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## An Analog Model for Global Macro Investing

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## **Abstract**

This study proposes a systematic model that is able to fit the Global Macro Investing universe. The Analog Model tests the possibility of capturing the likelihood of an optimal investment allocation based on similarity across different periods in history. Instead of observing Macroeconomic data, the model uses financial markets' variables to classify unknown short-term regimes. This methodology is particularly relevant considering that asset classes and investment strategies react differently to specific macro environment shifts.

**Keywords:** Global Macro, Asset Allocation, Trading Strategy

## 1. Motivation

While general investment strategies have been significantly stressed over the last decade, Global Macro strategies have been generating outstanding risk-adjusted returns<sup>1</sup>, avoiding the typical overconcentration of risk that Modern Portfolio Theory approaches usually carries<sup>2</sup>.

One might say that the roots of Global Macro investing date back to the early 70's when United States President Richard Nixon announced the end of the Bretton Woods system, suspending dollar's convertibility into gold and leading major currencies to start floating against each other<sup>3</sup>. Such liberalization of the markets created significant trading opportunities across fixed income and foreign exchange markets, as well as an increasing development of several derivative instruments. With such improvement on their investment landscape, practitioners began to invest on their expectations on monetary policy and macroeconomic disruptions across countries. In some cases, outstanding returns were achieved, which made famous several portfolio managers like George Soros or more recently Ray Dalio.

From those well-succeeded portfolio managers, Ray Dalio, besides his tremendous success, has been focusing on improving the public understanding of the global economy, providing insightful material about his practical economic template<sup>4</sup> that clearly differs from the traditional approach. According to his template, Dalio describes two major debt

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1 Credit Suisse Global Macro index posted an annualized return of 9,3% with a standard deviation of 5,4%, which contrasts with the 1,8% return of the MSCI World Index or the 2,8% of the S&P500, both with a volatility higher than 15% for the period between 2000 and 2014

2 Specially during high volatility periods; MPT approach seeks to reduce total variance of a portfolio returns by combining assets with different correlations, however due to the time-varying cross-correlation of financial assets returns, such approach tend to be stressed during high-volatility periods

3 International Monetary Fund, About IMF/History: The end of the Bretton Woods System (1972-1981)

4 See "*How the Economic Machine Works*" – Ray Dalio (2008)

cycles that rule the economy: a short-term cycle, commonly called the business cycle, and a long-term cycle. It is suggested that by perfectly understanding the forces behind both cycles, one is able to assess where the economy is and how it is likely to behave in the near future. In a conference for the *Council of Foreign Relations*, Dalio argued that the short-term credit cycle is shaped by growth and inflation “surprises” and that asset returns are conditioned by those variables. Besides an extremely interesting speech about deleveraging processes and debt cycles, Dalio also suggested that both short and long-term macro environments tend to repeat themselves across history and countries.

In fact such idea is a foundation of financial theory: growth and inflation influence discount factors, then expectations about future cash flows. Real inflation rate and inflation expectations influence asset valuation as well as the nominal expected cash flows of investments as a result, nominal interest rate changes accordingly. On the other hand, cash flow expectations are also a function of productivity shocks and growth prospects, which ultimately affect the current real value of assets. Conversely, changes in inflation and growth related variables tend to generate business cycle shifts, which are a key focus of investors’ strategic and tactical allocation decisions.

As a consequence, investors are bound to observe financial markets’ variables due to their forward-looking nature, therefore commonly considered leading indicators of future economic performance. In fact, the ability of financial variables to forecast changes in economic environments and their resulting influence on financial assets’ returns has been widely discussed in literature throughout the years. Fama and French (1989) analyzed the predictability of stock and bond returns across the business cycle, and identified the dividend yield, the term and the default spreads as major indicators for the time varying expected returns of both asset classes. Estrella and Hardouvelis (1991) had focused their

work on the capability of the term structure of interest rates to predict real economic activity, ultimately being a useful tool not only to private investors as well as to Central Banks. Estrella and Mishkin (1998) also addressed the advantages of using financial variables as leading indicators, more precisely, on their ability to predict recessions in the United States, concluding that observing the yield curve slope jointly with stock market returns' behavior provides a reliable indicator for predictions on macroeconomic environment shifts.

From an empirical perspective, Global Macro managers aim to allocate their capital on a strategic way, typically with a longer time horizon, and manage that allocation through a discretionary<sup>5</sup> approach to hedge against systematic risk. Macro investing is therefore mostly subjective, based on the manager's assessment of macroeconomic conditions. However, in the context of the present computer era this assessment can be done in a systematic manner.

Therefore, the aforementioned sensitivities of investments to economic environments are critical for investors' strategic asset allocation, but do also have a meaningful role on their discretionary decisions. In a recent publication on the *Journal of Portfolio Management*, Iltanen, Maloney and Ross (2014) approach and discuss to some extent the framework suggested by Dalio. The paper analyzes which Macro environments mostly influence investments, quantifying how the traditional asset classes and style investing strategies perform in each of those environments. Among other relevant conclusions, it is emphasized that certain environments are particularly challenging, being difficult to find any asset class or style investing strategy that can be able to deliver

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5 Or "tactical" approach. We define Strategic and tactical asset allocation as in Dalquist and Harvey (2001)

consistent returns. In addition, it is also concluded that major asset classes have different sensitivities to macro environments – a foundation basis of the benefits of systematic risk balancing, arising from the Modern Portfolio Theory.

Empirically, the focus on balancing exposures to target consistent risk adjusted returns has been in investors' agenda in recent years, with innovative approaches emerging on the asset management field. Among recent developments, Risk Parity<sup>6</sup> has been gaining prominence by suggesting balancing a portfolio's exposure through an allocation weighted on an equal share of risk of each asset class, which lead it to outstrip conventional asset allocation approaches over the last decade. In a different scope, Smart Beta<sup>7</sup> strategies are also gaining importance, providing a mix between active and passive investment, considering alternative weighting measures other than the CAPM beta factor like size, value, growth or momentum factors.

In the context of the current investment landscape and to provide a complement to the existing tools, we propose a model that seeks to provide an efficient allocation indicator and that also tries to capture small shifts on broad macroeconomic environments. In some extent it is our ambition to mitigate the challenging nature of some investment environments that ultimately hurt many portfolios, as highlighted in Ilmanen et al. (2014). At the same time we aim to test if by observing financial markets' variables to find similar periods in history, one is able to optimize its investment allocation in subsequent periods. The purpose of this analog approach is to capture shifts in short-term regimes that tend to be similar to other periods in history. Such approach aims to work as an investment

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<sup>6</sup> A concept introduced by *Bridgewater Associates* - "*All Weather Portfolio*" and recognized as the root of the Risk Parity approach. See "Engineer Targeted Returns and Risks" – *Bridgewater Associates* (White papers)

<sup>7</sup> See Jacobs and Levy (2014)

strategy but also as an effective model to identify which investments perform better during different periods.

