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A MACHINE LEARNING ALGORITHM APPLIED TO MACROECONOMIC FACTOR INVESTING

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ABSTRACT

This paper examines the extent to which macroeconomic indicators can be used to determine the optimal allocation of an extended Fama French 5-Factor model which includes the risk-free rate. The study is based on Modern Portfolio Theory (MPT) as developed by Markowitz (1952) and Smart Beta Investing. The algorithm combines MPT with two Machine Learning (ML) Algorithms (K-means Clustering and Random Forest) to predict the macroeconomic state and arrive at the according optimal 'tactical' portfolio allocation of each security over the investment period. The research contributes to the existing literature of ML Algorithm performance applied to Smart Beta macroeconomic strategies.

Keywords: smart beta, modern portfolio theory, fama and french, macros, machine learning

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1. INTRODUCTION

The goal of this research is to understand whether macroeconomic (macro) indicators help predict an optimal portfolio containing 5 Fama and French (FF) Factors and a risk-free (RF) rate by building a systematic model that determines the optimal weights of the chosen securities according to the macro state of the economy using two Machine Learning (ML) Algorithms: K-means clustering (unsupervised) and Random Forest (supervised) as well as a portfolio optimizer that is based on Modern Portfolio Theory (Markowitz, 1952). My motivation to conduct this investigation comes from my research on Smart Beta strategies that are designed to provide access to a wide range of return-enhancing risk premia believed to be unaccounted by the basic capital asset pricing model (CAPM).

Understanding the drivers of security returns is essential for investors who look to optimize or hedge their portfolios. Extensive research has been conducted in order to understand these drivers including the famous Fama and French study which found that 5 Factors: SMB ([Small Minus big]), HML ([High Minus Low]), MRP ([Market Risk Premium]), RMW ([Robust Minus Weak]) and CMA ([Conservative Minus Aggressive]), which will be later discussed, could explain as much as 94% of returns in diversified stock portfolios (Fama and French, 1993). My model uses these factor portfolios as securities, as opposed to using traditional stock picking, because by isolating the 'pure' characteristics that were found to drive returns of any security, we are able not only to understand the fundamental reason of outperformance but also correctly 'bet' on portfolios of securities that portray characteristics found to be advantageous in various scenarios. In addition to the factors, I have included a risk-free rate (1-month US T-bill) due to research demonstrating that a balanced portfolio of stocks and bonds is able to generate higher geometric returns (Arden, 2021) and withstand periods of high volatility as well as avoid extreme losses (QMA, 2020).

In addition to understanding traditional style factors, understanding the relationship between macro indicators and portfolio returns is equally important since the macro state of the economy is believed to have a systematic effect on returns. Empirical evidence suggests that factor strategies have historically exhibited cyclicality in the short run. For example, Standard and Poor studied the performance of factors across different business and market cycles and found that returns vary tremendously. It is, therefore, hypothesized that given the non-linear and regime-dependent relationship of macro variables and factor portfolios (MSCI (2014), S&P (2016), McMillan's (2020)), analysis of the impact of macro variables is critical for investors looking to optimize or hedge their portfolios. Given the *nonlinearity* in the relationship between macro variables and factor returns, I have chosen to use ML algorithms in my research as they are believed to be able to capture non-linear relationships between variables. Furthermore, given the evidence that the performance of factors varies across regimes, I have decided to use a clustering algorithm to generate various 'states' or 'clusters' that are hypothesized to have similar macro characteristics, to theoretically be able to better allocate my securities in various macro states.

Finally, provided that the risk averseness theory holds, the goal of investors is to maximize returns by incurring in the least possible risk. According to this theory, investors are expected to be compensated for bearing increased risk by receiving higher returns which is the basis of modern portfolio theory (MPT) first introduced by Markowitz (1952). After understanding the performance of securities across regimes, it is therefore, important to study how to best allocate securities in a portfolio to derive the highest utility possible (in this case, given by the maximization of returns per unit of risk) as MPT suggests. This will be the basis of the portfolio optimizer created by my algorithm.

2. LITERATURE REVIEW

As previously mentioned, the drivers of security returns have been extensively studied in the last decades, more specifically, security premiums, defined as the compensation for bearing systematic risk (Berk et al., 1999; Chan & Chen, 1991; N. F. Chen and Zhang, 1998; Chordia & Shivakumar, 2002; Fame and French, 1993; Liu & Zhang, 2008). In 1992, FF created a 3-Factor Model, that extended on the capital asset pricing model (CAPM) by adding size (SMB [Small Minus big])] and value (HML [High Minus Low]) risk factors to the market risk premium (MRP) that could explain as much as 95% of returns in diversified stock portfolios. A few years later, two additional factors, profitability (RMW [Robust Minus Weak]) and Investment (CMA [Conservative Minus Aggressive]) were added and the new FF-5 Factor Model was able to explain 71% to 94% of security returns.

In addition to style investing, macro strategies have been studied over the last decades in numerous markets across the globe where researchers attempt to understand the relationship between macro variables and stock prices. In the US and Japan, Industrial Production (IP), consumer price index (CPI) and long-term interest rate were found to be statistically significant variables (Humpe, 2009). In Germany, returns were found to be influenced by several Leading Indicators, exports, CPI and 3y German Government Bond yields during pre- and post-crisis periods (Celebi, 2019). In the Istanbul stock market, macro variables such as unanticipated inflation, term structure of interest rate, risk premium and money supply had significant effect in explaining the stock market returns in various portfolios (Rjoub, 2009). In New Zealand, the US dollar exchange rate and monetary conditions index (MCI) were shown to have significant impact on country beta. The term spread, inflation, GDP growth rate and default spread have been found to have a forward-looking capacity of economic activity and ability to explain premiums of size and book-to-market factors from FF ((Hahn, 2005), (Kelly, 2004)). The recent research adds to decades of literature on the study of macro determinants of equity returns which includes research that found expected inflation, default premium, term premium and interest rates to significantly affect equity prices (Nelson (1976), Keim and Stambaugh (1986), Campbell (1987), Fama (1977, 1988, 1990), Schwert (1981)). Similarly, research concluded that monetary policy was associated with stock returns (Pearce and Roley (1983, 1985), Friedman (1988), McQueen and Roley (1990), Fama (1981)). The research is extensive and has since included an increased number of variables from nominal to real factors (Wasserfallen (1989) and Chen (1991), Asprem (1989)).

Despite the popularity of linear regressions, the linearity in the relationship between macro variables and security returns is challenged by studies that demonstrate a *nonlinear* relationship. Researchers such as Shleifer and Robert (2003) and Humpe and Macmillan (2014), indicate that speculation is the main source of market's *nonlinear* behavior. In the Indian stock market, Gopinathan (2019) identifies strong cointegration and indicates non-linearity in the long-run relationship between macro variables and stock returns.

The previous studies concentrated on the significance of the risk premia attached to each macro factor while others analyzed the sensitivity of the stocks to changes in macro variables. However, there is limited research on the stability of the securities risk measures over time, despite clear evidence of sensitivities of equity returns and macro variables changing. Regardless of how one attempts to cluster and classify securities – from sector to industry to factor-based categories – research with historical analysis with more than 40 years of history, has demonstrated that performance varies greatly depending on the macro environment ((MSCI, 2014), (Panetta, 2002), (AQR, 2014)). Given the *nonstationary* of security returns due to the dynamism of macro conditions, global macro strategies have generated outstanding risk-adjusted returns (Guimarães, 2015) for more than 20 years (GCM, 2013). Research from Blackrock found that 6 macro factors – economic growth, real interest rates, credit, inflation, emerging markets, and liquidity – explain more than 90% of returns across different asset classes (Ang, 2020).

After understanding the main drivers of security returns from a style and macro factor investing, it is important to understand how an optimal portfolio structure including such factor portfolios would be structured. Ever since the famous paper from Markowitz (1952) that set the ground for MPT, the optimal allocation of securities within a diversified portfolio of assets has also been studied, from Equal weighted, Value-weighted, 60/40 Portfolio, Naïve Risk Parity, amongst others. The reality is that there is no consensus as to what is the best method to be used – for example, the naïve portfolio 1/N has been showed to outperform many complex methods – partially attributed to the long-run bullish trend in the stock market (Guo, 2019), indicating that we are 'miles to go before the gains promised by optimal portfolio choice can actually be realized out of sample' (Demiguel, 2009). The evaluation of the best portfolio optimizer lies outside the scope of this paper; thus, I have decided to assume a linear relationship between risk and return, and that investors are risk-averse, implying that the theoretical 'optimal' portfolio would be one that maximizes the returns and minimizes the risk, thus, basing the portfolio optimizer of my algorithm on MPT.

After choosing our investment universe, our dependent (factor returns) and independent (macro factors) variables, as well as the portfolio optimization model, the logical next step is choosing the Statistical Procedure to be used. In recent years, a rapid increase in the quantity and complexity of quantitative financial research has been witnessed due to advances in statistical techniques applied to finance (e.g., neural networks applied to Factor Investing (Lu, Zhichen 2019)) as the quality and depth of both financial and macro data has improved. Despite basic methodologies used being present in the literature, it is believed that most innovative ideas are not available to the public due to high levels of investment required. Machine Learning (ML) is a tool that when applied to the field of finance, can be defined as the use of algorithms to make (investment) decisions by finding patterns in each iteration, in the dataset. The popularity of ML algorithm trading and quantitative stock selection has generated more attention from individual and institutional investors in recent years ((MSCI a,b, 2021),(BlackRock, 2019)), driven by advancements in computer power. These algorithms provide an alternative to time-series regression typically used in academia. The superiority in performance of ML algorithms in out-of-sample data is mixed. Makridakis et al. (2018) compares the accuracy of popular ML algorithms with 8 traditional benchmarks and conclude that forecasting accuracy in ML models is lower than traditional methods. On the other hand, Chakraborty and Jopesph (2017) and Richardson et al. (2018) find that ML models produce more accurate forecasts than those of Artificial Intelligence and other benchmarks. Nevertheless, ML seem to perform better than standard statistical approaches when handling high dimension data with *nonlinear* relationships (CFA, 2020). The benefits of systematic algorithm trading include fast and effective order execution, reduction in and 'key man risk', ease of scalability and reduction in human errors. ML can be applied to finance to optimize portfolio construction by forecasting the optimal allocation of a given set of securities based on a specific set of variables believed to drive their returns, as it will be done in this paper.

The final step after choosing the model and securities used is deciding how to structure the algorithm to study the dataset. Many of macro models, as previously mentioned, classify economic cycles/economic periods according to a set of variables when studying the performance of securities over a period (SSGA, 2019), take the example of the popular "All Weather Portfolio" from Ray Dalio (Bridgewater, 2012).

Unfortunately, methodologies often dismiss the challenges of implementing the models in the real world – challenges that my algorithm will attempt to address. The first challenge is the classification of economic cycles/periods. Despite the popularity of certain sets of variables and cutoff 'definitions', there is no certainty as to the best approach to slice the timeframe in different stages of the economic cycle. Furthermore, despite empirical research confirming the correlation between a set of macro variables with capital market development such as low and stable inflation rates, economic growth, and a certain level of savings, adequate fiscal governance and strong current account balance (World Bank, 2020), the noise in capital markets makes it difficult for the relationship between macro variables and security returns to be modelled in defined and static scenarios – making flexible models (such as the ML models used in this research) that take into account the *nonstationarity* of variables, of potential superior value. Additionally, ML models such as Random Forests can help solve the overfitting (which raises questions regarding the real predictive power of the model) of the dataset that is present in a lot of the research.

