Empirical Analysis of Regime-Focused Asset Allocation Strategies within a Markov Switching Framework

by

Alan O'Sullivan BSc., MSc.

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Head of School: Professor Joseph Coughlan

Supervisor: Professor Gregory Connor

School of Business, National University of Ireland, Maynooth

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Summary

This thesis consists of three papers examining the relationship between key macro-economic variables and optimal asset allocation strategies. We find evidence that asset prices behave differently depending upon the underlying economic regime. A regime-based asset allocation strategy seeks to integrate a full suite of securities across the full business cycle. We find additional evidence supporting the linkages in the literature between dynamic portfolio optimization and tactical rebalancing across unique state spaces. Paper 1 seeks to test and confirm whether the joint distribution of equity, fixed income and gold returns pursue a dynamic, non-linear pattern. We illustrate the benefits of utilising a time-varying, Markov-switching regime-based framework to forecast expected returns. Long-run historical monthly returns dating back to 1968 were used to assess return predictability. We adopt a unique approach for our empirical analysis amongst the existing regime-shifting literature by segmenting our full 50-year sample period (1968-2019) into three specific regimes (1968-1983), (1984-2007) & (2008-2019). We find evidence that supports the presence of a low-volatility premium. Economic regimes appear to be ordered by the intrinsic nature of their volatility. We have produced robust evidence supporting the negative risk-reward relationship between international equity markets and volatility. Our findings support the theories that exposures to gold offer attractive diversification benefits, particularly to equity investors. Across all four of the individual study sample periods monthly gold returns outperform during periods of excess volatility.

Regime classification is structured upon a combination of empirical evidence and proven economic principles. Regimes are ordered in terms of factor exposures to economic growth, inflation and volatility. We construct a 2 x 2 factor model of growth and inflation characterised by a four-quadrant internal system. These internal regimes are classified by a combination of factors. The first order effects relate to the inter-relationship or covariance between growth and inflation. The second order effects constitute the policy response to this environment. Multiple linear modelling equations are used to identify causal relationships between dependent financial assets and our predictor variables. These were split between regime-agnostic, contiguous data sampling methods and regime-specific, non-contiguous data sampling. The findings appear consistent with the prevailing macroeconomic theory that broader equity market returns outperform gold, fixed income and commodity assets during specific market regimes and that gold should

outperform the S&P500 across inflationary regimes. In paper 3 there was a focus on whether dynamic asset allocation strategies can capture enhanced portfolio opportunities through profitable sector pivots, factor exposures and optimization. We developed a unique leading indicator framework utilising statistically significant predictor variables to inform the regime-based asset allocation process. Furthermore, robustness checks were conducted across a diverse range of assets including individual equity sectors, mutual funds, tradeable assets and investment factors. This study is distinctive in its approach of utilising this Bayesian grounded leading indicator framework and in the scope of the assets used to test its robustness.

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Chapter 1. Dynamic Asset Allocation under Multivariate Regime Switching

Abstract

Portfolio construction processes seek to capture excess returns through the optimal allocation of investment assets. Security outperformance or alpha is usually extracted through market timing ability or stock selection skill. If 90% of expected return variability[1] *is determined by asset allocation, then we should seek to determine what is driving these underlying processes. A constant expected return framework fails to capture the inherent dynamism of financial markets. The literature provides robust evidence in support of the relationship between the macroeconomy and investible securities. By improving our understanding of this relationship, we can increase the optimality of portfolio construction processes through a regime-based asset allocation approach. The latter focusses on capturing the stylized correlations between individual economic state spaces and financial assets. Regime-shifting parameters are captured and assessed through a selection of Markov-shifting dynamic models. There is evidence that security returns are ordered by the associated regime volatility and diversification benefits may be secured through tactical allocation to alternative strategies.*

[1] See Brinson et al study

1.1 Introduction

The focus of Chapter 1 is to explore whether regime shifts exist and if these individual state spaces exhibit common parameter characteristics. The Markov-switching model is utilised to determine the presence of regime specific asset behaviour with the motivation of improving asset allocation modelling and accounting for investor preferences. Our probabilistic model incorporates an n-state Markov chain to govern the transition between states. In Chapter 1, several different probabilistic models are specified including a Markov-switching dynamic regression (MSDR), a Markov-switching auto-regressive regression [MSAR], a Vector-autoregressive (VAR(x)] model with exogenous variables and a Markov-switching Vector-autoregressive Model (MS-VAR). Our findings in Chapter 1 support the existing literature verifying the existence of economic regimes which influence asset pricing over repeated market cycles (Timmermann, 2012, Guidolin & Hyde, 2008). There was evidence also that the duration of each expansion and recessionary period was influenced by the underlying economic environment. In the context of portfolio construction, we found evidence supporting the theories that exposures to gold offer attractive diversification benefits. In Chapter 2, a framework is developed to capture the explicit relationship between the key economic variables of growth and inflation, and asset price performance. Following on from the full-sample analysis, the study reviewed date-specific asset performance. A cross-reference of the sample specific asset pricing data with the regime-dependent asset prices showed evidence of consistency. The annualised means and volatilities in both the sample specific and date-specific economic regimes produce very similar results. Several statistically significant predictor variables are not constant across individual economic regimes. This finding supports the thesis that predictor variables are transitory in their significance due to the shifting influence of macroeconomic variables. There is also a fluctuating relationship between the portfolio assets and predictor variables.

In the previous chapter, the results showed that macroeconomic variables including the federal funds rate, consumer price index and the unemployment rate have statistical significance in determining the underlying economic regime. If these macroeconomic variables provide informational efficiency, then optimal asset allocation should develop from an ability to forecast these macro variables with preceding sources of market information captured through leading indicators including the ISM, University of Michigan survey and others. The research seeks to identify if the model has the capacity to consistently forecast which assets are optimal at $time_{t-1}$. A dynamic factor modelling approach is utilised through a Bayesian vector auto-regression model. The Bayes rule provides a formulaic framework which captures historical or prior information and combines this with the data available. Implicit in this framework is the thesis that proactivity and tactical asset allocation produces outperformance. Detailed vector-autoregression testing is carried out to identify statistically significant economic variables across multiple sample periods. For robustness several proxy assets where included in our analysis to test the consistency of the relationships between the assets and underlying economic regimes. This involved the incorporation of asset specific mutual funds, sector-specific equities, factors and the traditional assets themselves. We identified robust evidence of consistency in the relationship between asset-specific investment preferences and the underlying economic regime. A composite leading indicator framework of business and consumer indexes was constructed to forecast the underlying economic regime shifts. Back testing was utilised to examine the accuracy of our model across multiple regimes of the 50-year sample period. Our results supported the earlier findings of optimality through regime-based asset allocation.

Brinson et al., [1991] declared broadly that the asset allocation decision-making framework symbolized the primary input of importance in determining optimal portfolio construction. We argue instead that asset allocation need not be considered in isolation. To prove optimal, the process should take account of inherent regime shifts that are dynamic in nature. This paper employs a Markov-switching model approach to emphasise the important impact of external market environments [regimes] on the asset allocation processes. Through a detailed empirical investigation of 50 years of data, this paper examined the profitability profiles of static asset allocation models and regime-shifting approaches. Asset valuation in isolation provides an insular framework and lacks completeness. Regimes offer a comprehensive opportunity to assess layers of assets across multiple timeframes. These capture important insights into the properties of return distributions. Regime shifting models facilitate the capture of valuable information and classify regimes with different mean, variance and correlations across assets. Nominal equity returns are typically forecast to yield 7 to 8% per annum[2]. These projections are based off historical data covering almost a century of returns. It is important to emphasize

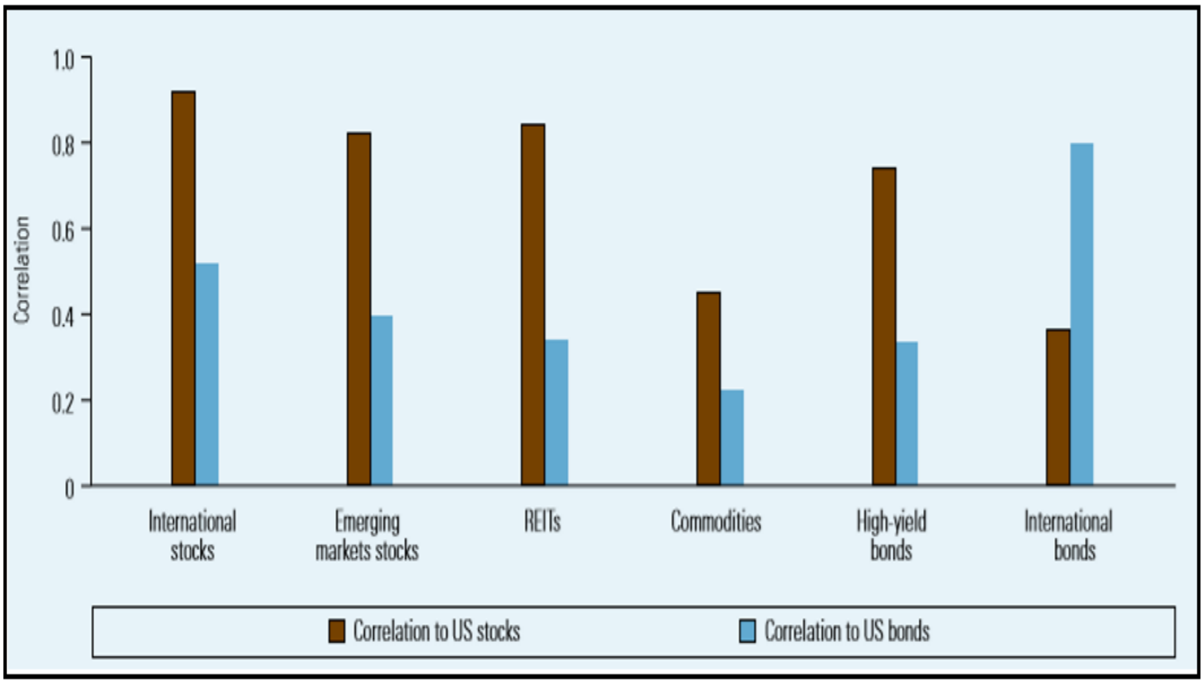
[2] Elroy, Dimson & March, (2002) *Triumph of the Optimists*

the concentrated origin of these returns during the most recent forty-year period[3] . This paper will argue that portfolios should not be constructed through static asset allocation modelling that fails to acknowledge prevailing regimes. Asset allocators should take account of dynamic market regimes which shift and manipulate asset prices through a complex network of economic inputs. The basis for this analysis is not controversial. Financial history provides potent evidence[4] that assets perform and react differently as market regimes change. A narrow focus on pure asset distribution fails to adequately prepare for the innate gyrations of market volatility across the business cycles. The focus of the study will be the examination of a regime-based asset allocation strategy that seeks to provide superior risk-adjusted performance against a range of traditional allocation models. The Great Financial Recession (GFR) exposed deep flaws in the traditional mean-variance optimization process. As Figure 1 illustrates, asset correlations turned positive as distress in the financial system increased and widely held beliefs around traditional diversification were left exposed.

[3] A brief synopsis of this period is instructive in conveying the attributes of secular-based asset allocation. In 1981 the federal funds rate peaked at 19%. This secular peak in interest rates coincided with almost 80 million of the *"baby boomer"* generation entering the workforce. This tailwind of human capital flushed through the system resulting in rising asset prices, decreasing interest rates and a debt-fuelled expansion. Almost forty years later the financial environment has shifted encompassed by historically low interest rates, $17 trillion in negative yielding debt, historically elevated asset prices and burgeoning debt-to-GDP ratios. Many of the so-called "Baby Boomer" generation who fuelled much of this extraordinary secular growth regime are now retiring or approaching retirement. This enormous shift in production capacity may fuel the next deflationary secular regime as $28 trillion in retirement assets are extracted. Ageing demographics in the developed world economies on top of rising hostilities against capitalism as a construct may further fuel deflationary pressures[3].

[4] Refer to Appendix

Figure 1.1: Naïve Diversification during the GFR



Source: JP. Morgan Guide to the Markets, 2021

Figure 1.1 displays the correlations between traditional asset classes such as US stocks/US bonds and alternative assets including REITs, Commodities and Credit during the 18-month period of the 2007/2009 Global Financial Crisis. We note several key observations. The correlation between US stocks and International/ Emerging stocks is almost 1 during this stressed environment. In addition, growth proxy assets (REITs & HY Bonds) with similar characteristics to equities also have very positive correlations with US stocks. Perhaps most surprising is the positive correlation between US bonds and equity markets with international stocks, emerging stocks and REITs indicating a 0.5, 0.4 and 0.35 correlation to US bonds during this period.

This research places secular growth regimes as the predominant factor input in asset allocation methodologies. From a regime perspective, it is evident that a sizeable proportion of assets were levered to long GDP right at the peak of the market correction. Many portfolios were highly dependent upon a precarious combination of short volatility[5] and positive secular growth strategies. The fallout from the GFR led to a period of introspection on why individual assets failed to provide protection through traditional diversification methods. Kaminsky (2011) has coined the phrase "*crisis alpha*" to describe a particular sub-set of assets that provide positive outperformance opportunities during such stressed environments. The crucial point of Kaminsky's thesis is that a fundamental re-think is required regarding how to factor diversification into portfolios. Instead of focussing on how asset A reacts or co-varies with asset B, the approach should focus more attention on how asset A & B individually respond to the underlying economic regime. The starting point for robust diversification, should be to identify assets that

[5] Investment strategy which explicitly profits in an environment of low volatility

flourish during prolonged periods of uncertainty, crisis and market volatility. The distinction between negative volatility cycles and positive volatility cycles is an important one. The former is associated with behavioural heuristics including fear, anxiety and distress. Positive volatility cycles are characterised by strong human emotions such as over-confidence, irrational exuberance and greed[6]. Recognition of these powerful behavioural sentiments is central to gaining deeper insights through the portfolio formulation process. Recency bias, from a portfolio construction perspective, may be defined as the negative implications associated with assigning future investment performance to a short window of historical asset pricing. The academic literature is littered with studies pointing to superior equity market returns post 1980. This is problematic for two reasons. Firstly, the notion that the consensus knowledge on investing should be informed through such a historically short window of time is not statistically robust. Secondly, asset price modelling which fails to capture regime-based factors implicitly ignores vital information that could enhance risk-adjusted performance.

Investors are not a homogenous collection of market participants. Their individual objections span a myriad of investor horizons, timelines and risk profiles. Thus, there may be a temptation to analyse portfolios within a narrow window that encapsulates just one generation of asset accumulation. This paper will contend that shorter periods of time-series analysis do not offer a microcosm for broader timeframes. As such, there remains a requirement to assess mainstream asset classes across multiple business cycles and market regimes. There is a responsibility to assess performance across the entire record of returns. Secular trends may distort asset performance leading to inaccurate extrapolation of past performance on future returns. The most recent forty-year period in capital markets offers a useful illustration to support this point. This period has been characterised by generational lows in volatility across asset classes, secular lows in price trend as well as secular lows in interest rates. The twenty-three-years leading up to the GFR was an incredible period of asset price growth. In fact, the relatively short period between 1984 and 2007 contributed to 90% of the total return of the historic 60/40 portfolio[7]. Many of the leading studies on international asset allocation focus their

[6] Kahneman, D. (2011) “Thinking, Fast and Slow”

[7] Cole, C. (2017) “Allegory of the Hawk and the Serpent”, Artemis Capital
A number of instrumental variables fuelled this asset appreciation including increased globalisation, technological advancement, secular declines in interest rates and the baby boomer’s phenomenon. Each of these factors was highly inflationary which fuelled equity markets during this period.

analysis on asset pricing during this period. This paper seeks to raise concerns with the approach of extrapolating expected portfolio performance from such biased, concentrated regimes. We will argue that this narrow focus may be storing up potential risks into the future.

1.2 Conditional & Unconditional expectations

The *constant* expected return framework neglects to decipher the *time-varying* nature of asset returns. If equity risk dominates most investor portfolios, this constant expected return framework may cultivate latent under-appreciation of portfolio volatility . This relates to the smoothened profile of constant expected returns. A common trend emerges across the literature applicable to regime-shifting modelling, namely that the joint distribution of equity and fixed income returns pursue a dynamic, non-linear pattern. The research advocates the benefits of focussing on time-varying returns. We use long-run historical data on security valuations and returns to assess return predictability. If the concept of time-varying returns appears plausible, then the onus should shift towards asset pricing models that capture the irregular characteristics of asset prices. We therefore utilise a regime-shifting *Markov* model to facilitate such analysis. In chapter one, we seek to explore whether regime shifts exist and if these individual state spaces exhibit common parameter characteristics. Can we distinguish between a secular generational regime and the normal business cycle? If so, what are the implications for asset allocation and investor preferences? Utilising a Markov-shifting regime model, we allow the states to be observable to investors who filter state probabilities from return distributions. Whilst we are unable to identify each state directly, we can focus our attention on the regime-shifting means, volatilities, cross- covariance's and autocorrelations of specific asset returns across different regimes. We cannot observe the state through the dependent variable. However, through interpretation of the parameters we can identify specific state space characteristics. Economic time series often exhibit dramatic breaks in their behaviour because of financial crises, unforeseen government policy action or so-called "black swan" events. We consider how we might capture the consequences of a dramatic change in the behaviour of a single variable y_t. Traditionally, the behaviour could be described with a simple 1st-order autoregression model. A probabilistic model is required governing the transition from S_t to S_{t2}. A Markov model is utilised as we do not observe S_t directly. Markov switching models assume that S_t is unobserved and follows a particular stochastic process namely an N-State Markov chain. The evolution of the

Markov chain is described by their transition probabilities. We only infer its operation through the observed behaviour of y_t. The parameters necessary to fully describe the probability law governing y_t include the variance [σ^2], the auto-regressive coefficients [φ], the intercepts c_1 and the state transition probabilities P_{11}, P_{22} . . . P_{NN}. We can observe the probability of being in state j given the information set t and the vector of population parameters: $\xi_{jt} = \Pr(S_t = j|\Omega_t : \theta)$

The process governing the underlying dynamics of the underlying regime is a 1st order Markov chain. Markov switching models seek to capture the asymmetry of economic activity (Hamilton, 1989), fat- tail events, non-linear probability distributions, time-invariant parameter estimation and time- varying asset premia across multiple business cycles/ regimes. In chapter one, we specify a number of different probabilistic models including a Markov-switching Dynamic regression [MSDR], a Markov-switching Auto-regressive regression [MSAR], a Vector-autoregressive [VAR(p)] model with exogenous variables and a Markov-switching Vector-autoregressive Model [MS- VAR].

We estimate the parameters of our Markov-switching models through Maximum Likelihood. We estimate θ by updating the conditional likelihood utilising a nonlinear filter. Following the Hamilton [1989] approach, we weigh the conditional densities by their individual probabilities to determine the marginal density of y_t. The assets selected include the S&P500, Nikkei225, Gold and the 10 Year US Treasury return. The analysis is segmented across both the full 50-year sample period [1968-2019] and three specific regimes [1968-1983], [1984-2007] & [2008-2019]. The primary purpose of segmenting our sample period was to identify whether the parameters were indeed consistent across multiple regimes. Whilst it may be difficult to identify the regimes against the standard means, the volatility (σ^2) estimates offer some useful insights. We can legitimately assume that the regimes are ordered by the intrinsic nature of their volatility. Regime 1 or s_1 is clearly a lower volatility regime whereby the second regime s_0 captures a classical bear market scenario for asset returns. We have produced strong evidence supporting the negative risk-reward relationship between international equity markets and volatility. Lower volatility regimes which may [for simplicity] be categorised as "*Bull markets*", consistently provide superior risk-adjusted returns for equities. The primary research question of this paper is to identify whether asset allocation may be optimised by investing in assets that consistently offer negative correlation features over different economic regimes. We find evidence supporting the theories that exposures to gold offer attractive diversification benefits, particularly to equity investors. Across all four of the individual study sample periods monthly gold returns outperform during periods of excess volatility. It is interesting to note that Gold outperforms the S&P500 over the 50-year sample of monthly returns.

The history of financial markets may best be analysed through individual regimes or state spaces of economic activity. Quite often such activity is compatible with changes in public policy conditions, regulatory environments and a multitude of additional secular changes. The ability to capture abrupt changes in financial market data and their subsequent persistence through regime shifting models has interested participants in both economic policy areas and asset allocation. *Ang & Timmermann* (2012) point to obvious policy mandate changes within the Federal Reserve from 1979 to 1982 culminating in a secular shift in the level of interest rates. These models assist in identifying the stylized behaviours of asset prices including time-varying correlations, fat tail distributions, heteroskedasticity and skewness. Empirical analysis of their returns over extended periods produces useful information from which specific time-orientated market relationships are derived. This study will focus particular attention on the regime-shifting means, volatilities, cross-covariance's and autocorrelations of specific asset returns across different regimes. Equity market risk-premia is a fundamental pillar of portfolio construction. Academic studies highlight the tactical benefits of over-weighting stock exposures over medium and longer-term investment horizons. Whilst these studies acknowledge the pivotal role that equities play in optimal asset allocation, there is growing recognition that longer-term historical performance conceals short-term underperformance and volatility traps[8]. The analysis of extensive data sets of historical equity returns reveals some interesting insights. It is important also to underscore the significant impact that certain heuristics and behavioural biases have on the historical record. Both *survivorship* and *success* biases should discount the weighting attributed to future outcomes or the extrapolation of expectations from present valuations. The prevailing consensus around annualised nominal equity returns gravitates towards the historical mean. The principal flaw with this central metric relates to an assumption surrounding *constant* expected returns. The *constant* expected return framework neglects to decode the *time-varying* nature of asset returns. This heavy assumption contradicts the stochastic nature of equity market probability distributions. Combined with recency bias[9],

[8] *Volatility trap* refers to a period of excessive market drawdown immediately after investor entry

[9] *Recency Bias* describes a negative investor sentiment by-product of assigning high probability asset return outcomes with the most recent historical returns

this framework may produce protracted periods of inferior expected returns. If equity risk dominates the majority of investor portfolios, a constant expected return framework implies latent under-estimation of portfolio risk. This relates to the smoothened profile of constant expected returns. This paper advocates the benefits of focussing on time-varying expected returns. We use long-run historical data on security valuations and returns to assess return predictability. As referenced by *Illmanen (2011)*, equity markets appear unique in their association with the historical record. For instance, fixed income and real estate analysts acquire their estimates of expected returns from market yields and rent/capital flows respectively. These are tangible, quantifiable units of measurement. In comparison, equity analysts shun dividend yields when assessing the long-run expected returns. If the concept of time-varying returns appears plausible, then the onus should shift towards asset pricing models that capture the irregular characteristics of equity market pricing dynamics. We therefore utilise a regime-shifting *Markov* model to reveal the time-varying nature of equity returns.

1.3. Literature Review

1.3.1 ***Constant Equity premium framework***

Sharpe's (1964) standard asset pricing model in financial theory encompassed a 1-period approach and implied a constant equity premium. Fama (1965) & Samuelson (1965) similarly produced a constant expected returns framework via the random walk model of asset pricing. Merton (1973) embodied conventional linear asset pricing modelling which focussed on a somewhat monotonic risk-return relationship. Growing challenges to the dominance of constant equity premiums emerged in the eighties as empirical evidence of cross-sectional inconsistencies emerged which confronted the rigidity of the CAPM and efficient markets framework. Fama & French (1989) seminal paper on observed return predictability emphasised the importance of time-varying risk premiums. They explained the variability of business cycles via the inter-section of rational and irrational market participants. Backus & Gregory (1993) examined models of time-varying risk premiums in numerical versions of dynamic asset-pricing theory. Their empirical analysis showed that the relationship could be nonmonotonic. Whitelaw (2000) produced a critique of static asset modelling. He examined the connection between expected return and volatility in a general equilibrium, exchange economy. The author incorporated two regimes characterised by shifting consumption growth practices and time-varying transition probabilities generating correlations that vary over time. Robert Shiller's (2000) work gave practical application to the predictability of equity market expected returns through his “CAPE” ratio. There is a large body of academic evidence in support of the notion of predictability in aggregate equity returns. The most common predictor variables include instruments such as the dividend yield, term spreads and the yield curve. *Keim & Stambaugh* (1986) conducted multivariate tests including several variables other than past returns to predict equity market returns. They utilised monthly excess returns on US stocks between 1930 and 1978. They noted the statistical significance of several variables including the yield spread between low-grade corporate bonds and 1-month treasury bills, the deviation of the S&P500 from its average and the level of stock prices based on “small cap” stocks. Closer scrutiny highlights deficiencies in such broad acceptance of the probable nature of equity returns. *Welch & Goyal* (2008) focus their attention on the predictive qualities of common equity valuation metrics including dividend price ratios, dividend yields, earnings-price ratios, dividend pay-out ratios and book-market ratios. The authors concentrate on the *out of sample* performance of these predictor variables. They conclude that the equity-risk premium is not predictable or readily identifiable through examination of these established valuation variables. *Ang & Bekaert* (2007) study aggregate equity market predictability in the international context focussing on returns in the US, UK, France, Germany and Japan. They conclude that both the dividend and earnings yield provide zero predictability. Utilising a simple present value model, their study covers a quarter century of returns commencing in February 1975 and concluding in December 1999. Their study does find evidence of equity market predictability in the short-term rate[10]. Pesaran & Timmermann (2002) adopt a two-stage forecasting methodology in their empirical analysis on the predictability of equity market returns. They are critical of assumptions which imply a time-invariant relationship between state variables and stock returns. Several prominent studies at the time including *Kandel & Stambaugh* (1996), *Brennan, Schwartz & Lagnado* (1997) and *Brandt* (1999) had all utilized a time-invariant forecasting methodology implying a stability of state space assumption. Pesaran & Timmermann (2002) instead emphasise the shifting nature of parameters that influence the relationship between security returns and state variables. The rationale for jumps in the parameters include shifting market sentiment or confidence,

[10] Ang & Bekaert utilized the 1-month Euro rates from Datastream as their short-term interest rate proxy

monetary policy design, market inefficiencies and black-swan events[11]. Regime switching models passing through a Markov processing framework imply some strong asset pricing assumptions. There is an embedded belief that financial markets historical performance tends to repeat and is cyclical in nature. Numerous studies support this mean reversion[12] thesis. *Fama & French* (1988b) and Poterba & Summers (1988) both find evidence of mean reversion in equity returns over longer-term horizons. Fama & French noted predictability only in periods between k=2 and k-7 years. The peak of the predictability over this long data set was noted at k=5 where β= -0.5. Therefore, a negative 10% return over five years is on average followed by a 5% positive return over the next 5 years. The Fama & French result are supportive of the "buy the dip" strategy. Poterba & Summers examined mean reversion by looking at the variance of holding period returns over different horizons – if stock returns are random iid, then variances of holding period returns should increase in proportion to the length of the holding period. However mean reversion is based upon the fundamental principle that the underlying process is stable. An interesting paradox emerges therefore whereby the theory supporting regime shifts assumes underlying conditions of stability which contradicts the very nature of regimes. Jorion (2003) used aggregate stock market indices on 30 different countries between 1921 and 1996. He found no evidence of mean reversion in real returns over 1 – 10 years. In fact, Jorion noted that the variance ratio statistics for UK/US declined with the length of the investment horizon. Some studies including *Chibb* (1998), *Pastor & Stambaugh* (2001) and *Pettenuzzo & Timmermann* (2020) have analysed stock returns through the prism of isolated and unique periods which are often determined as once-off events.

1.3.2 ***Regime switching models***

A common trend emerges across the literature applicable to regime-shifting modelling, namely that the joint distribution of equity and fixed income returns pursue a dynamic, non-linear pattern. *Ang & Bekaert* (2002) focussed their study on the benefits of international diversification. Whilst confirming that equity market correlations across global equity markets increased during highly volatile periods, the authors introduced a regime-based approach providing evidence in support of international equity diversification. *Ang & Chen* (2002) utilized a regime-based approach in identifying

[11] A Black Swan event is a metaphor coined by Economist Nassim Taleb to describe a surprise or unforeseen event which has the potential to radically shift the existing state space variables

[12] Term used to describe the phenomenon where extreme values (relative to the average) drawn from a distribution are likely to be followed by those closer to the average

asymmetric correlations between equity returns. They were able to distinguish between equity portfolio performances based on the conditional [downside] correlations during specific high volatility, low return regimes. *Garcia & Perron* (1996) adopt a variant of Hamilton's (1989) Markov switching model to rationalise the persistence of regime shifts in their auto-regressive model of ex-post real interest rates. Their results confirmed the presence of particular regime sub-sets utilising a three-regime based framework. How does one model secular regime change? This question has captured the concentration of authors and academics since *Hamilton's* seminal 1989 paper. Certain periods become observable quickly owing to the sharp nature of the policy design, environment or market shift. These are short-duration events in nature. However, their repercussions can persist in terms of second-order outcomes[13]. Much of the studies to date have focussed attention on stylized volatility trends associated with so-called *bull* and *bear* market environments (Pagan & Sossounev; 2003). RS models offer a framework however from which the stylized behaviour of asset returns, and their non-linear characteristics may be modelled. To classify specific regimes into autonomous sub-periods, we need to discriminate between time-varying parameters. The common trend in the literature is to differentiate market regimes by reference to positive or negative connotations of outcomes. A *"bad"* state for instance is routinely associated with higher risk, periods of elevated volatility, negative means and positive variance co-variances.

1.3.3 ***Regime specification***

Perhaps the most important subject for discussion in relation to model estimation is the specification of regimes. Ang & Timmermann (2012) insist that the number of regimes adopted should be based on economic reasoning. This approach has its own challenges and limitations given the latent characteristics of market regimes. In general, the response in the literature has been to minimise the number of regimes included in the estimation thereby broadening the catchment area enough to draw empirical inference. The specific baseline example encompasses a Markov-switching autoregressive model with just two regimes.[14] Whilst an obvious starting point, this paper seeks to explore additional regimes that earlier research may not have encapsulated. According to *Guidolin & Timmermann* (*2002*) four separate regimes are required to capture the joint distribution of stock and

[13] FED Chairman Volker's intervention in interest rate policy was successful in quelling inflation concerns and paved the way for a secular shift towards declining interest rates for the next 50 years back to the lower bound

[14] *N = 2 regimes captures the entire business cycle across an expansionary and recessionary phase*

bond returns. The authors assert that asset returns follow a much more complicated pathway than traditional assumptions. These often associate linear processes with stable coefficients. There is mounting evidence[15] that the joint distribution of asset returns are instead characterised by dynamic complex processes incorporating multiple regimes. Guidolin & Timmermann advance an opportunity cost framework from which to distinguish between asset returns across multiple states.[16] It is important to establish why investors need to be cognisant of market regimes and transition away from a singular focus on asset returns. Individual assets may offer leveraged opportunities for growth through concentrated allocations. The success of this strategy presumes market timing and security selection skills are in abundance. The academic evidence does not support this assumption. Furthermore, behavioural finance protagonists challenge the notion of market efficiency. Irrational market participants are continuously injecting uncertainty and volatility into the system through heuristic, emotive trading activity. Chi-Shang, Chu & Santoni (1996) utilize a volatility factor in their examination of market returns across multiple regimes. The authors contend that a six-regime based framework is necessary to accurately capture the probability distribution of equity market returns. A standardised *normal* volatility benchmark is constructed initially with regimes characterised by higher and lower degrees of volatility straddling the median range. Their findings associate the variation in the volatility of stock returns to regime shifts in returns. *Gray* (1996) constructed a generalized regime-switching (GRS) model to analyse short-term interest rates across varying market regimes. He concluded that the short-term interest rate displays shifting measures of mean reversion and alternative variants of conditional heteroskedasticity across each regime. *Guidolin and Timmermann* (2003) focus on the joint distribution of stock and bond returns embedded in a regime-switching dynamic framework. Utilising a four-state regime-based model the authors identify clear trends in the joint probability distribution of these assets. The four states include a *crash*, *slow growth*, *bull* and *bull burst* state. *Guidolin & Timmermann* identify consistent [and predictive] transitions over extended sample periods from the *crash* state to the *bull bust* state. These evolutions coincide with enhanced expected equity premia. This is unsurprising given the largely negative returns associated with negative volatility regimes.

