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Revealing Macro Momentum: A Systematic Global Macro Investing Strategy

Master Thesis

by

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Abstract

This thesis examines a systematic global macro investing strategy that utilizes a novel approach of investing called macro momentum. We find consistent abnormal returns after controlling for common asset pricing factors, global macro hedge fund indices, and a time-series momentum factor. Macro momentum generates returns that are significantly different from zero, and from other benchmarks. Our strategy displays a negative correlation to traditional strategies, and through a combination, we yield considerable diversification benefits as demonstrated by higher risk-adjusted returns and lower maximum drawdowns.

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1 Introduction

"Over the last 10 years, people were rewarded for investing in hedge fund strategies correlated with [market returns]. However, 2022 was the year to remind you that a hedge fund should ideally give you diversity as well." - Kenneth G. Tropin

The recent year has been tumultuous in terms of increasing uncertainty.[1] The world has experienced a series of disruptive shocks in the form of war, energy, food supplies, and inflation which turned out to be less transitory than expected. Transitioning from a zero-interest-rate-policy environment to raising interest rates at a pace not observed in the last 40 years, combined with mounting geopolitical uncertainty and global supply-chain disruptions, has created the perfect storm for volatile macroeconomic conditions. Historically these shocks have become more common in recent times, and according to Bloom et al. (2022), it would be wise to find a way to adjust to the new reality by tracking global events. Therefore, macro focused strategies can be particularly interesting for investors, allowing them to incorporate global macroeconomic conditions into their asset allocation framework.

The increased uncertainty resulted in a more challenging environment to navigate, as the bond-and-stock correlation turned positive, investors were stranded without their expected safe haven in fixed-income markets. Investors with a blend of bonds and equities were experiencing correlated drawdowns on both asset classes during the same period. While bonds diversify stocks when stocks sell off, stocks do not diversify bonds when bonds sell off (Page, 2020, p. 123-125).

One of the many victims of the recent turbulent market has been the classic 60/40 portfolio, which has experienced the worst year since the 1937 market crash. The 60/40 portfolio has long been considered a standard benchmark for investors with moderate risk appetite because of its balanced exposure to two

[1]Measured by the World Uncertainty Index (WUI). The index analyses the report from The Economist Intelligence Unit for 140 countries and counts the frequency of the word uncertainty and its variants.

relatively uncorrelated asset classes. While the long-term average correlation remains low between stocks and bonds, the yearly correlation has been close to the highest peak in the last 26 years (Jaisinghani and Msika, 2023), which bodes poorly for portfolios relying solely on bonds to diversify equity exposure. A strategy that performs well in most market conditions is highly sought after by investors, particularly in bad states where positive outcomes are most desired, such as recessions or market crashes. A rational economic explanation for this is that during bad states of the economy, investors face other troubles such as the risk of losing their job and reduced wages, reducing overall consumption. This means a reduced payoff from investments during a bad state will have a higher negative marginal impact on the investor (Gormsen and Greenwood, 2017). To attempt and provide a method by which investors can potentially navigate volatile macroeconomic times, we must first focus on the well-known financial concept of diversification. The formal theory as outlined by Markowitz (1952), states that by including assets that have a low correlation with each other, the portfolio can reap diversification benefits as one asset performs poorly, the other assets with a low correlation might perform better. This allows us to maintain or increase returns while not taking on more risk, as such, it is considered one of the only free lunches in investing. Despite being such a well-known concept, it remains one of the most perplexing problems in practice over time for investors to this day, as the diversification we seek seems to disappear when we need it the most (Page, 2018). Finding one single strategy that can solve this puzzle while generating reasonable excess returns is very challenging. On the other hand, combining two successful strategies that exhibit a low correlation with each other to achieve the same is likely a more reasonable approach. In 2017, Jordan Brooks presented a paper where he introduced a new and novel global application of momentum, which was fittingly named *macro momentum*. J. Brooks (2017) demonstrated that a combination of cross-sectional momentum and time-series momentum would be able to reduce drawdowns and generate higher risk-adjusted returns.

This thesis will build upon the macro momentum strategy by extending the sample data and exploring new relationships between potential indicators and asset classes. Our research question is: *Can capital allocation through macroeconomic signals enhance investors' performance?* We present the macro momentum strategy as initially outlined by J. Brooks (2017), using our own optimization approach. Also, we build upon the strategy by extending the sample data and exploring additional relationships between indicators and asset classes. Furthermore, we conduct empirical analysis to establish that the macro momentum strategy is novel and cannot be explained by common risk factors, while finding that it significantly differs from conventional momentum strategies.

First, we replicate the original strategy of J. Brooks (2017), using our own rolling-window mean-variance optimization with monthly rebalancing. Then we propose further adjustments, such as using Z-scores instead of quantiles for signals, additional asset classes, and indicators to improve the strategy's overall performance. After conducting regressions between our asset classes and indicators, we find that our bond asset class data does not align with the established relationship between its indicators, and instead propose to substitute it with commodities. Additionally, we strengthen our indicator signals with the Consumer Confidence Index and LIBOR, for business cycle and monetary policy, respectively. We create portfolios for every indicator and asset class, hence we can confirm that the returns of the strategy are not driven by a single asset class nor by a single indicator. We find the proposed adjustments to yield statistically significant improvements for the macro momentum strategy, the strategy improves from 0.92[2] to 1.55 Sharpe ratio for the period 1970 - 2023.

In order to establish whether one strategy is statistically superior, we confirm that all excess returns are statistically different from zero, as well as test for differences in means to examine whether the difference in performance could have arisen by chance. We find that the means are statistically different on a 1% significance level. Further, we introduce a time-series momentum strategy that is constructed on the same data, with a -0.20 correlation to our strategy, which provides great diversification benefits, particularly in periods of distress. We demonstrate that despite having two strategies fundamentally based on

[2]The original AQR strategy as presented by J. Brooks (2017) maintains a Sharpe ratio of 1.23 in the original period of 1970 - 2016. With an extended sample to 2023, the strategy underperforms, reducing its Sharpe ratio to 0.92

momentum, the macro momentum approach generates a unique portfolio with low correlations to traditional stand-alone forms of momentum. We apply the diversification concept from Markowitz (1952) on strategies rather than assets, and demonstrate how uncorrelated strategies can in combination yield superior results. Our time-series and macro momentum strategies generate Sharpe ratios of 0.89 and 1.55, and a maximum drawdown of 30.3% and 22.4%, for the period 1970 - 2023, respectively. Combining the strategies with equal weights increases the Sharpe ratio to 1.68 while reducing the maximum drawdown to 11.27%. The combined portfolio generates an excess return that is statistically different from both time-series and macro momentum. To examine the potential sources of returns, we examine whether common risk factors can explain the macro momentum's abnormal returns. When controlling for common risk factors, we demonstrate that these factors are unable to explain the returns of our strategy. We conclude that the strategy's returns are not a product of systematic risk premia.

Finally, we evaluate the performance of macro momentum relative to time-series momentum and global macro hedge fund indices. Once controlling for time-series momentum and macro indices, our alpha remains significant, despite dropping more than when we control for common risk factors. We demonstrate that the abnormal returns remain significant at 1% level, ranging from 8.4% to 12.24% for all regressions, corroborating our conclusions that the macro momentum strategy provides a novel approach in combining conventional momentum, while outperforming its benchmarks.

This thesis is organized as follows: We start with the literature review of previous works, which are seminal in their respective areas, relating to time-series, cross-sectional and macro momentum, as well as the mean-variance framework. We then review the data for this global strategy and the methodology for developing the macro momentum portfolio. Next, we discuss our results and findings. The final part concludes and provides ideas for future research.

2 Literature Review

There is a lack of existing research that focuses on approaches relating to exploiting economic news rather than price trends through the application of momentum strategies. Because of the limited academic literature, we will primarily focus on the seminal papers whose findings are critical for constructing and understanding the macro momentum approach presented in this thesis.

2.1 Macro Momentum

In the last 30 years, extensive research and empirical evidence show that the momentum premium persists over time across several asset classes and global markets. The concept has been widely documented by both practitioners and academic literature, and the growth in empirical research has been followed by a growth in popularity amongst investors since the concept was formally introduced by Jegadeesh and Titman (1993). Since that time, various new applications of momentum have been researched, one of them being the concept of macro momentum introduced by AQR in the publication from J. Brooks (2017), which serves as our primary reference paper for constructing the macro momentum portfolio presented in this thesis. The term is intended to describe the strategy's ability to profit from underlying macroeconomic drivers that are capable of influencing markets. Macro momentum is a systematic global strategy that involves taking long positions in asset classes where the fundamental macroeconomic trends are improving and shorting the asset classes where the macroeconomic trend is declining. Macro momentum is not a new form of momentum as it relies on previously established and documented variations of momentum, such as cross-sectional and time-series momentum. The novelty in Jordan Brooks' findings comes in the shape of how these well-known momentum variations are applied in order to exploit fundamental news directly instead of focusing on price trends, as traditionally done, while still relying on the methodology introduced by Jegadeesh and Titman (1993) and Moskowitz (2012).

Alongside Jordan Brooks, Scherer and Kessler (2013) are the only authors focusing specifically on macro momentum as a global strategy in their research, and are the first to apply the name macro momentum for their strategy. The authors find evidence that momentum across asset classes is driven by macroeconomic variables, which proves to be particularly successful during times of economic distress. Even though the implementation of macro momentum in the two papers is different, the underlying premise of reacting to changes in macroeconomic conditions remains the same. The primary difference in the fundamental approach to macro momentum is that Scherer and Kessler (2013) implement an overall simpler strategy focusing on cross-sectional momentum, while J. Brooks (2017) utilizes both cross-sectional and time-series momentum in his approach. Both papers demonstrate that the relationship between macroeconomic variables and asset classes is possible to exploit, and this thesis will expand on this available literature to further cement these relationships empirically. Similar to J. Brooks (2017), we create two sets of portfolios during our macro momentum portfolio construction. One set is long/short and relies on cross-sectional momentum, and another set consists of directional portfolios that rely on time-series momentum. Since our strategy requires the use of both forms of momentum, we will formally introduce the concepts in our literature review together with seminal works on each respective topic.

2.2 Cross-Sectional Momentum

Jegadeesh and Titman (1993) were the first to publish literature on the existence of momentum premiums in equities and introduce the concept of applying cross-sectional momentum to form an investment strategy. The authors demonstrate that buying stocks that have performed well historically and selling stocks that have performed poorly in the past, over 3 to 12-month holding periods, can yield abnormal returns. The concept of cross-sectional momentum, as demonstrated by Jegadeesh and Titman, is adapted and implemented in our thesis for our long/short portfolios, where we take positions not based on price trends, but on macroeconomic trends relative to the cross-sectional average. The primary difference with our approach besides exchanging price trends for macroeconomic trends,[3] is that we focus on global asset classes and we opt not to use any form of quantiles but instead use a Z-score approach to create portfolios consisting of winners and losers.[4]

2.3 Time-Series Momentum

The other set of portfolios we construct are called directional and are fundamentally based on the principles introduced by Moskowitz et al. (2011). The authors find that by constructing a strategy that bets purely on an asset's own continuation in returns rather than relative performance such as the cross-sectional approach, they are able to document superior performance than that of Jegadeesh and Titman (1993).[5] The time-series momentum approach is applied during the construction of our directional portfolios with a few adjustments to make it tailored for our strategy. Unlike the original approach, we do not apply the time-series momentum directly on price trends, but rather on the macroeconomic indicators. The 12-month time-series momentum of the indicators will dictate whether we go long or short on the different asset classes. The positions will be dependent on established relationships between asset classes and indicators.[6]

Comparing Cross-Sectional and Time-Series Momentum

The fundamental difference between these two momentum strategies is that cross-sectional momentum looks at performance relative to other assets to predict future relative outperformance. While time-series momentum is based on an asset's own absolute performance over a period of time to predict future return (Moskowitz et al. 2010). Despite sounding similar, these fundamental differences between the momentum strategies can mechanically produce vastly different results. To illustrate, time-series momentum will classify more stocks as winners than losers during strong markets, while the opposite is true during poor-performing

[3] Macroeconomic trends are measured by an indicator's performance over the last 12 months.

[4] Winners refer to assets whose indicators have performed well over the last 12 months and losers are assets whose indicators have performed poorly over the last 12 months.

[5] Goyal and Jegadeesh (2018) have argued that this is because of higher leverage. Whereas cross-sectional momentum is a zero-cost strategy, time-series momentum will often be net long, as a consequence of past returns being more often than not positive rather than negative.

[6] See table 1 and 16

market conditions. In comparison, cross-sectional momentum will classify the same amount of stocks as winners or losers independent of market conditions. From this, we can acknowledge that there is an element of market timing ingrained in traditional time series momentum, which is not present in cross-sectional momentum (Bird et al. 2017).

2.4 Mean-Variance Framework

In 1952 Harry Markowitz formally introduced the groundbreaking concept of diversification and mean-variance utility, which set the groundwork for the creation of the Capital Asset Pricing Model (CAPM) of William Sharpe (1964) and John Lintner (1965). The idea of mean-variance investing is directly related to that of diversification. An investor can exploit the way different assets interact with each other, one asset's losses can be canceled out by other assets in the portfolio performing well. This simple concept allows investors to increase their expected returns while at the same time reducing portfolio risk, which is why it is often referred to as the only free lunch in investing. In our thesis, we have adopted the idea of mean-variance to optimize our final portfolio, where we use the mean-variance framework to maximize the Sharpe ratio with a simple budget constraint. Naive use of mean-variance optimization has some weaknesses, such as the tendency to produce extreme portfolios with highly concentrated weights for extreme longs or shorts. This issue is often related to estimation errors in the return vectors and covariance matrix. At the time of optimization, we have four diversified global portfolios that already have been equally weighted, reducing the concern of concentrated weightings in one of the four portfolios. Further, we adopt the idea of diversification and apply it by combining two strategies with low correlation to obtain one strategy with superior risk-adjusted returns.

