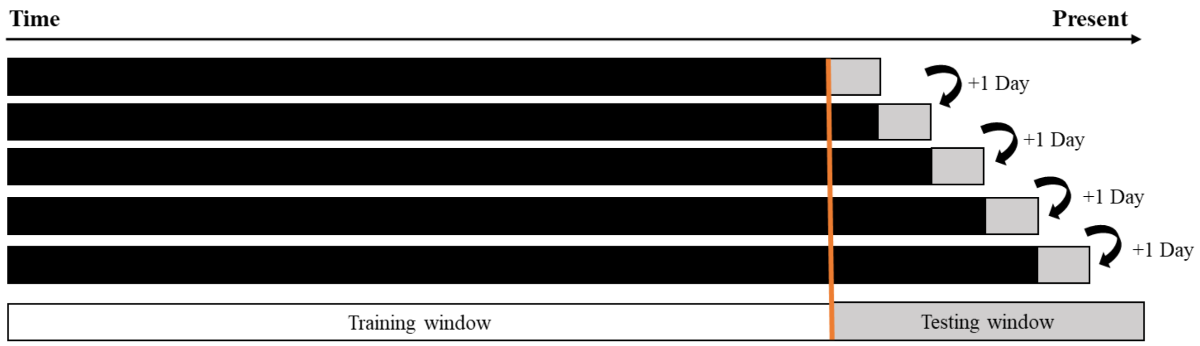
As Goulding notes, the use of slow strategies, due to their longer look-back durations, may result in underperformance at critical junctures, as they fail to identify early signs of market reversals. Conversely, rapid methodologies are more prone to noise and false signals, given that they respond promptly to emerging trends. This distinction highlights the necessity of a well-rounded strategy that integrates elements of both approaches in order to capture efficiency throughout different stages of the market (Goulding et al., 2023).

Consequently, it was reasonable to attempt to slow the signal in order to optimize the Combined Indicator, which incorporated fees and the risk-free rate, and to eliminate the noise and outliers of the Markov Switching Component. To validate the regime shift, an additional restriction was implemented, stating that a regime change would only occur if two, three, four, or five consecutive regimes were identified. This prevented the indicator from undergoing a significant number of shifts in a short period of time. Nevertheless, in order to avoid the forward-looking bias, which also affected the optimization result, the indicator had to be shifted for the corresponding days.

4.6. Investment Strategy Testing

Simulating a real-life scenario is essential to backtesting the investment strategy with the Combined Indicator. As a result, cross-validation with expanding windows has been applied. The maximum size of the training has been increased from some initial size with Expanding Windows. This approach maximizes the amount of data the models receive while still producing adequate training-test pairs.

Figure 7: Cross-Validation with expanding windows for Testing Window



Note: Illustration of the cross-validation method with expanding windows, in which the test window increases gradually while the training window stays fixed. Through time, this method facilitates the validation of the model's performance using an increasing volume of data.

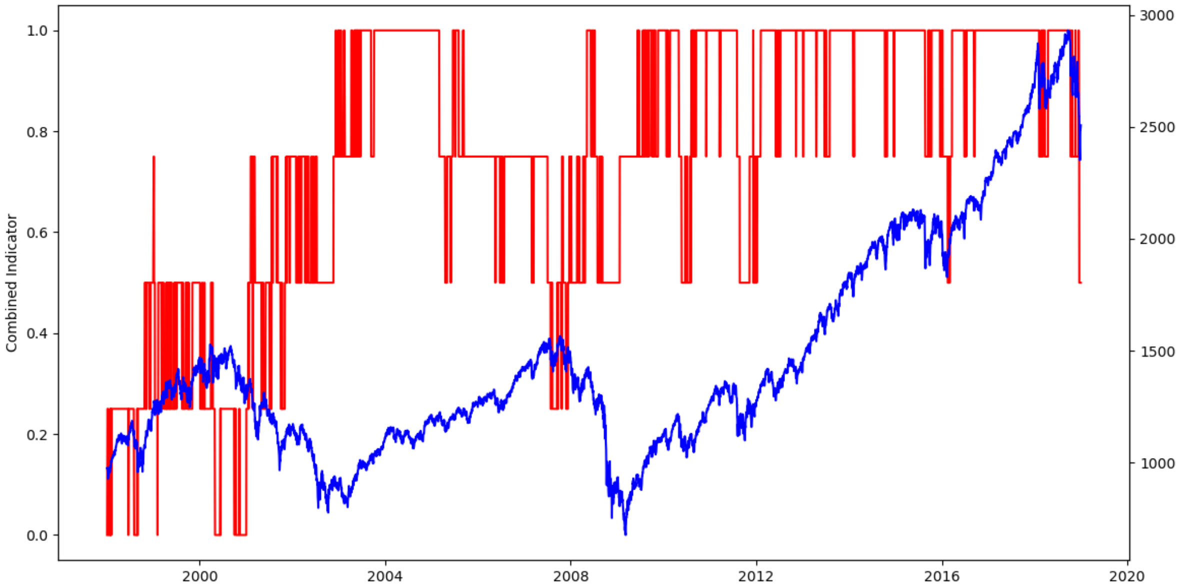
The unpredictability of crises such as the COVID pandemic must be taken into account when evaluating investment strategies for the turbulent period 2019 - 2023. Consequently, it is even more challenging to determine whether the indicator can successfully adapt to such events. As described by Nassim Nicholas Taleb, events of an extremely unlikely and unpredictable nature with a significant impact, such as the outbreak of an epidemic and the subsequent market turbulence, could be considered "Black Swans" (Taleb, 2007).