[15] Ang & Bekaert (2002 a,b), Ang & Chen (2002), Garcia & Perron (1996) and Grey (1991)

[16] Guidolin & Timmermann characterise their regimes in terms of a *crash, slow growth, bull* and *recovery* state

Guidolin & Timmermann [2007] pursue regime-based optimal asset allocation further under a multivariate regime switching framework. Deeper differentiations are made regarding the investor asset allocations during each specific regime leading to more granularity regarding optimal investor horizons. The authors assert that welfare costs associated with ignoring regime shifting factors could be significant. *Perez-Quiros and Timmermann* (2000) seek to develop the discourse past standard measurements of asset specific risk including means and variances of returns towards higher order moments of stock returns. They utilize a Markov switching model encompassing time-varying means, variances and weights. *Chi-Shang, Chu & Santoni* (1996) identify that an asymmetrical relationship exists between equity returns and associated volatility. A six-regime based Markov switching model is utilised in their study of the value-weighted New York Stock Exchange index from July 1962 to December 1993. *Cai* (1994) sought to capture the inherent variability of financial time-series data as well as the time-varying conditional second moments within specific regimes. Engle's autoregressive conditional heteroscedasticity (ARCH) model was combined with Hamilton's regime-switching model. The study focussed on two particularly important historical periods including the oil shock of the early seventies and Fed chairman Volker's interest rate policy shift in the late seventies. The analysis confirmed that these individual regime shifts had a significant influence on the properties of the data.[17]

1.3.4 ***Risk shifting and Manager skill***

There has been substantial academic exploration[18] investigating the ability of fund managers to time markets efficiently with less research[19] completed on market volatility timing. The evidence confirms a negative relationship between fund performance and volatility over time (*Busse*, 1999). The ability to increase (decrease) beta when market volatility is low (high) has the upside of navigating investors through periods of dangerous market volatility. *Busse* (1999) produced empirical evidence supporting the view that equities and volatility (via standard deviation) are negatively correlated. The empirical evidence confirmed that funds that reduced their systematic exposure when conditional volatility was high earned higher risk-adjusted returns. *O'Sullivan & Foran* (2017) conducted a similar exercise to test the correlation between UK equities (FTSE 100)

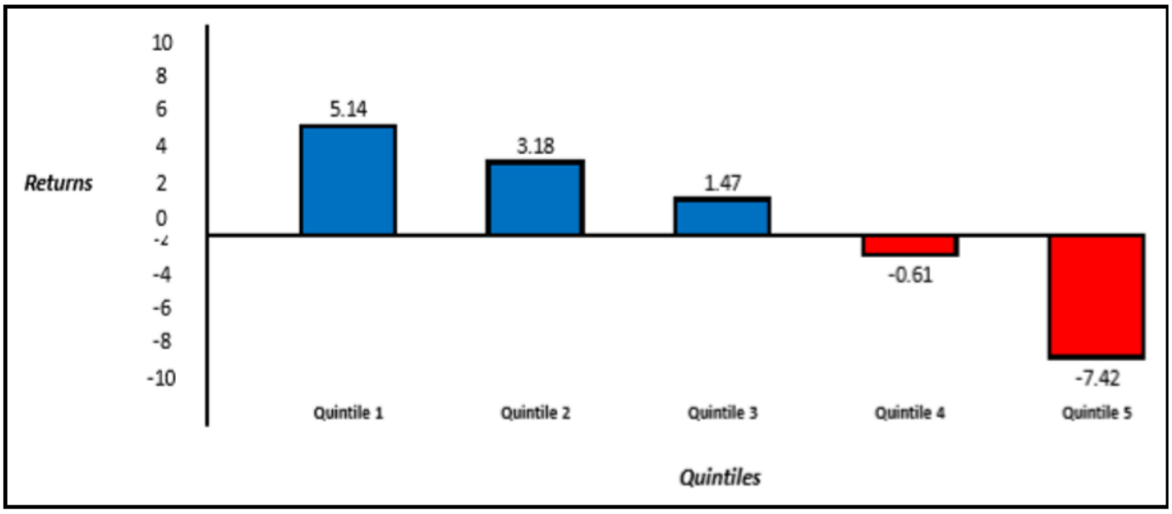
[17] Cai (1994) identified that the asymptotic variance of the Markov-Arch process for the continued realizations during the two specific regimes was more than 10 times higher than in other periods of the study.
[18] Mazuy, 1966, Henriksson, 1984 and Ferson & Schadt, 1996
[19] Apart from Busse, 1999, Giambona & Golec, 2007

and market volatility. Their UK data also exhibited a negative monthly correlation of -0.50 between January 1997 and February 2009. The evidence supports the notion therefore that market volatility timing matters. *Huang et al* (2009) investigate the performance consequences of risk shifting. Their study incorporates a sample of 2,335 U.S equity funds between 1980 and 2006. They utilised a holding-based measure during their investigation. The holding-based measure is defined as the difference between a fund's current holdings volatility and its past realized volatility. They find that active risk allocators perform *worse* than fund managers that maintain stable risk levels over time. *Huang et al* go further in producing evidence of degrees of under-performance associated with active risk allocation. Interestingly, they find evidence of inferior performance among those fund managers that focus on shifting towards idiosyncratic risk exposure. This underperformance among equity sector specialists may indicate that weaknesses lie less in their ability to time asset allocation changes and more in specific equity sector allocations. Active fund management will incur higher annualised trading costs due to the very nature of the portfolio management process. The authors try to explain the underperformance of "risk shifters" through a deeper analysis of the trading costs associated with implementing these risk-shifting strategies. The authors use fund turnover as a proxy for trading costs and sort funds into various sub-groups depending upon the level of turnover within each fund. They assign zero responsibility for the underperformance of high frequency risk allocators to increased trading costs or fund flows. They also identify three mediums through which active fund managers make risk allocation decisions. These include transitioning asset allocation between equity and cash holdings, concentrating greater equity holding in high versus lower beta stocks[20] and finally focussing on idiosyncratic portfolio tilts through sector concentration. *Baker & Haugen* (2012) conducted a comprehensive global review of the merit of holding equities form a relative risk perspective. Their study encapsulated numerous market cycles between 1990 & 2011 across 21 developed and 12 emerging economies. They concluded that a negative risk reward relationship presents in *all* developed and emerging market economies. It is interesting to note the study of active fund managers by *Clifford, Kroner & Siegel* (2001) in this context. Over a 20-year period between 1980 and 2000 covering almost 500 active funds less than 1% had an alpha greater than 5%. There is a 12.6%

[20] thereby exposing the portfolio to more systematic risks

spread between the performance of the lowest volatility (5.14) and highest volatility (-7.42)

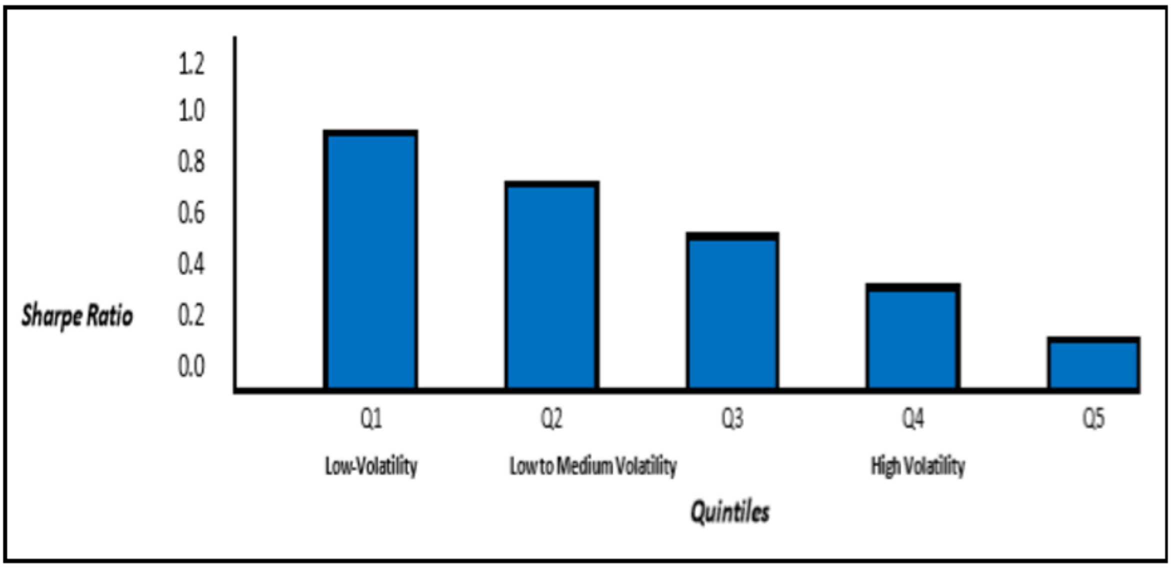
Figure 1.2: CAPM Alphas of volatility quintiles, US Equities (1970-2011)



Source: Clifford, Kroner & Siegel (2001)

Ramos & Hans (2012) focussed their analysis on the U.S equity market over the period 1970-2011. They favoured a broader assessment of the out-performance of low-volatility funds encompassing equity performance, CAPM alphas and Sharpe ratios. Standard equity returns reduce as volatility increased over the period. In fact, the lowest volatility quintiles for US equities between 1970 & 2011 exhibit the highest positive alpha recorded. Sharpe ratios which essentially measure the efficiency of returns further substantiate the "*negative risk-reward*" thesis outlined earlier. *Ramos & Hand* (2012) produced similar evidence as depicted in Figure 1.3 below.

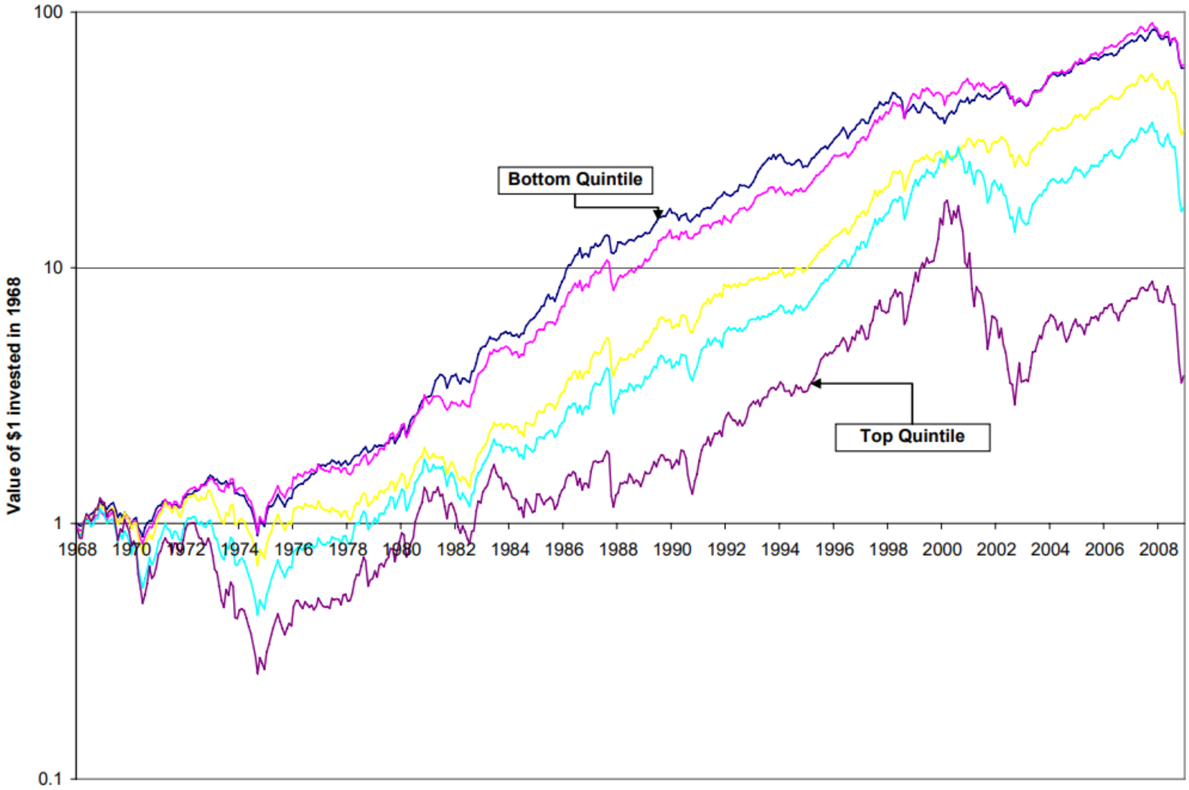
Figure 1.3: Sharpe ratios (annualised) by quintiles of volatility (1970-2011)



Source: *Ramos & Hand* (2012

Baker, Bradley & Wurglar (2011) undertook a comprehensive review of high and low volatility stocks spanning over 41 years between January 1968 and December 2008. Individual stocks were categorised into five groups determined by their total trailing volatility. Panel A (Fig.1.4) illustrates the deviating patterns of investor performance based on their preference for low-volatility versus high-volatility stocks. For instance, $1 invested in the lowest volatility portfolio (bottom quintile) in January 1968 would have appreciated to $59.55 over the forty-year period. In contrast, the same dollar invested in the highest volatility portfolio has depreciated below $1 and lost 90% of its value in real terms over the same period. The comparatively smoother investor journey for the lower volatile stocks is illustrated below.

Figure 1.4: Panel A data - $1 invested in January 1968



Source: Baker, Bradley & Wurglar (2011)

Blitz & Vliet (2006) provided further convincing international evidence of the relative out-performance of global low-volatility portfolios. Remarkably the authors recorded an annualised alpha spread of 12% between low & high volatility portfolios. The evidence was consistent across regions including the US, Europe and Japan. They observed also that there were no hidden factors to explain this relationship outside of the volatility anomaly and therefore concluded that investors were being charged an excessive premium for high-volatility stocks. Blitz & Vliet also made significant reference to the impacts of leverage restrictions and investor behaviour biases in their assessment

1.4 Estimation

1.4.1: Regime-based modelling

We are required to consider the evolution of y_t, where $t = 1, 2...T$, which is characterised by two states/regimes as set out in the models below:

$$\text{Regime 1: } y_t = \mu_1 + \varphi y_{t-1} + \varepsilon_t$$

$$\text{Regime 2: } y_t = \mu_2 + \varphi y_{t-1} + \varepsilon_t$$

The model parameters include the individual intercept terms $\{\mu_1, \mu_2\}$, auto regressive $\{\varphi_1, \varphi_2\}$ and white noise error $\{\varepsilon_t\}$ parameters with variance σ^2 across both regimes. The above models may be condensed further into equation 1 assuming that the timing component of the inherent switching mechanism is freely available. This assumption is problematic given s_t is never observable.

$$y_t = s_t\mu_1 + (1-s_t)\mu_2 + \varphi yt_{-1} + \varepsilon_t \tag{1}$$

S_t is 1 if the process resides in state 1 and 0 otherwise. If we do not observe s_t directly, we may only infer its operation through the observed behaviour of y_t. The Markov-switching framework allows the distillation of eq.1 into a simpler model whereby the unobserved s_t follows a Markov chain categorised by a state-dependent intercept term for *k* states.

$$y_t = \mu_{st} + \varphi yt_{-1} + \varepsilon_t \tag{2}$$

The single intercept term μ_{st} captures both potential regimes [i.e., $\mu_{st} = \mu_1$ when $s_t = 1$, $\mu_{st} = \mu_2$ when $s_t = 2$, ..., and $\mu_{st} = \mu_k$ when $s_t = k$]. Therefore, the parameters necessary to fully describe the probability law governing the dependent variable y_t if we assume a typical two state scenario are as follows:

- State_1 *Intercept*: μ_1
- State_2 *Intercept*: μ_2
- State_1 *AR* coefficient: φ_1
- State_2 *AR* coefficient: φ_2
- State_1 *Variance*: σ_1
- State_2 *Variance*: σ_2
- Transition Probabilities $[P_{11}, P_{22}]$

1.4.2 Model Specifications

1.4.2.1 Markov Processes

Markov switching models seek to capture the asymmetry of economic activity (Hamilton, 1989), fat-tail events[21], non-linear probability distributions, time-invariant parameter estimation and time-varying asset premia[22] across multiple business cycles and regimes. The historical record of equity returns provides useful insights. The distinguishing characteristics reveal that equities generally exhibit asymmetric fat tail distributions, and their unconditional returns are non-normal[23]. Equity volatility presents its own distinctive traits also such as volatility clustering, the notion that volatility is conditionally auto regressive, and that volatility follows an ARCH process[24]. Therefore, the equity premium is measured with substantial error and reflective of the high volatility associated with stock returns. If a variable y_t depends on its previous historical return, y_{t-1}, some random surprise element, ε_t, and some discrete regime process s_t, we can attempt to capture the particular regime following the model adopted by *Ang & Timmermann* (2012) in equation 3.

$$y_t = \mu_{st} + \phi_{st} y_{t-1} + \sigma_{st}\varepsilon_t, \qquad \varepsilon_t \sim iid(0,1) \tag{3}$$

Where.

μ_{st}: intercept

ϕ_{st}: autocorrelation

σ_{st}: volatility

It is important to specify the process organizing the underlying regime s_t. Markov processes are a general class of stochastic processes. Unlike Bernoulli & Poisson distributions which are memory-less in nature, Markov processes capture dependencies between different time periods. They describe the evolution of a system of some variables in the presence of some noise. Therefore, the motion itself is random. The new state is some function of the old state:

$N_{st} = f\,[O_{st}, \varepsilon]$

[21] Neftci (1984), Cecchetti, Lam & Mark (1990) and Pagan & Schwert (1990) also produced empirical work investigating the stylized features of equity market returns including volatility clustering, mean reversion and fat tail events

[22] A more detailed explanation of these stylized equity features are discussed in section 6.

[23] More persistent large negative outcomes than positive

[24] ARCH processes are persistent in daily, weekly and monthly data only

Where;

N_{st}: *New State*

O_{st}: *Old State*

ε: *Noise*

The *checkout counter example* is a commonly used analogy[25] to describe the properties of a Markov process. Customers arrive at the checkout counter via a Bernoulli stochastic process (P). Customers will be served for a random period of time. Likewise, this will exhibit a geometric probability distribution with parameter q. The hidden Markov process is best illustrated by imagining that a biased coin-flipping exercise takes place at each discrete time step (n). For example, one can imagine the checkout clerk hypothetically flipping coins to determine the probability that the customer's service period continues or concludes. Probability q will imply that the service has concluded, and probability 1-q means the service continues. Similarly, probability p will imply that a new customer has joined the queue and probability 1–p means that the queue size remains the same. These are geometric random variables with parameters p, q and are key inputs into the evolution of a system in the presence of random noise (*via the hidden Markov model*). A major assumption underpinning the model is that the individual Markov processes (*coin flips*) at arrival/ departure stages are independent of each other. Also, both processes are independent of each other. The primary take away from this process is that the future outcome is determined by the state of the system at that time. From the checkout counter analogy, an obvious question is whether the queue is long/empty or whether we are currently in an *expansionary* or *recessionary* phase. Therefore, the ability to capture some key information about the state of the queue at the present time may provide relevant information about the state of the queue into the future. This process lends itself to practical application or steps. Initially, we have to write down the set of possible states in our system. Next, we need to describe the possible transition probabilities between our states.

1.4.3 Finite State Markov Chains

The s_t in equation 1 describes the current situation of the state that we are looking at. We must assume that the current S_t is random [X_n = State] with n transitions after the state started operating. The set of possible states is finite. The process commences at some state x_o and then the transitions commence. The statistical distributions of these transitions are

[25] Prof. John Tsitsiklis, Massachusetts Institute of Technology

defined through a transition probability matrix [TPM]. For illustration, the conditional probability of P_{ij} may be written as:

$$P_{ij} = P(x_n + 1 = j|x_n = i) \tag{4}$$

Eq. 2 may assist in identifying whether if at the current point in time, we reside in state *i*, what the probability may be that next time, we find ourselves at state *j*. The *Markov property* states that the transition probability is not affected by past determinants of the process. The embedded assumption here is that additional information relating to the past [Eq. 5] has no bearing in making predictions about the future once we know where we are at the present time.

$$P_{ij} = P(x_n + 1 = j|x_n = i, x_n - 1,.........x_o) \tag{5}$$

Given that the Markov model places major significance on the existing state s_t, it is important to ensure that this state embodies all of the information that is relevant in determining what kind of transitions are going to occur next. We have outlined the general process for developing a Markov model here. Firstly, we must identify the possible states. Next, we should categorize the possible transitions and finally there is a requirement to isolate the transition probabilities. We will model regime changes arising from the outcome of an unobserved, discrete random variable. It is assumed that the latter follows a Markov process. Markov-switching models assume that s_t is unobserved and follows a particular stochastic process via an *N*-state Markov chain.

1.4.4: Markov Models specification

1.4.4a: **Markov-switching Dynamic regression** [MSDR]

$$y_t = \mu_s + X_t\alpha + Z_t\beta_s + \varepsilon_s \tag{6}$$

where y_t represents our dependent variable, μ_s is the regime-dependent intercept term, X_t is a vector of exogenous variables with state-invariant coefficients α, Z_t represents a vector of exogenous variables with state-dependent coefficient β_s, and ε_s is an i.i.d. normal error term. It is important to specify that the variance $\sigma^2 s$ are state dependent and lags of y_t may be expressed in both X_t and Z_t.

1.4.4b: **Markov-switching Auto-regressive regression** [MSAR]

$$y_t = \mu_{st} + \mathbf{X}_t\boldsymbol{\alpha} + \mathbf{Z}_t\boldsymbol{\beta}_{st} + \sum_{i=1}^{p} \theta_{i,st} \, (y_{t-i} - \mu_{st-i} - \mathbf{X}_{t-i}\boldsymbol{\alpha} - \mathbf{Z}_{t-i}\boldsymbol{\beta}_{st-i}) + \varepsilon_{st} \qquad (.7)$$

where y_t represents our dependent variable, μ_s is the regime-dependent intercept term, X_t is a vector of exogenous variables with state-invariant coefficients α, Z_t represents a vector of exogenous variables with state-dependent coefficient β_s, and ε_s is an i.i.d. normal error term. As with the MSDR model, the variance σ^2s are state dependent and lags of y_t may be expressed in both X_t and Z_t. $\theta_{i,st}$ is the *i*th auto-regressive [AR] term in state s_t. The intercept $\{\mu_{st-i}\}$ coefficients $\{\boldsymbol{\alpha}, \boldsymbol{\beta}_{st-i}\}$ and covariates $\{\mathbf{X}_{t-i}, \mathbf{Z}_{t-i}\}$ all represent the AR version of the variables at period t - i. A simple MS-AR model is specified below.

$$y_t = \mu_{st} + \phi_{st}y_{t-1} + \sigma_{st}\varepsilon_t, \qquad \varepsilon_t \sim iid(0,1) \qquad (8)$$

Where;

μ_{st}: intercept
ϕ_{st}: autocorrelation
σ_{st}: volatility

1.4.4c: **Vector-autoregressive Model** [VAR]

VAR(p) with endogenous variables

$$y_t = AY_{t-1} + B_0x_t + \mu_t \qquad (9)$$

Where

y_t is a K x 1 vector of endogenous variables,

A is a K x K_p matrix of coefficients,

B_0 is a K x M matrix of coefficients,

For illustration, equation 9 is highlighted with both the asset specific returns r_t and the predictor variables y_t listed below.

$$\begin{pmatrix} r_t \\ y_t \end{pmatrix} = \begin{pmatrix} \mu \\ \mu_{yt} \end{pmatrix} + A \begin{pmatrix} r_{t-1} \\ y_{t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_t \\ \varepsilon_{yt} \end{pmatrix}$$

r_t: **Asset returns**

1. $r_{t\ \mathbf{SP500}}$
2. $r_{t\ \mathbf{NIK225}}$
3. $r_{t\ \mathbf{Gold}}$
4. $r_{t\ \mathbf{10\ YrTrs}}$

y_t: **Predictor variables**

1. φ: CPI y_t^{φ}
2. β: PPI $y_{t\beta}$
3. φ: UNP $y_{t\varphi}$
4. θ: INDPRD $y_{t\theta}$
5. λ : CFNAI $y_{t\ \lambda}$

1.4.5: Likelihood function with latent states

The conditional density of our dependent variable(s) is therefore assumed to rely only on the prevailing economic regime s_t and is conveniently summarised as $f(y_t|s_t = i, y_{t-1}; \theta)$. There are *k* conditional densities for *k* states and θ represents a vector of parameters. We estimate θ by updating the conditional likelihood utilising a nonlinear filter. Following the Hamilton [1989] approach (as detailed in Appendix 1) we weigh the conditional densities by their individual probabilities to determine the marginal density of y_t.

1.5 Asset Allocation under Regime Switching

1.5.1 Data

We estimate the regime-switching models covered in section 1.3.2 on Equity returns,[26] Gold and 10-year US Treasuries. Using the model $y_t = \mu_{st} + \phi_{st} y_{t-1} + \sigma_{st}\varepsilon_t$, we assume that a variable y_t depends on its own history, y_{t-1}, random shocks, ε_t and some state-specific regime-process, s_t. The primary process determining the dynamics of each specific regime follows a Markov chain. A Markov chain represents a simple stochastic process whereby the distribution of future states depend only on the present state and not on how it arrived in the present state. A Markov model is a discrete finite system with N distinct states. At each times step t, the system shifts from its current state to the next state according to transition probabilities. The Markov property implies that these transitions are *memory-less* in so far as the future is independent of the past given the present.

Table 1.1 Parameter estimates

Table 1.6(a): Parameter Estimates
Sample Period: May 1968 – May 2019

	SP500		NIKKEI225		Gold		10 Year Treasuries	
	Estimate	Std Error	Estimate	Std Error	Estimate	Std Error	Estimate	Std Error
μ_0	-0.0029	0.0381	0.0026	0.0031	0.00062	0.0015	0.0044***	0.0009
μ_1	0.0106***	0.0017	0.0133***	0.0026	0.01739**	0.0068	0.0089***	0.0030
ϕ_0	0.1418**	0.0680	0.0512	0.0501	0.2239***	0.0506	0.0994**	0.0496
ϕ_1	0.1046*	0.0575	-0.0828	0.0879	0.3285***	0.0838	0.9300	0.0811
$\phi_{0,2}$					-0.1165 **	0.0450		
$\phi_{1,2}$					-0.1673 *	0.0861		
σ_0	0.0507	0.0033	0.0630	0.0025	0.0289	0.0012	0.0181	0.0007
σ_1	0.0232	0.0017	0.0276	0.0025	0.0744	0.0053	0.0345	0.0024
P11	0.9284	0.0317	0.9722	0.0126	0.9771	0.0099	0.9874	0.0069
P22	0.9497	0.0195	0.9383	0.0258	0.9275	0.0305	0.9617	0.0205
Dur. S1	13.974		36.018		43.708		79.65	
Dur. S2	19.897		16.232		13.803		26.17	

We report parameter estimates of the regime shifting model (Equation 1: MS-AR model) applied to the equity excess returns of the S&P500 & Nikkei225, returns on 10-Year US Treasuries and Gold. All returns are at the monthly frequency. Estimations are completed by maximum likelihood. The sample period is 1968:05 to 2019:05 for all four sets of assets.

[26] Equity returns are total returns (dividend plus capital gain) on the **S&P500** and the **Nikkei 225** in excess of Treasuries

1.5.2 Diagnostics

i. Tests for the presence of Unit roots

Our model assumes that the variables y_t and x_t are stationary. Initially, there was a requirement to check for the presence of unit roots in the raw price data. There is clear evidence of trending across most of the variables as evidenced in Table 1.5 and confirmed by the ADF tests below. Augmented Dickey-Fuller and Phillip Perron tests were conducted to test for the presence of unit roots in the data. The results indicated that the price and raw predictor data is non-stationary.

Table 1.2: **Tests for stationarity [S&P500, Gold, Nikkei 225]**

Dickey-Fuller test for unit root Number of obs = 612
Variable: SP500 Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	2.719	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.9991.

Dickey-Fuller test for unit root Number of obs = 612
Variable: GLD Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-0.242	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.9333.

Dickey-Fuller test for unit root Number of obs = 612
Variable: NIK225 Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-1.705	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.4285.

We report in Table 1.2 the results from our Augmented-Dickey Fuller tests on the raw price data for our dependent variables including the S&P500, Gold prices and the Nikkei 225. Given the results of the ADF tests for the presence of a unit root we fail to reject the null hypothesis for the presence of a unit root in the data and confirm that the **raw data is non-stationary**.

Table 1.3: **Tests for stationarity [Independent variables]**

Dickey-Fuller test for unit root Number of obs = 612
Variable: FFR Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-1.664	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.4496.

Dickey-Fuller test for unit root Number of obs = 612
Variable: PPI Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-0.733	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.8379.

Dickey-Fuller test for unit root Number of obs = 612
Variable: UNP Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-1.373	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.5951.

We report in Table 1.3 the results from our Augmented-Dickey Fuller tests on the raw price data for our independent variables including the Federal Funds rate, Producer Price index and the Unemployment rate. Given the results of the ADF tests, we fail to reject the null hypothesis for the presence of a unit root in the data and confirm that the **raw data is non-stationary**.

Table 1.4: **Tests for stationarity (Independent variables)**

Dickey-Fuller test for unit root Number of obs = 612
Variable: INPRD Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-0.370	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.9151.

Dickey-Fuller test for unit root Number of obs = 612
Variable: CPI Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	0.558	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.9865.

Dickey-Fuller test for unit root Number of obs = 612
Variable: CAPE Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-0.843	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.8061.

We report in Table 1.4 the results from our Augmented-Dickey Fuller tests on the **raw price data** for our independent variables including the Consumer Price Index, the CAPE ratio and the Unemployment rate. Given the results of the ADF tests for the presence of a unit root we fail to reject the null hypothesis for the presence of a unit root in the data and confirm that the **raw data is non-stationary**.

Table 1.5: Visual confirmation of non-stationarity in **Raw Prices** [S&P500, Gold, Nikkei 225]

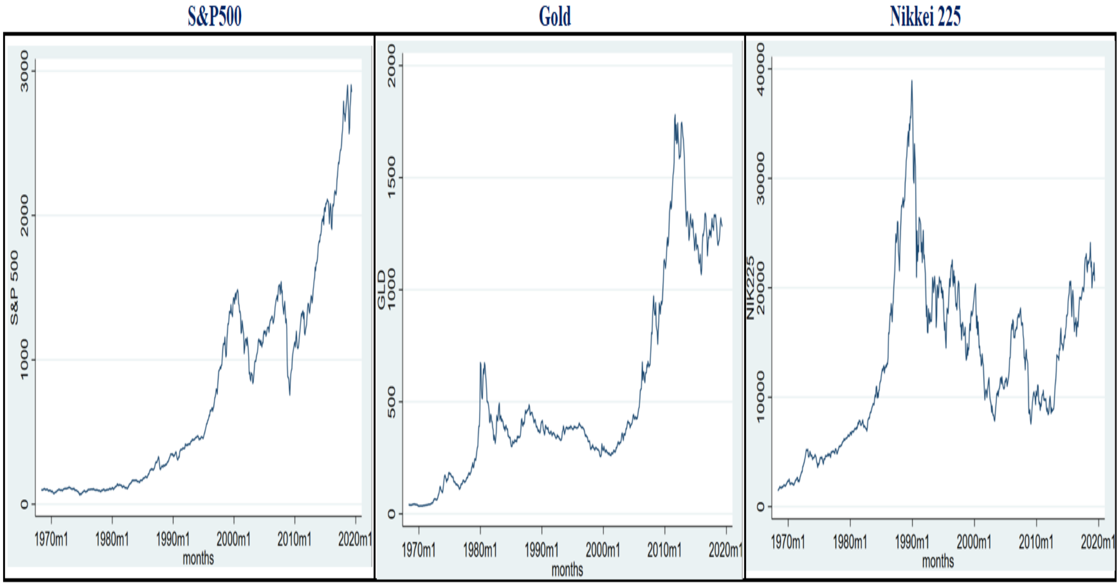


Table 1.5 displays the timeseries plots of the raw price data for the S&P500, Gold and the Nikkei225 Index. The presence of a unit root is visible through obvious trending in the data and this visual evidence supports the ADF test results on the raw price data.

Following our visual inspection and confirmation of non-stationarity, the variables were first differenced to correct for the presence of a unit root process. The Philip Perron and augmented-Dickey Fuller tests were completed. We concluded that post differencing all variables were stationary and we could proceed with the regressions. The results have been detailed below.

Table 1.6: ADF Tests on Dependent variables (S&P500, Gold, Nikkei 225)– **Post Differencing**

Dickey-Fuller test for unit root — Variable: SP500ROC — Number of obs = 612 — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-20.897	-3.430	-2.860	-2.570

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Dickey-Fuller test for unit root — Variable: GLDROC — Number of obs = 612 — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-18.614	-3.430	-2.860	-2.570

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Dickey-Fuller test for unit root — Variable: NIK225ROC — Number of obs = 612 — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-23.601	-3.430	-2.860	-2.570

MacKinnon approximate *p*-value for Z(t) = 0.0000.

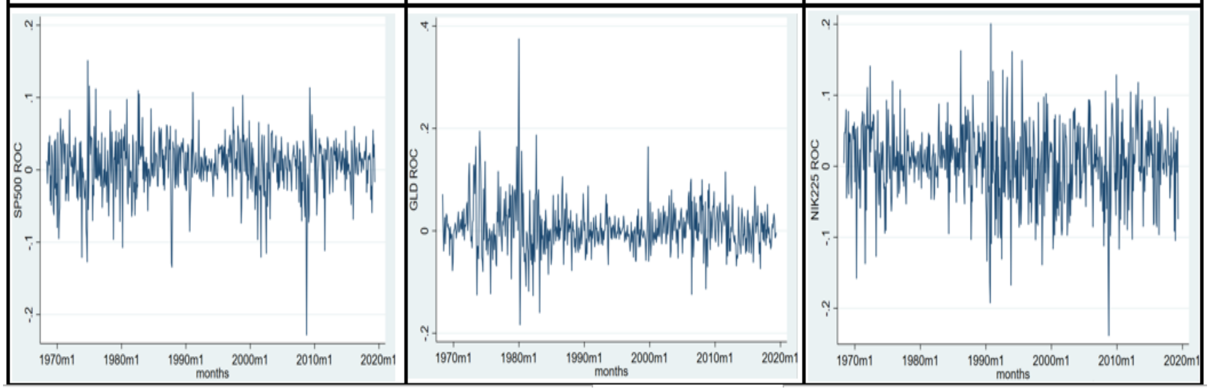


Table 1.6 displays the results of our ADF tests **post-differencing** our variables. The data is now stationary. Visual plots have been included below the ADF Output tables to show graphically that the data does not exhibit trending, positive autocorrelation or clustering.

ii Tests for the presence of Multicollinearity

The selection process for our predictor variables involved multiple regression and significance testing across both the full sample period and intermediate ranges. A short list of macroeconomic predictors were chosen for inclusion in the VAR models. There was concern about excessive correlation among the independent variables in the model. Detailed tests for the presence of multicollinearity and autocorrelation in the predictors were conducted.

Table 1.7: Correlation and Variance Inflation Factor Tests

	SP500	PPI	UNP	INPRD	CPI
SP500	1.0000				
PPI	0.8632	1.0000			
UNP	-0.3157	0.0383	1.0000		
INPRD	0.9155	0.9368	-0.2129	1.0000	
CPI	0.9003	0.9837	-0.0688	0.9718	1.0000

Variable	VIF	1/VIF
CPI	85.85	0.011648
PPI	48.52	0.020610
INPRD	29.76	0.033604
UNP	2.04	0.490853
Mean VIF	41.54	

We report in Table 1.7 the results from both our correlation analysis and variance inflation tests. There is clear evidence of positive correlation among the predictor variables in the left table. This is supported by the variance inflation factors for CPI, PPI and Industrial Production in the right-hand table.

Our primary macroeconomic predictors included the producer price index, consumer price index, industrial production and the unemployment rate. Whilst the latter does not appear to have a strong correlation with the other predictor variables, there is evidence of a strong positive correlation between CPI, PPI and Industrial production. Further statistical significance testing was carried out on alternative macroeconomic predictor variables including the federal funds rate and valuation predictors including the cyclically adjusted price-earnings ratio. Regression tests confirmed significance across the sample and sub-sample sets. Further testing for multicollinearity provided confirmation that the revised variable set did not have any multicollinearity issues and we could proceed with the vector-autoregression modelling.

Table 1.8: Correlation and Variance Inflation Factor Tests

	SP500	UNP	FFR	CAPE	CPI
SP500	1.0000				
UNP	-0.3157	1.0000			
FFR	-0.6767	0.0335	1.0000		
CAPE	0.7349	-0.5792	-0.5514	1.0000	
CPI	0.9003	-0.0688	-0.7039	0.6401	1.0000

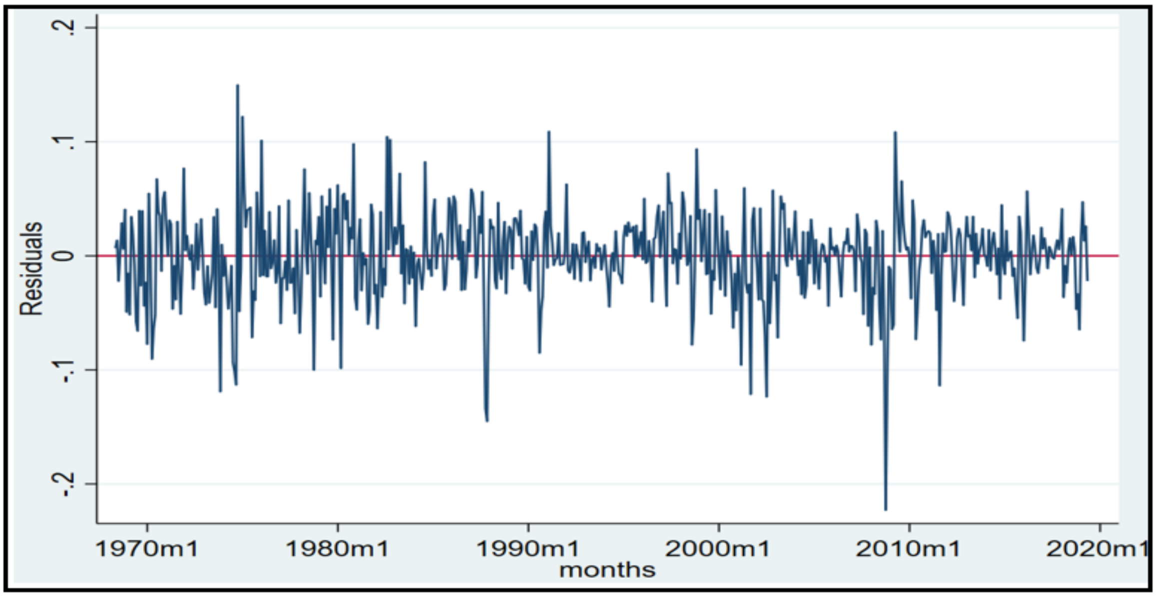
Variable	VIF	1/VIF
CAPE	3.58	0.278964
CPI	2.72	0.367803
FFR	2.15	0.465089
UNP	2.05	0.486763
Mean VIF	2.63	

We report in Table 1.8 the results from our revised correlation analysis and variance inflation tests. There is clear evidence of negative correlation among some of the predictor variables in the left table. This is supported by the variance inflation factors for CPI, Federal Funds Rate(FFR), the Unemployment Rate(UNP) and the Cyclically Adjusted Price Earnings(CAPE) ratio in the right-hand table.

iii Tests for the presence of Autocorrelation

Both the Durbin-Watson and Breusch Godfrey tests were used to detect the presence of autocorrelation in the data. We regressed our dependent variables as a function of the independent variables given our concern that the residuals were positively correlated. To provide robust statistical significance, our error terms should be randomly distributed. The Durbin Watson tests provided confirmation of zero autocorrelation with test results very close to 2. However, following the results of the Breusch Godfrey tests, we had to strongly reject the null hypothesis of zero autocorrelation. The residuals were graphed for clarity given the mixed evidence for the presence of autocorrelation amongst the residuals. The graph in figure 3 provides visual evidence of low levels of positive autocorrelation or clustering with random variation (observation by observation) across zero.

Figure 1.5: Visual evidence of Zero Autocorrelation



We report in Figure 1.5 the visual results from our graph plot of the model residuals. There appears to be very little evidence of positive autocorrelation or clustering amongst the error terms.