Additionally, most research solely relies on *in-sample* forecasts which simply demonstrates the accuracy of the model forecasting the data used to develop the model itself. To provide a test of the predictive power and applicability in a real-world scenario, *out-of-sample* tests prove to be more valuable. Models also usually have a fixed 'training' and 'testing' period which limits the ability of the researcher or users, to understand if the model accuracy changes over time when utilizing either (1) more data or (2) more recent data, since in theory, if the model were to be applied, practitioners would have to account for ongoing changes in the dynamics of the macro environment and the ever changing relationship between macro variables and security returns. To address these issues, my model will be the result of applying the model on *out-of-sample* data throughout the whole investment period, meaning, the model will be constantly learning from a rolling 'training' data and applying it to *unknown/out-of-sample data*, making it valuable to assess its performance in the real world. Furthermore, many models in academia do not account for trading fees – which can add up to large costs when implementing strategies, especially in high-frequency trading, potentially making the theoretically found 'alpha' or superior Sharpe Ratio (SR) vanish after real world application. My model includes trading fees when assessing its performance.

3. METHODOLOGY

Portfolio resilience is a goal of most investors who search for portfolios that can perform well in a diverse set of environments. One of the reasons for the popularity of factor investing is the search for increased portfolio resilience and returns. This paper aims to combine the success of Factor Portfolios in capturing and explaining systematic risk in equity securities while at the same time acknowledging the state of the economy as a key driver of the performance of capital markets by combining two ML methods in an algorithm – K-mean clustering and Random Forest. Furthermore, the algorithm was created acknowledging the potential applicability in a real-world scenario by considering real world problems such as trading fees and non-stationarity in the relationship between macro variables and equity returns as well as its applicability across different securities.

3.1.SUMMARY OF THE METHODOLOGY

As a first step, I base the optimal portfolio generation on Modern Portfolio Theory (MPT) as developed by Markowitz (1952). The second step combines the MPT model with two ML algorithms (K-means Clustering and Random Forest) to predict the macro state of the economy and arrive at a 'tactical' allocation of the Factor Portfolio in accordance with the predicted state. In the third and final step, I apply the model on a rolling basis and include trading fees when assessing portfolio performance to mimic the real-world performance of the model if it were to be applied by Institutional Investors.

3.2.DATA

Given the forward-looking nature of capital markets, the model differentiates itself from previous research in academia in that it includes macro and financial market variables that are thought to have the ability to reflect and predict the sentiment regarding the state of the economy. Given that research has shown that 6 macro variables (Economic Growth, Real Interest Rates, Credit, Inflation, Emerging Markets and Liquidity) explain more than 90% of the returns across different assets classes (Ang 2020), the model included 87 U.S. based macro variables that are believed to provide good indicators of the above (Table 1). The data was extracted from the Bloomberg Terminal in September of 2021. The 5 Factor Portfolio daily and monthly returns, as well as industry portfolio returns were extracted from the official website of FF. The macro variables pertain solely to the U.S. economy and capital market. The frequency ranges from monthly to quarterly but was aggregated into monthly data for model estimation. The FF Portfolio Returns were imported as daily data and aggregated to monthly returns to calculate the weights of the optimal monthly portfolios when applying the model. The series is adjusted for data release by lagging all variables by one month in the original model, except for the GDP growth rate which was lagged by one quarter. The data was lagged because monthly data that pertained, for example, to the month of January of 2020 is only released in February of the same year, hence, a lag is needed to estimate the impact of such variables in security returns when data was in fact available to the public markets. The data covers the period between January of 1990 to January of 2021, allowing us to test how the forecast the performance of the model across various stages of the business cycle.

The time-series for the macro factors was calculated as the change from one month to the other. Hence, yt = xt – xt -1 where yt is the monthly change of the variable, and x is the absolute value in reported in each month (t), with the exception of interest rates, some sentiment indexes and credit spreads of which absolute values have been used since the absolute value of sentiment indicators already indicates a positive/negative sentiment and credit spreads as well as interest rates were found to be statistically significant when predicting stock returns when data in absolute terms was utilized. (Welch and Goyal 2008; Gilchrist et al. 2009; Greenwood and Hanson 2013; Lin et al. 2014). The data is comprised of 59 hard variables (e.g., GDP growth rate) and 28 soft variables (e.g. Business Surveys) that can be classified in 10 different categories: Economic Activity (21 variables), Inflation (16), Market (15), Manufacturing and Industrial (9), Housing (7), Entire Economy (6), Labor Market (6), Credit (5) and Consumer Confidence (2) also found in Table 1.

3.3.STATISTICAL METHODS – THEORY OVERVIEW

The first algorithm utilized is K-Means Clustering. The algorithm is used to categorize data and it does not rely on defined classes and training examples of class labels. The program is not given labeled training data, instead, features are provided without conclusions and given the absence of a target variable, the program sees a structure and interrelationships in the data. In k-means clustering, the observations are partitioned into k non-overlapping clusters where k is a hyperparameter (meaning, it is defined by the user of the model). Each cluster is partitioned in such a way that the data points in the same cluster have the most similar characteristics. The clusters have a centroid (center of the cluster), and each observation is assigned to a given cluster based on its proximity to the centroid. The similarity between two observations, in this case, is defined as the distance between them, measured by the Euclidean distance.

$$Eclidean\ distance\ (a, b) = \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2}$$

K-means tries to minimize the distances within a cluster and maximize the distance between different clusters. In Graph 1, for example, the red point would be classified as a blue cluster as it has the smallest Euclidean distance from the blue centroid. Initially, k centroids are selected, and the clustering process starts. As new observations get assigned to the cluster, centroids are recalculated, resulting in reassignments of some observations and new centroids. This process continues until all observations are assigned and no new reassignment is made. In my model, clustering was used on the macro variables to create different 'regimes' that contain similar characteristics according to the 87 macro variables. The data was standardized by rescaling the variables (due to different units and scales of the variables). The standard scaler assumes that data is normally distributed and uniformizes the features such that the distribution is centered around 0, with a standard deviation of 1. One limitation of K-means is that the hyperparameter ‘k’ must be chosen before the clustering starts by the user, requiring us to have an idea of the nature of the dataset. For this paper, 3 methods were used to help determine the best number of k clusters: Davied Boulding Index, Silhouette Method and Elbow Method. The Elbow Method entails choosing the number of clusters for which the per cent of variance explained (R^2) is the highest. The Silhouette method measures how similar a data point is to its own cluster (cohesion) compared to the other clusters (separation). The silhouette coefficient is the ratio between the difference of the (a) average distance nearest the (b) other cluster minus the average distance inside the cluster, over the larger of (a) and (b). The silhouette ranges from -1 and +1 and a high value indicates that the data point is well placed in its own cluster. The Davies-Bouldin Index calculates the average similarity of each cluster with a cluster most like it, hence, the lower the DB index, the better the clusters are separated. The absolute value of the average of the resulting optimal cluster according to the 3 models was utilized.

After K-means, the second algorithm sed was a Random Forest (RanF) which is a supervised learning algorithm mainly used for classification problems. The model was developed in 2001 and it was an extension of Breiman’s work of classification trees (Graph 2). Classification trees are used when the target variable is categorical (which is the case of the clusters previously created in the K-means process). They assign observations to possible classifications at each node. The model defines a ‘top feature’ that is deemed to be the most important feature and a cutoff value. Observations that have values greater than the cutoff value are assigned to one classification while the remainder is assigned to other classifications. Every successive classification is expected to result in lower estimation errors and trees stop when the error cannot be further reduced, and a terminal node is reached. To avoid overfitting of the data, regularization criteria such as a maximum number of decision nodes, maximum tree depth are defined by the user of the model. In our case, a depth of 60 was utilized as it was found to yield the highest in and out-of-sample accuracy rate.

Random Forests (Graph 3) are a variant of classification trees whereby there are many uncorrelated classification trees that are trained using bagged data from the same dataset. Each tree is created by using a randomly selected subseet of the (macro) features; hence, each tree is different from one another - which mitigates the problem of overfitting. After obtaining the forest, when a new input sample is entered, each decision tree in the forest makes a judgement separately to see which category the sample belongs to and the class with the most classification times is the predicted class.

The construction process of a Random Forest is as follows:

1. N samples are randomly selected for replacement and are used to train the decision tree.
2. Each sample has M attributes when each node of the decision tree needs to be split and m attributes are selected from M attributes. Then, strategies such as information gain (measure by calculating Entropy – measure of uncertainty) are used to select one attribute as the split attribute of the node.
3. Each node is split according to step (2) until it can no longer be split.
4. Steps 1 to 3 are followed to build many decision trees to form a Random Forest.

As previously mentioned, when training the model, each tree learns from a random sample that are drawn with replacement (*bootstrapping*) which means that some samples are used multiple times. The idea is that by training each tree on different samples, although each tree might have high variance with respect to a particular set of training data, overall, the entire random forest will have a lower variance without increased bias. Predictions during testing are based on average or majority ranking of each decision tree. The process of training on bootstrapped subsets and averaging (bagging or *boostrap* aggregating) solves the problem of overfitting. The benefit of RanF includes improvement in prediction accuracy without a significant increase in the amount of calculation. Furthermore, the RanF is not sensitive to multivariate collinearity, and the results are relatively robust to missing and unbalanced data and can predict well the effect of thousands of independent variables (Yu, 2021). In the model created, the Random Forest's target vector is the vector with clusters created by the K-means for each month during the sample period and the features are the 87 macro variables. The output is a data frame that predicts the cluster according to the 87 macro variables for each month (**Table 2**).

Date	Cluster	87 Macroeconomic Variables
Jan-2000	2	$X_1, X_2, X_3, X_4 \ldots X_{87}$
Feb-2000	3	$X_1, X_2, X_3, X_4 \ldots X_{87}$
…	…	…
Nov-2019	0	$X_1, X_2, X_3, X_4 \ldots X_{87}$
Dec-2019	1	$X_1, X_2, X_3, X_4 \ldots X_{87}$

Table 2. *Representation of the Clustering Process Output Table*

Since our model has a rolling period from where we pull macro data from a fixed date (e.g. Jan-2000) but an end date that is rolling (e.g. we apply the model every single month after Jan-2005), it means that there will be *(z-d-1)* data frames where we continuously train the model and *(z-d)* predictions, where *z* is row number of the month before the date we first apply the mode and d is the row number of the last date in which we apply the model.

OPTIMAL MONTHLY PORTFOLIOS

The final step involves predicting the optimal weights of each security to be applied for the next period (*out-of-sample month*). For every month in the sample period, the weights of an optimal portfolio were generated by applying a modified version of Markowitz portfolio optimization model where the weights were generated such that the Sharpe Ratio is maximized, given the constrains of no short selling and weights adding up to 100%. The steps (for each month) include: (1) Calculating monthly returns of securities, (2) Calculating individual standard deviations and (3) Calculating the variance covariance matrix. Following that, an *optimizer* function was created, where it seeks to minimize the standard deviation of the SR of the portfolio by changing the weights of the security through 125 loops. The output of this *loop* is a data frame with the historical optimal weights for each month (that must sum 100%) that would have generated that maximized the SR. These weights will then be used to generate 4 different portfolios that will relate to the clusters (that characterize similar macro states) created in the previous step.

