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Macroeconomic Regimes for Conditional Simulations of Equity Portfolios

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Abstract

Changing macroeconomic conditions have the potential to strongly influence equity portfolio returns. This paper examines how key macroeconomic regimes affect the statistical characteristics of equity returns. We find that across a limited number of regimes, equities exhibit stable and well-defined properties, in- and out-of-sample. These findings are critical for investors wishing to incorporate their macroeconomic views in their investment decisions; they also facilitate reliable portfolio simulations and out-of-sample projections. Furthermore, we demonstrate that long-term factor models provide robust insights into portfolio behaviour within different macroeconomic contexts, even for portfolios with limited historical data.

Keywords: Macroeconomic Regimes, Equity Portfolios, Simulations

Disclosure Statement
The authors of this publication are employed by Scientific Portfolio, an EDHEC venture, a company selling financial software. The design of this software may draw on insights related to this research, which could ultimately potentially benefit Scientific Portfolio. The views and results presented in this article were not driven by the views or interests of Scientific Portfolio and are not a reflection of its points of view.

1. Introduction

1. Introduction

Equity markets are sensitive to shifts in macroeconomic conditions, prompting investors to form views on forthcoming regimes and adjust their strategies accordingly. As changes in the economic environment influence firms' cash flows and cost of capital, they fundamentally shape investors' opportunity sets (Flannery and Protopapadakis 2002). However, given the short track records typical of equity portfolios, it can be difficult for investors to gauge how these portfolios might behave during rare, cyclical economic phases. To address this critical lack of information, it is often necessary to resort to simulations, which provide a spectrum of plausible alternative scenarios for historical returns to probe risks and opportunities in varied market environments beyond those revealed from the past. As such, simulations constitute a key input to the investment decision-making process. Unfortunately, producing reliable expectations about a portfolio's behaviour in different macroeconomic regimes is challenging for a variety of reasons. For one, the extreme nature of events, such as financial crises, makes them rare, thereby complicating statistical estimation. Furthermore, relevant risk factors to which a portfolio is exposed are not independent, hence it is necessary to account for changes in their joint behaviour across different macroeconomic states. In this paper, we identify key differences in equity portfolios across macroeconomic environments and show how to efficiently estimate regime-dependent parameters with long-term risk factor models.

Simulations provide a way to access information that is not confined to the historical track record. To do so, they require two foundational elements: an accurate statistical distribution capturing a portfolio's return properties, and a suitable sample to calibrate these distributions. While suitable distributions to simulate equity returns have already been proposed (e.g. Bouchaud and Potters 2003; Jondeau, Poon, and Rockinger 2007), selecting appropriate samples for calibration—particularly within distinct macroeconomic regimes—poses a greater challenge. In particular, return distributions are not strictly stationary, i.e. their distribution is time dependent.[1] In practice, however, simulations often rely on static distributional assumptions, which by construction reproduce long-term return properties, but fail to capture the full spectrum of short-term return variability. For instance, the average (annualised) 10-year performance of the US stock market between 1984 and 2024 is 11%. However, depending on the time of measurement, this performance varies between -5% (around 2009) to 20% (at the beginning of the 2000s).

One of the most common methods for modelling dynamic return behaviours is the use of Markovian processes, which allow the parameters of a distribution to change according to transition probabilities. However, while theoretically sound, this approach faces several practical issues that reduce its appeal for simulations aimed at supporting investment decisions: transition probabilities are difficult to link to a clear macro-economic context (Blitz and van Vliet 2011), and the number of states considered must be limited both to preserve interpretability and to avoid the so-called curse of dimensionality (Bellman 1966), which in this case denotes the issue of the state grid growing exponentially with the addition of further state variables, often resulting in computational infeasibility.

In this paper, we develop an approach that addresses these issues by focusing on the selection of economically meaningful sample periods that exhibit stable, but significantly different, statistical

1 - The assumption of stationarity is strongly contradicted by well-known empirical facts, such as the presence of volatility clustering (Mandelbrot and Mandelbrot 1997). To capture such properties, more sophisticated time-series models are used nowadays, such as ARCH and GARCH processes (R. Engle 2002; Bollerslev 1987).

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properties compared to long-term returns. Instead of modelling transitions between distinct states, we identify samples that reflect macroeconomic conditions with sufficient stability for effective parameter calibration. This enables us to retain economic relevance and enhance the reliability of model parameters without relying on traditional state-based simulations.

Our contribution to the literature is three-fold.

First, we identify distinct macroeconomic scenarios that yield statistically different return distributions compared to long-term averages. Within-regime expected returns, and especially volatility, diverge significantly from 'normal times', highlighting the importance of adjusting expectations according to the specific macroeconomic regime.

Second, we find that certain regimes exhibit stable and robust statistical properties, with return distributions that remain consistent both in- and out-of-sample. This insight is valuable for investors wishing to align their portfolio's performance expectations with their views on the forthcoming regime (Elkamhi, Lee, and Salerno 2023): simulating returns using regime-dependent parameters, i.e. performing conditional simulations, leads to more reliable outcomes than simulations based on long-term information only. This approach is close in spirit to (Hoevenaars et al. 2014), and (Bekkers, Doeswijk, and Lam 2009) who suggest deriving expected returns from a combination of long-term historical data, economic theory and current market circumstances for strategic asset allocation.

Third, we address the practical limitation of short historical records that hinder a sound statistical assessment of a portfolio's behaviour within specific regimes. To sidestep the potential lack of data spanning multiple economic cycles, we show that for equity portfolios, linear factor models can efficiently extrapolate returns with reasonable accuracy, even with as few as five years of information.

This paper contributes to a rich body of literature exploring the impact of macroeconomic conditions on equity returns and risk premia, which supports the common practice of using macroeconomic variables to define market regimes. Since macroeconomic changes impact investment opportunities (Flannery and Protopapadakis 2002), they represent undiversifiable risk factors (Ross 1976) and thus should be priced in equilibrium (Merton 1973; Breeden 1979). While evidence on real-sector aggregates is more nuanced aggregates (Chen, Roll, and Ross 1986), macroeconomic conditions are widely recognized for their role in driving returns. For instance, inflation and money growth have shown a negative impact on market returns (Bodie 1976; Fama 1981), while industrial production, consumption, and labour income yield positive abnormal returns (Lamont 2001). There is also a vast literature that documents that returns and factor models behave very differently on days with announcements regarding e.g. inflation, unemployment and interest rates, such as in (Savor and Wilson 2014; 2013; Lucca and Moench 2015; Brusa, Savor, and Wilson 2020; Cujean and Jaeger 2023).These studies further confirm the ideas that macro-based regimes, regardless how they are defined, have a strong influence on market outcomes. Macroeconomic variables are deeply intertwined with equity markets and frequently serve as market predictors (Welch and Goyal 2008), Goyal et al. 2024). In the context of equity portfolios, studies by

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(Amenc et al. 2019) and (Esakia and Goltz 2023a) propose protocols to identify macroeconomic variables and market regimes significantly influencing equity risk factor returns. If macroeconomic aggregates affect risk premia, they likely influence other statistical properties, including volatility. Supporting this, research shows that macroeconomic conditions impact return volatility and distributions across regimes (Hamilton and Susmel 1994; Sinha 1996), with similar evidence documented for European markets (Errunza et al. 1994). Building on this literature, our study provides effective methods to reliably estimate equity returns' behaviour across distinct macroeconomic regimes. Our approach, described in detail in the following sections, reduces dependence on historical data, captures multidimensional risk interactions and allows for a broader spectrum of outcomes that can be later employed for forward-looking portfolio management through regime-dependent simulations.

The rest of the paper is organised as follows. Section 2 explains the data and the methods we use. Section 3 illustrates the results. Section 4 concludes, discussing the implications for investment practices.

2. Data, Variable Definitions, and Methods

2. Data, Variable Definitions, and Methods

In this section we describe the data used, how variables are defined and the methods we employ.

2.1 Remark on Probability Distributions for Simulations

Before we move on, a remark is necessary. The simulation of equity returns can offer key inputs to the investment process. As we have mentioned earlier, this requires the selection of a probability distribution that accurately fits the features of returns, such as mean, volatility, skewness and kurtosis. The choice of the return distribution does not belong to the scope of this paper, for the stylised facts of equity returns have already been studied quite extensively, such as in (Cont 2001). Instead, we focus on the identification of macroeconomic regimes that exert a meaningful influence on equity returns, we quantify their impact and provide an efficient approach to reliably estimate regime-dependent parameters that can be later used in conditional simulations. We therefore leave the actual simulations exercise for future research.