The original Durbin-Watson statistic provides evidence of intermediate serial correlation among the variables. The Cochrane-Orcutt procedure was used to address the autocorrelation issue. The transformed Durbin-Watson statistic in Table 1.9 of 1.983121 confirms the removal of autocorrelation in the residuals.

Table 1.9: Cochrane-Orcutt Procedure

Cochrane-Orcutt AR(1) regression with iterated estimates

Source	SS	df	MS			
Model	.01259303	4	.003148258	Number of obs	=	612
Residual	.861252571	607	.001418867	F(4, 607)	=	2.22
				Prob > F	=	0.0656
				R-squared	=	0.0144
				Adj R-squared	=	0.0079
Total	.873845601	611	.001430189	Root MSE	=	.03767

SP500ROC	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
PPIROC	.4044047	.2287701	1.77	0.078	-.0448724	.8536817
UNPROC	-.0789182	.0539919	-1.46	0.144	-.1849518	.0271155
INPRDROC	.0014397	.1036245	0.01	0.989	-.2020664	.2049457
CPIROC	-1.481051	.5989865	-2.47	0.014	-2.657389	-.304714
_cons	.0091995	.002439	3.77	0.000	.0044096	.0139895
rho	.16564					

Durbin-Watson statistic (original) = 1.671457
Durbin-Watson statistic (transformed) = 1.983121

We report in Table 1.9 the transformed Durbin-Watson statistic (1.983121) following the Prais-Orcutt procedure. The original Durbin-Watson statistic of 1.671457 is also referenced.

1.5.3 Equities

In this section our discussion will focus primarily on the results from the Markov-switching auto-regressive model detailed in equation 3. A Markov-switching dynamic regression model is included in the Appendices (Table 1.23) along with Vector Autoregressive (VAR) models (Tables 1.24 to 1.27). We can identify some common properties of regime-switching estimates from Table 1.11. In the interests of precision, two regimes have been selected. Whilst it may be difficult to identify the regimes against the standard means, the volatility (σ^2) estimates offer some useful insights. We can legitimately assume that the regimes are ordered by the intrinsic nature of their volatility. Regime 1 or s_1 is clearly a lower volatility regime whereby regime 2 (s_0) captures a classical bear market scenario for asset returns. The earliest empirical investigations covering regime switches and equity market performance noted evidence of inferior equity performance during periods of raised volatility. This "*equity puzzle*" was highlighted initially by Turner, Startz & Nelson (1989) and Hamilton & Susmel (1994). Both the S&P500 and the Nikkei225 exhibit a negative risk-return trade-off for the sample period with equities under-performing during periods of excessive volatility. It is interesting to note that whilst the scale of volatility is uniform [ranging from 2.32% to 6.3%] for both sets of equity returns, the under-performance reported across US equities during the sample period is much more severe [<0.294%> in S&P500 versus **0.26%** in **Nikkei225**]. The constant positive return in Japan is a surprise particularly when assessed against the respective durations. The Japanese Bear market lasts twice as long as their US counterpart [36 months versus 14 months in U.S]. There is mild evidence of serial correlation in the Nikkei225. It is instructive to review the summary statistics of these asset returns in Table 1.11. The mean expected monthly returns for the US & Japan are 0.55% and 0.58% respectively with an associated annualised volatility of 13.3% and 19.97%. The discrepancies noted in this initial observation of a wide sample are useful on the merits of a regime focussed approach. The regime switching model (*Eq. 5*) provides greater granularity of the return profile including the duration of negative cycle events which point to evidence of excessive market volatility in Japan. The mean returns for the Nikkei225 are obviously smoothened out across a longer sample period.

The primary purpose of segmenting our sample period was to identify whether the parameters were indeed consistent across multiple regimes. Table 1.19 provides evidence of consistency. Utilising a *Markov-switching AR* model (*Eq.5*), we sought to capture the variability of the mean returns, auto-correlation coefficients and asset return volatility. We have produced evidence supporting the negative risk-reward relationship between international equity markets and volatility. Lower volatility regimes which may (for simplicity) be categorised as "*Bull markets*", consistently provide superior risk-adjusted returns for equities. In the full sample period (612 mths) detailed in Table 1.19, a low volatility regime where annualised volatility was 8.04%[27] delivered a mean monthly return of 1.06%. If we categorise the high volatility regime as a "*Bear market*", the results are very clear also. The high volatility regime where annualised volatility was *17.56%* delivered a mean monthly return of negative <0.29%>. The regression results for the secular bull market period of 1984 to 2007 (Table 1.21) are even starker. During this period of low inflation, combined with strong growth and productivity, the low volatility regime (annualised volatility was *8.94%*) delivered a mean monthly return of 1.47%. In contrast, the higher volatility (Ann. Vol: *12.5%*) regime produced extremely poor mean returns of <4.5%> per month during this period. The *Markov Switching AR model* offers some additional insights into the specific duration of each regime. For instance, the duration of each individual bear market regime appears specific to environmental factors. One could reasonably assume that the secular bull market (1984-2007) would be dominated by lengthy periods of low volatility whilst the secular stagnationary backdrop of 1968-1983 should produce short, sharp periods of both given the heightened volatility of this period. The duration statistics in Table 1.21 appear to support the economic theory as the duration for the lower volatility regime bull market of '84-'07 is 42.3 months versus < 6 months for bear markets. There is little difference evident in Table 1.20 (1.63 vs 1.81) for the expected duration of bull & bear markets respectively for the stagflationary period between 1968 & 1984. The volatility is relatively constant during this period at 13.5%. The most recent period is interesting also when assessed from a market-timing perspective. Much has been already published regarding the folly of market timing strategies. Our study appears to support this assertion based on the comparatively large negative impacts of exposure to risk assets over a relatively short timeframe. For instance, between 1984 & 2007 (Table 1.21) and 2008 & 2019 (Table 1.22), the mean annualised monthly return during bear markets was <54%> and <17.16%> respectively. This is noteworthy against the backdrop of historically low volatility during this 35-year period and the fact that the bear market monthly durations were less than 6 & 4 months

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[27] Annualised volatility calculated by multiplying the monthly σ by SQRT(12)

respectively. It is interesting to note that whilst the mean monthly returns for the S&P500 are reported at 0.55% in Table 11, the monthly returns for the S&P500 across the 4 x Bull market regimes operate in a very tight range of 1.43% & 1.99%. Not surprisingly, bear market regimes offer much more volatility with mean monthly returns ranging from <4.5%> to <1.43%>.

The significant parameter estimates from the Nikkei225 MS-AR model relate more to its departure from the S&P500. Whilst the mean equity returns are less volatile in bear markets, the persistence of bear markets is notable. Each of the four sample periods exhibit extended bear market regimes of significant duration in comparison to lower volatility states. Most notably bear markets lasted over twice as long as bull markets between '68 & '84 (Table 1.20) and across the full sample period 1968-2019 (Table 1.19). The most recent period signals some major issues with the Japanese equity market given the variance between bear market regimes duration (34.46 mths) and the experience of lower volatility (1.33 mths). The contrasting experience of domestic U.S & Japanese investors is evident and worth noting in the context of challenging the broadly held assumption that equities always deliver positive returns.

1.4.4 Gold

The primary research question of this paper is to identify whether asset allocation may be optimised by investing in assets that consistently offer negative correlation features over different economic regimes. Precious metals are viewed as tactical safe haven strategies during periods of prolonged market volatility (Malik & Hood, 2011). We find evidence supporting the theories[28] that exposures to gold offer attractive diversification benefits, particularly to equity investors. Table 1.10 summarises the positive risk-reward relationship between periods of raised volatility and monthly gold returns. Across all four of the individual study sample periods monthly gold returns outperform during periods of excess volatility. It is interesting to note that Gold outperforms the S&P500 over the 50-year sample of monthly returns (Table 1.11). Further analysis of the regime specific mean returns in Tables 1.11-1.14 highlight the wide range of possible intra-regime monthly returns. For instance, gold performed strongly during the inflationary pressures of the secular *stagnation period* ('68 – '84) to 1.24%/mth. During this same period the

[28] Malik & Hood (2011) evaluated the role of gold as a hedge against extreme equity market volatility. The authors found that gold does offer safe haven/ negative correlation to equity market volatility. However, this relationship weakens during extreme market volatility.

S&P500 experienced its lowest performance with mean monthly returns of 0.28%/mth. During this relatively short period gold experienced double the volatility of equity returns. The durations of the low & high volatility regimes for the S&P500 and Gold are similar also in the sense that equities transitioned over very short rolling 1-to-2-month durations and Gold varied between 14 to 15 months. Over the 50-year sample the instability of gold is much more muted than equities with lower levels of volatility with durations of almost 4 years versus < 2 years for the S&P500. There is evidence also supporting the benefits of tactical asset allocating to gold positions based on the secular growth period ('84-'07). The volatility of gold during this and the most recent period has been much more subdued. There appears to be a correlation between the intrinsic volatility of gold and the duration of the regime-specific bear market. The "buy and hold" approach to equity investing would have proved a profitable strategy during this period with a low-volatility bull market lasting on average 8 times longer than its respective bear market (Table 1.21). Gold on the other hand offered brief (4.3mths) opportunities to avail of the positive risk-reward benefits of exposure during raised volatility. The most recent period ('08-'19) has highlighted the negative costs associated with holding an *insurance option* when volatility is low. Although the durations are low at just over 2 months, low-volatility gold markets have been punitive with negative monthly returns of <3.66%> (See Table 1.22). A possible explanation here may involve a rotation towards equities. Table 1.10 is utilized to synopsize the parameter estimates of Tables 1.19-1.22. As per the research to date, higher volatility equity regimes produce lower expected returns whereby higher volatility Gold & Bond regimes offer higher expected returns.

Table 1.10: Volatility regime consistency

Sample Period	S&P500	NIK225	Gold	10 Yr. TB
1968 - 2019	**HV = LR**	**HV = LR**	**HV = HR**	**HV = HR**
1968 - 1983	***	**HV = LR**	**HV = HR**	**HV = HR**
1984 - 2007	**HV = LR**	**HV = LR**	**HV = HR**	***
2008 - 2019	**HV = LR**	**HV = LR**	**HV = HR**	**HV = HR**

*** There was high volatility, lower returns in Treasury bonds during the 1984-2007 period although the difference was marginal. The relatively shorter period between 1968 & 1983 also produced countertrend results for the S&P500 with higher volatility producing higher returns.

1.5 Conclusion

This dissertation investigates the relationship between economic regimes and optimal portfolio construction. Dynamic asset allocation implies optimality is derived from interpreting the behaviour of assets at time$_{t-1}$ in advance of regime shifts as economic conditions change through the normal business cycle. This chapter has identified evidence in support of the literature proclaiming the existence of a low-volatility premium for equity investors. The Markov framework offers the opportunity to order regimes by the intrinsic nature of their volatility. This research supports the existing academic studies (Turner, Startz & Nelson (1989),Hamilton & Susmel (1994) which state that positive equity market performance is negatively correlated with high volatility economic regimes. For robustness our study encompassed both the full fifty-year sample period and individual sample periods ordered by the intrinsic nature of their specific growth and inflation dynamics. The evidence supporting the negative relationship between so-called "bear" market regimes of excessive volatility and equity performance were consistent. In addition, the research identified consistent evidence of the diversification benefits of exposure to gold during high-volatility regimes. In each of the four individual sample periods monthly gold returns outperformed during periods of excess volatility. In chapter 1 there is evidence that portfolio optimization may be increased through a reduced exposure to equities and increased exposure to gold during regimes ordered by excessive volatility.

1.6 Tables and Figures

Table 1.11: Summary statistics Asset Returns and Predictor Variables

Sample Period: **May 1968 – May 2019**

	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
S&P500	0.55094	3.8314	-22.804	15.104	-0.7501	6.4389
Nikkei225	0.5841	5.4609	-23.826	20.066	-0.3872	3.755
10 Year US Treasuries	0.61387	2.3713	-7.4118	13.2323	0.5406	5.23
Gold	0.57466	4.7611	-18.346	37.492	1.167	10.469
Federal Funds Rate	5.2629	3.8865	0.0700	19.100	0.745	3.755
Producer Price Index	0.29461	0.9205	-5.332	5.790	-0.2896	10.353
Unemployment Rate	6.143	1.626	3.400	10.80	0.6178	2.8062
Industrial Production Growth	0.18429	1.444	-6.500	4.566	-1.0172	7.7167
CPI	0.3287	0.368	-1.091	1.805	-0.0951	6.0764
CAPE Index	0.11778	3.6007	-19.522	12.445	-0.6546	5.6481
CFNAI Index	-0.2447	58.001	-2.37	2.6	0.4578	5.8802

Table 1.12: Summary statistics Asset Returns and Predictor Variables

Sample Period: May 1968 – Dec 1983

	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
S&P500	0.27983	4.42649	-12.7077	15.1043	-0.0094408	3.767856
Nikkei225	1.11978	4.3679	-15.7721	14.091	-0.4115151	4.673222
10 Year US Treasuries	0.54565	2.671	-7.4118	13.232	0.928341	6.32408
Gold	1.2376	6.7412	-18.346	37.492	1.011572	7.34739
Federal Funds Rate	8.572181	3.6745	3.2900	19.100	0.9838192	3.449441
Producer Price Index	0.58945	0.83005	-1.684	5.790	2.104211	12.43514
Unemployment Rate	6.517	1.832	3.400	10.80	0.257084	2.50285
Industrial Production Growth	0.21035	2.4388	-6.500	4.566	-0.6798362	3.02987
CPI	0.57678	0.35993	-0.40816	1.8058	0.4485256	3.163552
CAPE Index	-0.33709	3.82083	-12.569	11.37	-0.3120531	4.091513
CFNAI Index	0.44681	73.2	-2.37	2.6	0.4896495	5.271946

Table 1.13: Summary statistics Asset Returns and Predictor Variables

Sample Period: Jan 1984 – Dec 2007

	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
S&P500	0.76128	3.0368	-13.424	10.703	-0.1366377	3.565091
Nikkei225	0.31678	5.9056	-19.227	20.066	-0.1024536	2.664796
10 Year US Treasuries	0.76977	2.24891	-6.951	8.194	0.0667033	3.511025
Gold	0.26956	3.3923	-12.391	16.386	0.5320007	5.314523
Federal Funds Rate	5.297	2.362	0.9800	11.640	0.1024536	2.664796
Producer Price Index	0.19522	0.7648	-3.0116	2.918	-0.114992	5.713079
Unemployment Rate	5.682	1.0357	3.800	7.80	0.2542899	2.070926
Industrial Production Growth	0.23054	0.5083	-1.866	2.0524	-0.1549076	3.80959
CPI	0.2526	0.266	-0.8032	1.0222	-0.1526864	4.45028
CAPE Index	0.3943	3.3876	-12.486	11.203	-0.5401354	5.080666
CFNAI Index	-0.58537	52.065	-1.83	2.4	0.3056464	4.708092

Table 1.14: Summary statistics Asset Returns and Predictor Variables

Sample Period: **Jan 2008 – Dec 2019**

	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
S&P500	0.53514	3.8397	-22.804	11.352	-2.00532	12.60127
Nikkei225	0.47623	5.7655	-23.826	12.849	-0.7297489	4.471794
10 Year US Treasuries	0.34946	2.167	-5.0068	1.0127	0.7076488	5.684294
Gold	0.27082	3.6977	-11.325	11.489	0.0526721	3.342689
Federal Funds Rate	0.5942	0.7666	0.0700	2.980	1.452094	3.683454
Producer Price Index	0.08694	1.01205	-5.3326	2.986	-1.303838	7.897499
Unemployment Rate	6.5955	2.0458	3.600	10.00	0.1797377	1.604612
Industrial Production Growth	0.03143	0.75358	-4.336	1.517	-2.065864	11.96007
CPI	0.14298	0.3888	-1.9152	1.007	-1.25366	8.370146
CAPE Index	0.21334	3.6544	-19.522	12.445	-1.297767	9.327549
CFNAI Index	0.17647	45.564	-1.31	1.65	0.4859917	4.490722

Table 1.15: Two-State Markov Model Specification

Two-State Model: **May 1968 - May 2019**								
Regimes	Obs	Model Specification	Dep. Variable	Max Log-Likelihood	AIC	BIC	HQIC	Nr. of Parameters
2	611	$y_t = \mu_{st} + \phi_{st}y_{t-1} + \sigma_{st}\varepsilon_t$	SP500	1188.99	**-3.8595**	-3.8017	-3.8370	6
2	611	$y_t = \mu_{st} + \phi_{st}y_{t-2} + \sigma_{st}\varepsilon_t$	SP500	1187.82	-3.8554	-3.7831	-3.8273	8
2	611	$y_t = \mu_{st} + \phi_{st}y_{t-3} + \sigma_{st}\varepsilon_t$	SP500	1168.95	-3.7933	-3.7065	-3.7595	10
2	611	$y_t = \mu_{st} + \phi_{st}y_{t-4} + \sigma_{st}\varepsilon_t$	SP500	1168.76	-3.7923	-3.6909	-3.7529	12
2	611	$y_t = \mu_{st} + \phi_{st}y_{t-1} + \sigma_{st}\varepsilon_t$	NIKKEI225	946.22	**-3.0661**	-3.0084	-3.0436	6
2	611	$y_t = \mu_{st} + \phi_{st}y_{t-2} + \sigma_{st}\varepsilon_t$	NIKKEI225	933.57	-3.0231	-2.9509	-2.995	8
2	611	$y_t = \mu_{st} + \phi_{st}y_{t-3} + \sigma_{st}\varepsilon_t$	NIKKEI225	942.30	-3.0502	-2.9633	-3.0164	10
2	611	$y_t = \mu_{st} + \phi_{st}y_{t-4} + \sigma_{st}\varepsilon_t$	NIKKEI225	940.67	-3.0433	-2.9419	-3.0038	12
2	611	$y_t = \mu_{st} + \phi_{st}y_{t-1} + \sigma_{st}\varepsilon_t$	Gold	1111.68	-3.6068	-3.5491	-3.5843	6
2	611	$y_t = \mu_{st} + \phi_{st}y_{t-2} + \sigma_{st}\varepsilon_t$	Gold	1114.56	**-3.6156**	-3.5434	-3.5875	8
2	611	$y_t = \mu_{st} + \phi_{st}y_{t-3} + \sigma_{st}\varepsilon_t$	Gold	1113.95	-3.6130	-3.5262	-3.5792	10
2	611	$y_t = \mu_{st} + \phi_{st}y_{t-4} + \sigma_{st}\varepsilon_t$	Gold	1111.46	-3.6041	-3.5027	-3.5647	12
2	611	$y_t = \mu_{st} + \phi_{st}y_{t-1} + \sigma_{st}\varepsilon_t$	10-Year US T	1462.69	**-4.7539**	-4.6962	-4.7314	6
2	611	$y_t = \mu_{st} + \phi_{st}y_{t-2} + \sigma_{st}\varepsilon_t$	10-Year US T	1462.06	-4.7531	-4.6808	-4.725	8
2	611	$y_t = \mu_{st} + \phi_{st}y_{t-3} + \sigma_{st}\varepsilon_t$	10-Year US T	1459.56	-4.7461	-4.6593	-4.7123	10
2	611	$y_t = \mu_{st} + \phi_{st}y_{t-4} + \sigma_{st}\varepsilon_t$	10-Year US T	1457.04	-4.7391	-4.6376	-4.6996	12

Table 1.16: Two-State Markov Model Specification

Two-State Model: **May 1968 - Dec 1983**								
Regimes	Obs	Model Specification	Dep. Variable	Max Log-Likelihood	AIC	BIC	HQIC	Nr. of Parameters
2	187	$y_t = \mu_{st} + \phi_{st} y_{t-1} + \sigma_{st}\varepsilon_t$	SP500	322.95	**-3.3685**	-3.2302	-3.3125	6
2	186	$y_t = \mu_{st} + \phi_{st} y_{t-2} + \sigma_{st}\varepsilon_t$	SP500	320.91	-3.3432	-3.1698	-3.2729	8
2	185	$y_t = \mu_{st} + \phi_{st} y_{t-3} + \sigma_{st}\varepsilon_t$	SP500	327.23	-3.4079	-3.1900	-3.3232	10
2	184	$y_t = \mu_{st} + \phi_{st} y_{t-4} + \sigma_{st}\varepsilon_t$	SP500	323.38	-3.3628	-3.1182	-3.2637	12
2	187	$y_t = \mu_{st} + \phi_{st} y_{t-1} + \sigma_{st}\varepsilon_t$	NIKKEI225	336.67	**-3.5152**	-3.3770	-3.4592	6
2	186	$y_t = \mu_{st} + \phi_{st} y_{t-2} + \sigma_{st}\varepsilon_t$	NIKKEI225	336.48	-3.5105	-3.3371	-3.4402	8
2	185	$y_t = \mu_{st} + \phi_{st} y_{t-3} + \sigma_{st}\varepsilon_t$	NIKKEI225	325.89	-3.3935	-3.1846	-3.3088	10
2	184	$y_t = \mu_{st} + \phi_{st} y_{t-4} + \sigma_{st}\varepsilon_t$	NIKKEI225	333.47	-3.4726	-3.2279	-3.3734	12
2	187	$y_t = \mu_{st} + \phi_{st} y_{t-1} + \sigma_{st}\varepsilon_t$	Gold	276.97	-2.8767	-2.7385	-2.8207	6
2	186	$y_t = \mu_{st} + \phi_{st} y_{t-2} + \sigma_{st}\varepsilon_t$	Gold	277.06	-2.8717	-2.6982	-2.8014	8
2	185	$y_t = \mu_{st} + \phi_{st} y_{t-3} + \sigma_{st}\varepsilon_t$	Gold	278.33	**-2.8792**	-2.6704	-2.7946	10
2	184	$y_t = \mu_{st} + \phi_{st} y_{t-4} + \sigma_{st}\varepsilon_t$	Gold	269.92	-2.7818	-2.5371	-2.6826	12
2	187	$y_t = \mu_{st} + \phi_{st} y_{t-1} + \sigma_{st}\varepsilon_t$	10-Year US T	443.19	**-4.6545**	-4.5163	-4.5985	6
2	186	$y_t = \mu_{st} + \phi_{st} y_{t-2} + \sigma_{st}\varepsilon_t$	10-Year US T	441.16	-4.6362	-4.462	-4.5659	8
2	185	$y_t = \mu_{st} + \phi_{st} y_{t-3} + \sigma_{st}\varepsilon_t$	10-Year US T	440.58	-4.6334	-4.4245	-4.5487	10
2	184	$y_t = \mu_{st} + \phi_{st} y_{t-4} + \sigma_{st}\varepsilon_t$	10-Year US T	438.86	-4.6181	-4.3735	-4.5189	12

Table 1.17: Two-State Markov Model Specification

Two-State Model: Jan **1984 - Dec 2007**								
Regimes	Obs	Model Specification	Dep. Variable	Max Log-Likelihood	AIC	BIC	HQIC	Nr. of Parameters
2	286	$y_t = \mu_{st} + \phi_{st} y_{t-1} + \sigma_{st}\varepsilon_t$	SP500	596.22	-4.1135	-4.0112	-4.0725	6
2	285	$y_t = \mu_{st} + \phi_{st} y_{t-2} + \sigma_{st}\varepsilon_t$	SP500	595.02	-4.1055	-3.977	-4.0541	8
2	284	$y_t = \mu_{st} + \phi_{st} y_{t-3} + \sigma_{st}\varepsilon_t$	SP500	592.86	-4.0906	-3.9364	-4.0288	10
2	283	$y_t = \mu_{st} + \phi_{st} y_{t-4} + \sigma_{st}\varepsilon_t$	SP500	593.19	**-4.0932**	-3.9129	-4.0209	12
2	286	$y_t = \mu_{st} + \phi_{st} y_{t-1} + \sigma_{st}\varepsilon_t$	NIKKEI225	416.42	-2.8561	-2.7539	-2.8152	6
2	285	$y_t = \mu_{st} + \phi_{st} y_{t-2} + \sigma_{st}\varepsilon_t$	NIKKEI225	420.21	-2.8787	-2.7506	-2.8273	8
2	284	$y_t = \mu_{st} + \phi_{st} y_{t-3} + \sigma_{st}\varepsilon_t$	NIKKEI225	421.26	**-2.8821**	-2.7280	-2.8203	10
2	283	$y_t = \mu_{st} + \phi_{st} y_{t-4} + \sigma_{st}\varepsilon_t$	NIKKEI225	421.29	-2.8784	-2.6980	-2.8061	12
2	286	$y_t = \mu_{st} + \phi_{st} y_{t-1} + \sigma_{st}\varepsilon_t$	Gold	579.38	-3.9957	-3.8934	-3.9547	6
2	285	$y_t = \mu_{st} + \phi_{st} y_{t-2} + \sigma_{st}\varepsilon_t$	Gold	587.49	**-4.0526**	-3.9244	-4.0012	8
2	284	$y_t = \mu_{st} + \phi_{st} y_{t-3} + \sigma_{st}\varepsilon_t$	Gold	587.16	-4.0504	-3.8963	-3.9886	10
2	283	$y_t = \mu_{st} + \phi_{st} y_{t-4} + \sigma_{st}\varepsilon_t$	Gold	581.93	-4.0137	-3.8334	-3.9414	12
2	286	$y_t = \mu_{st} + \phi_{st} y_{t-1} + \sigma_{st}\varepsilon_t$	10-Year US T	687.22	**-4.7498**	-4.6476	-4.7088	6
2	285	$y_t = \mu_{st} + \phi_{st} y_{t-2} + \sigma_{st}\varepsilon_t$	10-Year US T	685.29	-4.7389	-4.6108	-4.6876	8
2	284	$y_t = \mu_{st} + \phi_{st} y_{t-3} + \sigma_{st}\varepsilon_t$	10-Year US T	684.91	-4.7388	-4.5847	-4.6770	10
2	283	$y_t = \mu_{st} + \phi_{st} y_{t-4} + \sigma_{st}\varepsilon_t$	10-Year US T	684.34	-4.7374	-4.557	-4.6651	12

Table 1.18: Two-State Markov Model Specification

Two-State Model: **Jan 2008 - Dec 2019**								
Regimes	Obs	Model Specification	Dep. Variable	Max Log-Likelihood	AIC	BIC	HQIC	Nr. of Parameters
2	135	$y_t = \mu_{st} + \phi_{st} y_{t-1} + \sigma_{st}\varepsilon_t$	SP500	280.92	-4.0433	-3.8711	-3.9733	6
2	134	$y_t = \mu_{st} + \phi_{st} y_{t-2} + \sigma_{st}\varepsilon_t$	SP500	282.48	-4.0669	-3.8506	-3.9790	8
2	133	$y_t = \mu_{st} + \phi_{st} y_{t-3} + \sigma_{st}\varepsilon_t$	SP500	283.43	**-4.0817**	-3.8209	-3.9758	10
2	132	$y_t = \mu_{st} + \phi_{st} y_{t-4} + \sigma_{st}\varepsilon_t$	SP500	282.99	-4.0757	-3.7700	-3.9515	12
2	135	$y_t = \mu_{st} + \phi_{st} y_{t-1} + \sigma_{st}\varepsilon_t$	NIKKEI225	209.41	-2.9840	-2.8118	-2.9140	6
2	134	$y_t = \mu_{st} + \phi_{st} y_{t-2} + \sigma_{st}\varepsilon_t$	NIKKEI225	213.79	**-3.0417**	-2.8254	-2.9538	8
2	133	$y_t = \mu_{st} + \phi_{st} y_{t-3} + \sigma_{st}\varepsilon_t$	NIKKEI225	213.03	-3.0230	-2.7623	-2.9171	10
2	132	$y_t = \mu_{st} + \phi_{st} y_{t-4} + \sigma_{st}\varepsilon_t$	NIKKEI225	201.86	-2.8465	-2.5407	-2.7222	12
2	135	$y_t = \mu_{st} + \phi_{st} y_{t-1} + \sigma_{st}\varepsilon_t$	Gold	260.76	-3.7447	-3.5725	-3.6747	6
2	134	$y_t = \mu_{st} + \phi_{st} y_{t-2} + \sigma_{st}\varepsilon_t$	Gold	258.47	-3.7087	-3.4924	-3.6208	8
2	133	$y_t = \mu_{st} + \phi_{st} y_{t-3} + \sigma_{st}\varepsilon_t$	Gold	260.64	-3.7390	-3.4782	-3.6330	10
2	132	$y_t = \mu_{st} + \phi_{st} y_{t-4} + \sigma_{st}\varepsilon_t$	Gold	265.16	**-3.8056**	-3.4998	-3.6814	12
2	135	$y_t = \mu_{st} + \phi_{st} y_{t-1} + \sigma_{st}\varepsilon_t$	10-Year US T	333.23	-4.8182	-4.6461	-4.7483	6
2	134	$y_t = \mu_{st} + \phi_{st} y_{t-2} + \sigma_{st}\varepsilon_t$	10-Year US T	333.16	-4.8230	-4.6072	-4.7355	8
2	133	$y_t = \mu_{st} + \phi_{st} y_{t-3} + \sigma_{st}\varepsilon_t$	10-Year US T	332.76	-4.8236	-4.5628	-4.7176	10
2	132	$y_t = \mu_{st} + \phi_{st} y_{t-3} + \sigma_{st}\varepsilon_t$	10-Year US T	330.48	-4.7953	-4.4895	-4.671	12
2	131	$y_t = \mu_{st} + \phi_{st} y_{t-4} + \sigma_{st}\varepsilon_t$	10-Year US T	335.59	**-4.8794**	-4.5282	-4.7367	12

Table 1.19: Parameter Estimates

Table 1.6(a): Parameter Estimates
Sample Period: May 1968 – May 2019

	SP500		NIKKEI225		Gold		10 Year Treasuries	
	Estimate	Std Error	Estimate	Std Error	Estimate	Std Error	Estimate	Std Error
μ_0	-0.0029	0.0381	0.0026	0.0031	0.00062	0.0015	0.0044***	0.0009
μ_1	0.0106***	0.0017	0.0133***	0.0026	0.01739**	0.0068	0.0089***	0.0030
ϕ_0	0.1418**	0.0680	0.0512	0.0501	0.2239***	0.0506	0.0994**	0.0496
ϕ_1	0.1046*	0.0575	-0.0828	0.0879	0.3285***	0.0838	0.9300	0.0811
$\phi_{0,2}$					-0.1165 **	0.0450		
$\phi_{1,2}$					-0.1673 *	0.0861		
σ_0	0.0507	0.0033	0.0630	0.0025	0.0289	0.0012	0.0181	0.0007
σ_1	0.0232	0.0017	0.0276	0.0025	0.0744	0.0053	0.0345	0.0024
P11	0.9284	0.0317	0.9722	0.0126	0.9771	0.0099	0.9874	0.0069
P22	0.9497	0.0195	0.9383	0.0258	0.9275	0.0305	0.9617	0.0205
Dur. S1	13.974		36.018		43.708		79.65	
Dur. S2	19.897		16.232		13.803		26.17	

Notes: The table reports parameter estimates of the regime shifting model (Equation 1: MS-AR model) applied to the equity excess returns of the S&P500 & Nikkei225, returns on 10-Year US Treasuries and Gold. All returns are at the monthly frequency. Estimations are completed by maximum likelihood. **The sample period is 1968:05 to 2019:05** for all four sets of assets. The asterisks*** represents statistical significance at the 1% level. The asterisks** represents statistical significance at the 5% level. The asterisks* represents statistical significance at the 10% level.

Table 1.20: Parameter Estimates

Table 1.6(b): Parameter Estimates
Sample Period: May 1968 – Dec 1983

	SP500		NIKKEI225		Gold		10 Year Treasuries	
	Estimate	Std Error	Estimate	Std Error	Estimate	Std Error	Estimate	Std Error
μ_0	-0.0184 **	0.0084	0.0130 ***	0.0034	-0.00045	0.0035	0.0034 **	0.0014
μ_1	0.0199 ***	0.0074	0.0107 **	0.0044	0.0166 *	0.0088	0.0074 *	0.0043
ϕ_0	0.4290 ***	0.1438	0.0130	0.0034	0.2236 *	0.1159	-0.0051	0.1021
ϕ_1	-0.2459 **	0.1223	-0.1985	0.1511	0.4575 ***	0.1050	0.1269	0.1140
$\phi_{0,2}$					-0.0898	0.0871		
$\phi_{1,2}$					-0.2640 **	0.1133		
$\phi_{0,3}$					0.2027 **	0.0883		
$\phi_{1,3}$					0.0742	0.1064		
σ_0	0.0362	0.0041	0.0189	0.0023	0.0264	0.0032	0.0143	0.0010
σ_1	0.0387	0.0042	0.0502	0.0033	0.0785	0.0067	0.0374	0.0031
P11	0.3879	0.1846	0.9570	0.0362	0.9302	0.0400	0.9816	0.0142
P22	0.4485	0.2735	0.9819	0.0151	0.9346	0.0387	0.9715	0.0223
Dur. S1	1.6339	0.493	23.3091	19.7030	14.3440	8.2400	54.391	42.010
Dur. S2	1.8132	0.8995	55.4909	46.7260	15.2980	9.0600	35.169	27.600

Notes: The table reports parameter estimates of the regime shifting model (Equation 1: MS-AR model) applied to the equity excess returns of the S&P500 & Nikkei225, returns on 10-Year US Treasuries and Gold. All returns are at the monthly frequency. Estimations are completed by maximum likelihood. **The sample period is 1968:05 to 1983:12** for all four sets of assets. The asterisks*** represents statistical significance at the 1% level. The asterisks** represents statistical significance at the 5% level. The asterisks* represents statistical significance at the 10% level.

Table 1.21: Parameter Estimates

Table 1.6(c): Parameter Estimates
Sample Period: **Jan 1984 – Dec 2007**

	SP500			NIKKEI225			Gold			10 Year Treasuries		
	Estimate		Std Error	Estimate		Std Error	Estimate		Std Error	Estimate		Std Error
μ_0	-0.0450	***	0.0092	-0.0208	***	0.0057	-0.0060	***	0.0021	0.0092	***	0.0018
μ_1	0.0147	***	0.0021	0.0352	***	0.0055	0.0077	**	0.0034	0.0067	***	0.0015
ϕ_0	0.0716		0.1427	0.2973	***	0.0897	-0.1838	***	0.0637	0.7527	***	0.0767
ϕ_1	0.0809		0.0635	-0.0465		0.0850	0.2546	***	0.0953	0.0391		0.0687
$\phi_{0,2}$	-0.3359	**	0.1509	0.2553	***	0.0835	-0.1974	***	0.0665			
$\phi_{1,2}$	-0.1066	*	0.0605	-0.3772	***	0.0686	-0.1757	*	0.0967			
$\phi_{0,3}$	-0.1287		0.1582	0.2527	***	0.0840						
$\phi_{1,3}$	-0.0505		0.0577	-0.2758	***	0.0910						
$\phi_{0,4}$	-0.6615	***	0.1699									
$\phi_{1,4}$	-0.0310		0.0541									
σ_0	0.0361		0.0052	0.0525		0.0032	0.0131		0.0024	0.0044		0.0015
σ_1	0.0258		0.0012	0.0372		0.0042	0.0398		0.0029	0.0230		0.0010
P11	0.8247		0.0771	0.4010		0.1176	0.6587		0.1048	0.0236		0.2007
P22	0.9763		0.0110	0.0851		0.0799	0.7665		0.0753	0.8725		0.0476
Dur. S1	5.7055		2.509	1.6694		0.3280	2.9303		0.9001	1.0240		0.2105
Dur. S2	42.301		19.75	1.0931		0.0955	4.2830		1.3820	7.8450		2.9300

Notes: The table reports parameter estimates of the regime shifting model (Equation 1: MS-AR model) applied to the equity excess returns of the S&P500 & Nikkei225, returns on 10-Year US Treasuries and Gold. All returns are at the monthly frequency. Estimations are completed by maximum likelihood. **The sample period is 1984:01 to 2007:12** for all four sets of assets. The asterisks*** represents statistical significance at the 1% level. The asterisks** represents statistical significance at the 5% level. The asterisks* represents statistical significance at the 10% level.