HOW K-MEANS, PORTFOLIO OPTIMIZATION AND RANDOM FOREST CONNECT

Since each month in the sample period has been classified by the Random Forest to one of the clusters created by K-means, we can obtain both the macro state classification and its respective optimal weight by month and year. After a vector of optimal weights (as calculated by the mean-variance approach) and cluster classification (from K-Means) was obtained for each month during the training period, an average of the optimal weights of each security (FF Factors and RF) of each cluster of the 4 clusters was performed. The model therefore generates K portfolios (in the original model, K=4) for every single rolling training period, by calculating the average of optimal weights that would have historically yielded the highest SR.

In summary, during the entire (rolling) test period, the model (1) classifies and predicts the current macro state, (2) calculates the historical average of optimal weights of each cluster and (3) applies the optimal weights according to the predicted cluster in the test period (the following month). This process is done on a rolling basis – where in each subsequent month, additional data is added to the model (*security returns and macro data from the previous month*). The original model is therefore monthly updated with a fixed starting date.

3.4.SUMMARY AND VISUALIZATION OF ENTIRE PROCESS

STEP 1 - FINDING PATTERNS

a) Table 3. Defining macro features by month and clustering during *training* period

Date	Macroeconomic Features
Jan-1990	$X_1, X_2, X_3, \ldots, X_{87}$
…	…
Dec-2000	$X_1, X_2, X_3, \ldots, X_{87}$

b) Table 4. K-means clustering output during *training* period

Date	Cluster	Macroeconomic Features
Jan-1990	1	$X_1, X_2, X_3, \ldots, X_{87}$
…	…	
Dec-2000	3	$X_1, X_2, X_3, \ldots, X_{87}$

STEP 2 - OPTIMAL PORTFOLIO CREATION

a) Table 5. Average Optimal Weights - Apply Markowitz Portfolio Theory

Date	HISTORICAL OPTIMAL PORTFOLIO WEIGHTS
Jan-1990	$W_{SMB}, W_{HML}, W_{MRP}, W_{RMW}, W_{CMA}, W_{RF}$
…	…
Dec-2000	$W_{SMB}, W_{HML}, W_{MRP}, W_{RMW}, W_{CMA}, W_{RF}$

b) Table 6. Average of Historical Optimal Portfolios

Cluster	Average of Historical Optimal Portfolio for each Cluster
0	$(\Sigma W_{SMB,0}, W_{HML,0}, W_{MRP,0}, W_{RMW,0}, W_{CMA,0}, W_{RF,0})/ N_{cluster\ 0}$
1	$(\Sigma W_{SMB,1}, W_{HML,1}, W_{MRP,1}, W_{RMW,1}, W_{CMA,1}, W_{RF,1})/ N_{cluster\ 1}$
2	$(\Sigma W_{SMB,2}, W_{HML,2}, W_{MRP,2}, W_{RMW,2}, W_{CMA,2}, W_{RF,2})/ N_{cluster\ 2}$
3	$(\Sigma W_{SMB,3}, W_{HML,3}, W_{MRP,3}, W_{RMW,3}, W_{CMA,3}, W_{RF,3})/ N_{cluster\ 3}$

STEP 3 - CLUSTERS PREDICTION AND ASSIGNING OPTIMAL PORTFOLIO

Since the model is done on a rolling basis, the clustering, random forest, and optimal portfolio calculation is estimated every month and applied to the following month – Step 1 and 2 are repeated until the end of the testing period. Hence, the resulting data frame (Table 7) that contains the results of continuously applying the model on an out-of-sample period.

Date	Cluster	Historical Optimal Portfolio Weights
Jan-2001	2	$(\Sigma W_{SMB,2}, W_{HML,2}, W_{MRP,2}, W_{RMW,2}, W_{CMA,2}, W_{RF,2})/ N_{cluster\ 2}$
…	…	
Dec-2019	3	$(\Sigma W_{SMB,3}, W_{HML,3}, W_{MRP,3}, W_{RMW,3}, W_{CMA,3}, W_{RF,3})/ N_{cluster\ 3}$

Table 7. Data frame representing output of model after applying the optimizer and clustering

4. EMPIRICAL RESULTS AND MODEL PERFORMANCE

The base model starts on the January 1, 1990, and ends on January 1, 2019. The end date was chosen to exclude the COVID-19 pandemic as, despite evidence of similar herding behavior of investors during previous infectious disease incidents (Bouri, 2021), the previous pandemics (2003 SARS and 2013-2016 Ebola) did not have similar impacts or magnitude across financial markets. ((Morris, 2020, (Ghaemi, 2021), (Bai, 2020), (Baker, 2020)). The portfolio creation date is assumed to be the end of April 1993 (which equates to the 40th month), which was picked randomly. The first month in which the strategy is applied and the performance is compared with the benchmark is, therefore, May 1993. For our benchmark, the S&P 500 was chosen as a proxy of the market since the Factor portfolios created by FF use securities from the US stock market and the RF used to calculate excess returns is the return of the 1-month US treasury bill. Our second benchmark is a Portfolio comprised of 70% in the S&P 500 and 30% in the Rf. The 70/30 split was deemed appropriate since the portfolio generated by our algorithm had its weight, on average, at 30% as well. The trading fees were assumed to be 20bps (industry standard) and the macro data was lagged by 1 month.

When analyzing in detail our Random Forest Algorithm we can observe (Table 8) that most features that were deemed as most relevant in predicting our clusters (periods of similar macro nature) were Interest Rates, Credit Spread; Economic Activity Indexes (such as Capacity Utilization and Export Price Index); Manufacturing & Industrial Activity, and Inflation. Despite some indicators such as Export Price Index not being deemed as having significant explanatory power for security returns (Nielsen, 2010), the model is successful on achieving its purpose – predicting the macro state of the economy and results are consistent with empirical research looking at the determinants of business cycles ((ECB, 2006), (FRBSF, 2010), (Demir, 2018)). The results of our strategy and benchmarks (Table 9 and Graph 4, 5, 6) demonstrate that our macro factor model had annualized returns (AR) of 2.97% and annualized volatility of 2.72% which results in a SR (SR) of 1.98, thus, underperforming both benchmarks according to returns but outperforming in terms SR: S&P 500 (AR: 2.97%, SR: 0.64), (AR: 8.09%, SR: 0.57). The kurtosis of the strategy (2.10) is higher than that of the benchmarks (1.42 and 1.43 respectively) implying that investors are likely to experience more occasional extreme (positive or negative) returns in the distribution. The strategy is less negatively skewed (-0.29) than the benchmarks (both at c. -0.69) which implies more frequent small losses and few large gains from the investment, which is generally preferred by investors. The cumulative returns of the portfolio demonstrate its resilience especially during major drawdowns (DD) compared to the benchmarks which can be seen as a potential added value of our portfolio, given that investors often look for robust strategies that are able to perform well, particularly during major drawdown periods (Table 10).

4.1.TAKING A CLOSER LOOK INTO MAJOR DRAWDOWN PERIODS

As previously mentioned, major losses and periods of high volatility were witnessed during the studied period with their respective years being: 1998, 2001, 2002, 2009 and 2020.

A closer look into these periods was taken to understand why the model was able to yield a low volatility of returns in comparison to the benchmark.

Starting in the years of 1997 to 1999, by looking at the plot of cumulative returns (Graph 7) we can see that the downturn and recovery was experienced between May and October of 1998 with the major DD of -14.58% in August of 1998 being triggered by the Asian Financial Crisis. During the period, our portfolio was able to return a low volatility (1.93%) and high SR (1.59) mainly due to the high allocation (Graph 8) in the Rf (~35% weight) and profitability factor RMW (~20%). Nevertheless, the portfolio failed to outperform both benchmarks as measured by both the SR and (Annualized) Returns (Table 9).

In the year between 2001 and 2003 (Graph 9) the market (Mkt-RF) saw a significant drop during the period (coinciding with both the 9/11 terrorist attack and dot-com bubble) while all other factors significantly outperformed. As we can observe from the plot of the optimal weights, the high value attributed to the RF (~30-35%) and a similar percentage (Graph 10) across all other factors (~5-20%) thus contribute to our portfolio outperforming the benchmarks (strategy annualized return: 4.79% vs -12.27% and -9.51% for the S&P 500 and 70/30 portfolio). This can be partially attributed to the nature of the crash – caused by the bubble created by investors investing in tech firms that mostly had large market capitalization, low to negative profitability, pay low to no dividends, have low book to market ratios and invest aggressively, thus, having the opposite characteristic to those favored by 4 of the FF factors SMB, RMW, HML and CMA.

In the years between 2008 and 2010 (Graph 11) which coincide with the subprime mortgage crisis, the market dropped significantly between April 2008 and started to recover in February 2009. The superiority of our returns (1.57%) vs the benchmarks (S&P 500: -12.27% and 70/30 Portfolio: -8.51%) can be attributed to the high allocation (Graph 12) in the RF (~30-50%), profitability factor (RMW) and size (SMB) since banks and firms that had major losses were mostly those with high levels of debt, thus, it may be the case that because high profitability is often related to high cash flows, those firms had a '*cushion'* to withstand any losses and deleverage, if necessary (reducing the perceived negative outlook from investors). The outperformance of SMB is hypothesized to be related to most firms defaulting being smaller firms unable to withstand the loss in revenues during the financial crisis which squeezed may have squeezed their margins and caused many to underperform.

Finally, from 2019 to 2021 (Graph 13), capital markets were (and continue to be) impacted by the COVID-19 crisis which started in late 2019. We can observe that all factors underperformed compared to the market (Mkt – RF) during the period and that weight allocation was somewhat similar (Graph 14). This result may be attributed to the nature of the crisis since the impact was not linked to a single financial or economic metric but to socioeconomic factors and policies implemented (such as lockdowns). This implies that despite firms having high profitability, investing conservatively, generating high dividends etc. the inability to conduct business and subsequent loss in revenues, for many firms, was out of their control, for example, some companies could switch from a brick and mortar to online business (such as retail companies) while others (such as airlines) had not alternatives. Thus, the out/under performance was dependent on the overall market sentiment, which reflected the perceived optimism which included views on the length of lockdowns, vaccination rates and geopolitical factors.

In summary, for all years analyzed, the main contributors to the low volatility (shown through the performance of all factors in (Graph 15) and higher SR during the crisis were the profitability factor (RMW) and Rf which have been shown to have allocations of around 10-25% and 30-40%, respectively, during the period. The superiority of returns was only witnessed in during the dotcom bubble and debt crisis while in all other years, the benchmarks showed higher annualized returns. The SR outperformance is therefore not a product of abnormal returns, but of lower volatility. This implies that the model is of potential value for real world applicability if practitioners can apply sufficient leverage to outperform the market returns. The robustness of the portfolio was tested to find the source of the added value of algorithm by conducting the sensitivity analysis as outlaid in the following section. The variables chosen for the sensitivity analysis include the portfolio creation date, end date of the rolling period, number and type of macro variables used, securities and data lags.

SENSITIVITY ANALYSIS – DATE OF PORTFOLIO CREATION

As observed in Table 11, early dates in which we theoretically 'create the portfolio' are associated with a higher SR, this may be due to the model having been able to learn and predict the macro state better when given data with similar nature (during similar states of the economic cycle) that have not witnessed impacts of yet unknown dynamics to the model.

