CATÓLICA LISBON
BUSINESS & ECONOMICS

Markov Regime-Switching Models: Implications for Dynamic and Long-short Strategies

Ana Barata Feyo Engelking Alves

Dissertation written under the supervision of

Professor Pedro Monteiro e Silva Barroso

Dissertation submitted in partial fulfilment of requirements for the MSc in Finance, at the Universidade Católica Portuguesa,
3rd of January 2024.

Abstract

Conventional wisdom posits that investors should refrain from market timing. Challenging this, recent work using Markov regime-switching models argues that the market and a set of other risk premiums can be effectively timed and thus investors can avoid periods of high volatility diminishing losses, whilst still taking advantage of positive returns in a stable economy. Existing literature focuses mostly on in-sample predictability. This thesis tests those conclusions in an out-of-sample setting, contributing to existing literature by further investigating how to time the market's conditions using a Markov regime-switching model. More specifically, I estimate regime presence based on different variables, such as market turbulence, inflation, and economic growth. Regimes relate to either a highly volatile state, defined by economic contraction, or a more stable state, defined by economic growth. Additionally, in this thesis, I analyze different assets and risk premiums' performance out-of-sample, by comparing both a regime-based dynamic and a long-short strategy against a static one. The regime-based strategies' allocations are adapted to maximize returns whilst diminishing volatility given the presence of the regimes identified.

I find that using a Markov regime-switching model to time the market and adjust portfolio allocations significantly decreases volatility, greatly improving risk-adjusted performance. However, regime-based strategies do not appear to yield higher returns than a simple static allocation. Truly, they struggle to outperform a static strategy and market benchmarks. Nonetheless, some strategies based on market turbulence produce interesting alphas, suggesting that more research on regime-based strategies is warranted.

Author: Ana Barata Feyo Engelking Alves – 152422038

Title: Markov Regime-Switching Models: implications for dynamic and long-short strategies

Keywords: Markov regime-switching models, dynamic strategy, long-short strategy, regime-dependent allocation, economic regime variables

Sumário

É do conhecimento geral que os investidores se devem abster da prática de *market-timing*. No entanto, o uso recente de modelos Markov de mudança de regime (MMMR) contraria esta afirmação, defendendo que é possível fazer *timing* do mercado e de um conjunto de prémios de risco, levando os investidores a evitar períodos de elevada volatilidade, diminuindo perdas, beneficiando simultaneamente de retornos positivos numa economia estável. A literatura existente foca-se maioritariamente numa previsão *in-sample*. A presente tese testa as conclusões prévias *out-of-sample* (OOS). Mais concretamente, identifico a presença de regimes baseada em diferentes variáveis, como turbulência de mercado, inflação e crescimento económico. Os regimes correspondem a um estado de grande volatilidade (contração económica), ou a um estado mais estável (crescimento económico). Adicionalmente, analiso o desempenho de diversos ativos e prémios de risco OOS, comparando uma estratégia dinâmica e uma longa-curta dependentes dos regimes *versus* uma estratégia estática. As alocações das estratégias baseadas em regimes são adaptadas para maximizar retornos, simultaneamente diminuindo a volatilidade, tendo em conta os regimes identificados.

Nesta tese, concluo que utilizar um MMMR para *timing* do mercado e para ajustar alocações de portfólio reduz significativamente a volatilidade, aumentando consideravelmente a *risk-adjusted performance*. No entanto, estratégias baseadas em regimes parecem não produzir retornos mais elevados comparativamente a uma estratégia estática. Efetivamente, estas estratégias não têm um desempenho superior a uma estratégia estática e ao mercado enquanto *benchmarks*. Não obstante, algumas estratégias baseadas em turbulência levam a *alphas* interessantes, o que sugere justificar-se mais investigação em estratégias baseadas em regimes.

Autor: Ana Barata Feyo Engelking Alves – 152422038

Título: Modelos Markov de Mudança de Regime: implicações para estratégias dinâmicas e longas-curtas

Palavras-chave: modelos Markov de mudança de regime, estratégia dinâmica, estratégia longa-curta, alocação baseada em regimes, variáveis económicas de regimes

Table of Contents

1. Introduction

The economy frequently undergoes regime shifts between two easily observable states: a low-volatility, steady state, generally characterized by economic growth, and a highly volatile state defined by economic contraction. Evidence of such states has been recorded in market turbulence[1], inflation[2] and GNP or GDP[3]. Regime shifts lead to departures from the ranges implied by long-term averages of means and covariances in performance, which presents challenges for portfolio construction and risk management. The goal of this thesis is therefore to build regime dependent portfolios investing in risk premiums and assets, which avoid losses of highly volatile states and still benefit from gains characteristic to a steady economy. To do so, I firstly identify the presence of each regime (steady or volatile) across different economic variables in-sample. Each economic variable impacts risk premiums and assets differently. To test this impact, I observe how risk premiums perform in-sample given the presence of either regime. I then forecast regimes for each economic variable and build investment strategies dependent on those regimes. Lastly, I test the regime dependent strategies out-of-sample against a static strategy. The regime dependent strategies consist of a dynamic[4] and a long-short[5] strategy.

Out-of-sample allocation using regimes is particularly hard, as many researchers use Markov regime-switching models to fit a dataset and identify the regimes in-sample, but not many attempt out-of-sample forecasting, so it is not self-evident how it can be done. However, Kritzman, Page and Turkington (2012) provide a method to building regime-switching models which can also be extended to forecast regimes. Ang and Bekaert (2002) show that volatile regimes in financial assets lead to downside correlations. Longin and Solnik (2001) and Campbell, Koedijk, and Kofman (2002) show that exposure to different countries' equity markets offers less diversification in bear markets than in bull markets. This also applies to

[1] Chow, Jacquier, Kritzman, and Lowry (1999) and Kritzman, Lowry, and Van Royen (2001).
[2] Kim (1993) and Kumar and Okimoto (2007).
[3] Hamilton (1989), Goodwin (1993), Luginbuhl and de Vos (1999), and Lam (2004).
[4] A dynamic strategy refers to an approach which involves actively and frequently adjusting the allocation of assets (or risk premiums as well, in this case) in a portfolio, based on current market conditions, trends or forecasts. In this thesis the dynamic allocation is dependent on the "current" regime.
[5] Long-short strategies are mainly used in hedge funds and institutional portfolios. However, independent investors can also adopt this strategy, which consists of taking long positions in assets that are expected to increase in value (meaning the investor gains the percentage return of the asset as its value goes up) and taking short positions in assets that are expected to decrease in value. This means that when an asset decreases in value, the investor gains the amount of percentage its value decreased in.

global industry returns[6], individual stock returns[7], hedge fund returns[8], and international bond market returns[9]. Given the evidence of non-stationarity, it's easy to presume it may be preferable to estimate regime shifts as a basis to construct portfolios and manage their risk as opposed to a long-term static strategy. In line with this idea, I find that regime-based portfolios are indeed successful in bettering risk adjusted performance, successfully decreasing volatility when compared to a static portfolio. Truly, regime dependent strategies consistently outperform the market and the static strategy after adjusting for risk, even though the static strategy yields higher excess returns than the dynamic and the long-short portfolios[10]. Given that the long-short strategy portfolio doesn't outperform as well as I intended it to, I present alternatives for investors to still benefit from a long-short regime-based strategy by evaluating how this strategy plays out using individual risk premiums and assets and find out that investors can indeed benefit from applying this strategy to specific risk premiums and assets.

Current literature on regime-switching models and their impact on asset allocation can be found in Section 2. This section is relevant as many of the practices implemented in my thesis are based on previous research, mainly that of Kritzman, Page and Turkington (2012). The data section of my thesis (Section 3) describes the risk premiums and assets used to build the portfolios given their specific strategy, as well as where to access them. To define these strategies, I start with applying a Markov-switching model in-sample, as to understand how each regime affects each risk premium. I then push this analysis out-of-sample to forecast regime switches in market turbulence, inflation, and economic growth (the "economic regime variables"). I tested the performance of multiple assets and risk premiums under each regime out-of-sample, using both a dynamic and a long-short strategy against a static allocation. The long-short strategy is not only applied to portfolios investing in all risk premiums or all assets simultaneously, but also individually, as to understand which of them perform better given the regime-switches. Section 4 provides an in-depth explanation of the aforementioned methodology. Section 5 presents my results for the portfolio strategies, as well as for the individual long-short applications. The limitations and the conclusion can be found at the end of this thesis, in Section 6 and 7.

---

[6] Ferreira and Gama (2004).
[7] Ang and Chen (2002).
[8] Van Royen (2002).
[9] Cappiello, Engle, and Sheppard (2003).
[10] Section 5 provides the results of all strategies using assets and risk premiums. Risk adjusted performance can be measured using the Sharpe ratio, alpha and information ratio.

2. Literature Review

James Hamilton introduces Markov regime-switching in 1989 with his paper "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle". He applies a Markov-switching regression to characterize changes in the parameter of an autoregressive process, using the time path of unobserved series to draw conclusions about an unobserved state variable. To do so, he observes regime switches through real data on U.S. GNP changes post-war, using an algorithm to identify "turning points" of the time series. Here the determinant is growth rate: positive growth rate indicates a "normal" state or "regime", whilst negative growth rate indicates a recession state. Hamilton (2016) extends his research, concluding that using a simple Markov chain is likely to give a reasonable approximation to key features of economic growth data, as opposed to using a highly parameterized description of the transition into and out of recession, which could lead to overfitting. This presents an obvious correlation with my thesis, since not only do I use a Markov regime-switching model to identify the "current" regime in- and out-of-sample, but also because one of the economic state variables used to do so is precisely based on U.S. GDP data (namely economic growth).

Clarke and De Silva (1998) apply a mean-variance asset allocation based on the identification of two regimes. They conclude that the efficient frontier for an investor varies across regimes, leading to a different portfolio allocation in an economy where assets are priced in capital markets so that their covariance with the state variables affects its expected returns and risk. This implies that instead of using long run estimates of expected risk and return averaged over a variety of economic states, the investor should condition markets' estimates on the prevailing economic environment and the resulting investment set. My thesis varies from this paper as I don't focus on a mean-variance asset allocation. However, the premise is the same: regimes represent the current economic environment, and allocation should be dependent on regimes, as to minimize risk and maximize return.

Ramchand and Susmel (1998) estimate several regime-switching models from international equity return data. They study the correlations between the U.S. and other world stock markets, defining the regimes by changes in correlations across markets and variances, and conclude that correlations between the major stock markets increase in periods of high volatility. Longin and Solnik (2001) and Campbell, Koedijk, and Kofman (2002), which I mentioned in the previous section of this thesis, further investigate this phenomenon, arriving to the same conclusion. This finding is relevant as we use U.S. market data to define the presence of regimes in equity turbulence, but we use those same identified regimes to allocate across foreign equity. Given that major stock markets reveal downside correlation, we can safely assume that the regimes identified using U.S. data will yield accurate estimations for foreign equity allocation.

Guidolin and Timmerman (2002) consider asset allocations based on a regime-switching model and restrict their attention to allocating wealth between a risk-free asset and domestic equity as well. In their paper, the investor's preferences depend not only on the first two moments of returns (mean and variance) to add explanatory power, but also on higher moments such as skewness and kurtosis. They capture regime variations in the risk premia, volatility, correlation, skewness, and kurtosis by integrating them in the CAPM equations. In my thesis, the Markov-switching model doesn't rely on any asset-pricing models such as the CAPM, given that the goal is to find a straightforward way to identify regimes and benefit from them, not model the regimes based on returns. Furthermore, I do not just allocate between a risk-free asset and equity, and the CAPM would not be as suitable for bonds and would present many limitations in terms of risk premiums. Guidolin and Timmerman (2005) extend their previous paper and find that regime-switching models capture both short-term and long-term variations in investment opportunities. This is evidently relevant for a dynamic and a long-short allocation, given that, by design, these strategies depend on the accurate identification of the current market regime. Guidolin (2011) concludes that Markov-switching models work well in all frequencies (daily, annual, etc.), although most financial economists prefer to use monthly data, which is also the case for my analysis.