5. Results

5.1. Model Forecasting Evaluation

Each of the above calculations and optimization strategies were put into action during the 21-year training window from 1998-2018. As a result, a comprehensive indicator is presented, which was formed from seven variables: S&P 500 Returns, CBOE Volatility Index, Corporate Bond Spread, Term Spread, 10-Year Real Interest Rate, US Money Supply M2 and S&P 500 P/E Ratio.

Figure 8: Combined Indicator and S&P 500 over Training Window



Note: The Combined Indicator (red) has been plotted against the S&P 500 (blue) to show the regimes compared to S&P 500 during Training Window. It is worth noting that the indicator showed lower values during the peak of the financial crises in 2001 and 2007-2008, which could indicate an early downturn.

As the regimes are clearly categorized, the summary statistics for each regime were calculated in the next step. However, unlike the summary statistics for the individual indicators, it must be noted that the Combined Indicator was shifted by one trading day, which can therefore influence the breakdown of the regimes.

Table 5: Summary Statistics of Combined Indicator Regimes during Training Window

	Days	Mean	Std	Min.	Median	Max.	Skew.	Kurt.
0	120	0.000053	0.01569	-0.06801	-0.0005	0.038922	-0.39535	2.281714
0.25	549	0.000772	0.012334	-0.05828	0.000782	0.050899	0.13761	2.10343
0.5	882	-0.00038	0.018805	-0.09035	0.000044	0.1158	0.093005	5.130557
0.75	1349	0.000325	0.012194	-0.06663	0.000739	0.070758	-0.01129	3.795568
1	2383	0.000335	0.007771	-0.04098	0.000545	0.0332	-0.45147	1.951399

Note: The data demonstrates changes in mean, volatility, and distribution forms between relatively stable (Regime 1) with minimal volatility and more variable (Regime 0.5) with more possibility for extreme values.

Overall, the summary statistics were different from the individual components. Their skewness, kurtosis and volatility varied according to the regime. Relatively speaking, regime 0.5 offered the biggest risk and the lowest mean returns because of its large maximum, minimum and standard deviation. Unfortunately, the 0.25 regime gained some of the highest mean returns at low risk. One reason for the change could be that the signal has moved, causing the extreme returns to occur during the transition periods. This may be related to the practice of including returns from rallies and rebounds. Regime 1, on the other hand, was the most stable environment according to the individual components, with the lowest volatility and almost normal distribution characteristics.

The summary statistics for each regime could help to understand the potential risk and return profile for strategic decisions in a training context. However, by combining the indicators and ultimately shifting the Combined Indicator, different results were achieved compared to the steps presented.

5.2. Investment Strategy Evaluation

Using the developed investment strategy from the previous chapter, the different returns and risk indicators for the separate strategies were first computed in order to test a potential investment strategy using the Combined Indicator.

Table 6: Performance Output of Investment Strategies during Training Window

	Cum. Return	Sharpe Ratio	Volatility	Max. Drawdown
(1) Markov Indicator	0.857366	0.324	**0.110**	-0.435
(2) Markov x Spread Indicator	1.233474	0.392	0.115	**-0.393**
(3) PCA Indicator	1.474833	0.345	0.165	-0.560
(4) Combined Indicator	1.451337	0.400	0.127	-0.405
(5) Combined Indicator (incl. Fees)	1.041300	0.331	0.127	-0.417
(6) Combined Indicator (incl. RF)	**1.941586**	**0.468**	0.127	-0.399
(7) Combined Indicator (incl. Fees and RF)	1.449566	0.399	0.127	-0.411
S&P 500	1.583259	0.332	0.192	-0.568

Note: The table compares key performance metrics across several investment metrics and strategies during Training Window, with the best performer in each category highlighted in bold.

