Regimes

AMARA MULLINER, CAMPBELL R. HARVEY, CHAO XIA, ED FANG, OTTO VAN HEMERT[1]

This version: March 4, 2025

ABSTRACT

We propose a new systematic method for detecting the current economic regime and show how to use this information for predicting returns. Rather than presupposing a set of possible regimes, we rely on economic state variables and determine for which historical dates the values of these variables were most similar. To establish our position in an asset today, we identify historically similar periods and measure subsequent performance of the asset. If the historical performance is positive, we initiate a long position; conversely, if it is negative, we initiate a short position. We illustrate the efficacy of our method on six common long-short equity factors over 1985-2024. Our results show that using this information our regime classification leads to significant outperformance. Interestingly, we also find important information in what we call anti-regimes – periods in the past that are the most *dis*similar to today.

Keywords: *Regime detection, turning points, similarity, factor timing, regime prediction, trading strategies, time-varying risk premia, macro regimes.*

JEL codes: G11, G12, G15, G32.

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[1] Harvey is at Duke University, the National Bureau of Economic Research and is an adviser to Man Group plc. The other authors are at Man Group plc. The authors would like to thank Alex Preston for valuable comments. Please direct correspondence to Otto.VanHemert@man.com.

Introduction

The real-time identification of the current economic regime is one of the biggest challenges in investment management. It is further complicated by the fact that there is no consensus as to the definition of regimes. Many focus on discretionary classifications based on economic growth and inflation. However, even with these two variables, the cutoffs for classifying 'high' or 'low' are unclear. Should there be a third, medium, state? Further, why just focus on inflation and growth? The world is more complex than these two economic variables.

Performance of assets can vary substantially across regimes (see, for example, Harvey et al. (2019) who study large equity selloffs and the defensive properties of various investments, and Neville et al. (2021), who focus on inflationary periods). However, in these papers regimes are determined ex-post, and so the results are useful when it comes to constructing a balanced portfolio that is robust to different regimes, but not for timing investments based on a real-time assessment of the current regime. In contrast, this paper does provide a point-in-time metric for timing investments.

Our paper proposes a systematic approach to regime selection. The user of our method needs to specify a set of economic variables. In our empirical example, we consider a constellation of seven variables. We transform these variables to look at annual changes and compute a z-score. Variable by variable, we identify times in the past that are similar. Our measure of similarity is the squared distance of today's value to each historical observation. For example, if the z-score today is 2.5, we look at historically similar times where the z-score is close to 2.5. If the value on a particular historical date was exactly 2.5, the squared distance would be zero. We then look at every historical date and aggregate the distances at each date across our seven variables. We refer to the aggregated similarity score as the global score. Those historical dates with the smallest aggregate distances (meaning that they are most like today) are our definition of similar regimes.

Once we have established similar dates in the past for a particular asset, we look at subsequent returns. So, if we observe subsequent historical returns that are very positive, this suggests that the ex-ante returns for that asset today are also positive. Importantly, once the historical regimes are established, we can apply this method to any asset.

Our method has several advantages. First, the method is systematic; regime classifications are automatic once the state variables are selected. Second, the method can easily be applied to a much larger set of economic state variables. Third, our method is largely non-parametric in that no parameters are being optimized. Finally, our method is simple, relying only on z-scores.

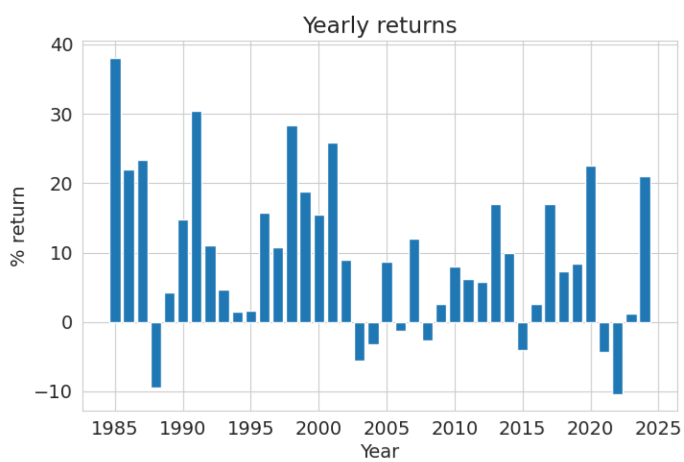
However, any systematic model requires choices to be made. In our method, the economic state variables need to be chosen. Choosing these variables – as with more parametric approaches – induces a type of look-ahead bias. Today, we know which variables have been important in the past. We can partially mitigate this issue by choosing variables that were important before our sample begins. Second, there is a choice as to how to represent the variable; for example, should we detrend it? If looking at rate of change, over what horizon? Third, we need to take a stand on the degree of similarity. For instance, is a z-score of 2.3 similar enough to 2.5? Fourth, we need to decide on the length of the observation period after the similar historical regime. Finally, there is a decision on how to weight the economic variables – we choose equal weights but that is a choice.

While the focus of the paper is on regime classification, our method also naturally identifies anti-regimes. These are historical times that are most different from today's state. We find there is important information in these anti-regimes.

The main contribution of our paper is methodological. However, we do apply our method to six popular long-short equity factors. We look at historical factor returns and go long a factor if the observed historical return subsequent to observing the regime at the investment date is positive, and short otherwise. We document a positive relation between the returns on this type of strategy and similarity. Indeed, the least similar historical dates do the worst in terms of performance. The alpha generated by a strategy that goes long the most similar and short the least similar is statistically significant, at three standard deviations from zero. Exhibit 1 suggests that the strategy is also a consistent performer and exhibits positive skewness. Notice that the excess returns are positive in 80% of the years. Furthermore, conditional on outperformance the average return is 13.3%. Conditional on underperformance, the average return is only -5.1%.

Exhibit 1: Long similarity and short dissimilarity

Yearly returns from regime model implementation at targeting 15% volatility.



The challenge of identifying economic regimes in real time has been extensively studied in the asset management literature. One prominent approach is the use of clustering and machine learning techniques to segment market environments. Kritzman, Li, Page, and Rigobon (2012) introduce a method to detect turbulent financial periods, demonstrating how shifts in market conditions can be systematically identified and used to adjust portfolio allocations. This approach lays the foundation for systematic regime detection by leveraging historical market conditions rather than relying on predefined classifications.