2.2 Definition of Regimes

A macroeconomic regime is typically understood as a specific phase or state of the economy, characterised by distinct levels or variations of indicators such as inflation, interest rates, and market volatility. However, there is no consensus on which specific indicators best capture a given regime. For instance, inflation is often proxied by the movements of consumer price indices, but also more complex indicators based on differences between the prices of inflation-linked debt instruments and short-term rates are used sometimes. This paper selects a sample of well-known macroeconomic variables following the criteria from (Amenc et al. 2019), namely that macro-economic variables must be reactive enough, preferably market-based, to rapidly reflect changes in investors' preferences; they must affect aggregate wealth, that is, they must be economically relevant; and their link with equity factor returns must have been documented in the literature. Table 1 presents the variables chosen according to these requirements.

Table 1: Macro-economic variables used to define regimes
This table reports the macro-economic variables used to define regimes. Tickers from the Federal Reserve Bank (FRED) are in parenthesis. The last two columns denote what types of regimes are considered.

Macro-economic variable	Definition	Start date	Change	Level
Short-Term Rates	3 months US treasury bills (DTB3)	1954	Absolute	Yes
Market Index	Broad US market index	1970	Percentage	No
Inflation	CPI (CPIAUCSL until 2003) and then 10-year break-even inflation rate (T10YIE)	1947	Absolute	Yes
Long-Term Rates	Treasury instruments 10 constant maturity yield (DGS10)	1962	Absolute	Yes
Dollar Index	Strength of dollar against a basket of major currencies (DXY)	1973	Percentage	Yes
Oil	Spot crude oil price (WTISPLC and DCOILWTICO)	1946	Percentage	No
Credit Spread	Difference between Moody's BAA (DBAA) and AAA (DAAA) corporate yields	1970	Absolute	Yes
Time Spread	Difference between Long-term and Short-term rates	1962	Absolute	Yes
Market Volatility	Instant GARCH volatility of Market Index until 1990, then VIX (VIXCLS)	1970	Percentage	Yes

2. Data, Variable Definitions, and Methods

We define as regimes periods that are associated with significant movements in the time-series of these macroeconomic variables, starting from 1974. Given the different nature of the indicators considered, it is not possible to define regimes by only considering the level of each of them. This is because some of them accrue over time, e.g. market indices, and therefore a regime based on their level would simply contain the returns of a given period. Generally, macroeconomic aggregates that are notably affected by inflation, such as oil prices, cannot be associated with level-based regimes. Hence, one must also consider changes in the variables, whose measurement is also affected by the type of indicator considered. Typically, changes in rates are better defined in terms of absolute point rather than percentages. Since both level-based and change-based regimes are shown to produce regimes associated with significant differences in performance for equity risk factors (Amenc et al. 2019), we tailor the definition of regimes to each individual indicator, employing both level and changes where possible, or only one of the two, as shown in Table 1.

In this paper, a regime corresponds to the days belonging to a month in which the level, or change, of a macro-economic variable is in the top quartile ('high regime') or bottom quartile ('down regime') at the end of that month. Depending on the macro-economic indicator, changes are either absolute or in percentage (see Table 1). For instance, the high-volatility regime contains every day of each month when market volatility is in its highest quartile at the end of the month. Regimes defined in this way are meant to capture large-to-extreme market moves, so that they can provide impactful yet plausible stress scenarios that can replace traditional and more subjective 'what-if' practices often used in portfolio analysis. The choice of defining regimes based on indicators at the monthly frequency and to include the entire month differs from the practice of only considering the days during which macro-economic indicators reach extreme values. Although less reactive, this definition aligns better with the investment horizon of institutional investors, who typically rebalance portfolios on a monthly or quarterly basis and set their views accordingly, as they cannot adjust their portfolios more frequently. Thanks to the historical depth of our macroeconomic indicators and the fact that we select a quarter of the months, each regime contains about 3,000 daily returns.

2.3 Properties of Returns Within Regimes and Associated Empirical Tests

Simulating the performance of a portfolio across various regimes allows investors to move beyond the limitations of a short historical track record. Asset managers who have not yet experienced a high-volatility environment can simulate how their portfolio would react under such conditions. For the results of this exercise to be meaningful, the regime under scrutiny needs to fulfil three important conditions.

Distinctiveness from full sample: First, the expected performance or risk of the portfolio during that regime must be significantly different from long-term returns. A regime is only relevant if it has a distinct impact on the portfolio's behaviour over the next period. To evaluate whether the distributional properties of returns within a regime differ from long-term ones, we first test whether the first two moments (mean and volatility) of the returns within each regime are statistically different from

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long-term ones. This is an important analysis, as these parameters are used when calibrating probability distributions for simulations. We find that unconditional and conditional return moments are remarkably different.

In-sample stability: Second, the statistical properties of a portfolio's returns within any given regime must be sufficiently stable and robust so that the behaviour within that regime is reliable. A quantity that quantifies well the stability of a distribution is the excess kurtosis. The kurtosis is a powerful indicator of stability, since it is directly proportional to the variation of the volatility within a sample, and hence indirectly to the variation of expected returns. Less excess kurtosis is associated with more stable within-sample risk and performance. As illustrated below, we find that within-regime kurtosis compares with that found in long-term returns. Furthermore, to provide a more comprehensive test including information beyond the first two moments, we measure the difference in the distributions between randomly drawn samples corresponding to a quarter of the returns within each regime and the remaining returns in the same regime using the two-sample Kolmogorov-Smirnov test (Kolmogorov, 1993; Smirnov, 1948). The two-sample Kolmogorov-Smirnov test (henceforth: KS) is a non-parametric test that returns the probability for two return samples to be drawn from the same distribution. This statistical test also confirms that long-term returns and returns in specific regimes differ considerably.

Robustness out of sample: Lastly, in the context of investment decisions, the reliability of regime characteristics out of sample is key. We estimate the robustness of regimes by performing two tests. The first one is similar to a cross-validation exercise: we drop at random one fourth of the dates belonging to a certain regime, and we re-evaluate the dates belonging to that regime with the modified sample. Measuring the dissimilarity in the return distribution belonging to the newly identified regime dates and the initial test dates that were dropped effectively amounts to measuring the out-of-sample robustness of the regime returns. Applying a KS test here, in fact, provides the probability that an unseen sample of returns (i.e., out-of-sample returns) are drawn from the same distribution as those belonging to the same regime in sample. To add perspective on the robustness of regime returns over time other than on their stability to the effect of randomness, in the second test, we measure the distance between the distribution of the returns over the last three years and the distribution of returns over the next three years, which provides a useful benchmark for the distance measured in the first test.

2.4 Other Considerations Pertaining to the Use of Regimes

Two additional elements affect the application of regimes in an investment process, namely the typical duration of each regime and its historical representativeness.

Regime predictions are generally made with the next investment horizon in mind; however, regimes vary significantly in duration. Some, such as those linked to elevated volatility, tend to last only a few months, while others may extend for longer periods. Understanding a regime's typical duration has practical implications, as it informs the manager's strategy to either mitigate risks or capitalise on the

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expected regime. Short-lived regimes might prompt the use of derivatives for protection or speculative gains, while longer-lasting regimes could necessitate strategic reallocation.

Historical representativeness, which refers to whether a regime recurs over time rather than being isolated to one period, is equally important for portfolio analysis and management. For example, high-interest-rate regimes have occurred during a single decade in the past 40 years, making the statistics from that regime biased by the specific market conditions of that moment in history. In contrast, regimes that recur over different periods reduce this historical bias and tend to provide more robust statistical insights. Our analysis, in line with (Amenc et al. 2019; Esakia and Goltz 2023a), suggests that regimes based on changes in macroeconomic variables—rather than levels—tend to be more evenly distributed historically, thereby providing a more balanced and representative framework for analysing portfolio performance.