Therefore, it is interesting to provide an empirical example of this **Analog Model** by analyzing a recent abnormal period. The months of September and October 2008 were one of the most stressful and dramatic periods in financial market's history, with the great majority of investors facing unrecoverable losses on their portfolios. During a very short period of time, the fourth largest American investment bank requested the biggest bankruptcy petition<sup>8</sup> of United States history and one of the most important insurance companies in the world was bailed out. The side effects of such events led the S&P500 Index to experience the most pronounced intraday swings of its history. Now imagine a hypothetical investor, who after such a troubled period analyzes the possibility of existing an analogous period in history, that could serve him as a roadmap. Obviously such analysis must be made not by the predominant events occurred during that period, but by observing the behavior of key financial markets' variables which could ultimately characterize the short-term macro regimes at that time. It is our ambition that by implementing the Analog Model, private and institutional investors might be able to optimize their allocation decisions throughout any macro environment.

The first section briefly summarizes the global macro investing landscape as well as the purpose of the model. The remainder of the paper is organized as follows: section two describes the methodology implemented and discusses its assumptions. The third section illustrates the empirical application of the model and evaluates its results. Section four

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<sup>8</sup> "Lehman Brothers became entangled in the subprime mortgage lending crisis" leading the investment bank to file for a Chapter 11 bankruptcy protection on September 15, with more than \$613 in total debt and \$639 billion in assets - *Harvard Business School Library: "History of Lehman Brothers"*

studies its robustness by analyzing it as an investment tool and its potential to identify major exposures across different macro environments. The fifth section concludes.

## **2. Methodology**

### **2.1. Model Setup**

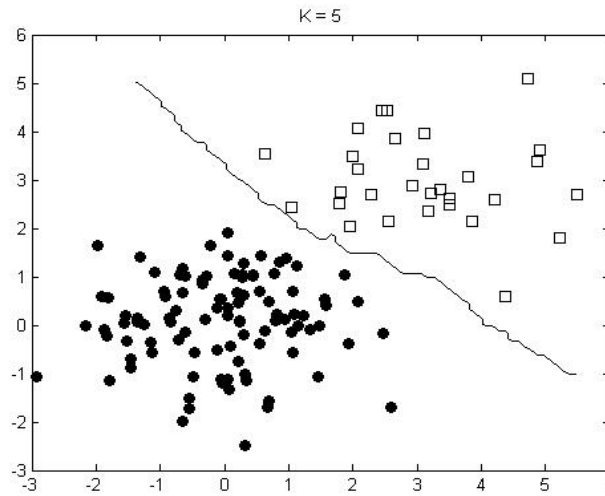
As previously stated, the purpose of this study is to build a systematic model with the ability to portray an unknown regime and subsequently identifying parallels with former periods in history. Therefore, the basic framework of the model stands for a supervised learning concept called k-nearest neighbor (k-NN) in which the procedures are not dependent on any specific assumptions regarding the underlying data, thus being adaptive to any kind of analyses. Given its procedures, this concept is starting to be recognized as an useful tool in financial markets prediction<sup>9</sup>.

Theoretically, in pattern recognition the k-NN algorithm is a method that allows classifying a specific data point according to its closest points in the whole dataset, using a “majority vote” system. Therefore, it classifies the unknown point based on the classification of its nearest neighbors.

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<sup>9</sup> For example Ramli, Ismail and Wooi (2013) tested the k-Nearest neighbor Method to predict currency crisis

**Table 1 - Graphic Representation K-NN Algorithm**



*Note: The unknown sample is assigned to the class most common amongst its K-nearest neighbors. In this simple case the sample would be classified either as a square or a circle.*

Given the purpose of our model, it would be interesting to apply such procedure. Therefore, to implement the algorithm into our framework we must start by defining i) how we characterize each short-term macro environment, ii) how the distance between the unknown period and the historical sample periods is performed and iii) based on the analogous periods found, how can this be translated into an investment decision.

To begin with, we will take the economic environment of each period, (approximately a month) as a matrix of different vectors. Those vectors represent the behavior of the market variables that we define as our benchmark indicators. Therefore, each period will be characterized as a matrix of those vectors:

$$M = \begin{bmatrix} X_{1,1} & \cdots & Z_{1,n} \\ \vdots & \ddots & \vdots \\ X_{20,1} & \cdots & Z_{20,n} \end{bmatrix}$$

Being  $M$  a matrix of the standardized daily changes of the financial markets' variables, which ultimately defines each short-term regime<sup>10</sup>.

The next step is related with the methodology developed to identify similarities between different periods. We have performed some variations to the original k-NN algorithm, since the performance of this classifier will clearly depend on the applied distance measure. Conceptually, there are different types of distance measures computed in the algorithm, being the Euclidean distance<sup>11</sup> between samples most commonly employed<sup>12</sup>. However in the **Analog Model**, instead of a linear distance measure, we calculate the correlation coefficient.

So, for a given unknown month that we pretend to classify (defined by a matrix  $A$ ) we compute the correlation coefficient between  $A$  and all the other months in history (defined as  $B_i$ ). Therefore, for a given  $A$  matrix that we want to classify, we calculate their distance to each month  $B_i$  that we have in sample:

$$\rho_i = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mni} - \bar{B}_i)}{\sqrt{(\sum_m \sum_n (A_{mn} - \bar{A})^2)(\sum_{mi} \sum_{ni} (B_{mni} - \bar{B}_i)^2)}}$$

At last, given the output of the previous computations, we will rank all the in-sample periods according to their distance to our unknown matrix  $A$ .

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<sup>10</sup> The matrix is defined by a vector of 20 points, since 20 corresponds to the trading days corresponding to a one month period, so 21 observations are considered in each period in order to compute the daily changes for each variable

<sup>11</sup> Euclidean distance is defined as:  $d_{(p,q)} = \sqrt{\sum_{i=1}^n (p_i - q_i)^2}$

<sup>12</sup> See Ramli, Ismail and Wooi (2013), Imandoust and Bolandraftar (2013) or Wang, Saligrama and Castañon (2011)

In order to get an investment decision ( $I_t$ ), which is our primary focus, we will get the 5 “closest” periods, the ones with the highest correlation with A. To illustrate the methodology developed so far, we will focus again on the example given in the first section and will show what kind of information the model would extract, considering the beforehand mentioned period of October 2008:

**Table 2 - Investment Decision**

<b>Unknown Period</b>	<b>Analogous Periods</b>	<b>Optimal Portfolio</b>	<b>Investment Decision</b>
<b>November 2008*</b>	June 11 to July 9, 1991	Bonds	<b>Bonds</b>
	June 9 to July 7, 1992	Bonds	
	July 8 to August 4, 1992	Bonds	
	October 20 to November 17, 1998	Equities	
	May 2 to May 30, 2001	Bonds	

*\* Recall that we want to classify October 2008 in order to get an investment decision for the subsequent month, in this case November 2008*

As illustrated in Table 1, the model identifies five different periods as the most similar to October 2008. The main goal is therefore, to identify an optimal investment decision ( $I_t$ ) for November 2008. Such decision would correspond to the portfolio that had the best performance during the subsequent months of each of the five identified analogous periods:

$$I_t = I^*_{t-s+1}(M^i_{t-s})$$

Being  $I^*_{t-s+1}$  the investment that yielded the most stable return<sup>13</sup> during the subsequent periods of each of the analogous months  $M_{t-s}$ . One can think the investment

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<sup>13</sup> The best performer is identified as the portfolio that had the highest info sharpe ratio:  $is = r_p/\sigma$  being  $r_p$  and  $\sigma$  the average return and standard deviation of the portfolio, respectively

decision as the simple statistical concept of the mode, since the model will use a “majority vote” system to decide on the allocation on time  $t$ . Therefore, the allocation is based on the portfolio which appears more often as the top performer, subsequently to the analogous periods.