A parallel strand of research focuses on regime-dependent investing. Ang and Bekaert (2004) explore the use of Markov regime-switching models to identify periods of high and low volatility in equity markets, showing that asset returns exhibit distinct behaviors under different regimes. Their work has been influential in demonstrating the empirical persistence of economic states and the benefits of accounting for regime shifts in asset allocation strategies. More recently, Asness (2016) looked at the possibility of using regime frameworks to inform factor timing decisions, while Asness, Frazzini, and Pedersen (2019) investigate how traditional style factors such as value and momentum perform across different macroeconomic regimes, finding that some factors are more resilient to inflationary shocks than others. This work underscores the importance of dynamically adjusting exposure based on prevailing economic conditions rather than assuming static factor premia. Kaya et al. (2010) provide a useful early model that helped to guide our thinking, recognizing in their paper that emphasizing current conditions rather than preset regime characteristics is a more useful way of considering a market landscape which is in constant evolutionary flux.

Gundersen et al. (2023) look at asymmetric and time-varying dependency structures between financial returns, employing a combination of regime-switching models and local Gaussian correlation to identify nonlinear relationships between assets and to identify performance trends under different market conditions. Shu and Mulvey (2025) use a jump framework to identify bull and bear regimes. Additionally, Kritzman, Kulasekaran and Turkington (2023) advance the concept of turbulence and fragility in markets, emphasizing that historical analogs can be used to classify periods of economic distress and stability. Their research aligns closely with our methodology, as it highlights the utility of past observations in identifying economically similar environments. However, unlike these prior studies, which either impose discrete regime classifications or rely on statistical models with predefined transitions, our approach allows for a more flexible definition of regimes by directly measuring historical similarity across multiple economic variables.

Our paper is structured as follows. The second section details the state variables that we choose and the transformations. The third part looks at the performance of the method during periods of crisis - the Global Financial Crisis, COVID-19, and the 2022 inflation surge. In the fourth section, we assess the predictive power of the model. Some concluding remarks are offered in the final section.

Economic state variables

Identification of Variables

For our empirical illustration, we use the seven economic state variables detailed in Exhibit 2: the S&P500 index level, 10-year bond yield minus 3-month treasury bill yield (slope of the US yield curve), WTI crude oil price, copper price, US 3-month treasury bill yield, VIX (pre-pended with realized volatility before 1990), and the US stock-bond correlation. For each variable, we take a 12-month change and then normalize it by computing the z-score over a rolling 10 years, capped to be within -3 and 3.

Inevitably, there is some look ahead bias in selecting economic state variables. That said, a similar list of variables would likely be proposed in the mid-1980s. Fama (1981) details the information in stock prices related to real activity. Crude oil prices were key to recessionary episodes in the 1970s and early 1980s. The cyclical properties of the yield curve were known as far back to Kessell (1965) and formed the basis of Harvey's work in the mid-1980s (see Harvey 1988, 1989). Copper was widely regarded as a bellwether indicator for the economy (see Bank of England, 1981). Inflation is reflected in the treasury bill yield. Volatility was a key indicator, reflected in the pioneering work of Engle (1982) and Bollerslev (1986). Perhaps the only economic variable included that is relatively new is the stock bond correlation. That said, this variable has always been a key input for asset allocation.

We use monthly data so that we can extend our history as far back as possible. For the correlation series we use a rolling three-year lookback. We run this on daily data before converting to monthly. In a similar fashion, we compute our volatility and stock-bond series on daily data and then map to monthly.

Although we refer to these as economic state variables, they are all financial variables. Again, we are only presenting an illustration of our method, and the user could add a range of different macroeconomic variables. That said, these state variables embed macroeconomic information. For example, the yield curve, the price of copper and the price of oil all strongly comove with economic growth. Monetary policy and inflation are reflected in nominal interest rates. Economic risk will be reflected in equity volatility.

Exhibit 2. Economic state variables and sources

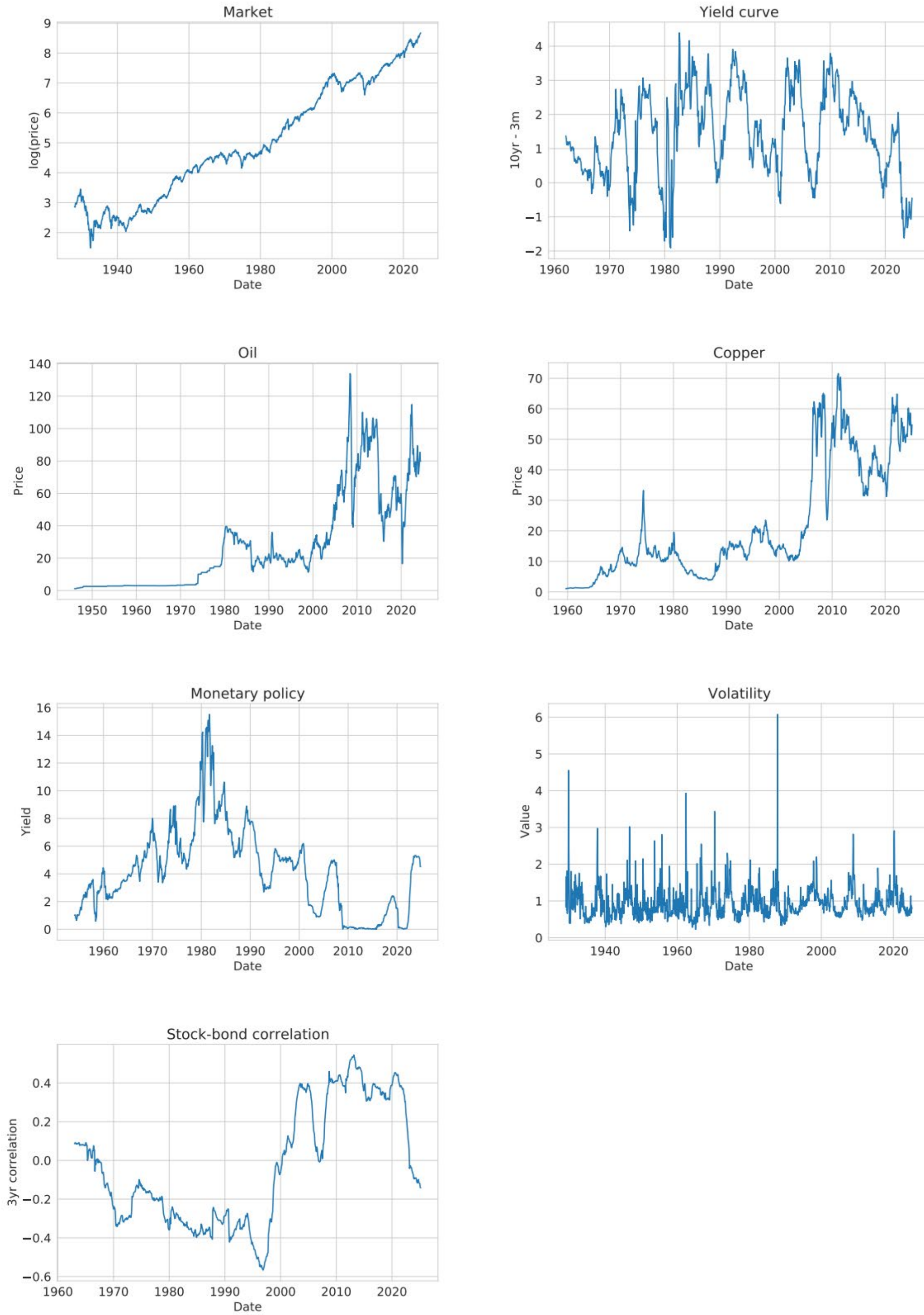
Our seven economic variables as well as the proxy variables that represent the state.