2.5 Model-Implied Returns and Out-of-Sample Simulations

In the context of investment decisions, understanding the impact of regimes on the invested portfolio is a key piece of information, because it will inform the decision taken in response to the macro-economic forecast. However, a robust impact analysis is often hard to obtain because of the typical shortness of the portfolio's track record. To obtain statistically significant information on the portfolio's behaviour in different regimes, data covering several business cycles is desirable, but rarely available, hence it is not possible to assess straight away the effect of macroeconomic shifts that a portfolio experienced firsthand.

One way to improve the statistical significance of performance and risk estimates in different regimes is to generate model-implied portfolio returns outside of the historical sample. Here we propose to do so by using the portfolio's exposures to different risk factors, which are usually available over long periods of time.

We define model-implied returns $\hat{r}$ as follows:

$$\hat{r}_t = \sum_{l=1}^{L} \beta_l f_{lt}$$

where β_l corresponds to the exposures of the portfolio to the risk factors f_l. This exposure is measured using the portfolio's historical track record, for each of the l=1,2,…,L. factors considered. In this paper, we compute exposures to the Scientific Beta equity risk factors (https://www.scientificbeta.com/). These factors are long-short factors representing the Size, Value, Momentum, Low Volatility, High Profitability and Low Investment risk factors, and are constructed to be uncorrelated to the market factor. It should be noticed that the procedure we employ works with any other set or risk factors with sufficiently long time-series, such as the Fama and French (1993) factors.

Extending a portfolio's return with this method is advisable under two conditions. First, the precision of the model, as measured by its R^2, must be high. This ensures that the residual returns, which represent

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the variation in returns driven by idiosyncratic risk and active management skills, are reasonably small, as we cannot extend unreproducible and firm-specific events outside of the historical sample. Second, the strategy followed by the portfolio must be sufficiently stable, and easy to represent in terms of exposure to risk factors. For instance, extending a strategy based solely on investing in undervalued stocks, typically defined as a “Value” strategy, can be done using the returns of the Value risk factor. Similarly, a purely sector-based strategy can be proxied by its exposure to sector-based risk factors. On the other hand, discretionary, actively managed strategies, may not yield accurate time-series extensions due to

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To test the reliability of a portfolio’s long-term extrapolation, we consider several strategies involving funds with very long track records, which we split into a calibration and test set. The size of the calibration set is taken at random ranging from 6 months to 10 years of daily returns which are also randomly drawn, resulting in potentially non-adjacent days. This sample is used to measure a portfolio’s exposures to risk factors. The portfolio’s returns are then extended onto the remaining sample, i.e., the test set, using model-based returns. We find that for funds with sufficiently high R^2, the extended returns are indeed quite precise, regardless of the period over which the exposures to risk factors are estimated.

Apart from enabling a robust analysis of regime impacts on the portfolio’s behaviour, the linear model approach has another important advantage, namely, to facilitate the simulation of reliable out-of-sample returns. Because risk factors have very long-term historical track records, their properties within each regime are estimated with high statistical confidence. Hence, one can efficiently calibrate probability distributions, including their correlations and moments, to simulate their returns. The out-of-sample returns of a portfolio within a given regime are then readily obtained by multiplying its exposures β to risk factors with their simulated returns. This approach provides reliable simulations of a portfolio’s behaviour in any given regime. To better illustrate one such procedure, consider using a simple Gaussian distribution. In this case, the simulated returns r_t^{sim} of a portfolio are obtained via the formula:

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$$r_t^{sim} = \beta\ (\mu + \ \Omega^{1/2}\varepsilon_t)$$

where μ is the vector of risk factors' expected returns during the regime, Ω is their covariance matrix, and $\varepsilon_t \sim N(0,1)$ are Gaussian white noise. To calibrate moments higher than the second, such as skewness and kurtosis, it is necessary to resort to non-Gaussian distributions, such as Student-t distributions. Moreover, to keep track of the co-variation among factors and the evolution of parameters over time, more advanced multivariate simulation frameworks such as GARCH models are needed. The discussion of how to perform simulations goes beyond the scope of this paper, which instead focuses on the estimation of regime-dependent parameters that can be employed later in conditional (i.e., in contrast to long-term or unconditional) simulations. We refer the reader to (Engle and Patton 2001) for a good review of simulation methods.

3. Results

3. Results

After describing the methods and the data we use, we now present the results from our analysis.

3.1 Distinctiveness, Stability and Robustness

3.1.1 Distinctiveness

To quantify how regime returns differ from long-term returns, we compute the difference between the performance and the volatility of the Scientific Beta US market factor returns (henceforth: the market or market returns) within regimes and those of the whole sample. The standard errors were obtained via the Welch and Levene test (Levene, 1960) for expected returns and volatility, respectively. Results are reported in the left and middle panel of Table 2. In most cases, regimes exhibit significantly different volatility compared to long-term returns, with differences that are often also economically significant: for instance, when inflation is low in levels, market return volatility is 4.14 percentage points higher than its entire history. On the other hand, expected returns do not significantly change from long-term ones in all regimes (left panel). This happens consistently only for regimes defined by market levels and volatility (unsurprisingly so given that we are considering market expected returns). Hence, it appears that regimes tend to influence risk more than performance. For instance, an increase in credit spreads, which indicates a higher risk of multiple defaults, or a decrease in short-term rates, tend to coincide with significantly higher market volatility, but do not have a clear impact on its expected return, i.e., on its direction.

Table 2: Difference in returns and risk (annualised volatility) between regimes and long-term
This table reports difference in expected returns (left panels) and annualised volatility (centre panel) for market returns between 1970 and 2024. Statistics significant at the 1%, 5% and 10% confidence levels are denoted by (***), (**) and (*). The p-values for the mean and the volatility are obtained using the Welch and Levene test, respectively. The third panel reports p-values for the KS test between the distribution of regime and long-term returns. For readability, p-values corresponding to at least 10% confidence level are in bold.

	$\Delta E[R]$(%)				ΔVolatility(%)				KS test			
	change down	change ip	level low	level high	change down	change up	level low	level high	change down	change up	level low	level high
Credit Spread	9.81*	-4.88	-0.59	7.41	-1.45**	2.82***	-3.89***	2.48***	0.29	**0.00**	**0.00**	**0.00**
Dollar Index	15.64**	-10.48*	--	-	0.32	0.82**	-	-	**0.01**	**0.03**	-	-
Inflation	-4.51	6.38	-0.43	-4.58	2.96***	-0.39	4.14***	-2.31**	**0.05**	0.37	**0.00**	**0.02**
Long-Term Rates	-1.24	-8.31	-	-	3.34***	-1.31	-	-	0.19	**0.05**	-	-
Market Index	-51.33***	85.62***	-	-	2.43***	-1.40	-	-	**0.00**	**0.00**	-	-
Oil	-7.94	8.58	-	-	2.41***	-1.18**	-	-	**0.00**	**0.09**	-	-
Short-Term Rates	-4.76	-8.84*	1.17	0.49	4.51***	-1.74*	3.82***	-2.37**	0.11	**0.02**	0.15	**0.04**
Time Spread	-3.08	-2.69	-2.69	-5.37	1.12***	3.62***	1.21***	1.86	0.36	0.12	0.12	0.70
Market Volatility	40.97***	-36.28***	25.88***	-26.71***	-0.55	2.32***	-8.47***	6.76***	**0.00**	**0.00**	**0.00**	**0.00**

In the right panel of Table 2, we report the p-value for a two-sample KS test that we use to compare within-regime return distributions with long-term return distribution. A low p-value of the KS test signifies that the return distributions are different, since it corresponds to the probability that the returns are drawn from the same distribution. Similar to what happens for the volatility, in most cases

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we can reject the hypothesis that the distribution of regime returns is the same as the distribution of the returns in the full-sample, as most of the p-values are below the typical confidence level of 5%. This observation strongly motivates the inclusion of regimes in investment processes and hints at the fact that overlooking them in a simulation exercise might lead to misleading results.

3.1.2 Stability

We now turn to examining the stability of the return distributions via two methods. First, we compute the difference between the excess kurtosis of market returns within each regime and that of long-term returns. Results are reported in Table 3 (left panel). Strikingly, almost all regimes exhibit a strong reduction in excess kurtosis over the long-term market returns. As the market excess kurtosis is around 17, the reductions observed in many cases are indeed important. For example, when short-terms rates are very high in levels (third-to-last row), the excess kurtosis shrinks by about 15, which means market returns resemble more a Gaussian distribution (whose excess kurtosis is zero) than other more involved distributions. The smaller excess kurtosis within regimes indicates that their statistical stability is higher than the long run.