Table 1.22: Parameter Estimates

Table 1.6(d): Parameter Estimates
Sample Period: **Jan 2008 – Dec 2019**

	SP500		NIKKEI225		Gold		10 Year Treasuries	
	Estimate	Std Error	Estimate	Std Error	Estimate	Std Error	Estimate	Std Error
μ_0	0.0148 ***	0.0025	0.0108 ***	0.0002	-0.0366 ***	0.0040	0.0027 ***	0.0007
μ_1	-0.0143	0.0098	0.0107 **	0.0044	0.0135 ***	0.0037	0.0041 *	0.0022
ϕ_0	0.1890 **	0.0865	0.8646 ***	0.0040	-0.4126 ***	0.1076	-0.5142 ***	0.0252
ϕ_1	0.3785 **	0.1873	0.0281	0.7812	0.1782 **	0.0910	0.2488 **	0.1009
$\phi_{0,2}$	-0.1305 *	0.0700	0.0398 ***	0.0041	0.4910 ***	0.1135	-0.1768 ***	0.0225
$\phi_{1,2}$	-0.4135 *	0.2141	0.0487	0.0779	-0.1746 **	0.0832	-0.0774	0.1058
$\phi_{0,3}$	-0.0807	0.0655			0.2659 ***	0.0892	-0.1915 ***	0.0284
$\phi_{1,3}$	0.3864 **	0.1959			-0.2228 **	0.0968	0.1725 *	0.1046
$\phi_{0,4}$					0.3420 ***	0.0870	-0.1056 ***	0.0351
$\phi_{1,4}$					-0.0210	0.0876	0.0500	0.1011
$\phi_{0,5}$							-0.2667 ***	0.0278
$\phi_{1,5}$							-0.0237	0.1069
σ_0	0.0167	0.0024	0.0005	0.0002	0.0152	0.0022	0.0020	0.00038
σ_1	0.0529	0.0066	0.0501	0.0031	0.0293	0.0023	0.0215	0.0014
P11	0.8842	0.0602	0.2503	0.2173	0.5112	0.1254	0.000	0.0020
P22	0.7366	0.1067	0.9709	0.0151	0.8415	0.0517	0.7788	0.0530
Dur. S1	8.6385	4.4930	1.3340	0.3867	2.0461	0.5251	1.0000	0.0020
Dur. S2	3.7976	1.539	34.457	18.000	6.3095	2.0608	4.5202	1.1014

Notes: The table reports parameter estimates of the regime shifting model (Equation 1: MS-AR model) applied to the equity excess returns of the S&P500 & Nikkei225, returns on 10-Year US Treasuries and Gold. All returns are at the monthly frequency. Estimations are completed by maximum likelihood. **The sample period is 2008:01 to 2019:12 for all four sets of assets**. The asterisks*** represents statistical significance at the 1% level. The asterisks** represents statistical significance at the 5% level. The asterisks* represents statistical significance at the 10% level.

Table 1.23: Markov-Shifting AR Model - Parameter Estimates

	Sample Period: May 1968 – Dec 1983											
	SP500			NIKKEI225			Gold			10 Year Treasuries		
2- State MS-AR Model	$y_t = \mu_{st} + \alpha_{st} y_{t-1} + \varphi_{st} Z_t + \sigma_{st}\varepsilon_t$			$y_t = \mu_{st} + \alpha_{st} y_{t-1} + \varphi_{st} Z_t + \sigma_{st}\varepsilon_t$			$y_t = \mu_{st} + \alpha_{st} y_{t-1} + \varphi_{st} Z_t + \sigma_{st}\varepsilon_t$			$y_t = \mu_{st} + \alpha_{st} y_{t-1} + \varphi_{st} Z_t + \sigma_{st}\varepsilon_t$		
	Estimate		Std Error	Estimate		Std Error	Estimate		Std Error	Estimate		Std Error
μ_0	-0.1320	***	0.00057	-0.0457	***	0.0079	0.0227	***	0.0085	0.0021		0.0029
μ_1	0.0055	***	0.0013	0.0298	***	0.0003	-0.0196		0.0201	0.0171	***	0.0062
$\alpha 1$	-0.7120	***	0.0112	-2.6720	***	0.0164	0.1689		0.1074	-0.0535		0.1123
$\alpha 2$	-0.0804		0.0790	0.0256			0.3061	*	0.1855	-0.0472		0.1165
φ_0	-5.7330	***	0.0989	4.5420	***	0.2552	-6.6840	***	1.4675	0.5625		0.5059
φ_1	0.4724	**	0.2058	-1.6910	***	0.0768	5.3639		3.3763	-0.5157		1.0470
β_0	-0.1383	***	0.0257	-1.6210	***	0.0838	-0.1202		0.4881	-0.3019	*	0.1809
β_1	-0.5655	***	0.1855	-0.7557	***	0.0194	3.5296	***	1.1551	-2.5220	***	0.7879
ϕ_0	-0.7903	***	0.1120	-1.4730	***	0.0129	-0.0173		0.1157	0.0571		0.0456
ϕ_1	0.1247	***	0.0349	-0.0219	**	0.0085	0.2274		0.2863	0.3751	***	0.1095
$\theta 1$	0.2481	***	0.0151	-2.0510	***	0.0254	-0.0327		0.1527	0.0544		0.0609
$\theta 2$	-0.1378	***	0.0480	0.2373	***	0.0099	0.0490		0.3758	-0.2004		0.1708
$\lambda 1$	0.0037	***	0.0004	0.0555	***	0.0005	-0.0018		0.0062	0.00055		0.0020
$\lambda 2$	0.1583	***	0.0020	-0.0003		0.0004	0.0086		0.0092	-0.00099		0.0057
σ_0	0.0010		0.00018	0.0014		0.00031	0.0324		0.0034	0.0139		0.0010
σ_1	0.0394		0.0021	0.0358		0.0020	0.0636		0.0065	0.0319		0.0026
P11	0.41570		0.1197	0.08160		0.07080	0.8464		0.0676	0.9819		0.0140
P22	0.93626		0.0208	0.89708		0.02664	0.8167		0.0823	0.9732		0.0213
Dur. S1	1.71147		0.3508	1.08891		0.08397	6.50997		2.8677	55.2348		42.710
Dur. S2	15.68987		5.1425	9.71690		2.51600	5.45590		2.4522	37.3700		29.790

Table 1.24: Parameter Estimates May 1968 – May 2019/ May 1968 – Dec 1983

Sample Period: May 1968 – May 2019

SP500					NIKKEI225					Gold					10 Yr. TB				
		HV = LR					HV = LR					HV = HR					HV = HR		
High Vol	μ_0	Low Return	-0.29%		High Vol	μ_0	Low Return	0.26%		Low Vol	μ_0	Low Return	0.06%		Low Vol	μ_0	Low Return	0.44%	***
Low Vol	μ_1	High Return	1.06%	***	Low Vol	μ_1	High Return	1.33%	***	High Vol	μ_1	High Return	1.74%	**	High Vol	μ_1	High Return	0.89%	***
High Vol	σ_0		5.07%		High Vol	σ_0		6.30%		Low Vol	σ_0		2.89%		Low Vol	σ_0		1.81%	
Low Vol	σ_1		2.32%		Low Vol	σ_1		2.76%		High Vol	σ_1		7.44%		High Vol	σ_1		3.45%	
Dur. S1		13.97	Bear Market		Dur. S1		36.02	Bear Market		Dur. S1		43.708			Dur. S1				
Dur. S2		19.90	Bull Market		Dur. S2		16.23	Bull Market		Dur. S2		13.803			Dur. S2				

Sample Period: May 1968 – Dec 1983

SP500					NIKKEI225					Gold					10 Yr. TB				
		HV = HR					HV = LR					HV = HR					HV = HR		
Low Vol	μ_0	Low Return	-1.84%	**	High Vol	μ_0	High Return	1.30%		Low Vol	μ_0	Low Return	0.35%		Low Vol	μ_0	Low Return	0.34%	***
High Vol	μ_1	High Return	1.99%	***	Low Vol	μ_1	Low Return	1.07%	***	High Vol	μ_1	High Return	0.88%	**	High Vol	μ_1	High Return	0.74%	***
Low Vol	σ_0		3.62%		Low Vol	σ_0		1.89%		Low Vol	σ_0		2.64%		Low Vol	σ_0		1.43%	
High Vol	σ_1		3.87%		High Vol	σ_1		5.02%		High Vol	σ_1		7.85%		High Vol	σ_1		3.74%	
Dur. S1		1.63			Dur. S1		23.31	Bull Market		Dur. S1		14.34			Dur. S1		79.65		
Dur. S2		1.81			Dur. S2		55.49	Bear Market		Dur. S2		15.30			Dur. S2		26.17		

Table 1.25: Parameter Estimates

Sample Period: Jan 1984 – Dec 2007

SP500					NIKKEI225					Gold					10 Yr. TB				
HV = LR					HV = LR					HV = HR					HV = LR				
High Vol	μ_0	Low Return	-4.50%	***	High Vol	μ_0	Low Return	-2.08%	***	Low Vol	μ_0	Low Return	-0.60%	***	Low Vol	μ_0	High Return	0.92%	***
Low Vol	μ_1	High Return	1.47%	***	Low Vol	μ_1	High Return	3.52%	***	High Vol	μ_1	High Return	0.77%	**	High Vol	μ_1	Low Return	0.67%	***
High Vol	σ_0		3.61%		High Vol	σ_0		5.25%		Low Vol	σ_0		1.31%		Low Vol	σ_0		0.44%	
Low Vol	σ_1		2.58%		Low Vol	σ_1		3.72%		High Vol	σ_1		3.98%		High Vol	σ_1		2.30%	
Dur. S1		5.71		Bear Market	Dur. S1		1.67		Bear Market	Dur. S1		2.93			Dur. S1		54.39		
Dur. S2		42.30		Bull Market	Dur. S2		1.09		Bull Market	Dur. S2		4.28			Dur. S2		35.17		

Sample Period: Jan 2008 – May 2019

SP500					NIKKEI225					Gold					10 Yr. TB				
HV = LR					HV = LR					HV = HR					HV = HR				
Low Vol	μ_0	High Return	1.48%	***	Low Vol	μ_0	Low Return	1.08%	***	Low Vol	μ_0	Low Return	-3.66%	***	Low Vol	μ_0	Low Return	0.27%	***
High Vol	μ_1	Low Return	-1.43%		High Vol	μ_1	High Return	1.07%	**	High Vol	μ_1	High Return	1.35%	***	High Vol	μ_1	High Return	0.41%	***
Low Vol	σ_0		1.67%		Low Vol	σ_0		0.05%		Low Vol	σ_0		1.52%		Low Vol	σ_0		0.20%	
High Vol	σ_1		5.29%		High Vol	σ_1		5.01%		High Vol	σ_1		2.93%		High Vol	σ_1		2.15%	
Dur. S1		8.64		Bull Market	Dur. S1		1.33		Bull Market	Dur. S1		2.05			Dur. S1		1.00		
Dur. S2		3.80		Bear Market	Dur. S2		34.46		Bear Market	Dur. S2		6.31			Dur. S2		4.52		

Chapter 2. Regime Classification based on macroeconomic factors

Abstract

Once we establish that distinct economic regimes exist, we next develop a regime classification framework to investigate the persistence of these macroeconomic relationships. The academic literature provides robust evidence for the importance of economic growth and inflation in determining future financial conditions. An objective, rules-based economic regime classification framework is adopted incorporating independent measures of both growth and inflation across the fifty-year sample period. This study investigates the extent to which the underlying economic environment influences asset allocation. Using a combination of sample-specific and regime-dependent asset prices, we identify consistent performance attributes across our selected assets. The fluctuating nature of our predictor variables across economic regimes validates the view that shifting macroeconomic conditions influence asset performance behaviour over time.

2.1 Introduction

There is evidence that economic regimes exist and more importantly influence asset pricing over repeated market cycles (Timmermann, 2012, Guidolin & Hyde, 2008). In chapter one, we identified the presence of regime specific economic environments that influenced asset performance. We confirmed that market regimes appear to be ordered by the intrinsic nature of their volatility. Our results supported the academic evidence supporting the "*low-volatility*" factor or *equity puzzle* whereby stocks appear to consistently outperform during low volatility regimes. In Chapter one, we produced strong evidence supporting the negative risk-reward relationship between international equity markets and economic regimes characterised by volatility. There was evidence also that the duration of each expansion and recessionary period was influenced by the underlying economic environment. In the context of portfolio construction, our findings support the theories that exposures to gold offer attractive diversification benefits. This discovery is particularly useful to equity investors given the associated findings that high volatility regimes result in equity market underperformance. It was observed across all four of the individual study sample periods that gold outperformed in regimes of excessive volatility. There also appears to be a correlation between the intrinsic volatility of gold and the duration of the regime-specific bear market. The primary empirical findings from chapter one revealed that higher volatility equity regimes produce lower expected returns whilst higher volatility gold and fixed income regimes offered higher expected returns. If specific regimes exist, is it possible to classify these based on an economic and policy methodology? In chapter 2 we have constructed a framework that seeks to capture the explicit relationship between key economic variables including growth and inflation, central bank policy and asset prices. We develop a robust framework upon which to **classify** our individual state spaces. Regime classification is structured upon a combination of empirical evidence and proven economic principles. Regimes are ordered in terms of factor exposures to economic growth, inflation and volatility. We construct a 2 x 2 factor model of growth and inflation characterised by a four-quadrant internal system. These internal regimes are classified by a combination of factors. The first order effects relate to the inter-relationship or covariance between growth and inflation. The second order effects constitute the policy response to this environment.

This study seeks to reflect the relationship between our dependent financial assets and independent macroeconomic variables. Simple multiple linear modelling equations are used in this investigation. To identify causal relationships between dependent financial assets and our predictor variables, we conducted several multiple linear regressions. These were split between regime-agnostic, contiguous data sampling methods and regime-specific, non-contiguous data sampling. We produced summary statistics for each economic regime classification with some interesting observations. Consistent with the prevailing macroeconomic theory, broader equity market returns outperformed gold, fixed income and commodity assets during regime 1. The latter is categorised as an economic environment with rising growth and decreasing inflation. We observed that gold outperformed the S&P500 across both inflationary regimes (Reflation & Stagflation). The scale of outperformance during the stagflationary type regime was extreme with gold producing a mean annualized return of 23% versus 2.4% for the S&P500. We observed that US Treasuries produced their strongest returns in the deflationary regime. This is consistent with an economic environment where monetary policy is loosening, and bond prices are appreciating in response. Following on from our full-sample analysis, the study reviewed date-specific asset performance. We cross-referenced the sample specific asset pricing data with the regime-dependent asset price. In general, we find consistency insofar as the annualised means and volatilities in both the sample specific and date-specific economic regimes produce very similar results. We initially screened many predictor variables to assess the predictability of asset returns across several unique economic regimes. We determined that a constant relationship between our statistically significant predictor variables and asset returns across economic regimes would violate the arguments for RBAA. We observe that the statistically significant predictor variables are not constant across individual economic regimes. Can we conclude that these predictor variables are transitory in their significance due to the shifting influence of macroeconomic variables? We also observe a fluctuating relationship between our portfolio assets and predictor variables. Additional observations include the statistical significance of economic specific predictor variables. For example, regime 3 encompasses a slowing growth and rising inflation environment and we note a visible shift with the inclusion of inflation sensitive explanatory variables which were not observable across other regimes.

The data set for our study was analysed in three specific approaches. Firstly, multiple linear regressions were completed for each of the dependent variables across the full 50-year dataset (1970-2020). Next, regressions were completed with the data categorised under specific economic regimes. Finally, instead of allowing the macroeconomic environment to determine each regime, three individual sample segments of the full 50-year dataset were extracted and analysed individually. We will review each of these processes in more detail in the following sections. The main research question in chapter 2 is whether a model which utilizes these core inputs has the ability to consistently and accurately identify inflections in the performance of key factor exposures, across asset classes, 3-6 months ahead of the market consensus. The primary data signal relates to the rate of change of the underlying factor and whether it is either increasing or decreasing. The model is structured across a 2 x 2 factor model incorporating growth and inflation. This 2 x 2 factor model captures four distinctive regimes. These regimes are determined by the prevailing economic conditions. There is a third latent factor relating to government policy which is mapped in second derivative terms. A brief description of each regime is detailed below. Dynamic asset allocation seeks to capture enhanced investment opportunities through profitable sector pivots, factor exposures and optimal asset allocation. The research seeks to identify if the model has the capacity to accurately forecast which sectors are optimal at time t and time t_{+1}.

The regimes are classified as follows:

Regime 1: Accelerating Growth and Decelerating Inflation or an "*Optimal*" regime

Regime 2: Accelerating Growth and Accelerating Inflation or a "*Reflationary*" regime

Regime 3: Decelerating Growth and Accelerating Inflation or a "*Stagflationary*" regime

Regime 4: Decelerating Growth and Decelerating Inflation or a "*Deflationary*" regime

The economic factors may be summarised more intuitively in Table 2.1 below when expressed in terms of the overlying environmental market conditions.

Table 2.1: Four Quadrant Economic Regime Framework

Disinflationary boom	Inflationary boom
Disinflationary stagnation	Inflationary stagnation

A "*Disinflationary boom*" is an economic environment characterised by accelerating growth and decelerating Inflation. An "*Inflationary boom*" is an economic environment characterised by accelerating growth and accelerating Inflation. A "*Inflationary stagnation*" is an economic environment characterised by decelerating growth and accelerating inflation. Finally, a "*Disinflationary stagnation*" is an economic environment characterised by decelerating growth and decelerating inflation. There are two core principles underpinning the composition of our regime classifications. These include an appreciation of (i) how the cyclical growth environment traverses' other significant drivers of asset returns and (ii) the parameters that segment the regimes themselves. The core drivers of asset returns from a regime space perspective include *volatility*, *growth* expectations, the *discount rate* and *inflation*.

2.2 Aim of research

Our aim for this paper is to test whether a significant relationship exists between the broader macro-economic environment and optimal asset allocation. We will provide evidence that business-cycle neutral investment strategies are both static and reactive in nature. There is strong evidence that investable securities behave differently depending upon the underlying economic regime. A regime-based asset allocation strategy seeks to integrate a full suite of securities across the entire business cycle. This paper supports the view that portfolios should be rebalanced at appropriate exit and entry points from one economic regime to another.

2.3 A review of the literature

2.3.1 Relevance of Study

There is evidence that financial markets do not operate in a vacuum. On the contrary, markets move and are shaped by macro-economic forces including the changing rate of growth and inflation. Table 2.2 provides evidence in support of the thesis that assets perform differently across varying stages of the business cycle. Academic studies[29] have shown that the underlying macro-economy has a significant influence on optimal investment performance. We rank optimality of investment performance by the efficiency of the risk-adjusted return measure. Noble laureate in economic sciences, William Sharpe (1998) introduced a risk efficiency ratio that sought to capture the unit return per unit of risk undertaken. A slight adjustment is made from the return to account for the risk-free rate of return. We aim to demonstrate that the tactical portfolio adjustments arising from our interpretation of the business cycle produced stable and lower volatility outcomes. It is prudent at this point to highlight that *regime-based asset allocation* is a distinct portfolio construction methodology from crude *market-timing* applications. The latter relies exclusively on short-term market mis-pricings while the former is medium term in definition and takes a portfolio approach as opposed to a security selection emphasis.

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[29] Bhansali (2011), Farrell (2011), Blitz, Van Vliet (2008)

Implicit in a regime-based asset allocation framework is the belief that individual asset returns will vary across economic regimes leading to performance drag over the short-term. This is consistent with the works of Kollar, (2013) and Van Vliet (2008). There is extensive research in the field of expectations theory and asset price movement. Hommes et al (2008) found evidence of trend-chasing behaviour, positive feedback expectations and common group behaviours among the participants of their study. Schooley, D. & Worden, D. (1996) utilised multivariate regression analysis of the 1989 survey of consumer finances which indicated that US households' decision processes to invest| or not in risky assets relies significantly on their own expectations of risk. Campbell, J.Y & Vuolteenaho, T. (2004) studied inflation expectations and the impact on the aggregate stock market. They found that the level of inflation explained approximately 80% of the timeseries variation in equity market mispricing. It is evident that economic expectations have a marginal impact on the decision to deploy investor capital.

2.3.2 Asset Allocation

Our starting point is the distinction between various practices of asset allocation. These may be categorised in terms of static/strategic asset allocation and a more dynamic or tactical approach. Strategic asset allocation (SAA) does not distinguish between specific growth and inflation cycles. An investment thesis endorsing this approach is based upon long-term capital market assumptions, static allocations, and a constant opportunity set. Capital market expectations are determined using a combination of historical returns, simulations and future expectations based on fundamental analysis. The individual asset weights are determined by the target portfolio returns and risk budget. Once the SAA has been determined, a suitable benchmark is chosen for portfolio evaluation. The SAA approach is inherently business-cycle neutral in its approach. Tactical Asset Allocation may be defined as an investment mandate which deviates at any time from the long-term targeted asset class weights. The investment manager may seek to exploit perceived short-term mis-pricing opportunities to enhance returns. The primary philosophical distinction between strategic and tactical asset allocation resides in one of the central tenants of modern portfolio theory (Markowitz, 1952). Harry Markowitz recognised that un-systematic or diversifiable risks could be offset by the inclusion of a minimum selection of individual equities[30]. Systemic risks are un-diversifiable however and SAA provides explicit risk management by centralising investor objectives (and constraints) to their

[30] Typically, the target number of individual stocks ranges between 40 and 50

targeted exposure to systemic risk. Another major distinction rests in the view that long-term optimal asset allocation benefits more from the high-level asset allocation decision as opposed to the security selection contribution[31]. More recent research[32] in this area has argued that active management could explain up to 50% of the total return variability. Kirtzman, Page (2013) have contended that active fund management was instead the most important factor in determining optimal asset allocation. All studies referred to the selectivity bias of the data, time period selectivity and survivorship bias. Active portfolio management or Tactical Asset Allocation is centred around the assumption of superior security selection and enhanced market timing skill[33].

2.3.3 Regime based Asset Allocation

Regime-based asset allocation belongs to the breed of tactical asset allocators that seek to identify portfolio adjustments as new information becomes available. Financial markets are both dynamic and abrupt in nature. We will discuss some of these in the context of regime classifications, most notably volatility clustering, time-varying correlations, skewness and leptokurtosis. New trends also tend to persist for some time. Regime-switching models are equipped to capture this dynamism and the stylized behaviour of financial timeseries. Antti Ilmanen (2011) highlights the enormous transformation in asset allocation approaches within the investment management profession since the 1990s. Prior to 1990, the common approach to distributing assets in a portfolio was centred upon the belief in a single-risk factor, constant expected returns, a narrow focus on asset means and variances, rational participants and frictionless efficient markets. There is at least some consensus in 2022 about the market environment. Today's economic models seek to capture a world dominated by randomness[34], unpredictability, time-varying risk premia, a multitude of risk factors and skewness in returns(Kollar, 2013). The philosophical foundation of TAA is that financial markets are inefficient. If this is the case, can we reliably impose a strict SAA model framework which relies principally on asset class fundamentals and valuations. Ilmanen (2011) has completed detailed analysis on the time-varying nature of asset class risk premia. For example, from 1822 to 2002 the 20-year rolling average equity risk premium in the United States ranged

[31] Refer to Brinson, Hood, Beebower (1986), Brinson, Siner, Beebower (1991), Ibbotson, Kaplan, (2000)
[32] Refer to Ibbotson (2010), Kirtzman, Page (2013)
[33] The assumption that active fund managers routinely display superior stock selection and market timing is dubious. Research from O'Sullivan & Foran (2017) sought to differentiate between fund manager luck & skill.
[34] Taleb, N (2009) Fooled by randomness

from -2.5% to 15%. The estimated bond risk premium or advantage of holding long-duration bonds over short-duration fixed income in the United States varied from -3% to 5% between 1982 and 2010. Credit risk-premiums of owning corporate debt over sovereign debt also exhibited wide variations ranging from -0.2% to 2.1% in the US from 1920 to 2010[35].

2.3.4 Motivation

Investor Psychology

Investors are motivated more by a fear of capital loss than any potential anticipation of investment gain (Kahneman, 2011). This phenomenon has been well documented in the literature and increased the focus on behavioural finance in portfolio construction. An investor's ability to enhance their longer-term risk-adjusted returns through greater engagement with market regimes adds an additional layer of risk management. Asset allocation is the process of selecting constituents in a portfolio that produces long term optimal returns for a given risk budget. Much has been written of the importance of asset allocation to long-horizon investment returns (Brinson et al. 1986, Ibbotson & Kaplan, 2006). There has been less focus on the advantages of regime-based asset allocation. Like assets, economic regimes vary in terms of stylized behaviour across varying market cycles. The traditional strategic asset allocation (hereafter SAA) approach has profited from several structural and duration-based factors. SAA strategies have benefitted from a joint tailwind of structurally declining interest rates[36] and the secular growth trends of the last 40 years[37]. SAA has embedded time-diversification factors which also account for the historically strong performance of this investment philosophy. Exposure to duration is optimal as evidenced [Siegal 2007, Guidolin & Timmermann, 2007) in the literature. Time-weighted diversification outperforms asset-weighted diversification.

The success or otherwise of tactical asset-allocation strategies including regime-based asset allocation has much to do with the persistence of certain economic conditions. This research paper poses a further question: can we identify "optimal" and "sub-optimal" economic environments which enhance (reduce) portfolio performance in excess of the alternative all-weather asset allocation approach. It is important to distinguish between explicit market-timing strategies and tactical asset allocations more broadly. The academic evidence supporting low-volatility factors accompanied with the destructive

[35] Illmanen, A. (2011)
[36] Interest rates peaked in the early 1980's and have moved secularly lower over the last 40 years
[37] most notably the baby-boomer generation led growth of the 80s, 90's.

behaviour of investors at periods of maximum drawdown reinforce the benefits of maximising exposures to positive economic environments and limiting exposures to negative economic regimes. Sheikh & Sun, (2012) seek to differentiate tactical asset allocation from regime-based allocation (R.B.A.A) in terms of frequency and underlying economic conditions. R.B.A.A may be measured in terms of years, not months and the pivot points determining the regime shifts are linked to structural economic shifts. The portfolio weightings are determined by the specific regime and not the time horizon.

2.3.5 Business Cycle

There is now consensus of the existence of a *business cycle*. There are varying theories surrounding the typical constituents or phases of the business cycle and its duration. However, its existence is a universal reality. There is also robust evidence (Guidolin & Hyde, 2012) that asset classes perform differently during different stages of the business cycle. It appears reasonable therefore if the opportunity arises to rebalance the portfolio optimally based on the asset and the stage of the cycle.

Table 2.2: Asset class returns over different growth/ inflation regimes 1970-2019

Frequency	Regime	S&P500	Nikkei 225	10 Yr T	Corp. Bonds	Commod	Gold	USDXY
31%	Disinflationary Boom	8.6% [12.84%]	5.33% [18.26%]	5.91% [7.094%]	7.05% [4.85%]	1.15% [9.75%]	1.873% [13.48%]	1.86% [7.80%]
22%	Inflationary Boom	6.7% [12.78%]	9.31% [14.55%]	2.85% [7.43%]	4.16% [6.05%]	12.18% [8.12%]	9.03% [19%]	0.45% [8.74%]
23%	Inflationary Stagnation	2.4% [14.37%]	6.01% [13.77%]	7.055% [8.90%]	6.75% [7.2%]	6.75% [10.55%]	21.2% [19.42%]	<2.72%> [8.16%]
25%	Disinflationary Stagnation	10.42% [14.4%]	4.65% [16.73%]	15.05% [9.12%]	10.22% [6.52%]	<2.79%> [8.44%]	1.66% [13.82%]	<1.04%> [8.98%]

We note in Table 2.2 the varying performance of individual assets during different economic regimes. The returns are noted first in each column followed by the respective volatility in brackets. For instance, the annual returns of the S&P500 during a "Disinflationary Boom" period are 8.6% with an annualised volatility of 12.84%.

There are several patterns to be observed from Table 2.2. The fundamental observation is that the optimal asset varies across each regime. For instance, the S&P500 is the dominant asset unsurprisingly in a disinflationary boom period. Stocks underperform both commodities and gold however in an inflationary boom market environment. Commodities are the optimal asset to own in this regime with an average annualised return of 12.18%. Commodities continue to provide solid returns in an inflationary stagnation regime [6.75%]. However, gold is the leading asset class returning 21.2% on an annual basis. Both gold and commodities underperform on a relative basis in a disinflationary stagnation market regime. 10-year treasuries are the dominant performer in this regime as evidenced by annualised returns of 15.05%. Both the S&P500 and the Nikkei exhibit strong annualized returns of 10.42% and 4.65% respectively. This may surprise given that the rate of change in GDP will be declining in such an environment. We can also make some general observations about each asset classes performance relevant to the underlying growth and inflation regimes. In general equities tend to perform better in disinflationary environments than inflationary environments. The fixed income assets tend to perform better in low growth "stagnation" type market environments. Both gold and commodities outperform equities during periods of persistent inflation.

2.3.6 Macroeconomics

Valuation methodology is often the benchmark used for entry and exit points in determining whether asset prices are "expensive" or "cheap". This paper will show that valuation is just one of the constituents to consider. Important macro-economic variables including growth and inflation should also be included. Optimal asset allocation requires leading information on the probable direction of global and regional economies. A singular focus on value may prove counter-productive if the macro-economic backdrop shifts. This paper will demonstrate that incorporating the economic environment into asset pricing models enhances the asset allocation process. We assert that underlying economic variables[38] shift and change in a similar fashion to the movement of asset prices. There has been a move in recent years away from traditional portfolio construction determined by the underlying assets towards a factor approach to asset allocation. The seminal works of Fama & French (1993) and Carhart (1998) were instrumental in starting this movement. There is an inherent relationship between macroeconomic conditions and risk factor performance. The academic evidence supports the position that these risk factors are the primary drivers of asset class returns. An analysis of these risk factors is constructive in making this association. For example, fixed income assets have several in-built risk factors linked directly to macro-economic risk premia including interest rate risk, inflation, credit and liquidity risks. The literature predominantly defines the economic state of the world as a function of expected GDP growth and expected inflation.

[38] Including growth and inflation dynamics

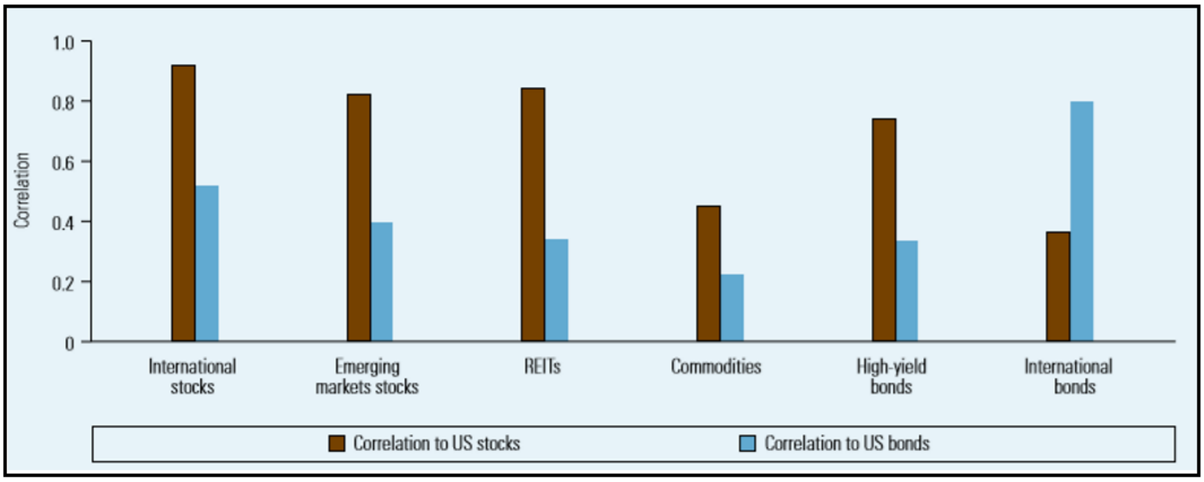
The empirical evidence suggests that risk factor performance anticipates the macroeconomic environment[39]. This finding would confirm the assertion that equity market returns are a leading indicator for GDP growth. Can we model the relationships between risk factor performance and the subsequent GDP and inflation rates? A research paper released by PIMCO in 2010 sought to examine this relationship. Their investigations determined that GDP growth expectations propel risk assets performance. The study reinforced the conception of the broader equity market acting as a leading indicator with equities under-performing in expectation of bad news on the economic front. The obvious fault-lines with these conclusions lie in the over-reliance on past performance and historical covariances. The empirical evidence does however allow us to devise forward-looking outlooks and assists with modelling the historical relationships between macroeconomic states and risk-factor performance. There is evidence that a rebalancing approach based on macroeconomic regimes produces more stable returns with lower volatility (Miroslav, K. 2013).

2.3.7 Diversification

The Great Financial Recession (GFR) of 2008 forced investment practitioners and academics alike to reconsider the practical adaptability of their asset pricing models during stressed environments. A phenomenon labelled "naïve diversification" emerged post GFR. Investment portfolios were constructed with a strong equity bias linked to the secular growth factor. This resulted in "diversified" portfolios containing proportionate allocations to public equities, private equity, corporate bonds, hedge funds, REITs and direct real estate. The robustness of a portfolio is tested during a shock, 3-sigma event. Unfortunately for investors the individual constituents of these assets were highly positively correlated during this stressed event and the correlations pushed very close to 1 (See Figure 2.1).

[39] Viewpoint's discussion Paper, 2010

Figure 2.1: Naïve Diversification during the GFR
Correlations between select market segments and traditional asset classes



Source: JP. Morgan Guide to the Markets, 2021

Figure 2.1 displays the correlations between traditional asset classes such as US stocks/US bonds and alternative assets including REITs, Commodities and Credit during the 18-month period of the 2007/2009 Global Financial Crisis. We note several key observations. The correlation between US stocks and International/ Emerging stocks is almost 1 during this stressed environment. In addition, growth proxy assets (REITs & HY Bonds) with similar characteristics to equities also have very positive correlations with US stocks. Perhaps most surprising is the positive correlation between US bonds and equity markets with international stocks, emerging stocks and REITs indicating a 0.5, 0.4 and 0.35 correlation to US bonds during this period.

Another stylized feature of asset class returns in general has been the positive correlation exhibited across all major asset classes. Research undertaken by Page, Taborsky (2010) found that the average correlations among the major asset class groups during the period 1994 to 2009 was 39% for the full sample and 30% in quiet periods. However, during stressed periods the correlations rose to 51%. Further evidence de-linking the diversification benefits of allocating to corporate bond and equities was also produced. The correlations between credit risk premiums and equity returns reached their height when equities fell over 10%. There is further evidence that not only are correlations more positive than traditional diversification strategies would imply but these correlations time-vary in the extreme. The 24-month rolling correlation between US equities and government bond returns from 1929 to 2009 swung between a range of -55% to +70%. The shorter 6-month rolling correlations indicated much wider variances of between -90% and +90%[40]. Ilmanen (2011) has conducted extensive research across multiple markets on the subject of risk premia. He contends that the failure of diversification (evident during the GFR), grew from the penetration of equity risk premia across most growth assets. Developed market equity returns from 1990 to 2009 were positively

[40] Taborsky, 2010 & Taborsky, 2011

corelated with U.S equities, emerging market equities, U.S Corporate High Yield Bonds, Investment grade Bonds, commodity futures, Global real estate and U.S real estate. Investors were left with a naive sense of protection through a diversified strategy that appeared to be dominated by one factor – equity risk premium. There has been a notable shift away from the traditional portfolio construction approach concentrated on pure asset allocation towards one determined largely by their factor exposures. The influence of the macro-economic environment is clear given the empirical evidence[41] linking risk factors to individual market regimes. There is evidence that the average correlations between 1994 and 2009 among the major risk factors was 2% for the full sample, 2% during calm market environments and 1.6% during stressed periods[42]. Prior to the GFR, investment professionals primarily utilised a bottom-up, micro-finance approach that centred upon relative valuations and narrow discounted cash-flow analysis. The extreme drawdowns experienced during 2008/2009 forced many to revaluate their restricted frame of reference and incorporate broader macroeconomic analysis into the investment framework.