Variable	Proxy	Data source	Start date
Market	S&P500	Bloomberg	1927
Yield curve	US 10-year yield minus US 3-month yield	Internal data & St Louis FRED	1962
Oil	WTI Spot Crude Oil price	St Louis FRED	1946
Copper	Copper futures price	Internal data	1959
Monetary policy	US 3-month yield	St Louis FRED	1954
Volatility	Realized volatility of S&P500 stitched with the VIX Index (from 1990)	Bloomberg	1929
Stock-bond correlation	S&P500 and US 10-year yield	Bloomberg & internal data	1962

The raw data for the state variables is detailed in Exhibit 3. Given the varying distributions and scales, it is clear that some of the data series require transformation, which we will discuss next.

Exhibit 3. Raw economic state variables

Our seven raw economic variables. Data sources are provided in Exhibit 2.

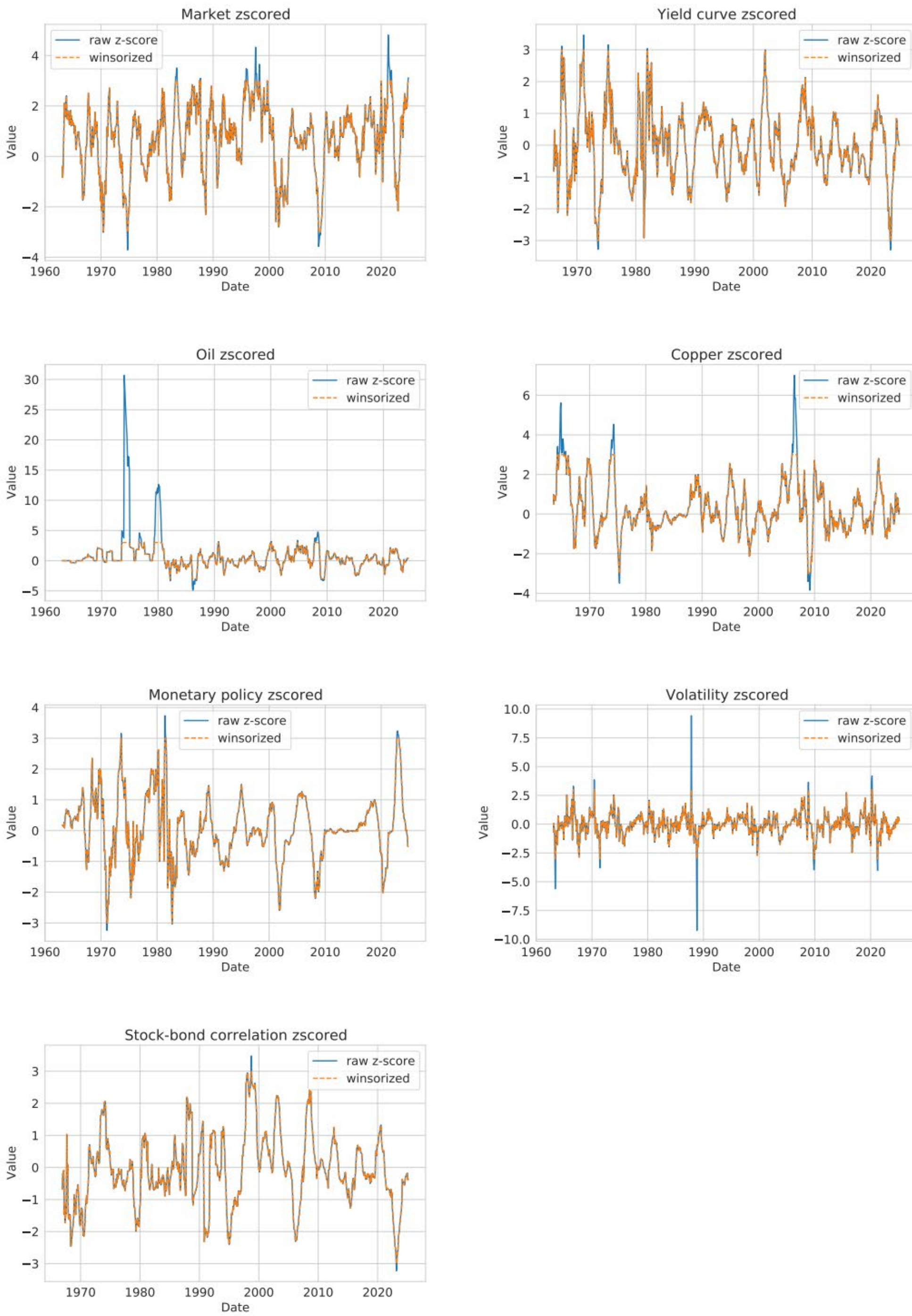


Source: Data sources are provided in Exhibit 2.