Every indicator has also been computed separately to provide a more comprehensive picture and facilitate comparison. Furthermore, the Combined Indicator has been computed (5) included Fees, (6) included Risk-Free and (7) included Fees and Risk-Free. Especially, the (6) Combined Indicator including Risk-Free Rate outperformed the S&P 500 significantly between 1998 and 2018. By contrast, strategy (6) generated 194.16% instead of 158.33%. In addition, strategy (6) had a Sharpe ratio of 0.468 versus 0.332 for the S&P 500, largely due to its lower volatility. It is noteworthy to observe that the (2) Markov x Spread Indicator and the (3) PCA Indicator, as separate indicators, may have lower Sharpe Ratios than the (4) Combined indicator. This supported the question of whether a combination of the different indicators improves the result.

On the other hand, adding transaction costs was necessary to gauge the feasibility of the investment strategy. Transaction fees and the risk-free rate were included in strategy (7) Combined Indicator. This strategy differed significantly from strategy (6), which did not include transaction costs. Though the Sharpe Ratio indicated that the approach still outperformed the S&P 500, transaction fees appeared to have a significant impact. Frequent switching of the Two-State Markov Component seemed to raise transaction fees, even though modifying the Two-State Markov Model with the US Corporate Spread Indicator appeared to improve the results shown in the (2) Markov x Spread Indicator.

Consequently, the implementation of the optimization strategy with subsequent regimes likely facilitated a modest degree of optimization with respect to the Combined Indicator, which incorporated both transaction fees and the risk-free rate:

Table 7: Performance Output of Strategy (7) with Subsequent Regimes during Training Window

(7)	Cum. Return	Sharpe Ratio	Volatility	Max. Drawdown
Combined Indicator (incl. Fees and RF)	1.449566	0.399	**0.127**	-0.411
2 Subsequent Regimes	**1.482238**	**0.405**	**0.127**	-0.412
3 Subsequent Regimes	1.430878	0.397	**0.127**	**-0.400**
4 Subsequent Regimes	1.378442	0.388	0.128	-0.417
5 Subsequent Regimes	1.460460	0.399	0.128	-0.406
S&P 500	1.583259	0.332	0.192	-0.568

Note: The introduction of the restriction on subsequent rules has only a minor impact on the performance. The best performing strategy in each category is shown in bold.

In order to identify further explanations, a sensitivity analysis was carried out with various fee structures and subsequent regimes. The following dilemma was at the forefront: if the number of confirmation days for subsequent regimes is high, the indicator must be shifted by more days, which can delay the early detection of changing regimes. On the other hand, many subsequent regimes prevent rapid regime changes, which reduces transaction fees.

Table 8: Sharpe Ratio Sensitivity of Strategy (7) with Transaction Fees during Training Window

(7)	0.0%	0.1%	0.2%	0.3%
Combined Indicator (incl. Fees and RF)	**0.468**	**0.434**	0.399	0.365
2 Subsequent Regimes	0.437	0.415	0.393	0.372
3 Subsequent Regimes	0.433	0.409	0.385	0.362
4 Subsequent Regimes	0.453	0.428	**0.403**	**0.378**
5 Subsequent Regimes	0.443	0.417	0.391	0.365
S&P 500	0.332	0.332	0.332	0.332

Note: The table shows how different fee structures affect the Sharpe Ratio of subsequent strategies. With rising fees, the Sharpe Ratio improved only minimally with the subsequent regimes.

The effect between fees and consecutive regimes on the Sharpe Ratio is seen in Table 8. For the Sharpe Ratio, the Combined Indicator without subsequent regime confirmation delivered the best results until fees of 0.1%. Fees exceeding 0.1% delivered the best performance with the introduction of four subsequent regimes. Similar results can be seen in Table 9 when considering the cumulative returns.

Table 9: Return Sensitivity of Strategy (7) with Transaction Fees during Training Window