SENSITIVITY ANALYSIS – END DATE OF ROLLING PERIOD

Given the same starting date for the portfolio creation (Dec-1994, which corresponds to the portfolio with highest SR), the model performs best for an earlier end date (Table 12). Interestingly, the SR is best when the end date coincides to the period of the 2008 crisis which is hypothesized to be because it can successfully predict the optimal weights that decrease the volatility during the financial crisis. As previously mentioned, FF factors outperformed the S&P 500 during the debt crisis, thus, the outperformance of the algorithm may be attributed to the preferred allocation towards all factors other than the MRP during the period.

SENSITIVITY ANALYSIS – NUMBER AND TYPES OF FACTORS

For the 'relevant features', the criteria to exclude the features involved removing features with the least importance as observed. For example, the model with 77 factors excluded the bottom 10 features with the lowest "importance score" according to the table and graph below. We can observe that there is a negative relationship between features and SR. The SR improves as we exclude irrelevant factor as expected since the model theoretically able to achieve a lower Gini impurity faster (increasing chance of homogeneity in the trees and accuracy of predictions). Nevertheless, the last sensitivity which involved excluding all interest rates did not improve the SR significantly which gives us the first clue that the value added from the model may not come from the macro variables.

CHANGE IN MONTHLY LAGS

There is no clear relationship between the monthly lag and SR. A monthly lag of 5 months and 1 month yield the highest SR. Note that in this model we have used the 100th row for portfolio creation due to the model failing to create sufficient clusters for every single period.

CHANGE IN SECURITIES USED

The model seems to work best for FF Factors models. Nevertheless, it also generated a superior SR even for industry portfolios. Both the sensitivity of macro factors and security choice gives us the second clue that makes us question whether the source of value of the model truly lies on the macro features or from the choice of securities (FF factors) and the modified mean-variance portfolio optimizer. This will be discussed in the next section.

MODEL PERFORMANCE WITHOUT MACRO VARIABLES

I have decided to take this research one step further after the sensitivity analysis with different macro variables and securities led me to believe that the source may not lie on the macro feature forecasts. To understand the true source of value of this model I have created 3 other alternative algorithms: The 1st algorithm generates a portfolio of the rolling 60 months window with fixed start date of the optimal portfolio weights; the 2nd generates a portfolio of the rolling 60 months window with a flexible start date of the optimal portfolio's weights and finally, the last algorithm generates an equal weighted Portfolio.

After creating 3 alternative models, we have observed (Table 15) that the equal weighted portfolio had a substantially lower sharpe ratio in comparison to the other strategies, which further supports the hypothesis that the value from my model comes from the portfolio optimizer created in the algorithm. This can be attributed to the similar risk-return nature of certain long-short Fama French portfolios over the investment period which could explain the higher SR (1.36) of the rolling mean strategy (where the average of optimal weights of all historical months prior the month the portfolio is applied). This is also supported by the graphs 16 and 17 which imply that despite the cluster prediction (predicted economic state) changing drastically over the investment period, the weight allocation of each factor was somewhat stable, thus, average weights of each security in the 4 portfolios was likely very similar. Hence, the algorithm could have potentially failed to generate higher sharpe ratio if the risk-return relationship of the optimal weights of factor portfolios (generated by our portfolio optimizer) had changed, meaning, if it demonstrated large deviations from the mean optimal portfolio.

CONCLUSION

In this research I have created a macro factor investing model that predicts the macroeconomic regime and generates a portfolio that invests on 5 Fama and French Factors (MRP, SMB, HML, RMW, CMA) and the risk-free rate (RF), by using a mix of 87 soft and hard macro variables related to the US economy. The aim was to understand the extent to which one could create a portfolio of factors where the optimal allocation of each security was dependent on the different macro states of the economy, based on available public data.

The model was able to outperform both benchmarks (70/30 Portfolios and S&P 500) in almost all scenarios in the sensitivity analysis especially during crisis and major downturns, proving to be a robust model in periods of high volatility which is usually when investors need it the most. However, as previously explained, the macro variables, have not proven to significantly improve the allocation of the Fama French factors in comparison to a simple rolling average of historical optimal portfolios weights. This may be due to how the algorithm was structured since the target variable was only *indirectly* linked to the portfolio weights due to the fact that the random forest, as a model, is not able to generate a vector as output (only a single discrete categorical variable), thus, I could not study the *direct* impact of macro variables on the weights themselves, leaving me with an oversimplification of the ‘optimal portfolios’ by generating 4 portfolios which were the average of historical optimal weights in each macro regime, leaving the algorithm with room for increased precision in estimated weights. Nevertheless, the model has shown to be valuable even when excluding the macroeconomic variables. The creation of the 3 alternative algorithms and their performance assessment indicates that the Sharpe Ratio outperformance may come from both the choice of factor portfolios and the risk-free rate as our securities as well as the portfolio optimizer created and used in all algorithms. The choice of securities improved the Sharpe Ratio of the model and enabled us to achieved low volatility during economic downturns/shocks mainly due to the similar risk-return relationship across factor portfolios during the investment period which led to the optimal weights of a diversified portfolio containing 5 of Fama French factors and the risk-free rate, being somewhat stable over time. Furthermore, Factor Portfolios and the risk free demonstrated low volatility throughout the whole investment period, further supporting this hypothesis.

To conclude, my model can be of potential value for long-term investors (e.g., pension funds) that seek to hedge positions during macro downturns. The results indicate that a portfolio containing a risk-free security and Fama French 5 factor portfolios demonstrate similar risk-return relationships across the last 20 decades and indicates the value of having a balanced portfolio that includes both stocks and fixed income to create a robust portfolio that can tolerate economic downturns or volatile environments. It also highlights the complex nature in the relationship of financial markets and macro variables, thus, demanding an alternative, more complex model, to further study this relationship.

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APPENDIX:

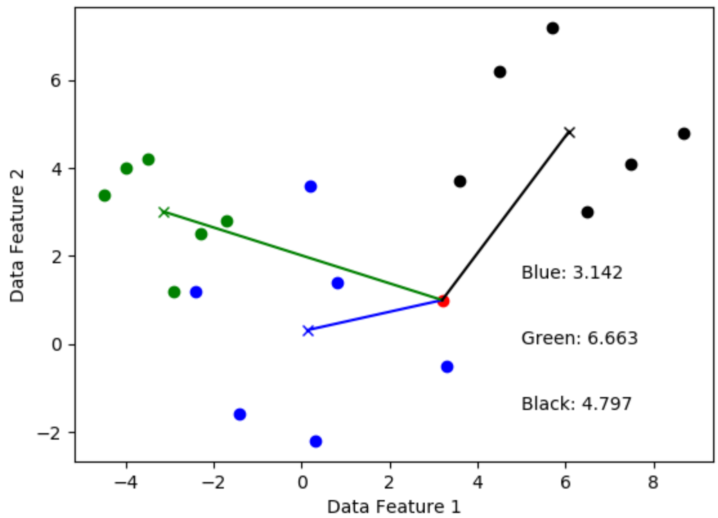
Ticker	Name	Soft/Hard	Category	Original Frequency
SBOITOTL INDEX	NFIB Small Business Optimism	Soft	Consumer Confidence	M
CONSSENT Index	U. of Mich. Sentiment	Soft	Consumer Confidence	M
CICRTOT Index	Consumer Credit	Hard	Credit	M
MOODCAAA Index	Moody's Corporate Bond Spread AAA	Hard	Credit	D
MOODCBAA Index	Moody's Corporate Bond Spread BAA	Hard	Credit	D
BASPCAAA Index	US Corporate AAA 10 Yr Spread	Hard	Credit	D
BICLB10Y Index	US Corporate BAA 10 Year Spread	Hard	Credit	D
IP YOY Index	US Industrial Production YOY	Soft	Economic Activity	M
USTGTTCB Index	Advance Goods Trade Balance	Hard	Economic Activity	M
NHSPATOT Index	Building Permits	Hard	Economic Activity	M
NHCHATCH Index	Building Permits MoM	Hard	Economic Activity	M
MTIBCHNG Index	Business Inventories	Soft	Economic Activity	M
CGNOXAI% Index	Cap Goods Orders Nondef Ex Air	Soft	Economic Activity	M
CGSHXAI% Index	Cap Goods Ship Nondef Ex Air	Soft	Economic Activity	M
CPTICHNG Index	Capacity Utilization	Hard	Economic Activity	M
CFNAI Index	Chicago Fed Nat Activity Index	Soft	Economic Activity	M
CONCCONF Index	Conf. Board Consumer Confidence	Soft	Economic Activity	M
CONCEXP Index	Conf. Board Expectations	Soft	Economic Activity	M
CONCPSIT Index	Conf. Board Present Situation	Soft	Economic Activity	M
EXP1CMOM Index	Export Price Index MoM	Hard	Economic Activity	M
EXP1CYOY Index	Export Price Index YoY	Hard	Economic Activity	M
IMP1XPM% Index	Import Price Index ex Petroleum MoM	Hard	Economic Activity	M
IMP1CHNG Index	Import Price Index MoM	Hard	Economic Activity	M
IMP1YOY% Index	Import Price Index YoY	Hard	Economic Activity	M
IP CHNG Index	Industrial Production MoM	Hard	Economic Activity	M
FRNTTNET Index	Total Net TIC Flows	Hard	Economic Activity	M
CONSCURR Index	U. of Mich. Current Conditions	Soft	Economic Activity	M

SAARTOTL Index	Wards Total Vehicle Sales	Hard	Economic Activity	M
FLSLCHAN Index	Bureau of Economic Analysis Real Final Sales of GDP Dollars SA Chain 2012 Price	Hard	Entire economy	Q
FLSLCHA% Index	Bureau of Economic Analysis Real Final Sales of GDP Dollars SA Chain 2012 Price	Hard	Entire economy	Q
COMFBTWR Index	Langer Economic Expectations	Soft	Entire economy	M
LEI CHNG Index	Leading Index	Soft	Entire economy	M
FDDSSD Index	Monthly Budget Statement	Hard	Entire economy	M
CONSEXP Index	U. of Mich. Expectations	Soft	Entire economy	M
NHSPSTOT Index	Housing Starts	Hard	Housing	M
NHCHSTCH Index	Housing Starts MoM	Hard	Housing	M
USHBMIDX Index	NAHB Housing Market Index	Soft	Housing	M
NHSLTOT Index	New Home Sales	Soft	Housing	M
NHSLCHNG Index	New Home Sales MoM	Soft	Housing	M
SPCSUSA Index	S&P CoreLogic CS US HPI NSA Index	Hard	Housing	M
SPCSUSAY Index	S&P CoreLogic CS US HPI YoY NSA	Hard	Housing	M
CPUPAXFE Index	CPI Core Index SA	Hard	Inflation	M
CPUPXCHG Index	CPI Ex Food and Energy MoM	Hard	Inflation	M
CPI XYOY Index	CPI Ex Food and Energy YoY	Hard	Inflation	M
CPURNSA Index	CPI Index NSA	Hard	Inflation	M
CPI CHNG Index	CPI MoM	Hard	Inflation	M
CPI YOY Index	CPI YoY	Hard	Inflation	M
DGNOXTCH Index	Durables Ex Transportation	Soft	Inflation	M
PCE CMOM Index	PCE Core Deflator MoM	Hard	Inflation	M
PCE CYOY Index	PCE Core Deflator YoY	Hard	Inflation	M
PCE DEFM Index	PCE Deflator MoM	Hard	Inflation	M
PCE DEFY Index	PCE Deflator YoY	Hard	Inflation	M
PITLCHNG Index	Personal Income	Hard	Inflation	M
PCE CRCH Index	Personal Spending	Hard	Inflation	M
PCE CHNC Index	Real Personal Spending	Hard	Inflation	M
CONSPXMD Index	U. of Mich. 1 Yr Inflation	Hard	Inflation	M
CONSP5MD Index	U. of Mich. 5-10 Yr Inflation (Inflation	Soft	Inflation	M