Table 3: Regime stability: kurtosis and KS test
The left panel of the table shows the difference between the excess kurtosis of the regime market returns and long-term market returns. The right panel reports p-values of KS test between the distribution of returns belonging to the full regime and to 500 random subsamples within the same regime, each with length of a quarter of a year. The number in parenthesis correspond to the same test performed between the random subsamples and long-term market returns. Market returns use for this test span the period 1970 - 2024. For readability, p-values corresponding to at least 10% confidence level are in bold.

	Difference in kurtosis between regime and long-term returns				In-sample KS test based on random subsamples			
	change down	change up	level low	level high	change down	change up	level low	level high
Credit Spread	-10.76	-12.49	-11.01	-7.62	0.49 (0.42)	0.45 (**0.03**)	0.50 (**0.04**)	0.47 (**0.03**)
Dollar Index	17.16	-3.88	-	-	0.51 (0.20)	0.54 (0.24)	-	-
Inflation	-6.15	-12.62	-5.49	-14.49	0.46 (0.14)	0.55 (0.49)	0.50 (**0.10**)	0.54 (**0.28**)
Long-Term Rates	7.23	-14.08	-	-	0.50 (0.31)	0.54 (0.32)	-	-
Market Index	-12.38	-12.95	-	-	0.52 (**0.00**)	0.49 (**0.00**)	-	-
Oil	-11.08	-12.36	-	-	0.51 (**0.06**)	0.47 (0.34)	-	-
Short-Term Rates	6.13	-13.91	-3.76	-14.54	0.51 (0.23)	0.50 (0.25)	0.49 (0.27)	0.50 (0.30)
Time Spread	-9.76	8.75	-5.10	14.33	0.55 (0.39)	0.53 (0.25)	0.52 (0.27)	0.50 (0.49)
Volatility	-12.07	-9.21	-15.83	-15.08	0.50 (**0.04**)	0.57 (**0.00**)	0.55 (**0.00**)	0.54 (**0.00**)

In order to assess and quantify the distributional stability of returns within regimes, we draw at random 500 (non-overlapping) subsamples of returns with the size of a quarter of a year each belonging to the same regime, and then we conduct a KS test between each subsample and the full regime's return distribution. The resulting p-value of the KS test provides the probability that any portion of the regime has returns distributed like the full regime. In the right panel of Table 3, we report the average of these p-values across the 500 random subsamples. The typical likelihood is about 50%, which means we cannot reject the hypothesis that within-regime return distributions are very stable. This contrasts sharply with the low p-values obtained when comparing the random subsamples to the long-term

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returns (in brackets). These results are very positive and even surprising, given that the definition of regimes we have used does not explicitly target return stability.

These tests imply that equity returns within the selected macro-economic regimes have return distributions that are both statistically stable and distinct from long-term returns. Notably, in many cases, any two subsamples of returns drawn within the same regime have distributions closer to each other than to generic long-term returns, a fact that provides a stable basis for regime-focused investment strategies.

3.1.3 Robustness

We assess the out-of-sample robustness of regimes by carrying out the cross-validation (CV)-like exercise explained in Section 2.3. For illustration, consider short-term rates. First, we define the high-level regime by selecting the months in which the short-term rates are in the top-quartile of their distribution on the entire sample. One fourth of all dates belonging to this regime, taken randomly, are dropped from the sample. The dropped sub-sample is considered a test sample. Then, the high-level short-term rate regime is redefined using the remaining sample. Performing a KS test between the returns of the test sample and those belonging to the redefined regime period amounts to testing whether any yet unseen period that would be categorised as a high-level short-term rates regime has the same return distribution as other already observed regimes of the same type. In other words, this procedure measures the probability that future returns behave analogously to past returns within the same regime. We do this exercise for each of the regimes defined earlier.

Results are displayed in Table 4. As most of the p-values are high, we cannot reject the null hypothesis: the returns from past regime instances are likely to be drawn from the same distribution as returns belonging to the same regime in the future. This likelihood is as high as 40% for most regimes, with no statistical evidence of distributional differences across the regimes considered. As a benchmark, when we measure the probability that market returns drawn from any arbitrary three-year period resemble those from the following three years, it is of the order of 8%. This indicates that macro regimes tend to have lasting statistical properties that are very distinct from long-term returns. Hence, the stability of the macroeconomic regimes extends out of sample, enhancing their reliability for forward-looking investment decisions.

In Table 4, the number in brackets shows the p-values for the KS test between the regimes identified with this CV-like exercise and the long-term returns. In this way, we test whether the distinctiveness of regimes from the long run is robust to perturbations in the data. Differently from the other values, most of them are very low, and often lower than the classical confidence threshold of 1%, 5% or 10%, thus confirming the in-sample results observed earlier that show that regime returns have statistically different distributions compared to long-term returns.

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Table 4: Out-of-sample robustness.
The table reports p-values for KS test between a regime test sample and a redefined regime sample, according to the CV-like procedure described in Section 2.3 and 3.1.3. The number in parenthesis corresponds to the same test performed between the samples drawn within the regime and long-term market returns. The distributions refer to market returns between 1970 and 2024. For readability, p-values corresponding to at least 10% confidence level are in bold.

	Out-sample KS test			
	change down	change up	level low	level high
Credit Spread	0.42 (0.21)	0.37 (**0.00**)	0.37 (**0.00**)	0.40 (**0.00**)
Dollar Index	0.42 (**0.00**)	0.43 (**0.01**)	-	-
Inflation	0.39 (**0.08**)	0.33 (0.59)	0.35 (**0.04**)	0.38 (0**0.01**)
Long-Term Rates	0.41 (**0.05**)	0.45 (**0.01**)	-	-
Market Index	0.48 (**0.00**)	0.50 (**0.00**)	-	-
Oil	0.38 (**0.01**)	0.44 (**0.02**)	-	-
Short-Term Rates	0.34 (**0.02**)	0.41 (**0.01**)	0.39 (**0.01**)	0.43 (**0.03**)
Time Spread	0.38 (0.48)	0.34 (**0.04**)	0.37 (**0.04**)	0.36 (0.53)
Market Volatility	0.42 (**0.00**)	0.40 (**0.00**)	0.50 (**0.00**)	0.41 (**0.00**)

3.2 Duration and Historical Representativeness

As we mentioned above, a regime needs to be not too short-lived and to recur over time in order to meaningfully influence the investment process. We address these two points in the following.

The left panel of Table 5 reports the average duration in days of each regime, while the right one shows the maximum duration. Level-based regimes are generally longer than change-based regimes. For example, low-level credit spread periods last 211 days on average, which is more than four times the length of low-change credit spread regimes, which end within 40 days. This difference has practical investment implications: focusing on changes in macroeconomic indicators implies a more dynamic approach than considering their levels, hence one should carefully pick the type of regime to use, even if one should bear in mind that regimes defined with levels are not possible for all variables. Most change-based regimes conclude within a quarter (right panel), while level-based regimes can last up to a few years but rarely exceed one year on average. Exceptions to these observations include inflation and short-term rates, which exhibit especially prolonged durations. We also find that a regime extends beyond a month only one third of the times, while in most cases it is immediately followed by a non-regime, or 'normal' month. This insight is valuable when incorporating forecasts into investment strategies, as knowing whether the current regime is likely to persist for just one month versus several months significantly impacts management decisions and allows one to choose the most appropriate response between temporary hedging or more long-term portfolio adjustments.

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Table 5: Regime duration
This table shows the average and maximum duration (in days) in each of the macroeconomic regimes considered on the left and right panels, respectively.