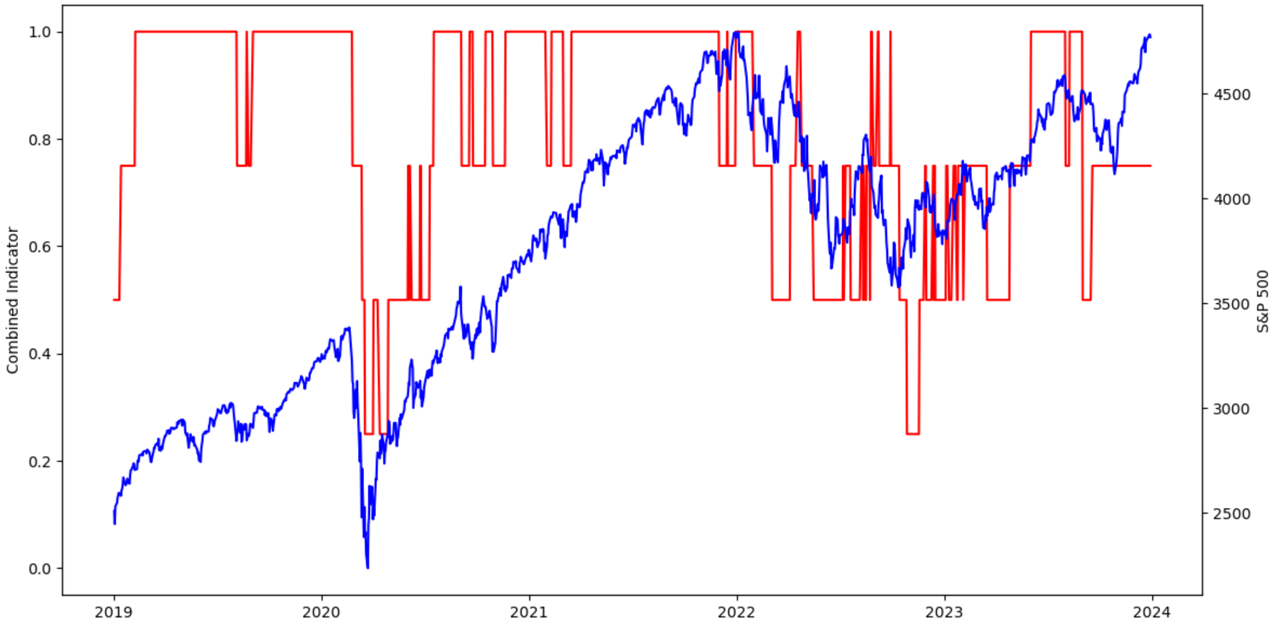
(7)	0.0%	0.1%	0.2%	0.3%
Combined Indicator (incl. Fees and RF)	**1.941586**	**1.684358**	1.449566	1.235259
2 Subsequent Regimes	1.703974	1.552243	1.408990	1.273746
3 Subsequent Regimes	1.684108	1.519511	1.364970	1.219873
4 Subsequent Regimes	1.839141	1.655792	**1.484241**	**1.323734**
5 Subsequent Regimes	1.772633	1.584453	1.409003	1.245423
S&P 500	1.583259	1.583259	1.583259	1.583259

Note: The table shows how different fee structures affect the cumulative returns of subsequent strategies. With rising fees, returns improved only minimally with the subsequent regimes.

5.3. Out-of-Sample Performance

The variables, parameters and computations from the training window have been tested on an out-of-sample dataset from January 1st, 2019 to December 31st, 2023. Daily forecasts have been made using the expanding window method. Since there was no regime change on the first trading day, the out-of-sample indicator started with the same regime as it ended within the Training Window.

Figure 9: Combined Indicator and S&P 500 over Test Window



Note: The Combined Indicator (red) has been plotted against the S&P 500 (blue) to show the regimes compared to S&P 500 during the Test Window. The indicator fell sharply at the same time as the COVID crisis slumped.

The indicator is correlated with the S&P 500 when analyzing the years 2019-2023. However, unlike the Dotcom Bubble and the Global Financial Crisis, which were detected early in the Training Window, the COVID crisis in February/March 2020 is detected late. This could be the result of an unexpected exogenous shock that the input parameters are unable to detect over time. For further insight and analysis of the different regime characteristics, the same calculations as for the Training Window were performed. Similar to the training set, the summary statistics for each regime were calculated in Table 10:

Table 10: Summary Statistics of Combined Indicator Regimes during Test Window

	Days	Mean	Std	Min.	Median	Max.	Skew.	Kurt.
0	-	-	-	-	-	-	-	-
0.25	38	0.001415	0.029739	-0.05183	-0.001814	0.093828	0.80958	1.232500
0.5	218	0.001908	0.018075	-0.11984	0.001292	0.092871	-0.68836	12.497903
0.75	378	-0.000015	0.014686	-0.09511	0.000565	0.049396	-1.14601	6.461767
1	624	0.000470	0.008125	-0.03528	0.001002	0.024348	-0.93285	2.690243

Note: The statistics showing a different distribution of mean returns and standard deviation than in the training set. However, according to the standard deviations, the regimes could be classified effectively.

The calculated statistics from Table 10 show that the regimes are correctly clustered according to the standard deviation. However, when considering the mean returns, a completely different pattern emerges. Here, the lowest result was found in Regime 1 and 0.75. This could indicate the assumption made in the training set that the transition phases, such as 0.25 are the most effective due to rebounds that increase the mean returns. Looking at both the training and test windows, it can be said that the transition periods such as 0.25 and 0.75 performed the best.