2.5 Indicator and Asset Class Relationships

We follow the relationships between asset classes and indicators as presented by J. Brooks (2017). However, with our additional commodity asset class and indicators such as the Consumer Confidence Index (CCI) and LIBOR, we establish sensible relationships that have been documented in prior research. Reicher and Utlaut (2013) examine the impact of inflation on commodity prices and document that a rise in short-term inflation causes a rise in short-term commodity prices. Credit Suisse (2019) empirically demonstrates that commodities are positively related to business cycle expansion. Bernanke and Kuttner (2005) find that expansionary monetary policy has a positive relationship with commodities. Hsu et al. (2011) find a positive relationship between consumer confidence indices (CCI) and equity returns.

3 Data

The primary data is as described in J. Brooks (2017), however, some adjustments have been necessary to make as not all data have been accessible to us. While Jordan Brooks has collected data from Bloomberg, DataStream, Citi, Reuters, IFS, OECD, and Consensus Economics, we rely on Bloomberg, DataStream, Global Financial Data, OECD, and Federal Reserve Economic Data. In cases of shortcomings on our primary platforms (Bloomberg and DataStream), we attempt to supplement with data from Global Financial Data. The data collected includes not only the data that has been essential to replicate the macro momentum strategy but also data that has been used to implement additional adjustments to the strategy in search of improvements. We gathered primarily monthly data from December 1969 to April 2023. We have chosen the same set of countries as J. Brooks (2017) for all our asset classes and indicators. Any discrepancies between which countries are present between asset classes and indicators are likely due to data availability.

Asset Classes

Equities

For equities, we use Bloomberg, and then Global Financial Data when needed to supplement historical data if necessary. We collected monthly stock prices from total stock return indices in the following countries: Australia, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Netherlands, New Zealand, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

Bonds

For the bond asset class, we use monthly 10-year government bond yields from Global Financial Data for the following countries: Australia, Canada, Denmark, Germany, Japan, Sweden, Switzerland, the United Kingdom, and the United States.

Currencies (FX[7])

Data for the currency asset class is from DataStream and Global Financial Data for the following countries: Australia, Canada, Denmark, Germany, Japan, Sweden, Switzerland, the United Kingdom, and the United States..

Interest Rates

All interest rates data is from IMF Data - IFS for the following countries: Australia, Canada, Europe (Euribor), New Zealand, Switzerland, the United Kingdom, and the United States.

Indicators

Business Cycle

Both the data for quarterly GDP and monthly Consumer Price Indices is from OECD for the following countries: Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Netherlands, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

International Trade

Currency exchange rate indices are from DataStream and Global Financial Data for the following countries: Australia, Canada, Denmark, Europe, Hong Kong, Japan, New Zealand, Sweden, Switzerland, the United Kingdom, and the United States.

[7] FX refers to foreign exchange, and will be used interchangeably with currencies in this thesis.

Monetary Policy

To capture one-year changes in the front end of the yield curve, we use two-year government note yields and T-bills yields from Global Financial Data for the following countries: Australia, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Netherlands, New Zealand, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

Risk Sentiment

Data for risk sentiment, which consists of equity market excess returns, is from Bloomberg, alongside the 3-month LIBOR rate which serves as the risk-free rate. The equity returns collected are consistent with the countries mentioned in the equity class.

Additional Data

These are additional asset classes and indicators which are not present in J. Brooks' strategy, they are utilized in our own adjusted version of the strategy.

Commodities

This asset class is not included in J. Brooks (2017). It is our own addition to the strategy. The commodity index is from Bloomberg and is called the Bloomberg Commodity Index.

Consumer Confidence Index (CCI)

Monthly data for consumer confidence indices are directly from OECD, for the following countries: Australia, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Netherlands, New Zealand, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

Risk Factors

Asset Pricing Models

Monthly developed markets data for the three-factor model from Fama and French (1993), the four-factor model of Carhart (1997), and the five-factor model of Fama and French (2016) are from Kenneth R. French Data Library.[8]

4 Methodology

Our methodology is based upon the framework outlined by J. Brooks (2017) which focuses on building a global macro momentum strategy based on several macroeconomic indicators. The indicators are used to act as signals determining the respective short and long positions in each asset class. The indicators which are used as signals are business cycle, international trade, monetary policy and risk sentiment. The global macro momentum strategy uses four major asset classes which are equity indices, currencies, government bonds and interest rates.

Table 1: Signal Relationships

Asset Class	Business Cycle		International Trade	Monetary Policy	Risk Sentiment
	Growth 1y Change in GDP	Inflation 1y Change in CPI	Competitiveness 1y FX Deprecation	Policy Tightening 1y Change in 2y Yield	Sentiment 1y Equity Market Return
Equities	+	+	+	-	+
Bonds	-	-	-	+	-
Currencies	-	-	-	+	+
Interest Rates	+	-	+	-	-

This table shows the relationships between indicators and asset classes. A positive (negative) sign indicates that when indicators are increasing it is bullish (bearish) for the given asset class, and the opposite when the indicators are decreasing.

As an example, increasing growth, declining inflation, increasing competitiveness, policy easing and improving risk sentiment are each bullish signals for equities. Furthermore, we want to empirically examine the relationships using our data to check if the signs align with the established relationships. In order to examine the relationships empirically we run the following OLS (Ordinary Least Squares) regressions.

$$\begin{aligned} r_{i,t}^{asset\ classes} &= \beta_0 \ + \ \beta_1 (Policy\ Tightening)_t \ + \ \beta_2 (Compentiveness)_t \\ &+ \ \beta_3 (Risk\ Sentiment)_t \ + \ \beta_4 (Growth)_t + \beta_5 (Inflation)_t + u_t \end{aligned} \tag{1}$$

where i = Equity, Bonds, Currencies and Interest rates

[8] `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

After performing the regression for each asset class separately we obtain the following results for the coefficients which are shown in table 2.

Table 2: Regression Results

Asset Class	Business Cycle		International Trade	Monetary Policy	Risk Sentiment
	Growth 1y Change in GDP	Inflation 1y Change in CPI	Competitiveness 1y FX Deprecation	Policy Tightening 1y Change in 2y Yield	Sentiment 1y Equity Market Return
Equities	-0.069	-0.130	0.101	-0.246	0.009
	(-1.308)	(-0.945)	(1.230)	(-1.470)	(0.751)
Bonds	-0.470	0.206	0.008	0.306	0.044
	(-0.663)	(0.586)	(0.053)	(0.733)	(1.527)
Currencies	0.006	0.069	0.012	-0.039	0.003
	(0.191)	(1.007)	(0.285)	(-0.438)	(0.519)
Interest Rates	-0.003	0.0002	-0.010	0.059^{***}	0.003^{***}
	(-0.944)	(0.018)	(-1.239)	(3.348)	(3.761)

This table shows the beta coefficients of the regressions which have been performed for each asset class using our indicators as the independent variables. The sample is monthly from 1970-2023. The numbers in parentheses are t-statistics adjusted according to the Newey and West (1987) procedure. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

By comparing table 1 and table 2 we are able to assess the empirical relationships between the asset classes and indicators that hold for our sample. Overall, we find that 9/20 of the beta coefficient signs align with the relationships presented in table 1. The sample used is from 1970 - 2023, however, we observe that the relationships tend to vary in different sub-periods as the relationships are subject to change over time. The equity class is the one that corresponds the most with the established relationships, with 4/5 signs aligning, while bonds corresponds the least, with only one sign aligning according to table 1. Further, none of the beta coefficients are significant at any common significance levels[9] except monetary policy and risk sentiment for interest rates which are significant indicators at all common significance levels.

4.1 Asset Class Construction

J. Brooks (2017) implements the macro momentum strategy across four major asset classes, therefore we also aim to reproduce the strategy using the same four asset classes. To construct the global equity indices asset class, we first gather total return equity indices for all countries. Subsequently, we create an

[9] All common significance levels refer to 10%,5% and 1%.

equal weighted global equity index, by averaging across the returns from all country's indices. The global government bond asset class is built by using 10-year government bonds for the bond asset class, using the bond yields we calculate the return for each country´s bond and lastly we create our global government bond index by taking an equal weighted average of each country's bond return. To construct the global currency asset class, we first gather currencies against the U.S. Dollar. Afterwards we compute the currencies returns and aggregate all currency´s returns to form our currency index asset class using an equally weighted approach. The final asset class is created by gathering the policy interest rates for the interest rate asset class. Following that, we calculate the absolute change for each policy rate and aggregate across interest rates to form an equally weighted interest rate index.

Adjustments of Macro Momentum

The original strategy by J. Brooks (2017) is adjusted in order to find improvements and obtain overall superior results. We choose to replace the bond asset class with commodities in our own macro momentum strategy, due to bonds' poor performance and strong deviation from our established relationships.

4.2 Indicator Construction

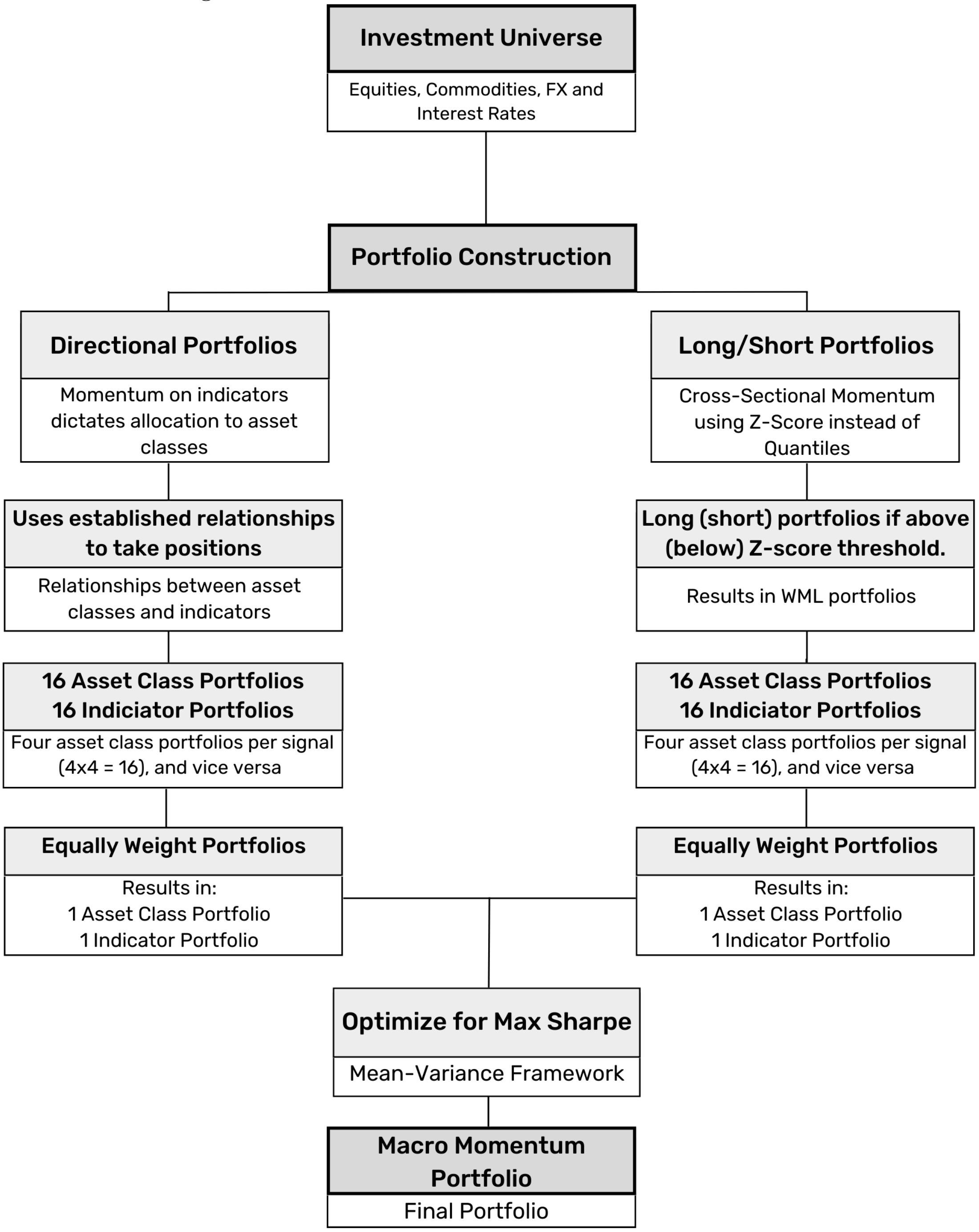
To construct the business cycle signal we create an equal weighted GDP and inflation index, by calculating one-year absolute changes for both GDP and inflation, and subsequently taking an equal weighted average, we obtain the business cycle signal. The international trade signal is constructed by first creating an equal weighted index of each country's currency index against a basket of major currencies in global markets. Further the international trade signal is created by taking one year changes. This signal measures competitiveness, as a currency depreciates export competitiveness increases. Monetary policy signals are constructed by mainly using two year government bonds and their respective T-bill rate for the periods where we lack data for two year bonds. Moreover, the monetary policy signal is constructed by taking one-year absolute changes. This signal captures whether monetary policy is expansionary or contractionary. Risk sentiment signal uses one-year equity market excess returns. First, we create a synthetic risk-free rate security over the period of 1970-2023, starting at a base of 100, which is then subsequently invested in the monthly LIBOR rate. Further, we calculate one-year changes of both our global equity market index and the risk-free rate security. Finally, one-year equity market excess return was calculated as the difference between the equity market index return and the return of the risk-free rate using our synthetic security. This signal measures whether the risk sentiment of the financial market participants is increasing or declining.