	Average duration in days				Max. duration in days			
	change down	change up	level low	level high	change down	change up	level low	level high
Credit Spread	40.45	46.00	237.82	211.22	120	94	1673	608
Dollar Index	39.13	38.59	-	-	94	92	-	-
Inflation	60.84	60.52	206.74	626.00	213	212	1005	2436
Long-Term Rates	44.00	43.90	-	-	94	120	-	-
Market Index	40.11	43.43	-	-	154	121	-	-
Oil	44.57	42.88	-	-	122	92	-	-
Short-Term Rates	56.31	52.37	1,172.50	536.75	182	244	2526	1613
Time Spread	42.17	34.79	236.41	154.50	92	62	669	396
Market Volatility	35.27	32.76	56.69	83.31	61	59	364	335

Quantifying the historical representativeness of regimes is a more challenging task; however, we can proxy for it by counting the number of days in a given year that are classified as a regime. Figure 1 reveals that most regimes are well spread across the sample period. This is especially true for change-based regimes, which are triggered by abrupt changes in macroeconomic indicators. Level-based regimes, instead, tend to cluster around specific periods, suggesting that macro-based regimes help explain the well-documented return volatility clusters observed in practice. For instance, high-inflation periods are longer-lasting in the 70s, whereas low-inflation regimes are longer and more predominant around the 2000s. This observation leads to an important implication: conducting portfolio analysis using full-sample distribution moments rather than conditional ones may introduce significant bias and result in impaired investment choices. Moreover, the more even spread of regime-based changes make them more amenable to analysis, as they provide a more balanced and representative framework. Given the longer duration of inflation and interest rate level regimes, investors should exercise particular caution when making investment decisions in these periods.

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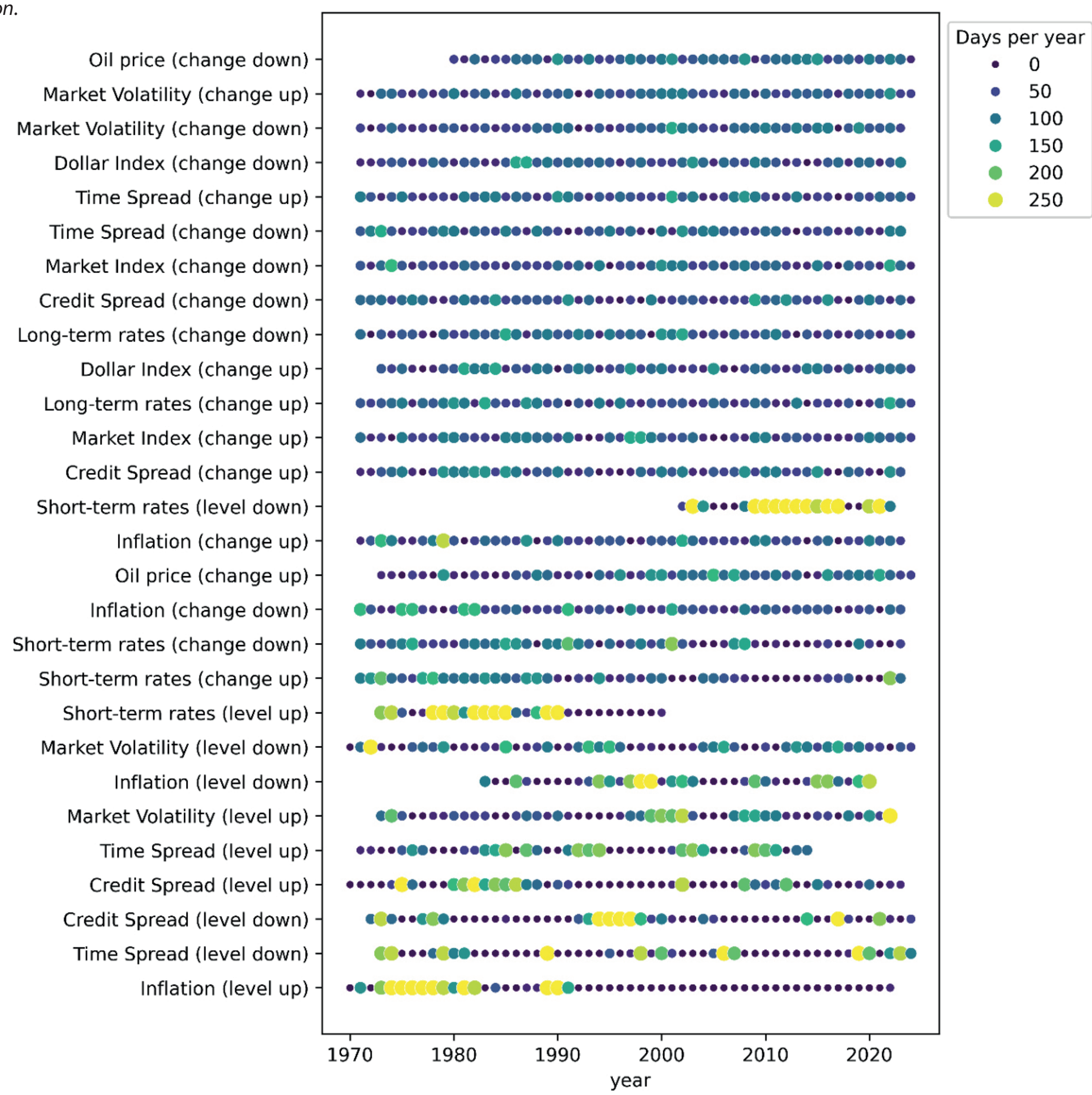
Figure 1: Historical representativeness of regimes
This figure shows the number of days per year that belong to each of the regimes considered, assigning lighter colours to higher numbers as indicated in the caption.



3.3 Long-Term Model-Implied Returns

The findings in the previous sections show that regime returns have very stable distributions that markedly differ from their long-run counterparts, both in and out of sample. The analysis of a portfolio's behaviour in any given regime is thus key information to make timely and informed investment decisions. As mentioned earlier, portfolios with long historical track records are a rare specimen in finance. New strategies, or those that have undergone material changes, often lack the historical data required to conduct a sound statistical examination under repeated macro-economic stress scenarios. Extending a portfolio's time-series through its factor exposures is an efficient and viable method to mitigate this problem, as we demonstrate in the following.

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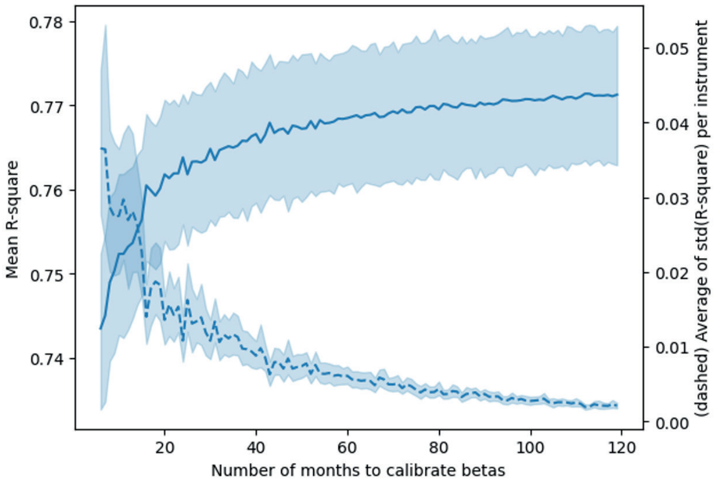
To test whether factor models lead to sufficiently precise extended portfolio returns, we consider the 83 US equity funds from Morningstar with very long track records, spanning at least 40 years of data (January 1972 - September 2023). Long time-series are necessary to assess the precision of our approach. We use a factor model consisting of the six Scientific Beta Equity Risk Factors reported in Table 1. We compute the exposure of the sample of funds to the risk factors over random periods of increasing length ranging between 6 and 120 months, and then we use these exposures to extend the funds' returns over the remaining part of the sample, hence obtaining $\hat{r}_t$ as introduced earlier. Then we compare the returns generated with the model to the actual returns.

The goodness of such model-implied returns is evaluated by computing their R^2 compared to the true returns. Figure 2 shows the average R^2 across the funds as a function of the length of the random periods used to compute the initial factor loadings, with shaded areas denoting the 95% confidence interval. The mean R^2 is particularly high, hovering around an average of 75%, which denotes a negligible decrease from the average R^2 of 77% that results from model-based returns calibrated on the full history of 40 years. Increasing the length of the calibration set improves the precision of the extension, but past about five years, only with a marginal increase, as represented by the concavity of the curve in the figure. The overall quality of the model-based extension, measured by the standard deviation of the R^2, also reaches its maximum with calibration sets of about five years.