Table 11: Performance Output of Investment Strategies during Test Window

	Cum. Return	Sharpe Ratio	Volatility	Max. Drawdown
(1) Markov Indicator	0.563614	**0.850**	**0.113**	**-0.161**
(2) Markov x Spread Indicator	0.475622	0.685	0.125	-0.197
(3) PCA Indicator	**0.654525**	0.631	0.188	-0.297
(4) Combined Indicator	0.578909	0.699	0.146	-0.229
(5) Combined Indicator (incl. Fees)	0.516250	0.644	0.146	-0.233
(6) Combined Indicator (incl. RF)	0.609566	0.725	0.146	-0.238
(7) Combined Indicator (incl. Fees and RF)	0.545692	0.670	0.146	-0.231
S&P 500	0.902685	0.712	0.213	-0.339

Note: The table compares key performance metrics across several investment metrics and strategies during the Test Window, with the best performer in each category highlighted in bold.

It is worth noting that of all the strategies, the stand-alone (3) PCA Indicator had the highest return but did not outperform the S&P 500. From a risk and return perspective, the (1) Markov Switching Model had the highest Sharpe Ratio and even outperformed the S&P 500. Interestingly, the adjusted (3) Markov x Spread Indicator performed worse than the standalone

(1) Markov Indicator, most likely due to the strong and very volatile period during the COVID crisis, which caused the (1) Markov Indicator to switch regimes earlier than the (2) Markov x Spread, as reflected in the remarkable volatility of 0.113 and the lowest drawdown of -0.161. The Sharpe Ratio of the investment strategy, however, beat the S&P 500 under a risk/return methodology when taking into account the (6) Combined Indicator including risk-free rate. Nevertheless, as the model evaluation also makes evident, transaction costs need to be taken into account while evaluating investment options. Thus, the S&P 500 buy-and-hold strategy outperformed the (7) Combined Indicator, which combines risk-free rate and fees.

Table 12: Performance Output of Strategy (7) with Subsequent Regimes during Test Window

(7)	Cum. Return	Sharpe Ratio	Volatility	Max. Drawdown
Combined Indicator (incl. Fees and RF)	0.545692	**0.670**	**0.146**	-0.231
2 Subsequent Regimes	0.543634	0.660	0.149	**-0.229**
3 Subsequent Regimes	**0.547813**	0.660	0.150	-0.246
4 Subsequent Regimes	0.525101	0.631	0.153	-0.271
5 Subsequent Regimes	0.438496	0.553	0.153	-0.261
S&P 500	0.902685	0.712	0.213	-0.339

Note: The introduction of the restriction on subsequent rules has only a minor impact on the performance.

When the optimization approach was examined with the following schedules to avoid switching too often in Table 12, the returns increased only marginally and the Sharpe Ratio did not improve. Considering different fee structures, following sensitivity was calculated in Table 13 and 14:

Table 13: Sharpe Ratio Sensitivity of Strategy (7) with Transaction Fees during Test Window

(7)	0.0%	0.1%	0.2%	0.3%
Combined Indicator (incl. Fees and RF)	**0.725**	**0.698**	**0.670**	**0.642**
2 Subsequent Regimes	0.703	0.681	0.660	0.638
3 Subsequent Regimes	0.701	0.681	0.660	0.640
4 Subsequent Regimes	0.671	0.651	0.631	0.611
5 Subsequent Regimes	0.593	0.573	0.553	0.533
S&P 500	0.712	0.712	0.712	0.712

Note: There was no improvement with the introduction of subsequent regimes. However, with the absence of fees, the Sharpe Ratio of the Combined Indicator outperformed the S&P 500.

Table 14: Return Sensitivity of Strategy (7) with Transaction Fees during Test Window

(7)	0.0%	0.1%	0.2%	0.3%
Combined Indicator (incl. Fees and RF)	**0.609566**	**0.577310**	0.545692	0.514701
2 Subsequent Regimes	0.593147	0.568198	0.543634	0.519448
3 Subsequent Regimes	0.595832	0.571642	**0.547813**	**0.524340**
4 Subsequent Regimes	0.572221	0.548485	0.525101	0.502065
5 Subsequent Regimes	0.483108	0.460634	0.438496	0.416687
S&P 500	0.902685	0.902685	0.902685	0.902685

Note: With rising fees, returns improved minimally with the subsequent regimes, but without outperforming the S&P 500.