Ang and Bekaert (2002a) investigate the optimal international asset allocation when returns follow various regime-switching processes. They conclude that the existence of high-volatility bear market regimes doesn't eliminate the benefits of international diversification. Ang and Bekaert (2004), observe the impact of regimes on asset allocation using foreign equity and U.S. equity. They calculate expected excess returns based on an adaptation of the CAPM, determining the excess returns of each security by the security's sensitivity to the market return, an idiosyncratic term and the idiosyncratic term's volatility. The authors conclude that investors can benefit from exploiting the changes between low- and high-volatility regimes but didn't take transaction costs into consideration. However, they also conclude that regime-switching strategies are relatively robust to transaction costs, as the probability of staying in the same regime is high. Given this finding, I don't take transaction costs into consideration in my long-short and dynamic strategies, as the results should remain accurate.

Kritzman, Page and Turkington (2012) apply a Markov-switching model to identify regimes based on economic variables such as market turbulence, inflation and economic growth. They then compare a dynamic regime-based strategy with a static strategy, investing in assets and risk premiums. They use a maximum likelihood estimate to fit the Markov-switching model to the data and conclude that regime-based allocations yield a positively lower volatility and sometimes higher excess returns. In my analysis, I follow this paper's methodology, extending the out-of-sample period used by the authors and further examine how the regimes perform in a long-short strategy. Extending the out-of-sample period reevaluates the accuracy of the results found by the authors, as those results can present bias simply given the period used, and applying a long-short regime-based strategy allows me to find out if there are further methods that lead to benefitting from the regime identification, given that regime-based allocations are not exclusive to a dynamic strategy.

Nystrup *et al.* (2018) use model predictive control to dynamically optimize a portfolio based on forecasts of the mean and variance of financial returns given by a hidden Markov model with time-varying parameters, assuming zero-interest cash as the alternative to stock indices. After accounting for transaction costs, they find that the model predictive control outperforms a static allocation, realizing both a higher return and a significantly lower risk. Once again, this method differs from the one used in this thesis but also confirms the accuracy of Markov-switching models.

Nystrup, Kolm and Lindstroem (2020), proposed an online classifier to determine the hidden state a new observation belongs to, without depending on historical observations and without compromising persistence. In this paper, they find that the maximum likelihood estimation (MLE) requires at least a thousand observations to be able to compete, in terms of accuracy, with their proposed jump estimator. Although I use the MLE method to estimate regimes without using more than a thousand observations, the identification of regimes in-sample suggests its accuracy.

Most literature focuses on Markov regime-switching models as a base for allocating between a risk-free asset and equity (whether domestic or foreign), modelling regimes using returns, whether directly or using an asset pricing model. This method has shown to successfully yield higher returns and lower risk than a static allocation, regardless of if transaction costs are taken into consideration or not. Using a MLE or an alternative regime estimation model seems to yield accurate regime identifications across authors. Kritzman, Page and Turkington (2012) stood out as investigating further than a simple mean-variance allocation between a risk-free asset and a stock index based on regimes modeled in returns. They identify regimes based on various economic state variables and then allocate across assets and risk premiums given their most accurate predictor (meaning variable) and achieve interesting results: not only does the dynamic portfolio based on risk premiums yield a higher annualized excess return by almost 1%, but they also lower risk by almost 2%. Although the asset's dynamic portfolio doesn't lead to a higher annualized excess return, yielding a similar value to the static portfolio, it is successful in diminishing risk by more than 1%. My thesis not only expands this analysis out-of-sample by 14 years to test the accuracy of its results, but I also used the regimes identified to understand how investors could benefit from a long-short strategy based on those regimes out-of-sample, which is not explored by literature focused on regime dependent asset allocation.

3. Data

In this thesis, the analysis is focused on the out-of-sample performance of a dynamic and a long-short strategy which are both based on regime identification and compare their performances against a static strategy. To do so, I retrieved data on different risk premiums[11] from various data sources, such as the FRED website, DataStream, Kenneth French, and the HFR website. Given that this type of data is not accessible to all investors, I also retrieved data on more commonly accessible assets, such as stocks and bonds.

Exhibit 1 shows the risk premium data sources. Risk premiums are classified based on how they should be affected by equity and currency turbulence, inflation, and economic growth (see Section 4.1.2). Equity turbulence is expected to affect the most significant number of risk premiums. The appropriate risk premiums for inflation are Gold, Treasury Inflation-Protected Securities (TIPS), and the yield curve. For economic growth, the focus is Stocks versus Bonds and Cyclical versus Noncyclical Stocks (which were considered as described in Exhibit 1). Both risk premiums in the currency turbulence section have the particularity of having an end date of August 2015, sooner than the others (which all end in July 2023), given the difficulty to find

[11] The "risk premiums" designation here is consistent with the data used by Kritzman, Page and Turkington (2012) and diverges from the more typically used form of the return of an asset in excess of the risk-free rate.

values for the data proxy. As all strategies will use the same available data, this does not represent bias in pure comparison terms. I didn't forward fill the currency risk premiums so as not to manipulate the results of the strategies out-of-sample. Treasury Inflation Protected Securities (TIPS) have only been available in the United States since 1997. Data on their returns was only available after January 2002, a year after the beginning of my out-of-sample analysis. However, as I calculate the performance of the risk premiums in-sample (prior to January 2001), given the regimes present at each moment in time (check Section 4.2.1), I backfilled the TIPS historical returns until January 1997 using a regression model, which only affects one year of my out-of-sample analysis (from January 2001 until January 2002).

Exhibit 1. Data on Risk Premiums

Risk premiums are defined closely following Kritzman, Page and Turkington (2012). Data on risk premiums was retrieved mainly from DataStream, Kenneth French's website, and the FRED website. As it is not possible to perfectly replicate the data, I retrieved the data which most closely represented that which was used by the authors.

Risk Premium	Start Date	Data Proxy
Equity Turbulence		
Global Stocks - Bonds	Jan-73	Fama French Factors (Kenneth French)
Equity Market Neutral Hedge Funds - Cash	Jan-90	Equity Market Neutral Composite (HFRI)[1] minus JPMorgans 1 Month Cash (FRED)
Emerging - Developed Equity	Jul-90	Emerging minus Developed Equity (Kenneth French)
Small - Cap Premium	Feb-79	Russel 2000 minus Russel 1000 (DataStream)
Equity Momentum	Jul-36	Momentum-sorted portfolios, Top Decile minus Bottom Decile (Kenneth French)
Credit Spread	Feb-89	ICE BofA US Corporate Index Total Return Value (FRED) - Risk Free Rate (Kenneth French)
High-Yield Spread	Oct-86	ICE BofA US High Yield Total Return Index Value- 10-Year Treasury Constant Maturity (FRED)
Emerging Market Bond Spread	Dec-98	ICE BofA Emerging Markets Index Total Return Value (FRED) - Risk Free Rate (Kenneth French)
Currency Turbulence		
FX Carry Strategy	Feb-76	FX Carry Strategy[2]
FX Value Strategy	Feb-76	FX Value Strategy[2]
Inflation		
Gold - Cash	Feb-78	S&P/GSCI Gold Index minus JPMorgan U.S. 1 Month Cash (DataStream)
TIPS - Nominal Bonds	Jan-97	S&P US TIPS 10Y Index[3] (DataStream minus Risk Free (Kenneth French)
U.S. Yield Curve (10Y-2Y)	Jan-89	S&P US Treasury Bond 7-10Y Index - Price Index minus S&P US Treasury Bond 1-3Y Index - Price Index (DataStream)
Economic Growth		

Global Stocks - Bonds	Jan-73	Fama French Factors (Kenneth French)
U.S. Cyclical - Noncyclical Stocks	Jul-36	10 Industry Returns[4] (Kenneth French)

[1] Source: HFR Inc., www.hfr.com, © 2023 HFR, Inc. All rights reserved.

[2] FX Value and Carry Barroso, P., Kho, F., Rouxelin, F., & Yang, L. (2018). Cutting the gordian knot of carry and imbalances. Available at SSRN 3232396.
[3] I backfilled historical returns prior to January 2002 using a regression model.
[4] I defined cyclical industries as durable goods, manufacturing, high technology, shops, energy and telecommunications. Non-durable goods, health and utilities were defined as noncyclical industries.

Exhibit 2 shows the asset class data source[12]. As we can see, all the data is publicly accessible, making it straightforward for any investor to obtain. However, as returns for government bonds aren't directly available, I had to perform an approximation for the monthly returns[13].

Exhibit 2. Asset Class Data

Asset class data was retrieved closely following Kritzman, Page and Turkington (2012), from DataStream and the FRED website. As it is not possible to perfectly replicate the data, I retrieved the data which most closely represented that which was used by the authors.

Asset Class	Start Date	Data Proxy
U.S Equity	Jan-01	S&P 500 Index (DataStream)
Foregin Equity	Jan-01	MSCI EAFE Index (DataStream)
U.S. Government Bonds	Jan-01	Government Bonds for United States (FRED)[1]
U.S. Corporate Bonds	Jan-01	ICE BofA AAA US Corporate Index Total Return Value (FRED)
Cash	Jan-01	1 Month Cash JPMorgan (DataStream)

[1] To calculate U.S. Government Bond's returns I applied the approximation method presented by Tuckman and Serrat (2012). Fixed income securities: tools for today's markets.

4. Methodology

4.1. Markov Regime-Switching Model

4.1.1. Introducing Hidden Markov Regime-Switching Models

Identifying the regime present at a given moment is relevant in the context of asset allocation. Investors can benefit from timing the market conditions given how they impact specific assets. Markov regime-switching models are helpful in this context as they recognize the regime present during each moment in time over a sample due to identifying unobservable underlying states. As Kritzman, Page and Turkington (2012) point out, a direct example of how the

[12] The "asset class data source" designation here is consistent with the data used by Kritzman, Page and Turkington (2012) and the common designation of asset class: equities, fixed income, cash and cash equivalents, real estate, etc.
[13] I applied the approximation method presented by Tuckman and Serrat (2012). Fixed income securities: tools for today's markets.

Markov-switching models identify the present state would be to imagine someone who wears a heart rate monitor. Whilst the person is asleep, we observe a low average nonvolatile heart rate. If the person wakes up, however, the heart rate level rises, as well as its volatility. Even if we don't *know* that the person is awake, we could make that observation given the increase in heart rate and its volatility. Thus, without absolute knowledge that the person is asleep or awake, we can infer that they are in either state given the observation of specific characteristics. For each of these states or "regimes", the heart rate follows a particular distribution (if asleep, with a lower mean and a lower volatility, and if awake, with a higher mean and higher volatility). Given that the observed regimes change over time, the term "Markov regime-switching process" arises. "Hidden" stems from the unobservable regime variables.

Hidden Markov Models (HMM) can also be applied to infer the hidden state of financial markets. They match the tendency of financial markets to abruptly "switch" their behavior as well as the occurrence of the new behavior persisting for multiple periods after a change (Ang and Timmermann (2012)).

In an HMM, the probability distribution that generates an observation depends on the state of an unobserved Markov chain.

The initial probability of being in a regime *i* is given by
$Pr(X_1 = i) = p_i$,

with X_1 being the first observed regime in the Markov chain.

The transition probability matrix $\Gamma = \{\gamma_{ij}\}$ with γ_{ij} designating the probability of a transition from regime i to regime j, is as follows:

$$\Gamma = \begin{pmatrix} y_{11} & y_{12} \\ y_{21} & y_{22} \end{pmatrix},$$

and

$\gamma_{ij} = Pr(X_t = j | X_{t-1} = i)$,
with *t* signifying time.