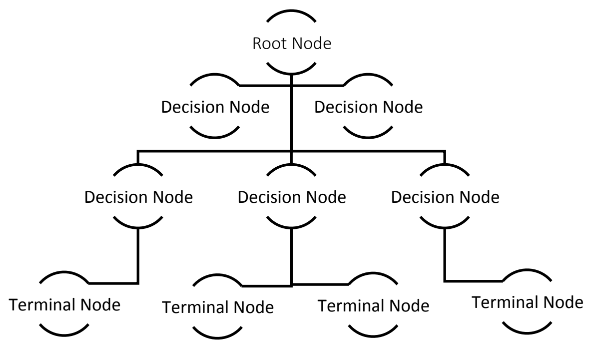
	Expectation)			
NFP TCH Index	Change in Nonfarm Payrolls	Hard	Labor market	M
NFP PCH Index	Change in Private Payrolls	Hard	Labor market	M
INJCJC Index	Initial Jobless Claims	Hard	Labor market	W
NAPMEMPL Index	ISM Employment	Soft	Labor market	M
PRUSTOT Index	Labor Force Participation Rate	Hard	Labor market	M
USURTOT Index	Unemployment Rate	Hard	Labor market	M
USMMMNCH Index	Change in Manufact. Payrolls	Hard	Manufacturing & Industrial	M
TMNOCHNG Index	Factory Orders	Soft	Manufacturing & Industrial	M
NAPMPMI Index	ISM Manufacturing	Soft	Manufacturing & Industrial	M
NAPMNEWO Index	ISM New Orders	Soft	Manufacturing & Industrial	M
NAPMPRIC Index	ISM Prices Paid	Soft	Manufacturing & Industrial	M
IPMGCHNG Index	Manufacturing (SIC) Production	Soft	Manufacturing & Industrial	M
CHPMINDX Index	MNI Chicago PMI	Soft	Manufacturing & Industrial	M
OUTFGAF Index	Philadelphia Fed Business Outlook	Soft	Manufacturing & Industrial	M
IP Index	US Industrial Production	Soft	Manufacturing & Industrial	M
H15T10Y Index	Constant Maturity Rate 10Y US Fixed Income	Hard	Market	D
H15T1Y Index	Constant Maturity Rate 1Y US Fixed Income	Hard	Market	D
H15T20Y Index	Constant Maturity Rate 20Y US Fixed Income	Hard	Market	D
H15T2Y Index	Constant Maturity Rate 2Y US Fixed Income	Hard	Market	D
H15T30Y Index	Constant Maturity Rate 30Y US Fixed Income	Hard	Market	D
H15T3M Index	Constant Maturity Rate 3M US Fixed Income	Hard	Market	D
H15T3Y Index	Constant Maturity Rate 3Y US Fixed Income	Hard	Market	D
H15T5Y Index	Constant Maturity Rate 5Y US Fixed Income	Hard	Market	D

H15T7Y Index	Constant Maturity Rate 7Y US Fixed Income	Hard	Market	D
EURUSD Curncy	EUR USD Exchange Rate	Hard	Market	D
GB12 Govt	Generic US 1Yr Government Bill	Hard	Market	D
US0003M Index	ICE LIBOR USD 3 Month	Hard	Market	D
FRNTTOTL Index	Net Long-term TIC Flows	Hard	Market	M
SMART MONEY FLOW INDEX	SMART MONEY INDEX	Hard	Market	D
USGG10YR Index	US Generic Govt 10 Yr	Hard	Market	D

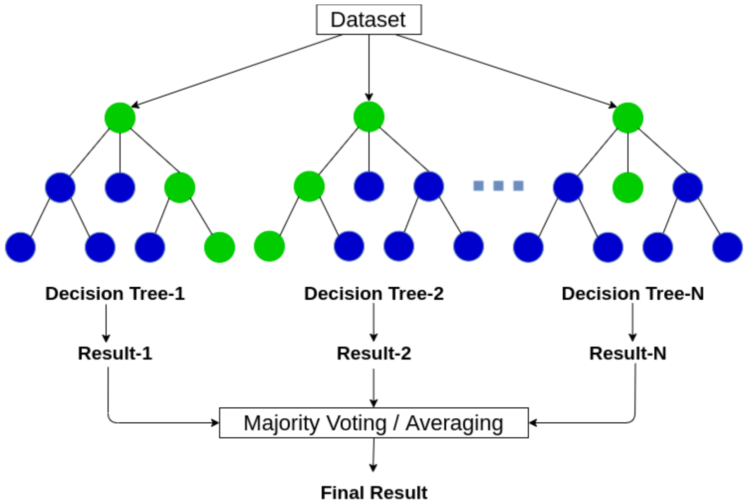
Table 1 *List of all macro variables included in the algorithm and relevant details.*



Graph 1 *– A Graphical Representation of K-Means Algorithms. Source: Towards Data Science. "Quantum machine learning: distance estimation for k-means clustering*



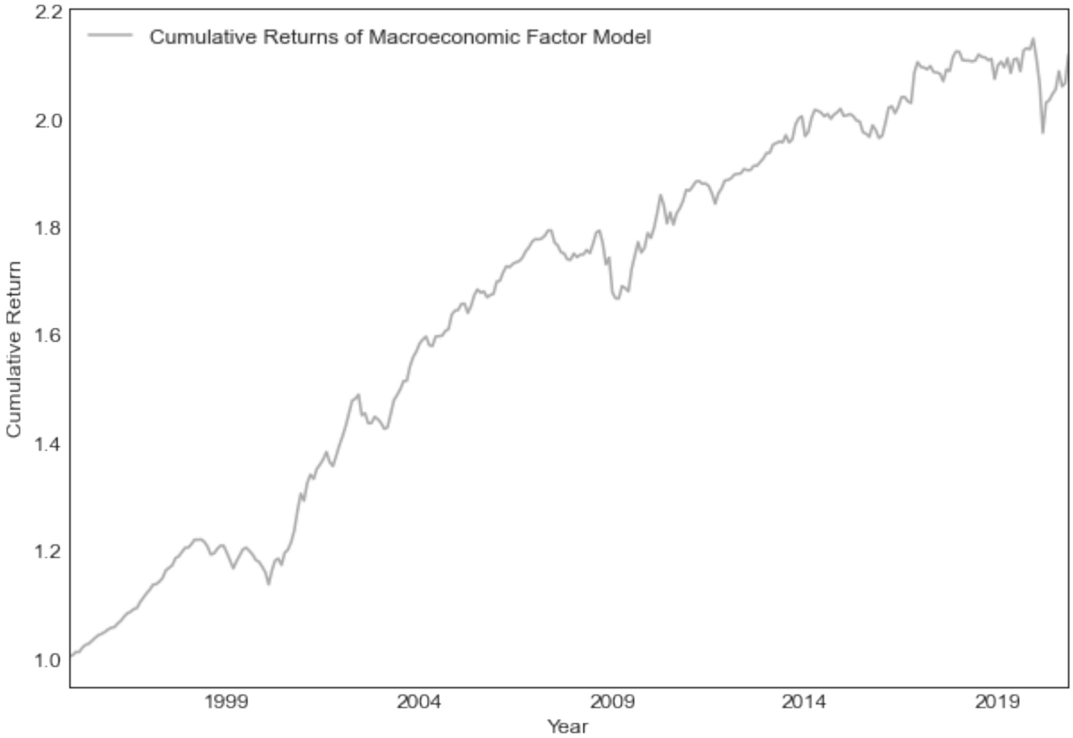
Graph 2 *– Representation of Classification Trees.*



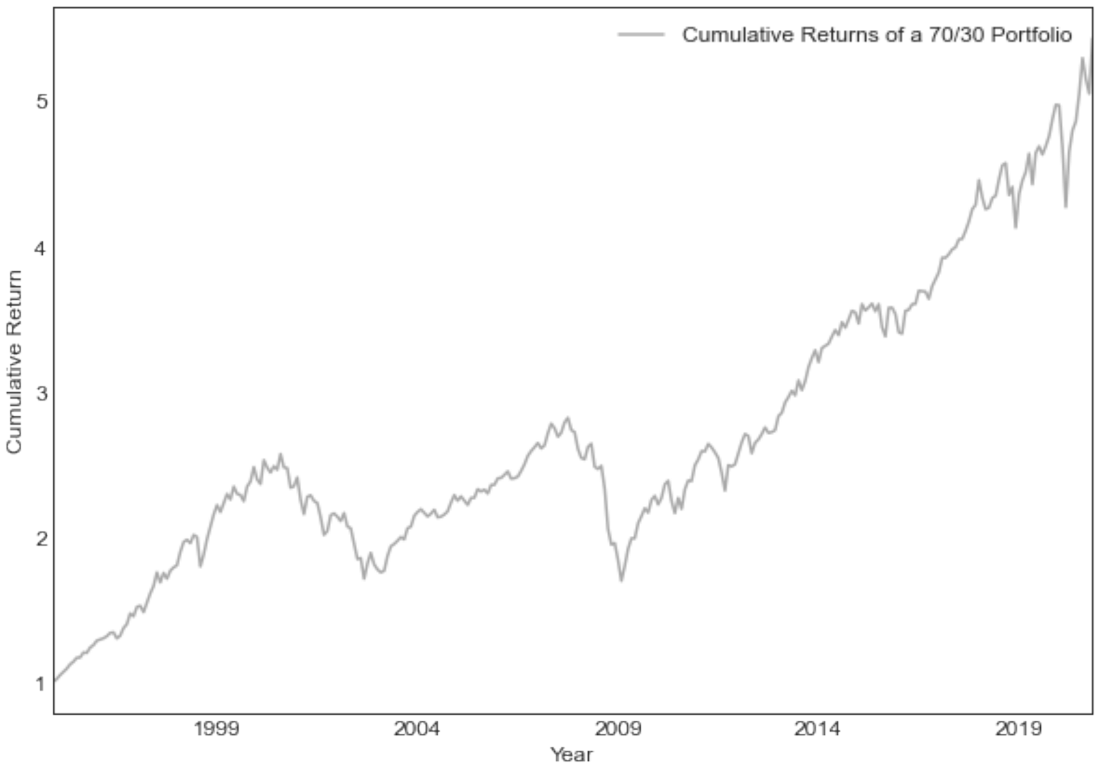
Graph 3. *Representation of a Random Forest. Link:* ***Source****: AI Pool. Link: https://ai-pool.com/a/s/random-forests-understanding*