Finally, the Combined Indicator derived from the out-of-sample dataset from 2019 to 2023 could not match the outcomes from the training set. The overall performance was lowered by the probable late identification of market downturns, including the COVID crisis and the substantial impact of transaction costs, even though the Sharpe Ratio of some strategies, like the Markov Switching Model, exceeded the S&P 500. Performance metrics were not much improved by limitations to lower the frequency of regime changes, underscoring the difficulty of striking a balance between transaction costs and market reactivity.

6. Conclusion and limitations

This work was developed to create a comprehensive indicator that incorporates macroeconomic, sentiment and fundamental data. As a result, the indicator is intended to be an aid for a long-term investment horizon, but also to take into account small changes due to shorter-term indicators such as volatility changes, which should only change the allocation to a small extent.

The analysis of the training set showed that various market characteristics, such as high mean returns and periods of low volatility, can be clustered into regimes using well-known models such as the Two-State Markov Switching Model and Principal Component Analysis. Thus, the Combined Indicator showed great results in detecting early signals of a downturn based on the classification of regimes, notably the Dotcom Bubble and the Global Financial Crisis.

However, the results shown in the training set and model development have not all been reflected in the results of the out-of-sample test set. Unlike in the training set, the Combined Indicator, including fees and a risk-free rate, did not outperform the S&P 500's buy-and-hold strategy on a risk-adjusted basis. Nevertheless, standalone indicators like the Markov Indicator could beat the S&P 500 on a risk-adjusted basis, showing the benefits and drawbacks of each indicator.

In essence, most of the introduced strategies depend on the investor's specific objective and are also strongly characterized by transaction costs. Certainly, the Combined Indicator can be helpful in getting an overall impression of different market dynamics, even if the out-of-sample results are not convincing. As the test period has been affected by a black swan event like the COVID crisis, the investment strategies could be tested in a different period using a rolling test window. Since this crisis has differed significantly from the previous ones, particularly the changes in macroeconomic factors, which might be one of the reasons why the Combined Indicator has underperformed the S&P 500. In addition, risk-free rates have fallen significantly during this period, which also has an impact on the performance of the model, which invests the remaining allocation in risk-free rates.

In addition, it could be argued that the results could change dramatically if different or more variables were used. In particular, the financial articles used to select the prospective predictors were often published years after the out-of-sample testing began. Therefore, some assumptions may no longer be valid given the market dynamics of the financial environment.

In further possible research, the model could be extended in the future to include additional indicators or alternative weighting methods. One possible strategy could be to develop a dynamic investment strategy that switches between the models depending on the current market situation and optimizes returns by adapting the investment strategies to the characteristics of the market regimes. In addition, a modified definition of the investment strategy could be used that takes better account of time lags and transition periods. In addition, a strategy to reduce transaction costs while maintaining the desired result could be the subject of future studies.

Finally, specific conclusions can be drawn from the results of the indicators presented, which can be useful in the increasing dependence on data in the financial world and help with rapid market assessment based on predefined variables.

Appendix

Table 15: Summary Statistics of Input Data

	Mean	Std	Min.	Median	Max.	Skew.	Kurt.
S&P 500	3367.45	1617.47	676.53	4769.83	4796.56	-0.435037	-1.65023
S&P 500 Returns	-0.001287	0.008712	-0.12	-0.002826	0.1158	0.308691	21.03338
CBOE Volatility Index	16.55	6.97	9.14	12.77	82.69	2.87836	12.64633
Corporate Bond Spread	1.23	0.66	0.53	0.94	6.56	4.364289	25.25359
Term Spread	0.23	1.5	-1.89	-1.00	3.85	0.762871	-0.85145
10-Year Real Interest Rate	1.71	0.82	-0.42	2.082461	4.127623	-0.555618	0.16975
US Money Supply M2	6031.99	5594.99	1736.10	3889.2	21722.3	1.286519	0.74111
University of Michigan: Inflation Expectation	5.11	2.2	0.40	4.9	7.3	-0.09425	-1.8209
US Unemployment Rate	5.91	1.38351	3.40	6.2	14.8	1.224464	4.44900
Risk-Free Rate	0.009992	0.005967	0	0.012	0.026	-0.22708	-0.361
University of Michigan: Consumer Sentiment	88.19	10.29	50	90.8	112	-1.17354	1.65949

Figure 10: Comparison of Cumulative Returns of respective Strategies – Training Window