Additional Indicators

We also add additional signals when constructing our own macro momentum strategy. We add two more indicators under business cycle and monetary policy which are the Consumer Confidence Index (CCI) and LIBOR. The Consumer Confidence Index will be the third indicator under business cycle while LIBOR will be the second indicator under monetary policy. The methodology of business cycle and monetary policy construction stays the same as AQR construction of business cycle hence the three indicators of business cycle will have a weight of 0.25 instead of 0.5 each. CCI contributes to the business cycle by providing an indication of future developments of households' consumption and savings. We find that by combining LIBOR with our existing monetary policy signal, we are able to achieve improved performance for the macro momentum strategy.

4.3 Portfolio Construction

Figure 1: Macro Momentum Construction Process



This figure displays the macro momentum portfolio construction from start to end. The figure starts with showing our investment universe, further we show how we split the construction into directional and long-short portfolios and how the cross-sectional and time series momentum is applied. For both directional and long-short, we construct four asset class portfolios per indicator and four indicator portfolios per asset class, resulting in 16 asset class portfolios and 16 indicator portfolios (i.e. 64 portfolios in total). Finally the portfolios are aggregated using an equal weighted approach, at the end, the remaining four portfolios are optimized with monthly rebalancing to obtain the final macro momentum portfolio.

For each indicator within each asset class we form two types of portfolios: long-short and directional portfolios. Long-short portfolios take long (short) positions in assets with favorable (unfavorable) macroeconomic trends relative to the cross-sectional average. While directional portfolios take long positions in assets with favorable macroeconomic trends and short positions in assets with unfavorable macroeconomic trends, regardless of trends in other markets. Our long-short portfolios are designed to be market-neutral at all points in time, while our directional portfolios are designed to be market-neutral on average. Using the long-short and directional portfolios we create three composite[10] portfolios which are as follows: Asset class portfolios (what if we traded on all macro momentum signals, but only in a particular market such as equities or bonds). Indicator portfolios (what if we traded on macro momentum in all markets i.e., all the asset classes, but only using one particular signal such as business cycle or monetary policy). Macro momentum portfolio (an aggregate portfolio which is formed by taking an equal weighted average across all asset class and indicator portfolios). To perform the portfolio construction we create an optimization algorithm where we optimize monthly using three year rolling returns. We build our optimization algorithm based on the mean-variance framework as presented in Markowitz (1952).

$$\sum_{i=1}^{4} w_i x_0 = x_0 \sum_{i=1}^{4} w_i = x_0 \tag{2}$$

Before we formally introduce our optimization problem, we define each element mathematically.

$$\mu = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_n \end{bmatrix} \tag{3}$$

We set the μ vector to be the vector of expected returns for i assets and we set Σ as the covariance matrix which is symmetric and positive semi-definite.

[10]A composite portfolio consists of asset class portfolios, indicator portfolios and macro momentum portfolio.

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \dots & \sigma_{1n} \\ \sigma_{21} & \sigma_2^2 & \dots & \sigma_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{n1} & \sigma_{n2} & \dots & \sigma_n^2 \end{bmatrix} \tag{4}$$

The diagonal elements of the Σ matrix is the assets variances which we denote with σ_n^2 while the off-diagonal elements are the covariances between the assets which we denote by σ_{ij} where i and j are asset i and j. We use w to denote the weight vector which consists of each asset's weights in the portfolio.

$$w = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} \tag{5}$$

Now that we have defined all the elements, we formally define the portfolio's expected return and standard deviation which are as follows:

The portfolio's expected return can be expressed as $w^T \mu$ and the portfolios standard deviation can be expressed as $\sqrt{w^T \Sigma w}$.

Finally, we formally state the optimization problem which is

$$\max_w \frac{w^T \mu - rf}{\sqrt{w^T \Sigma w}} \tag{6}$$
$$s.t. \ 1^T w = 1$$

Hence, our objective function is the portfolio's Sharpe ratio, i.e. we maximize the portfolio's Sharpe ratio given the budgetary constraint that all our weights should sum up to 1, which represents a leverage constraint. Analytically[11], we derive the following solution for our maximization problem.

$$w_t = \frac{\Sigma^{-1} \mu_e}{1^T \Sigma^{-1} \mu_e} \tag{7}$$

w_t is our weight vector which consists of portfolio weights, Σ^{-1} is the inverse

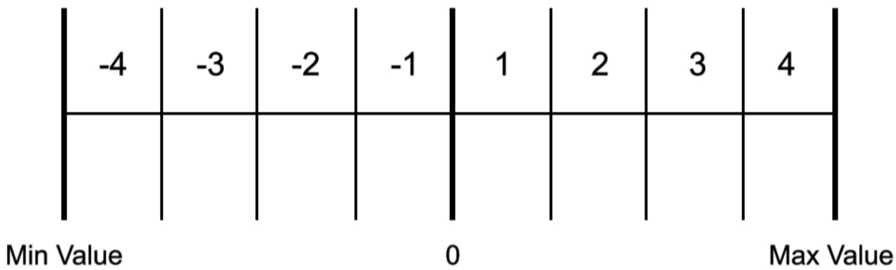
[11] We perform the optimization numerically while here we show the analytical solution.

of covariance matrix, $\mathbf{1}^T$ is a transposed vector of ones and $\mu_e = \mu - rf\mathbf{1}$ is a vector of excess returns. Within this portfolio optimization algorithm we construct the long-short and directional portfolios as follows for each asset class and indicators.

4.3.1 Long-Short Portfolio Construction

For our first attempt to form the long-short portfolios we used a quantile based approach. Our quantile based approach works as demonstrated in figure 2.

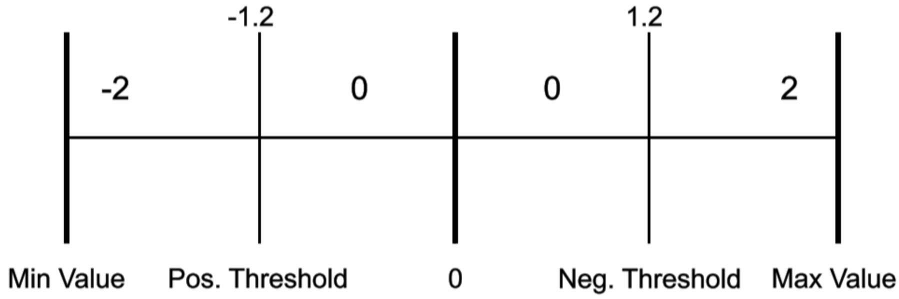
Figure 2: Signal Intensity using Quantiles



This figure shows the eight quantiles which we use to form the long-short portfolios. The figure contains negative and positive quantiles where the max and min values are 4 and -4, respectively.

We utilized quantiles to determine our signal intensity, but this approach unfortunately yielded poor results, this was caused by too strict precision, due to high granularity. Another issue with too many quantiles is that it can cause the numerical optimization to be too restrictive (i.e. the quantile rank of the signal forces the exact asset allocation, leaving no space for optimization). As a result, we develop an improved approach that is easier to interpret, utilizing Z-scores instead of quantiles. The Z-score approach allows us to calibrate the model by finding a threshold Z-score that better discriminates the signal's values by looking at the relative magnitude of the signal compared to the predetermined thresholds.

Figure 3: Signal Intensity Using Z-Score



This figure shows how we construct the long-short portfolios using the Z-scores approach. The Z-score approach consists of a minimum Z-score and a maximum Z-score which is set to -2 and 2 respectively. We set the thresholds to be -1.2 and 1.2 and if the Z-score lies between the thresholds the signal will be assigned a value of zero. Further, we construct the Z-score by taking the signal value minus its median and dividing by the difference between the 80% and 20% quantile. We use the median instead of mean because the mean can be influenced by outliers.

In the Z-score approach we do not distinguish between positive and negative values. The approach consists of one negative and one positive threshold; if the Z-score lies between the thresholds, the signal will be discarded and assigned a value of 0. If the Z-score is above the positive threshold or below the negative threshold, it is considered as a strong signal and therefore will be included, thus having an impact on the optimization. Lastly, using the signal intensities we create a set of positive weights and a set of negative weights that add up to zero, and which will form the basis of our long-short portfolios.

4.3.2 Directional Portfolio Construction

Directional portfolios are constructed by taking a 100% position in assets with favorable macroeconomic trends and a -100% position in assets with unfavorable macroeconomic trends. To determine the signal direction i.e., when to go long and short we use the relationships which are stated in table 1. For example increasing growth, increasing competitiveness, risk sentiment and declining inflation together with an expansionary monetary policy are indicating a bullish signal for equities i.e., we long the equity asset class when the direction of the signal aligns with the relationships stated in table 1.

4.3.3 Asset Class Portfolios

The idea behind asset class portfolios is what if we traded on all macro momentum signals, but only in a particular market such as equities or bonds. We use four signals to construct the portfolios and for each asset class we construct eight portfolios (four long-short and four directional) i.e., one long-short and one directional portfolio per signal for a given asset class, hence a total of 32[12] portfolios. Lastly, the asset class portfolios are formed by taking an equal weighted average of each of the eight portfolios. Mathematically illustrated as follows: Each of the eight portfolios will be given a weight corresponding 1/8 and the weighted average will be taken for a given asset class: $rp_{asset\ class\ j} = \Sigma w_i r_i$ $i = 1 \dots N$ where i denotes the numbers of the portfolios which in our case is equal to 8, j is the jth asset class which goes from $1 \dots j$ and w_i denotes the weight factor for a given portfolio which is set to 1/8. Σ here represents the summation sign and not the covariance matrix.

4.3.4 Indicator Portfolios

The idea behind the indicator portfolios is what if we traded on macro momentum in all markets (equities, bonds, currencies and interest rates), but only using one signal such as business cycle or monetary policy, i.e., we trade on all four asset classes by only using one signal at a time. We construct the indicator portfolios by creating eight asset class portfolios i.e., (four long-short and four directional). Using one indicator at a time and trading on all four asset classes, we obtain one long-short and one directional portfolio per signal, hence a total of 32 portfolios. To create the indicator portfolios we take an equal weighted average of each of the eight asset class portfolios and mathematically we can illustrate the process as follows: Each of the eight portfolios will be given a weight corresponding 1/8 and the weighted average will be taken for a given indicator. $rp_{indicator\ j} = \Sigma w_i r_i$
$i = 1 \dots N$

where i denotes the numbers of the portfolios per indicator which in our case is equal to 8, j represents the jth indicator portfolio which goes from $1 \dots 4$ and

[12] 4 asset classes * (4 long-short portfolios + 4 directional portfolios) = 32 portfolios

w_i denotes the weight factor for a given portfolio which is set to 1/8 .

4.4 Macro Momentum Strategy Construction

The macro momentum portfolio is constructed by taking an equal weighted average across all 32 asset class and 32 indicator portfolios (i.e. all 64 portfolios). More specifically, we have 16 long-short and 16 directional portfolios for both asset classes and indicators further we take an equal weighted average across 16 long-short asset class and indicators portfolios and 16 directional asset class and indicator portfolios such that we obtain four portfolios in total. To get the final portfolio, we maximize the Sharpe ratio of our macro momentum portfolio which is rebalanced monthly and consists of the four constructed portfolios.[13]

Lastly, our optimization algorithm is flexible in such a way that it is possible to add more assets and expand the investment universe. The algorithm is also flexible to add more signals beyond our original five i.e., easily extendable for more indicators. However the optimization algorithm shows weaknesses regarding using sub-universes of the asset class, for example using sub-sectors of the S&P 500 which is in line with the findings of Ribeiro and Loeys (2006).

4.5 Beyond AQR's Framework

After replicating the signals as presented by J. Brooks (2017), we decide to implement the concept of macro momentum using our own indicators. This was done by modifying the original asset classes to investigate whether using other asset classes and other indicators could yield superior performance. We decide to exclude the bond asset class from our investment universe and include commodities instead. Commodities have proven to be an attractive asset class, particularly in times of turmoil. Furthermore, by looking at our regression betas shown in table 2 we find that the signs of the beta coefficients do not align well with the indicators for the bond asset class. We further add two additional indicators and combine them with our existing indicators.

The chosen indicators are the LIBOR rate and Consumer Confidence index

[13] Each portfolio consists of one series of returns.

(CCI), the LIBOR indicator is combined with our existing monetary policy signal while CCl is added to our existing business cycle signal. LIBOR rates should provide a reflection of the expected path of monetary policy and risk premiums related to credit and liquidity (Cui et al. 2016). Hence, an increase in LIBOR rate has a negative impact on equities, interest rates, and commodities while a positive impact on currencies. The consumer confidence index (CCI) provides an indication of future developments of household consumption and savings, hence CCI is used to supplement our business cycle indicator with future expectations. We construct the CCI indicator by first gathering CCI data for each country within our investment universe and thereafter equally aggregating each country's change in CCI into an index to form a global CCI index. Using the relationships asserted by J. Brooks (2017) and our own assumptions we assert the following relationships between each asset class and indicators presented in table 16.