Importance Contribution (Original Model)			
Ticker	**Name**	**Category**	**Importance**
H15T10Y Index	Constant Maturity Rate 10Y US Fixed Income	Market	8,2%
H15T5Y Index	Constant Maturity Rate 5Y US Fixed Income	Market	8,0%
H15T3Y Index	Constant Maturity Rate 3Y US Fixed Income	Market	7,3%
H15T20Y Index	Constant Maturity Rate 20Y US Fixed Income	Market	6,3%
H15T30Y Index	Constant Maturity Rate 30Y US Fixed Income	Market	5,6%
H15T7Y Index	Constant Maturity Rate 7Y US Fixed Income	Market	5,3%
H15T2Y Index	Constant Maturity Rate 2Y US Fixed Income	Market	4,8%
MOODCAAA Index	Moody's Corporate Bond Spread AAA	Credit	4,3%
H15T1Y Index	Constant Maturity Rate 1Y US Fixed Income	Market	3,7%
H15T3M Index	Constant Maturity Rate 3M US Fixed Income	Market	3,4%
MOODCBAA Index	Moody's Corporate Bond Spread BAA	Credit	3,4%
CPTICHNG Index	Capacity Utilization	Economic Activity	2,9%
EXP1CMOM Index	Export Price Index MoM	Economic Activity	1,8%
EXP1CYOY Index	Export Price Index YoY	Economic Activity	1,7%
IMP1XPM% Index	Import Price Index ex Petroleum MoM	Economic Activity	1,5%
USMMMNCH Index	Change in Manufact. Payrolls	Manufacturing & Industrial	1,4%
EURUSD Curncy	EUR USD Exchange Rate	Market	1,3%
IMP1CHNG Index	Import Price Index MoM	Economic Activity	1,3%
CPI YOY Index	Consumer Price Index YoY	Inflation	1,3%

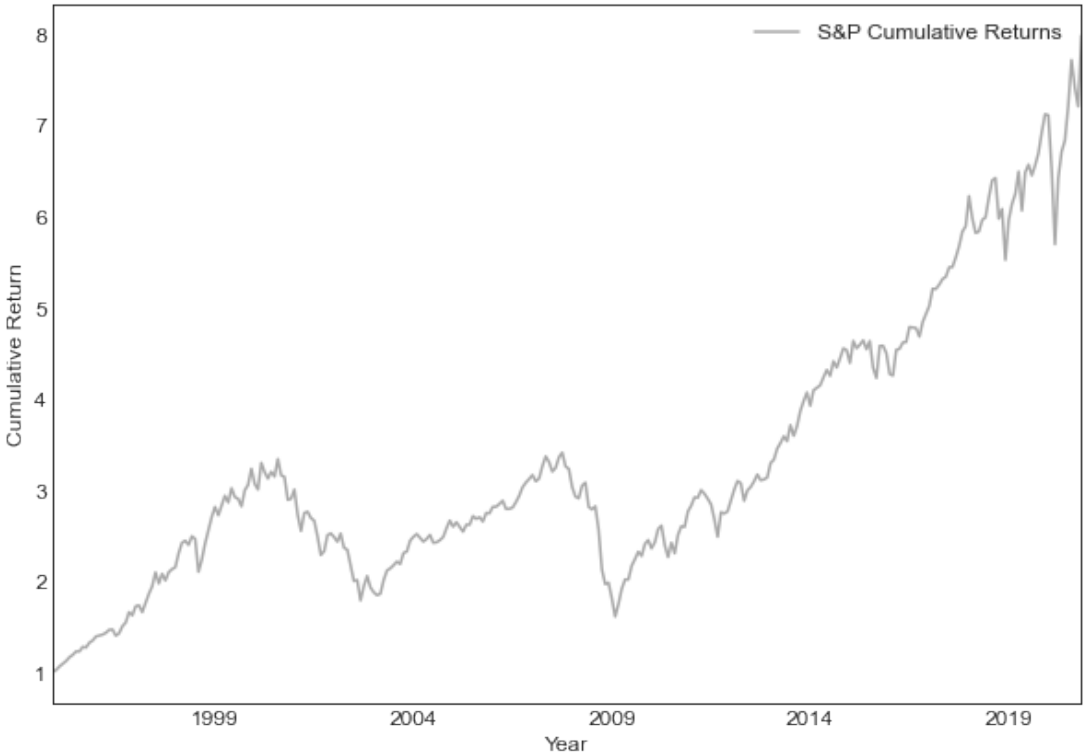
Table 8*. Details of Top Importance Contributors to the Random Forest Algorithm.*



Graph 4. *Cumulative Return Our Portfolio*



Graph 5. *Cumulative Return 70/30 Portfolio*



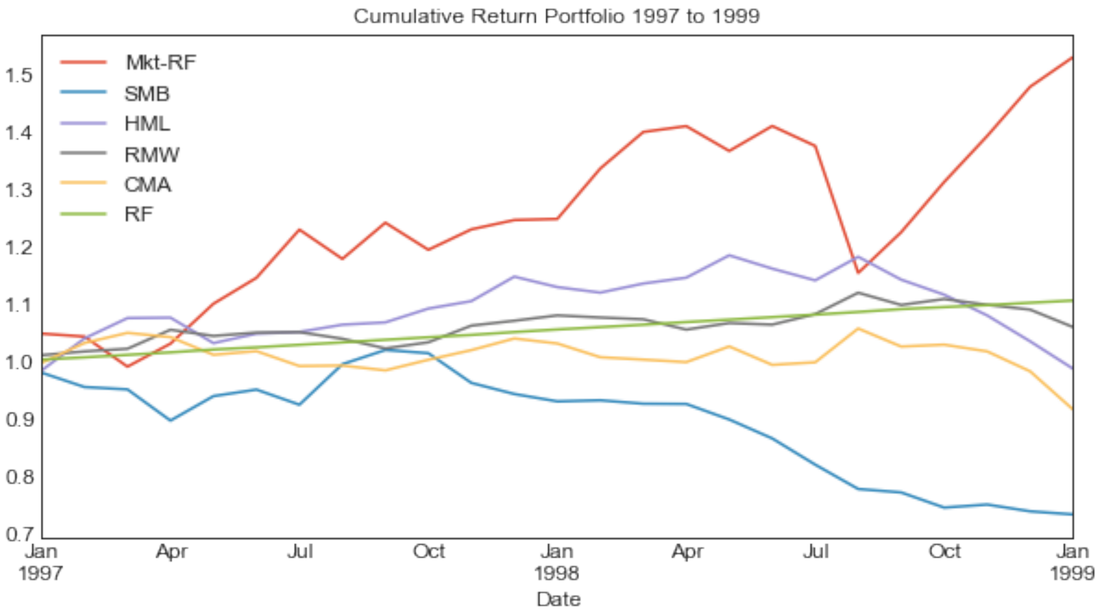
Graph 6. *Cumulative Return of the S&P 500.*

Annualized Returns and Volatility of Portfolio and Benchmark During Most Volatile Periods										
Start Date	End Date	Return Portfoli	Vol Portfolio	Sharpe Ratio	Return S&P	Vol S&P	Sharpe Ratio	Return 70/30	Vol 70/30	Sharpe Ratio
1997-01	1999-01	3,06%	1,93%	1,59	28,16%	18,15%	1,55	20,29%	12,70%	1,60
2001-01	2003-01	4,79%	3,39%	1,41	-18,80%	19,47%	-0,97	-12,85%	13,63%	-0,94
2008-01	2010-01	1,57%	3,87%	0,40	-12,27%	23,09%	-0,53	-8,51%	16,16%	-0,53
2019-01	2020-11	1,37%	5,33%	0,26	21,37%	20,49%	1,04	15,06%	14,34%	1,05

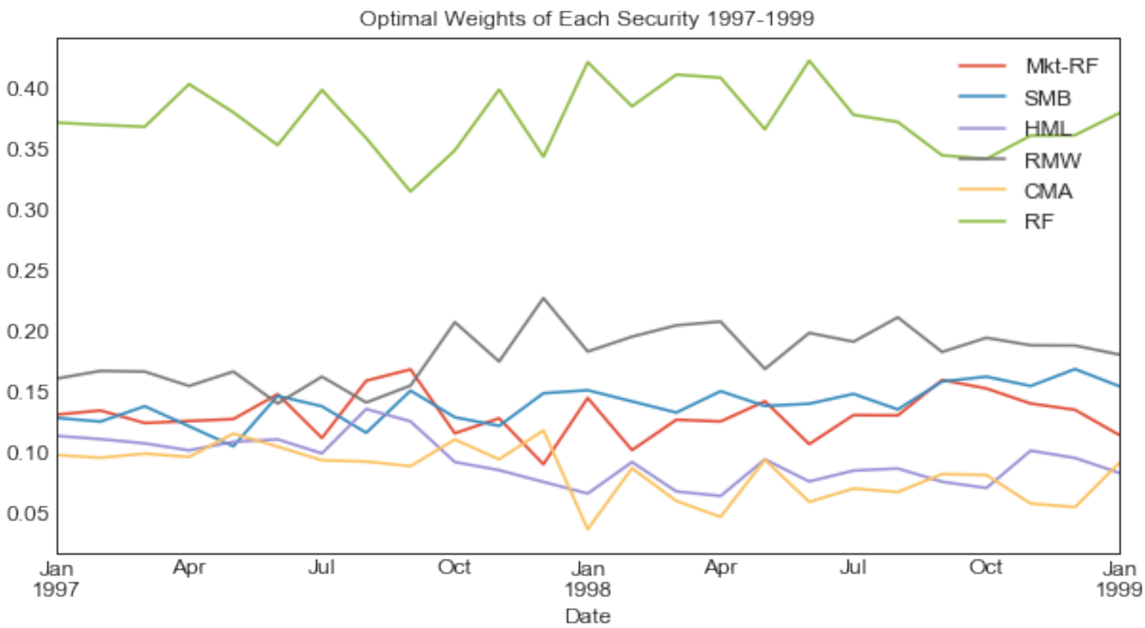
Table 9. *Returns and Volatility during Periods of High Volatility*

Major Drawdown Dates	Return Portfolio	Return S&P	70/30 Portfolio
1998-08	-14,58%	-0,73%	-10,15%
2002-09	-0,79%	-11,00%	-7,69%
2008-10	-1,58%	-16,94%	-11,85%
2020-03	-4,17%	-12,51%	-8,75%