Next, we compute an adjustment similar to a z-score, whereby we divide the one-year difference by the standard deviation of the rolling one-year differences, computed over 10 years. Note the one-year difference will induce some persistence. We finish by winsorizing at ±3 to control for outliers. We plot our series in Exhibit 4 from the latest start date, 1963, to match how our model would handle these series. The orange represents the winsorized data. The winsorization is most evident for the oil price in the 1970s and volatility around the stock market crash of 1987.

Exhibit 4. Transformed economic state variables

Our seven transformed economic variables. We use an adjustment similar to a z-score, whereby we divide the one-year difference by the standard deviation of the rolling one-year differences, computed over 10 years. Finally, we winsorize at ±3.



Source: Data sources are provided in Exhibit 2.

Descriptive statistics

Next, we assess the properties of the transformed series. We do this both individually (autocorrelations) and across series (correlations). Given the nature of the one-year difference in the numerator, we expect to see strong short-term autocorrelation in Exhibit 5. As expected, the autocorrelation largely vanishes by 12 months. While we are not exactly performing a z-score, note that the means are close to zero and the standard deviations near one.

Exhibit 5. Persistence of the economic state variables

The autocorrelations of our seven economic variables. High autocorrelations in the first few months are anticipated, given the nature of the one-year difference in the numerator.

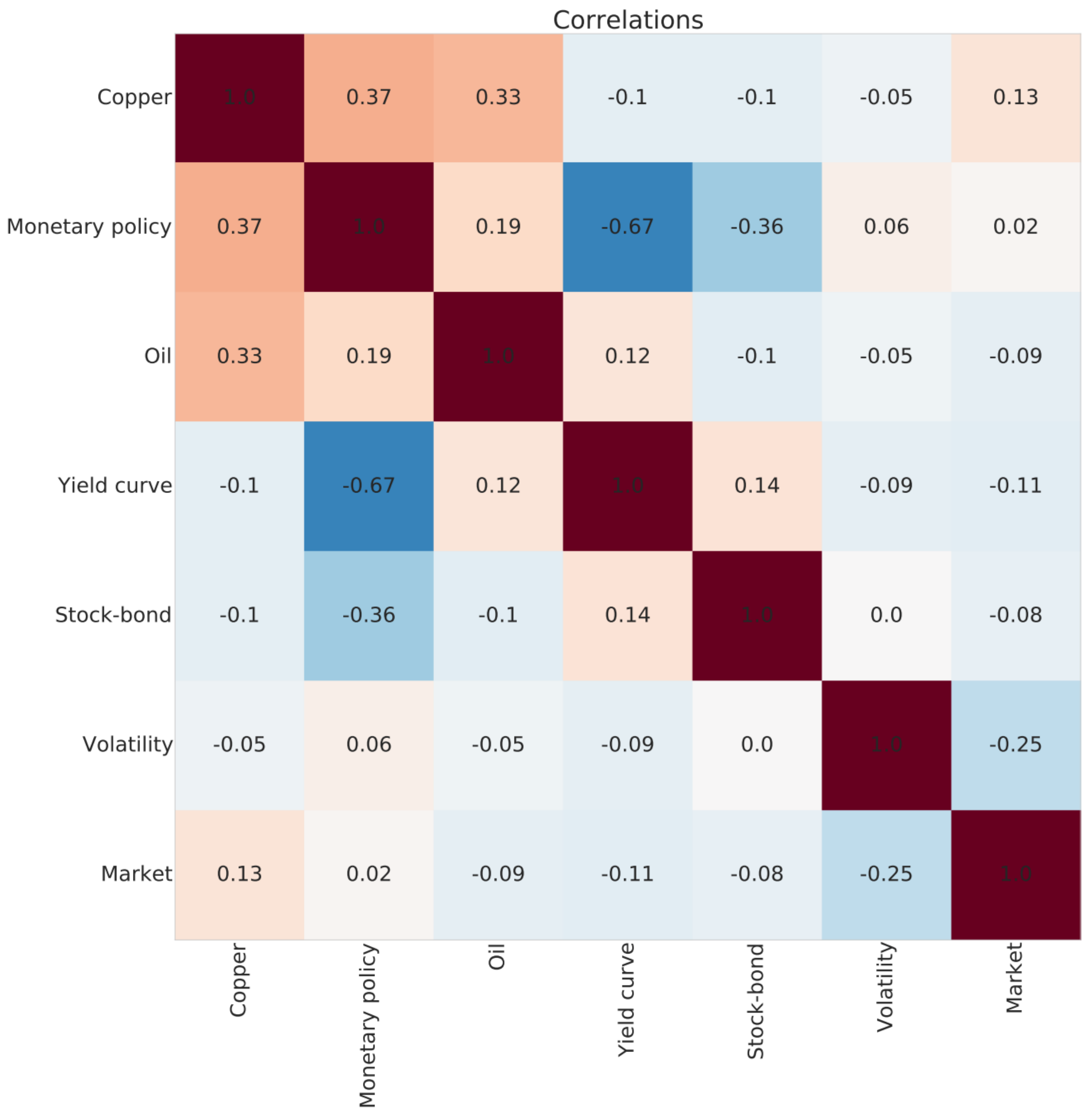
	Autocorrelations							
	1 month	3 month	12 month	3 year	10 year	monthly mean	std	frequency
Market	0.92	0.76	-0.08	0.04	-0.02	0.49	0.89	monthly
Yield curve	0.91	0.73	-0.13	-0.17	0.04	-0.07	0.98	monthly
Oil	0.90	0.71	0.03	0.09	0.00	0.24	0.97	monthly
Copper	0.93	0.78	0.01	0.00	-0.06	0.15	0.94	monthly
Monetary policy	0.95	0.82	0.14	-0.26	0.14	0.13	0.98	monthly
Volatility	0.54	0.26	-0.31	-0.07	-0.04	0.05	0.97	monthly
Stock-bond	0.93	0.76	0.07	-0.32	0.10	-0.10	0.98	monthly

The cross-correlations of the variables are presented in Exhibit 6. The correlations are generally low, with one of the highest positive correlations occurring between the two commodities - oil and copper - at 0.33. The largest negative correlation is between the yield curve and the 3-month bill – but that correlation is mechanical, given the definition of the yield curve.

The low average absolute cross-correlations suggest that the seven economic variables chosen contain independent information. This provides some diversification. In a way, these variables deliver a non-parametric basis for a signal. It is always best when signals are uncorrelated. Put differently, if all the economic variables were highly correlated, we would be identifying regimes with a single variable – providing no diversification.