Figure 2: Precision of model-based return extension
The figure shows the average R^2 of the extended returns based on factor models for a sample of 83 US equity funds with at least 40 years of data from Morningstar (top solid line) relative to their true returns. The bottom dashed line shows its cross-sectional standard deviation. Both lines are shown as function of the length of the calibration set used to compute factor betas, which ranges between 6 and 120 months.



The previous findings show that extending the funds' systematic returns using betas estimated even over a limited history delivers a precision comparable to doing the same with betas estimated over the full history. Is the precision of the procedure sensitive to the period used for the calibration? To test this, we randomly draw 100 different periods of 5 years each and estimate the factor exposures of each fund every time. Then, we extend the returns through the factor model to the remaining part of the sample and compute the R^2 compared to true returns. Finally, to have a simple and meaningful

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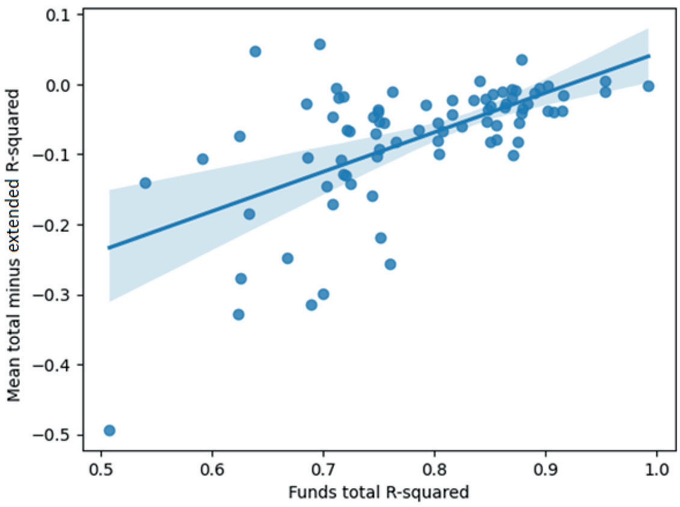
metric of the change in model precision, we take the difference to the R^2 obtained with betas estimated using the full sample. In Figure 3, we report the average results for each fund across the 100 trials, ordered by the R^2 based on full-sample exposures, which we call total R^2 (x-axis). For funds with a high total R^2, whose returns are mainly driven by systematic factors, the precision of the extended returns is only marginally affected by the calibration sample. When the total R^2 is below 80%, the extension procedure tends to exhibit more erratic behaviour. In other words, the higher the full-sample model precision, the more reliable it is to extend returns beyond the available sample, as we mentioned earlier. This means that adding specific risk factors may improve the precision of the model-based extension, for instance by considering industry-based risk factors for industry-based portfolios.

Figure 3: Sensitivity of model-based return extension to calibration sample
This figure shows the average of differences in R^2 using exposures evaluated with random periods of 5 years and total R^2 obtained with betas calibrated on the full sample. The average is taken across 100 random periods for each fund. The averages are ordered by total R^2 (x-axis). Returns refer to a sample of 83 US equity funds with at least 40 years of data from Morningstar.



3.4 Regime Impact Analysis for Different Types of Funds

So far, we have focused on the impact of regimes on market returns. To examine how equity portfolios with different factor exposures— or styles—are affected, we form 7 equal-weighted portfolios of equity funds following seven distinct factor strategies, namely Tech, Energy, Low Risk, Small Size, Tracker ESG, Tracker and Value. Specifically, we start from a universe of 650 US equity funds from Morningstar, and to each of the portfolios all the funds whose name contains keywords belonging to that strategy. For instance, the Low-Risk portfolio is composed of funds with “Defensive”, “Low Volatility” and/or “Low Risk” in their name. Similarly, the funds used in the Value and Small Size portfolios have “Value” and “Small” in their title. The Tech and Energy portfolios are simply sector-based index trackers. The Tracker portfolio is an ETF replicating the performance of the S&P 500, whereas its ESG equivalent replicates the “ESG enhanced” version of the MSCI USA. The detailed list of the funds composing each portfolio is reported in Table A.1 in the Appendix.

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In Table 7, we report the active performance (e.g. in excess of the market) of each portfolio strategy in different regimes.[2] The Energy sector portfolio has the highest volatility and tracking error and therefore exhibits large active performance in high volatility regimes. It is also sensitive to oil prices, as economic intuition would suggest: the active return is as low as -14% in down-oil-price-change periods, but as high as 7% in up-periods. The Small Size portfolio is also more volatile than the market, and it is very sensitive to credit events. The Low-Risk portfolio performs best during market downturns, and it is sensitive to variations in short-term rates. Interestingly, a few strategies are insensitive to some regimes like inflation (e.g. Tracker and ESG Tracker) or time spread (like Low Risk and Small Size). In other words, macroeconomic regimes affect strategies differently, and so a case-by-case analysis is indeed required to compare their impact of on a portfolio's performance in order to best inform investment decisions.

Table 6: Active performance of portfolios of funds across regimes
The table shows the active performance (e.g. in excess of the market) in annualised percentage points for the 7 portfolios of funds described in Section 3.4. The statistical significance of the performance with 1%, 5% and 10% thresholds is denoted by (***), (**) and (*).

Macro-economic variable	Regime type	direction	Tech	Energy	Low Risk	Small Size	Tracker ESG	Tracker	Value
Credit Spread	change	down	4.62**	11.21***	-4.60***	10.85***	-1.79***	-0.09	5.28***
		up	-2.45	-9.74***	4.12***	1.63	-0.74	0.14	1.36
	level	low	3.54**	3.67	-2.45**	1.22	-1.38**	0.01	0.07
		high	-1.05	-2.24	2.37**	7.88***	-1.58**	0.18*	5.15***
Dollar Index	change	down	4.33**	-3.86	-1.38	5.12**	-2.86***	-0.09	1.44
		up	-1.95	1.83	1.76	3.04	0.09	0.19	2.82*
Inflation	change	down	-2.48	-7.96**	3.98***	6.01***	-0.25	0.16	4.01***
		up	4.02**	12.96***	-4.12***	7.57***	-1.71**	0.04	4.03**
	level	low	2.49	-6.12	-0.45	3.44	-1.17	-0.00	0.96
		high	0.73	7.92***	-0.53	8.87***	-0.16	0.01	5.13***
Long-Term Rates	change	down	-4.62**	-14.24***	6.71***	0.21	-1.18	0.11	0.90
		up	2.81	20.44***	-4.13***	7.96***	0.33	0.27**	5.44***
Market Index	change	down	-10.24***	-12.77***	10.25***	-12.15***	6.66***	0.58***	-4.29**
		up	8.59***	9.50***	-6.68***	25.62***	-7.30***	-0.34***	11.71***
Market Volatility	change	down	7.90***	4.55	-5.40***	13.74***	-4.83***	-0.21*	5.54***
		up	-4.31*	-7.17*	5.26***	-8.16***	3.49***	0.45***	-3.30*
	level	low	4.98***	2.54	-2.89***	8.62***	-3.63***	-0.15*	3.51***
		high	-4.13	-6.81	4.51**	-3.07	2.37**	0.50***	-0.06
Oil	change	down	-3.40	-13.50***	5.33***	-0.39	-0.26	0.26*	0.57
		up	4.34**	7.00*	-3.43**	10.05***	-1.91***	-0.14	4.50**
Short-Term Rates	change	down	-5.39**	-8.34**	5.72***	-0.59	-0.70	0.35***	1.69
		up	5.52***	1.83	-2.64**	1.77	-0.34	0.01	-0.41
	level	low	1.02	-3.00	-0.36	1.72	-1.52*	0.13	1.07
		high	2.41*	0.99	-0.62	5.21***	-1.13*	0.03	2.43*
Time Spread	change	down	2.01	-11.59***	1.86	-1.36	-1.40*	-0.08	-2.18
		up	-0.90	7.76**	-0.81	4.14*	-0.66	0.32**	4.02***
	level	low	2.04	-6.81	-0.03	-2.19	-1.41*	0.11	-1.84
		high	-3.03*	7.77***	1.54	4.43**	-0.12	0.31***	4.69***

2 - Because we measure active performance, the very small performance figures reported for the Tracker correspond to the difference between the performance of the index and the replicating portfolio, which is very close to it. Differences are often insignificant, but what is meaningful is that some regimes nonetheless significantly affect the portfolio's replication quality, such as long-term rates.