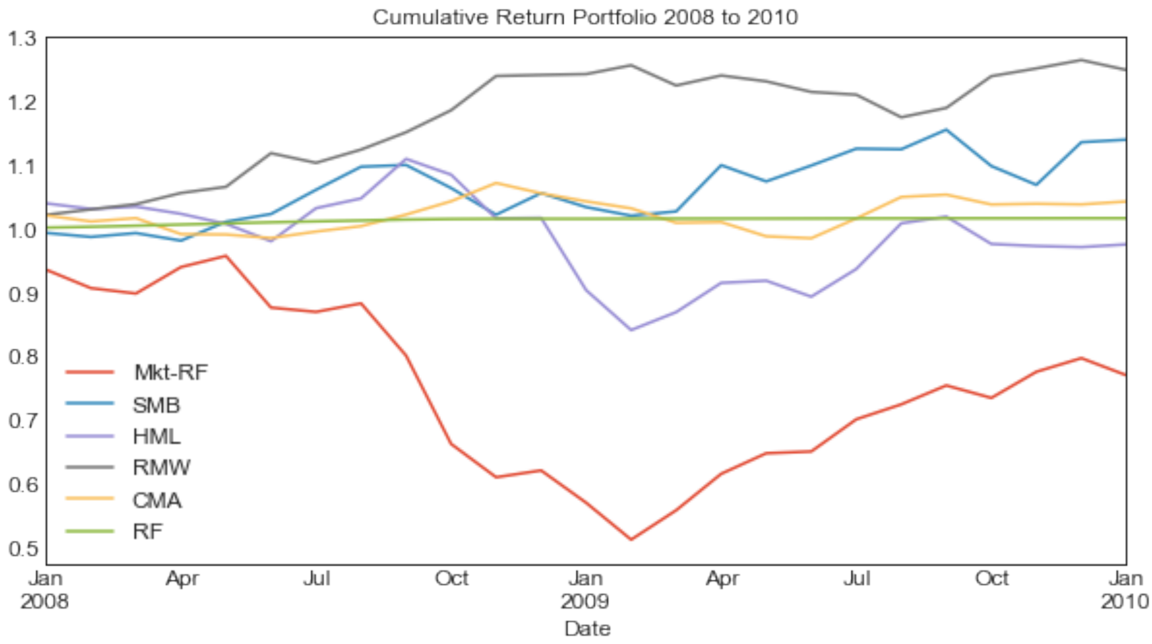
Table 10. *Dates and Returns of Major Drawdown periods*



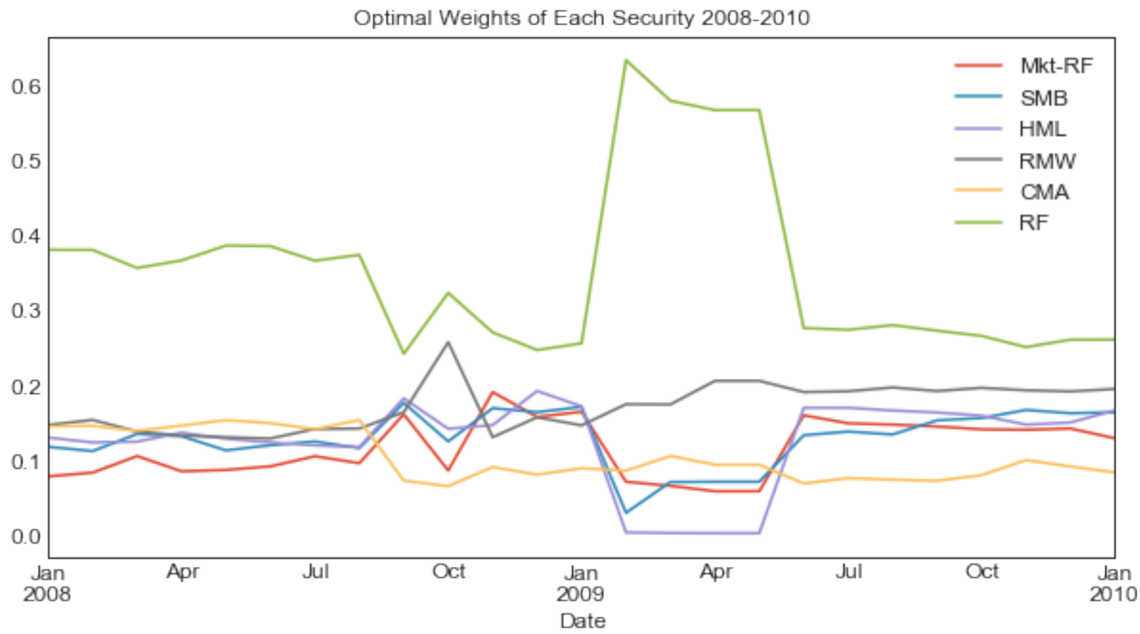
***Graph** 7. Plot with the cumulative return of each factor between 1997 and 1999.*



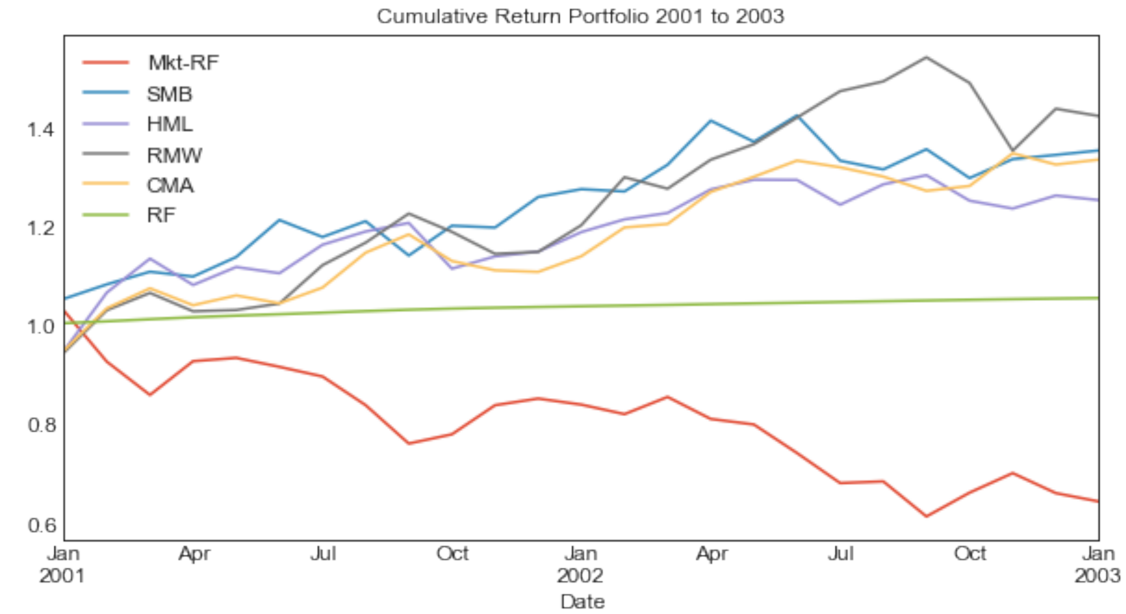
***Graph 8**. Plot with the optimal weights of each factor between 1997 and 1999.*



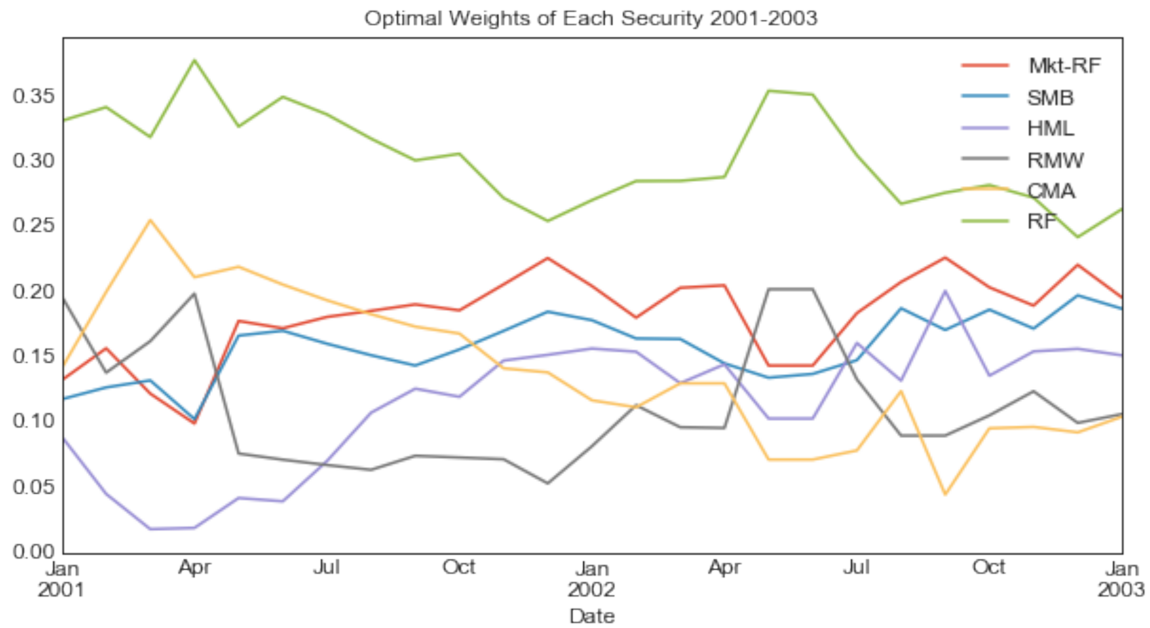
Graph 9. *Plot with the cumulative return of each factor between 2008 to 2010.*



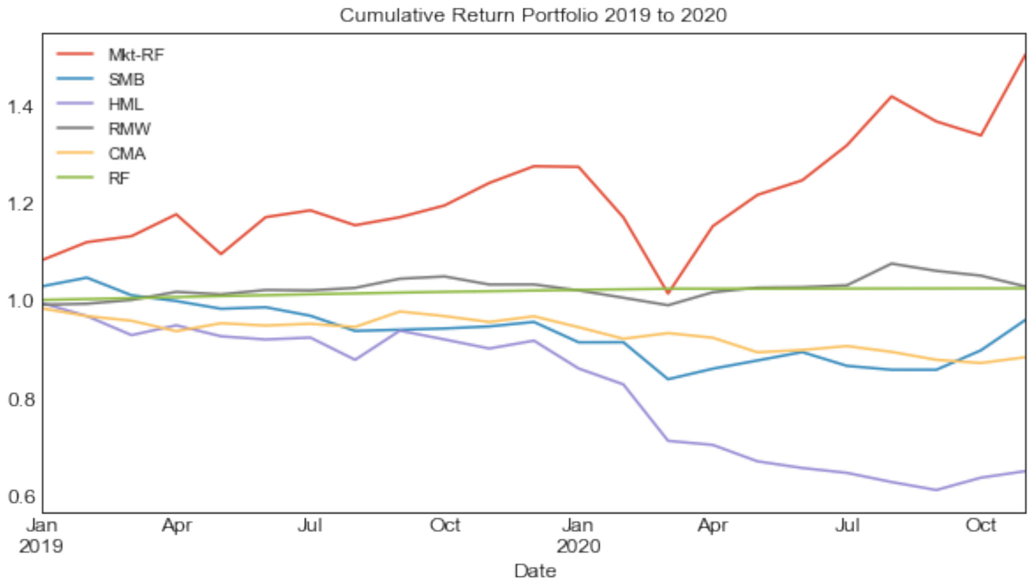
Graph 10. *Plot with the optimal weights of each factor between 2008 and 2010.*