Exhibit 6. Correlation of the economic state variables

The cross-correlations of our seven economic variables. The low correlations suggest a diversifying set of variables containing independent information.



Determining similar dates

We now apply our distance-based similarity metric. This runs on an iterative basis, whereby each month we compute the Euclidean distance between each historical month and the month in question. We are then able to aggregate across our variables, to obtain one global score.
The Euclidean distance, d, is defined by:

$$d_{Ti} = \sqrt{\sum_{v}^{V} (x_{iv} - x_{Tv})^2}$$

On a selected month T, for every historical month i, we calculate a sum of squares of the V transformed variables. We do so by computing the absolute difference between the value of each variable at month i, x_{iv}, and the value of each variable at month T, x_{Tv}. We sum across variables before taking the square root, to give us our similarity score, d_{Ti}, for every month up to month T. Historical months with smaller similarity scores are the most similar to today.

To be clear, this calculation must be done historically for every historical month. For example, if the variable has a score of 2.5 in December 2024, we calculate the distance between each historical month and 2.5. If the score was 2.1 in November 2024, we need to again calculate the difference between all historical months and the 2.1.

Similarity in action: Three crisis periods

To illustrate how our method works, we choose three different situations of stress: the Global Financial Crisis, COVID-19, and the 2022 inflation surge. For specific months, we examine the full history and pick the 15% most similar months (i.e., the 15% of months with the lowest values of the global score). We exclude the last three years (36 observations) when measuring similarity, as this helps us to avoid loading up on momentum. We show this masked period in grey. A lower value for the global score would imply more similarity with the month in question.

Exhibit 7 considers the global score as of January 2009. To be clear, the time series measures the similarity between all historical dates and January 2009. Notice that the global score at the point of observation is zero by construction. The most similar dates have the lowest values and include all observed recessions – including the double dip recessions in the 1980s. To preview our trading strategy, we would take a long position in an asset in February 2009 that exhibits positive returns after historically similar regimes.

Exhibit 7. Historical similarity to January 2009 during the Global Financial Crisis

The most similar months to January 2009, during the Global Financial Crisis. We use the full history and select the 15% most similar months. We exclude the last three years to avoid loading up on momentum. We show this masked period in grey. A lower value for the global score would imply more similarity with the month in question. We see our model include the double dip recessions in the 1980s as similar months.

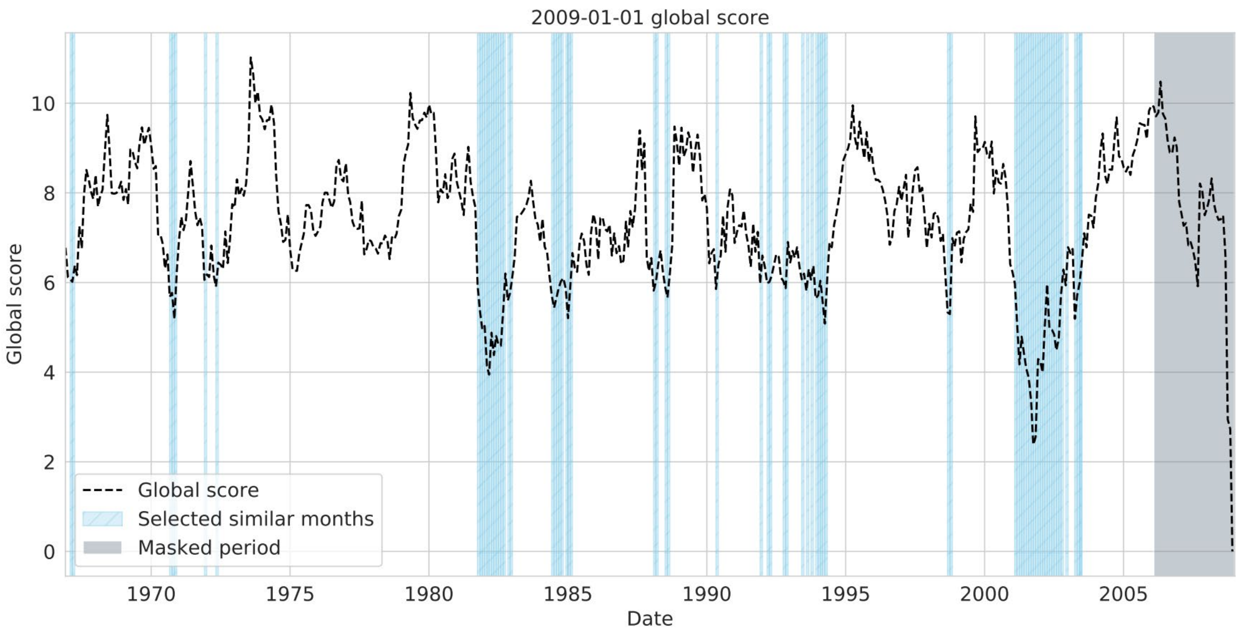
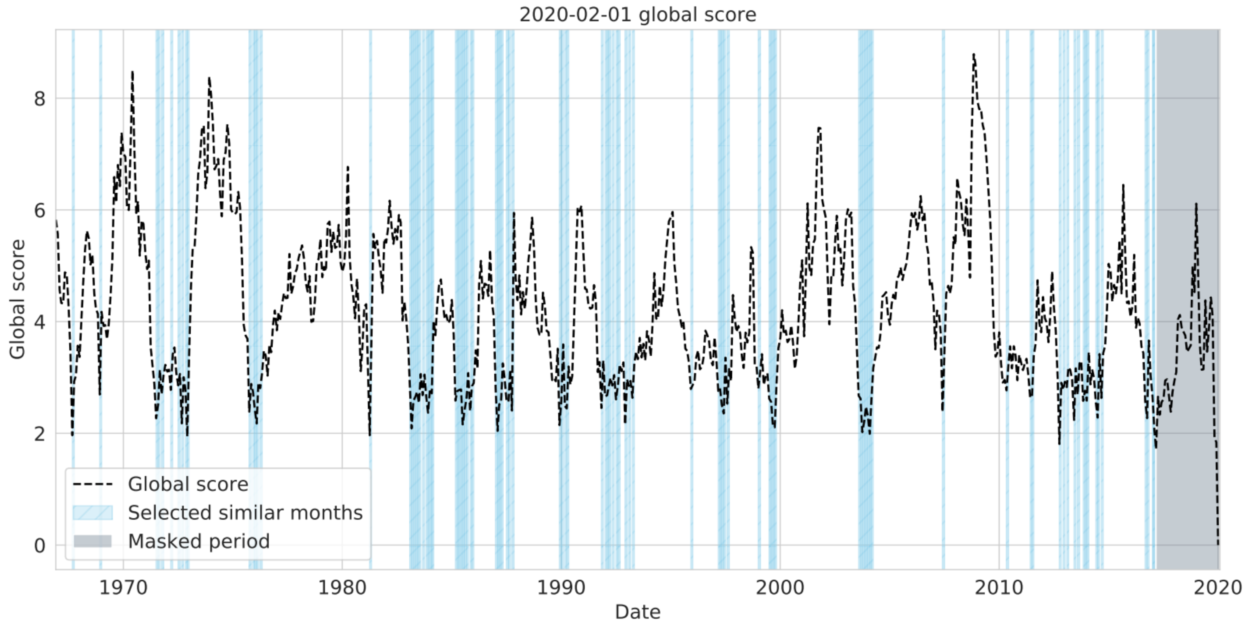
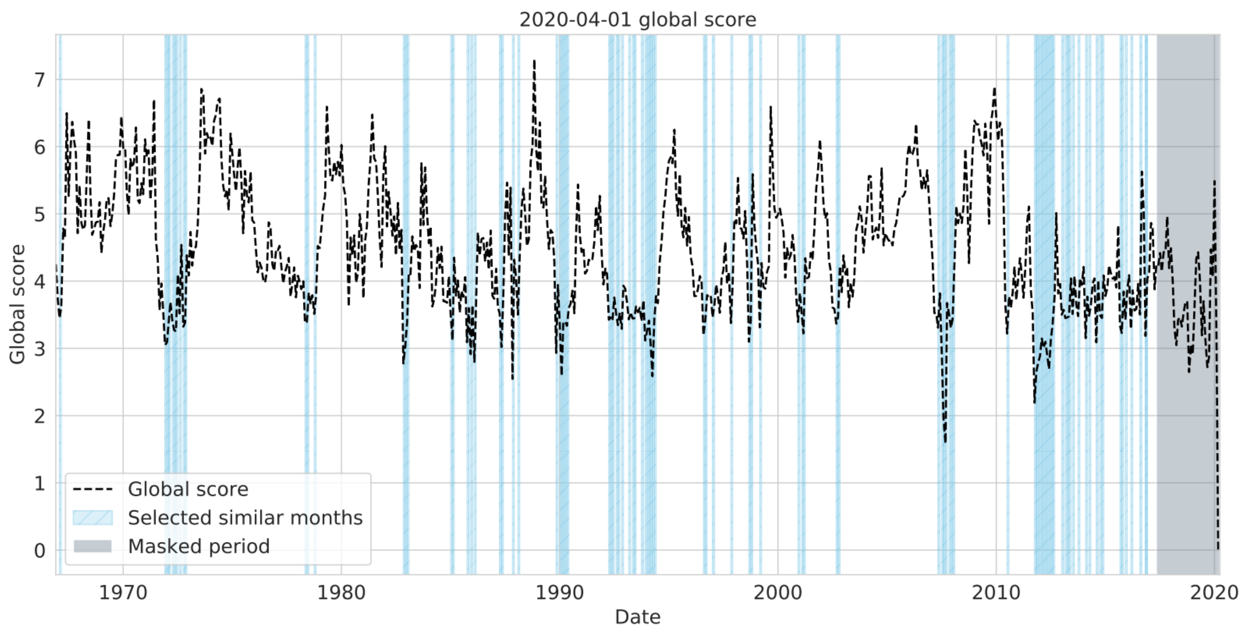