## **2.2. Variables**

Now that we have defined the model set up, it is our focus to discuss the building blocks of the short-term macro environments that will allow the model to effectively predict the likelihood of an optimal allocation, based on analogous periods. Thus, our research and implementation will follow this purpose. An important differentiation in the proposed model is the fact that instead of using macroeconomic data, which typically is backward looking, we intend to use financial market’s variables that according with the Financial literature, have the ability to reflect and predict short-term macro shifts<sup>14</sup>.

Term structure of interest rates and the yield curve slope are key indicators of monetary policy, future economic activity, credit demand and inflation, being extensively studied due to their forward looking capacity. Wright (2006) studied the predictability power of using the term structure of interest rates jointly with the yield curve slope instead of using the term structure alone, to predict recessions. Conversely, Estrella and Trubin (2006) also documented the sensitiveness of the yield curve to changes in overall financial markets conditions<sup>15</sup>. They prove that the 10 year - 3-Month yields’ spread provides the most reliable indicator to predict changes in the economic environment, being the actual

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<sup>14</sup> We have tested the implementation of the model using Macroeconomic Indicators, but as we expected without relevant results, probably due to their backward looking nature

<sup>15</sup> The paper states that yield curve slope depends on technical factors and economic fundamentals. The importance of technical factors relates with the demand for different maturities by different types of investors. Hence, a permanent shift in the relative importance of investors, produces permanent shifts in the slope of the yield curve

level of the spread the most accurate leading indicator<sup>16</sup>. In the context of such findings, our focus will be on both the level of the term structure: the 3-month, two and ten year constant-maturity rates as well as in the slope of the yield curve. We apply the same methodology early introduced by Estrella and Mishkin (1996) and Estrella and Trubin (2006) and derive the spread between the 10-year and the 3-month rates, and the ten and two year term spread defined by Fama and French (1986), in order to analyze the time-varying term premium. Both the term structure and spreads have a clear business cycle pattern<sup>17</sup>, showing encouraging results in predicting economic regimes, thus with a high potential to fit our ambition of capturing short-term market movements.

From a different perspective, stock market returns' and the market risk premium are recognized as main indicators of investors' sentiment and growth prospects. As an illustration of that ability in Ilmanen, Maloney and Ross (2014) or in Estrella and Mishkin (1998) the notion that the behavior of stock returns is essential to identify macro environments, is emphasized. However one is able to find several approaches on the literature as well as different sets of stock returns that may present a predictive nature. Therefore, this was the set of variables that have been more stressed throughout this study in order to have an indicator that would be able to capture both, growth and inflation and other macroeconomic expectations as well as short-term investor's sentiment. As a result we will analyze different sets of market variables to assess the market risk premium, being stock market returns' behavior and the rate of change of the currency market our primary

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<sup>16</sup> In the recent Financial Crisis of 2008 the Treasury-Eurodollar Spread (TED spread) was widely used by both Central Banks and market participants as a measure of the magnitude of the crisis. In Ilmanen, Maloney and Ross (2014) the TED spread is also considered to measure liquidity since "the spread tends to widen when market concerns on banking sector credit risk rise or funding liquidity conditions deteriorate"

<sup>17</sup> Fama (1988) argues that short term interest rate shifts during business cycle is a "mean reverting" tendency since "the 10 year rises less than the 3-month bill rate during expansions and falls less during contractions"

focus. While growth and inflation are the most relevant macro indicators, which ultimately have more impact on financial variables, we also stressed different dimensions of their impact. We propose an alternative approach in which a volatility measure of stock market returns and the Default spread introduced by Fama and French (1989) are implemented.

### 2.3. Data and Implementation

Having described the basic framework and the set of variables that fit our intentions, each period would be defined as:

$$\text{Primary Case: } m'_i = f(FED_t, STY_t, LTY_t, TERM_t, MRP_t, FX_t)$$

$$\text{Alternative Case: } m'_i = f(FED_t, STY_t, LTY_t, TERM_t, DEF_t, Vol_t)$$

Where  $FED_t$  is the 3-month constant maturity rate,  $MTY_t$  stands for the mid-maturity rate: 2 year constant maturity treasury yield,  $LTY_t$  is the 10 year constant maturity rate, the  $TERM_t$  is the spread between the 10 year and the 3-month rate,  $MRP_t$  is the rate of change of the S&P500 Index returns and  $FX_t$  is the rate of change of the Euro-Dollar exchange rate. On the alternative case  $DEF_t$  is the spread between the Moody's Investment Grade Corporate Bond Index<sup>18</sup> and the 10-year constant maturity rate  $Vol_t$  is the stock market volatility measured as the difference between the daily maximum and minimum of the S&P500 Index<sup>19</sup>.

As for the empirical application, the asset classes chosen for the implementation of the model are representative of real-life tactical allocation decisions that are typically faced by asset managers. Following such requisites, we will focus on United States Equity

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<sup>18</sup> MOODCBAA <Index> available on Bloomberg

<sup>19</sup> Calculated as  $vol = (P_{high} - P_{low})/P_{last}$

and Government Bonds, and a Cash asset. For U.S equities as well as to Bonds we use the S&P500 Futures Rolling Strategy and the U.S Bond Futures Rolling Strategy<sup>20</sup>. As for the cash asset we use the FED Funds rate. Regarding the Style and Equity approaches, the data source is from the Keneth R. French's Data Library and that is presented with more detail in the appendix 1.

The implementation will be similar across all applications. The data frequency consists on daily observations during the training set, which comprises the period between 1985 until August 2014. The model is trained on a 20% portion of the data (approximately the period between 1985 and 1990) and tested on the remaining 80%, thus starting to be implemented in 1991. However, as the sample size increases, the model's training set increases at the same proportion. Moreover, the impact of transaction costs will not be considered based on the monthly rebalancing of the portfolio<sup>21</sup>.