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3.5 Properties of Equity Risk Factors Across Regimes

As mentioned in the introduction, we have provided ample empirical evidence that market returns have stable and distinct distributions during certain macro-economic regimes, which makes static yet regime-dependent distributions quite reliable for simulation purposes. Furthermore, we have seen that it is possible to efficiently extend a short portfolio track record through factor models when risk factors are the main drivers of its returns. The typical length of the time-series available for risk factors, which often cover several decades, serves this purpose well.

We now briefly address a practical consideration that would arise by running regime-based simulations for equity returns. Since the latter are modelled through their exposures to risk factors, what is crucial for simulations are the distribution parameters relative to the risk factors in each regime. Both the performance and the volatility of the factors vary widely conditionally on regimes. For volatility, the ratio between the smallest and largest values across regimes for any given factor is around 2, but it reaches almost 3 for the size and volatility factors (unreported results). Performance variations are even larger. Whereas the average (annualised) performance of the six market neutral factors we consider ranges between 3% and 5%, they can reach values almost ten times as high in some regimes. For portfolios that are highly exposed to some risk drivers, this information is crucial, as we have indeed seen in Section 3.4.

Other than their marginal (e.g. individual) moments, the co-movements are also important. For example, if two factors move in the same direction in normal times, but go in opposite directions in specific regimes, the parameters used for simulations should take this into account. As an illustration, we show the average correlation between factors across different regimes in Table A.2 in the Appendix, where we report only regimes referring to macro indicators for reasons of space. The correlation matrix between factors is sometimes significantly affected by the regime: the difference between the minimum and the maximum value of the average correlation is generally around 0.15, which is large. For instance, the profitability factor has an average correlation of -0.28 with the other factors in low inflation-level regimes, but of -0.12 in the up-regime. Therefore, regime-driven changes in the correlation structure should also be taken into account when carrying out conditional simulations.

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4. Conclusion

The use of macroeconomic forecasts is a widely accepted component of investment processes, yet certain critical aspects of macroeconomic regimes, such as their statistical relevance and the nature of returns within these regimes, remain under-documented. Our research addresses this gap by exploring how regime-based approaches can refine portfolio assessments and better support strategic investment decisions. Our objective is to provide guidance to assess how a portfolio strategy might perform in alternative scenarios, thus going beyond the limits dictated by historical data.

We consider a set of macroeconomic variables selected for their impact on equity returns and define regimes using monthly data going back to 1974. We find that returns of equity portfolios in these regimes have distinct statistical properties compared to long-term returns. These statistical properties remain stable within regimes and are also robust both in and out of sample. Stability and robustness are desirable for investment processes, as they enable more reliable simulations and enhance the utility of macroeconomic forecasts.

Also, we show that analysing the impact of macro-economic regimes on a portfolio, which is often challenging due to the typical shortness of historical track records, can be efficiently achieved by using simple factor models to extend the returns to a larger sample. The precision of this procedure is remarkedly high for most equity funds, even when evaluating their exposures using relatively short periods of data. We find that about five years of historical returns achieves a precision close to that obtained with full-length time-series. Hence, our approach offers investors practical insights, helping them better anticipate regime-related risks and take timely action, such as hedging in response to shorter-lived regimes or adjusting allocations during more extended periods of risk.

Our findings further reveal that funds following different factor or sector strategies show significant performance variations across the identified regimes. For actively managed portfolios, these variations highlight the value of a regime-based perspective in portfolio construction, particularly in strategies driven by macroeconomic trends. This approach enables a bottom-up allocation that is sensitive to macro-based performance opportunities and ensures that portfolios remain aligned with desired risk levels in response to relevant economic shifts.

The findings of our research suggest that taking a regime-based approach and combining it with existing simulation methods that use e.g. static distributions, leads to a more nuanced understanding of portfolio behaviour in diverse economic environments and thus to better support for strategic investment decisions. Conditional simulations of this type can also act as an improvement on 'what-if' stress scenarios, which are often ad hoc and lack the real-world context of macroeconomic fluctuations. Regime-simulations offer, in fact, more practical and data-driven testing, which ultimately refines investors' ability to prepare for and manage the impacts of extreme scenarios such as those we measure in this paper. Given the robustness of the regimes we identify, the conclusions that investors draw from conditional simulations are reliable for future scenarios as well. For example, knowing that the portfolio risk budget is likely to remain within a specific range in some time periods constitutes valuable information for those investors interested in maintaining a desired risk level throughout

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their holding period. These insights are especially useful for both active investors who tactically adjust macro exposures to capture short-term opportunities, and fundamentally driven investors who seek long-term consistency but aim to avoid unintended macro-driven risks. For both groups, understanding regime-driven return behaviour supports a more effective risk management approach that aligns with their unique investment objectives.

Ultimately, by capturing the distinct dynamics of macroeconomic regimes, our research provides a valuable toolkit for investors to manage risk, optimise portfolio strategies, and remain reactive in an increasingly complex economic landscape.

Appendix

Appendix

Table A.1: Composition of the fund portfolios
The table shows the composition of the portfolios of funds described in Section 3.5.

Portfolio	Constituents
Tech	Columbia Seligman Technology and Information Fund Fidelity Select Enterprise Technology Services Portfolio Goldman Sachs Technology Opportunities Fund JNL/Mellon Capital Information Technology Sector Fund
Energy	JNL/Mellon Capital Energy Sector Fund
Low Risk	AQR Large Cap Defensive Style Fund MFS Low Volatility Equity Fund
Small Size	Vanguard Tax Managed Small Cap Fund Hartford Small Cap Growth HLS Fund Victory Integrity Small/Mid-Cap Value Fund PIMCO StocksPLUS® Small Fund Delaware Ivy Small Cap Growth Fund Fidelity Small Cap Index Fund Crossmark Steward Values-Focused Small-Mid Cap Enhanced Index Fund LSV Small Cap Value Fund Praxis Small Cap Index Fund
Tracker ESG	Amundi Index Solutions – Amundi S&P 500 ESG Transamerica Large Core ESG Fund LLB Aktien Nordamerika ESG (USD) Goldman Sachs US Equity ESG Portfolio SSGA Lux SICAV - State Street US ESG Screened Index Equity Fund DWS ESG Core Equity Fund
Tracker	Invesco S&P 500 Index
Value	Delaware Ivy Value Fund Victory Integrity Small/Mid-Cap Value Fund Multi-Manager Value Strategies Fund Crossmark Steward Values-Focused Small-Mid Cap Fund Virtus NFJ Large-Cap Value Fund Dunham Large Cap Value Fund LSV Small Cap Value Fund Natixis International Funds (Lux) I - Harris Associates U.S. Value Equity Fund VY® Columbia Small Cap Value II Portfolio

Appendix

Table A.2: Average correlation between equity risk factors across different regimes
This table shows the average correlation between each of the equity risk factors reported in the columns (details given in Table 1 in the main text) and the rest of the same set of factors across the regimes defined in the rows. Data refers to the period 1974-2024.