2.3.8: Regime-based Asset Allocation

In 2004 Merrill Lynch introduced their "Investment Clock" theory for allocating assets based on a pure macroeconomic framework. They separated the business cycle into four distinct economic regimes of *reflation*, *recovery*, *overheat* and *stagflation*. The portfolio management implications for differentiating between individual regimes are clear – assets should perform differently dependent upon the underlying economic regime. Their investment framework described a stagflationary environment as one where GDP growth slows, and inflation remains elevated. The overheat regime is one characterised by rising inflationary pressures and policy interventionism via contractionary monetary policy. The recovery period moves in close step with the underlying economy with real GDP, employment and company profits increasing. Unsurprisingly the model designates stocks as the optimal asset class during this regime. A reflationary environment is one of slowing economic growth (as measured by GDP) and slowing inflation. The policy response here is to stimulate economic activity by lowering rates. This expansionary government policy action is supportive of bonds. We note some additional interesting observations relating

[41] Taborsky, (2010); Taborsky, Page, Pederson, (2010); Bhansali (2011), Bhansali (2007); Ilmanen (2011)
[42] The risk factors chosen include asset class sources of return, credit risk premium, yield curve slope, duration, currency exposures, macro risk factors including economic growth, inflation and illiquidity.

to asset returns and their inherent volatility. In general,[43] the low-volatility premium holds across both the S&P500 and the Nikkei225. A strategy of reducing equity market volatility over the longer term has produced excess returns based on several academic studies (Chow, Hsu, Kuo & Li., 2014, Eraker, 2008). Whilst a low volatility factor enhances stock index returns; it detracts from gold returns. Gold has experienced its strongest gain during periods of higher volatility. Inflationary regimes are associated with higher gold price volatility whereas disinflationary regimes are associated with higher equity price volatility. Fixed income assets exhibit slightly greater volatility during periods of declining growth. The empirical evidence would suggest that this is a function of monetary policy and momentum in bond prices. Johnson, R. et al. (2003) noted that corporate bond returns have a strong association with central bank monetary policy. The authors noted that bond market indexes exhibited higher returns during periods of dovish policy measures[44]. The modern role of fixed income in a broader portfolio has received much attention post GFR. The positive correlation between equity and fixed income markets, most notably in the 1970s & 1980s has been covered extensively in recent publications [Campbell et al. (2014), Baele, Bekaert and Inghelbrect (2010), Campbell, Sunderam, and Viceira (2013) and Guidolin & Timmermann (2006)].

[43] There is one outlier – the disinflationary stagnation environment produces over 10% annualised returns from the S&P500

[44] Expansionary monetary policy most typically described as an environment where interest rates are being reduced by the Federal Reserve to stimulate the US economy

2.4 Econometric Framework

2.4.1 Multiple Linear Regression

This study seeks to reflect the relationship between our dependent financial assets and independent macroeconomic variables. Simple multiple linear modelling equations are used in this investigation. To identify causal relationships between dependent financial assets and our predictor variables, we conducted several multiple linear regressions. These were split between regime-agnostic, contiguous data sampling methods and regime-specific, non-contiguous data sampling.

The mathematical model of a multiple linear regression is

$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n + \varepsilon \qquad 1$$

where y is the dependent variable; $x_1, x_2, \ldots, x_n$ are the n independent predictor variables; β_0 is the intercept – or the predicted value of y when all the predictor variables are 0; β_1, $\beta_2, \ldots \beta_n$ are the regression coefficients and ε is the disturbance term with distribution $N(0,\sigma^2)$. We may still use the term "linear" in describing multiple linear regressions given our assumptions that the response variable is directly related to a linear combination of the explanatory variables. Equation 2 below sets out a sample of the multiple linear regressions taken during this research. The dependent variable is the monthly % change in return on the 10 Year US treasury bond during a specific regime[45]. The predictor variables include the % change US Corporate Bond Index, US building permits, M2 money velocity and the unemployment rate.

$$\%\Delta \text{US T} = \beta_0 + \beta_1 \text{US Corp.} + \beta_2 \text{US Bldg. Perm} + \beta_3 M_2 + \beta_4 \text{Unemp} + \varepsilon \qquad 2$$

2.4.2 Economic regime Framework

We can review the economic regime framework in more detail prior to analysing the results from Table 2.3 further. Economic cycles vary by their very nature. There have been eight officially recognised business cycles since December 1969[46]. A study of these is useful in analysing the differences in terms of expansion, contraction, peak to trough duration and trough to peak recovery time (months). The great financial recession 0f

[45] The regime here is characterised by low growth and low inflation

[46] National Bureau of Economic Research (NBER)

2007-2009 was the steepest market contraction lasting 18 months in total. Prior to the February 2020 Covid-19 market decline, the shortest business cycle contraction occurred between January 1980 and July 1980 lasting just 6 months. The longest expansion (from trough to peak) has occurred in recent years. The economic expansion that occurred post technology bubble market sell-off lasted 120 months. The most recent expansion following the market lows of March 2009 exceeded this by 8 months (128 months). There appears to be a trend in the economic cycle data with business cycles lasting longer over time. This may however be a transitory phenomenon.

Table 2.3: US Business Cycle Contractions & Expansions 1969-2020

Peak month (Peak Quarter)	Trough month (Trough Quarter)	Contraction *Duration, peak to trough*	Expansion *Duration, trough to peak*	Cycle *Duration, trough to trough*	*Duration, peak to peak*
December 1969 (1969Q4)	November 1970 (1970Q4)	11	106	117	116
November 1973 (1973Q4)	March 1975 (1975Q1)	16	36	52	47
January 1980 (1980Q1)	July 1980 (1980Q3)	6	58	64	74
July 1981 (1981Q3)	November 1982 (1982Q4)	16	12	28	18
July 1990 (1990Q3)	March 1991 (1991Q1)	8	92	100	108
March 2001 (2001Q1)	November 2001 (2001Q4)	8	120	128	128
December 2007 (2007Q4)	June 2009 (2009Q2)	18	73	91	81
February 2020 (2019Q4)	April 2020 (2020Q2)	2	128	130	146

Source: National Bureau of Economic Research

The National Bureau of Economic Research (NBER) provides a chronology of US business cycles. This chronology is maintained by the NBER Business Cycle Dating Committee. Economic recessions and expansions are framed in terms of their economic activity peaks and troughs. An expansion is defined as that period between a trough and a peak. A contraction or recession is defined as that period between an economic peak and trough. We notice some clear trends from Table 2.3. Economic recessions generally do not persist and contractions in excess of 12 months are rare events. Economic expansions last longer on average. Whilst expansion appears to be the normal state of the economy, the time that it takes the economy to reach its previous peak can be protracted. The NBER define a recession as an economic contraction that broadly impacts the wider economy and persists for several months. The NBER methodology for determining economic peaks & troughs is based on aggregate economic activity and data sources including real personal income less transfers, personal consumption expenditures, retail sales, industrial production and nonfarm payroll employment[47]. In general terms, we can

[47] Source: NBER

assign four stages to a typical business/ economic cycle. The descriptions of these will vary depending on the source chosen. We will define these purely based on the underlying economic activity. An economic recovery phase is a market environment defined by recovering consumer confidence, increased spending and gradually improving sentiment. Both company profits and earnings increase, and employment numbers begin to improve also. This initial recovery phase leads into the expansion phase where company profits and asset appreciation are now being reflected in burgeoning stock markets. A general wealth effect emerges as consumers feel more positive about the broader economy. Employment reaches its peak and wage pressures begin to emerge as the employment market starts to tighten. Inflation pressures may start to emerge. Inevitably as investors chase asset price performance the economic cycle moves into the euphoria stage. Speculation and confidence are at its peak. Company profits are negatively impacted by rising cost pressures and earnings growth start to decline. The euphoria associated with asset price speculation leads to increased market volatility and investors sell out of their positions as pessimism enters the general market psychology. The economy enters a slowdown as consumer sentiment and spending decline in response to government intervention[48]. As consumer spending and incomes are intrinsically related, declines in spending lead to declines in income and a general market recession. The four-quadrant economic regime framework captures the transition through a normal business cycle. We can associate the *disinflationary boom* period with the recovery and expansion phase. Economic growth is recovering quickly, and inflation is muted. This should be a strong economic environment for equities and other growth assets including corporate bonds and real estate. The data from Table 2.2 supports this assertion. The *inflationary boom* regime is an extension of the disinflationary boom as wage costs and general household & industrial inflation pressures start to increase. As consumer price inflation (CPI), personal consumption expenditures (PCE) and producer price inflation (PPI) all start to increase inflation impacts the real yield of equities and other inflation sensitive assets. Unsurprisingly commodities are a good hedge in this environment, and this is evident in the Table 2.2 returns. As inflationary pressures persist, wage costs rise impacting profits and earnings. Inflation may also lead to contractionary central bank monetary intervention leading to less disposable income as debt-servicing costs rise. Decreased disposable

[48] Central banks generally raise interest rates to regulate demand for goods and services. This hawkish policy response can lead to a precipitous market decline as sentiment and consumer spending is negatively impacted

income should negatively impact spending, consumer sentiment and retail sales. Combined with concerns around asset prices and decreasing investment, the rate of change in economic growth may turn negative. If growth slows and inflation persists, we are in an *inflationary stagnation* or stagflation[49] regime. In any inflationary environment the purchasing power of capital is silently being eroded as the cost of goods and services rises and the denominated value of the currency does not. Assets that are finite in quantity including precious metals should outperform in such a regime. Table 2.2 supports this thesis with gold outperforming both equities, fixed income and commodities. Eventually central banks are forced to raise rates sufficiently higher to curb inflationary pressures. The unintended consequences of such policy action may trigger a recession as higher interest rates reduce disposable income further and negatively impact demand. A *disinflationary stagnation* is characterised by declining growth rates and low inflation. Consumer sentiment is low, and governments may need to stimulate the economy to avoid a deflationary spiral. Monetary policy tools[50] may be deployed at this point which inevitably leads to lower interest rates. Given the inverse relationship between bond prices and yields, lower rates support fixed income returns as evidenced in Table 2.2. Fixed income assets including 10-Year U.S Treasuries and Corporate Bonds outperform in such an environment.

2.4.3 Methodology

The data set for our study was analysed in three specific approaches. Firstly, multiple linear regressions were completed for each of the dependent variables across the full 50-year dataset (1970-2020). Next, regressions were completed with the data categorised under specific economic regimes. Finally, instead of allowing the macroeconomic environment to determine each regime, three individual sample segments of the full 50-year dataset were extracted and analysed individually. We will review each of these processes in more detail in the following sections.

Full Sample Multiple Linear Regressions

We first ran multiple linear regressions of the full sample of data without specifying the independent regimes. These regime agnostic regressions were completed for each of our

[49] The term is a combination of the word's stagnation and inflation. It seeks to describe an economic environment characterised by slow growth, rising unemployment and inflation. It is most associated with the decade of the 1970s

[50] Central banks may adopt conventional monetary policy through open market operations and/or more unconventional methods such as Quantitative easing

financial assets. The regressions were analysed, and predictor variables selected for the final model based on statistical significance. Table 2.27 reports estimated coefficients for our first multiple linear regression model where the dependent variable is the S&P500. The sample period is January 1, 1970, to December 31, 2020. The dependent variable is the monthly percentage change in the S&P500 index. The eleven independent variables are a combination of investment assets and macroeconomic variables. The Macroeconomic variables include Personal Income and Personal Consumption Expenditures (PCE) both sourced from the U.S Bureau of Economic Analysis, M2 money velocity and the consumer price index (CPI). Commodity based regressors include the % changes in the prices of aluminium and iron ore. Additional predictor variables include heavy weight trucks which includes trucks with more than 14,000 lbs gross vehicle weight and the yield on triple A-rated corporate bonds. Table 2.28 reports estimated coefficients for our second regime-agnostic multiple linear regression model where the dependent variable is Gold. The sample period is January 1, 1970, to December 31, 2020. The dependent variable is the monthly percentage change in the gold fixing price[51]. The twelve independent variables are a combination of investment assets and macroeconomic variables. The Macroeconomic variables include the US Dollar index, M2 money velocity and crude oil prices. Commodity based regressors include the % changes in the prices of sugar, cotton, rubber, and platinum. Additional predictor variables include the producer price index for iron & steel and the house price index. Table 2.29 reports estimated coefficients for our third regime-agnostic multiple linear regression model where the dependent variable is the monthly returns on the 10 Year US treasury bond. The sample period is January 1, 1970, to December 31, 2020. The dependent variable is the monthly percentage change in the returns on the 10-year US Treasury bond. The eleven independent variables are a combination of investment assets and macroeconomic variables. The Macroeconomic variables include Personal Income and Personal Consumption Expenditures (PCE) both sourced from the U.S Bureau of Economic Analysis, US building permits and PPI All Commodities data. Commodity based regressors include the % changes in the prices of copper. Additional predictor variables include the US Corporate Bond index.

[51] *Price sourced from London Bullion market, based in US Dollars*

Regime-specific Multiple Linear Regressions

The study next focussed on "regime specific" samples of the data to establish if a causal relationship exists between the dependent financial assets and independent predictor variables. These regressions would provide support for our thesis on the benefits of adopting a regime-based asset allocation framework. The regimes were classified according to the variance of the major growth and inflation proxies against their long-term averages. The classification procedure is explained in greater detail in section four. These regime-specific regressions were completed for each of our financial assets. The regressions were analysed, and predictor variables selected for the final model based on statistical significance. The initial analysis focussed on the S&P500. Table 2.30 reports estimated coefficients for the four non-contiguous multiple linear regression models. The dependent variable is the monthly percentage change in the S&P500 index. We categorise regime 1 as an economic environment where the % change in growth is increasing and the % change in inflation is decreasing. The sample period is January 1, 1970, to December 31, 2020. Regime 1 or "*Optimal*" is captured with seven statistically significant regressors. We categorise regime 2 as an economic environment where the % rate of change in growth is increasing and the % rate of change in inflation is increasing. Regime 2 or "*Reflation*" is captured with nine statistically significant regressors. Regime 3 is categorised as an economic environment where the % rate of change in growth is decreasing and the % rate of change in inflation is increasing. Regime 3 is captured with ten statistically significant regressors Regime 4 or "*Stagflation*" is captured with ten statistically significant regressors. We categorise regime 4 as an economic environment where the % rate of change in growth is decreasing and the % rate of change in inflation is decreasing. Regime 4 or "*Deflation*" is captured with seven statistically significant regressors. A deeper analysis of the results is covered in Section 4. Table 2.31 reports estimated coefficients for the four non-contiguous multiple linear regression models where the dependent variable is the monthly percentage change in the gold fixing price. The regime categorizations follow those of the S&P500. The sample period is January 1, 1970, to December 31, 2020. Regime 1 is captured with seven statistically significant regressors. Regime 2 is captured with seven statistically significant regressor]. Regime 3 is captured with seven statistically significant regressors and Regime 4 is captured with four statistically significant regressors. Table 2.32 reports estimated coefficients for the four non-contiguous multiple linear regression models where the dependent variable is the monthly percentage change in the returns on the 10-year US Treasury bond. The sample period is January 1, 1970, to December 31, 2020. Regime 1 is captured with eight statistically significant regressors. Regime 2 is captured with seven statistically significant regressors. Regime 3 is captured with five statistically significant regressors. Regime 4 or “Deflation” is captured with six statistically significant regressors.

Sample-specific Multiple Linear Regressions

The study next focussed on “sample specific” or time specific segments of the data to establish if a causal relationship exists between the dependent financial assets and independent predictor variables. Along with the regime-specific analysis, these regressions should support our thesis on the benefits of adopting a regime-based asset allocation framework. The sample periods were classified according to general economic conditions of growth and inflation over the sample periods. Table 2.33 reports estimated coefficients for the three regime-specific sample periods as specified by the regime classification matrix. The first sample period is between January 1970 and December 1982. As per Table 2.21, this period may be classified as a high inflation & low growth period. We have classified each regime based upon the Growth | Inflation model referenced in Table 2.20. For illustration, if the % change in growth is above the long-term mean and % change in inflation is below the long-term mean, we log state regime number **1**. This is colour coded with a darker green. Colour coding per regime has been used to aid in the description. Each month receives a classification based on the prevailing growth and inflation environment. Regime 1 encompasses higher economic growth and low inflation. Regime 2 is characterised by persistent economic growth and increasing inflation. Regime 3 may be categorised as a “stagflationary” economic environment where growth has turned negative and high inflation is persistent. Regime 4 is categorised by low inflation and low growth. The evidence from Table 2.21 would suggest a regime dominated by persistent inflationary pressures and lower growth prospects. R2 & R3 constitute regimes of higher-than-average inflation. It is evident that the 1970 to 1982 period was dominated by higher-than-average inflation with inflationary pressures remaining persistent for 75% of the period. A detailed discussion of the empirical results follows in Section 4. The second sample period is between January 1983 and December 1999. As per Table 2.22, this period may be classified as a low inflation & high growth period. The evidence from Table 2.22 would suggest a regime dominated by a persistent disinflationary environment and stronger growth prospects. R1 & R2 constitute regimes of higher-than-average growth. It is evident that this period was dominated by higher-than-average growth with disinflationary pressures remaining persistent for 65% of the period. The third sample period is between January 2000 and December 2020. As per Table 2.23, this period may be classified as a low inflation & low growth period. The dependent variable is the monthly percentage change in the S&P500 index. The evidence from Table 2.23 would suggest a regime dominated by a persistent disinflationary environment and sluggish growth. R1 & R4 constitute regimes of lower-than-average inflation. It is evident that this period was dominated by lower growth (57%) with disinflationary pressures remaining persistent for 66% of the period.

2.5 Data and Empirical Findings

2.5.1 Asset class review

Equities

The Standard & Poor's 500 (S&P500) largest companies by market capitalisation and the Nikkei 225 have been selected to represent the international equity content. Both sets of time-series have a long historical record. The sample period dates to January 1970 with varying sample periods chosen. The international equity sources were broadened out to include the German DAX and the Hang Seng Index with data prices available from January 1990. Table 2.19 provides details of the equity specific mutual funds used in this study. The analysis reviews 94 individual funds across 9 specific sectors.

Fixed Income

To determine a broader understanding of the fixed income market, this study incorporated both sovereign and corporate bonds. The Federal reserve publishes the yield-to-maturity of Treasury bonds. As the treasury bond returns earned by investors are unavailable, standard textbook formulae were utilized to convert the yield-to-maturity data to investor returns. The starting date for our 10-year treasury timeseries is January 1970. End of month data on the yield-to-maturity became available in January 1962. The transformation formula[52] for converting the yield-to-maturity to investment returns was sourced from Tuckman & Serrat (2012). The methodology for calculating the 10-year bond returns is described below. Given the yield-to-maturity and outstanding maturity on the bond, the interest rate sensitivity or modified duration of a risk-free bond at par value can be approximated by

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[52] Tuckman, B.; Serrat, A. Fixed Income Securities Tools for Todays Markets, 3rd ed.; John Wiley and Sons Ltd.: Hoboken, NJ, USA, 2012.

$$D_t(Y_t,M_t)=1/Y_t*[1-1/(1+0.5*Y_t)^{2*M_t}] \quad 1$$

Y_t is the yield-to-maturity at time t. The remaining maturity of the bond at time t is captured by M_t. The non-linear relationship between the price and the yield of a bond is captured by C_t in eq. 2 below. The convexity of a par bond can be captured with the equation

$$C_t(Y_t,M_t)=2/(Y_t^2)*[1-1/(1+0.5*Y_t)^{2*M_t})]-(2*M_t)/[Y_t*(1+0.5*Y_t)]^{2*M_t+1} \quad 2$$

It is possible to calculate the investment return over period t if the yield is known at the start and end point of the period along with the maturity of the bond. Following the convention of Swinkles, L. (2019) we note

$$R_t(Y_{t-1},Y_t, M_t) = Y_{t-1}-D_t*(Y_t-Y_{t-1}) + \frac{1}{2}*C_t*(Y_t-Y_{t-1})^2 \quad 3$$

Y_{t-1} as represented as the first term on the right-hand side of eq.3 should be expressed as a percentage per period that the return is measured or $(1+Y_t)^{1/2}-1$ of the annual yield if we are formulating a monthly return series. Eq. 3 indicates that if the interest rate remains static, the two terms on the right equal to zero and the return reverts to the return at the start of the period. An increase in the yield will reduce the return. To formulate our return series for corporate bonds, we sourced the yield on the Moody's seasoned AAA rated corporate bond from the FRED.ie economics portal. The return series is computed using the same convention as detailed for the 10-year US Treasury bond. This bond acts as an index of performance for the top-rated corporate bond by credit quality[53].

Commodities

To gain a broad exposure to the commodity type assets we selected gold and a wide spectrum of individual commodities. Energy was stripped out owing to its incessant volatility as a more stable proxy for the commodity complex was preferred. General market volatility is captured through equity assets and the study was keen to control for cross-asset volatility correlations. Our monthly commodity prices were sourced from the World Bank. The World Bank produces a comprehensive data set on monthly commodity prices covering agricultural, industrial, energy and metals. Our analysis included sixteen individual commodities with price data dating back to 1970. Our gold returns were sourced from the Federal Reserve Economic Database (https://fred.stlouisfed.org).

[53] The credit quality ratings are provided by the Moody's Investor Service

Monthly returns of the spot price of gold were generated by taking the log difference of the price change as per the convention for calculating the equity market rate of change.

2.5.2 Predictor variable review & selection

It was important that the predictor variables selected captured the broader macro-economic relationships between individual asset classes and the underlying regimes. The research undertaken in chapter 1 was influential in the screening of economic predictor variables. At the outset of the study, an initial selection process drew upon a considerable sample of potential variables. The inclusion of predictor variables (in each regime) is based upon economic theory, technical analysis[54] and statistical significance. The existing literature offered useful insights also and assisted with the ultimate selection process. Finally, practical consideration was given to those consistent and reasonable economic relationships between predictors and the normal[55] business cycle. Examples of the latter include the consistent relationship between demand for *heavyweight truck consumption* and economic recessions or the strong positive relationship between the growth rate of *M_1 money supply* and inflation (DeGauwe & Polan, 2001). The literature offered support for the inclusion of leading indicators including the *University of Michigan consumer sentiment survey*, *personal income* and the *Industrial Production Index.*

The inflation, growth and commodity-based predictor variables have been summarised in Tables 2.4 to 2.6.

[54] Multiple charts were constructed and analysed to visually assess the technical significance of each predictor variable in respect of NBER recessionary periods and other important macroeconomic variables.
[55] "normal" in the sense of encompassing the four typical stages of every business cycle including recovery, expansion, boom and slowdown

Table 2.4: Initial listing of inflation predictor variables

INFLATION		Source
	Predictor Variables	
1	CPI	Bureau of Labor Statistics
2	PCE	Bureau of Economic Analysis
3	WTI Crude Oil	Haver Analytics.
4	Avg Hourly Earnings	Bureau of Labor Statistics
5	Union Membership	Bureau of Labor Statistics
6	Age Wave	Bureau of Labor Statistics
7	Productivity: Non Farm Business	Bureau of Labor Statistics
8	Price Deflators	Bureau of Economic Analysis
9	Retail Sales	Census Bureau
10	CPI: Durable Goods	Bureau of Labor Statistics
11	China: CPI	China NBS
12	Output Gap	Congressional Budget Office and Bureau of Economic Analysis
13	Resource Utilization Rate	Congressional Budget Office, Bureau of Labor Statistics, and Federal Reserve Board
14	NAIRU	Congressional Budget Office
15	US Money Multiplier	Federal reserve Board
16	M2 Velocity	Federal reserve Board
17	Wage Inflation/ Unemp rate	Bureau of Labor Statistics
18	Unemployment Rates	Bureau of Labor Statistics
19	JOLTS	Bureau of Labor Statistics and National Federation of Independent Business.
20	NFIB small bus survey	Bureau of Labor Statistics and National Federation of Independent Business.
21	Quits Rate	Bureau of Labor Statistics and The Conference Board.
22	Consumer confidence index	Bureau of Labor Statistics and The Conference Board.
23	Average Hourly earnings: Manuf	Bureau of Labor Statistics
24	Employment Cost Index	Bureau of Labor Statistics

Table 2.5: Initial listing of predictor variables for economic growth

	GROWTH	
	Predictor Variables	
		Source
1	Goods	Bureau of Economic Analysis
2	Durable Goods	Bureau of Economic Analysis
3	Motor Vehicles	Bureau of Economic Analysis
4	New Motor Vehicles	Bureau of Economic Analysis
5	Personal Income	Bureau of Economic Analysis
6	Employee Compensation	Bureau of Economic Analysis
7	Wages	Bureau of Economic Analysis
8	Private industry spending	Bureau of Economic Analysis
9	Government Spending	Federal Reserve Economic Database
10	Heavy Weight Truck Consumption	Federal Reserve Economic Database
11	Non-Farm Payrolls	Federal Reserve Economic Database
12	M1 Money Velocity	Federal Reserve Economic Database
13	M2 Money Velocity	Federal Reserve Economic Database
14	Personal Consumption Expenditure	Federal Reserve Economic Database
15	Total Consumer Credit	Federal Reserve Economic Database

16	US Permits	Federal Reserve Economic Database
17	US Unemployment Claims	Federal Reserve Economic Database
18	US Unemployment Rate	Federal Reserve Economic Database
19	Federal Funds Rate	Federal Reserve Economic Database
20	Producer Price Index [All Companies]	Federal Reserve Economic Database
21	House Price Index	Federal Reserve Economic Database
22	Industrial Production Index	Federal Reserve Economic Database
23	Yield Spread*	Federal Reserve Economic Database
24	Consumer Price Index	Federal Reserve Economic Database
25	S&P500 Earnings	Robert Shiller Database
26	CAPE ratio**	Robert Shiller Database
27	Crude Oil	Federal Reserve Economic Database
28	Copper	World Bank
29	Ironore	World Bank
30	Aluminimum	World Bank

Notes: *10-Year Treasury constant maturity minus federal funds rate
** Cyclically Adjusted Price-Earnings ratio

Table 2.6: Listing of commodities assets in study

	Commodity	Source
1	PPI Iron Steel	Federal Reserve Economic Database
2	PPI Wheat	Federal Reserve Economic Database
3	Swanwood	World Bank
4	Crude Oil	World Bank
5	Sugar US	World Bank
6	Tobacco	World Bank
7	Cotton	World Bank
8	Rubber	World Bank
9	Urea	World Bank
10	Aluminum	World Bank
11	Iron Ore	World Bank
12	Copper	World Bank
13	Lead	World Bank
14	Tin	World Bank
15	Nickel	World Bank
16	Zinc	World Bank
17	Gold	World Bank
18	Platinum	World Bank
19	Silver	World Bank

2.5.3 Final dataset

The final data set comprised 48 predictor variables consisting of 19 commodity-based predictors, 12 growth-based predictors and 17 inflation-based predictor variables. It is not practical to provide descriptions on all 48 predictor variables. In the interests of brevity, we have confined our analysis to the variables that proved to be statistically significant in this study. These are listed below in Tables 2.7 to 2.9 along with brief descriptions in the following section.

Table 2.7: Statistically significant predictor variables – S&P500

Asset	Sample Period 1	Sample Period 2	Sample Period 3
S&P500	**1970 - 1982**	**1983-1999**	**2000-2020**
	Nikkei225**	Nikkei225	Nikkei225
	10 Year Treas**	10 Year Treasury	10 Year Treasury
	Heavy Weight Tr	US Corp. Bond Index*	US Corp. Bond Index
	M1 Velocity	USDXY*	USDXY
	Crude Oil	EconUncIndx*	EconUncIndx
	Iron Ore	UMSENT*	UMSENT
	AAA Yield	Gold*	Gold
	Personal Income*	PPIACO	Personal Income
		NFP	Copper
		M1V	Doll/ Yen
		Aluminium	

Note: ** Confirms statistical significance across all three individual regimes
* Confirms statistical significance across any two individual regimes

Table 2.8: Statistically significant predictor variables – **Gold**

Asset	Sample Period 1	Sample Period 2	Sample Period 3
Gold	**1970 - 1982**	**1983-1999**	**2000-2020**
	USDXY**	USDXY	USDXY
	Unemployment Claims*	US Corp. Bond Index	Unemployment Claims
	Crude Oil	S&P500*	S&P500
	Sugar	PPI Iron & Steel*	PPI Iron & Steel
	Silver*	Heavy Weight Trucks	Silver
	Platinum*	M2 Velocity	Platinum
		CPI	10 Year Treasury
		UM Sentiment Index	Econ Uncert Index
		Rubber	HSE Pr Index
		Aluminium	

Note: ** Confirms statistical significance across all three individual regimes
* Confirms statistical significance across any two individual regimes

Table 2.9: Statistically significant predictor variables – **10 Year US Treasuries**

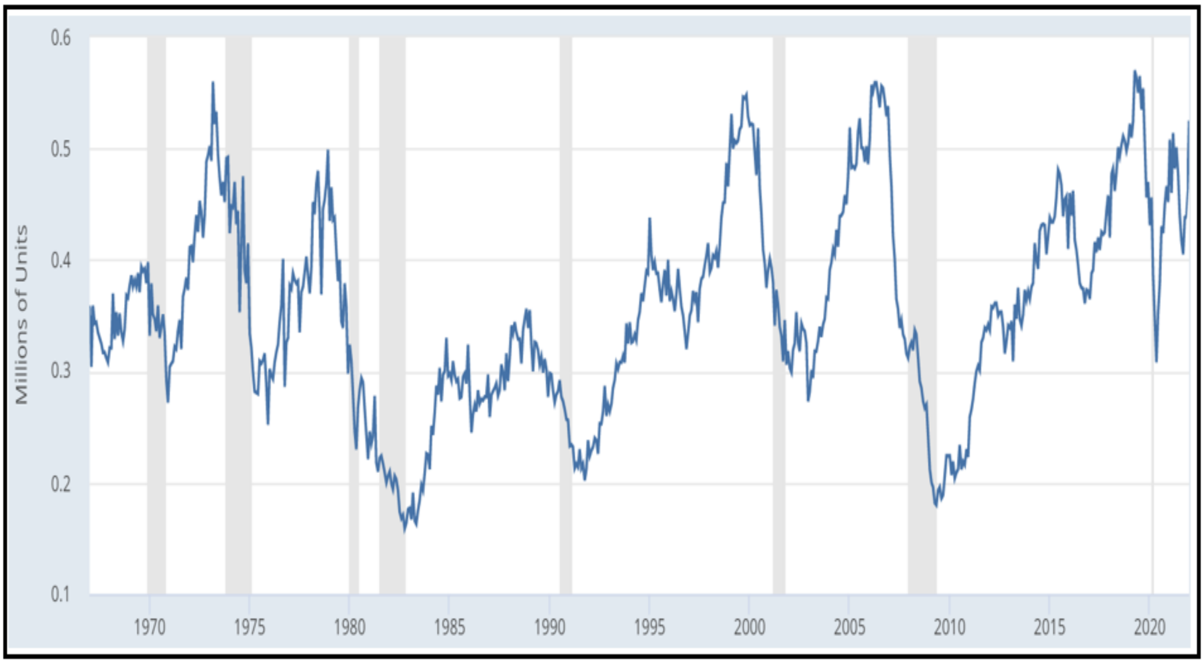
Asset	Sample Period 1	Sample Period 2	Sample Period 3
10 Yr Treas	**1970 - 1982**	**1983-1999**	**2000-2020**
	S&P500**	S&P500	S&P500
	US Corp. Bond Index**	US Corp. Bond Index	US Corp. Bond Index
	M1 Velocity	Treas 10Yr FF	PPIACO
	CPI	PCE	AAA
	Unemployment Rate	Unemployment Claims	Industrial Production Index
	Aluminium		Federal Funds Rate

2.5.4 Causal Predictors – Brief descriptions

Heavy-weight Truck consumption

Heavy weight trucks are trucks with more than 14,000 pounds gross vehicle weight[56]. The variable is measured in millions of units and sourced from the US Bureau of economic analysis.

Figure 2.2: Heavy-weight Truck consumption (1970-2020)



Source: Federal Reserve Economic Database
Notes: Figure 2.2 indicates the seasonally adjusted rate [per millions of units] of Heavy-weight trucks purchased.
The lightly grey shaded areas represent official recession periods as dated by the NBER.

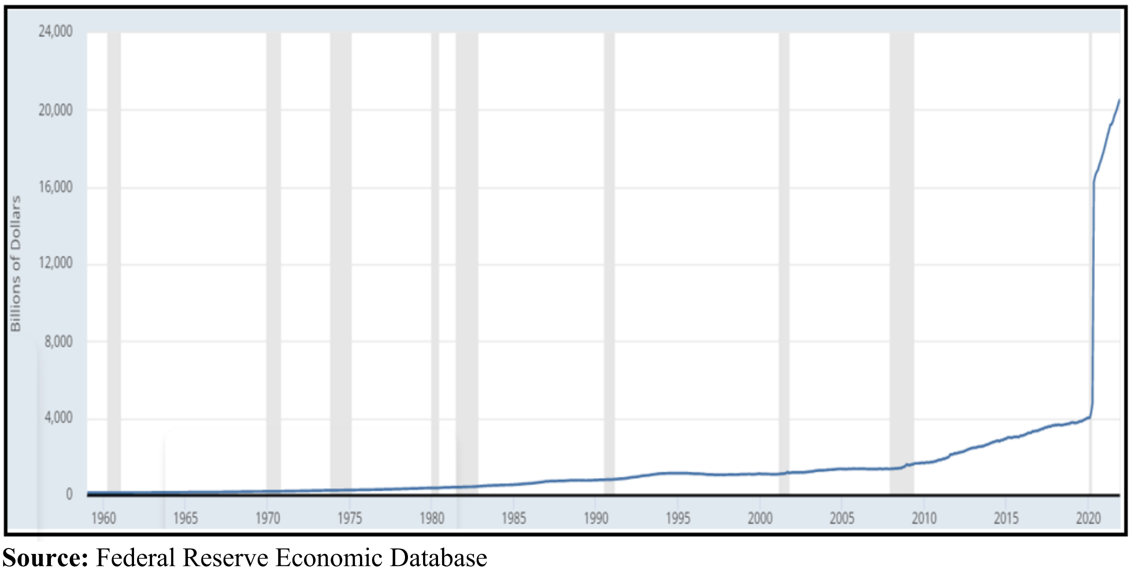
It appears that this predictor acts as a leading indicator of economic growth. The consumption rate appears to decline approx. 12 months in advance of the start of an economic recessionary period. It may also act as a useful indicator of the bottom of the business cycle as evident most notably in March 2009 when sales started to recover from their lows.

[56] Definition sourced from FRED.ie

M1 Money velocity

M1 money supply seeks to capture the amount of "hard" money supply in circulation in a specific country. M1 specifically consists of currency outside the US treasury, Federal reserve banks and vaults[57]. It also includes demand deposits at commercial banks and other checkable deposits. The variable is measured in billions of US dollars and is sourced from the Board of Governors of the Federal Reserve System. The variable is released monthly. Milton Friedman famously stated in 1963 that "*inflation is always and everywhere a monetary phenomenon*". De Gauwe & Polan, (2001) sought to test Friedmans assertions using a sample of 160 countries between 1970 and 2000. They find a strong positive relation between the growth rate of money and inflation. The authors temper this initial finding however by noting that the prevalence of hyperinflation among a section of the full sample skews the results. In fact, the relationship between inflation and money growth for lower inflation countries is weak. Hossain, A. (2005) investigated the causal relationship between money growth, inflation and economic growth. The study period covered almost 50 years of economic data (1954-2002) and the empirical findings indicated a short-run bi-directional causality between money supply growth and inflation.