Consistent with a given distribution π_i each regime produces observations Y_t. For a discrete distribution, where Y_t can only have/ take up a limited set of values, the equation $\pi_{i(s)} =$

$Pr(Y_t = s|X_t = i)$ implies that the probability of Y_t being a particular value *s* is determined by the current regime X_t. Although the Markov chain can be in more than two regimes, in my analysis I assume it is either in regime X_t = 1 or X_t = 2, consistent with the literature present in Section 2.

The transition probability matrix $\Gamma = \{\gamma_{ij}\}$ has a stationary distribution π if $\pi^T\Gamma = \pi^T$ and $1^T\pi = 1$, where π is a 2-by-1 vector with unconditional probabilities of each state and 1 is a column vector with all entries equal to one. The Markov chain is then said to be stationary, with a constant probability distribution over the states if $\delta = \pi$, where δ is the initial distribution, meaning $\delta_i = Pr(X_{1 = i})$. This means that if the Markov chain starts in a stationary distribution, it remains in that distribution along a sample.

Consider, as an example, a two-regime model with normal conditional distributions where Y_t is normally distributed with a regime-specific mean μ_{X_t} and standard deviation $\sigma^2_{X_t}$:

$Y_t \sim N(\mu_{X_t}, \sigma^2_{X_t})$,

where *N*(·) denotes the normal distribution probability density function and

$$\mu_{X_t} = \begin{cases} \mu_1, if\ X_t = 1, \\ \mu_2, if\ X_t = 2, \end{cases} \quad \sigma^2_{S_t} = \begin{cases} \sigma_1^2\ if\ X_t = 1, \\ \sigma_2^2\ if\ X_t = 2, \end{cases} \quad \text{and } \Gamma = \begin{pmatrix} 1 - y_{12} & y_{12} \\ y_{21} & 1 - y_{21} \end{pmatrix}.$$

When X_t (the current state) is known, the distribution of Y_t depends only on X_t and not on former states or observations. The sojourn times, as in, the lengths of time the Markov regime-switching process spends in a particular regime before switching to another one, are presumed to be geometrically distributed:

$Pr(staying\ t\ times\ in\ state\ i) = y_{ii}^{t-1}(1 - y_{ii})$.

The geometric distribution exhibits a memoryless characteristic, meaning that the duration until the next shift from the current state is independent of the time already spent in that state (Nystrup (2017)).

Markov-switching models resemble regressions with hidden regime variables. As we cannot observe the underlying states X_t, and can only observe the data Y_t, I used a "maximum likelihood estimation" to identify the regimes and parameters that best fit the data.

4.1.2. Economic Regime Variables

The regimes identified in this study are based on different time series, namely financial market turbulence (including equity and currency turbulence), inflation and economic growth. Definitions will be given shortly. Each variable (time series) is supposed to capture a specific area of economic activity and provide a compact dataset for my analysis. The regimes identified in each economic activity serve as a base for the dynamic and the long-short allocation.

<u>Financial Market Turbulence</u>

Financial market turbulence is characterized by asset prices acting unusually in comparison to their historical patterns of behavior. This includes drastic price fluctuations of assets, a breakdown in their usual correlation, and a convergence of typically uncorrelated assets (Chow, Jacquier, Kritzman, and Lowry (1999). To account for this, financial turbulence is measured using the multivariate distance measure, also known as the squared Mahalanobis distance:

$$d_t^2 = (y_t - \mu)\Sigma^{-1}(y_t - \mu)' ,$$

where:
d_t = daily turbulence score,
y_t = 1-by-N vector of asset returns for period t, where N is the number of assets,
μ = sample average vector of historical returns,
Σ = sample covariance matrix of historical returns.

Kritzman and Li (2010) demonstrates that this statistical description is highly aligned with financial events in history which are vastly considered turbulent. In this thesis I calculate a daily turbulence index for U.S. equities using returns from the 10 Industry Portfolios[14] from Kenneth French's Library and a turbulence index for G-10 currencies using currency returns versus the U.S. dollar.[15] Each component was equally weighted within each of the indexes. Mean and covariance are estimated using the equally weighted historical returns for the past 3 years for currencies and 10 years for equities (as a rolling window, for the Mahalanobis distance

[14] Equities' Industry Portfolios are consumer nondurables, consumer durables, manufacturing, energy, high technology, telecommunications, shops, healthcare, utilities and other.
[15] Currencies, priced in U.S. dollars, include AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, and SEK. All currency data was retrieved from DataStream.

calculation). The equities' window is longer in order to capture longer equity market cycles, consistent with Kritzman and Li (2010). After having calculated the daily turbulence scores for each index, I averaged them monthly to create two monthly time series, one for each index. The equity and the currency turbulence score time series begin in July 1936 and January 1974, respectively, and end in July 2023.

Inflation

I calculate inflation using monthly percentage changes in the U.S. Consumer Price Index for All Urban Consumers from February 1947 until July 2023, using data from the Federal Reserve Economic Data (FRED) website.[16]

Economic Growth

Economic growth is measured using quarterly percentage growth in the U.S. real gross national product (GNP) starting in the second quarter of 1947 and finishing in the last quarter of 2023, also from the FRED website.

4.1.3. In-Sample Regimes in Market Turbulence, Inflation and Economic Growth

I applied a Markov two-regime-switching model to each of the four variables individually: equity and currency turbulence, inflation, and economic growth. For each variable, observations from regimes 1 and 2 are assumed to be normally distributed with a given mean and standard deviation (specific to each regime). I use a simple model to avoid overfitting. As previously described, the transition matrix is a 2 x 2 matrix. For each variable, I solved for the factors that best explain the data in-sample, which begins at the start date described in the above section and ends in December 2000. Table 1 shows the persistence, the mean, and the standard deviation of the two regimes for each variable. Persistence here is defined as the estimated transition probability of staying in the current regime ($y^{11}$and y^{22}). Regimes are observed on a monthly basis, consistent with the turbulence scores calculated, as well as the inflation rate data. Economic growth is measured using quarterly data.

[16] Federal Reserve Bank Economic Data, St. Louis Research https://fred.stlouisfed.org

Table 1: Markov-Switching Model: Estimation Results

The estimation results of the Markov regime-switching model refer to the persistence, average and standard deviation of the normal and the event regime for each economic variable. The event regime is defined by a higher volatility than the normal regime, paired with a higher mean. Persistence is higher for the normal regime. The standard errors of each estimate indicate that the differences in mean and standard deviation across regimes are statistically significant.

	Regime 1 (Normal)			Regime 2 (Event)		
	Persistence	Mu	Sigma	Persistence	Mu	Sigma
Equity Turbulence	94.64%	2.46	0.51	94.49%	3.84	1.04
Standard Error	11.00	0.28	0.06	11.00	0.44	0.12
Currency Turbulence	93.31%	2.31	0.97	64.91%	4.62	2.79
Standard Error	10.56	0.26	0.11	7.71	0.54	0.32
Inflation Rate	99.00%	0.21%	0.19%	97.07%	0.59%	0.47%
Standard Error	18.17	0.47	0.05	17.93	0.13	0.87
Economic Growth	90.33%	1.18%	0.84%	67.31%	-0.06%	0.94%
Standard Error	15.02	0.26	0.12	12.38	0.31	0.11

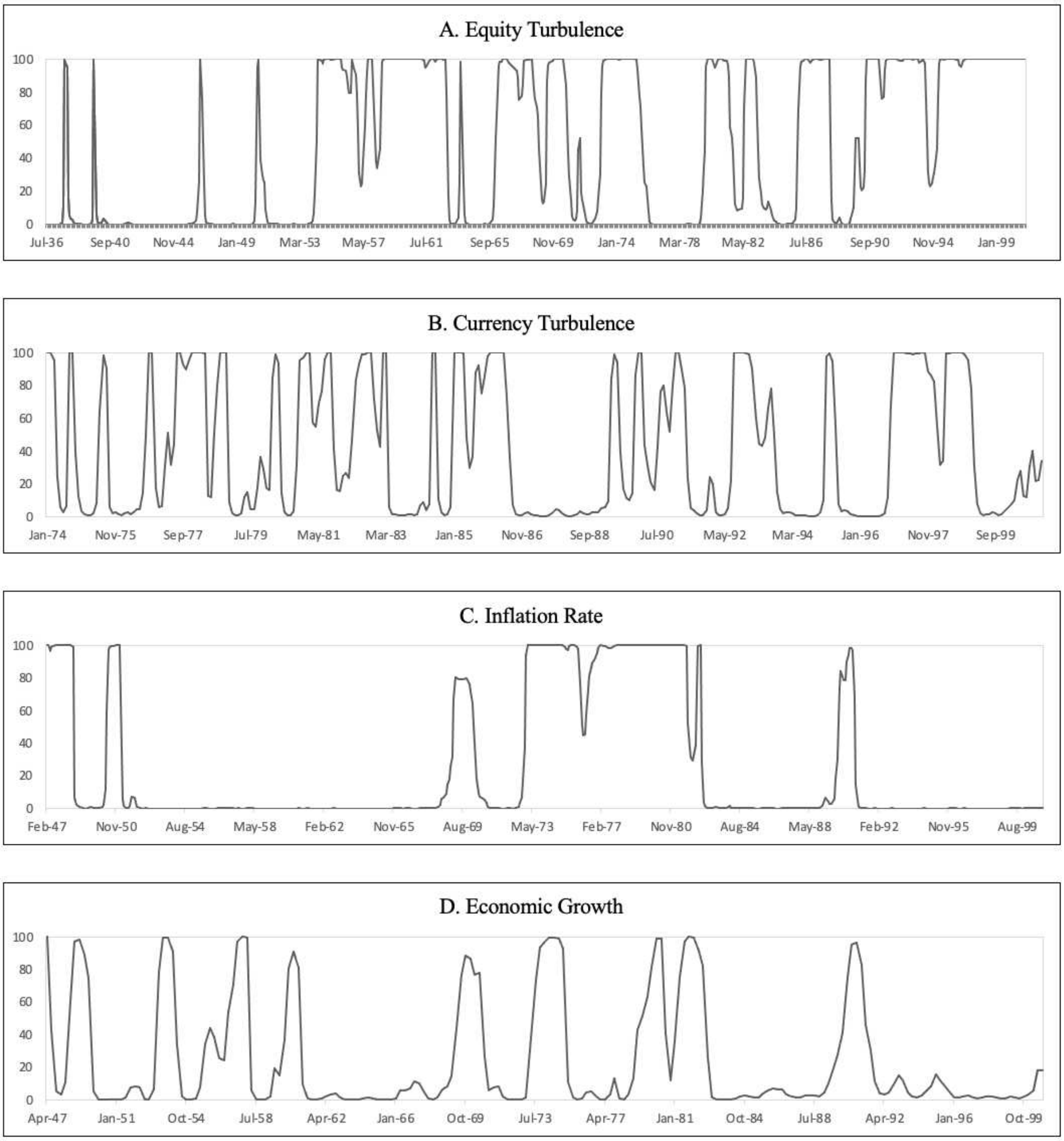
Note: persistence is defined as the estimated transition probability of staying in the same regime.

The results of the Markov-switching model indicate the presence of a "normal" and an "event" regime in each time series. We can observe that the "normal" regime is more persistent in each time series, meaning the estimated transition probability of staying in the "normal" regime (y^{11}) is higher than that of the "event" regime (y^{22}). Still, all persistence percentages are above 50%. We can notice as well that the average investment conditions for all variables are more challenging for the "event" regime, characterized by a higher μ, paired with a higher volatility (Σ). As there are no constraints in the model to align this way, we can be assured that these are the properties that best explain the data. The natural reaction to the difference in both regimes is inherent to the results displayed above: when turbulence is higher, we reduce portfolio risk and when a recession is present, the government stimulates the economy, eventually leading to a more stable economy. We can note that the inflation regimes are highly persistent, which could be due to the self-reinforcing cycle of higher wages and higher prices.