Macro-economic variable	Regime type	direction	value	size	momentum	profitability	investment	volatility
Market Index	change	up	0.02	-0.00	-0.25	-0.15	0.10	0.09
		down	0.05	0.04	-0.21	-0.13	0.14	0.11
Inflation	change	up	0.01	0.01	-0.21	-0.14	0.11	0.09
		down	0.03	0.01	-0.21	-0.14	0.12	0.09
	level	high	0.05	0.04	-0.07	-0.28	0.11	0.05
		low	-0.05	-0.05	-0.18	-0.12	0.09	0.08
Market Volatility	change	up	0.03	0.01	-0.21	-0.13	0.14	0.12
		down	-0.01	-0.02	-0.18	-0.13	0.09	0.06
	level	up	0.05	0.03	-0.25	-0.09	0.16	0.14
		down	-0.04	-0.05	-0.14	-0.19	0.05	-0.01
Short-Term Rates	change	up	0.06	0.03	-0.15	-0.19	0.13	0.09
		down	-0.01	-0.04	-0.16	-0.13	0.10	0.07
	level	high	0.02	0.03	-0.14	-0.23	0.10	0.06
		low	-0.11	-0.09	-0.11	-0.10	0.04	0.01
Long-Term Rates	change	up	0.03	0.03	-0.21	-0.14	0.11	0.08
		down	0.01	0.00	-0.17	-0.11	0.14	0.10
Credit Spread	change	up	0.06	0.04	-0.24	-0.14	0.14	0.13
		down	-0.02	-0.01	-0.18	-0.14	0.08	0.07
	level	high	-0.04	-0.02	-0.11	-0.14	0.10	0.07
		low	0.03	0.00	-0.22	-0.18	0.09	0.02
Time Spread	change	up	-0.01	-0.02	-0.18	-0.11	0.11	0.07
		down	0.04	0.03	-0.15	-0.14	0.14	0.10
	level	high	-0.11	-0.08	-0.01	-0.09	0.09	0.04
		low	0.06	0.05	-0.28	-0.13	0.14	0.10
Oil	change	up	0.02	0.01	-0.25	-0.12	0.10	0.09
		down	0.04	0.03	-0.27	-0.09	0.14	0.12
Dollar Index	change	up	0.03	0.02	-0.21	-0.13	0.13	0.11
		down	-0.03	-0.02	-0.13	-0.15	0.09	0.05

References

References

- Amenc, Noël, Mikheil Esakia, Felix Goltz, and Ben Luyten. 2019. 'Macroeconomic Risks in Equity Factor Investing'. *The Journal of Portfolio Management* 45 (6): 39–60.
- Bekkers, Niels, Ronald Q. Doeswijk, and Trevin W. Lam. 2009. 'Strategic Asset Allocation: Determining the Optimal Portfolio with Ten Asset Classes'. *Journal of Wealth Management* 12 (3): 61–77.
- Bellman, Richard. 1966. 'Dynamic Programming'. *Science* 153 (3731): 34–37.
- Blitz, David, and Pim van Vliet. 2011. 'Dynamic Strategic Asset Allocation: Risk and Return Across Economic Regimes'. Tech. report.
- Bodie, Zvi. 1976. 'Common Stocks as a Hedge against Inflation'. *Journal of Finance* 31 (2): 459–70.
- Bollerslev, Tim. 1987. 'A Conditionally Heteroskedastic Time Series Model for Speculative Prices and Rates of Return'. *Review of Economics and Statistics*, 542–47.
- Bouchaud, Jean-Philippe, and Marc Potters. 2003. *Theory of Financial Risk and Derivative Pricing: From Statistical Physics to Risk Management*. Cambridge University Press.
- Breeden, Douglas T. 1979. 'An Intertemporal Asset Pricing Model with Stochastic Consumption and Investment Opportunities'. *Journal of Financial Economics* 7 (3): 265–96.
- Brusa, Francesca, Pavel Savor, and Mungo Wilson. 2020. 'One Central Bank to Rule Them All'. *Review of Finance* 24 (2): 263–304.
- Campbell, John Y, Andrew W Lo, A Craig MacKinlay, and Robert F Whitelaw. 1998. 'The Econometrics of Financial Markets'. *Macroeconomic Dynamics* 2 (4): 559–62.
- Chen, Nai-Fu, Richard Roll, and Stephen A. Ross. 1986. 'Economic Forces and the Stock Market'. *Journal of Business* 59 (3): 383–403.
- Cont, Rama. 2001. 'Empirical Properties of Asset Returns: Stylized Facts and Statistical Issues'. *Quantitative Finance* 1 (2): 223–36.
- Cujean, Julien, and Samuel Jaeger. 2023. 'Asset Pricing on FOMC Announcements'. Tech. report.
- Elkamhi, Redouane, Jacky S. H. Lee, and Marco Salerno. 2023. 'Practical Applications of Portfolio Tilts Using Views on Macroeconomic Regimes'. *Practical Applications*.
- Engle, Robert. 2002. 'Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models'. *Journal of Business & Economic Statistics* 20 (3): 339–50.
- Engle, Robert F, and Andrew J Patton. 2001. 'What Good Is a Volatility Model?' *Quantitative Finance* 1: 237-245.
- Errunza, Vihang, Kedreth Hogan Jr, Omesh Kini, and Prasad Padmanabhan. 1994. 'Conditional Heteroskedasticity and Global Stock Return Distributions'. *Financial Review* 29 (3): 293–317.
- Esakia, Mikheil, and Felix Goltz. 2023a. 'Targeting Macroeconomic Exposures in Equity Portfolios: A Firm-Level Measurement Approach for out-of-Sample Robustness'. *Financial Analysts Journal* 79 (1): 37–57.
- ———. 2023b. 'Targeting Macroeconomic Exposures in Equity Portfolios: A Firm-Level Measurement Approach for Out-of-Sample Robustness'. *Financial Analysts Journal* 79 (1): 37–57.
- Fama, Eugene F. 1965. 'The Behavior of Stock-Market Prices'. *Journal of Business* 38 (1): 34–105.
- ———. 1981. 'Stock Returns, Real Activity, Inflation, and Money'. *American Economic Review* 71 (4): 545–65.
- Fama, Eugene F, and French, Kenneth R. 1993. 'Common Risk Factors in the Returns on Stocks and Bonds'. *Journal of Financial Economics*, 33(1), 3-56.

References

- Flannery, Mark J., and Aris A. Protopapadakis. 2002. 'Macroeconomic Factors Do Influence Aggregate Stock Returns'. *Review of Financial Studies* 15 (3): 751–82.
- Goyal, A., Welch, I., & Zafirov, A. (2024). A comprehensive 2022 look at the empirical performance of equity premium prediction. *The Review of Financial Studies*, 37(11), 3490-3557.
- Hamilton, James D, and Raul Susmel. 1994. 'Autoregressive Conditional Heteroskedasticity and Changes in Regime'. *Journal of Econometrics* 64 (1–2): 307–33.
- Hoevenaars, Roy P. P. M., Roderick D. J. Molenaar, Peter C. Schotman, and Tom B. M. Steenkamp. 2014. 'Strategic Asset Allocation for Long-Term Investors: Parameter Uncertainty and Prior Information'. *Journal of Applied Econometrics* 29 (3): 353–76.
- Jondeau, Eric, Ser-Huang Poon, and Michael Rockinger. 2007. *Financial Modeling under Non-Gaussian Distributions*. Springer Science & Business Media.
- Kolmogorov, Andrey. 1933. 'Sulla determinazione empirica di una legge didistribuzione'. *Giornale Dell'instituto Italiano Degli Attuari*, 4, 89-91.
- Lamont, Owen A. 2001. 'Economic Tracking Portfolios'. *Journal of Econometrics* 105 (1): 161–84.
- Levene, H. (1960). 'Robust Tests for Equality of Variances'. *Contributions to Probability and Statistics,* 278-292.
- Lucca, David O, and Emanuel Moench. 2015. 'The Pre-FOMC Announcement Drift'. *Journal of Finance* 70 (1): 329–71.
- Mandelbrot, Benoit B, and Benoit B Mandelbrot. 1997. *The Variation of Certain Speculative Prices.* Springer.
- Merton, Robert C. 1973. 'An Intertemporal Capital Asset Pricing Model'. *Econometrica: Journal of the Econometric Society*, 867–87.
- Ross, Stephen A. 1976. 'The Arbitrage Theory of Capital Asset Pricing'. *Journal of Economic Theory* 13 (3): 341–60.
- Savor, Pavel, and Mungo Wilson. 2013. 'How Much Do Investors Care about Macroeconomic Risk? Evidence from Scheduled Economic Announcements'. *Journal of Financial and Quantitative Analysis* 48 (2): 343–75.
- ———. 2014. 'Asset Pricing: A Tale of Two Days'. *Journal of Financial Economics* 113 (2): 171–201.
- Smirnov, Nickolay. 1948. 'Table for Estimating the Goodness of Fit of Empirical Distributions'. *The Annals of Mathematical Statistics*, 19(2), 279-281.
- Sinha, C. 1996. 'Changing Business Conditions and Regime Switching in Stock Returns'. Working Paper, Vanderbilt University
- Welch, Ivo, and Amit Goyal. 2008. 'A Comprehensive Look at the Empirical Performance of Equity Premium Prediction'. *Review of Financial Studies* 21 (4): 1455–1508.

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