Figure 2.3: M1 Money Supply (1970-2020)



Source: Federal Reserve Economic Database

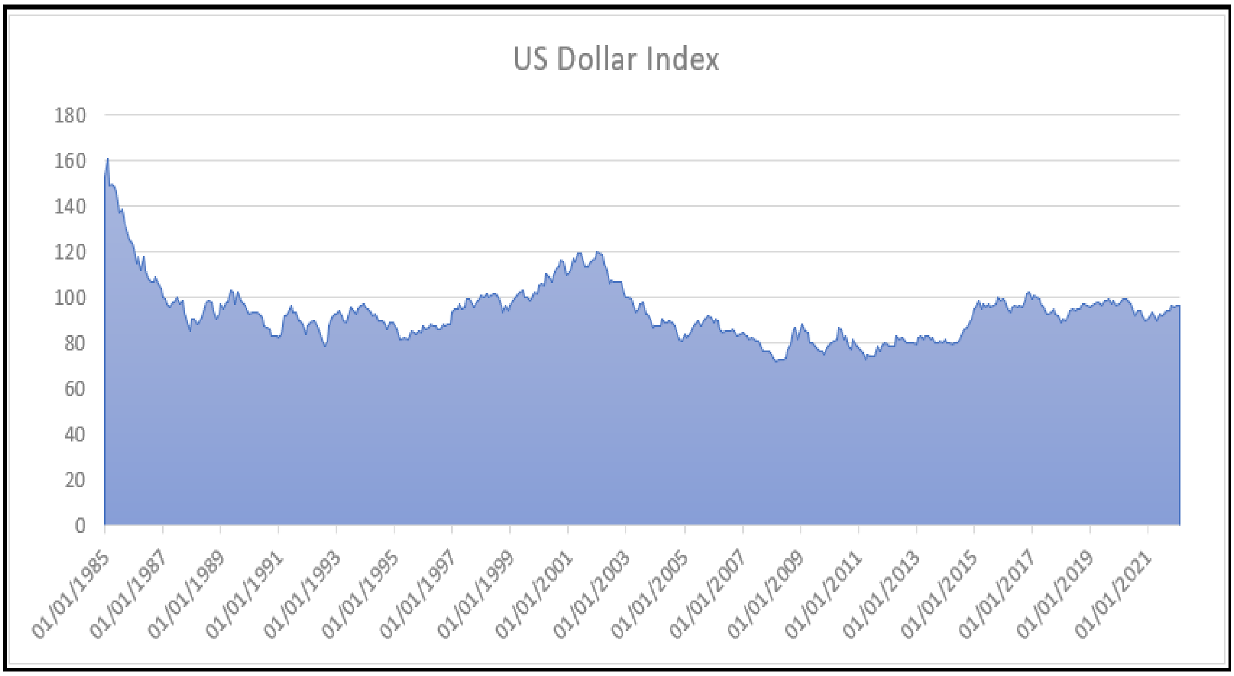
Notes: Figure 2.3 indicates the seasonally adjusted rate [per billions of US$] M1 money supply. The clear acceleration of this metric is noticeable initially post the GFR and exponentially post the Covid-Pandemic of February 2020. The lightly grey shaded areas represent official recession periods as dated by the NBER.

[57] Definition sourced from FRED.ie

US Dollar Index

The DXY or the US Dollar Index is a measure of the value of the US dollar relative to the value of a basket of other currencies. This currency basket comprises the Euro, Swiss Franc, Japanese Yen, Canadian dollar, British pound and Swedish Krona. The respective weights of the index are trade-weighted with Europe being the dominant component of the index. A rising dollar index signifies strength in the US dollar relative to its primary trading partners. The direction of the USDX should have implications for economic growth, inflation and asset class performance.

Figure 2.4: US Dollar Index (1985-2021)

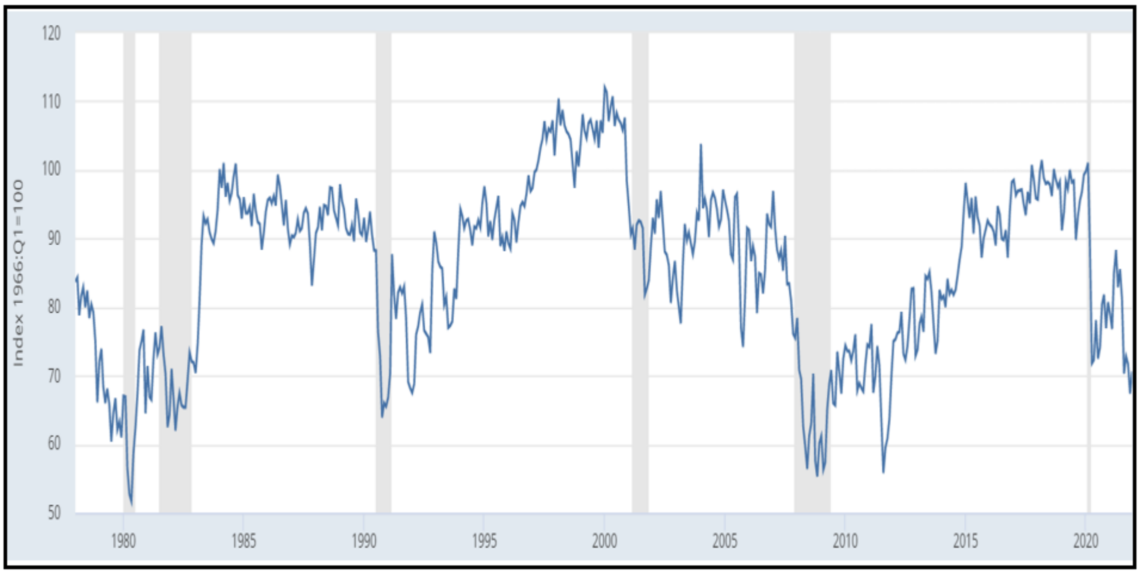


Source: Federal Reserve Economic Database
Notes: Figure 2.4 is a graphical depiction of the US dollar index

University of Michigan Consumer Sentiment Survey (UM Sent)

The UM Sentiment survey seeks to capture important information from both an economic growth and inflation perspective. The survey is a monthly gauge of consumer confidence in the United States and conducted by the University of Michigan. Qualitative information is gathered through telephone exchanges with consumers. Short and longer-term confidence in consumers personal economy and the broader economy are analysed.

Figure 2.5: University of Michigan Consumer Sentiment (1978-2020)



Source: Federal Reserve Economic Database
Notes: Figure 2.5 illustrates the non-seasonally adjusted UM sentiment survey of consumer confidence [Index level]. The lightly grey shaded areas represent official recession periods as dated by the NBER.

It appears that this predictor acts as a leading indicator of economic growth. The survey index appears to decline sharply approx. 6 to 12 months in advance of the start of an economic recessionary period. It may also act as a useful indicator of the bottom of the business cycle as evident most notably in March 2009. The survey results appear volatile over shorter periods. However, it may be useful to identify longer-term trends in the data.

Personal Income

Data on personal income for citizens of the United States is sourced from the US Bureau of Economic Analysis. The data is captured in billions and is seasonally adjusted. The Federal Reserve Economic Database defines personal income as income that persons receive in return for their provision of labour, land and capital used in current production. It can also be defined as a measure of the maximum amount of goods and services an individual can consume in each period without reducing their net worth[58]. The BEA has a broad measure of income which includes employee compensation and the associated benefits [health insurance for example]. Carvalho & Rezai (2016) explore the relationship between personal income inequality and aggregate demand. The authors found evidence of wage inflation and aggregate demand becoming more wage-led in economic environments where income inequality is being reduced.

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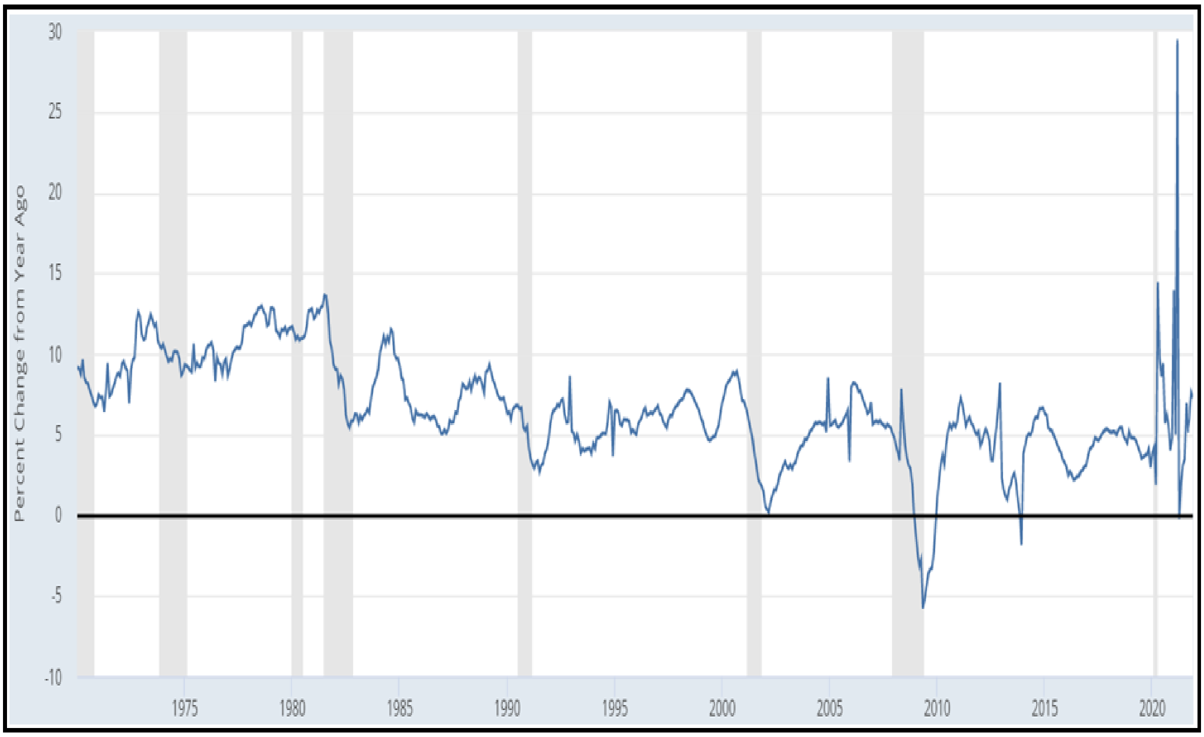
[58] Income definition sourced from the Congressional research service paper on Personal Income, 30th November 2020.

Figure 2.6: Personal Income (1978-2020)



Source: Federal Reserve Economic Database
Notes: Figure 2.6 illustrates the seasonally adjusted rate of Personal Income with the % change from 1 year ago. The lightly grey shaded areas represent official recession periods as dated by the NBER.

Like the U.M sentiment survey and HVT Trucks data, the Personal Income data acts as a good leading indicator of economic downturns. It is notable also that this predictor variable provides useful information to asset allocators looking to identify the trough of a particular business cycle.

Unemployment claims

Continued claims of unemployment insurance are sourced from the US Employment and Trading administration. The data is released on a weekly basis and measures the number of people that have filed an initial claim and who have also experienced a week of unemployment leading to a continued claim. Common sense dictates that periods of positive economic growth should be associated with lower unemployment figures. Eychenne et al. (2011) refer to the positive output gap whereby economic productivity exceeds its potential. Okun's law captures a situation where workers become scarcer due to a maximum requirement for all available resources.

Figure 2.7: Unemployment Claims (1970-2020)

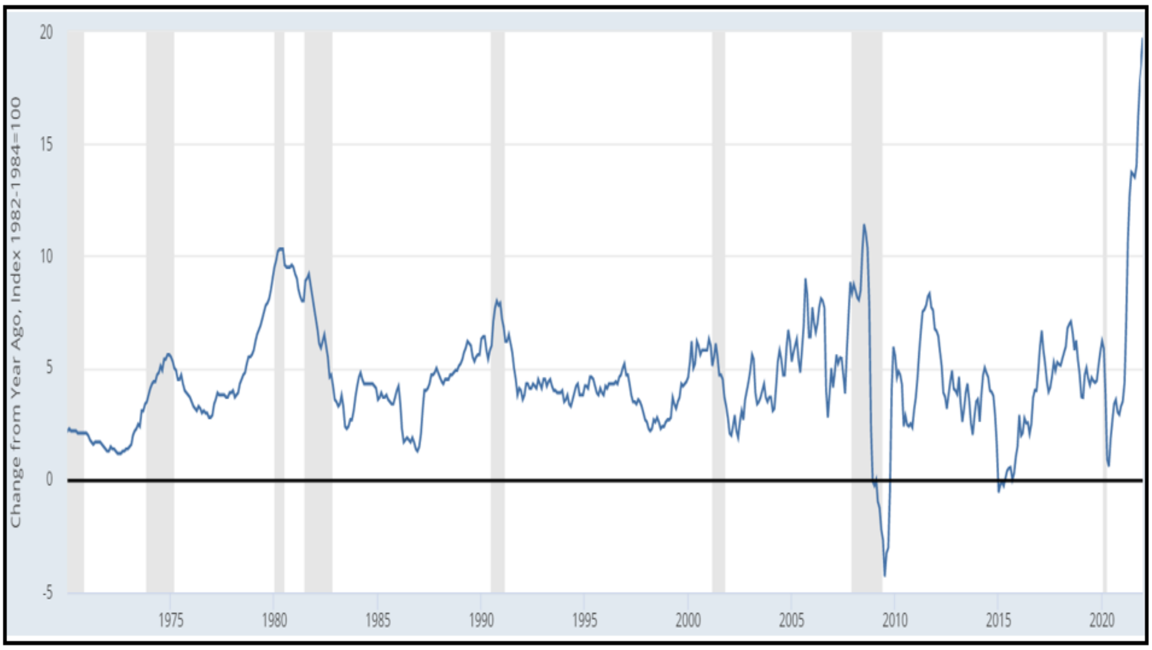
Source: Federal Reserve Economic Database
Notes: Figure 2.7 illustrates the seasonally adjusted number of weekly continued claims filed in the United States dating back to 1968.

Epstein & Yelden (2008) undertake global analysis of the relationship between the central adoption of a new inflation-targeting [IT] approach and employment. They find evidence that countries adopting an inflation-targeting approach have not produced excess economic growth or improved the employment numbers. As per Figure 6, Unemployment claims does provide some useful information in anticipating recessionary periods.

Consumer Price Index (CPI)

The CPI data for this study was sourced from the Bureau of Labor statistics via the Federal Reserve Economic Database. For ease of interpretation, we transformed the unit scale on the vertical axis from a seasonally adjusted index to a measure of the index change on an annual basis. This makes Fig. 2.8 more analytically intuitive. The CPI for all urban consumers calculates the average monthly change in the price for goods and services. According to the federal reserve economic database, the index accounts for 88% of the total population including wage earners, self-employed, short-term workers, those unemployed and retirees. The consumer prices information is collated each month from approx. 4000 US households and 26,000 retailers, The price index captures the rate of change across common household expenditure items including housing, food, fuel, clothing, service fares, utility costs and travel outlays. Price changes are allocated weightings dependent upon their significance. It is commonly accepted that inflation is a lagging economic indicator. It is also a statistical measurement and prone to sampling error.

Figure 2.8: Consumer Price Index (1970-2020)



Source: Federal Reserve Economic Database
Notes: Figure 2.8 illustrates the seasonally adjusted Consumer Price Index [CPI] measured as the Index change from one year previous. The lightly grey shaded areas represent official recession periods as dated by the NBER.

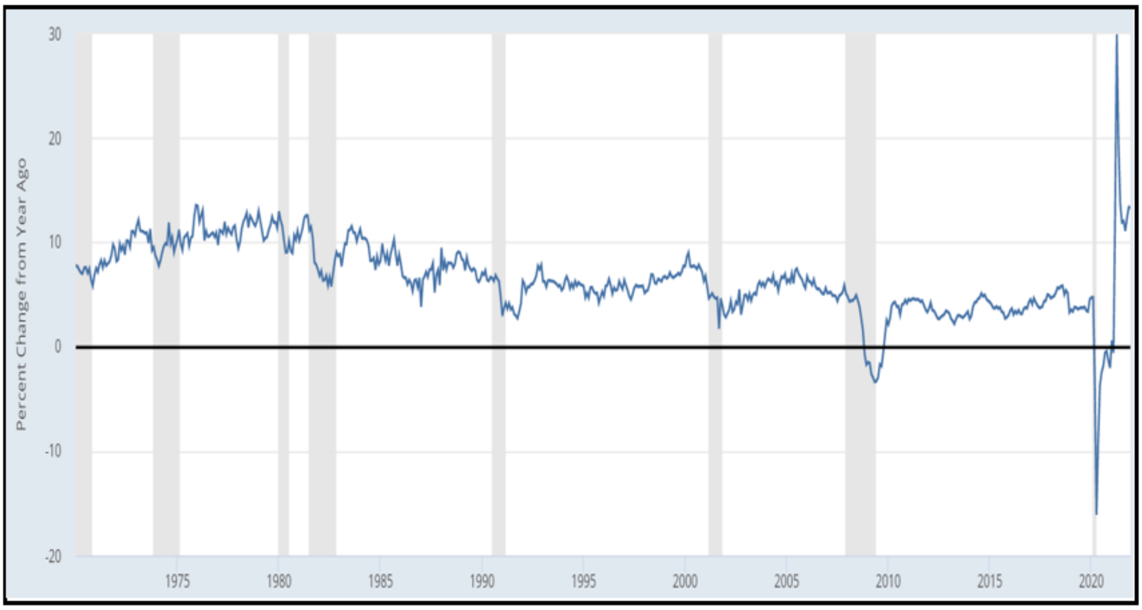
Anderson (2011) studied the relationship between money growth, economic growth and the consumer price index in eight developed countries. He found evidence of positive correlation between money growth and financial asset price inflation across most time periods (short, medium and long term). There was evidence of positive correlation between money growth and consumer inflation only over longer sample periods. Economists have struggled with the task of forecasting inflation. The federal reserve relies on an alternative measure of inflation – Personal Consumption Expenditures (PCE). McNulty et al (2007) highlights four distinct differences between the two measures. Both measures are derived using different index level formulas[59]. The relative weightings for the individual item prices are based on different data sources with CPI focussing on household surveys and PCE relying on business surveys. Thirdly, CPI focuses primarily on expenditure at the household level while PCE concentrates on the goods and services that are purchased. Lastly, there are seasonal and price adjustments that differ across both measures.

[59] CPI uses a modified Laspeyres formula whilst PCE is calculated using the Fisher-ideal formula

Personal Consumption Expenditure (PCE)

The PCE data for this study was sourced from the US Bureau of Economic Analysis (BEA) via the Federal Reserve Economic Database. For ease of interpretation, we transformed the unit scale on the vertical axis from a seasonally adjusted index to a measure of the index change on an annual basis.

Figure 2.9: Personal Consumption Expenditures (1970-2020)



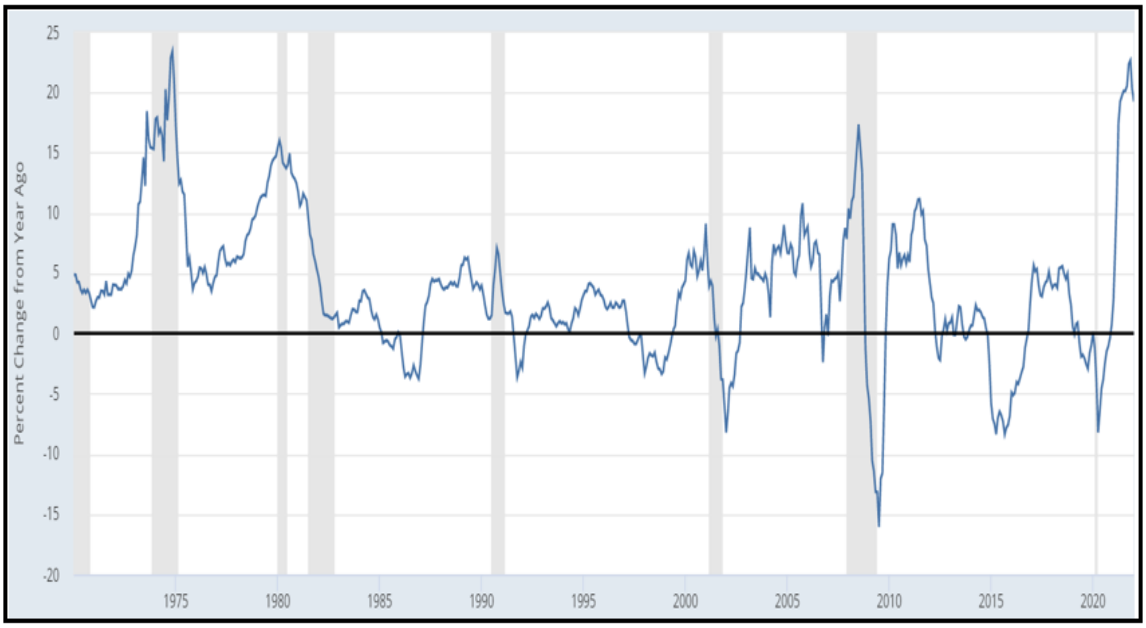
Source: Federal Reserve Economic Database
Notes: Figure 2.9 illustrates the seasonally adjusted Personal Consumption Expenditure Index [PCE] measured as the Index change from one year previous.

Battistin, E. (2003) identifies some potential data quality issues associated with the PCE measure of inflation. He is critical of the over-reliance on this survey-based approach which relies on numerous data points that may ultimately enhance the error distribution. Battistin recommends that an overlapping questionnaire approach focussing on a reduced sample of consumption behaviour may produce more accurate results.

Producer Price Index by Commodity

The Producer Price Index captures the average change over time in the selling price that domestic producers charge for their output. The data for this study was sourced from the US Bureau of Labour statistics (BLS) via the Federal Reserve Economic Database. For ease of interpretation, we transformed the unit scale on the vertical axis from a seasonally adjusted index to a measure of the index % change on an annual basis. How do we differentiate between the various measures of growth and inflation including the consumer price index, personal consumption expenditures and producer price index? Akcay, S. (2011) examined the causal relationship between the consumer price index and the producer price index. The study focussed on five predominantly northern European countries including Finland, Sweden, the Netherlands, Germany and France. The research identified both unidirectional and bidirectional causality utilising the Granger no-causality test[60]. Figure 2.10 shows the PPI movements dating back to 1970. We can map the CPI onto this PPI chart (see Figure 2.11).

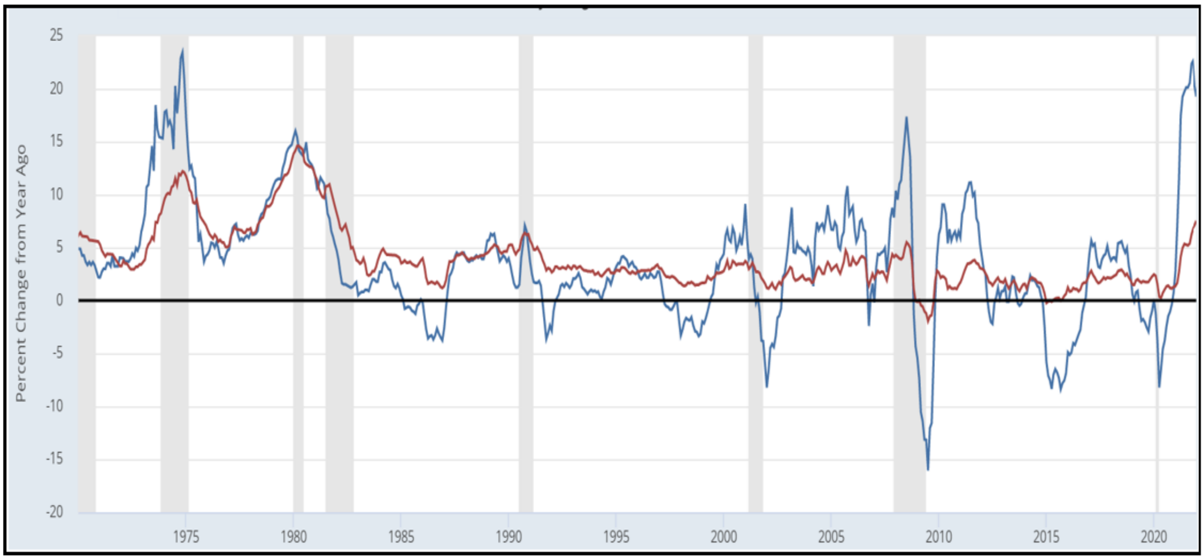
Figure 2.10: Producer Price Index by Commodity (1970-2020)



Source: Federal Reserve Economic Database
Notes: Figure 2.10 illustrates the non-seasonally adjusted Producer Price Index by Commodity [PPIAC] measured as the annual percentage change

The producer price index is much more volatile than the CPI. More importantly, PPI tends to lead the consumer price inflation index as evident from the spikes up in 1973, 1987, 2002 and most recently in 2020.

Figure 2.11: Producer Price Index & Consumer price Index (1970-2020)



[60] The Granger no-causality test was developed by Toda & Yamamoto (1995)

Industrial Production Index

The Industrial Production Index measures the real output for all manufacturing, gas & utilities, and mining & electricity in the United States. The index comprises 312 individual series and these are classified by market and industry groupings. This economic indicator is highly correlated to both US Gross Domestic Product and the S&P500. It therefore acts as a very useful proxy indicator for economic growth in the economy.

Figure 2.12: Industrial Production Index (1970-2020)

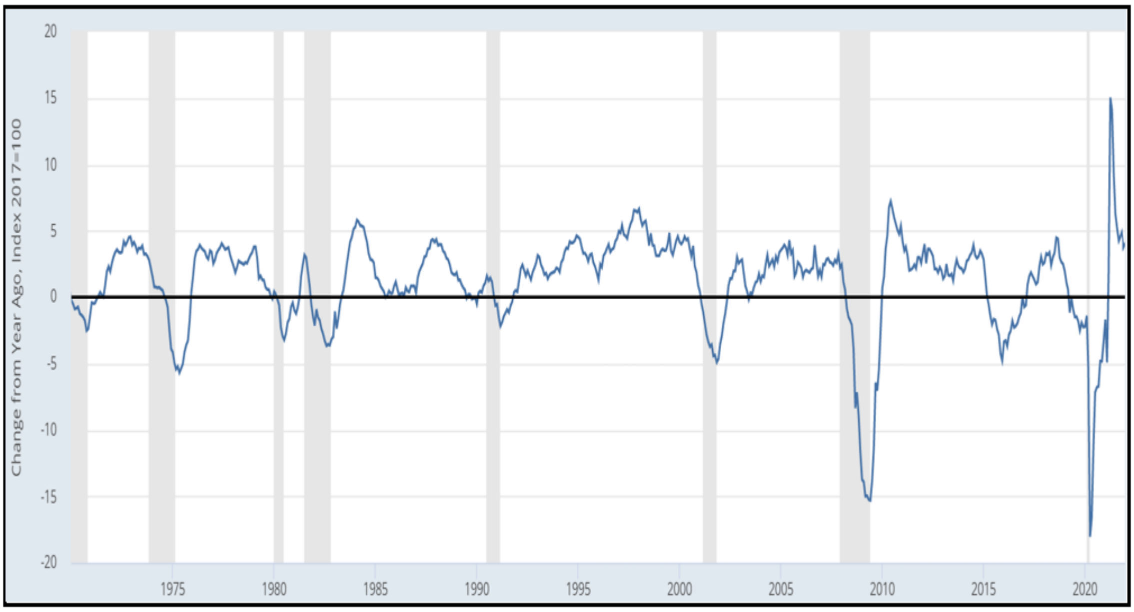
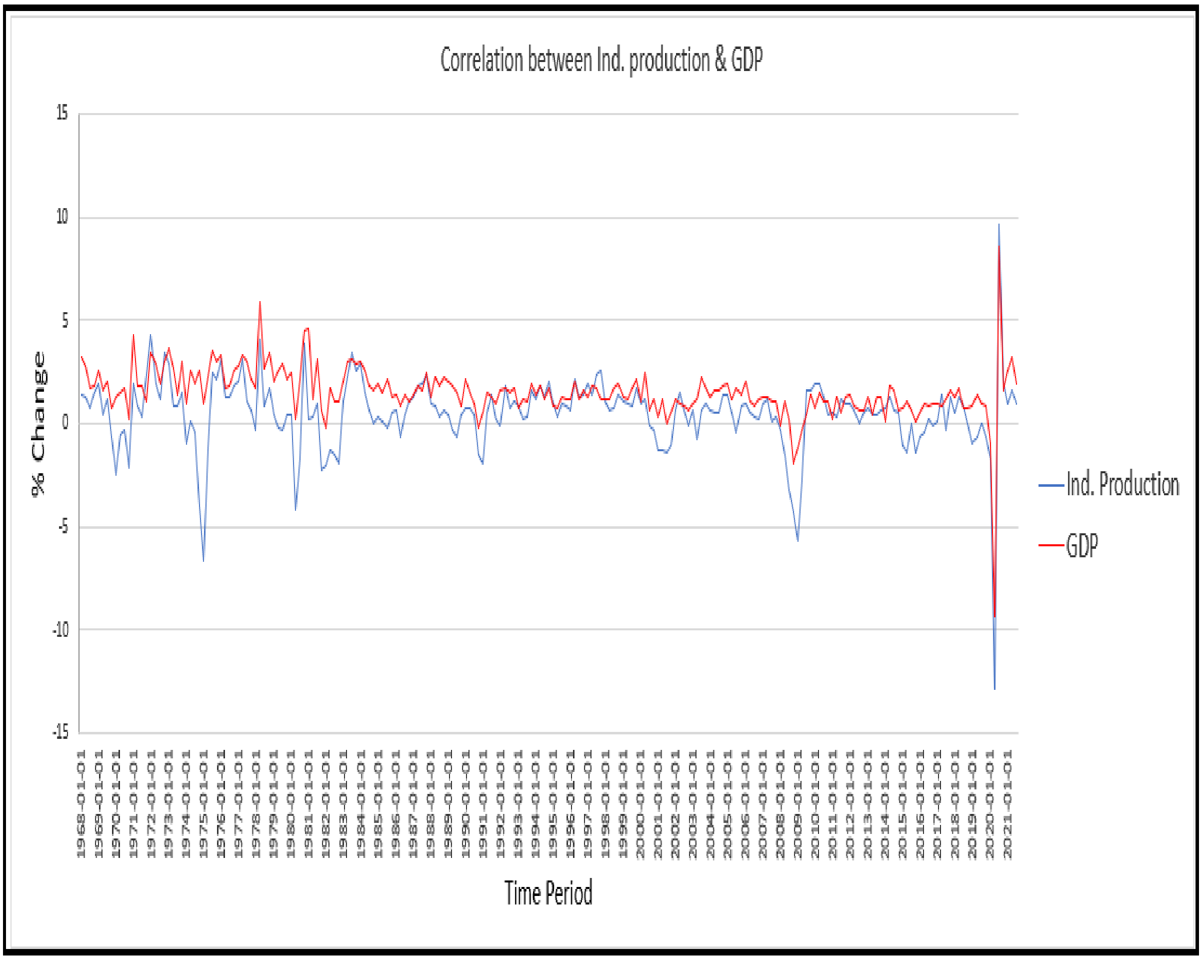


Figure 2.12 illustrates in graphical format the embedded volatility associated with a variable that has a high sensitivity to economic growth. Sirucek, M. (2012) reviewed the impact of several key economic variables including industrial production on a select number of stock indices between 1999 and 2012. This study noted that the level of industrial production was a significant determinant in the performance of equity markets. The literature has perhaps unsurprisingly found evidence of a strong positive relationship between industrial production and equity markets (*Cutler, Poterba, Summers* (1989). *Mukherjee*, *N.* (1995) identified positive correlation between increased industrial production rates and the Japanese stock market. The positive correlation between industrial production and gross domestic product is evidenced in Figure 2.13 below.

Figure 2.13: Positive correlation between Ind. Production & GDP (1970-2020)



We have utilised this positive relationship in constructing the economic regime classification framework. The obvious proxy for economic growth is GDP. However, GDP data is released on a quarterly basis. The majority of our timeseries are monthly data. Therefore, we require a proxy for GDP data on a monthly time-series. We conducted several correlation tests seeking to identify economic variables that were highly correlated to growth. The Industrial Production index indicated a very high positive correlation score of 0.78 with GDP between 1970 and 2020.

2.6: Empirical Findings

The study uses adjusted monthly closing prices from January 1970 to December 2019 for seven individual investment assets and forty-eight predictor variables. This extensive selection of predictor variables is drawn from a varied collection of sources. These include economic, financial, monetary and commodity-based data. We compute the percentage change in monthly returns for both assets and predictor variables. This study encompasses a 50-year data sample. Our first step is to test for the presence of unit roots in the data and examine if the variables follow a stationary process. We utilise both the Augmented Dickey-Fuller (ADF)[61] and Phillips-Perron (PP)[62] tests for a stationary process.

2.6.1 Hypothesis Testing

Our first step was to conduct each stage of the multiple linear regressions. This involved the (i) full-sample regressions, the (ii) regime-specific regressions and the (iii) sample-specific regressions. After a protracted and detailed initial screening period of predictor variables, statistically significant regressors were added to the models. We next needed to complete some standard tests for the presence of multicollinearity, autocorrelation and heteroscedastic errors. The Durbin-Watson test was initially used for the presence of Autocorrelation. In many of the regressions, the D-W test revealed strong evidence of the presence of autocorrelation. There are problems however in relying solely on the use of the Durbin-Watson test for autocorrelation given its restrictiveness to one lag and its heavy assumption that the residuals are normally distributed. Alternatively, the Breusch-Godfrey test is less sensitive to the assumption of normality and allows us to test for the presence of serial correlation through several lags.

Table 2.10 shows the annualised means, standard deviations, skewness and excess kurtosis for each of the seven-return series. The summary statistics are regime agnostic. It is interesting to note that gold is the strongest performing asset over the 50-year period of our study along with a marginally higher standard deviation than the Nikkei 225. Tables 2.11 – 2.14 denote the summary statistics for each economic regime. Table 2.11 captures the annualised means and standard deviations for a high growth | low inflation economic regime. Regime 1 is classified as an economic environment where the rate of change of growth is increasing into a decreasing inflationary regime There are 188 monthly observations that capture this expansionary economic environment. Both the S&P500 and the Nikkei produce annualised means of 8.942% and 5.463% respectively. Gold produces the highest level of volatility during this period (16.387%) yet produces the lowest relative performance of 1.889%. Table 2.12 captures the annualised means and standard deviations for a high growth | high inflation economic regime. Regime 2 is classified as an economic environment where the rate of change of growth is increasing into an increasing inflationary regime There are 135 monthly observations that capture

[61] Dickey & Fuller (1979)
[62] Philips & Perron (1988)

this economic environment. Both the S&P500 and the Nikkei maintain strong annualised means of 6.898% and 9.718% respectively. Again, Gold produces the highest level of volatility during this period (19%). However, the risk-adjusted Sharpe ratio is improved by a stronger performing gold (9.417%). The fixed income components underperform in regime 2. This may be a function of policy action from central banks raising the discount rate which inevitably negatively impacts bond prices. Table 2.13 captures the annualised means and standard deviations for a low growth | high inflation economic regime. Regime 3 is classified as an economic "*stagflationary*" environment where the rate of change of growth is decreasing into an increasing inflationary regime There are 139 monthly observations that capture this economic environment over the 50-year sample period. Both the S&P500 and the Nikkei underperform, producing annualised means of 2.4% and 6.179% respectively. During this peak period of inflationary pressures, Gold maintains its high level of volatility (19%) and produces significant returns in excess of 23% per annum. Non-energy commodities underperformed with annualised means of 4.6% and an excessive volatility of over 10%. Both US Treasuries (7.288%) and US Corporate bonds (6.966%) provide stable annualised means during this period. Table 2.14 captures the annualised means and standard deviations for a low growth | low inflation economic regime. Regime 4 is classified as an economic "deflationary" environment where the rate of change of growth is decreasing into a disinflationary regime There are 150 monthly observations that capture this economic environment over the sample period. Both the Gold and non-energy commodities underperform, producing annualised means of 1.674% and -2.759% respectively. Treasury bonds are the strongest performing asset (16.139%) followed by US Corporate bonds (10.72%). This is a particularly volatile period for equities with the annualised standard deviations of the S&P500 and the Nikkei 225 hitting 14% & 17% respectively. Despite the poor growth backdrop, US stocks provide strong returns (10.934%) with the Nikkei 225 producing returns of 4.754%.

2.6.2 Comment on regime classification

The economic classification of each regime in Table 2.11 to Table 2.14 is determined by the methodology described in Table 2.20. Individual market regimes are defined by the rate of change in both growth and inflation for each asset class and whether that rate of change in percentage terms falls above or below a pre-defined long-run average. The summary statistics are derived from the underlying economic regime as determined by the classification methodology detailed in Table 2.20. The full 50-year sample is equally exposed to each of the four economic regimes. Consistent with both the ECRI and NBER data series, regime 1 is the most frequent making up 31% of the entire sample period. Deflationary or recessionary periods account for approx. a quarter of the data with both reflation and stagflationary regimes making up an equal share of approx. 22% each.