As shown in table 13, increasing CCI has a positive effect on equities, currencies and commodities while a negative effect on interest rates. Increasing LIBOR rate has a negative effect on equities, commodities and interest rates while a positive effect on currencies due to increasing demand for currencies. Furthermore, increasing inflation, growth and risk sentiment also has a positive effect on commodities while monetary policy and increasing international trade has a negative effect on commodities. Additionally, we want to examine if the signs in table 13 align with our data empirically, in order to investigate this we run the following linear regressions using Ordinary Least Squares method (OLS).

$$r_{i,t}^{asset\ classes} = \beta_0 + \beta_1(Policy\ Tightening)_t + \beta_2(Competiveness)_t + \beta_3(Risk\ Sentiment)_t + \beta_4(Growth)_t + \beta_5(Inflation)_t + \beta_6(Libor)_t + \beta_7(CCI)_t + u_t \tag{8}$$

Where i = Equity, Currency, Interest rates and Commodity.

According to table 6 the signs of growth and CCI do not align with the relationships in table 16 for equities, while for commodities we observe that all signs align except for policy tightening. For currencies, the signs which do not align are international trade, growth, policy tightening and LIBOR. Lastly, the signs for interest rates related to inflation, CCI, policy tightening and risk sentiment do not align. Furthermore, indicator CCI is significant at 10% significance level for both equities and commodities. The indicators which are significant for interest rates are growth, CCI, policy tightening, and risk sentiment.

5 Results

In this section, we will first present descriptive statistics of asset classes and the indicators, thereafter we will present the performance of AQR macro momentum followed by showing asset class and indicator portfolios. Afterwards we present the performance of our macro momentum strategy followed by comparisons with benchmarks such as the global 60/40, U.S. bonds and S&P 500 index. Subsequently, we examine the diversification benefits of macro momentum combined with a time-series momentum strategy. Lastly, we present the cumulative excess returns and the result section ends with evaluating strategies performance to common risk factors and global macro hedge fund indices.

Table 3: Descriptive Statistics of Asset Classes and Indicators

	Mean	Std.	Min	Max	T
Equities	0.85%	4.16%	-24.30%	20.10%	637
Bonds	0.80%	16.54%	-3.04%	2.57%	637
Currencies	0.04%	-0.06%	-7.97%	9.79%	637
Commodities	0.40%	4.8%	-21.34%	29.20%	637
Interest Rates	-0.01%	0.41%	-4.17%	5.23%	637
Growth	-0.06%	2.86%	-12.81%	24.04%	637
Inflation	0.05%	1.64%	-5.08%	5.36%	637
CCI	-0.01%	0.15%	-1.04%	0.76%	637
International Trade	0.15%	2.03%	-5.75%	9.21%	637
Policy Tightening	-0.09%	1.13%	-2.76%	3.67%	637
LIBOR	3.65%	2.82%	0.11%	1.23%	447
Risk Sentiment	5.51%	17.23%	-46.80%	50.20%	637

This table shows descriptive statistics for our constructed asset classes and the indicators. We show the mean, standard deviation, minimum and maximum of all asset classes and indicators together with the number of observations. Bonds and risk sentiment exhibit large standard deviations, while risk sentiment exhibits a large spread between min and max as well. This can be partly attributed to extreme outliers as evident from the box plots10 11. The statistics are from 1970 until 2023, except for LIBOR since its data starts from February 1986.

Correlation Analysis

Table 4 and 5 examines the correlation amongst the indicators and asset classes, respectively. We find that within both asset classes and indicators there is a low correlation. The asset classes seem to diversify each other as half of the correlations are negative, and the other half is positive. The correlations in general are quite low with an average of -0.044, ranging from -0.36 to 0.15. Indicators also exhibit a relatively low correlation, albeit higher than the asset classes. The average indicator correlation is 0.13 with the correlations ranging from -0.32 to 0.52. The highest correlations are observed between monetary policy and inflation and CCI and growth, with 0.52 and 0.45 correlation values, respectively.

Table 4: Correlations Matrix - Asset Classes

	Equities	Bonds	Currencies	Interest	Commodities
Equities	1.00				
Bonds	0.04	1.00			
Currencies	−0.19	−0.02	1.00		
Interest	−0.03	0.03	0.15	1.00	
Commodities	0.12	0.14	−0.36	−0.02	1.00

This correlation matrix shows the correlations between asset classes which we use as our investment universe. The correlations which are shown are from 1970 until 2023.

Table 5: Correlations Matrix - Indicators

	Monetary Policy	Int. Trade	Risk Sentiment	Growth	Inflation	CCI	LIBOR
Monetary Policy	1.00						
Int. Trade	−0.25	1.00					
Risk Sentiment	−0.03	0.11	1.00				
Growth	0.16	0.06	0.34	1.00			
Inflation	0.52	−0.32	−0.20	0.09	1.00		
CCI	0.05	0.10	0.19	0.45	−0.04	1.00	
Libor	−0.22	0.15	0.01	−0.11	−0.13	−0.03	1.00

This correlation matrix shows the correlations between the indicators. The correlations are calculated from 1970 until 2023 for all indicators except LIBOR. The correlation for LIBOR is calculated from February 1986.

5.1 Evaluating AQR Macro Momentum

We begin by examining the performance of our AQR replication before moving on to our own macro momentum strategy. Table 6 shows the performance of the AQR macro momentum strategy over the full sample (1970-2023), as well as for each sub-samples over this time period. The performance of the strategy has been consistent over the last 53 years, a period which includes a variety of financial market conditions such as multiple wars, stagflation, price shocks, financial crisis and pandemics. One of the important features of the strategy is that the performance of the strategy is neither driven by a single asset class nor by a single indicator.

Table 6: AQR Macro Momentum Performance

Time Period	Excess Returns	Volatility	Sharpe	Corr. S&P 500	Corr. Bond
AQR Replication 1970-2016	11.28%*** (0.004)	9.48%	1.23	0.03	0.04
AQR Extension 1970 - 2023	11.78%*** (0.005)	12.87%	0.92	0.05	-0.06
Sub-Samples					
1970 - 1979	6.40%*** (0.007)	7.27%	0.87	-0.30	0.04
1980 - 1989	15.44%*** (0.007)	7.32%	2.10	0.22	-0.20
1990 - 1999	8.33%*** (0.008)	8.31%	1.00	0.15	0.04
2000 - 2009	14.57%*** (0.010)	11.20%	1.30	-0.07	-0.13
2010 - 2016	13.53%*** (0.015)	13.92%	0.97	0.14	0.29
2017 - 2023	12.71%*** (0.043)	37.89%	0.34	0.10	-0.37

This table displays the consistent performance of the AQR macro momentum strategy. More specifically, it shows the annualized excess returns of the strategy together with the annualized volatility, and Sharpe ratio. This table also displays the strategy´s correlation to the U.S. bond market and S&P 500 index. First the table shows the strategy´s performance from January 1970 until December 2016 which we refer to as AQR replication period, since AQR has performed their strategy from 1970-2016. Further we extend the AQR macro momentum strategy to April 2023 and we show the performance of the AQR macro momentum strategy by sub-samples. Similar to J. Brooks (2017) we use the LIBOR rate as our risk free rate, prior to 1985 we use the U.S. Federal funds rate instead, since LIBOR did not exist before this. The numbers in the parentheses are standard errors. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

By looking at table 6, we observe a Sharpe ratio of 1.23 over a nearly 50 year period, however the strategy´s Sharpe ratio falls to 0.92 when the sample is extended to 2023. The strategy exhibits a significant excess return of 11.28% for the period of 1970-2016, and 11.78% when extending the sample to 2023. When extending the sample we also observe that the full sample volatility has increased from 9.48% to 12.87% which can be explained by the recent volatile periods such as the Covid pandemic, geopolitical uncertainty and higher inflation which has led to contractionary monetary policy. Further the strategy exhibits a positive but low correlation to both U.S. 10 year bonds and S&P 500 index from 1970-2016. However, the correlation towards U.S. 10 year bonds turns negative when we look at the full-sample. Looking at the performance of the strategy by sub-samples, we observe significant excess returns for all sub-samples, furthermore, an interesting observation is that the strategy displays a negative correlation to both U.S. 10 year bonds and S&P 500 index during the global financial crisis.

Table 7: Asset Class Portfolios

Time Period	Equities	FX	Bonds	Interest Rates	AQR-MMOM
AQR Replication	4.96%***	3.79%***	1.98%***	0.41%***	11.28%***
1970-2016	(0.003)	(0.002)	(0.004)	(0.0006)	(0.004)
Sharpe Ratio	0.67	0.95	0.21	0.39	1.23
AQR Extension	4.66%***	3.07%***	1.82%**	0.34%***	11.78***
1970 - 2023	(0.003)	(0.002)	(0.008)	(0.0005)	(0.005)
Sharpe Ratio	0.64	0.77	0.1	0.33	0.92
Sub-Samples					
1970 - 1979	0.51%	2.52%***	0.33%	-	6.40%***
	(0.006)	(0.003)	(0.002)		(0.007)
1980 - 1989	7.15%***	6.39%***	5.14%***	-	15.44%***
	(0.007)	(0.004)	(0.004)		(0.007)
1990 - 1999	5.91%***	0.41%	0.52%	2.57%***	8.33%***
	(0.007)	(0.003)	(0.005)	(0.0006)	(0.008)
2000 - 2009	0.42%	2.46%***	0.82%	1.20%***	14.57%***
	(0.007)	(0.003)	(0.006)	(0.0008)	(0.010)
2010 - 2016	5.72%***	1.67%***	1.93%	0.29%***	13.53%***
	(0.007)	(0.004)	(0.023)	(0.0001)	(0.015)
2017 - 2023	3.02%***	-1.63%***	1.18%	0.12%**	12.71%***
	(0.008)	(0.004)	(0.061)	(0.0005)	(0.043)

This table shows annualized excess returns for portfolios formed by asset class and AQR macro momentum strategy. We first show excess returns together with Sharpe ratios from 1970-2016 which we refer to as the AQR replication period, the results for the extended sample are also shown. Further, we show portfolios excess returns by sub-samples. The asset class portfolios are formed by optimizing each asset class individually on all indicators, the optimization is performed monthly from 1970-2023. The interest rates asset class starts from 1990 onwards due to availability of data. Similar to J. Brooks (2017) we use the LIBOR rate as our risk free rate, prior to 1985 we use the U.S. Federal funds rate instead, since LIBOR did not exist before this.The numbers in the parentheses are standard errors. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Indicator Portfolios

Time Period	Business Cycle	International Trade	Monetary Policy	Risk Sentiment	AQR-MMOM
AQR Replication	2.45%***	2.62%***	2.44%***	1.94%***	11.28%***
1970-2016	(0.001)	(0.002)	(0.001)	(0.002)	(0.004)
Sharpe Ratio	0.72	0.74	0.65	0.66	1.23
AQR Extension	2.61%***	2.89%***	3.02%***	1.66%***	11.78***
1970 - 2023	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
Sharpe Ratio	0.4	0.37	0.38	0.34	0.92
Sub-Samples					
1970 - 1979	0.76%***	1.12%***	1.07%***	0.11	6.40%***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.007)
1980 - 1989	4.07%***	7.07%***	3.86%***	4.36%***	15.44%***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.007)
1990 - 1999	1.08%***	1.65%	1.85%***	2.09%***	8.33%***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.008)
2000 - 2009	2.28%***	0.27%	0.2%	0.81%**	14.57%***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.010)
2010 - 2016	1.95%***	1.04%*	2.94***%	1.19%**	13.53%***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.015)
2017 - 2023	4.31%*	7.2%***	7.68%***	0.18%	12.71%***
	(0.023)	(0.020)	(0.022)	(0.018)	(0.043)

This table shows annualized excess returns for indicator portfolios and AQR macro momentum strategy. We first show excess returns together with Sharpe ratios from 1970-2016 which we refer to as the AQR replication period, the results for the extended sample are also shown. Further, we show portfolios excess returns by sub-samples. Similar to J. Brooks (2017) we use the LIBOR rate as our risk free rate, prior to 1985 we use the U.S. Federal funds rate instead, since LIBOR did not exist before this. The numbers in the parentheses are standard errors. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

By looking at both asset class and indicator portfolios we find that AQR macro momentum strategy is driven neither by a single asset class nor by a single indicator. The performance of macro momentum strategy is rather driven by all 32 asset class and indicator portfolios. Further, by looking at table 7 & 8 we observe significant excess returns for all indicator and asset class portfolios from 1970-2023. However, the bond asset class exhibits the most insignificant sub-period excess returns. Which is further motivation for our own macro momentum strategy where we substitute bonds with commodities. Moreover, the Sharpe ratios of both asset class and indicator portfolios have fallen when extending the sample period from 2016 to 2023.

5.2 The Macro Momentum Strategy

This section introduces the results of our own macro momentum strategy, which consists of commodities instead of bonds and two additional indicators, CCI for business cycle and LIBOR for monetary policy.