### **3. Empirical Application**

To illustrate the empirical application and robustness of the model, three approaches are suggested. First we will implement a simple approach in which our investment decision is based on the traditional asset allocation decision – Equities, Bonds and Cash. Furthermore, we will extend this analysis to a dynamic approach that matches real-life portfolio balancing allocation. Afterwards, we will implement the model to style investing decisions, considering Value, Size and Momentum strategies as our investment universe. Finally we will assess the capability of the model to extract equity investing decisions

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<sup>20</sup> Rolling Futures strategies are available on Bloomberg as FRSIUUSE for Equity and FRSIUSB for Bonds

<sup>21</sup> We estimate that for the type of liquid investment considered (S&P500 Index Futures and 10-Year Treasury bond futures) transaction costs including bid/ask spread and brokerage fees should not exceed 2 basis points per contract. Therefore, a monthly rebalance should not represent a significant retraction on returns

that may capture efficient industry sector exposure, which ultimately can be a useful tool for equity portfolio construction.

### 3.1.1. Asset Allocation

The analog model was first applied to the simplest set of asset allocation. The main purpose of this first application is to test the adherence and ability of the model to capture the likelihood of certain regimes, consequently providing an optimal investing decision. Therefore, the asset universe considered is composed by Equities, Bonds and Cash, with the portfolio being fully invested in only one of those assets during each period<sup>22</sup>.

<b>Table 3 – Analog Model Base Case</b>			
	<b>Equity/Bond/Cash (Primary)</b>	<b>Equity/Bond/Cash (Alternative)</b>	<b>Global 60/40*</b>
Annualized Return	8,20%	5,70%	8,30%
Annualized Standard Deviation	9,90%	10,50%	11,40%
Sharpe Ratio	0,83	0,54	0,74
Maximum Drawdown	-25,3%	-32,5%	-41,1%
Positive months	66%	61,5%	62,9%
Market Beta	0,25	0,32	-0,05
Skweness	-2,15	-1,43	-0,8
Kurtosis	19,02	8,96	20,48

*\*Note: Global 60/40 portfolio is constructed with the S&P500 index Rolling Futures Strategy FRIUSE <Index> Bloomberg returns and US Treasury Bonds Futures Rolling Strategy FRIUSB <Index> Bloomberg*

The results for the base case clearly show that the Analog Model (when considering the primary set of financial variables) generates an encouraging performance. The model is able to achieve stable returns throughout the sample, presenting somehow an ability to extract an efficient allocation by actively managing the simplest portfolio exposures, which was one of our primary objectives. Such results allow concluding that the model is

<sup>22</sup> In this case we are only considering the possibility of being fully invested to assess if the model is able to provide a proper allocation. However in the remaining of the paper different sets of allocation are considered, obviously achieving a better Sharpe

able to extract an efficient asset allocation, given the short-term macro environment, avoiding the largest drawdown that a hypothetical passive strategy would generate. The Analog Model presents a consistent performance, with a lower standard deviation of returns and a percentage of positive months that to some extent shows the model is often right. Nevertheless, using the alternative set of variables described in section 2, the model does not provide the same behavior in returns as in the primary case. The drawdown is not significantly improved and the ability to generate excess returns when compared with the classic approach is inexistent.

### **3.1.2. Dynamic Analog**

The previous implementation of the Analog Model demonstrated its ability to satisfy our main purpose, therefore it is now our intention to extend the analysis for a next level and simulate an empirical application that fits real-life strategic allocation decisions.

In this case we will only consider two sets of asset classes: Equities and Bonds, but with a variable weighting scheme. Our set of possible investments is now extended, although we only have two asset classes. Therefore, the model will be again fully invested across the sample but in each period it would be possible to be invested in Bonds and Equities at the same time although with different weights. Hence, the combination of possible weights is defined by:

$$w_B = 1 - w_E, \forall 0 \leq w_B \leq 1.$$

Subsequently, the allocation decision for each period will be defined by the allocation that provided the most stable returns on the subsequent period of the analogous

month<sup>23</sup>. Therefore, we will have different weights of Equities and Bonds in each period, being their asset allocation dynamic:

<b>Table 4 - Dynamic Equity/Bond Portfolio</b>			
	<b>Dynamic Portfolio (Primary)</b>	<b>Dynamic Portfolio (Alternative)</b>	<b>Global 60/40*</b>
Annualized Return	10,60%	7,80%	8,30%
Annualized Standard Deviation	8,40%	7,70%	11,40%
Sharpe Ratio	1,27	1,02	0,74
Maximum Drawdown	-16,7%	-21,1%	-41,1%
Positive months	68,4%	66%	62,9%
Market Beta	0,21	0,24	-0,05
Skweness	0,085	-1,34	-0,8
Kurtosis	7,03	14,5	20,48

*\*Note: Global 60/40 portfolio is constructed with the S&P500 index Rolling Futures Strategy FRIUSE <Index> Bloomberg returns and US Treasury Bonds Futures Rolling Strategy FRIUSB <Index> Bloomberg*

The results obtained when applying such methodology clearly show the ability of the model to extract an optimal asset allocation given the short-term macro environment, especially if we consider the primary set of variables<sup>24</sup>. The purpose of generating consistent absolute returns, with a lower correlation with the market is patent here – a key feature of Global Macro trading strategies. Furthermore, comparing with 60/40 approach, the dynamic model significantly outperforms.

The ability of the Analog Model to provide a reliable asset allocation given the proposed primary set of market variables arises in these first two implementations. Such results in some degree prove the robustness of the model as well as its ability to be implemented as a Global Macro investment strategy not only due to the returns generated

<sup>23</sup> An important note should be made regarding this approach since given the increasing range of possible portfolios to invest, now we are only considering the closest period

<sup>24</sup> The alternative set of variables from now on will be abandoned, given the lack of significance of its results. It was considered as a representation of the alternative set of variables tested in this study, that however did not proved to be relevant for our conclusions

but also to its ability to provide a reliable weight optimization when considering the most common asset classes.

### **3.2. Style Investing**

Following the conclusion obtained through the previous implementations we will extend our analysis to a different scope, which relates with style investing decisions.

Concerning this approach, our focus is to test the ability of the Analog Model to identify, which Investment Styles do perform better considering analogous period. Such motivation relates with the findings provided in the literature like in Rau (2012) or in Guidolin and Timmermann (2005) that despite common style investment strategies typically outperform the market, they also tend to face downturns during different market cycles. Consequently, our purpose is to test if the Analog Model is able to be allocating to the styles that are outperforming, given the short-term macro environment.