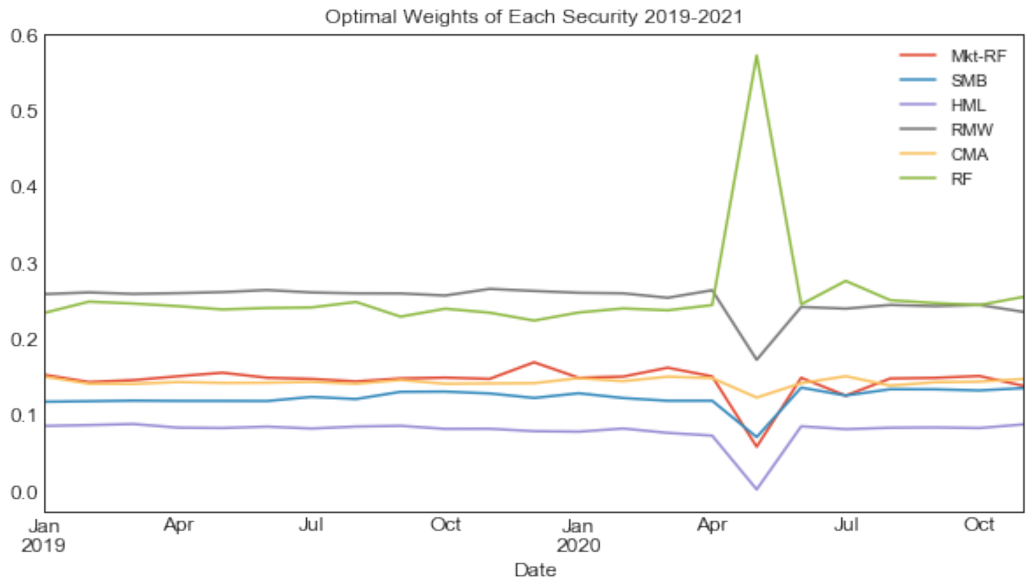
Graph 11. *Plot with the cumulative return of each factor between 2001 and 2003.*



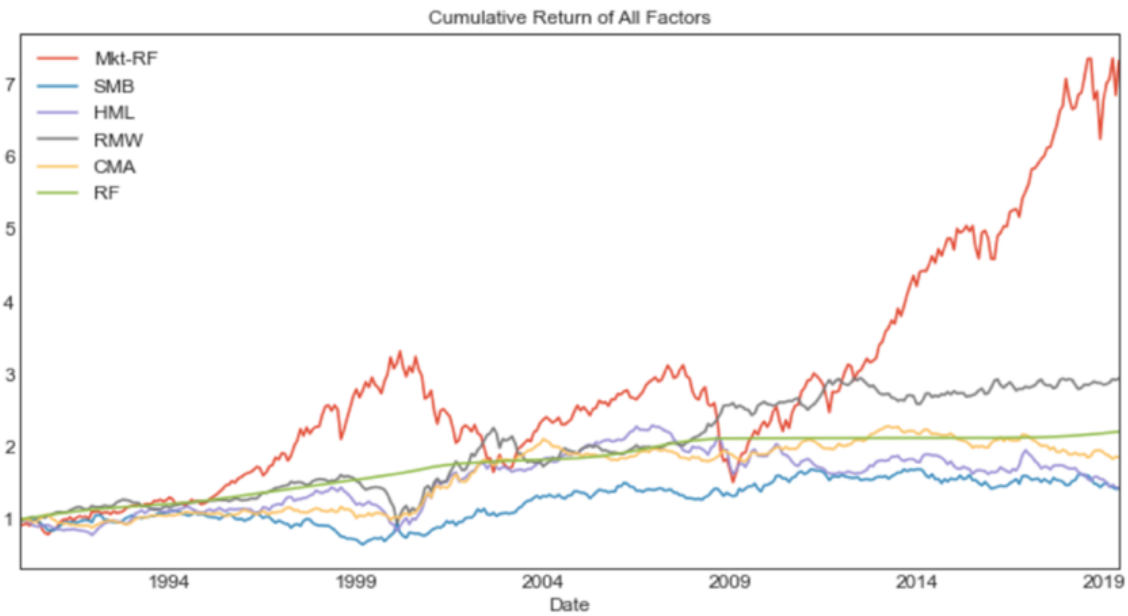
Graph 12. *Plot with the optimal weights of each factor between 2001 to 2003.*



Graph 13. *Plot with the cumulative return of each factor between 2019 and 2021.*



Graph 14. *Plot with the optimal weights of each factor between 2019 and 2021.*



Graph 15. *Cumulative Return of all factors.*

Date of Portfolio Creation	SR Portfolio	SR Portfolio (Net of Fees)	SR S&P	SR 70/30	SR 60/40	Start SR Date	End SR Date
40	1,168	0,963	0,5721	0,6438	0,6834	1993-04	2018-11
60	1,147	0,960	0,597	0,665	0,703	1994-12	2018-11
80	1,059	0,903	0,519	0,579	0,613	1996-08	2018-11
100	0,929	0,790	0,378	0,432	0,462	1998-04	2018-11
120	1,127	0,941	0,325	0,372	0,400	1992-12	2018-11
140	1,007	0,775	0,411	0,450	0,471	2001-08	2018-11
160	0,952	0,749	0,639	0,678	0,699	2003-04	2018-11
180	0,794	0,578	0,521	0,559	0,581	2004-12	2018-11

Table 11. *SR for different dates of portfolio creation of strategy and benchmarks*

SENSITIVITY REDUCTION OF FACTORS							
Number of Relevant Factors	SR Portfolio	SR Portfolio (Net of Fees)	SR S&P	SR 70/30	SR 60/40	Start SR Date	End SR Date
87	1,147	0,960	0,597	0,665	0,703	1994-12	2018-11
77	1,055	0,960	0,597	0,665	0,703	1994-12	2018-11
67	1,079	0,959	0,597	0,665	0,703	1994-12	2018-11
57	1,103	0,959	0,597	0,665	0,703	1994-12	2018-11
47	1,102	0,959	0,597	0,665	0,703	1994-12	2018-11
37	1,134	0,955	0,597	0,665	0,703	1994-12	2018-11
27	1,124	0,955	0,597	0,665	0,703	1994-12	2018-11
All factors excluding interest rates (72 factors)	1,107	0,958	0,597	0,665	0,703	1994-12	2018-11

Table 12. *SR of Portfolio and Benchmark for various numbers of relevant factors*

Lag in months	SR Portfolio	SR Portfolio (Net of Fees)	SR S&P	SR 70/30	SR 60/40	Start SR Date	End SR Date
1	0,969	0,792	0,378	0,432	0,462	01/04/1998	01/11/2018
2	0,896	0,784	0,378	0,432	0,462	01/04/1998	01/11/2018
3	0,915	0,791	0,378	0,432	0,462	01/04/1998	01/11/2018
4	0,873	0,791	0,378	0,432	0,462	01/04/1998	01/11/2018
5	0,969	0,792	0,378	0,432	0,462	01/04/1998	01/11/2018
6	0,870	0,793	0,378	0,432	0,462	01/04/1998	01/11/2018
7	0,958	0,792	0,378	0,432	0,462	01/04/1998	01/11/2018
8	0,850	0,782	0,378	0,432	0,462	01/04/1998	01/11/2018
9	0,870	0,782	0,378	0,432	0,462	01/04/1998	01/11/2018

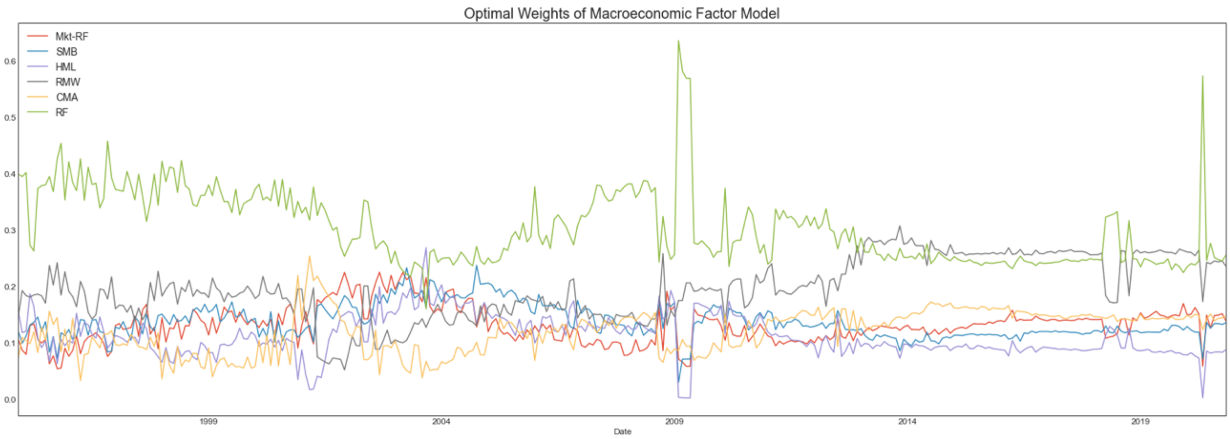
Table 13. *SR of Portfolio and Benchmark for different lags in the macro data.*

Securities	SR Portfolio	SR Portfolio (Net of Fees)	SR S&P	SR 70/30	SR 60/40	Start SR Date	End SR Date
Fama French 5 Factors includes Risk Free	1,147	0,960	0,597	0,665	0,703	1994-12	2018-11
Fama French 3 Factors includes Risk Free	1,259	0,958	0,597	0,665	0,703	1994-12	2018-11
10 Industry Portfolios	0,850	0,828	0,597	0,665	0,703	1994-12	2018-11
12 Industry Portfolios	0,812	0,808	0,597	0,665	0,703	1994-12	2018-11
17 Industry Portfolios	0,741	0,733	0,597	0,665	0,703	1994-12	2018-11

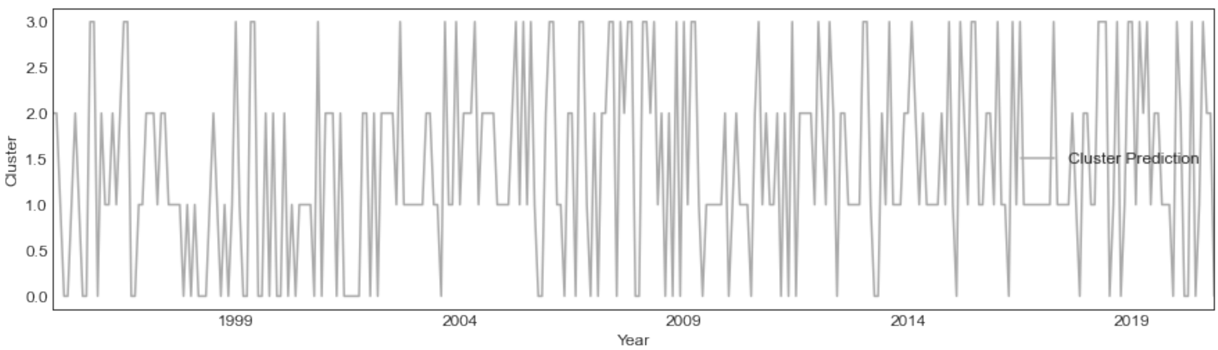
Table 14. *SR for the algorithm applied to different securities and benchmarks*

Strategy	Sharpe Ratio	Sharpe Ratio (Net of Fees)	Start Date	End Date
Rolling Mean of Optimal Strategy (Fixed Start)	1,360	1,230	Jan-1990	Jan-2019
Rolling Mean of Optimal Strategy (Flexible Start Date)	1,190	1,170	Jan-1990	Jan-2019
Equal-weighted Portfolio	0,915	0,915	Jan-1990	Jan-2019

Table 15. *Sharpe Ratio of Portfolio and Benchmark for different models without macro factors.*



Graph 16. *Optimal Weights of Macro Factor Model During the Investment Period*



Graph 17. *Cluster Prediction over the testing period*