Table 9: Macro Momentum Performance

Time Period	Excess Returns	Volatility	Sharpe	Corr. S&P 500	Corr. Bond
MMOM 1970-2016	15.87%*** (0.004)	9.54%	1.66	0.055	0.148
MMOM 1970 - 2023	14.66%*** (0.004)	9.47%	1.55	0.001	0.122
Sub-Samples					
1970 - 1979	9.08%*** (0.011)	12.44%	0.73	-0.22	0.072
1980 - 1989	20.26%*** (0.008)	8.74%	2.32	0.367	0.150
1990 - 1999	11.97%*** (0.008)	9.27%	1.29	0.283	0.11
2000 - 2009	18.74%*** (0.010)	11.48%	1.63	-0.123	0.291
2010 - 2016	9.98%*** (0.007)	6.72%	1.49	0.131	0.1143
2017 - 2023	5.05%*** (0.009)	8.24%	0.61	-0.396	-0.21

This table displays the consistent performance of the macro momentum strategy. More specifically, it shows the annualized excess returns of the strategy together with the annualized volatility, and Sharpe ratio. This table also displays the strategy´s correlation to the U.S. bond market and S&P 500 index. First the table shows the strategy´s performance from January 1970 until December 2016 and then we extend the sample period to April 2023 and lastly, we show the performance of the macro momentum strategy by sub-samples. Furthermore, in this strategy we change the bond asset class with commodities and add two additional indicators such as Consumer Confidence Index (CCI) and LIBOR. Similar to J. Brooks (2017) we use the LIBOR rate as our risk free rate, prior to 1985 we use the U.S. Federal funds rate instead, since LIBOR did not exist before this. The numbers in the parentheses are standard errors. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

By looking at table 9, we observe that macro momentum strategy has a Sharpe ratio of 1.66 with an excess return of 15.87% from over a nearly 50 year period (i.e. 1970-2016). Between this period the strategy has a volatility of 9.54% with a positive correlation to both U.S. 10 year bonds and S&P 500 index. When we perform the strategy over a 53 year period (until 2023) we obtain a Sharpe ratio of 1.55 with an excess return of 14.66%, additionally the strategy has a volatility of 9.47% with close to zero correlation to the S&P 500 index. Further, the strategy delivers a Sharpe ratio of 1.63 during the period of 2000-2009 which includes the global financial crisis, during this period the strategy exhibited a desirable negative correlation to the S&P 500 index and a positive correlation to U.S. 10 year bonds. Moreover, all excess returns are significant at 1% level.

5.3 Further Evaluations and Comparisons

Table 10: Performance Comparisons

Time Period	MMOM	AQR-MMOM	Bonds	S&P 500	60/40
Excess Returns	14.66%***	11.78%***	-3.52%***	06.36%***	4.84%***
1970-2023	(0.004)	(0.005)	(0.0004)	(0.006)	(0.0034)
Volatility	9.47%	12.87%	1.09%	15.38%	8.61%
Sharpe Ratio	1.55	0.92	-3.23	0.41	0.56
Sub-Samples					
1970 - 1979	9.08%***	6.40%***	-6.95%***	-3.08%**	0.48%
	(0.011)	(0.007)	(0.0009)	(0.015)	(0.007)
1980 - 1989	20.26%***	15.44%***	-7.7%***	6.1%***	7.6%***
	(0.008)	(0.007)	(0.0016)	(0.015)	(0.008)
1990 - 1999	11.97%***	8.33%***	-4.68%***	12.75%***	6.00%***
	(0.008)	(0.008)	(0.0008)	(0.012)	(0.008)
2000 - 2009	18.74%***	14.57%***	-2.75%***	-2.64%*	0.4%
	(0.010)	(0.010)	(0.0009)	(0.015)	(0.009)
2010 - 2016	9.98%***	13.53%***	-0.19%**	12.53%***	5.61%***
	(0.007)	(0.015)	(0.0008)	(0.014)	(0.008)
2017 - 2023	5.05%***	12.71%***	-1.95%***	11.29%***	4.3%***
	(0.009)	(0.043)	(0.0009)	(0.019)	(0.009)

This table shows annualized excess returns for AQR macro momentum, macro momentum, U.S.10-Year Bonds, S&P 500 index and Global 60/40 portfolio for a period of 1970-2023. Further, this table displays the volatilities, Sharpe ratios and shows excess returns by sub-samples. Macro momentum displays a superior performance in comparison to the other strategies. Similar to J. Brooks (2017) we use the LIBOR rate as our risk free rate, prior to 1985 we use the U.S. Federal funds rate instead, since LIBOR did not exist before this. The numbers in the parentheses are standard errors. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

As can be seen from table 10, the global 60/40 portfolio[14] has an excess return of 4.84% with a volatility of 8.61% over the full sample. Further, in this period

[14] The global 60/40 portfolio is constructed by investing 60% in global equities and 40% in global bonds. We use the same set of assets as the macro momentum strategy and the portfolio is rebalanced on a monthly basis.

the global 60/40 has a Sharpe ratio of 0.56, in comparison the S&P 500 has experienced a Sharpe ratio of 0.4, and an excess return of 6.36%, with a volatility of 15.38%. During the same period, the U.S. 10 year bond has experienced a negative Sharpe ratio of 3.23 with a negative excess return of 3.52%. Further, we observe that all excess returns are significant at 1% level and finally we would like to examine if the return of our macro momentum strategy is different from the AQR macro momentum, U.S. 10 year bonds, S&P 500 and the global 60/40. To examine whether macro momentum´s return is statistically different from other strategies, we conduct a test of difference in means assuming returns of the strategies are approximately normally distributed, see figures 6 in appendix for the distribution of returns. Further, we are assuming unequal and unknown variances. The null and alternative hypothesis can be stated as:

$$H_0 : \mu_{MMOM} = \mu_i \quad vs \quad H_1 : \mu_{MMOM} \neq \mu_i$$

$$i = AQR\ macro\ momentum,\ U.S.\ 10 - year\ bond\ \ S\&P\ 500\ and\ global\ 60/40$$

We calculate the test statistics and degrees of freedom as follows:

$$t = \frac{(\bar{X}_{MMOM} - \bar{X}_i) - (\mu_{MMOM} - \mu_i)}{\sqrt{(\frac{s^2_{MMOM}}{n_{MMOM}} + \frac{s^2_i}{n_i})}} \tag{9}$$

$$df = \frac{(s^2_{MMOM}/n_{MMOM} + s^2_i/n_i)^2}{s^4_{MMOM}/n^3_{MMOM} + s^4_i/n^3_i} \tag{10}$$

where $\bar{X}_{MMOM}$ and $\bar{X}_i$ refers to macro momentum´s and strategy´s (i)th sample excess returns , μ_{MMOM} and μ_i are macro momentum´s and strategy´s (i)th population means which we assume to be zero, s^2_{MMOM} and s^2_i are macro momentum´s and strategy´s (i)th sample variances and n is the number of observations which is 639 for all strategies. The t-statistics for the tests are shown in table 11.

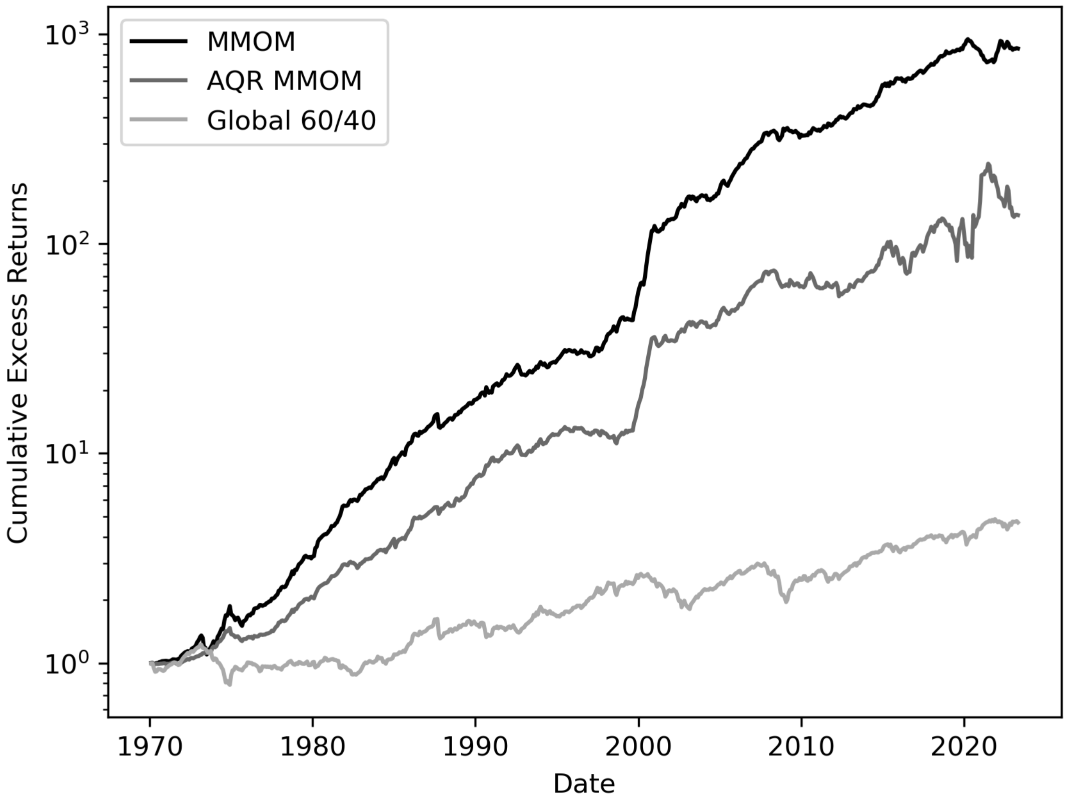
Table 11: Test of Difference in Means

Strategies	t-Statistics	Degrees of Freedom
AQR MMOM	4.56	1174
U.S. 10-Year Bonds	48.20	656
S&P 500	11.62	1063
Global 60/40	19.39	1267

This table shows t-statistics and degrees of freedom for a test of difference in means between our macro momentum strategy (MMOM) and the AQR macro momentum strategy (AQR MMOM), U.S. 10 Year Bonds, S&P 500 and global 60/40. The t-statistics and df is calculated by using formula (8) and (9).

By looking at table 11 we observe that all t-statistics have high values indicating that they are higher than the critical values given the calculated degrees of freedom. The critical value for the calculated degrees of freedom is 2.58 for 1% level, meaning that we can reject the null hypothesis that the excess return of macro momentum strategy is the same as other strategies. Hence, we can conclude that macro momentum´s excess return is significantly different from returns of AQR macro momentum, U.S.10 Year bond, S&P 500 and global 60/40 at 1% level. Thereby, we observe that macro momentum strategy yields superior performance compared to the other benchmarks in our test. Furthermore, we show the cumulative excess returns of our macro momentum, AQR macro momentum and global 60/40 over our full-sample.

Figure 4: Cumulative Excess Returns - Traditional Benchmarks



This figure shows the cumulative excess returns on a logarithmic scale from 1970-2023 for macro momentum (MMOM), AQR macro momentum (AQR MMOM) and the global 60/40 portfolio.

Figure 4 shows how much an investor would have earned in excess of the risk-free rate, if she invested \$1 in 1970 at the respective strategies and held it until 2023. If an investor invested \$1 in macro momentum in 1970 she would have an amount of \$855 in 2023, while if she invested in AQR macro momentum she would have \$137 in 2023. Lastly, if an investor invested \$1 in a global 60/40 portfolio and held it until 2023 she would have an amount of \$5. Figure 4 clearly shows the benefit of investing in macro momentum strategy which yields superior cumulative excess return than both AQR's macro momentum and global 60/40.

Table 12: Time-Series Momentum and Macro Momentum

	Time-Series Momentum	Macro Momentum	50/50 Combination
Excess Returns 1970-2023	10.38%*** (0.004)	14.66%*** (0.004)	12.57%*** (0.003)
Volatility	11.71%	9.47%	7.46%
Sharpe Ratio	0.89	1.55	1.68
Correlation	-0.20		
Max Drawdown	30.3%	22.4%	11.27%

This table compares our macro momentum strategy with a time-series momentum strategy and demonstrates the diversification benefits of combining both strategies. The time-series momentum strategy (TSMOM) has been constructed by using an equal weighted average of one-month, three month and twelve-month time-series momentum strategies on the same set of assets as the macro momentum strategy. The correlation in the table represents the correlation between the time-series and macro momentum strategy, which is negative, and thus the diversification benefits of combining the strategies are high, which can be seen from the improved Sharpe ratio and max drawdown. The numbers in the parentheses are standard errors. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

We further like to test the following hypotheses to check whether the strategies returns are statistically different from each other.

$$H_0 : \mu_{TSMOM} = \mu_{50/50} \quad vs \quad H_1 : \mu_{TSOM} \neq \ \mu_{50/50}$$

$$H_0 : \mu_{MMOM} = \mu_{50/50} \quad vs \quad H_1 : \mu_{MMOM} \neq \ \mu_{50/50}$$

$$H_0 : \mu_{TSMOM} = \mu_{MMOM} \quad vs \quad H_1 : \mu_{TSMOM} \neq \ \mu_{MMOM}$$

Table 13: Test of Difference in Means Between Strategies

Strategies	t-Statistics	Degrees of Freedom
TSMOM & 50/50	-3.98	1084
MMOM & 50/50	4.39	1212
TSMOM & MMOM	-7.18	1224

This table shows t-statistics and degrees of freedom for a test of difference in means between TSMOM & 50/50, MMOM & 50/50 and TSMOM & MMOM. The t-statistics and df is calculated by using formula (8) and (9).

We find that the average excess returns of all strategies are significantly different from zero. Additionally from conducting a test of difference in means, we find all means to be different from each other at all common significance levels. The diversification benefits of combining the time-series momentum strategy and our macro momentum strategy lead to superior risk-adjusted returns while reducing the maximum drawdown to an impressive 11.27% for the combined strategy.