Exhibit 8 looks at two months in the COVID-19 period: February and April 2020. This was a period of a large drawdown and a sharp recovery. There are no obvious visual patterns here. This is likely because the COVID-19 crisis was so unique (at least in the last 100 years). As such, much more historical data would be needed to get close to a historical similarity. That said, even though there are no obvious patterns, there might be information in the similar global scores for a trading strategy.

Exhibit 8. Historical similarity to February/April 2020 during the COVID-19 crisis.

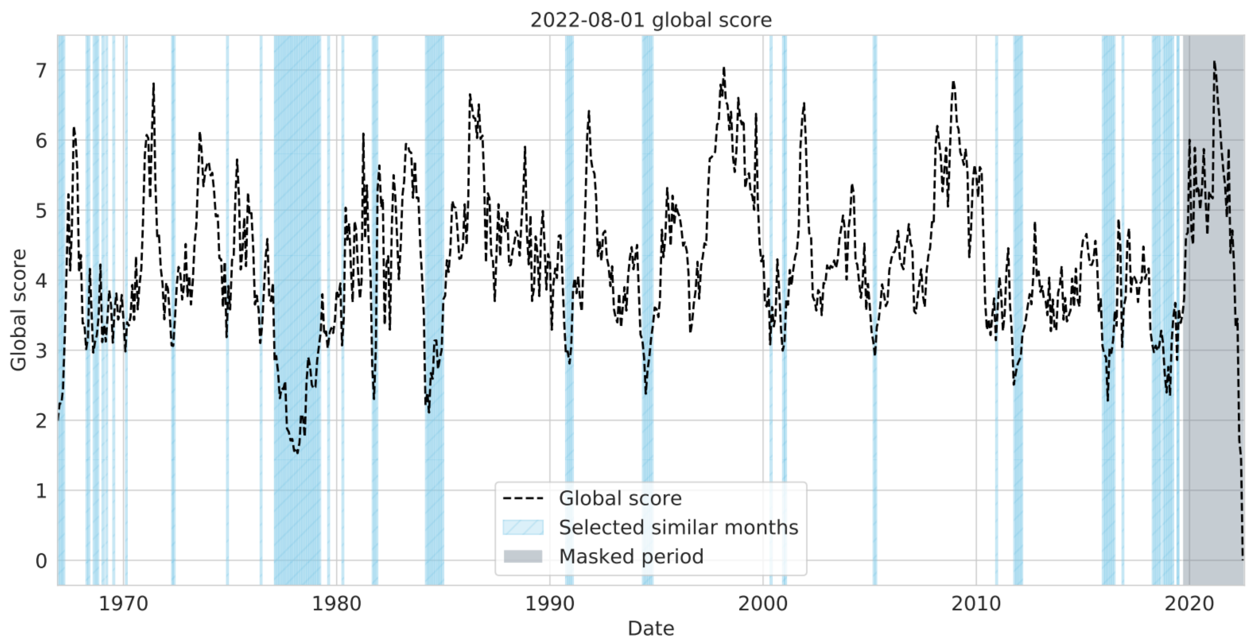
The most similar months to February and April 2020 – two months during the COVID-19 crisis. We again use the 15% most similar months and the full history, as well as exclude the last three years. Here our model struggles to identify prior regimes, likely because of the unique nature of the COVID-19 crisis.