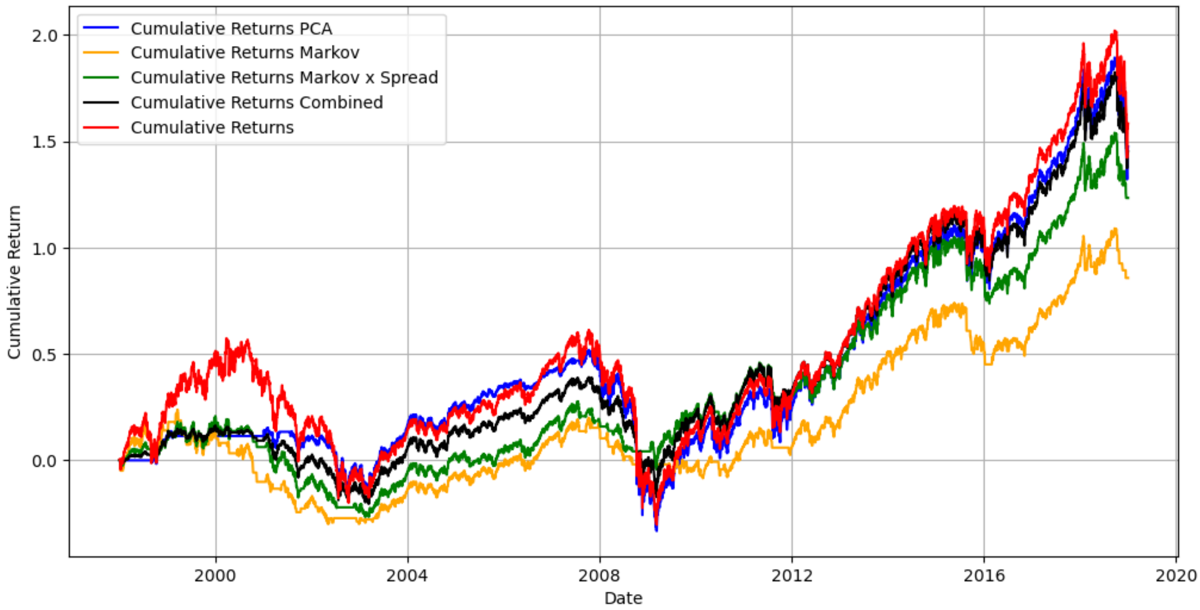


Figure 11: Comparison of Cumulative Returns of Combined Strategy – Training Window

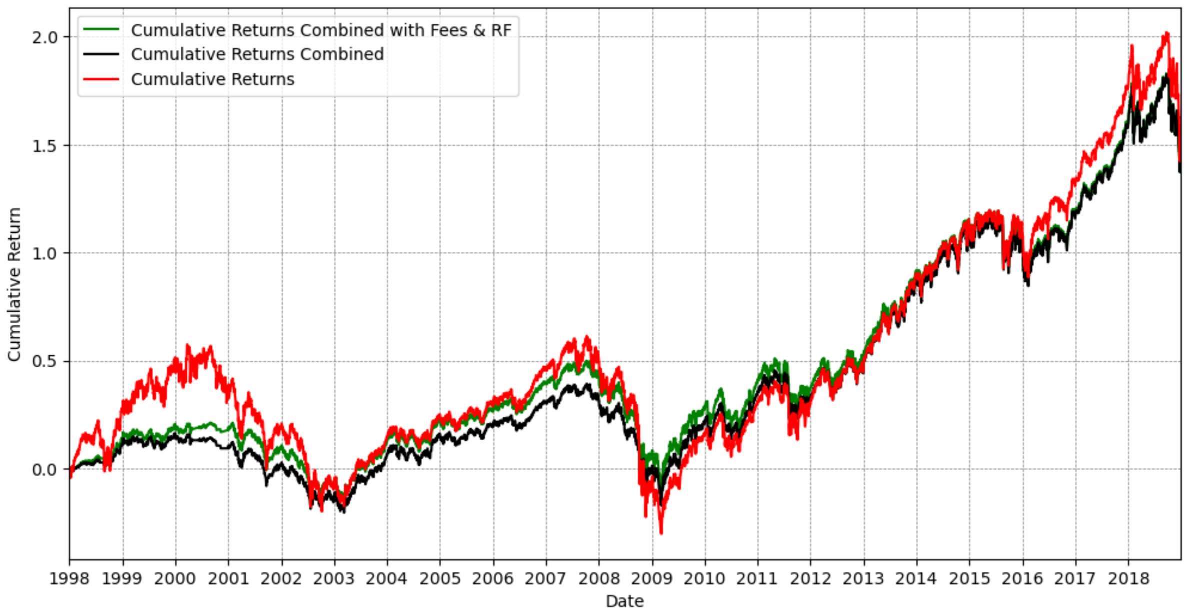


Figure 12: Comparison of Cumulative Returns of respective Strategies – Test Window