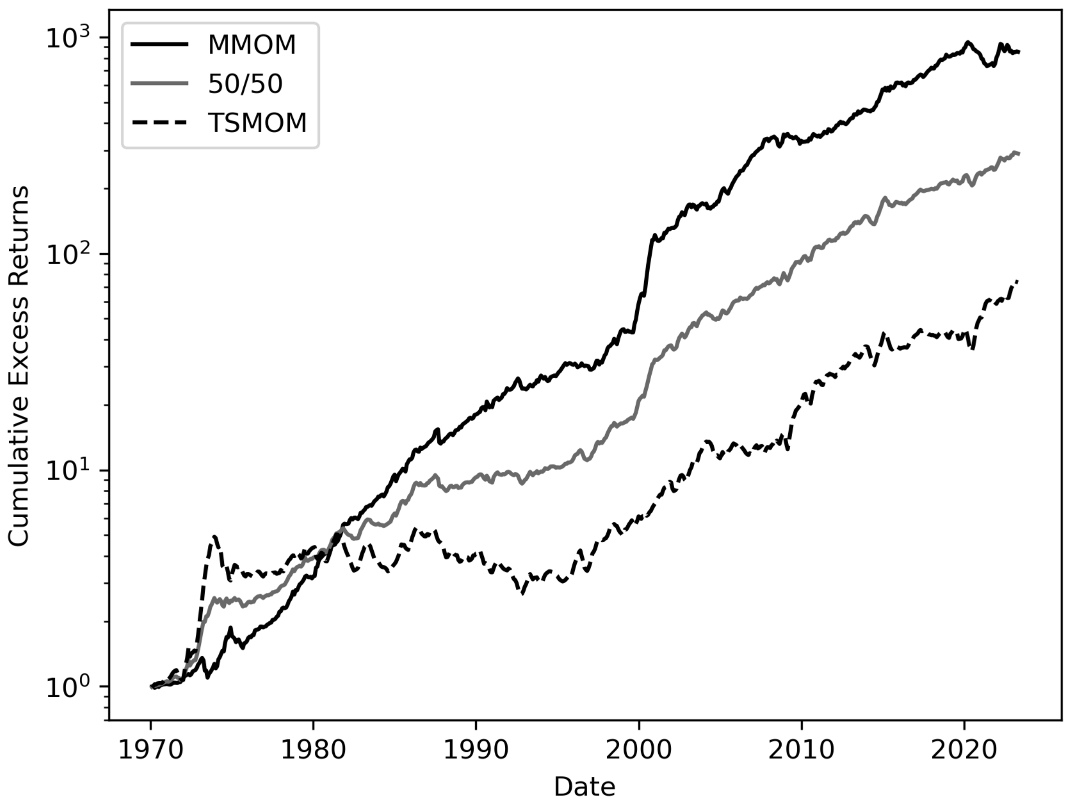
Mathematically these diversification benefits can be given by

$$var(r_p) = w_{TSOM}^2 var(r_{TSOM}) + w_{MMOM}^2 var(r_{MMOM}) + 2 w_{TSOM} w_{MMOM} cov(r_{TSOM}, r_{MMOM})$$
$$= w_{TSOM}^2 var(r_{TSOM}) + w_{MMOM}^2 var(r_{MMOM}) + 2 w_{TSOM} w_{MMOM} \rho_{TSOM,MMOM}\, \sigma_{TSOM} \sigma_{MMOM}$$

Where r_{TSOM} denotes time-series momentum returns, r_{MMOM} denotes macro momentum returns and w_{TSOM} and w_{MMOM} represent the portfolio weights held in the time-series momentum and macro momentum strategy, respectively.

Low correlations correspond to large diversification benefits. The low correlation in the above equation reduces the total portfolio variance. Low correlation between strategies indicates that time-series momentum is more likely to perform well when the macro momentum performs poorly. This relationship is documented in figure 12 and figure 13. which displays a drawdown comparison. Because of this relationship, we are able to lower our overall portfolio risk. The more dissimilar these two strategies are, the greater the benefit we get by adding them to our portfolio. The same mean-variance principles that are applied towards assets can be successfully applied towards strategies as well. Further, we show the cumulative excess returns for the time-series momentum (TSOM) macro momentum (MMOM) and a combination of these two strategies.

Figure 5: Cumulative Excess Returns - Momentum Strategies



This figure shows the cumulative excess returns on a logarithmic scale from 1970-2023 for macro momentum (MMOM), combined strategy of macro momentum and time-series momentum, and time-series momentum (TSOM).

The results are consistent with our findings, the macro momentum strategy significantly outperforms the other benchmark strategies. Additionally, we are able to observe that the pattern of the macro momentum strategy is similar to that of AQR macro momentum, however, the macro momentum performs better under crash periods such as the Global Financial Crisis and the Covid-19 crash.

5.4 Macro Momentum and Risk Factors

In order to evaluate our macro momentum strategy, we need to go beyond simple returns and risk-adjusted returns to observe whether our strategy returns are a result of systematic risk premia. To address concerns that the strategy might be explainable by common risk factors, we run OLS regressions on the strategy's excess return and the factors in each model to explore how much of the returns can be explained by common factors and if the strategy can add value beyond the exposure to these common risk factors. Factors from the following models are evaluated; CAPM by Sharpe (1964) and Lintner (1965), the three-factor model from Fama and French (1993), the four-factor model of Carhart (1997), and the five-factor model of Fama and French (2016). We examine this by running the regressions which are shown in the appendix 11.

Table 14: Time Series Analysis of Macro Momentum

	CAPM	FF3	Carhart	FF5
α_{MMOM}	12.00***	12.00***	10.56***	12.24***
	(6.35)	(6.48)	(5.79)	(5.84)
MKT	0.0004	0.0019	0.0424	-0.0007
	(0.011)	(0.054)	(1.151)	(-0.018)
HML		0.026	0.010	0.014
		(0.319)	(1.041)	(0.125)
SMB		-0.126	-0.159*	-0.134
		(-1.349)	(-1.826)	(-1.460)
MOM			0.153***	
			(2.737)	
RMW				-0.050
				(-0.321)
CMA				0.027
				(0.183)
Adj. R^2	-0.003	-0.001	0.038	-0.004
# Obs.	390	390	390	390

This table provides the results of a time-series regression with the excess return on the macro momentum strategy as the dependent variable. $\alpha MMOM$ denotes the average annualized excess returns which are unexplained by CAPM, Fama-French three-factor, Carhart, and Fama-French five-factor, respectively. Explanatory factors consist of market excess return (MKT), value factor (HML), size factor (SMB), momentum factor (MOM), profitability factor (RMW), and investment factor (CMA). The monthly data spans from 1990 to 2023. The numbers in parentheses are t-statistics adjusted according to the Newey and West (1987) procedure. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Our macro momentum strategy exhibits a negative and significant loading on SMB at 10% a significance level, which indicates the strategy is tilted towards large-cap stocks. This seems like a reasonable result given that the majority of equity indices are based on domestic large cap stocks. The strategy also has a positive and significant loading on the momentum factor on all common significance levels. Considering the strategy is fundamentally constructed using conventional momentum, one would expect some exposure to the momentum factor, which is constructed from cross-sectional momentum. The strategy is able to generate significant annual alpha that ranges between 10.56% and 12.24% for all factor models. The alpha is also significant for all common significance levels, while the adjusted R^2 lies between -0.4% and 3.8% for all regressions. These results suggest that the macro momentum strategy can not be explained by common risk factors.

Analyzing the AQR macro momentum strategy, we can observe that the strategy has a positive significant exposure to market risk at a 10% significance level. Market risk is the only significant factor, and the momentum factor does not explain any of the strategy's returns. As a result, the adjusted R^2 lies between 1.2% and 3.2%, while all the alphas are significant at a 5% level. Suggesting that, similar to our macro momentum, the common risk factors cannot explain the strategy's returns. Despite being constructed using the same approach, our macro momentum strategy's additional asset class and indicators shift the factor exposures compared to the AQR replication strategy.

Since macro momentum returns were not explained by common risk factors, we further want to investigate if macro momentum´s returns can be explained by time-series momentum (TSMOM) factor, Dow Jones Credit Suisse Global Macro Hedge Fund Index (DJCS) and Credit Suisse All Hedge Global Macro Index (CS). To investigate this we run the following one-factor regressions.

$$r_{MMOM_t} = \alpha + \beta_{TSMOM_t} + u_t$$
$$r_{MMOM_t} = \alpha + \beta_{DJCS_t} + u_t$$
$$r_{MMOM_t} = \alpha + \beta_{CS_t} + u_t$$

After performing the above regressions using Ordinary Least Squares method (OLS) we obtain the following coefficients which are shown in table 15.

Table 15: Time Series Analysis of Macro Momentum

	TSMOM	DJCS Index	CS Index
α_{MMOM}	8.88***	8.40***	9.12***
	(5.52)	(3.10)	(4.76)
β	0.26***	0.21	0.03
	(6.78)	(1.45)	(0.48)
Adj. R^2	0.12	0.027	-0.003
# Obs.	460	89	224

This table provides the results of a time-series regression with the excess return on the macro momentum strategy as the dependent variable. $\alpha MMOM$ denotes the average annualized excess returns which are unexplained by time series momentum (TSMOM) factor,Dow Jones Credit Suisse Global Hedge Fund Index (DJCS), and Credit Suisse All Hedge Global Macro Index (CS), respectively. Explanatory variables consist of time series momentum factor (TSMOM),Dow Jones Credit Suisse Global Hedge Fund Index excess return, and Credit Suisse All Hedge Global Macro Index (CS) excess return. The monthly data spans from 1985 to 2023 for TSMOM, 2006 to 2013 for DJCS and 2004-2023 for CS. The data for both DJCS and CS is acquired from Bloomberg and TSMOM factor from AQR. The numbers in parentheses are t-statistics adjusted according to the Newey and West (1987) procedure. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively

By looking at table 15, we observe that macro momentum strategy has a positive significant exposure towards time series momentum (TSMOM) factor with a coefficient value of 0.26. Further, we observe that the strategy has no significant exposure towards DJCS and CS and as a result the adjusted R^2´s are 0.027 and -0.003 respectively. The TSMOM factor exhibits a high adjusted R^2 of 0.12 which indicates that some of the strategy´s returns are explained by time series momentum. Moreover, macro momentum delivers significant abnormal returns at 5% level, after controlling for TSMOM, DJCS and CS respectively.

6 Conclusion

In this thesis, we construct an asset allocation strategy using macroeconomic signals, which we label as macro momentum. We combine cross-sectional and time-series momentum and optimize with our own mean-variance framework to assemble the macro momentum strategy. Over a 53-year period, we find significant risk-adjusted returns, and the strategy boasts a Sharpe ratio of 1.55. Our macro momentum strategy is not only distinct from time-series momentum, cross-sectional momentum, and global macro hedge fund indices but also distinct from the replication of AQR's macro momentum. Despite being related to the aforementioned strategies, we find that the macro momentum strategy outperforms them through risk-adjusted and abnormal returns. To corroborate our findings, we conduct a test of difference in means and find that our strategy's return is significantly different from our benchmarks. Macro momentum exhibits consistent and strong performance during turbulent market periods, such as during the sup-period 2000-2009, where the strategy generates a Sharpe ratio of 1.63, while exhibiting a negative correlation to indices such as the S&P 500. We apply the diversification theory to our advantage by combining our strategy with time-series momentum, as they both exhibit a negative correlation. The combined strategy is able to deliver a superior Sharpe ratio of 1.68 and a maximum drawdown of 11.27% over a 53-year period, in comparison, our macro momentum strategy exhibits a maximum drawdown of 22.4% over the same period. We show that macro momentum returns cannot be explained by common asset pricing factors, and we obtain significant and positive alphas. After controlling for the time-series momentum factor, Dow Jones Credit Suisse Macro Index and Credit Suisse All Hedge Macro Index, we still obtain significant alpha of 8.88%, 8.4%, and 9.12%, respectively, despite our strategy demonstrating a positive and significant exposure towards the time-series momentum factor.

An interesting topic for future research would be to test different optimization frameworks and objective functions and to examine whether there are additional improvements to be made, and if the performance fundamentally changes from our documented results. This strategy could also benefit from a more technical analysis of the signal robustness by examining the changes in behaviors of the selected indicators, this would require an extensive study of historical data and distributions of our indicators in relation to asset classes. It would also be interesting to conduct further research on capturing dynamic signal relationships by considering that relationships between indicators and asset classes are not necessarily static and could change over time.

References

Bernanke, B. S. and K. N. Kuttner (2005). What Explains the Stock Market's Reaction to Federal Reserve Policy? *The Journal of Finance* 60.3. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2005.00760.x, pp. 1221–1257. DOI: 10.1111/j.1540-6261.2005.00760.x.

Bird, R., X. Gao, and D. Yeung (2017). Time-series and cross-sectional momentum strategies under alternative implementation strategies. *Australian Journal of Management* 42.2. Publisher: SAGE Publications Ltd, pp. 230–251. DOI: 10.1177/0312896215619965.

Bloom, N., H. Ahir, and D. Furceri (2022). Visualizing the Rise of Global Economic Uncertainty. *Harvard Business Review*.

Brooks, J. (2017). A Half Century of Macro Momentum. URL: https://www.aqr.com/Insights/Research/White-Papers/A-Half-Century-of-Macro-Momentum.

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance* 52.1. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1997.tb03808.x, pp. 57–82. DOI: 10.1111/j.1540-6261.1997.tb03808.x.

Credit Suisse (2019). Business Cycle Risk: Diversifying With Commodities.

Cui, J., F. In, and E. A. Maharaj (2016). What drives the Libor–OIS spread? Evidence from five major currency Libor–OIS spreads. *International Review of Economics & Finance* 45, pp. 358–375. DOI: 10.1016/j.iref.2016.04.002.

Eichenbaum, M. and C. L. Evans (1995). Some Empirical Evidence on the Effects of Shocks to Monetary Policy on Exchange Rates*. *The Quarterly Journal of Economics* 110.4, pp. 975–1009. DOI: 10.2307/2946646.

Fama, E. F. and K. R. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33.1, pp. 3–56. DOI: 10.1016/0304-405X(93)90023-5.

— (2015). Dissecting Anomalies with a Five-Factor Model. Rochester, NY. DOI: 10.2139/ssrn.2503174.

Gormsen, N. and R. Greenwood (2017). Rainy Day Stocks - Working Paper - Faculty & Research - Harvard Business School. URL: https://www.hbs.edu/faculty/Pages/item.aspx?num=52149.