More than two decades ago, Fama and French (1992) documented the Value and Size anomalies. In a similar extent, Jegadeesh and Titman (1993) and Asness (1994) first introduced the momentum anomalie that have been subject for numerous studies by academics throughout the years. Therefore, such style investment strategies are nowadays observed across different regions and asset classes<sup>25</sup>, which encourages us for the following implementation. Thus, we will decompose our set of investment alternatives through Value, Size and Momentum portfolios<sup>26</sup> believing that despite the abnormal returns generated by these style-investing strategies, one can be able to extract the optimal style investment strategy during short-term macro environment shifts:

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<sup>25</sup> As documented in Asness, Moskowitz and Pedersen (2012)

<sup>26</sup> Appendix 1 describes the data for this implementation

<b>Table 5 – Style Investing Analog</b>					
	<b>Analog Model</b>	<b>Value</b>	<b>Size</b>	<b>Momentum</b>	<b>Equal Weight*</b>
Annualized Return	17,80%	16,00%	16,80%	17,00%	16.60%
Annualized Standard Deviation	18,10%	11,90%	14,50%	20,70%	8.40%
Sharpe Ratio	0,99	1,34	1,16	0,82	1.97
Maximum Drawdown	-73,5%	-21,6%	-39%	-73,2%	-22.7%
Positive months	62,90%	65%	64%	61%	75.30%
Market Beta	0,02	0,06	-0,15	0,05	-0.015
Skweness	-0,69	0,06	0,31	-0,62	-0.09
Kurtosis	2,88	1,89	6,32	1,38	1.52

*\*Equal weighted style investing portfolio across the sample*

Table 5 illustrates that the implementation of the Analog Model to achieve the aforementioned purpose does not generate the consistent results provided in the previous implementations. Despite presenting stable returns, the model appears to follow a Momentum strategy during the sample, being unable to avoid the significant drawdown faced by this strategy. Moreover, an investor would be better off if it would follow a simple equally weighted portfolio with these investing styles.

The assumption that certain market regimes would benefit specific style investment strategies is not verified, although we believe they could be extracted somehow. This kind of long/short strategies generally carries less macro risk exposures, however the model does not capture this ability - a fact that is discussed and that we attempted to explain in the fourth section of this paper.

### **3.3. Industry Groups' exposure**

Despite the not so satisfactory results from the previous approach, the third and last empirical application of the model tries to explore a similar behavior.

In this framework we aim to explore if the tendency of certain Industry Groups to present uncorrelated returns during different phases of the business cycle, can be captured by the Analog Model. Despite not being so discussed by academics, this behavior is discussed by Global Asset Management firms and Investment Banks<sup>27</sup> that typically manage their equity portfolio exposure weighting on factors related with the business cycle, such as corporate earnings growth, interest rates or inflation<sup>28</sup>. Therefore, the data for this implementation can be found in appendix 2, and table 6 presents the descriptive statistics for this approach:

<b>Table 6 – Industry Analog</b>			
	<b>Analog Model</b>	<b>Equal Weight*</b>	<b>S&amp;P500 Index</b>
Annualized Return	17,60%	12,50%	9,50%
Annualized Standard Deviation	23,90%	15,40%	13,80%
Sharpe Ratio	0,74	0,81	0,68
Maximum Drawdown	-74,90%	-58%	-56,70%
Positive months	65,60%	65,20%	63%
Market Beta	0,14	0,24	-
Skweness	-0,23	-1,11	-1,15
Kurtosis	3,83	6,83	4,52

*\*Equal weighted industry group portfolio across the whole sample*

By observing the obtained results, one can conclude that despite the model being able to generate excess returns when compared with its benchmark – the S&P500 Index, it is neither able to serve our purpose nor to present a robustness that would encourage an investor to implement the model as an Equity allocation indicator. The main reason is the fact that it presents a quite unstable standard deviation of returns across the sample, confirmed by the massive maximum drawdown. Such conclusions are evidence against

<sup>27</sup> See for example “The Business Cycle Approach to Equity Sector Investing” - *Fidelity Investments, Market Research* or “Sector Performance During the Business Cycle” – *CME Group, Financial Research & Product Development*

<sup>28</sup> The basic idea is that for instance, during “Expansion” phases Health Care or Technology sectors tend to outperform the broader market, while in recession phases “defensive” stocks are preferred, such as high dividend yield sectors like Utilities or Telecom

its ability to provide a reliable allocation sign. However, as in the case of the style investing approach, possible reasons will try to be demystified by evaluating the model robustness and allocation across the sample.

#### **4. Robustness of the Model**

The previous section presented different applications of the Analog Model that provided us different conclusions. Now we aim to assess the robustness of the model by i) attempting to identify patterns on the model's allocation and if it coincides with general Financial Theory and ii) focus on the results and examine how the different approaches perform across broad macro environments. The main focus of this section is also to compare the obtained results with the conclusions of Iltanen et. al (2014) therefore, if the Analog Model is able to mitigate the challenging nature of certain macro environments.

Typical asset returns' analysis is implemented considering broad macroeconomic regimes such as growth and inflation<sup>29</sup>. In this section we will consider growth and inflation environments as well as Volatility and Liquidity regimes as in Iltanen, et. al (2014). Table 7 presents the macro environments considered as well as their estimation procedure:

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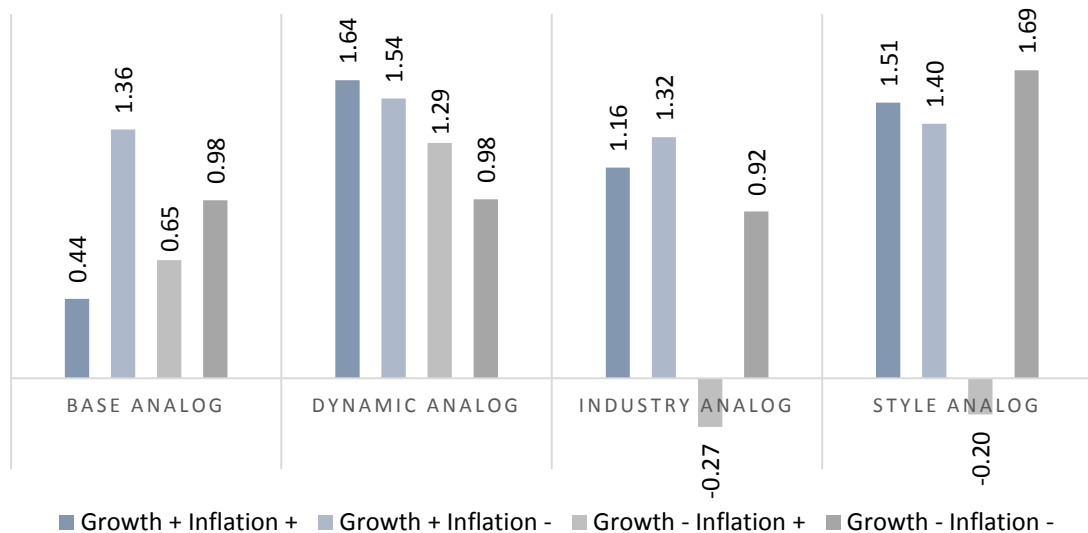
<sup>29</sup> See for example Fama (1981), Amihud (2002) or "The All Weather Story" – *Bridgewater Associates* (White Papers)

Table 7 - Indicators for Macro Environments			
<b>Growth</b>	Quarterly Real GDP Growth	Current growth > 2-year average	<b>Growth Up</b>
		Current growth < 2-year average	<b>Growth Down</b>
<b>Inflation</b>	CPI YoY Growth	Current growth > 5-year average	<b>Inflation Up</b>
		Current growth < 5-year average	<b>Inflation Down</b>
<b>Volatility</b>	CBOE VIX Index	VIX > 1-year average	<b>Bearish</b>
		VIX < 1-year average	<b>Bullish</b>
<b>Liquidity</b>	FED Fund Rate	Rate Hike	<b>Liquidity Down</b>
		Rate Cut	<b>Liquidity Up</b>

Source: S&P Dow Jones Indices, McGraw Hill Financial, Federal Reserve, Bloomberg

Following the definition of the macro environments that we want to assess, a Growth/Inflation matrix<sup>30</sup> was created to evaluate how the different implementations behaved:

**Table 8 - Performance Across Broad Macro Regimes**



<sup>30</sup> See appendix 4 for the definition and framework of the growth/inflation matrix

Table 8 displays the performance<sup>31</sup> of the model across the sample and during each of the beforehand-defined environments.