Given the normal conditional distributions of the two-regime model (as described in the first part of Section 4), I estimated a 95% confidence interval for the persistence estimates of each time series by adding and subtracting the standard error 1.96 times from the individual estimates. At a 5% confidence level, 6 of the 8 regimes show a persistence statistically greater than 50% (with the exceptions being the currency turbulence and the economic growth's event regime). The standard errors of each estimate for mu and sigma indicate that for each variable, the differences in mean and standard deviation across regimes are also statistically meaningful and not due to random chance.

Figure 1 shows the in-sample probability of each variable being in the event regime. We can observe that the regimes across variables have a slight correlation, although not unusually high. During the Recession of 1981 to 1982, all the variables were in the event regime, providing comfort in the accuracy of the model.

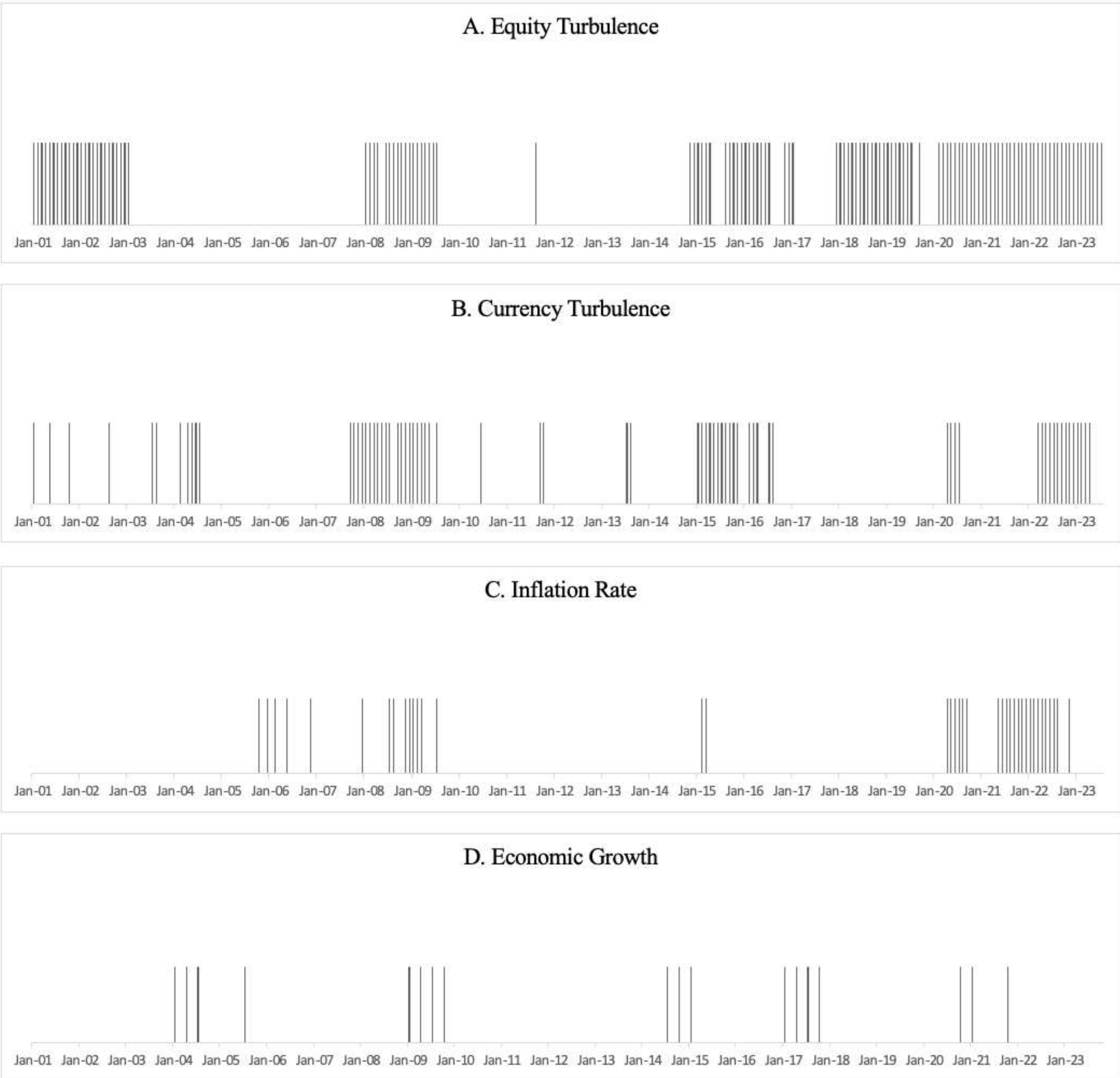
Figure 1: In-Sample Probability of Event Regime



4.1.4. Out-of-Sample Regime Forecasts

The in-sample results reveal that the Markov-switching models successfully delineate past data. However, they don't unveil whether a dynamic or a long-short process based on the out-of-sample regime identification would outperform a static process. The out-of-sample data ranges from January 2001 until July 2023. To test the out-of-sample performance, I calibrated the Markov-switching model each month, using an expanding window of data from inception to that point in time. Figure 2 shows the out-of-sample monthly event regime forecasts.

Figure 2. Out-of-Sample Event Regime Forecasts



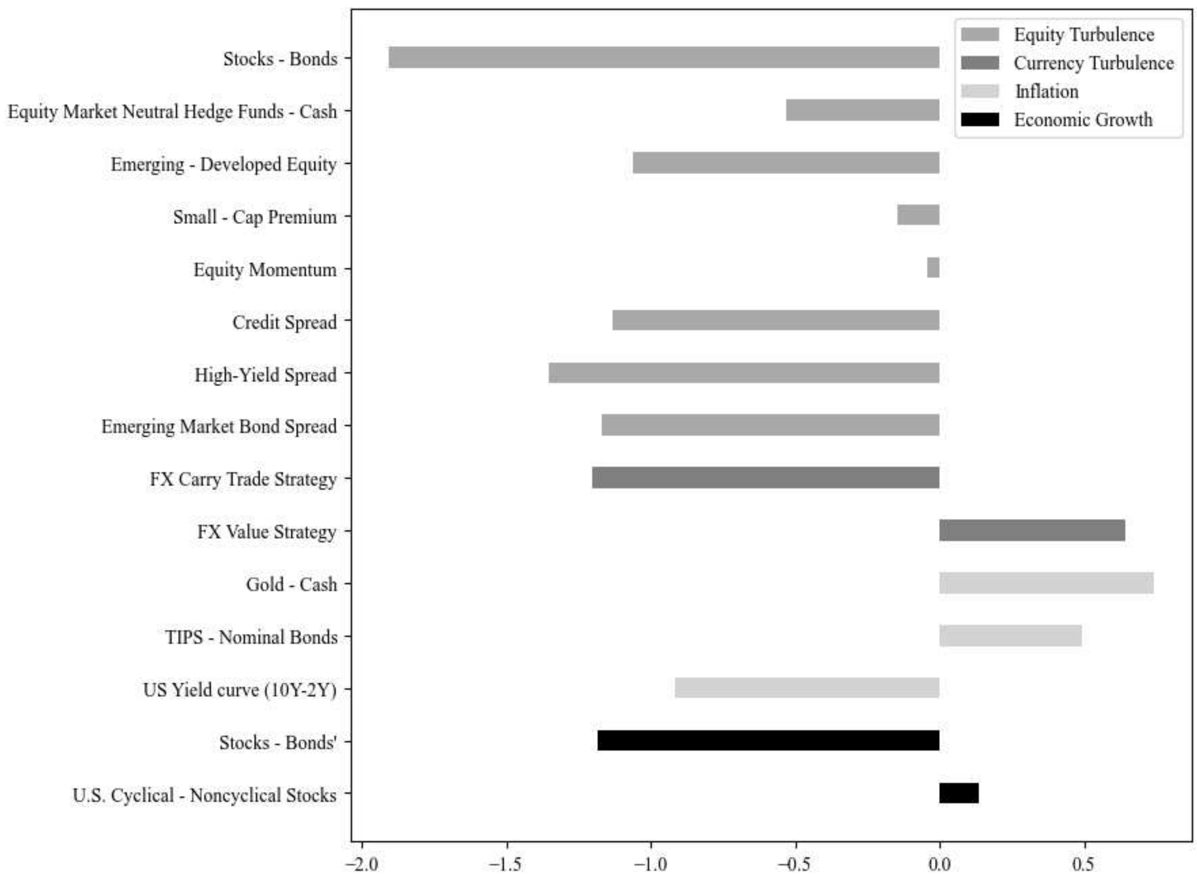
The forecasts show substantial persistence (consistent with the in-sample analysis), except for the economic growth event regime, which didn't last for more than 3 monthly observations (1 quarter). The frequency doesn't match the frequency of the risk premiums or the assets (which is monthly), but this doesn't create bias for my analysis given that the relevance of the regimes for a dynamic and long-short strategy lies mostly on their shift from one regime to the other, and not necessarily on their presence at each moment of the sample itself (as observed in Section 4.2).

4.2. Dynamic Tilts and Regime-Dependent Long-Short Allocation

4.2.1. Risk Premiums

To define the tactical asset allocation (TAA) tilts for my out-of-sample dynamic and long-short strategy, I must first understand how the risk premiums are affected by the regimes in-sample (hence why the data on risk premiums ranges from prior to the beginning of my out-of-sample analysis, until the end of it). To do so I calculated the in-sample risk premium performance, as seen in Figure 3, which shows how the risk premiums perform during the event regime in comparison to the normal regime, normalized by the standard deviation. Risk premiums which outperform the normal regime when in the event regime will be my "defensive trades".

Figure 3. In-sample risk premium performance: (event mean – nonevent mean) / volatility



Although the (FX) value strategy is expected to outperform the currency turbulence event regime, similarly to how "Gold – Cash" and "TIPS – Nominal Bonds" are expected to outperform during the high-inflation regime, I didn't expect the "Cyclical – Noncyclical Stocks" to outperform the recession regime. However, to remain consistent, this risk premium is used as a defensive trade as well.

Table 2 shows the TAA defensive tilts, which are consistent with the work of Kritzman, Page and Turkington (2012). The logic followed here is simple: the risk premiums start with an exposure of 10%, which is then reduced in the presence of the event regime of the corresponding variable. For example, "Stocks - Bonds" has an exposure of 10%. In the presence of equity turbulence, its exposure drops by 5%. If the equity turbulence and the economic growth variables are in the event regime, the resulting exposure to "Stocks – Bonds" would be 0 (= 10% - 5% - 5%). However, the exposure described in Table 2 is not fixed across the out-of-sample. The percentage allocated to each risk premium is affected by the growth of the risk premiums' returns themselves. This means that if, for example, Stocks – Bonds grows by 5%, the event regime tilt will then be calculated as follows: 10% * 1.05 – 5%. This is to ensure there is no bias when calculating cumulative returns, given that assuming a constant exposure of 10% (minus tilts) is unrealistic and most likely not implementable on a practical level. Allocation was then capped at a minimum of 0%, assuming that if the natural data growth led to negative allocation percentages, those wouldn't be taken into consideration. For the static allocation, I assumed an equal-weighted portfolio including all the risk-premiums present in the table, except for the defensive trades. Here, once again, we do not assume the allocation remains constant out-of-sample, but that the allocation weights are subject to the natural growth of the returns.

Table 2. Risk Premiums and Recommended Dynamic TAA Tilts

In this table we can observe the used risk premiums for the static, dynamic, and long-short strategy. The initial exposure refers to the static and dynamic strategies, as the exposure grows or diminishes gradually throughout the out-of-sample period given the returns of each risk-premium. Turbulence refers to either equity or currency turbulence. Recession is representative of the economic growth variable, whilst inflation refers to its own variable. Negative and positive tilts in the presence of the event regime of each variable are indicative of the dynamic strategy's allocation.