2.5.3 Date specific Regime Classifications

January 1970 – December 1982

The twelve-year period between January 1970 and December 1982 was characterised by low average growth levels and rising inflationary pressures. It may be possible to cross-reference the sample-specific asset pricing data in this section with the regime-dependent asset prices in section 3.1. For instance, Table 2.15 reports summary statistics for each asset captured during this sample period January 1970 to December 1982. The data spans a sample of the full period and there are 156 monthly observations. The statistically significant t-statistics have a double asterisk. Section 2.1 characterise a low growth | high inflationary regime as "stagflation" or regime number 3. Table 2.13 captures the annualised means and standard deviations for a low growth | high inflation economic regime over the 50-year sample period. The S&P500 underperforms the Nikkei225, producing annualised means of 2.4% and 6.179% respectively. The equity market performance reported in Table 2.15 of both the S&P500 and the Nikkei225 appears to reinforce these findings with the S&P500 and Nikkei225 reporting annualised means of 3.309% and 11.133% respectively. Similarly, gold produces the strongest performance (23.383%) in regime number 3 as replicated in Table 2.15 (21.358%). In general, the annualised means and standard deviations in both the sample specific "low growth|high inflationary" regime period and Regime number 3 produce very similar results. This suggests a level of consistency in the data dependent upon the underlying economic regime.

January 1983 – December 1999

The 17-year period between January 1983 and December 1999 was characterised by high average growth levels and decreasing inflation rates. Table 2.16 reports summary statistics for each asset captured during this sample period January 1983 to December 1999. The data spans a sample of the full period and there are 204 monthly observations. The statistically significant t-statistics have a double asterisk. Section 2.1 characterise a high growth | low inflationary regime as "Optimal" or regime number 1. Table 2.11 captures the annualised means and standard deviations for a high growth | low inflation economic regime over the 50-year sample period. The S&P500 substantially outperforms the Nikkei225 across both regime classifications on an absolute basis and risk-adjusted metric[63]. Table 2.16 reports annualised means for the S&P500 & Nikkei225 of 14.253% and 6.471% respectively. The corresponding equity market performance reported in Table 2.11 of both the S&P500 and the Nikkei225 appears to reinforce these findings with the S&P500 and Nikkei225 reporting annualised means of 8.942% and 5.463% respectively. The underperformance of gold and commodities is consistent across both Table 2.11 and Table 2.16. The fixed income returns are also very similar in terms of their annualised means and standard deviations whether the assessment is made on a regime-specific classification (Table 2.11) or sample specific period (Table 2.16). Some additional consistencies are worth noting. US Corporate bonds exhibit strong risk/return ratios across both regime classifications. The asset volatility[64] of gold relative to its under-performance and scaled volatilities appear constant across both the economic regime classification and regime sample period approach.

January 2000 – December 2019

The 20-year period between January 2000 and December 2019 was characterised by lower average growth levels, persistently lower inflation rates and continual central bank interventionism. It may be possible to cross-reference the sample-specific asset pricing data in this section with the regime-dependent asset prices. **Table 2.17** reports summary statistics for each asset captured during this sample period January 2000 to December 2019. The data spans a sample of the full period and there are 252 monthly observations. Section 2.1 characterise a low growth | disinflationary regime as a “deflation” or regime number 4. **Table 2.14** captures the annualised means and standard deviations for a low growth | low inflation economic regime over the 50-year sample period. It is interesting to note from **Table 2.14** that the actual S&P500 and Gold annualised mean is very different that captured through the strict economic regime classification model. The S&P500 realised return underperforms its regime classification counterpart by circa 6% p.a. The 10.934% annualised mean may capture the incessant “buy-the-dip”[65] investment mandate whereby government intervention may be distorting the rational expectations of asset pricing. The Nikkei225 and US Corporate bond both exhibited similar returns with the other assets displaying much greater disparity than the earlier timeseries. Additional

[63] William Sharpe (1964), Superior risk-adjusted returns determined by a higher relative Sharpe ratio for the S&P500 than the Nikkei225
[64] Volatility is measured by Annualised Standard Deviations
[65] Cole, C. 2017 “The Alchemy of Finance”

research might question whether the intervention of central bank policies have manipulated the price movement

2.7. Summary

The proposition that subjective investor judgements have value rely on the belief that financial assets do not exist in a vacuum. Instead, assets co-exist amongst macroeconomic variables, monetary policies and market sentiment. This paper seeks to align these rational decision-making processes with a regime-based asset allocation framework[66]. The fundamental principle driving RBAA is that an awareness of economic regimes and their diverging macroeconomic forces shape and influence the direction of financial assets. RBAA is the antithesis of static asset allocation. The underlying question throughout this research paper is whether an economic regime-focussed asset allocation strategy supports informational alpha and superior risk-adjusted performance.

2.7.1 Full Sample

We attempt to initially answer these questions by focussing on the behaviour of financial assets and a selection of key predictor variables over a 50-year sample period. Should we expect a constant relationship to exist between these explanatory variables and the assets in our study? If we identify shifts, deviations and structural breaks in these relationships, does this offer important information to the asset allocation process. Table 2.27 reports estimated coefficients for the multiple linear regression model for the sample period January 1, 1970, to December 31, 2020. The dependent variable is the monthly percentage change in the S&P500 index. The eleven independent variables are a combination of investment assets and macroeconomic variables. The Macroeconomic variables include Personal Income and Personal Consumption Expenditures (PCE) both sourced from the U.S Bureau of Economic Analysis, M2 money velocity and the consumer price index (CPI). Commodity based regressors include the % changes in the prices of aluminium and iron ore. Additional predictor variables include heavy weight trucks which includes trucks with more than 14,000 lbs gross vehicle weight and the yield on triple A-rated corporate bonds. Consistent with economic theory, positive increases in personal income and personal consumption are supportive of US equity markets. Similarly, a 1% rise in both the Nikkei225 and US Corporate bond price index result in positive performance for the S&P500. Increases in treasury yields, AAA rated bond yields M2 money velocity

[66] RBAA or regime-based asset allocation infers that there is some informational benefit for investors to study the movement of economic regimes in determining their overall asset allocation

negatively impacts the S&P500. A 1% rise in CPI results in a 1.24% decline in the S&P500. Both Aluminium and Iron ore are important commodities and linked intrinsically to positive economic growth. The results from Table 2.27 are consistent with that thesis indicating positive relationship between the s&p500 and both variables.

We can also take a full sample analysis of gold and its primary predictor variables. Table 2.28 reports estimated coefficients for the multiple linear regression model for the sample period January 1, 1970, to December 31, 2020. The dependent variable is the monthly percentage change in the gold fixing price*. The twelve independent variables are a combination of investment assets and macroeconomic variables. The Macroeconomic variables include the US Dollar index, M2 money velocity and crude oil prices. Commodity based regressors include the % changes in the prices of sugar, cotton, rubber, and platinum. Additional predictor variables include the producer price index for iron & steel and the house price index. The negative correlation between the US dollar and gold has been widely cited in the literature. Capie et al. (2005), Baur & Lucey, 2010 & Reboredo, (2013) have all pointed to the use of gold as a strong hedge against the dollar index over time. Zhou et al. (2017) highlight three specific reasons for this consistent negative correlation. The primary rationale given is that both gold and the US dollar act as a reserve asset for central banks. A strengthening US dollar should therefore reduce the requirement for holding gold as a safe haven. Consistent with economic theory, our sample indicates that a positive increase in the US Dollar index results in 0.28% drop in the spot price of gold. Joy (2011) noted that gold and the dollar are not always negatively correlated particularly during stressed market events. A long horizon sample covering 50 years does not allow us to interrogate this further. According to our sample, there exists a negative long-term relationship between equities and gold. A 1% rise in the Nikkei225 and S&P500 results in a decline of approx. 0.11%. Research conducted by the World Gold Council (2003) noted that there was no statistically significant correlation between returns on gold and changes in the measures of GDP, CPI and rates. Financial assets including the main equity markets are heavily influenced by the market expectations of growth, inflation and the discount rate. This may explain the negative correlation between the S&P500 and the Nikkei225 in our sample. We may also note that a 1% rise in M2 velocity result in 0.5% increase in the returns of gold. The Federal reserve economic database defines M2 as the frequency at which one unit of currency is used to purchase domestically produced goods and services within a given period. A rising M2 velocity may be associated with greater inflationary pressures and hence the rational linkages to higher gold prices. There appears to be a general trend, although difficult to confirm this over such a long sample, that financial assets are negatively correlated to gold returns. For instance, a 1% rise in the US house price index also have a negative impact (-0.53%) on gold returns. Some brief additional commentary on the other results. We note that there exist positive performance relationships between Crude oil, sugar, rubber and platinum. It is difficult to assign causality here across a 50-year sample period. We may propose in relation to Crude Oil that there exists a common embedded volatility premium (Illmanen, 2011) with both oil prices and gold offering some protection during periods of above average inflation.

We can also take a full sample analysis of 10 Year US Treasury bond returns and its primary predictor variables. Table 2.29 reports estimated coefficients for the multiple linear regression model for the sample period January 1, 1970, to December 31, 2020. The dependent variable is the monthly percentage change in the returns on the 10-year US Treasury bond. The eleven independent variables are a combination of investment assets and macroeconomic variables. The macroeconomic variables include Personal Income and Personal Consumption Expenditures [PCE] both sourced from the U.S Bureau of Economic Analysis, US building permits and PPI All Commodities data. Commodity based regressors include the % changes in the prices of copper. Additional predictor variables include the US Corporate Bond index. The regression results noted earlier in the analysis of international stocks and gold appears consistent. For instance, a 1% increase in equity returns leads to a negative outcome for US treasuries. Similarly, a 1% increase in personal income accounts for a statistically significant 0.23% decline in US treasury returns. The same increase in personal expenditures results in a 0.27% decline. What is driving this relationship? The literature posits that stronger personal income and personal expenditures increase inflationary pressures leading to implications for inflation and rate expectations. The inverse relationship between rising rates and bond prices may explain this negative relationship. Table 2.29 provides evidence of negative relationships between established leading indicators[67] of inflation such as copper and the Producer Price Index (for all Commodities). Higher commodity prices, including copper, could be a leading indicator of inflationary pressures. If this relationship holds, higher

[67] A "leading indicator" provides insightful economic data which forecasters may draw causal inference from

copper prices should lead to increasing Treasury yields. Akram, T. & Das, A. (2019) noted that this is a natural function of investors seeking higher yield premium for protection from inflation. Higher yields lead to lower prices as evidenced in this paper's regressions. Does this relationship hold consistently across multiple market cycles, however? To answer this question, we need to delve deeper focussing on smaller segments of the sample data. Our study concentrates on regimes to answer these questions.

2.7.2 Regime based analysis

Tables 2.30 to 2.32 captures statistically significant predictor variables based on multivariate linear regressions with non-contiguous sampling. Our full 50-year dataset is segmented into one of four possible regimes according to the classification process detailed in section 2.1. Table 2.30 specifically reports estimated coefficients for the four non-contiguous multiple linear regression models. The dependent variable is the monthly percentage change in the S&P500 index. We categorise regime 1 as an economic environment where the % change in growth is increasing and the % change in inflation is decreasing. The sample period is January 1, 1970, to December 31, 2020. Regime 1 or "Optimal" is captured with seven statistically significant regressors. We categorise regime 2 as an economic environment where the % rate of change in growth is increasing and the % rate of change in inflation is also increasing. Regime 2 or "Reflation" is captured with nine statistically significant regressors. We categorise regime 3 as an economic environment where the % rate of change in growth is decreasing and the % rate of change in inflation is increasing. Regime 3 or "Stagflation" is captured with ten statistically significant regressors. Finally, Regime 4 is categorised as an economic environment where the % rate of change in growth is decreasing and the % rate of change in inflation is also decreasing. Regime 4 or "Deflation" is captured with seven statistically significant regressors. A more granular review of the individual regressors is informative.

There are some common trends immediately noticeable. Firstly, the statistically significant predictor variables are not constant across the individual economic regimes. For instance, crude oil is a significant explanatory variable in regimes 1 and 3 only. The cost per unit of Heavy-weight industrial trucks is statistically significant during the *stagflationary* (R.3) regime and does not appear significant in any of the other regimes. Similarly, gold appears in both *optimal* (R.1) and *reflation* (R.2). Why are these predictor variables transitory in their significance if not for the shifting influence of macroeconomic variables? Secondly and perhaps more importantly is the fluctuating nature of the relationship between our independent variables and predictors. A 1% increase in gold returns leads to a negative 0.31% decrease in the returns of the S&P500 during the *optimal* phase. This is intuitively appealing as long-horizon empirical work supports the negative correlation between gold and US equities. We may pose the question; whether this short-horizon causal relationship holds throughout the sample or whether it reflects the shorter-term dynamics. Evidence from Table 2.30 would appear to support the latter as during the reflation period a 1% increase in gold returns lead to a 0.16% increase in the S&P500. Our approach will be to infer the causality from the underlying economic regime and not the assets themselves. Regime 2 is characterised as an economic environment where the % rate of change in growth is increasing and the % rate of change in inflation is also increasing. Whilst regime 1 is dominated by persistent growth, inflation is decreasing and the benefits to investors of holding an asset like gold diminishes. The utility of gold exposure increases in regime 2 as inflation expectations increase. Table 2.30 would appear to capture the shifting relationship between the S&P500 and gold from regime 1 to regime 2 where economic growth persists but inflationary expectations/pressures start to impact investor preferences. The evidence against potential spurious fluctuations of causality is supported by the consistency of certain relationships. For instance, a 1% increase in the Nikkei225 consistently accounts for a positive increase in the S&P500[68]. We note similar results for US corporate bond index across all three regimes (excl. Stagflation or regime 3). Thirdly, this study supports the argument that individual regimes operate in their own ecosystem or economic environment. We note for instance that both unemployment and non-farm payrolls (NFP) appear statistically significant in regime 4 only. This may be surprising given the focus placed on general employment in the US economy and the NFP release at the end of each month. We finally notice evidence of regime or economic specific results. For illustration, regime 3 or stagflation incorporate an economy of slowing growth and rising inflation. We note a visible shift with the inclusion of inflation sensitive explanatory variables including CPI, AAA Yield, the

[68] This consistency ranges across the four regimes in a tight band from 0.22% to 0.38%.

credit spread[69], Heavy weight trucks cost per unit and Crude Oil. Significantly, none of these five predictors are statistically significant in subsequent regime (4).

Table 2.31 reports estimated coefficients for the four non-contiguous multiple linear regression models for the monthly returns in the gold fixing price. The regime categorisation process follows the same convention as per Table 2.30. The sample period is January 1, 1970, to December 31, 2020. There are some common trends immediately noticeable. Again, the statistically significant predictor variables are not constant across the individual economic regimes. For instance, personal consumption expenditures (PCE) and M2 velocity are significant explanatory variable in regimes 1 only. Regime 1 is dominated by increasing growth prospects. Rising PCE is consistent with a growing economy and increased investment flows into the stock market. We have already identified that gold returns are negatively corelated to the S&P500 so there could be cross-asset correlations evident here. Most interesting is the appearance of "*total consumer credit*" during the inflationary regime 2 and regime 3. This explanatory variable is not statistically significant in either of the dis-inflationary periods (regime 1 or 4). A 1% rise in consumer credit leads to a 0.73% and 1.16% increase in gold returns. There is evidence in the literature that excessive credit fuels inflationary pressures which may be supportive of safe haven type assets like gold. The producer price index for iron and steel (PPI Iron & Steel) is a stable proxy for economic growth. The predictor is statistically significant and has a negative influence on gold returns in both regime 1 & 2. It is not statistically significant in periods of declining growth. It is interesting to note that a rise in equity market returns have a negative impact on gold returns during growth regimes 1 & 2. Neither the S&P500 or the Nikkei225 are statistically significant during the declining growth regimes. Why are these predictor variables transitory in their significance if not for the shifting influence of macroeconomic variables? Secondly and perhaps more importantly is the fluctuating nature of the relationship between our independent variables and predictors. A 1% increase in sugar returns leads to a positive 0.31% increase in the returns of gold during the *stagflationary* phase. However, the relationship turns negative during the *deflationary* regime as a 1% rise in sugar returns leads to a negative -0.19% decrease in gold returns.

The evidence against potential spurious fluctuations of causality is supported by the consistency of certain relationships. For instance, a 1% increase in the US Dollar Index consistently accounts for a decrease in gold returns[70]. We note similar results for US corporate bond index across all three regimes (excl. Stagflation or regime3). Thirdly, this study supports the argument that individual regimes operate in their own ecosystem or economic environment. We note for instance that predictor variables crude oil and

[69] As measured by the 10 Year Treasury constant maturity minus the Federal Funds rate [Noted at Treas10YFF in regression table 2.15]

[70] This consistency ranges across the four regimes in a tight band from -0.24% to -0.38%.

unemployment claims appear statistically significant only in regime 3. Stagflation incorporates an economy of slowing growth and rising inflation. Our study is consistent with the empirical work of Thaver, R.L & Lopez, J. (2016) who revealed a positive long-run relationship between the price of gold and unemployment. The authors attempted to model gold prices as a function of the unemployment rate utilising three data sample specific[71] periods using the Pearson cointegration model. A 1% increase in the unemployment rate led to a 0.22% increase in gold during regime 3. Crude oil also offered positive explanatory power for gold returns during this stagflationary regime. Le, TH. & Chang, Y. (2011) investigated the relationship between gold and oil using monthly data between 1986 and 2011. They identified that the effect of oil prices on gold prices was non-linear in nature and that optimal gold price forecasting benefits from the inclusion of oil price data.

Table 2.32 reports estimated coefficients for the four non-contiguous multiple linear regression models. The dependent variable is the monthly percentage change in the returns on the 10-year US Treasury bond and the sample period is January 1, 1970, to December 31, 2020. The regime categorisation process follows the same convention as per Table 2.30. There are some common trends immediately noticeable. Like the S&P500 and Gold regression tables previously, the statistically significant predictor variables are not constant across the individual economic regimes. For instance, the predictor variable US (building) permits has explanatory power in regimes 1 and 4 only. The common denominator is an economic regime characterised by disinflationary pressures. Both regimes capture a negative relationship where a 1% rise in the number of building permits results in marginal losses in 10-year US treasuries. US building permits are associated with positive economic growth and have provided useful leading indicators of the relative health of the real estate market. Given the inverse relationship between treasury yields and returns, building permits may signal increased asset price appreciation in housing causing asset price inflation. Evans, C.L & Marshall, D.A (2004) list inflation shocks as a primary determinant of nominal treasury yield curves. Secondly and perhaps more importantly is the fluctuating nature of the relationship between our independent variables and predictors. The unemployment rate provides positive explanatory power for US Treasury returns in regime 2 and 3 whereby a 1% rise in unemployment produces a

[71] Three distinct models were selected under different conditions: Model 1: 1978-2016 | Model 2: 1990-2016 | Model 3: 2008-2016

marginal positive return in both these inflationary regimes. The economic theory would suggest that rising unemployment should influence monetary policy makers to reduce rates to stimulate the economy. Lower rates support Treasury prices and returns. Interestingly, the relationship between the returns on 10-year US treasuries and our unemployment variable shifts negative during regime 4. An economic environment characterised by lower-than-average growth and lesser than average inflation. The key question is what has happened during this period to shift the relationship negative between our predictor variable unemployment and the returns on the 10-year US treasury bond. Is it possible that business cycle forces (late- cycle policy action) are driving rates higher thereby negatively impacting returns? Further research is required on the broader implications of the transition factor between economic regimes.

2.8 Conclusion

In this chapter market regimes were classified according to the characteristics of their long-run macroeconomic variables including growth and inflation. For robustness, our fifty-year sample was analysed across both non-contiguous, strictly regime-based criteria and recognised economically classified sample periods categorised by the NBER. In general, the annualised means and volatilities of both the sample specific "growth| inflationary" regimes and recognised sample categories produced very similar results. This consistency is captured by the behaviour of model parameters across common economic environments. This suggests a level of uniformity in the data dependent upon the underlying economic regime. This relationship appears to have broken down during the final low growth| low inflationary regime (2007-2019) which may account for a degree of market distortion from the unconventional monetary policy action of global central banks. This dislocation requires further investigation. The initial analysis focussed on the long-run relationship between statistically significant predictor variables and dependent assets with economic causality clearly identifiable and supported by the existing literature. To identify whether these relationships were consistent across economic regimes, a more forensic approach is necessary centred upon concentrated data analysis of shorter duration. A segmentation of the data analysis identified transience among certain predictor variables leading to the conclusion that shifting macroeconomic conditions directly influence these relationships. Also, the nature of the corelation between our predictor variables and dependent assets fluctuated, conditional upon the underlying economic regime indicating a shifting macroeconomic environment. Finally, the predictor variables themselves could be classified according to the underlying economic regime with inflation sensitive variables offering greater statistical significance across regimes 3 and 4 for instance.

2.9 Tables and Figures

Table 2.10: Summary Statistics 1970 – 2020 Full Data Sample without regime classifications

Sample Period	1970 - 2020						
Regime Classification	All Regimes						
	S&P500	**Nikk225**	**Gold**	**Non-Energy**	**US Corp. Bond**	**US Treasury**	**USDXY**
Annualised Mean	7.453	6.376	8.074	3.432	7.361	8.016	-0.200
Annualised Std. Dev	13.573	16.165	16.488	9.541	6.140	8.207	8.389
Observations	612	612	612	612	612	612	612
Maximum	15.104	15.280	37.493	11.646	11.972	13.232	9.443
Minimum	-22.804	-24.799	-18.347	-16.573	-9.463	-7.412	-8.146
Skewness	-0.985	-0.615	1.151	-0.097	0.411	0.543	0.246
Kurtosis	7.467	5.123	10.410	6.483	11.282	5.215	3.936
Median	11.573	8.239	1.679	1.655	6.174	5.595	-0.074
t-statistic	**3.793****	**2.738****	**3.374****	**2.529****	**8.286****	**6.731****	-0.171

Notes: Summary statistics for each asset class in our study spanning the full sample period [1970-2020]. There are 612 monthly observations. The statistically significant t-statistics have a double asterisk.

Table 2.11: 1970 – 2020 Full Data Sample **with** regime classifications [**Regime 1**]

Sample Period	1970 - 2020						
Regime Classification	1						
Economic Environment	*High Growth | Low Inflation*						
	S&P500	**Nikk225**	**Gold**	**Non-Energy**	**US Corp. Bond**	**US Treasury**	**USDXY**
Annualised Mean	8.942	5.463	1.889	1.157	7.279	6.070	1.882
Annualised Std. Dev	12.843	18.393	13.493	9.747	4.851	7.094	7.797
Observations	188	188	188	188	188	188	188
Maximum	11.181	15.280	16.387	8.285	3.730	6.420	7.778
Minimum	-22.804	-24.799	-15.956	-16.573	-9.463	-6.952	-5.385
Skewness	-2.023	-0.572	0.272	-0.681	-1.912	-0.147	0.159
Kurtosis	12.712	5.096	6.408	9.423	16.254	4.047	3.509
Median	14.557	2.892	1.050	-1.212	6.746	4.433	2.448
t-statistic	**2.649****	1.147	0.549	0.467	**5.750****	**3.296****	0.947

Notes: Summary statistics for each asset captured in regime 1. Regime 1 is classified as an economic environment where the rate of change of growth is increasing into a decreasing inflationary regime. The data spans the full sample period (1970-2020). There are 188 monthly observations. The statistically significant t-statistics have a double asterisk **.

Table 2.12: 1970 – 2020 Full Data Sample **with** regime classifications (**Regime 2**)

Sample Period	1970 - 2020
Regime Classification	2
Economic Environment	*High Growth | High Inflation*

	S&P500	Nikk225	Gold	Non-Energy	US Corp. Bond	US Treasury	USDXY
Annualised Mean	6.898	9.718	9.417	12.884	4.245	2.887	0.450
Annualised Std. Dev	12.784	14.554	19.008	8.818	6.051	7.434	8.740
Observations	135	135	135	135	135	135	135
Maximum	9.747	14.698	37.493	10.430	8.013	6.418	8.607
Minimum	-12.088	-16.356	-12.280	-6.856	-6.988	-6.570	-8.146
Skewness	-0.339	-0.499	2.211	0.291	-0.050	-0.034	0.233
Kurtosis	3.681	5.216	16.648	4.739	7.348	3.170	4.704
Median	5.190	8.679	0.899	13.638	3.017	1.779	0.000
t-statistic	1.755	**2.146****	1.594	**4.633****	**2.308****	1.286	0.172

Notes: Summary statistics for each asset captured in regime 2. Regime 2 is classified as an economic environment where the rate of change of growth is increasing into an increasing inflationary regime. The data spans the full sample period (1970-2020). There are 135 monthly observations. The statistically significant t-statistics have a double asterisk **.

Table 2.13: 1970 – 2020 Full Data Sample **with** regime classifications (**Regime 3**)

Sample Period	1970 - 2020
Regime Classification	3
Economic Environment	*Low Growth | High Inflation*

	S&P500	Nikk225	Gold	Non-Energy	US Corp. Bond	US Treasury	USDXY
Annualised Mean	2.400	6.179	23.383	4.602	6.966	7.288	-2.687
Annualised Std. Dev	14.372	13.770	19.426	10.553	7.205	8.906	8.166
Observations	139	139	139	139	139	139	139
Maximum	15.104	8.989	19.436	11.646	11.972	13.232	6.766
Minimum	-12.708	-13.643	-18.347	-7.865	-7.350	-7.412	-7.001
Skewness	-0.284	-0.879	0.425	0.366	0.912	0.886	0.280
Kurtosis	4.605	4.365	4.855	4.419	10.645	7.096	3.559
Median	4.106	9.313	14.095	3.336	4.106	6.030	-4.385
t-statistic	0.562	1.486	**3.713****	1.454	**3.189****	**2.696****	-1.134

Notes: Summary statistics for each asset captured in regime 3. Regime 3 is classified as an economic environment where the rate of change of growth is decreasing into an increasing inflationary regime. The data spans the full sample period (1970-2020). There are 139 monthly observations. The statistically significant t-statistics have a double asterisk **.

Table 2.14: 1970 – 2020 Full Data Sample **with** regime classifications [**Regime 4**]

Sample Period	1970 - 2020
Regime Classification	4
Economic Environment	*Low Growth | Low Inflation*

	S&P500	Nikk225	Gold	Non-Energy	US Corp. Bond	US Treasury	USDXY
Annualised Mean	10.934	4.754	1.674	-2.759	10.720	16.139	-1.035
Annualised Std. Dev	14.396	16.729	13.819	8.443	6.524	9.122	8.988
Observations	150	150	150	150	150	150	150
Maximum	11.352	12.922	18.702	7.794	11.262	10.127	9.443
Minimum	-21.156	-18.146	-12.645	-10.774	-5.067	-4.418	-6.064
Skewness	-1.100	-0.532	0.588	-0.271	1.246	0.728	0.330
Kurtosis	8.199	4.435	6.129	5.497	9.846	3.927	3.774
Median	16.128	9.462	-1.139	-4.455	8.862	9.128	-1.061
t-statistic	**2.559****	0.983	0.425	-1.170	**5.542****	**5.835****	-0.409

Notes: Summary statistics for each asset captured in regime 4. Regime 4 is classified as an economic environment where the rate of change of growth is decreasing into a decreasing inflationary regime. The data spans the full sample period (1970-2020). There are 150 monthly observations. The statistically significant t-statistics have a double asterisk **.

Table 2.15: 1970-1982 Low Growth & High Inflationary environment

Sample Period	1970 - 1982
Economic Environment	*Low Growth | High Inflation*

	S&P500	Nikk225	Gold	Non-Energy	US Corp. Bond	US Treasury	USDXY
Annualised Mean	3.309	11.133	21.358	5.921	5.430	8.329	0.199
Annualised Std. Dev	16.061	13.101	24.470	11.325	8.686	9.522	7.953
Observations	156	156	156	156	156	156	156
Maximum	15.104	10.972	37.493	11.646	11.972	13.232	8.607
Minimum	-12.708	-16.322	-18.347	-7.865	-7.350	-7.412	-8.146
Skewness	0.006	-0.728	1.021	0.465	1.083	0.936	0.289
Kurtosis	3.665	5.376	6.841	3.980	8.501	6.407	5.285
Median	0.122	10.138	5.370	3.758	0.000	4.660	0.000
t-statistic	0.732	**2.918****	**2.875****	1.836	**2.200****	**3.040****	0.090

Notes: The twelve-year period between January 1970 and December 1982 was characterised by low average growth levels and rising inflationary pressures. Table 2.1.6 reports Summary statistics for each asset captured during this sample period. The data spans a sample of the full period (1970-1982). There are 156 monthly observations. The statistically significant t-statistics have a double asterisk **.

Table 2.16: 1983-1999 High Growth & Low Inflationary environment

Sample Period	1983 - 1999						
Economic Environment	*High Growth | Low Inflation*						
	S&P500	Nikk225	Gold	Non-Energy	US Corp. Bond	US Treasury	USDXY
Annualised Mean	14.523	6.471	-2.612	0.651	10.266	10.213	-0.397
Annualised Std. Dev	11.177	16.242	11.905	7.637	5.245	7.997	9.359
Observations	204	204	204	204	204	204	204
Maximum	10.703	15.280	16.387	10.430	6.397	8.194	9.443
Minimum	-13.425	-16.356	-15.956	-7.653	-3.714	-4.538	-7.001
Skewness	-0.685	-0.368	0.346	0.436	0.210	0.282	0.243
Kurtosis	6.407	3.961	7.448	5.575	4.120	3.254	3.406
Median	13.206	5.133	-2.165	-0.913	9.978	9.139	-0.214
t-statistic	**5.031****	1.596	-0.916	0.350	**7.714****	**5.034****	-0.175

Notes: The 17-year period between January 1983 and December 1999 was characterised by high average growth levels and decreasing inflation rates. Table 2.16 reports Summary statistics for each asset captured during this sample period. The data spans a sample of the full period (1983-1999). There are 204 monthly observations. The statistically significant t-statistics have a double asterisk **.

Table 2.17: 2000-2020 Low Growth & Low Inflationary environment

Sample Period	2000-2020						
Economic Environment	*Low Growth | Low Inflation*						
	S&P500	Nikk225	Gold	Non-Energy	US Corp. Bond	US Treasury	USDXY
Annualised Mean	4.543	3.450	9.357	4.190	6.248	6.076	-0.288
Annualised Std. Dev	13.560	17.751	12.759	9.714	4.709	7.462	7.835
Observations	252	252	252	252	252	252	252
Maximum	11.352	14.698	11.489	7.831	4.081	10.127	7.778
Minimum	-22.804	-24.799	-12.391	-16.573	-9.463	-6.952	-6.022
Skewness	-1.936	-0.662	-0.009	-0.972	-1.810	0.241	0.221
Kurtosis	11.053	5.280	3.548	8.432	14.728	4.548	3.561
Median	14.139	7.910	5.232	3.271	7.124	4.061	-0.796
t-statistic	1.504	0.877	**3.225****	**1.940****	**5.913****	**3.631****	-0.168

Notes: The 20-year period between January 2000 and December 2020 was characterised by lower average growth levels and persistently lower inflation rates. Table 2.17 reports Summary statistics for each asset captured during this sample period. The data spans a sample of the full period (2000-2020). There are 252 monthly observations. The statistically significant t-statistics have a double asterisk **.

Table 2.18: Data Sample Periods & Predictor Variables

Number	Sample Periods	
Data Sample 1	1970-1979|1980-1989| 1990-1999|2000-2009| 2010-2020	
Data Sample 2	1968-1984| 1985-2007|2008-2020	
Data Sample 3	1970-1982| 1983-1999|2000-2020	
Assets		
Equities	S&P500	Nikkei 225
Alternatives	Gold	Commodities
Fixed Income	US Corp. Bond	10 Yr. Treasury
Predictor Variables		
Unemp. Cl	Fed. Funds	US. Permits
Hse. Price Indx	Unemp Rate	PCE Dg
DGS11	Earnings	AAA
Ind. Prd. Index	PPIACO	CPI
PPI Com	PPI Wheat	CAPE
U.Mich. SentSurv	CFNAI	
Commodity Variables		
Crude Oil	Urea	Rubber
Sugar US	Tobacco	Cotton
Durable Goods	Gold	Tin
PPI Com	PPI Wheat	Zinc
Iron Ore	Nickel	Copper
Aluminum	Platinum	Silver

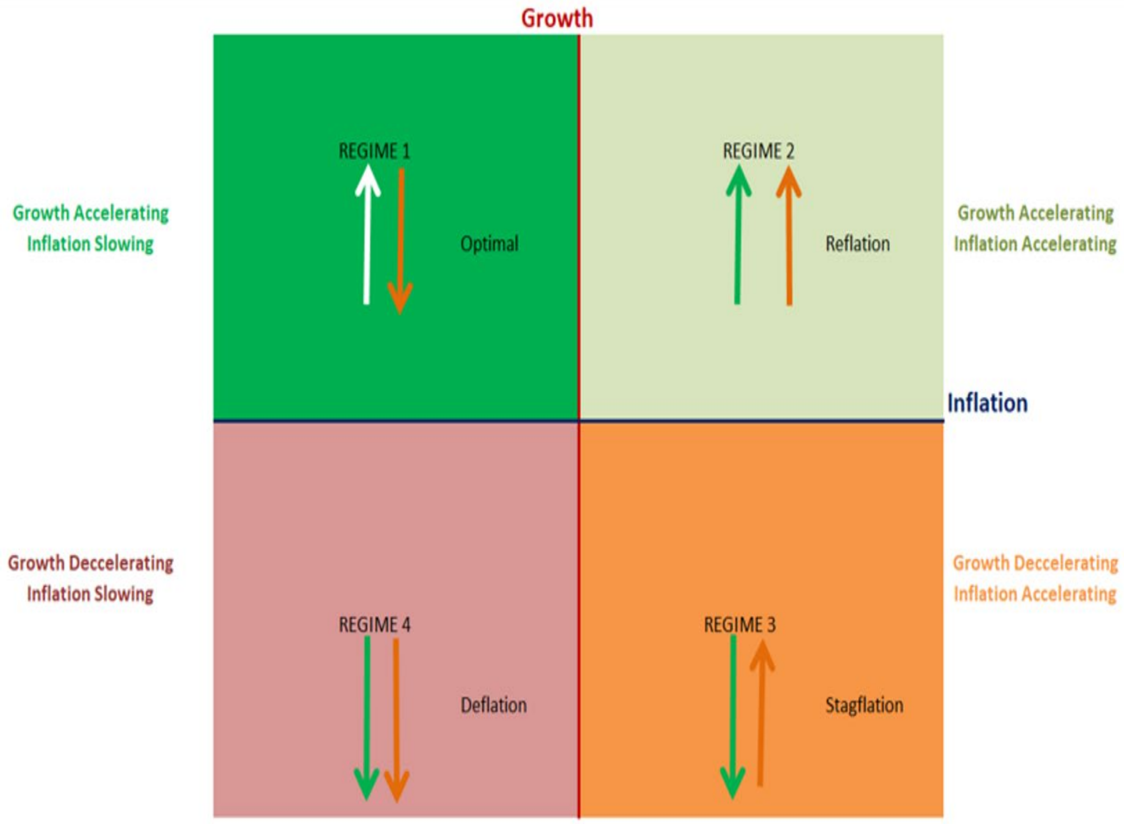
Notes: The Table reports the three different data sample periods along with the sets of predictor variables. The predictor variables include a range of sentiment indicators, economic indicators, and commodity variables. The analysis is completed initially by decade and then two subsequent sets of sample periods. The dependent assets are categorised into equities (S&P500, Nikkei 225), commodities (Gold, Commodities) and fixed-income instruments (US Corp. bonds, 10 Yr. Treasuries).