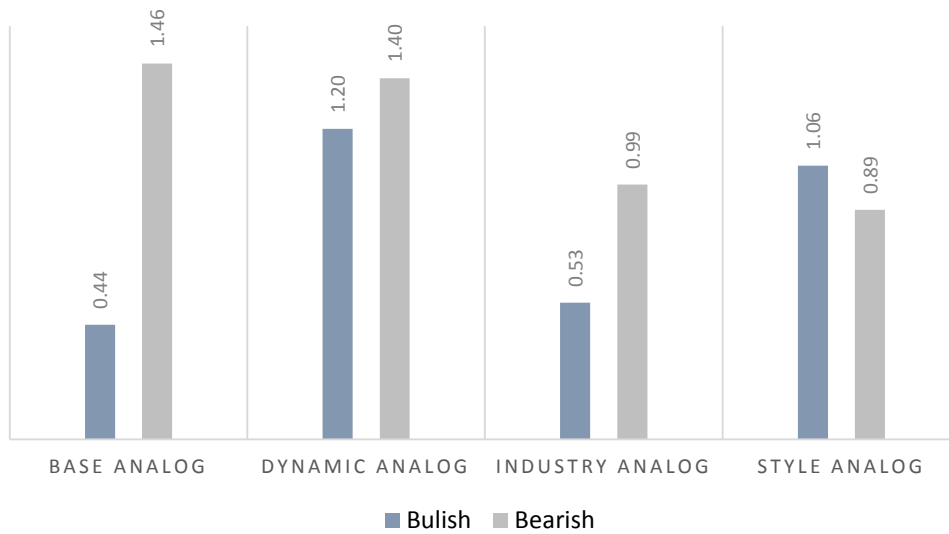
As previously demonstrated, the Dynamic Analog proves to be resilient even in the most adverse scenario described in Ilmanen et al. (2014) which occurs when slow growth and rising inflation coincides. Moreover, even the Base Analog approach is able to present some resilience in that kind of environment. In a different extent, the implementation of the model within equity investing strategies (the style investing and Industry Group allocation) is not effective in avoiding the typical downturn during that same regime, which somehow confirm our first interpretation of the results – the Analog Model is not able to effectively predict an adequate allocation within this frameworks during adverse environments.

Regarding the performance of the Analog Model in different liquidity environments, the conclusions are certainly more positive:

### **Table 9 - Performance Across Volatility Regimes**

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<sup>31</sup> On this and following macro simulations, performance is measured through info Sharpe Ratio :  $is = r_p/\sigma$  being  $r_p$  and  $\sigma$  the average return and standard deviation of the portfolio, within each environment; Further information can be found on appendix 3

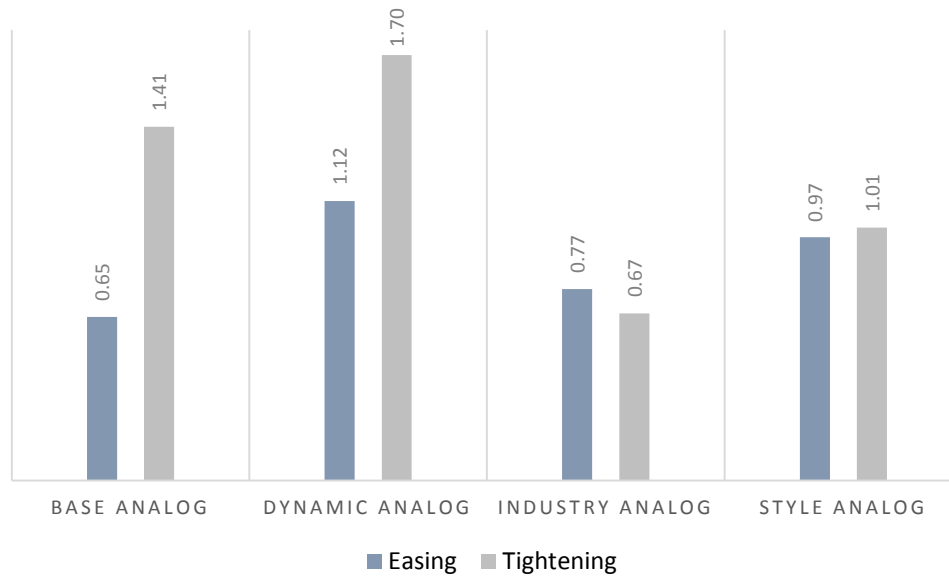


The performance of the model during “bearish” phases is robust through the sample, for all the considered approaches. Such result shows the model is able to perform well when general investor’s sentiment is negative, while typical asset classes and investment strategies are usually harmed<sup>32</sup>. Moreover, the asset allocation models (Base and Dynamic Analog) prove once more their ability to optimize the investment decision regardless of the market environment.

The last macro regime considered, relates with the liquidity of the market. Table 10 presents the performance of the approaches, given different liquidity regimes:

**Table 10 - Performance Across Liquidity regimes**

<sup>32</sup> According to what Ilmanen et al. (2014) describes



Ilmanen et al. (2014) describes illiquidity regimes as the most challenging for investments. Therefore, we are curious to analyze how effective is the Analog Model in providing a proper asset allocation during such regimes. As illustrated above, the model was able to capture an effective Style allocation during both easing and tightening regimes. As for the Industry sector exposure, the results coincide with the results obtained in Ilmanen et. al (2014), with the strategy not being able to generate consistent risk adjusted returns during that kind of environment, however without presenting negative performance, as one could expect.

The overall conclusion is that the implementation of the Analog Model is effective to strategic asset allocation decisions across any kind of macro regimes but it fails when we consider equity investing approaches, such as style investing or industry sector exposures, since the model is not able to avoid the common pitfalls arising during challenging macro environments such us low growth/high inflation environments.