Goyal, A. and N. Jegadeesh (2017). Cross-Sectional and Time-Series Tests of Return Predictability: What Is the Difference? Rochester, NY. DOI: 10.2139/ssrn.2610288.

Hsu, C.-C., H.-Y. Lin, and J.-Y. Wu (2011). Consumer Confidence and Stock Markets: The Panel Causality Evidence. *International Journal of Economics and Finance* 3.6. Number: 6, p91. DOI: 10.5539/ijef.v3n6p91.

Jaisinghani, S. and M. Msika (2023). Closest Stock and Bond Correlation Since 1997 Hinders Diversity. *Bloomberg.com.*

Jegadeesh, N. and S. Titman (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance* 48.1. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1993.tb04702.x, pp. 65–91. DOI: 10.1111/j.1540-6261.1993.tb04702.x.

Kessler, S. and B. Scherer (2013). Momentum and macroeconomic state variables. *Financial Markets and Portfolio Management* 27.4, pp. 335–363. DOI: 10.1007/s11408-013-0215-8.

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics* 47.1. Publisher: The MIT Press, pp. 13–37. DOI: 10.2307/1924119.

Markets, S. P. (2023). Here's (Almost) Everything Wall Street Expects in 2023. *Bloomberg.com.*

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance* 7.1. Publisher: [American Finance Association, Wiley], pp. 77–91. DOI: 10.2307/2975974.

Moskowitz, T. J. (2010). Explanations for the Momentum Premium. URL: https://www.aqr.com/Research-Archive/Research/White-Papers/Explanations-for-the-Momentum-Premium.

Moskowitz, T. J., Y. H. Ooi, and L. H. Pedersen (2011). Time Series Momentum. Rochester, NY. DOI: 10.2139/ssrn.2089463.

Page, S. (2020). Beyond Diversification: What Every Investor Needs to Know About Asset Allocation. Google-Books-ID: JdwBEAAAQBAJ. McGraw Hill Professional. 337 pp.

Page, S. and R. A. Panariello (2018). When Diversification Fails. *Financial Analysts Journal* 74.3. Publisher: Routledge _eprint: https://doi.org/10.2469/faj.v74.n3.3, pp. 19–32. DOI: 10.2469/faj.v74.n3.3.

Reicher, C. P. and J. F. Utlaut (2013). Monetary policy shocks and real commodity prices. *The B.E. Journal of Macroeconomics* 13.1. Publisher: De Gruyter, pp. 715–749. DOI: 10.1515/bejm-2012-0083.

Ribeiro, R. and J. Loeys (2006). Exploiting cross-market momentum. *JPMorgan Investment, Strategy.*

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk*. *The Journal of Finance* 19.3. _eprint: https://onlinelibrary.wiley.com 6261.1964.tb02865.x, pp. 425–442. DOI: 10.1111/j.1540-6261.1964.tb02865.x.

Appendix

Tables

Table 16: Relationships Between Asset Classes and Indicators

Asset Class	Business Cycle			International Trade	Monetary Policy		Risk Sentiment
	Growth 1y change in GDP	Inflation 1y Change in CPI	CCI 1y change in CCI	Competitiveness 1y FX Depreciation	Policy Tightening 1y Change in 2y Yield	Increasing Libor 1y Change in Libor	Sentiment 1y Equity Returns
Equities	+	+	+	+	-	-	+
Commodities	+	+	+	-	-	-	+
Currencies	-	-	-	-	+	-	+
Rates	+	-	+	+	-	-	-

This table shows the relationships between indicators and asset classes. A positive (negative) sign indicates that when indicators are increasing it is bullish (bearish) for the given asset class, and the opposite when the indicators are decreasing. Modifications to the AQR replication have been made and this table displays the relationships for our macro momentum strategy. The changes include substituting the bond asset class with commodities and two new indicators are added which are LIBOR and consumer confidence index (CCI).

Table 17: Regression Results

Asset Class	Business Cycle			International Trade	Monetary Policy		Risk Sentiment
	Growth 1y change in GDP	Inflation 1y Change in CPI	CCI 1y change in CCI	Competitiveness 1y FX Depreciation	Policy Tightening 1y Change in 2y Yield	Increasing Libor 1y Change in Libor	Sentiment 1y Equity Returns
Equities	-0.024	-0.142	-2.212*	0.123	-0.276	-0.080	0.010
	(-0.445)	(-1.062)	(-1.945)	(1.478)	(-1.627)	(-1.227)	(0.822)
Commodities	0.027	0.089	2.798*	-0.028	0.117	-0.056	0.005
	(0.359)	(0.542)	(1.788)	(-0.295)	(0.599)	(-0.916)	(0.337)
Currencies	-0.007	0.073	0.460	0.013	-0.051	-0.021	0.003
	(-0.208)	(1.073)	(0.785)	(0.327)	(-0.576)	(-0.692)	(0.520)
Rates	-0.009	0.002	0.231*	-0.01	0.054***	-0.008	0.0031***
	(-2.146)	(0.219)	(1.960)	(-1.178)	(3.237)	(-1.424)	(3.823)

This table shows the beta coefficients of the regressions which have been performed for each asset class using our indicators as the independent variables. In contrast to our previous table 2, here we have included commodities as an asset class and CCI and LIBOR as indicators. These new changes impacted the currency's sign towards growth, from positive to negative. It is now aligned with our established asset class and indicator relationships. The sample is monthly from 1970-2023. The numbers in parentheses are t-statistics adjusted according to the Newey and West (1987) procedure. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table 18: Description of Regression Variables

Variable		Description
Monetary Policy		Captures monetary policy trends using one-year in two-year yields.
International Trade		Captures international trade trend using one-year changes in spot exchange rates against an export weighted basket.
Risk Sentiment		Captures changes in risk sentiment using one-year market excess returns.
Business Cycle	Growth	Captures part of the business cycle trend using one-year changes in real GDP growth.
	Inflation	Captures part of the business cycle trend using one-year changes in CPI inflation

This table describes the variables which are used as the independent variables in the OLS regressions and shows what each independent variable measures.

Table 19: Time Series Analysis of AQR's Macro Momentum

	CAPM	FF3	Carhart	FF5
$\alpha_{MMOM_{AQR}}$	9.36***	8.52**	8.76**	8.64**
	(2.77)	(2.60)	(2.57)	(2.28)
MKT	0.140*	0.159*	0.153*	-0.122
	(1.687)	(1.940)	(1.880)	(0.920)
HML		0.213	0.201	0.445
		(1.267)	(1.245)	(1.601)
SMB		0.081	0.086	0.075
		(0.599)	(0.626)	(0.426)
MOM			-0.026	
			(-0.331)	
RMW				0.132
				(0.375)
CMA				-0.430
				(-1.391)
Adj. R^2	0.012	0.022	0.023	0.032
# Obs.	390	390	390	390

This table provides the results of a time-series regression with the excess return on the AQR replication macro momentum strategy as the dependent variable. $\alpha MMOM$ denotes the average annualized excess returns which are unexplained by CAPM, Fama-French three-factor, Carhart, and Fama-French five-factor, respectively. Explanatory factors consist of market excess return (MKT), value factor (HML), size factor (SMB), momentum factor (MOM), profitability factor (RMW), and investment factor (CMA). The monthly data spans from 1990 to 2023. The numbers in parentheses are t-statistics adjusted according to the Newey and West (1987) procedure. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively

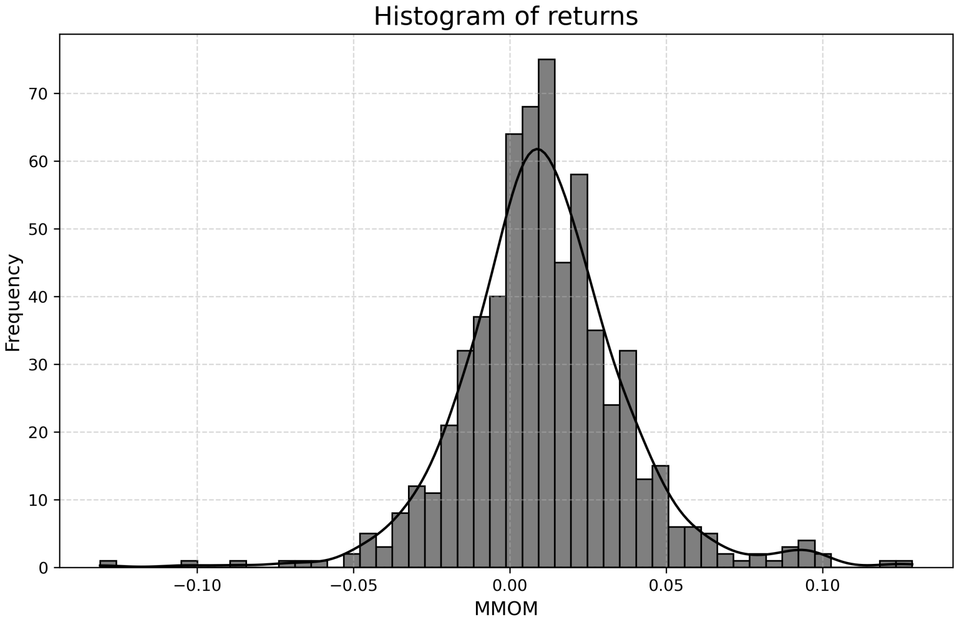
Table 20: Description of Regression Variables

Variable		Description
Monetary Policy	Policy	Captures monetary policy trends using one-year changes in two-year yields.
	LIBOR	Captures monetary policy trends using one-year changes in the LIBOR rate.
International Trade		Captures international trade trend using one-year changes in spot exchange rates against an export weighted basket.
Risk Sentiment		Captures changes in risk sentiment using one-year market excess returns.
Business Cycle	Growth	Captures part of the business cycle trend using one-year changes in real GDP growth.
	Inflation	Captures part of the business cycle trend using one-year changes in CPI inflation
	CCI	Captures part of the business cycle trend using one-year changes in Consumer Confidence Index (CCI).

This table describes the variables which are used as the independent variables in the OLS regressions and shows what each independent variable measures.

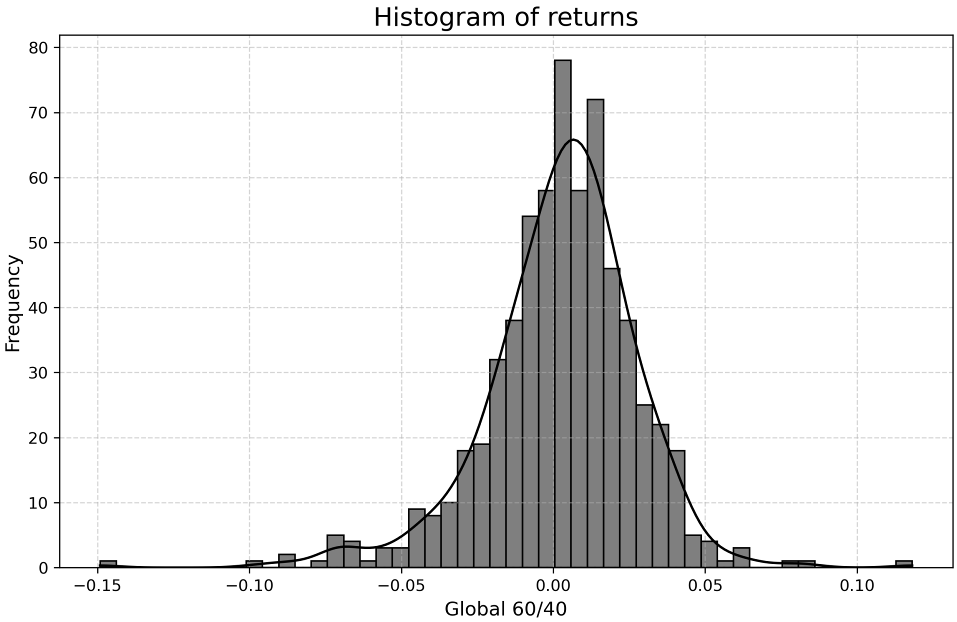
Figures

Figure 6: Histogram of Macro Momentum Returns



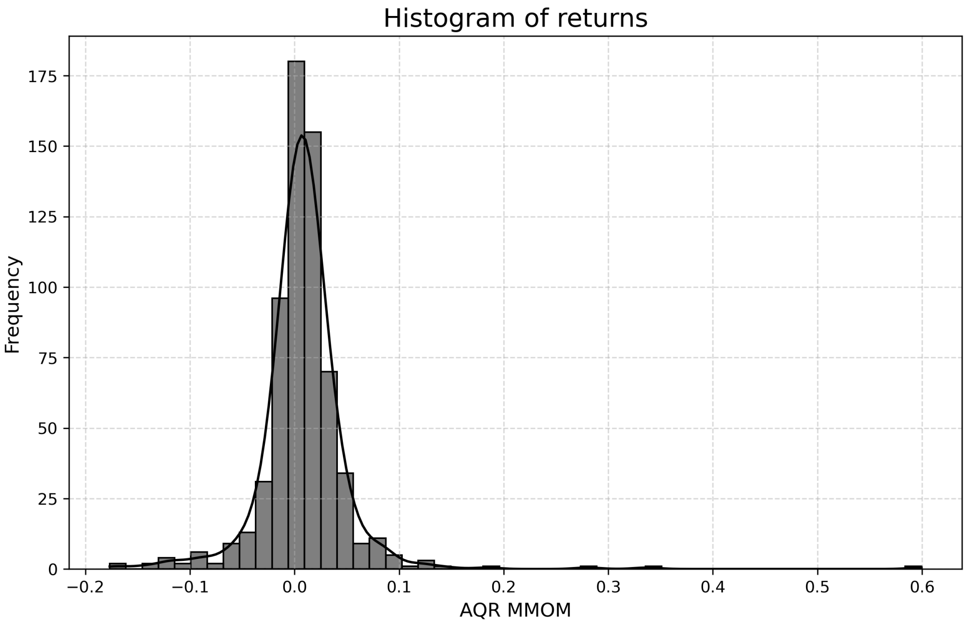
This figure shows the distribution of returns from the macro momentum strategy. The normal distribution is shown as the black line.