Finally, we look at the inflation surge of 2022, particularly August 2022 in Exhibit 9. At this point in time, the Fed was still characterizing inflation as "transitory" even though the surge was evident. In contrast to COVID-19, there is plenty of experience with inflation within our sample, including the 1970s and 1980s. Our model shows this month is most similar to the inflation period following the Iranian revolution of 1977-1980. It also loads onto a few months from the 1966-1970 inflation period associated with the ending of the Bretton Woods, the OPEC oil embargo inflation period of 1972-1974 and Reagan's boom between 1987 and 1990.

Exhibit 9. Historical similarity to August 2022 during the inflation surge.
Most similar months to August 2022, during the inflation surge. Using 15% of the most similar months, we see our model home in on the Iranian revolution of 1977-1980, a few months from the 1966-1970 inflation period associated with the ending of the Bretton Woods, the OPEC oil embargo inflation period of 1972-1974 and Reagan's boom between 1987-1990.



Assessing the Predictive Power of the Regime Model

We illustrate the efficacy of our methodology on six long-short stock factors: using the Fama-French five research factors (Market, Size, Value, Profitability and Investment) plus the 12-month Momentum factor. Essentially, we are testing whether our systematic regime classification could be a useful tool for factor timing.

There is a long history of research examining time variation in factor returns which traces back to at least Ferson and Harvey (1991). Ilmanen et al. (2021) present over a century of evidence. Various different approaches have been pursued. Early work, like Ferson and Harvey used linear regressions to predict factor returns. Arnott et al. (2020) and Ehsani and Linnainmaa (2022) analyze the role of momentum in factor timing. Others such as Polk et al. (2020), Favero et al. (2021) look at the relation between macro state variables and factor timing.[2] In a sense, our work is most similar to linking macro state variables to factor returns.

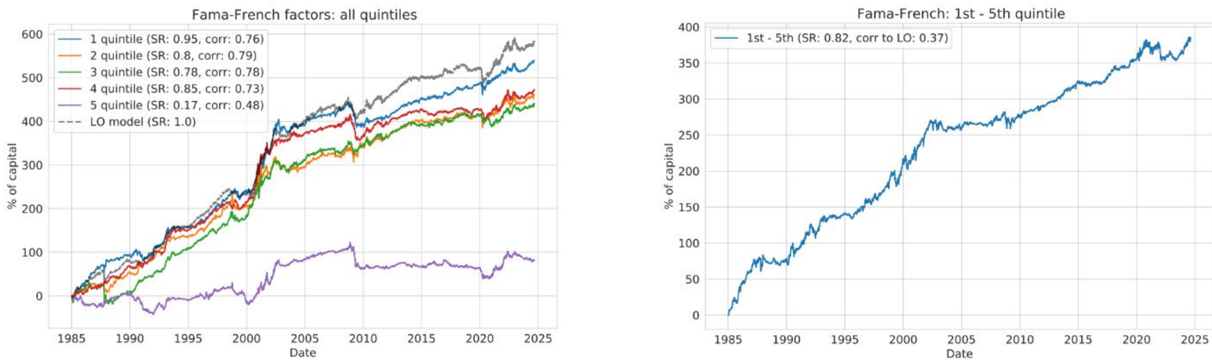
The one thing that we know is that factor timing is difficult as emphasized by Asness (2016) and Asness et al. (2017). Many of the previous approaches are highly parametric and open the risk of overfitting. Our approach is much more non-parametric.

Exhibit 10 shows the performance of investing in the six factors using the 20% most similar historical dates (quintile 1). We are long a factor if the average of returns subsequent to the most similar dates was positive, and short if it was negative. So, we are using the regime method to "time" the factors. The performance shown is when aggregating across the six timed factors on an equally-weighted basis. We repeat this exercise for the other quintiles, and so quintile 5 utilizes the 20% most *dis*similar dates. We see that quintile 1 performs best, i.e., trading in the direction of returns subsequent to the most similar dates. We also see that quintile 5 performs worst, i.e., trading in the direction of returns subsequent to dissimilar dates.

[2] See Haddad, Kozak, and Santosh (2020) as well as Lehnherr, Mehta and Nagel (2024) for an analysis of optimal factor timing.

Exhibit 10: Assessing the predictability using six long-short stock factors

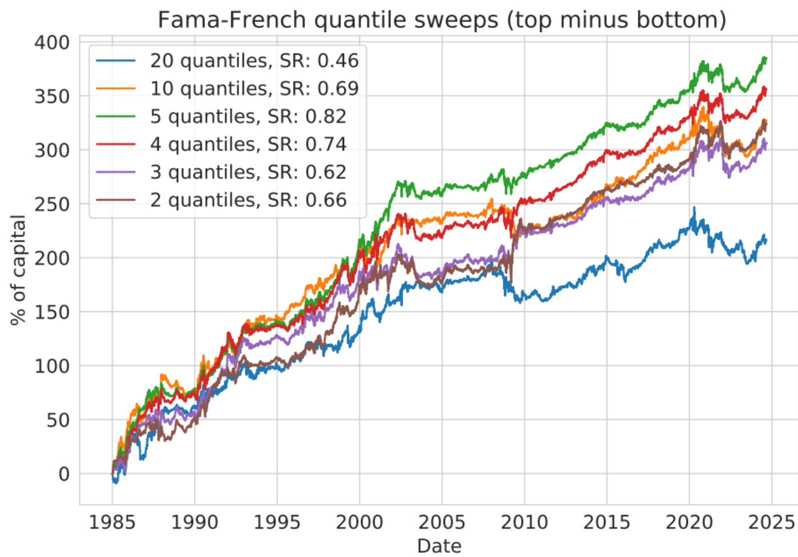
The performance of investing in six long-short stock factors (Market, Size, Value, Profitability, Investment, Momentum). For the quintile 1 portfolio, the direction taken in a factor is based on returns subsequent to the 20% most similar historical dates. The quintile 5 portfolio utilizes the 20% most dissimilar returns. The long-only portfolio is a long position in all six factors throughout the sample. The performance is shown for 1985-2024. Input data starts well before 1985 to allow for rolling-window calibrations. SR refers to Sharpe ratio and corr is the correlation with the long only (LO) equally weighted portfolio.