Following the previous analysis, an interesting way to evaluate why the model presents such behavior is to assess its allocation pattern throughout the different

approaches implemented. Given the previous conclusions of this section we will demonstrate the model allocation across a growth/inflation matrix<sup>33</sup>:

**Table 11 - Allocation across Broad Macro Regimes**

		- <b>Inflation</b> +	
<b>Growth</b>	+	<b>Equities/Bonds</b>  <b>Momentum</b>  <b>Utilities</b>	<b>Equity</b>  <b>Value</b>  <b>Durable Goods</b>
	-	<b>Bonds</b>  <b>Momentum</b>  <b>Energy</b>	<b>Bonds</b>  <b>Momentum</b>  <b>Energy</b>

Evaluating the allocation pattern, one can conclude that the Analog Model presents an ability to follow what Financial Theory suggests concerning the asset allocation across broad macro regimes. Nevertheless does not present that ability when considering style investing or industry sector allocations. Although we should recall that the investment decision of the model is based on the Info Sharpe ratio generated in analogous periods. This fact leads to some persistency on the allocation decision based on the stable performance of some investments during the sample that only carries negative returns in more troubled period, in which apparently the model presents a tendency to be invested in. For that same reason, overall, the model tends to be invested most of the times in a Momentum strategy when considering the style investing approach,

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<sup>33</sup> Recall appendix 4 for an explanation of the Inflation/Growth matrix

suffering from the almost same drawdown of this strategy during a specific period of the sample. Regarding the Industry sector exposure, despite observing some reasonable allocation in a low Growth and negative inflation environment, the model seems to not follow a specific pattern, being its allocation almost randomly distributed with the results not being significant for relevant conclusions.

## **5. Conclusion**

The Analog Model provides a reliable systematic approach for Global Macro Investing since is able provide a helpful benchmark to guide investors toward more likely outcomes, assuming any short-term macro environment.

Throughout this paper we have shown the main motivations to create the Analog Model as well as its key assumptions and computation. We have provided the results of the model into three common investment approaches: Asset Allocation, Style Investing and Equity Investing. Therefore some important conclusions can be drawn from our analysis.

The model is able to provide an insightful roadmap for asset allocation decisions. The Dynamic variation of the model allows overcoming the common drawbacks arising from short-term macro environment shifts. However, when applied to style and equity investing approaches, the model suffers from the same pitfalls that commonly hurt general investment strategies. Through a deeper analysis on the behavior of the model across broad macroeconomic environments and relating the results obtained with the conclusions found in Ilmanen, Maloney and Ross (2014), we prove the robustness of the Dynamic Analog model. Therefore, we believe the Analog Model can effectively be implemented within a Global Macro Investing universe.

We conclude by suggesting that the inability of the model to extract optimal style and equity investment decisions allows for further research. The variables that we find reliable indicators to find analogous periods are certainly not the same that allow investors to extract the likelihood of Equity and Style allocations. Moreover, more diversified implementations may also be subject for further research, namely a dynamic model between Industry or Style investing strategies and Bonds.

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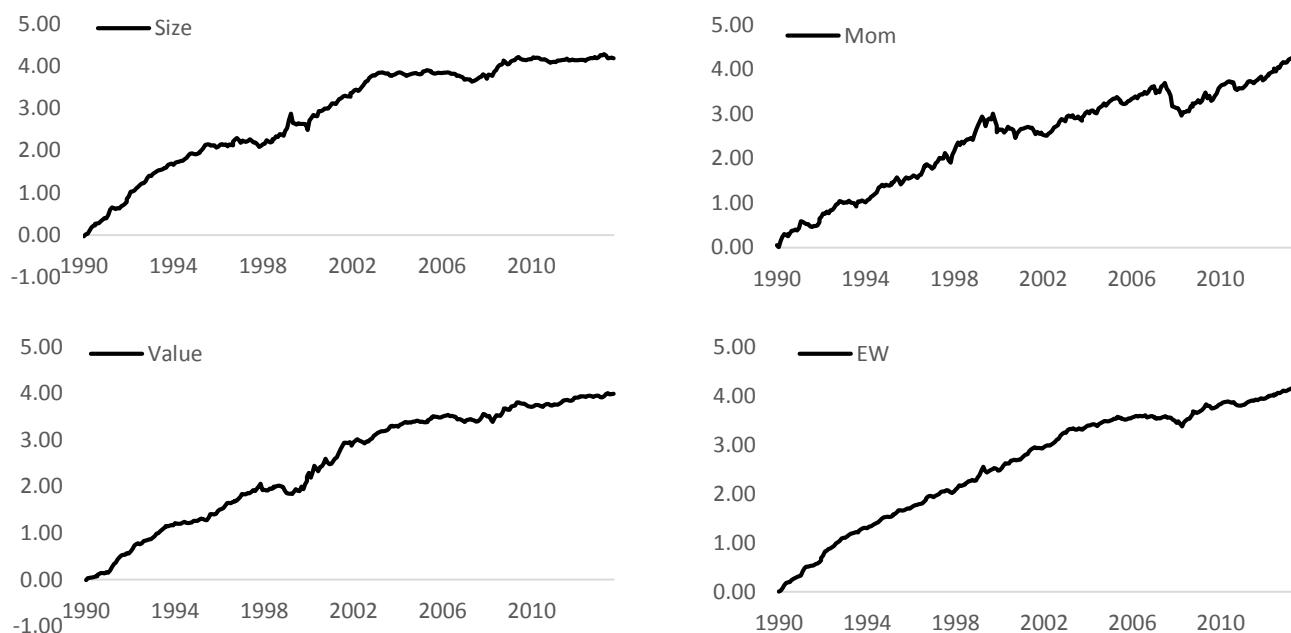
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## Appendix 1 – Data on Style Investing Strategies

Data Frequency: Daily Observations (1985.01.01 – 2014.07.31)

Source: Portfolios for the composition of each strategy obtained from Kenneth French's website<sup>34</sup>

**Figure A.1 – Cumulative Returns on a \$1 exposure to each factor and to the Equal weighted portfolio**



## Appendix 2 – Data on Industry Sector Exposure

Data Frequency: Daily Observations (1985.01.01-2014.07.31)

Source: Kenneth French's website

Industry Sector Portfolios replicate the performance of the broad sectors considered, being representative of the sectors that typically outperform the market in each of the commonly defined phases of the business cycle: Early, Mid, Late and Recession phases<sup>35</sup>.