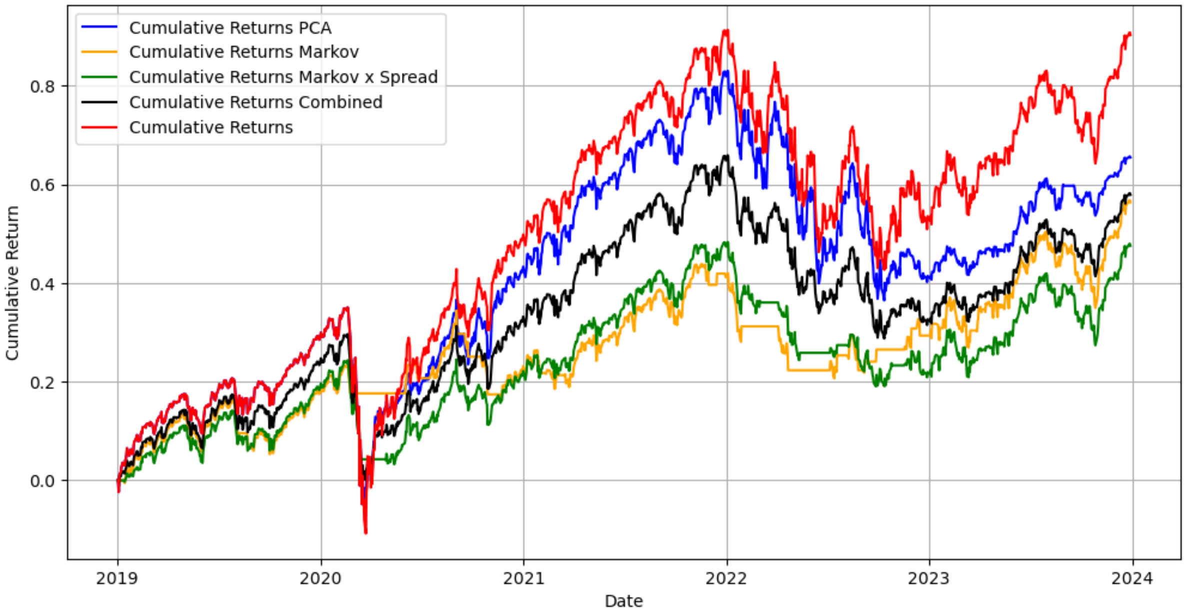
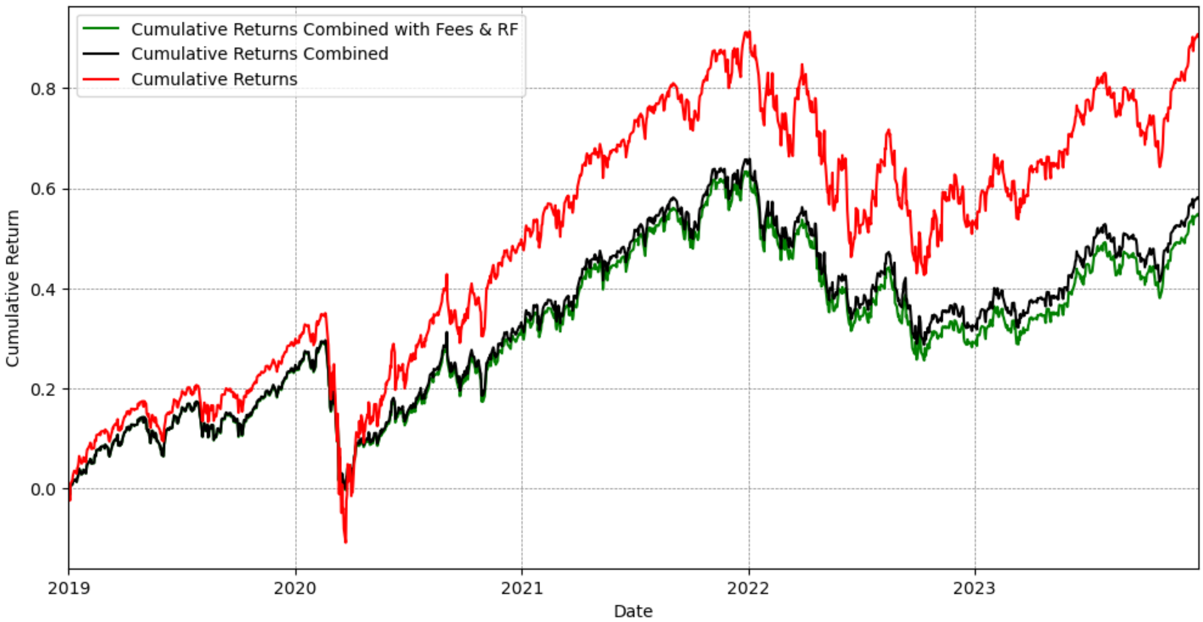


Figure 13: Comparison of Cumulative Returns of Combined Strategy – Test Window



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