		Event Regime Tilts		
	Initial Exposure	Turbulence	Recession	Inflation
Risk Premiums				
Stocks - Bonds	10%	-5%	-5%	

Equity Market Neutral Hedge Funds - Cash	10%	-5%		
Emerging - Developed Equity	10%	-5%		
Small - Cap Premium	10%	-5%		
Equity Momentum	10%	-5%		
Credit Spread	10%	-5%		
High-Yield Spread	10%	-5%		
Emerging Market Bond Spread	10%	-5%		
US Yield curve (10Y-2Y)	10%			-5%
FX Carry Trade Strategy[1]	10%	-5%		
Defensive Trades				
Gold - Cash	0%			10%
TIPS - Nominal Bonds	0%			10%
U.S. Cyclical - Noncyclical Stocks	0%		10%	
FX Value Strategy[1]	0%	10%		
Sum of absolute values	100%	45%	15%	25%

[1] Based on currency turbulence

Table 3 illustrates the long-short strategy given the presence of the normal regime. This table is a variation of Table 2, where instead of using negative TAA tilts, we go short (sell) on the risk premiums during the event regime and instead of the positive TAA tilts, we go long (buy) in the presence of a normal regime. The defensive trades operate the opposite way, and we go long in the event regime, and short in the normal regime, consistent with our in-sample performance of the risk premiums (see Figure 3).

To better understand the impact of regimes on investment strategies, I decided to do two applications for the long-short strategy. One generates a portfolio investing in all risk premiums and following the logic described in Table 3 simultaneously. This means that for "Stocks – Bonds" if we are in the presence of the normal regime in both equity turbulence and economic growth, we go long. If just one of the economic variables is in the event regime, we go short, even if the other is in the normal regime.

The second application evaluates how every individual risk premium performs given the long-short strategy present in Table 3, but I observe the impact of the turbulence and the economic growth on the "Stocks – Bonds" individually, to understand which economic variable is more accurate in predicting the regimes that actually result in a better performance against a static strategy.

Table 3. Risk Premium Long-Short Strategy: Normal Regime

A plus (+) symbol indicates buying (going long) in the normal regime, whilst a minus (-) symbol indicates selling (going short) in the same circumstance. This assumes that for a risk premium with a (+) present on the table, we go long in the normal regime but short in the event regime's presence. The opposite for a risk premium with a (-) present in the table: in the normal regime we short, and in the event regime we go long.

	Turbulence	Economic Growth	Inflation
Risk Premiums			
Stocks - Bonds	(+)	(+)	
Equity Market Neutral Hedge Funds - Cash	(+)		
Emerging - Developed Equity	(+)		
Small - Cap Premium	(+)		
Equity Momentum	(+)		
Credit Spread	(+)		
High-Yield Spread	(+)		
Emerging Market Bond Spread	(+)		
US Yield curve (10Y-2Y)			(+)
FX Carry Trade Strategy[1]	(+)		
Defensive Trades			
Gold - Cash			(-)
TIPS - Nominal Bonds			(-)
U.S. Cyclical - Noncyclical Stocks		(-)	
FX Value Strategy[1]	(-)		

[1] Based on currency turbulence

4.2.2. Assets

Using the same event regime probabilities predicted in Figure 2, I implemented the defensive tilts shown in Table 4, anticipating turbulent, recessionary, or inflationary periods. Similarly to Table 2, Table 4 describes the initial allocation, but the natural growth of the data influences the percentage of allocation that is subject to the defensive tilts. Unlike the risk premiums, I didn't test the in-sample performance of the assets, since the economic variables regimes' impact on each asset is more straightforward to predict. The dynamic strategy assumes the static allocation's strategy given the presence of the normal regime for all variables. U.S. equity is obviously negatively impacted by equity turbulence and recession (the economic growth's event regime). Foreign equity isn't impacted by the economic growth given that the recession was measured using U.S. GNP data but is also impacted by the equity turbulence. Equity turbulence was also measured using U.S data but, as previously mentioned in Section 2 by multiple authors, regimes in financial assets lead to high downside correlations across different countries' equity markets, which leads to assuming that U.S. based regime identification of equity turbulence is accurate for foreign equity as well. Both U.S. government and corporate bonds are affected positively by the presence of turbulence, whilst the first is also positively impacted by the presence of a recession. During periods of high inflation, allocation to cash increases. The static portfolio allocation operates under the typical 60/40 allocation to stocks and bonds. Stocks are then subdivided into U.S. and foreign equity. Bonds are subdivided into U.S. government and corporate bonds. Similarly to the dynamic allocation, the weights of the static allocation are only representative of the initial allocation, being then subjected to the natural growth of the returns. Initial allocations, as well as tilts, are consistent with those implemented by Kritzman, Page and Turkington (2012).

Table 4. Asset Classes and Recommended Tilts

In this table we can observe the assets used for the static, dynamic, and long-short strategy. The initial exposure refers to the static and dynamic strategies, as the exposure grows or diminishes gradually throughout the out-of-sample period given the returns of each asset. Turbulence refers to equity turbulence. Recession is representative of the economic growth variable, whilst inflation refers to its own variable. Negative and positive tilts in the presence of the event regime of each variable are indicative of the dynamic strategy's allocation.

		Event Regime Tilts		
	Static Allocation	Turbulence	Recession	Inflation
U.S. equity	30%	-5%	-10%	
Foreign equity	30%	-5%		
U.S. government bonds	20%	5%	10%	-5%
U.S. corporate bonds	20%	5%		-5%
Cash	0%			10%
Sum of absolute values	100%	20%	20%	20%

Table 5 illustrates the long-short strategy in the presence of the normal regime. A plus (+) indicates going long and a minus (-) indicates going short on an asset, when in the presence of the normal regime for each economic variable (similarly to Table 3). This implies that in the event regime, the allocations operate the opposite way: if for U.S. equity we go long when equity turbulence is in the normal regime, we go short in the turbulence event regime. Equivalently to the risk premium long-short strategy, I also did two long-short applications for the assets: first, the perfect replication of the table for a full portfolio, assuming that, for the assets affected by more than one variable, if one variable goes short, we go short on that asset, even if the other economic variables are in the normal regime assuming a long position for the assets with a (+) on Table 5, and the opposite for assets with a (-) (to go short on these assets, only one variable needs to be in the normal regime). Secondly, I also did an individual asset long-short strategy, which seems more intriguing than the analysis done on the risk premiums, as there are more assets affected by more variables than there were risk premiums.

Table 5. Asset Long-Short Strategy: Normal Regime

A plus (+) symbol indicates buying (going long) in the normal regime, whilst a minus (-) symbol indicates selling (going short) in the same circumstance. This assumes that for an asset with a (+) present on the table, we go long in the normal regime but short in the event regime's presence. The opposite for an asset with a (-) present in the table: in the normal regime we short, and in the event regime we go long.

	Turbulence	Economic Growth	Inflation
U.S. equity	(+)	(+)	
Foreign equity	(+)		
U.S. government bonds	(-)	(-)	(+)
U.S. corporate bonds	(-)		(+)
Cash			(-)

5. Out-of-Sample Results

5.1. Static, Dynamic and Long Short Portfolios

Table 6 compares the performance, before costs, of the constant exposure portfolio, the dynamic process and the long-short strategy based on the risk premiums. I measure the static and the dynamic strategies performance using returns instead of excess returns, as implemented by Kritzman, Page and Turkington (2012). The static strategy yields the highest Sharpe ratio. However, all strategies' Sharpe ratios beat the S&P500's average Sharpe ratio in the last 22 years (the period of my sample)[17]. The alpha and the information ratio of the regime-based strategies were calculated using both the market and the static strategy's returns as benchmarks. The static strategy was only evaluated against the market for obvious reasons. The dynamic strategy shows a positive alpha both against the static strategy and the market itself at a 5% and 1% confidence level, respectively, revealing better risk-adjusted performance regardless of the static's strategy higher annualized return. It's information ratio of 0.35 and 0.21 suggest a modest level of excess return per unit of risk taken when using the static strategy and the market as benchmarks, respectively. The static strategy also has a positive alpha against the market, which is higher than that of the dynamic's strategy at a 1% confidence level, paired with a higher information ratio. However, by anticipating crises, the dynamic strategy was successful

[17] According to curvo.eu the average Sharpe ratio for the period of January 2001 to July 2023 was 0.42 https://curvo.eu/backtest/en/portfolio/s-p-500-

in reducing the annualized volatility, the skewness, the 5% value at risk and the maximum drawdown, indicating smaller declines during the worst performing periods (revealing, again, better risk management), which is easily attributable to the defensive approach of the TAA tilts given the regimes, but could also be driven by the defensive trades used by the dynamic strategy and overlooked by the static one.

Although the long-short strategy (based on excess returns, unlike the static and dynamic strategy, given that we borrow at the risk-free rate), yielded a considerably lower Sharpe ratio than the two previously observed strategies, it was also successful in reducing risk compared to the static strategy, as evidenced by the lower volatility, 5% value at risk, maximum drawdown and higher alpha and information ratio against the market. Similarly to the dynamic strategy, its alpha against the static strategy is also positive, but shows no statistical significance. The long-short strategy's alpha against the market shows no statistical relevance, although positive as well.

Table 6. Static, Dynamic and Long-Short Strategy Performance: Risk Premiums

This table presents a comparison of the performance between the three investment strategies using risk premiums – static, dynamic, and long-short. Alphas and information ratios are annualized, consistent with other metrics. The skewness, 5% value-at-risk and the maximum drawdown are obtained observing the monthly returns.

	Static	Dynamic		Long-Short
Annualized Return	5.83%	4.03%	Annualized Excess Return	2.02%
Annualized Volatility	4.34%	3.66%	Annualized Volatility	3.99%
Annualized Sharpe Ratio	1.06	0.76	Annualized Sharpe Ratio	0.52
Alpha (against static)	-	2.65%	Alpha (against static strategy)	2.32%
	-	(2.28**)		(0.92)
Information Ratio (against static)	-	0.35	Information Ratio (against static)	0.27
Alpha (against market)	4.52%	2.99%	Alpha (against market)	1.44%
	(4.33***)	(2.70***)		(0.38)
Information Ratio (against market)	0.33	0.21	Information Ratio (against market)	0.09
Skewness	-0.98	0.02	Skewness	0.16
5% Value at Risk	-2.03%	-1.63%	5% Value at Risk	-1.78%
Maximum Drawdown	-11.92%	-8.07%	Maximum Drawdown	-11.42%

Significance levels marked with *, **, and *** correspond to two-tailed t-statistics indicating confidence levels of 90%, 95%, and 99%, respectively[18].

Table 7 presents the same data as Table 6 for the assets-based portfolio. Once more, the dynamic strategy doesn't outperform the static strategy in terms of annualized returns, but its volatility is almost half as the static's one. This is reflected in a higher Sharpe ratio, and the alpha against the constant exposure strategy is 3.03% and relevant at a 1% confidence level, indicating a statistically significant better risk-adjusted performance once again. The less negative skewness, 5% VaR and maximum drawdown further perpetuate this analysis. Both strategies present positive alphas against the market, although not statistically relevant, coupled with moderately positive performance against the market given their information ratios of 0.19 and 0.27 for the static and the dynamic strategy, respectively.

The long-short strategy shows, once again, a positive alpha against the static strategy, but with no statistical significance. However, its 5% value-at-risk as well as the maximum drawdown outperform the static and dynamic portfolios. Interestingly, the static and the long-short strategy's Sharpe ratios are equivalent, with the dynamic strategy beating them both. Truly, the dynamic strategy performs better in comparison to the other strategies not only in terms of a higher Sharpe ratio, but also given its higher alphas and information ratios.

Table 7. Static, Dynamic and Long-Short Strategy Performance: Assets

This table presents a comparison of the performance between the three investment strategies using assets – static, dynamic, and long-short. Alphas and information ratios are annualized, consistent with other metrics. The skewness, 5% value-at-risk and the maximum drawdown are obtained observing the monthly returns.