As factors tend to have positive returns on average, the timed portfolio is far more likely to be long a factor, and in particular strong factors. Indeed, the quintile 1 returns are 0.76 correlated to a static long-only portfolio, going long all six factors all the time. The other quintile returns have a positive correlation to the long-only portfolio as well. This means we can create a less correlated difference portfolio by going long the quintile 1 portfolio and short the quintile 5 portfolio, as is illustrated in the right-hand side panel of Exhibit 10. This difference portfolio has an impressive 0.82 Sharpe ratio, while only being 0.37 correlated to the long-only portfolio. The alpha is significant, being three standard errors from zero. In essence, the difference portfolio combines two elements: returns today that are most similar to returns subsequent to similar dates in the past and returns today that are most *dis*similar to returns subsequent to *dis*similar dates in the past.

We repeated the similar-dissimilar difference portfolio for different quantile choices and found our result to be robust, as can be seen in Exhibit 11. The performance for quartiles or quintiles is very similar. Not unexpectantly, there is some degradation when a large number of quantiles is used (20).

Exhibit 11: Similar-dissimilar portfolio performance for different quantile choices
The performance of investing in six long-short stock factors (Market, Size, Value, Profitability, Investment, Momentum) for a variety of quantiles. For each quantile choice we show the performance of our similar-dissimilar strategy over 1985-2024.



Conclusions

Knowing where we stand today in terms of the prevalent economic regime is important information for the investment process. Often, we discover we were in a regime well after the fact. The classic example of this is the NBER's dating of recessions, where it is sometimes the case that the beginning date of the recession is declared after the recession is over. Many have tried to overcome this issue using various types of rules. For example, the Sahm rule gives us early identification of recessions (historically only three months late) but is based on a single variable. It is risky using a single variable because it is subject to false signals (as evidenced by the false positive in 2024).

We present a systematic method to identify economic regimes. Our method assesses the similarity of any month to the history of a selection of economic time series. The user specifies the economic time series as well as the tolerance for similarity. The method is non-parametric, using simple z-scores to measure how similar a month is compared to each historical month. Importantly, the user can specify many economic variables to achieve a type of diversification that is not possible with a single or even dual variable method.

While our paper is methodological, we do show briefly how it might be employed to guide an investment process. We use our method to actively time six well-known factors. For example, for a particular factor at a certain month, we look for all similar historical months based on a set of economic variables. Given those historical months, we look at the average subsequent 1-month returns. If the subsequent return in similar historical regimes is positive, we go long and if negative we go short. We aggregate all factors and find there is important information in the similarity. The strategy based on the most similar periods does well. We also find that in the anti-regime months (the most dissimilar), the performance is poor. A long-short strategy of similarity vs. dissimilarity produces performance that is significant, with an alpha that is three standard deviations from zero.

There are many research enhancements that are possible here. Currently, we equally weight all economic variables. One can imagine a dynamic weighting based on predictive performance. This would potentially flag some structural changes and down-weight economic variables that become less relevant during certain times. Further, we assess similarity with respect to particular months. If the investment horizon is longer than a month, it might be reasonable to look at similarity relative to a quarter or even longer. These and related ideas are for future research.

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Appendix

Exhibit A1. Individual factor analysis of similarity

The performance of individually investing in six long-short stock factors (Market, Size, Value, Profitability, Investment, Momentum), utilizing quintiles for the similar month selection. For the top quintile portfolio, the direction taken in a factor is based on returns subsequent to the most similar historical dates. The bottom quintile portfolio utilizes the most dissimilar returns.

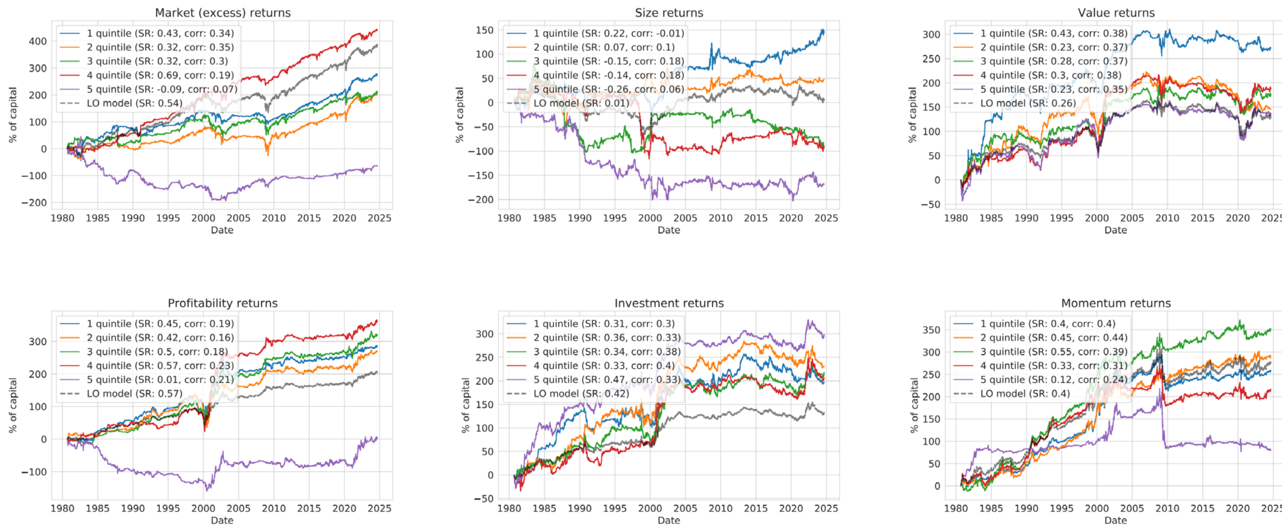

Exhibit A2. Individual factor analysis long-short similarity

The performance of individually investing in six long-short stock factors (Market, Size, Value, Profitability, Investment, Momentum). Performance is shown for the similar-dissimilar strategy over 1985-2024 for each factor.