Figure 7: Histogram of Global 60/40 Returns



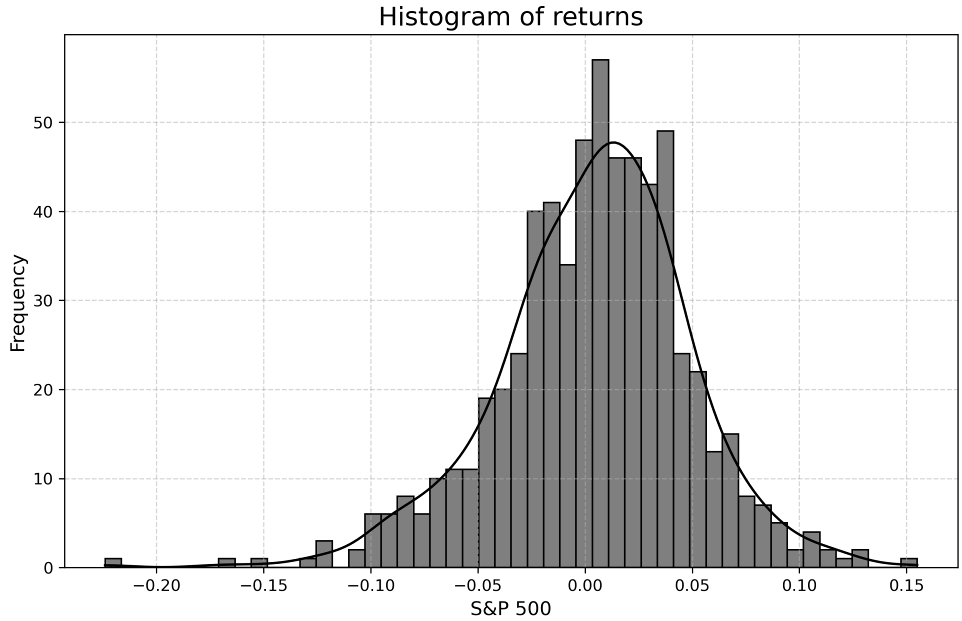
This figure shows the distribution of returns from the global 60/40 strategy. The normal distribution is shown as the black line.

Figure 8: Histogram of AQR's Macro Momentum Returns



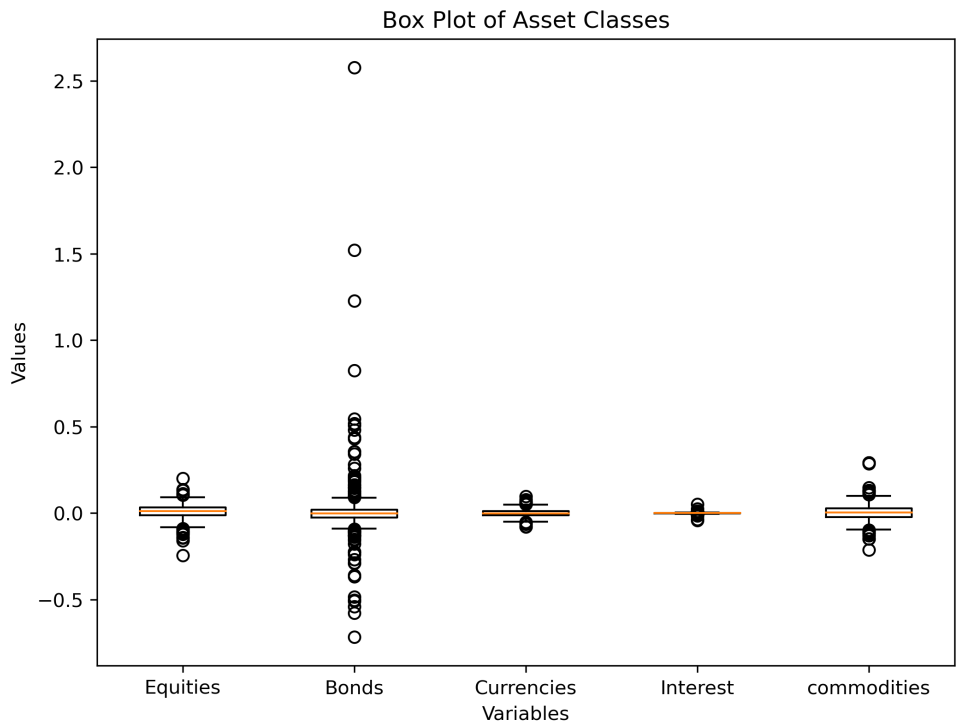
This figure shows the distribution of returns from the AQR's macro momentum strategy. The normal distribution is shown as the black line.

Figure 9: Histogram of S&P 500 Returns



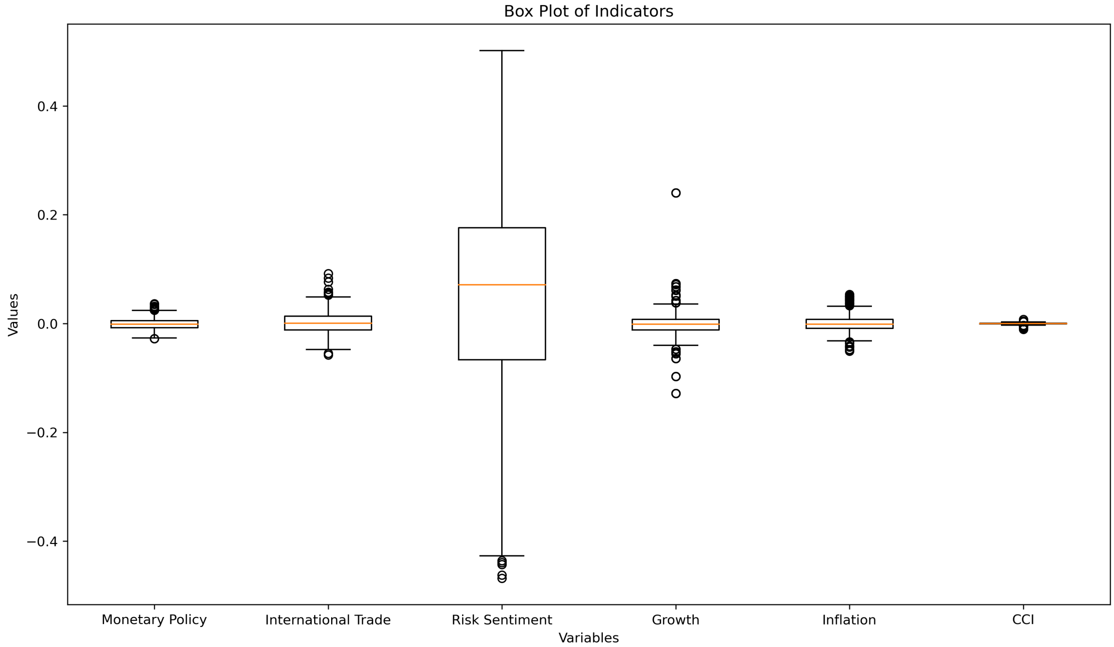
This figure shows the distribution of returns from the S&P 500. The normal distribution is shown as the black line.

Figure 10: Box Plot of Asset Classes



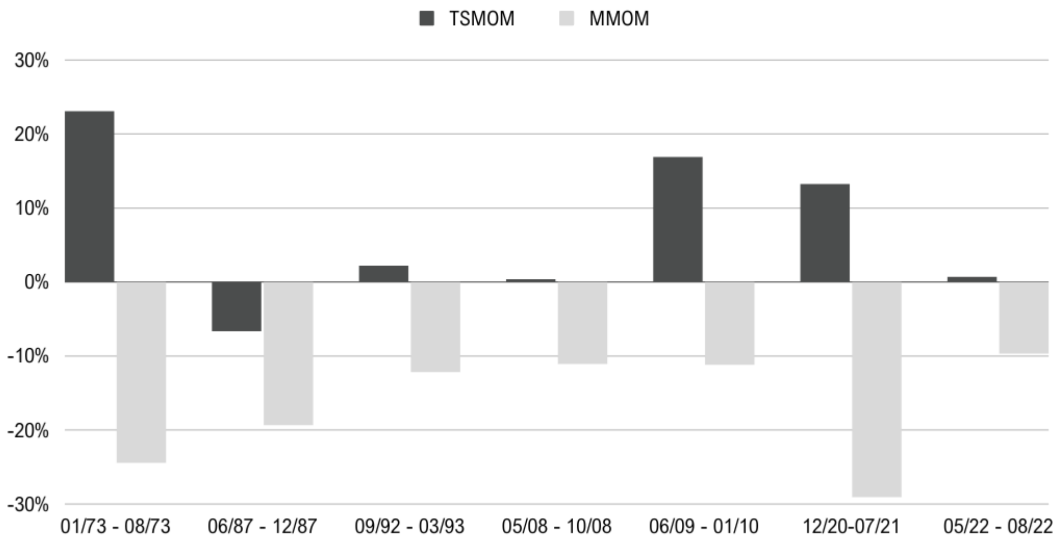
This figure shows a box plot which visualizes the variability of values in our dataset. It can be used to detect outliers in our asset class series. We observe from the box plot that bonds exhibit extreme outliers while commodities only exhibit a potential outlier. Further, the rest of our asset classes look normal without showing any extreme outliers.

Figure 11: Box Plot of Indicators



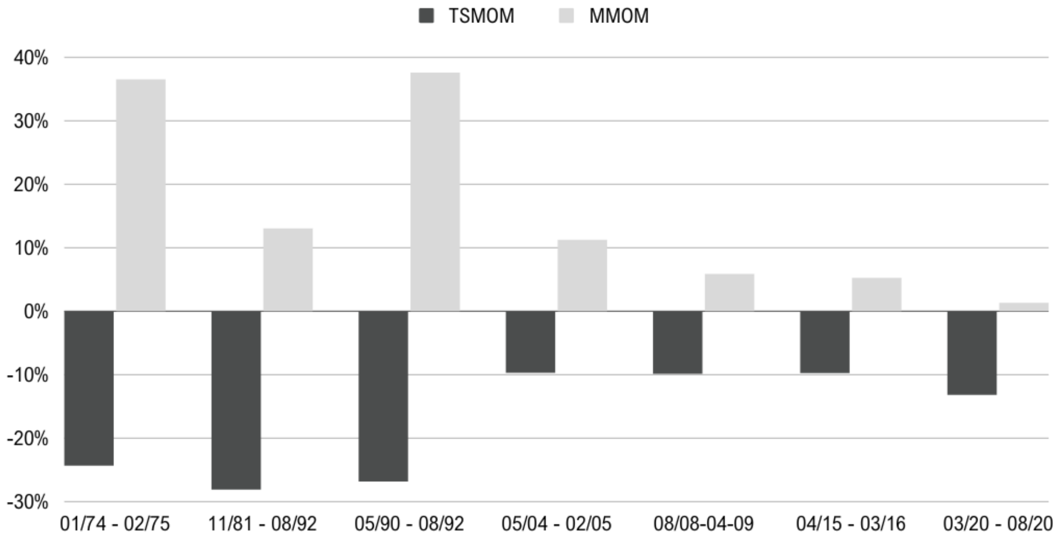
This figure shows a box plot which visualizes the variability of values in our dataset. It can be used to detect outliers in our indicator series. We observe from the box plot that risk sentiment and growth exhibits extreme outliers while the rest of our indicators look normal without showing any extreme outliers. This box plot does not include indicator LIBOR.

Figure 12: Macro Momentum - Seven Largest Drawdowns



This figure shows the cumulative excess returns during macro momentum's seven largest drawdowns. The returns are shown for both the time-series momentum (TSOM) and macro momentum strategy (MMOM). This figure demonstrates that the two strategies hedge each other during tail events. The dates are shown in the format MM/YY.

Figure 13: Time-Series Momentum - Seven Largest Drawdowns



This figure shows the cumulative excess returns during time-series momentum's seven largest drawdowns. The returns are shown for both the time-series momentum (TSOM) and macro momentum strategy (MMOM). This figure demonstrates that the two strategies hedge each other during tail events. The dates are shown in the format MM/YY.

Factor Regressions

$$R_{it} - R_{Ft} = \alpha_i \; + \; \beta_i(R_{Mt} - R_{Ft}) \; + \; u_{it} \tag{11}$$

$$R_{it} - R_{Ft} = \alpha_i \; + \; \beta_i(R_{Mt} - R_{Ft}) \; + \; \gamma_i SMB_t \; + \delta_i HML_t \; + \; u_{it} \tag{12}$$

$$R_{it} - R_{Ft} = \alpha_i \; + \; \beta_i(R_{Mt} - R_{Ft}) \; + \; \gamma_i SMB_t \; + \delta_i HML_t \; + \theta_i MOM_t \; + \; u_{it} \tag{13}$$

$$R_{it} - R_{Ft} = \alpha_i \; + \; \beta_i(R_{Mt} - R_{Ft}) \; + \; \gamma_i SMB_t \; + \delta_i HML_t \; + \lambda_i RMW_t + \; \psi_i CMA_t + \; u_{it} \tag{14}$$