	Static	Dynamic		Long-Short
Annualized Return	9.87%	7.31%	Annualized Excess Return	4.07%
Annualized Volatility	21.09%	11.04%	Annualized Volatility	9.81%
Annualized Sharpe Ratio	0.41	0.54	Annualized Sharpe Ratio	0.41
Alpha (against static)	-	3.03%	Alpha (against static)	1.39%
	-	(4.49***)		(1.20)
Information Ratio (against static)	-	0.77	Information Ratio (against static)	0.38
Alpha (against market)	1.23%	2.70%	Alpha (against market)	1.26%
	(0.83)	(1.33)		(0.69)

[18] This is applicable to all tables throughout this thesis.

Information Ratio (against market)	0.19	0.27	Information Ratio (against market)	0.07
Skewness	-1.10	-0.79	Skewness	-1.13
5% Value at Risk	-7.44%	-4.88%	5% Value at Risk	-4.24%
Maximum Drawdown	-50.73%	-44.80%	Maximum Drawdown	-33.62%

5.2. Individual Risk Premiums and Assets Long-Short Strategy

Given that in the previous results, the long-short strategy didn't perform as I expected, I delved deeper into understanding how one can benefit from using the regimes for a long-short strategy based on the risk premiums and assets I collected. To do so, as previously described, I applied the tactics present in Table 3 and Table 5 on the risk premiums, and the assets, respectively, but this time observing how they perform individually. What I find more interesting is that given that we're not observing a whole long-short portfolio, we can better understand which of the economic variables (in the cases where more than one variable affects the same risk premium or asset) yields a more accurate "hedging" regime identification, thus leading to positive alphas against the static strategy on each risk premium and asset, as well as against the market.

What I first noticed across all individual observations, is that several risk premiums' and assets' excess returns outperform the static strategy's excess returns. However, in the cases in which the long-short strategy underperforms, the difference of the excess returns between both strategies is more extreme than when the static allocation underperforms. This means that in the cases when the long-short strategy underperforms, the excess returns are incredibly lower than they are in the static strategy, whilst when the static strategy underperforms against the long-short strategy, the discrepancy isn't as big (see Appendix A.1. through A.4.) for the full tables of results including excess returns, volatility, etc.). Curiously, the annualized volatility of the observations also doesn't show much difference between the static and long-short strategy, apart from the risk premiums, when we go long in the normal regime. Here, the volatility of the long-short strategy is consistently lower than that of the static strategy, with special emphasis in the Stocks – Bonds risk premiums (for both equity turbulence and recession) and the Equity Momentum risk premium. Most 5% values at risk, as well as the maximum drawdown, seem to benefit from the regime identification and adaptation for the long-short strategy, which is consistent with what we observed in Tables 6 and 7.

Table 8 presents the alphas and information ratios for the risk premium's static and long-short applications (when going long in the normal regime, and short otherwise). Both are measured against the market as a benchmark, with the long-short strategy also being evaluated against the static allocation's returns as a benchmark.

The Stocks – Bonds risk premium (affected by equity turbulence) shows favorable alphas against both the market and the static allocation benchmarks, with statistical significance at the 1% level, standing at 9.21%[19] and 8.50%, respectively. The long-short strategy's information ratio against the market is 0.34, which compared to the static allocation's information ratio of -0.42 is highly impressive. However, the same risk premium, when affected by the economic growth's regimes, shows an underwhelming performance, with a negative alpha of -4.94% against the market, and -5.18% against the static allocation[20]. This could possibly explain why the dynamic strategy lost on returns against the static allocation, given that Stocks - Bonds is expected to be one of the most profitable risk premiums. As the dynamic allocation's Stocks-Bonds was affected simultaneously by the equity turbulence and the economic growth, it might have missed out on some relevant positive returns because of the recession regime, which is clearly made evident by the long-short's negative excess return on this risk premium (see, again, Appendix Table A.1.). The Emerging Market Bond Spread risk premium also shows a promising alpha of 3.32% against the market, with a 10% confidence level. Its alpha against the static strategy, at 4%, is statistically relevant at a confidence level of 5%, paired with an information ratio of 0.37. Although the difference between the long-short and the static's strategy excess returns remains at only 0.30% (with the long-short strategy ahead), the regime shifts minimized the long-short's risk by more than ⅓ when compared to the static allocation. Altogether, the Stocks – Bonds (influenced by the equity turbulence), the Emerging Market Bond Spread and the Carry Strategy are the only risk premiums that yield a statistically significant alpha against a static strategy (all paired with a significant alpha against the market as well). However, we can also note that the long-short strategy is more prone to yield positive alphas against the market than the static strategy through the whole sample.

[19] Note that this is consistent with previous work showing that the stock market has weak risk-adjusted performance in volatile times (Fleming *et al.* (2003), Marquering & Verbeek (2004) and Moreira and Muir (2017)).

[20] This is consistent with the stock market risk premium being higher in recessions (Shiller, R. J. (1981), Campbell, J. Y., & Shiller, R. J. (1988), Campbell, J. Y. (1991), Muir, T. (2017) Kroencke, T. A. (2022)).

Table 8. Risk Premiums: long when normal regime, short when event regime

This table evaluates the performance of both the static and the long-short strategies based on risk premiums, when going long in the normal regime and short in the event regime. Risk premiums are categorized under equity and currency turbulence, inflation, and economic growth. Alphas and information ratios are tested using both the static strategy and the market as benchmarks. Both are measured based on monthly data.

			Against Market		Against Static	
			Alpha	Information Ratio	Alpha	Information Ratio
Equity Turbulence	**Stocks - Bonds**	**Static**	-1.76%	-0.42	-	-
			(-1.88*)			
		Long Short	9.21%	0.34	8.50%	0.31
			(3.03***)		(2.86***)	
	Equity Market Neutral Hedge Funds - Cash	**Static**	-0.61%	-0.04	-	-
			(-3.39***)			
		Long Short	1.07%	0.07	1.04%	0.24
			(0.20)		(1.02)	
	Emerging - Developed Equity	**Static**	0.56%	0.03	-	-
			(0.03)			
		Long Short	1.16%	0.06	1.51%	0.09
			(0.23)		(0.35)	
	Small - Cap Premium	**Static**	-0.78%	-0.05	-	-
			(-0.81)			
		Long Short	-0.19%	-0.01	-0.36%	-0.02
			(-0.51)		(-0.76)	
	Equity Momentum	**Static**	0.03	0.07	-	-
			(1.14)			
		Long Short	-5.41%	-0.19	-1.81%	-0.03
			(-0.30)		(-0.73)	
	Credit Spread	**Static**	0.82%	0.05	-	-
			(-0.24)			
		Long Short	0.71%	0.04	0.85%	0.10
			(0.36)		(0.76)	
	Emerging Market Bond Spread	**Static**	1.46%	0.10	-	-
			(0.36)			
		Long Short	3.32%	0.18	4.00%	0.37

			(1.74*)		(2.15**)	
Currency Turbulence	**FX Carry Strategy**	**Static**	-0.62%	-0.04	-	-
			(-0.92)			
		Long Short	3.91%	0.22	3.67%	0.35
			(1.77*)		(1.72*)	
Inflation	**High-Yield Spread**	**Static**	2.91%	0.20	-	-
			(1.22)			
		Long Short	2.43%	0.16	1.42%	0.17
			(0.93)		(0.68)	
	U.S. Yield Curve	**Static**	-1.26%	-0.07	-	-
			(-1.96*)			
		Long Short	-0.43%	-0.02	-0.27%	-0.05
			(-1.30)		(-0.75)	
Economic Growth	**Stocks - Bonds**	**Static**	-1.76%	-0.42	-	-
			(-1.88*)			
		Long Short	-4.94%	-0.22	-5.18%	-0.23
			(-1.50)		(-1.57)	

Table 9 presents the results for the risk premiums of the defensive trades, when we go short in the normal regime, and long in the event regime. What first stands out is how the long-short strategy really underperforms for the FX Value Strategy risk premium at a 1% significance level, both against the market and the static allocation, presenting highly negative alphas. The TIPS – Nominal Bonds and the Cyclical – Noncyclical risk premiums benefit slightly from the long-short allocation, although with no statistical significance, whilst the Gold – Cash risk premium suffers a reduction in the alpha against the market, the information ratio and the excess returns, with a negative alpha against the static strategy. In this table we cannot identify any risk premium that benefits against the static strategy in a statistically significant way. However, a negative alpha is also potentially useful for asset allocation as it suggests a simple way to profit from the trade by doing the inverse of the strategy. The long-short individual application is useful in understanding where the dynamic strategy failed, as well as obviously and more directly, the global long-short portfolio.

Table 9. Risk Premiums: long when event regime, short when normal regime

This table evaluates the performance of both the static and the long-short strategies based on risk premiums, when going short in the normal regime and long in the event regime. Risk premiums are categorized under currency turbulence, inflation, and economic growth. Alphas and information ratios are tested using both the static strategy and the market as benchmarks. Both are measured based on monthly data.

			Against Market		Against Static	
			Alpha	**Information Ratio**	**Alpha**	**Information Ratio**
Currency Turbulence	**FX Value Strategy**	**Static**	-0.05%	-0.01	-	-
			(-0.61)			
		Long Short	-4.45%	-0.96	-3.52%	-1.33
			(-3.43***)		(-2.75***)	
Inflation	**TIPS - Nominal Bonds**	**Static**	1.35%	0.27	-	-
			(0.26)			
		Long Short	1.83%	0.35	0.60%	0.31
			(0.58)		(0.14)	
	Gold - Cash	**Static**	6.42%	0.90	-	-
			(1.86*)			
		Long Short	2.16%	0.30	-1.65%	-0.33
			(0.67)		(-0.48)	
Economic Growth	**Cyclical - Noncyclical Stocks**	**Static**	-4.42%	-1.29	-	-
			(-2.44**)			
	-	**Long Short**	-1.31%	-0.23	-0.97%	-0.19
			(-0.67)		(-0.55)	

Table 10 presents the results for the assets, when going long in the normal regime, and short in the event regime. What is instantly made evident is how both the U.S. Equity and the Foreign Equity highly benefit from the long-short strategy, with alphas against the market of 9.23% and 11.68%, at a 1% confidence level, and alphas against the static strategy of 9.27% and 8.68%, respectively, the first at a 1% confidence level, and the second at a 5% confidence level.

The curious results for the static strategy when it comes to the negative alphas could simply be due to the data used, since I measured U.S. equity using the S&P500 Index, and the market benchmark is the Kenneth French's 3 Factors market returns, which bases itself on NYSE, AMEX and NASDAQ firms, "good shares and price data at the beginning of t, and good return data for t".[21] However, as the long-short still beats the static strategy when it comes to the Foreign Equity risk premiums, we can assume its performance is relevant. The equities' information ratios lead me to conclude that the regime identification does indeed benefit the long-short strategy when compared to the static allocation. The remaining assets show no statistical relevance against the static strategy, although the government bond's long-short strategy shows positive alphas and high information ratios against the market and the static strategy (however with lower excess returns, as seen in Appendix A.3.).

Table 10. Assets: long when normal regime, short when event regime

This table evaluates the performance of both the static and the long-short strategies based on assets, when going long in the normal regime and short in the event regime. Assets are categorized under equity turbulence, inflation, and economic growth. Alphas and information ratios are tested using both the static strategy and the market as benchmarks. Both are measured based on monthly data.