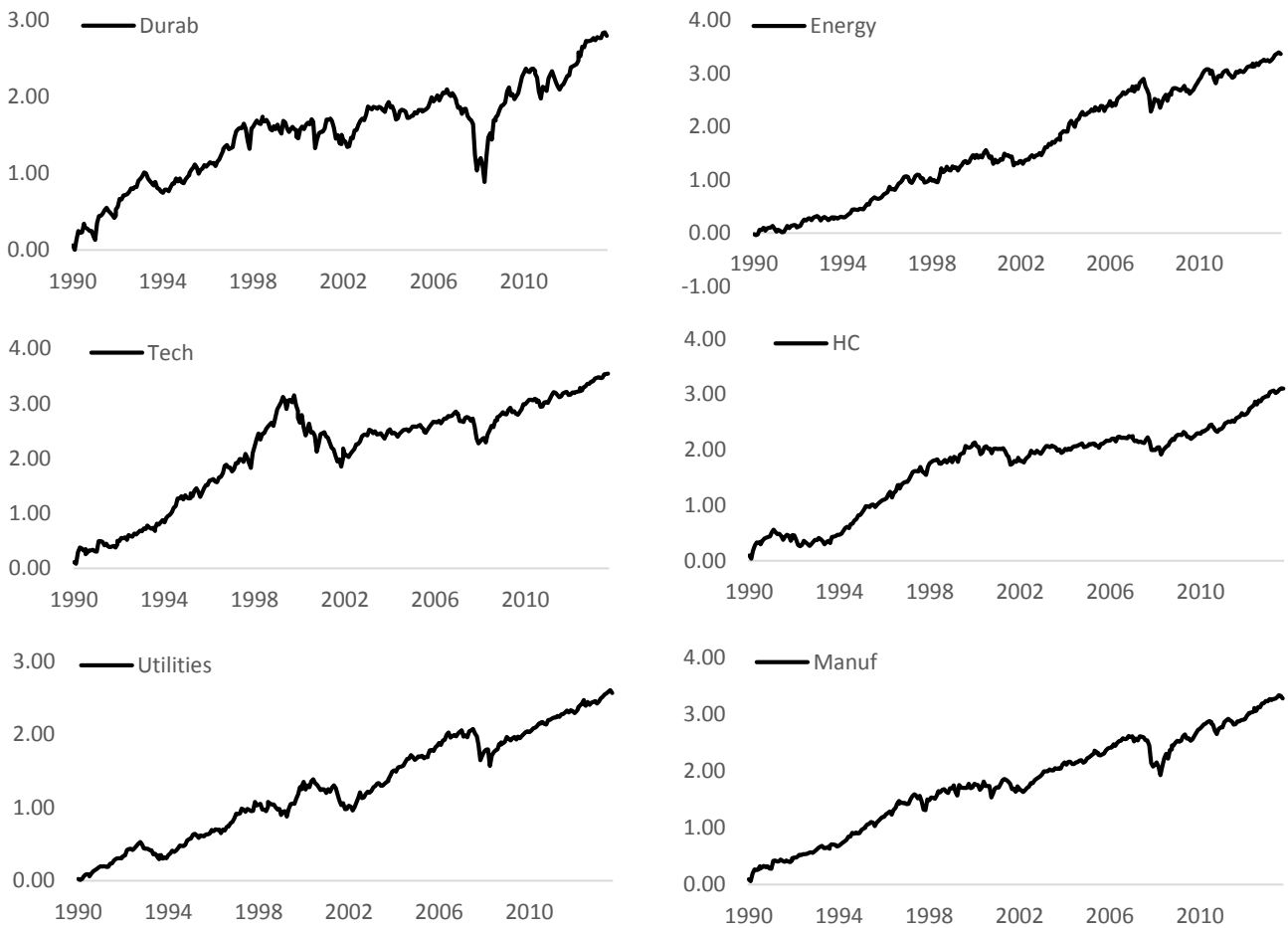
<sup>34</sup> [http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\\_library.html](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)

<sup>35</sup> See "The Business Cycle Approach to Equity Sector Investing" - *Fidelity Investments, Market Research* for a more detailed explanation

**Table A.2 – Summary Statistics for the Industry Sector Portfolios**

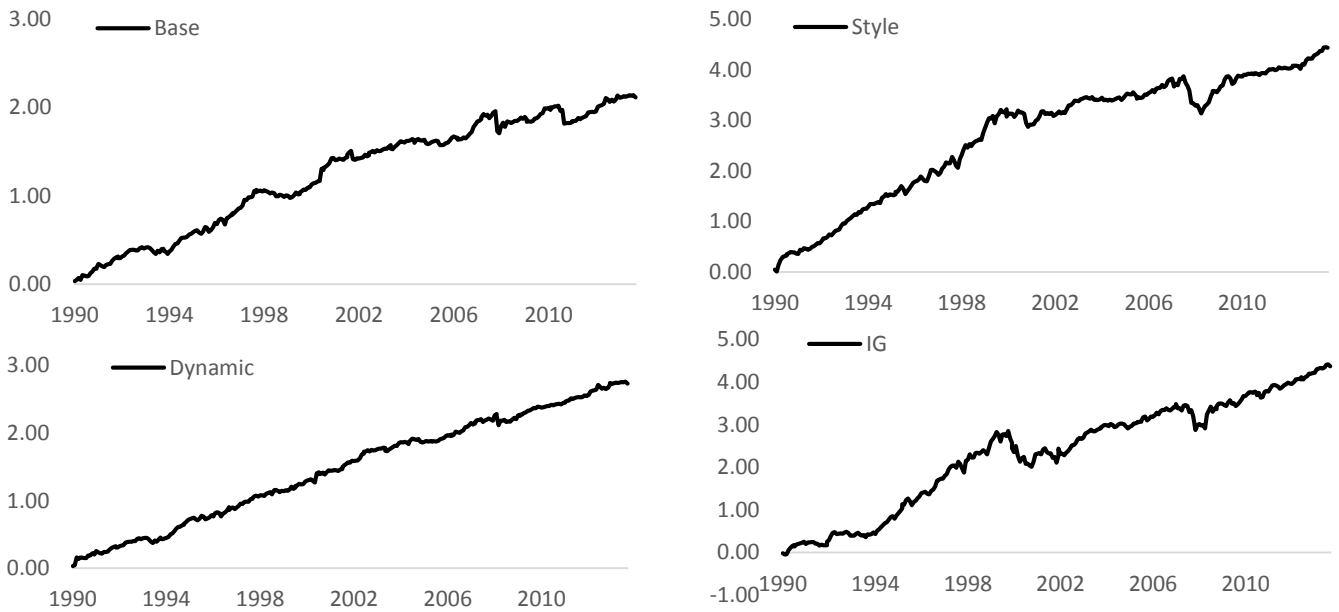
	Durable Goods	Energy	Technology	Healthcare	Utilities	Manufacturing
Annualized Average Return	11.2%	13.5%	14.2%	12.5%	10.3%	13.1%
Annualized Standard Deviation	25.9%	19.4%	24.7%	16.0%	14.4%	17.9%
Sharpe	0.43	0.70	0.58	0.78	0.71	0.73
Maximum Drawdown	-121%	-61.8%	-130%	-39.7%	-50.5%	-69.1%
Positive Months	58%	63%	61.9%	63.5%	64.5%	64.5%
Skewness	-0.42	-0.91	-0.29	-0.36	-1.19	-0.88
Kurtosis	6.19	4.09	1.91	1.12	5.52	6.36

**Figure A.2 – Cumulative Returns on a \$1 exposure to each Industry Sector**



### Appendix 3 – Returns of each strategy each regime

**Figure A.3 – Cumulative Returns on a 1\$ exposure considering each Analog Model implementation**



### Appendix 4 – Growth / Inflation matrix definition

Source: Bridgewater Associates - *“All Weather Story – How Bridgewater Associates created the All Weather investment strategy, the foundation of the ‘Risk Parity’ movement”*

The Inflation/Growth diagram is a central building block of Bridgewater’s “All Weather Portfolio” and also commonly used by practitioners. The main idea is that asset classes can offset each other during growth and inflation shocks. Furthermore, the diagram is useful to explain alpha diversification by overlapping asset allocation in growth/inflation environments.