			Against Market		**Against Static**	
			Alpha	**Information Ratio**	**Alpha**	**Information Ratio**
Equity Turbulence	**U.S. Equity**	**Static**	-0.27%	-0.23	-	-
			(-0.29)			
		Long Short	9.23%	1.19	9.27%	1.18
			(3.02***)		(3.10***)	
	Foreign Equity	**Static**	-5.09%	-1.14		
			(-1.45)			
		Long Short	11.68%	1.47	8.68%	1.05
			(3.30***)		(2.44**)	
Inflation	**Government Bonds**	**Static**	2.24%	0.48	-	-
			(1.06)			
		Long Short	2.48%	0.50	1.31%	0.80
			(1.28)		(0.63)	
	Corporate Bonds	**Static**	3.00%	0.68	-	-
			(1.66*)			
		Long Short	2.74%	0.59	0.81%	0.56
			(1.40)		(0.43)	
Economic Growth	**U.S. Equity**	**Static**	-0.27%	-0.23	-	-

[21] Kenneth R. French - Description of Fama/French Factors. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html

			(-0.29)			
		Long Short	-5.41%	-0.82	-5.68%	-0.88
			(-1.64)		(-1.72*)	

Finally, Table 11 presents the results of the static and long-short strategy when going long in the event regime, and short in the normal regime, relating to the defensive trades. Once again, the alphas and information ratios show no positive results against the static strategy or the market that are statistically significant. Truly, it deeply underperforms in terms of excess returns, volatility maximum drawdown, and 5% value at risk (see Appendix A.4.).

Table 11. Assets: long when event regime, short when normal regime

This table evaluates the performance of both the static and the long-short strategies based on assets, when going short in the normal regime and long in the event regime. Assets are categorized under equity turbulence, inflation, and economic growth. Alphas and information ratios are tested using both the static strategy and the market as benchmarks. Both are measured based on monthly data.

			Against Market		**Against Static**	
			Alpha	**Information Ratio**	**Alpha**	**Information Ratio**
Equity Turbulence	**Government Bonds**	**Static**	2.24%	0.48	-	-
			(1.06)			
		Long Short	-1.21%	-0.26	-2.05%	-1.34
			(-2.13**)		(-2.72***)	
Equity Turbulence	**Corporate Bonds**	**Static**	3.00%	0.68	-	-
			(1.66*)			
		Long Short	-2.66%	-0.58	-3.78%	-2.16
			(-3.12***)		(-4.01***)	
Inflation	**Cash**	**Static**	-12.71%	-0.91	-	-
			(-0.13)			
		Long Short	-8.37%	-0.61	-7.78%	-0.44
			(-0.07)		(-0.12)	
Economic Growth	**Government Bonds**	**Static**	2.24%	0.48	-	-
			(1.06)			
		Long Short	0.18%	0.04	0.26%	0.12
			(0.83)		(0.80)	

6. Limitations

Markov regime-switching models are useful tools to capture the behavior of variables across different states or regimes. However, estimating its parameters is complex and computationally intensive, especially as the number of regimes and variables increases. Thankfully, in most financial analysis using Markov regime-switching models, the number of regimes are assumed to be two, given that distinguishing between a higher number of regimes can lead to misleading results. Nonetheless, there aren't many studies testing and specifying the appropriate number of regimes to use in applications similar to the one done in this thesis, and again, the incorrect specification of the number of regimes can also lead to deceptive results. For example, in this thesis, the regime identification leads us to significant risk mitigation, but this comes at a cost: we continuously lose out on excess returns when compared to the static strategy. It could be relevant to discern between 3 regimes: we would still assume the two previously identified regimes, one of high volatility, the "event regime", and a more stable regime, the "normal regime" but identify a turning point between both. This way, positive turning points from the event regime to the normal regime lead to a higher percentage allocation to specific assets and risk premiums affected by the specific regimes, but not as high as during the normal regime, whilst a negative turning point from the normal regime to the event regime would cause us to hedge against the possible bear market, although not as much in percentage as we would in the presence of the actual "bear market" regime (the event regime). The "middle" regime identification would lead us to still hedge from extreme volatility, whilst still benefiting from potential returns that are currently being missed out on in my two-regime application.

The determination of the hidden state that each observation belongs to depends on the method used. In this thesis, I used a maximum likelihood estimation, which, as Nystrup *et al.* (2020) mention, might potentially not be the most accurate estimator, except for observations above a thousand. This presents a further limitation, as my economic variable data doesn't range for 1000 observations (with inflation being the closest to it, at 918 observations). However, given the results and the success in avoiding high volatility, I'm inclined to assume the regime identification remains accurate.

The sample period and the frequency of the data are further constraints. Would daily observations yield more accurate results? This would obviously be hard to implement in real life, as most individual investor's goal isn't daily portfolio management, especially given transaction costs. Annual data is too broad to be useful. However, as I test out-of-sample using a growing window, I must take into consideration how historical data might create misleading regime identifications. This is especially the case for the "economic growth" variable. As the data is quarterly, our number of observations in-sample are reduced drastically in comparison to the other economic variables. However, as Hamilton (2016) concluded, using HMM to identify regimes in GDP or GNP data is more accurate than other more parameterized models, regardless of the method used to estimate the unobservable regimes.

Furthermore, we cannot forget that the Markov models can lead to potential overfitting to historical data[22], which in itself can lead to poor out-of-sample forecasting performance.
The regime identification is also dependent on the variables it is observing. Had I used different data for my economic regime variables, the regimes identified by the Markov model would have been different, thus leading to a distinct allocation in the dynamic and long-short strategies. Even with the data I used, the Mahalanobis distance turbulence scores would have been different had I used a different period window for the calculation of the mean and covariance. The scores themselves are purely an approximation used to consider more data to "create" the market turbulence variables. The returns for the government bonds used in the assets' applications are also an approximation which can lead to bias in the results that relate to it. The dynamic allocations were illustrative (and consequently the long-short strategy allocations), and it is still necessary to take into consideration the fact that different allocations given the presence of specific regimes might influence specific risk premiums and assets in a different way than assumed in my thesis. Although I closely followed the work of Kritzman, M., Page, S., & Turkington, D. (2012) in terms of allocations and tilts, an additional development when it comes to using Markov regime-switching models based on economic variables could be to venture further into risk premiums' and assets' impact given multiple variables, thus yielding the most accurate allocation (whether for a dynamic or a long-short strategy). The in-sample evaluation of the effect of the event regime on the performance of risk premiums doesn't necessarily indicate future performance, the same way past returns don't necessarily reflect future returns. The entirety of these factors needs to be taken into consideration when evaluating the performance of the Markov regime-switching dependent strategies. However, I can't directly attribute fault to any of these aspects when it comes to the underperformance of the excess returns of the regime dependent strategies when compared to

[22] Guidolin, M. (2011), Wang, M., Lin, Y. H., & Mikhelson, I. (2020).

the static strategy, particularly given that I was able to diminish risk significantly and that my choices were not arbitrary.

7. Conclusion

Markov regime-switching models have proven themselves to be effective in diminishing risk due to identifying periods of more volatility. However, they do not seem to yield higher excess returns when compared to a typical static strategy (and this is before transaction costs), and ultimately the mitigation of risk doesn't always lead to a higher Sharpe ratio. This suggests that by avoiding periods of high volatility, the regime-based portfolios not only avoid extreme losses, but also potential sizeable gains in returns.

Nonetheless, the regime-dependent portfolio strategies always yield a positive alpha against the market and the static strategy's returns. This is particularly true for a dynamic strategy using assets, which beats the static strategy in a statistically significant way, both in alpha and information ratio, with a higher Sharpe ratio, a higher alpha against the market, more positive skewness, and smaller 5% value at risk and maximum drawdown. This could be relevant for conservative investors.

The long-short portfolio examined in my study doesn't seem to yield any relevant results against both the static and the dynamic strategy. However, investors might still benefit from applying this strategy to specific risk premiums and assets. U.S. equity and foreign equity (influenced by equity turbulence) seem to benefit substantially against the static strategy when their allocation is regime dependent. Stocks – Bonds and the Emerging Market Bond Spread (both influenced by the equity turbulence) are risk premiums which also profit from the regime identification, along with the FX Carry strategy (affected by currency turbulence). It's interesting that the variables which seem to yield more positive results are those based on equity and currency turbulence, as these are the variables which account not only for historical data, but also for their mean and covariance given a specific historical period. Granted this would not have been possible for inflation and economic growth given the data used, but as Hamilton (2016) mentioned, using a Markov chain to estimate regime-switches in economic growth is more appropriate than other models which might lead to overfitting. The fact that the equity turbulence regimes yield similar results in both the U.S and the foreign equity goes in accordance with Ang and Bekaert's, Ramchand and Susmel's, Campbell *et al.*, and Longing and Solnik's research: the correlation between stock markets increase in periods of high volatility, thus the regimes identified using U.S. market data accurately predict foreign equity turbulence out-of-sample.

Assumedly, investors can benefit from regime based long-short applications in specific risk premiums and assets, mainly those based on market turbulence. This can suggest that regime identification using windows of historical data (such as the Mahalanobis distance scores for equity and currency turbulence) may lead to more accurate predictions than inflation and economic growth regimes. However, it may also mean that the latter economic variables simply aren't good reflectors of the movement of returns of the risk premiums and assets impacted by them. Kritzman, M., Page, S., & Turkington, D. (2012) don't present any test on how each economic variable impacts each risk premium and asset in-sample. They solely assume the impact of specific economic variables on risk premiums and assets, and then test how they perform in-sample given that assumption. The economic variables' impact, which the authors assigned to the assets, seems rather easy to predict, but risk premiums do not have such a straightforward relationship with the presented indicators of regimes. The long-short application revealed a bit more about the predictive ability of each variable for their specific risk premium. More specifically, if we observe the individual long-short strategy of the Stocks – Bonds risk premium, we can infer that equity turbulence is a good predictor of its performance. On the contrary, the allocation given the economic growth variable leads to underwhelming performance. This is true for other risk premiums as well.

By observing the negative alphas, we can assume the opposite strategy presented by the authors and adopted by me in the long-short strategy, but the dynamic strategy suffers in comparison to the static allocation regardless. Just because the regime dependent strategy reveals less volatility, I can't presume it is given positive returns. There is simply less deviation from the mean of those returns, which can still be negative (or simply less positive than that of the static strategy).

Given the success in avoiding highly volatile periods using a Markov-switching model based on economic variables, I assume that modelling regimes directly in returns, similarly to Clarke and De Silva (1998), might lead to more concrete and positive results in allocating across assets or risk premiums. Although this option could lead to overfitting, the regimes would be forecasted based on the actual historical returns of each asset, being modeled specifically according to that asset's performance. This would obviously be considerably more exhaustive as we would have to forecast out-of-sample regimes for each single risk premium and asset, and then allocate according to each individual switch in regime, which could be costly in terms of transactions, but empirically could lead to more accurate results which would not only reduce risk, but ultimately also generate higher returns than a traditional static allocation. This approach could also eliminate the aforementioned issue: we wouldn't have to test the predictive power of each economic variable on each asset and risk premium.

In short, the main take-away from this study is that the dynamic and long-short strategies fail to outperform against a static or market benchmark, regardless of their global lower volatility. Still, some strategies using turbulence deliver interesting alphas which suggests more research on this topic is granted.

Appendix

Appendix A.1. Risk Premiums: long when normal regime, short when event regime

This table evaluates the performance of both the static and the long-short strategies based on risk premiums, when going long in the normal regime and short in the event regime. Risk premiums are categorized under equity and currency turbulence, inflation, and economic growth. Skewness, maximum drawdown and 5% value-at-risk are measured observing monthly returns.

			Annual. Excess Return	Annual. Volatility	Skewness	Max. Drawdown	VaR (5%)
Equity Turbulence	**Stocks - Bonds**	**Static**	6,04%	15,82%	-0,49	-53,64%	-8,03%
		Long Short	5,75%	4,57%	0,06	-51,06%	-7,56%
	Equity Market Neutral Hedge Funds - Cash	**Static**	0,00%	2,67%	-0,93	-16,59%	-1,19%
		Long Short	1,19%	0,76%	0,33	-9,91%	-1,10%
	Emerging - Developed Equity	**Static**	0,85%	10,82%	-0,02	-58,66%	-4,66%
		Long Short	1,51%	3,12%	-0,12	-47,35%	-5,09%
	Small - Cap Premium	**Static**	-0,12%	9,20%	-0,19	-34,82%	-4,21%
		Long Short	-0,18%	2,66%	0,11	-32,08%	-4,06%
	Equity Momentum	**Static**	-4,22%	31,27%	-1,49	-80,70%	-15,52%
		Long Short	0,73%	9,02%	1,20	-79,79%	-13,30%
	Credit Spread	**Static**	1,14%	5,12%	-0,57	-24,68%	-2,44%
		Long Short	0,49%	1,48%	0,33	-17,61%	-2,37%
	Emerging Market Bond Spread	**Static**	2,52%	6,26%	-2,49	-32,33%	-1,95%
		Long Short	2,82%	1,81%	2,02	-24,68%	-2,13%

Currency Turbulence	**FX Carry Strategy**	**Static**	0,73%	7,99%	-0,83	-36,88%	-4,61%
		Long Short	3,87%	2,28%	0,41	-14,10%	-3,19%
Inflation	**High-Yield Spread**	**Static**	4,81%	8,73%	-1,47	-37,38%	-2,91%
		Long Short	4,17%	2,53%	-1,90	-21,10%	-2,91%
	U.S. Yield Curve	**Static**	-1,25%	5,63%	0,14	-25,73%	-2,66%
		Long Short	-0,93%	1,63%	-0,19	-26,60%	-2,40%
Economic Growth	**Stocks - Bonds**	**Static**	6,04%	15,82%	-0,49	-53,64%	-8,03%
		Long Short	-5,05%	4,59%	-0,05	-83,76%	-7,84%

Appendix A.2. Risk Premiums: long when event regime, short when normal regime

This table evaluates the performance of both the static and the long-short strategies based on risk premiums, when going short in the normal regime and long in the event regime. Risk premiums are categorized under currency turbulence, inflation and economic growth. Skewness, maximum drawdown and 5% value-at-risk are measured observing monthly returns.

			Annual. Excess Return	**Annual. Volatility**	**Skew-ness**	**Max. Drawdown**	**VaR (5%)**
Currency Turbulence	**FX Value Strategy**	**Static**	-0,47%	2,23%	0,53	-35,29%	-3,93%
		Long Short	-3,58%	2,21%	-0,33	-59,58%	-4,16%
Inflation	**TIPS - Nominal Bonds**	**Static**	1,27%	2,04%	-0,26	-21,86%	-2,97%
		Long Short	1,35%	2,04%	-0,24	-19,76%	-2,99%
	Gold - Cash	**Static**	5,21%	4,82%	0,01	-43,55%	-6,13%
		Long Short	0,92%	4,84%	-0,13	-53,58%	-7,27%
Economic Growth	**Cyclical - Noncyclical Stocks**	**Static**	-0,12%	3,59%	0,60	-45,06%	-5,66%

		Long Short	-0,86%	3,59%	-0,12	-40,24%	-5,81%

Appendix A.3. Assets: long when normal regime, short when event regime

This table evaluates the performance of both the static and the long-short strategies based on assets, when going long in the normal regime and short in the event regime. Assets are categorized under equity turbulence, inflation and economic growth. Skewness, maximum drawdown and 5% value-at-risk are measured observing monthly returns.

.

			Annual. Excess Return	**Annual. Volatility**	**Skew-ness**	**Max. Drawdown**	**VaR (5%)**
Equity Turbulence	**U.S. Equity**	**Static**	7,51%	4,56%	-0,50	-51,67%	-8,01%
		Long Short	5,80%	4,58%	0,01	-51,11%	-7,61%
	Foreign Equity	**Static**	0,37%	5,21%	-0,91	-58,21%	-8,16%
		Long Short	8,72%	5,15%	0,43	-41,70%	-7,53%
Inflation	**Government Bonds**	**Static**	2,55%	1,47%	-0,63	-24,00%	-2,41%
		Long Short	2,34%	1,47%	-0,72	-18,24%	-2,36%
	Corporate Bonds	**Static**	3,82%	1,63%	-1,39	-20,83%	-2,25%
		Long Short	3,21%	1,64%	-1,42	-19,15%	-2,25%
Economic Growth	**U.S. Equity**	**Static**	7,51%	4,56%	-0,50	-51,67%	-8,01%
		Long Short	-5,53%	4,60%	-0,01	-86,01%	-7,88%

Appendix A.4. Assets: long when event regime, short when normal regime

This table evaluates the performance of both the static and the long-short strategies based on assets, when going short in the normal regime and long in the event regime. Assets are categorized under equity turbulence, inflation and economic growth. Skewness, maximum drawdown and 5% value-at-risk are measured observing monthly returns.

			Annual. Excess Return	Annual. Volatility	Skewness	Max. Drawdown	VaR (5%)
Equity Turbulence	**Government Bonds**	**Static**	2,55%	1,47%	-0,63	-24,00%	-2,41%
		Long Short	-0,80%	1,49%	-0,24	-31,15%	-2,26%
Equity Turbulence	**Corporate Bonds**	**Static**	3,82%	1,63%	-1,39	-20,83%	-2,25%
		Long Short	-2,04%	1,66%	-0,85	-46,98%	-2,29%
Inflation	**Cash**	**Static**	-13,42%	12,97%	-0.66	-99,48%	-20,27%
		Long Short	-8.65%	12.97%	0.37	-93.94%	-19.70%
Economic Growth	**Government Bonds**	**Static**	2,55%	1,47%	-0,63	-24,00%	-2,41%
		Long Short	0,26%	1,49%	-0,08	-19,73%	-2,67%

References

Ang, A., & Bekaert, G. (2002). International Asset Allocation With Regime Shifts. The Review of Financial Studies, 15(4), 1137–1187.

Ang, A., & Bekaert, G. (2004). How Regimes Affect Asset Allocation. Financial Analysts Journal, 60(2), 86-99.

Ang, A., & Chen, J. (2002). Asymmetric correlations of equity portfolios. Journal of Financial Economics, 63(3), 443-494.

Ang, A., & Timmermann, A. (2012). Regime Changes and Financial Markets. Annual Review of Financial Economics, 4, 313-337.

Barroso, P., Kho, F., Rouxelin, F., & Yang, L. (2018). FX Value and Carry. Available at SSRN 3232396.

Campbell, J. Y., & Shiller, R. J. (1988). The dividend-price ratio and expectations of future dividends and discount factors. The Review of Financial Studies, 1(3), 195-228

Campbell, J. Y. (1991). A variance decomposition for stock returns. The Economic Journal, 101(405), 157-179.

Campbell, R., Koedijk, K., & Kofman, P. (2002). Increased Correlation in Bear Markets. Financial Analysts Journal, 58(1), 87-94.

Cappiello, L., Engle, R. F., & Sheppard, K. (2006). Asymmetric Dynamics in the Correlations of Global Equity and Bond Returns. Journal of Financial Econometrics, 4(4), 537–572.

Chow, G., Jacquier, E., Kritzman, M., & Lowry, K. (1999). Optimal Portfolios in Good Times and Bad. Financial Analysts Journal, 55(3), 65-73.

Clarke, R. G., & de Silva, H. (1998). The Journal of Portfolio Management, 24(2), 57-64.

Ferreira, M. A., & Gama, P. M. (2005). Have World, Country, and Industry Risks Changed over Time? An Investigation of the Volatility of Developed Stock Markets. The Journal of Financial and Quantitative Analysis, 40(1), 195-222.

Fleming, J., Kirby, C., & Ostdiek, B. (2003). The economic value of volatility timing using “realized” volatility. Journal of Financial Economics, 67(3), 473-509.

Goodwin, T. H. (1993). Business-Cycle Analysis with a Markov-Switching Model. Journal of Business & Economic Statistics, 11(3), 331-339.

Guidolin, M. (2011). Markov Switching Models in Empirical Finance. In D.M. Drukker (Ed.), Missing Data Methods: Time-Series Methods and Applications (Advances in Econometrics, Vol. 27 Part 2, pp. 1-86).

Guidolin, M., & Timmermann, A. (2002). Asset allocation under multivariate regime switching. Journal of Economic Dynamics and Control, 31(11).

Guidolin, M., & Timmermann, A. (2005). Journal of Economic Dynamics and Control, 31(11).

Hamilton, J. D. (1989). A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle. Econometrica, 57(2), 357-384.

Hamilton, J. D. (2016). Chapter 3 - Macroeconomic Regimes and Regime Shifts. In Handbook of Macroeconomics, Volume 2.

Kritzman, M., & Li, Y. (2010). Skulls, Financial Turbulence, and Risk Management. Financial Analysts Journal, 66, 30-41.

Kritzman, M., Lowry, K., & Van Royen, A.-S. (2001). Risk, Regimes, and Overconfidence. The Journal of Derivatives, 8(3).

Kritzman, M., Page, S., & Turkington, D. (2012). Regime Shifts: Implications for Dynamic Strategies. Financial Analysts Journal, 68(3).

Kumar, M. S., & Okimoto, T. (2007). Dynamics of Persistence in International Inflation Rates. Journal of Money, Credit and Banking, 39(6), 1457-1479.

Lam, P.-S. (2004). A Markov-Switching Model of GNP Growth with Duration Dependence. International Economic Review, 45(1), 175-204.

Longin, F., & Solnik, B. (2001). Extreme Correlation of International Equity Markets. Journal of Finance, 56(2), 649-676.

Luginbuhl, R., & de Vos, A. (1999). Bayesian Analysis of an Unobserved-Component Time Series Model of GDP with Markov-Switching and Time-Varying Growths. Journal of Business & Economic Statistics, 17(4), 456-465.

Marquering, W., & Verbeek, M. (2004). The economic value of predicting stock index returns and volatility. Journal of Financial and Quantitative Analysis, 39(2), 407-429.

Moreira, A., & Muir, T. (2017). Volatility-managed portfolios. The Journal of Finance, 72(4), 1611-1643.

Muir, T. (2017). Financial crises and risk premia. The Quarterly Journal of Economics, 132(2), 765-809.

Nystrup, P., Kolm, P. N., & Lindström, E. (2020). Greedy Online Classification of Persistent Market States Using Realized Intraday Volatility Features. Journal of Financial Data Science, 2(3), 25-39.

Nystrup, P., Madsen, H., & Lindström, E. (2018). Dynamic Portfolio Optimization Across Hidden Market Regimes. Quantitative Finance, 18(1), 83-95.

Ramchand, L., & Susmel, R. (1998). Volatility and Cross Correlation Across Major Stock Markets. Journal of Empirical Finance, 5(4), 397-416.

Shiller, R. J. (1981). Do stock prices move too much to be justified by subsequent changes in dividends? The American Economic Review, 71(3), 421-436.

Tuckman, B., & Serrat, A. (2012). Fixed Income Securities: Tools for Today's Markets (4th ed.). John Wiley & Sons Ltd.

Van Royen, A.-S. (2002). Financial Contagion and International Portfolio Flows. Financial Analysts Journal, 58(1), 35-49.

Wang, M., Lin, Y.-H., & Mikhelson, I. (2020). Regime-switching factor investing with hidden Markov models. Journal of Risk and Financial Management, 13(12), 1-15.

Acknowledgments

First and foremost, I want to express my gratitude to Professor Pedro Barroso, for his patience and constant availability throughout the past months.

I want to thank José, Keef, Anderson and Vidigal, for being the support I needed during my bachelor's to get me here. I couldn't have done any of it without you. You always believed in me, even when I didn't. I'm eternally grateful for your trust.

To Sofia, my best friend, for being my company through hour-long study and work sessions the past years and pushing me towards my goals (and for literally everything).

To my mother, Silvia, for being the strongest pilar in my life. I couldn't have achieved anything without your constant support and motivation. You created the perfect balance in everything around me to ensure I succeed.

To my brothers, Jaime and Francisco, for bringing lightness into my busy days.

To Ari who, without any responsibility to do so, supported me through my school years. Thank you for still being here.