Table 2.19 Investment Fund details

Fixed Income	Sample	02/2000 to 11/2021
	Nr. Of Funds	105
	Nr. Of Strategies	42
Sectors		
USD Investment Grade	Fixed Intest	Off Mt Fixed Int - EUR
Sterling Corporate Bond	UK Index - Linked Gilts	Fixed Int - Asia Pacific
Fixed Int - Emerging Markets	GBP Corporate Bond	Global EM Bonds
Sterling Strategic Bond	Fixed Int - GBP	UK Gilts
EUR Investment Grade	Convertible	Fixed Int - USD Government
EUR Short/ Medium Maturity	EUR Securitised	USD Short/ Medium Maturity
Fixed Int - Asia Pacific	Sterling Long Bond	EUR Investment Grade
Fixed Int - Emerging Markets	Fixed Int - Global	Global Mixed Bond
Sterling High Yield Retail	EUR Investment Grade	FO Fixed Int - Global
Targeted Absolute Return	GBP Corporate Bond	Global EM Bonds - Blended
Global High Yield	USD Securitised	Fixed Int - USD Long Maturity
Global High Yield	Absolute Return	
Global High Yield	USD High Yield	GBP High Yield
Sterling Corporate Bond Retail	USD Investment Grade	USD High Yield
Equities	Sample	02/2000 to 11/2021
	Nr. Of Funds	94
	Nr. Of Regions	9
Regions		
Europe incl. UK	Europe exl. UK	North America
International	UK	Emerging Markets
Small Cap Europe	Japan	Irish
Commodities	Sample	02/2000 to 11/2021
	Nr. Of Funds	20
	Nr. Of Sectors	3
Sectors		
Commodity & Energy	IA Commodity/Natural Resources	Gbl ETF Commodity & Energy

Notes: The Table reports strategic, sector and region-specific descriptions of the full selection of funds utilised in this study. The sample covers the period 2000 to 2021 and includes the mean monthly returns, annualised volatilities, and respective Sharpe ratios for each fund. The study encompasses 94 individual equity funds covering 9 unique regions. There are 20 commodity-based funds spanning 3 different sectors. There are 105 fixed-income funds covering a broad selection of that market universe within excess of 42 different strategies.

Table 2.20a: Economic regime Framework



Notes: The Table provides a framework for our regime-based asset allocation model. There are four economic quadrants determined by the % change in growth and inflation. Regime 1 or the "Optimal" quadrant is characterised by increasing economic growth and decreasing inflation. Regime 2 or the "Reflation" quadrant is characterised by increasing economic growth and increasing inflation. Regime 3 or the "Stagflation" quadrant is characterised by decreasing economic growth and increasing inflation. Regime 4 or the "Deflation" quadrant is characterised by decreasing economic growth and decreasing inflation.

Table 2.20b: Economic Regime Summary

							Predominant Regime				
Sample Period	High Infl	116	74.4%	Low Infl	40	25.6%		R1	21	R2	57
1970 - 1982	High Gr	78	50.0%	Low Gr	78	50.0%	High Inflation with flat growth	R4	19	R3	59
Sample Period	High Infl	72	35.3%	Low Infl	132	64.7%		R1	92	R2	42
1983 - 1999	High Gr	134	65.7%	Low Gr	70	34.3%	Low Inflation with High Growth	R4	40	R3	30
Sample Period	High Infl	82	34.2%	Low Infl	158	65.8%		R1	71	R2	33
2000 - 2019	High Gr	104	43.3%	Low Gr	136	56.7%	Low Inflation with Low Growth	R4	87	R3	49

Notes: The Table provides summary details of both inflation and growth regimes. The initial sample period (1970-1982) is categorised as a period of high inflation and flat growth. The sample period (1983-1999) is categorised as a period of low inflation and high growth. The ample period (2000-2019) is categorised as a period of low inflation and low growth.

Table 2.21: Regime Classification | 1970 to 1982

Year	Jan	Feb	Mar	Apr	May	June	Jul	Aug	Sep	Oct	Nov	Dec
1970	4	3	3	3	4	3	2	4	3	3	3	2
1971	1	4	4	1	2	2	4	4	1	1	1	2
1972	1	2	1	1	4	1	3	1	1	2	1	1
1973	1	2	3	3	2	3	1	3	1	2	2	3
1974	3	3	3	3	2	3	2	3	3	3	3	3
1975	3	3	3	2	3	2	2	1	2	2	3	2
1976	1	2	1	2	2	3	2	2	2	3	1	2
1977	3	2	2	2	2	2	3	3	2	3	2	3
1978	3	2	2	2	2	2	3	2	2	2	2	2
1979	3	2	2	3	2	3	3	3	3	2	3	3
1980	2	3	3	3	3	3	4	2	2	2	2	2
1981	3	3	2	3	2	2	2	3	3	4	4	4
1982	4	1	4	3	3	3	3	4	4	4	4	4

R1	21
R2	57
R3	59
R4	19

	Obs	% Obs		Obs	% Obs
High Infl	116	74.4%	Low Infl	40	25.6%
High Gr	78	50.0%	Low Gr	78	50.0%

Notes: The Table reports the first sample data period. The period 1970 to 1982 is segmented by economic regime. We have classified each regime based upon the Growth | Inflation model referenced in Table 2.3. If the % change in growth is above the long-term mean and % change in inflation is below the long-term mean, we log state regime number **1**. This is colour coded with a darker green. Colour coding per regime has been used to aid the description. If the % change in growth is above the long-term mean and % change in inflation is also above the long-term mean, we log state regime number **2**. This is colour coded with a lighter green. If the % Change in growth is below the long-term mean and % change in inflation is above the long-term mean, we log state regime number **3**. This is colour coded with a dark yellow. If the % change in growth is below the long-term mean and % change in inflation is also below the long-term mean, we log state regime number **4**. This is colour coded red. Each month receives a classification based on the prevailing growth and inflation environment. Regime 1 encompasses higher economic growth and low inflation. Regime 2 is characterised by persistent economic growth and increasing inflation. Regime 3 may be categorised as a "stagflationary" economic environment where growth has turned negative and high inflation is persistent. Regime 4 is categorised by low inflation and low growth. The evidence from Table 2.4 would suggest a regime dominated by persistent inflationary pressures and lower growth prospects. R2 & R3 constitute regimes of higher-than-average inflation. It is evident that this period was dominated by higher-than-average inflation with inflationary pressures remaining persistent for 75% of the period.

Table 2.22: Regime Classification | 1983 to 1999

Year	Jan	Feb	Mar	Apr	May	June	Jul	Aug	Sep	Oct	Nov	Dec
1983	1	4	1	2	2	1	2	1	2	1	1	1
1984	2	2	1	2	1	1	2	3	3	4	1	4
1985	4	2	3	3	3	4	4	1	1	3	1	1
1986	1	4	4	4	1	3	1	4	2	1	1	1
1987	3	2	3	2	2	2	1	2	2	1	1	1
1988	4	1	2	2	3	2	3	2	3	2	1	1
1989	2	3	2	3	3	4	4	1	4	3	1	1
1990	3	2	2	4	1	2	3	2	3	3	4	4
1991	3	4	4	1	1	1	4	4	2	4	4	4
1992	4	2	2	1	1	3	1	4	1	2	1	4
1993	2	2	3	1	4	1	1	4	1	2	1	1
1994	1	3	2	1	1	2	4	2	1	1	1	1
1995	2	3	2	3	1	1	4	1	1	3	1	1
1996	3	2	3	2	1	1	4	1	1	4	1	1
1997	1	1	1	4	1	1	1	1	1	1	1	1
1998	1	4	4	1	1	4	4	1	4	1	4	1
1999	1	1	1	2	1	4	1	1	3	1	1	1

R1	92
R2	42
R3	30
R4	40

	Obs	% Obs		Obs	% Obs
High Infl	72	35.3%	Low Infl	132	64.7%
High Gr	134	65.7%	Low Gr	70	34.3%

Notes: The Table reports the second sample data period. The period 1983 to 1999 is segmented by economic regime. We have classified each regime based upon the Growth | Inflation model referenced in Table 2.3. If the % change in growth is above the long-term mean and % change in inflation is below the long-term mean, we log state regime number **1**. This is colour coded with a darker green. Colour coding per regime has been used to aid the description. If the % change in growth is above the long-term mean and % change in inflation is also above the long-term mean, we log state regime number **2**. This is colour coded with a lighter green. If the % change in growth is below the long-term mean and % change in inflation is above the long-term mean, we log state regime number **3**. This is colour coded with a dark yellow. If the % change in growth is below the long-term mean and % change in inflation is also below the long-term mean, we log state regime number **4**. This is colour coded red. Each month receives a classification based on the prevailing growth and inflation environment. Regime 1 encompasses higher economic growth and low inflation. Regime 2 is characterised by persistent economic growth and increasing inflation. Regime 3 may be categorised as a "stagflationary" economic environment where growth has turned negative and high inflation is persistent. Regime 4 is categorised by low inflation and low growth. The evidence from Table 2.22 would suggest a regime dominated by a persistent disinflationary environment and stronger growth prospects. R1 & R2 constitute regimes of higher-than-average growth. It is evident that this period was dominated by higher-than-average growth with disinflationary pressures remaining persistent for 65% of the period.

Table 2.23 Regime Classification | 2000 to 2019

Year	Jan	Feb	Mar	Apr	May	June	Jul	Aug	Sep	Oct	Nov	Dec
2000	4	2	2	1	1	3	4	4	2	4	4	4
2001	3	3	4	3	3	4	4	4	3	4	4	4
2002	1	3	2	2	1	1	4	3	4	4	1	4
2003	2	3	3	4	4	4	1	3	2	4	1	4
2004	2	2	3	1	2	4	1	4	4	2	1	1
2005	1	2	3	2	4	1	3	2	3	1	1	1
2006	3	4	2	2	3	1	4	1	4	4	4	1
2007	4	2	2	2	3	4	4	1	1	4	2	4
2008	3	4	3	3	3	3	3	4	4	1	4	4
2009	3	3	4	4	4	3	1	1	1	1	1	1
2010	2	1	2	1	1	1	1	1	1	4	4	1
2011	3	3	2	3	3	1	1	1	4	1	4	1
2012	2	2	3	1	4	4	1	3	3	1	1	1
2013	4	2	1	4	4	4	4	1	1	4	1	1
2014	3	2	2	3	2	1	1	4	1	4	1	4
2015	4	3	3	4	3	3	1	4	4	4	4	4
2016	1	4	3	2	3	2	1	4	4	4	4	1
2017	3	4	1	1	4	4	4	4	3	1	1	4
2018	3	2	1	2	3	1	1	1	4	4	4	4
2019	4	3	3	3	1	4	4	1	4	4	1	4

R1	71
R2	33
R3	49
R4	87

	Obs	% Obs		Obs	% Obs
High Infl	82	34.2%	Low Infl	158	65.8%
High Gr	104	43.3%	Low Gr	136	56.7%

Notes: The Table reports the third sample data period. The period 2000 to 2019 is segmented by economic regime. We have classified each regime based upon the Growth | Inflation model referenced in Table 2.3. If the % change in growth is above the long-term mean and % change in inflation is below the long-term mean, we log state regime number **1**. This is colour coded with a darker green. Colour coding per regime has been used to aid the description. If the % change in growth is above the long-term mean and % change in inflation is also above the long-term mean, we log state regime number **2**. This is colour coded with a lighter green. If the % change in growth is below the long-term mean and % change in inflation is above the long-term mean, we log state regime number **3**. This is colour coded with a dark yellow. If the % change in growth is below the long-term mean and % change in inflation is also below the long-term mean, we log state regime number **4**. This is colour coded red. The evidence from Table 2.23 would suggest a regime dominated by a persistent disinflationary environment and sluggish growth. R1 & R4 constitute regimes of lower-than-average inflation. It is evident that this period was dominated by lower growth [57%] with disinflationary pressures remaining persistent for 66% of the period.

Table 2.24: Standard versus Rolling Correlations [1968 – 1984]

Standard Correlation	S&P 500	Nikkei225	Gold	Non-Energy	US CorpB Indx	10 Year Treas
S&P 500	1.0000	0.1571	0.0302	-0.0608	0.3356	0.3056
Nikkei225	0.1571	1.0000	0.0144	0.0481	0.0639	-0.0686
Gold	0.0302	0.0144	1.0000	0.3472	-0.0928	-0.0509
Non-Energy	-0.0608	0.0481	0.3472	1.0000	-0.1350	-0.1836
US CorpB Indx	0.3356	0.0639	-0.0928	-0.1350	1.0000	0.8478
10 Year Treas	0.3056	-0.0686	-0.0509	-0.1836	0.8478	1.0000

Avg. Ann Roll Vol	S&P 500	Nikkei225	Gold	Non-Energy	US CorpB Indx	10 Year Treas
S&P 500	1.0000	0.1494	-0.0689	0.0299	0.4053	0.3223
Nikkei225	0.1494	1.0000	-0.0265	0.1460	-0.0295	-0.1192
Gold	-0.0689	-0.0265	1.0000	0.1757	0.0316	0.0163
Non-Energy	0.0299	0.1460	0.1757	1.0000	-0.1462	
US CorpB Indx	0.4053	-0.0295	0.0316	-0.1462	1.0000	0.7462
10 Year Treas	0.3223	-0.1192	0.0163	-0.1942	0.7462	1.0000

Notes: The Table reports the standard and rolling [12-month] average correlations for the six asset classes covered in this study [S&P500, Nikkei 225, Gold, Non-Energy commodities, US Corporate Bond Index and 10 Year US Treasury returns]. The sample period for these correlations is 1968 to 1984.

Table 2.25: Standard versus Rolling Correlations [1984 – 2007]

Standard Correlation	S&P 500	Nikkei225	Gold	Non-Energy	US CorpB Indx	10 Year Treas
S&P 500	1.0000	0.1571	0.0302	-0.0608	0.3356	0.3056
Nikkei225	0.1571	1.0000	0.0144	0.0481	0.0639	-0.0686
Gold	0.0302	0.0144	1.0000	0.3472	-0.0928	-0.0509
Non-Energy	-0.0608	0.0481	0.3472	1.0000	-0.1350	-0.1836
US CorpB Indx	0.3356	0.0639	-0.0928	-0.1350	1.0000	0.8478
10 Year Treas	0.3056	-0.0686	-0.0509	-0.1836	0.8478	1.0000

Avg. Ann Roll Vol	S&P 500	Nikkei225	Gold	Non-Energy	US CorpB Indx	10 Year Treas
S&P 500	1.0000	0.1494	-0.0689	0.0299	0.4053	0.3223
Nikkei225	0.1494	1.0000	-0.0265	0.1460	-0.0295	-0.1192
Gold	-0.0689	-0.0265	1.0000	0.1757	0.0316	0.0163
Non-Energy	0.0299	0.1460	0.1757	1.0000	-0.1462	
US CorpB Indx	0.4053	-0.0295	0.0316	-0.1462	1.0000	0.7462
10 Year Treas	0.3223	-0.1192	0.0163	-0.1942	0.7462	1.0000

Notes: The Table reports the standard and rolling [12-month] average correlations for the six asset classes covered in this study [S&P500, Nikkei 225, Gold, Non-Energy commodities, US Corporate Bond Index and 10 Year US Treasury returns]. The sample period for these correlations is 1984 to 2007.

Table 2.26: Standard versus Rolling Correlations (2008 – 2020)

Standard Correlation	S&P 500	Nikkei225	Gold	Non-Energy	US CorpB Indx	10 Year Treas
S&P 500	1.0000	0.1571	0.0302	-0.0608	0.3356	0.3056
Nikkei225	0.1571	1.0000	0.0144	0.0481	0.0639	-0.0686
Gold	0.0302	0.0144	1.0000	0.3472	-0.0928	-0.0509
Non-Energy	-0.0608	0.0481	0.3472	1.0000	-0.1350	-0.1836
US CorpB Indx	0.3356	0.0639	-0.0928	-0.1350	1.0000	0.8478
10 Year Treas	0.3056	-0.0686	-0.0509	-0.1836	0.8478	1.0000

Avg. Ann Roll Vol	S&P 500	Nikkei225	Gold	Non-Energy	US CorpB Indx	10 Year Treas
S&P 500	1.0000	0.1494	-0.0689	0.0299	0.4053	0.3223
Nikkei225	0.1494	1.0000	-0.0265	0.1460	-0.0295	-0.1192
Gold	-0.0689	-0.0265	1.0000	0.1757	0.0316	0.0163
Non-Energy	0.0299	0.1460	0.1757	1.0000	-0.1462	
US CorpB Indx	0.4053	-0.0295	0.0316	-0.1462	1.0000	0.7462
10 Year Treas	0.3223	-0.1192	0.0163	-0.1942	0.7462	1.0000

Notes: Standard and rolling [12-month] average correlations for the six asset classes covered in this study (S&P500, Nikkei 225, Gold, Non-Energy commodities, US Corporate Bond Index and 10 Year US Treasury returns). The sample period for these correlations is 1968 to 1984.

Table 2.27: Multi-Variable Linear Regression [S&P500 | Full Sample]

Dependent Variable	Sample Period	Obs	Regressors	Regime	Economic environment
S&P500	1970 - 2021	611	12	**Full Sample**	Multi-Regime

	Coefficients	Standard Error	P-value	
Intercept	0.00163	0.0024	0.501	
Nikkei225	0.3343	0.0287	0.000	
US Corp. Bond Index	0.7103	0.1031	0.000	
10 Year Treasury	-0.2452	0.0726	0.001	
Personal Consumption	0.5736	0.1664	0.001	Adjusted R Square
Personal Income	0.6331	0.1757	0.000	0.3622
Heavy Weight Trucks	-0.0475	0.0207	0.022	Durbin-Watson Test Stat
M2 Velocity	-0.466	0.2559	0.069	**1.9267**
AAA Yield	-0.089	0.0500	0.075	
CPI	-1.2373	0.4221	0.004	
Aluminium	0.045	0.0261	0.085	
Iron Ore	0.0519	0.0199	0.009	

Notes: The Table reports estimated coefficients for the multiple linear regression model. The sample period is January 1, 1970, to December 31, 2020. The dependent variable is the monthly percentage change in the S&P500 index. The eleven independent variables are a combination of investment assets and macroeconomic variables. The Macroeconomic variables include Personal Income and Personal Consumption Expenditures [PCE] both sourced from the U.S Bureau of Economic Analysis, M2 money velocity and the consumer price index [CPI]. Commodity based regressors include the % changes in the prices of aluminium and iron ore. Additional predictor variables include heavy weight trucks which includes trucks with more than 14,000 lbs gross vehicle weight and the yield on triple A-rated corporate bonds. The statistically significant asset class regressors include the Nikkei 225, the US Corporate Bond Index and 10 Year US Treasury returns.

Table 2.28: Multi-Variable Linear Regression (Gold | Full Sample)

Dependent Variable	Sample Period	Obs	Regressors	Regime	Economic environment
Gold	1970 - 2021	611	12	**Full Sample**	Multi-Regime

	Coefficients	Standard Error	P-value		
Intercept	0.0041	0.0020	0.037		Adjusted R Square
USDXY	-0.2866	0.0571	0.000		0.4486
M2 Velocity	0.5066	0.2781	0.069		Durbin-Watson Test Stat
Hse Price Index	-0.5300	0.2913	0.069		1.5528
AAA Yield	-0.1120	0.0470	0.018		
Crude Oil	0.0387	0.0115	0.001		**Transformed** Adjusted R Square
PPI Iron & Steel	-0.1850	0.0848	0.030		0.4559
Sugar	0.0783	0.0250	0.002		**Transformed** Durbin-Watson Test Stat
Cotton	-0.0462	0.0308	0.135	Cochrane–Orcutt	1.974307
Rubber	0.0419	0.0226	0.065		
Platinum	0.4960	0.0267	0.000		
Nikkei 225	-0.1036	0.0347	0.003		
S&P500	-0.1133	0.0413	0.006		

Notes: The Table reports estimated coefficients for the multiple linear regression model. The sample period is January 1, 1970, to December 31, 2020. The dependent variable is the monthly percentage change in the gold fixing price*. The twelve independent variables are a combination of investment assets and macroeconomic variables. The Macroeconomic variables include the US Dollar index, M2 money velocity and crude oil prices. Commodity based regressors include the % changes in the prices of sugar, cotton, rubber, and platinum. Additional predictor variables include the producer price index for iron & steel and the house price index. The statistically significant asset class regressors include the Nikkei 225 and returns on the S&P500.

**Price sourced from London Bullion market, based in US Dollars*

Table 2.29: Multi-Variable Linear Regression [10 Year Treasuries | Full Sample]

Dependent Variable	Sample Period	Obs	Regressors	Regime	Economic environment
10 Year US Treasury	1970 - 2021	611	12	**Full Sample**	Multi-Regime

	Coefficients	Standard Error	P-value
Intercept	0.0016	0.0011	0.172
S&P500	-0.0699	0.0211	0.001
Nikkei 225	-0.0540	0.0163	0.001
US Corp. Bond Index	0.8053	0.0452	0.000
Personal Consumption	-0.2705	0.1068	0.012
Personal Income	-0.2330	0.1029	0.024
Wages	0.2281	0.1185	0.055
Government	0.5471	0.1878	0.004
US Permits	-0.0333	0.0120	0.006
PPI All Commodities	-0.2382	0.0736	0.001
AAA Yield	-0.0995	0.0255	0.000
Copper	-0.0407	0.0106	0.000

	Adjusted R Square
	0.4883
	Durbin-Watson Test Stat
	2.307
	Transformed Adjusted R Square
	0.5300
	Transformed Durbin-Watson Test Stat
Cochrane–Orcutt	2.00768

Notes: The Table reports estimated coefficients for the multiple linear regression model. The sample period is January 1, 1970, to December 31, 2020. The dependent variable is the monthly percentage change in the returns on the 10-year US Treasury bond. The eleven independent variables are a combination of investment assets and macroeconomic variables. The Macroeconomic variables include Personal Income and Personal Consumption Expenditures [PCE] both sourced from the U.S Bureau of Economic Analysis, US building permits and PPI All Commodities data. Commodity based regressors include the % changes in the prices of copper. Additional predictor variables include the US Corporate Bond index. The statistically significant asset class regressors include the Nikkei 225 and S&P500 returns.

Table 2.30: Multi-variable regression with non-contiguous sample (Dep Variable: **S&P500**)

Dependent Variable	Sample Period	Obs	Regressors	Regime	Economic environment
S&P500	**1970 - 2021**	188	7	**1**	High Growth/ Low Inflation

	Coefficients	Standard Error	P-value		
Intercept	0.0027	0.0020	0.189		Adjusted R Square
Nikkei225	0.2185	0.0401	0.000		0.5095
US Corp. Bond Index	1.003	0.1707	0.000		Durbin-Watson Test Stat
10 Year Treasury	-0.3877	0.1154	0.001		0.7171
Aluminium	0.0701	0.0421	0.098		Breush-Godfrey
Gold	-0.3093	0.0618	0.000	chi2	7.538
Crude Oil	0.0547	0.0254	0.033	Prob>chi2	0.1101
Platinum	0.1961	0.0536	0.000	df	4

Dependent Variable	Sample Period	Obs	Regressors	Regime	Economic environment
S&P500	**1970 - 2021**	134	9	**2**	High Growth/ High Inflation

	Coefficients	Standard Error	P-value		
Intercept	0.0118	0.0043	0.007		
Nikkei225	0.3491	0.0649	0.000		Adjusted R Square
US Corp. Bond Index	0.4541	0.1579	0.005		0.3421
Gold	0.1609	0.0730	0.029		Durbin-Watson Test Stat
Platinum	-0.2099	0.0708	0.004		0.7891
PPI All Commodities	-1.4541	0.4625	0.002		Breush-Godfrey
Copper	0.0708	0.0425	0.098	chi2	0.013
Cotton	0.1157	0.0582	0.049	Prob>chi2	0.9088
Rubber	-0.1222	0.0536	0.0240	df	1
Ironore	0.2003	0.0703	0.007		

Dependent Variable	Sample Period	Obs	Regressors	Regime	Economic environment
S&P500	**1970 - 2021**	139	10	3	Low Growth/ High Inflation

	Coefficients	Standard Error	P-value		
Intercept	0.0043	0.0078	0.581		
Nikkei225	0.3886	0.0759	0.000		Adjusted R Square
10 Year Treasury	0.3583	0.1331	0.008		0.3281
Ironore	0.1813	0.0600	0.003		Durbin-Watson Test Stat
Rubber	0.0764	0.0438	0.084		1.406298
Crude Oil	-0.0301	0.0173	0.056		Breush-Godfrey
Personal Income	1.1240	0.4867	0.022	chi2	21.472
Heavy Weight Trucks	-0.1558	0.0395	0.000	Prob>chi2	0.0439
AAA Yield	-0.1958	0.1146	0.090	df	12
CPI	-2.0850	1.0830	0.056	Cochrane-Orcut	1.498514
Treas10YFF	-0.0048	0.0022	0.030		

Dependent Variable	Sample Period	Obs	Regressors	Regime	Regime
S&P500	**1970 - 2021**	150	8	4	Low Growth/ Low Inflation

	Coefficients	Standard Error	P-value
Intercept	0.00242	0.0030	0.423
Nikkei225	0.3964	0.0502	0.000
US Corp. Bond Index	1.0200	0.1631	0.000
10 Year Treasury	-0.4678	0.1176	0.000
Personal Income	0.6810	0.3322	0.042
Personal Consumption	0.9850	0.3766	0.010
NFP	-2.4380	1.2470	0.053
Unemployment Rate	-0.1250	0.0763	0.104

Notes: The Table reports estimated coefficients for the four non-contiguous multiple linear regression models. The dependent variable is the monthly percentage change in the S&P500 index. We categorise regime 1 as an economic environment where the % change in growth is increasing and the % change in inflation is decreasing. The sample period is January 1, 1970, to December 31, 2020. Regime 1 or "Goldilocks" is captured with seven statistically significant regressors. We categorise regime 2 as an economic environment where the % rate of change in growth is increasing and the % rate of change in inflation is increasing. Regime 2 or "Reflation" is captured with nine statistically significant regressors]. We categorise regime 3 as an economic environment where the % rate of change in growth is decreasing and the % rate of change in inflation is increasing. Regime 3 or "Stagflation" is captured with ten statistically significant regressors]. We categorise regime 4 as an economic environment where the % rate of change in growth is decreasing and the % rate of change in inflation is decreasing. Regime 4 or "Deflation" is captured with seven statistically significant regressors.

Table 2.31: Multi-variable regression with non-contiguous sample (Dep Variable: **Gold**)

Dependent Variable	Sample Period	Obs	Regressors	Regime	Economic environment
Gold	**1970 - 2021**	188	7	1	High Growth/ Low Inflation

	Coefficients	Standard Error	P-value		
Intercept	0.0037	0.0023	0.112		Adjusted R Square
USDXY	-0.2394	0.0860	0.006		0.5775
PCE	-0.5354	0.3194	0.095		Durbin-Watson Test Stat
M2 Velocity	0.7547	0.4356	0.085		0.55061
PPI Iron & Steel	-0.2270	0.1121	0.044		Breush-Godfrey
Platinum	0.3238	0.0504	0.000	chi2	3.963
S&P500	-0.3301	0.0549	0.000	Prob>chi2	0.1378
Silver	0.2427	0.0369	0.000	df	2

Dependent Variable	Sample Period	Obs	Regressors	Regime	Regime
Gold	**1970 - 2021**	134	9	2	High Growth/ High Inflation

	Coefficients	Standard Error	P-value		
Intercept	-0.0112	0.0046	0.017		
USDXY	-0.3856	0.0939	0.000		Adjusted R Square
PPI Iron & Steel	-0.4622	0.1740	0.009		0.7694
Platinum	0.2378	0.0567	0.000		Durbin-Watson Test Stat
Nikkei225	-0.1354	0.0557	0.017		0.53423
Silver	0.3410	0.0349	0.000		Breush-Godfrey
PPI All Commodities	0.9516	0.4069	0.021	chi2	1.248
Total Consumer Credit	0.7264	0.4339	0.097	Prob>chi2	0.2639
				df	1

Dependent Variable	Sample Period	Obs	Regressors	Regime	Economic environment
Gold	**1970 - 2021**	139	7	3	Low Growth/ High Inflation

	Coefficients	Standard Error	P-value		
Intercept	-0.0053	0.0053	0.320		
USDXY	-0.3261	0.1260	0.011		Adjusted R Square
Platinum	0.1998	0.0664	0.003		0.6368
Silver	0.2849	0.0380	0.000		Durbin-Watson Test Stat
Total Consumer Credit	1.1567	0.6071	0.059		0.75389
Unemployment Claims	0.2168	0.1071	0.045		Breush-Godfrey
Crude Oil	0.0493	0.0155	0.002	chi2	0.031
Sugar	0.0905	0.0333	0.008	Prob>chi2	0.8598
				df	1

Dependent Variable	Sample Period	Obs	Regressors	Regime	Regime
Gold	**1970 - 2021**	150	8	4	Low Growth/ Low Inflation

	Coefficients	Standard Error	P-value		
Intercept	0.0052	0.0027	0.057		Adjusted R Square
USDXY	-0.2126	0.0996	0.035		0.4021
Platinum	0.3814	0.0440	0.000		Durbin-Watson Test Stat
Sugar	-0.1939	0.0927	0.035		0.78851
Treas 10Yr FF	-0.0005	0.0002	0.030		Breush-Godfrey
				chi2	2.408
				Prob>chi2	0.1207
				df	1

Notes: The Table reports estimated coefficients for the four non-contiguous multiple linear regression models. The dependent variable is the monthly percentage change in the gold fixing price. We categorise regime 1 as an economic environment where the % change in growth is increasing and the % change in inflation is decreasing. The sample period is January 1, 1970, to December 31, 2020. Regime 1 or "Goldilocks" is captured with seven statistically significant regressors. We categorise regime 2 as an economic environment where the % rate of change in growth is increasing and the % rate of change in inflation is increasing. Regime 2 or "Reflation" is captured with seven statistically significant regressors]. We categorise regime 3 as an economic environment where the % rate of change in growth is decreasing and the % rate of change in inflation is increasing. Regime 3 or "Stagflation" is captured with seven statistically significant regressors]. We categorise regime 4 as an economic environment where the % rate of change in growth is decreasing and the % rate of change in inflation is decreasing. Regime 4 or "Deflation" is captured with four statistically significant regressors].

Table 2.32: Multi-var regression with non-contiguous sample (Dep Variable: US Treasury)

Dependent Variable	Sample Period	Obs	Regressors	Regime	Economic environment
10 Year US Treasury	**1970 - 2021**	188	7	1	High Growth/ Low Inflation

	Coefficients	Standard Error	P-value		
Intercept	0.0016	0.0012	0.167		
US Corp. Bond Index	0.90303	0.0886	0.000		Adjusted R Square
US Permits	-0.0667	0.0250	0.008		0.3831
Rubber	-0.0614	0.0182	0.001		Durbin-Watson Test Stat
Treas 10Yr FF	-0.0033	0.0011	0.005		**0.99639**
PPI All Commodities	-0.5046	0.1841	0.007		Breush-Godfrey
				chi2	4.784
				Prob>chi2	0.1883
				df	3

Dependent Variable	Sample Period	Obs	Regressors	Regime	Regime
10 Year US Treasury	**1970 - 2021**	135	9	2	High Growth/ High Inflation

	Coefficients	Standard Error	P-value		
Intercept	0.0002	0.0014	0.866		
US Corp. Bond Index	0.8039	0.0734	0.000		Adjusted R Square
Personal Consumption	-0.7879	0.2253	0.001		0.647
Treas 10Yr FF	-0.0004	0.0001	0.016		Durbin-Watson Test Stat
AAA Yield	-0.1400	0.0478	0.004		**0.59568**
Unemployment rate	0.0827	0.0507	0.106		Breush-Godfrey
M1 Velocity	-0.8816	0.1993	0.000	chi2	0.732
NFP	1.1732	0.4933	0.019	Prob>chi2	0.3924
				df	1

Dependent Variable	Sample Period	Obs	Regressors	Regime	Economic environment
10 Year US Treasury	**1970 - 2021**	139	7	3	Low Growth/ High Inflation

	Coefficients	Standard Error	P-value		
Intercept	-0.0038	0.0022	0.087		Adjusted R Square
US Corp. Bond Index	0.7752	0.0800	0.000		0.445
Personal Consumption	-0.5173	0.2964	0.083		Durbin-Watson Test Stat
Treas 10Yr FF	0.0024	0.0012	0.053		0.8256
Unemployment rate	0.0832	0.0469	0.079		Breush-Godfrey
Wages	1.1370	0.3249	0.001	chi2	0.433
				Prob>chi2	0.5107
				df	1

Dependent Variable	Sample Period	Obs	Regressors	Regime	Regime
10 Year US Treasury	**1970 - 2021**	150	8	4	Low Growth/ Low Inflation

	Coefficients	Standard Error	P-value		
Intercept	0.0010	0.0021	0.629		Adjusted R Square
US Corp. Bond Index	0.8846	0.0837	0.000		0.4707
US Permits	-0.0915	0.0301	0.003		Durbin-Watson Test Stat
Unemployment rate	-0.0525	0.0123	0.000		1.208847
M2 Velocity	1.474284	0.3043	0	chi2	1.781
				Prob>chi2	0.182
				df	1

Notes: The Table reports estimated coefficients for the four non-contiguous multiple linear regression models. The dependent variable is the monthly percentage change in the returns on the 10-year US Treasury bond. We categorise regime 1 as an economic environment where the % change in growth is increasing and the % change in inflation is decreasing. The sample period is January 1, 1970, to December 31, 2020. Regime 1 or "Goldilocks" is captured with seven statistically significant regressors. We categorise regime 2 as an economic environment where the % rate of change in growth is increasing and the % rate of change in inflation is increasing. Regime 2 or "Reflation" is captured with seven statistically significant regressors]. We categorise regime 3 as an economic environment where the % rate of change in growth is decreasing and the % rate of change in inflation is increasing. Regime 3 or "Stagflation" is captured with seven statistically significant regressors]. We categorise regime 4 as an economic environment where the % rate of change in growth is decreasing and the % rate of change in inflation is decreasing. Regime 4 or "Deflation" is captured with four statistically significant regressors].

Table 2.33: Regime Specific MV Regressions [Dep. Variable: S&P500]

Asset	Sample Period	Obs	Regressors
S&P500	**1970 - 1982**	156	8

	Coefficients	Standard Error	P-value	Adjusted R Square
Intercept	-0.0159	0.0067	0.0190	
Nikkei225	0.1655	0.0860	0.0560	
10 Year Treasury	0.5113	0.1209	0.0000	
Personal Income	1.8830	0.7047	0.0080	0.3108
Heavy Weight Trucks	-0.1332	0.0406	0.0010	
M1 Velocity	2.0010	0.5360	0.0000	
Crude Oil	-0.0403	0.0192	0.0380	
Iron Ore	0.3365	0.0763	0.0000	
AAA Yield	-0.2591	0.1308	0.0500	

Asset	Sample Period	Obs	Regressors
S&P500	**1983 - 1999**	204	11

	Coefficients	Standard Error	P-value	Adjusted R Square
Intercept	0.0117	0.0031	0.0000	
Nikkei225	0.2261	0.0387	0.0000	
US Corp. Bond Index	0.9194	0.1852	0.0000	
10 Year Treasury	-0.2780	0.1212	0.0230	
USDXY	0.1202	0.0701	0.0880	
EconUncIndx	-0.0097	0.0029	0.0010	
UMSENT	0.1181	0.0460	0.0110	0.3986
Aluminium	0.0808	0.0303	0.0080	
Gold	-0.1021	0.0545	0.063	
PPIACO	-0.9151	0.3901	0.0200	
NFP	-2.5150	1.1398	0.0290	
M1V	-0.5705	0.3116	0.0690	

Asset	Sample Period	Obs	Regressors
S&P500	**2000 - 2020**	204	11

	Coefficients	Standard Error	P-value	Adjusted R Square
Intercept	0.0007	0.0015	0.6360	
Nikkei225	0.3592	0.0332	0.0000	
US Corp. Bond Index	0.9110	0.1174	0.0000	
10 Year Treasury	-0.4177	0.0786	0.0000	
USDXY	-0.1128	0.0695	0.1060	
EconUncIndx	-0.0086	0.0018	0.0000	0.7151
UMSENT	0.0009	0.0002	0.0010	
Doll/ Yen	-0.1590	0.0603	0.0090	
Gold	-0.0921	0.0420	0.0290	
Personal Income	0.3008	0.1258	0.0180	
Copper	0.0545	0.0250	0.0300	

Notes: The Table reports estimated coefficients for the three regime-specific sample periods as specified by the regime classification matrix. The first sample period is between **January 1970 and December 1982**. As per Table 2.21, this period may be classified as a high inflation & low growth period. The second sample period is between **January 1983 and December 1999**. As per Table 2.22, this period may be classified as a low inflation & high growth period. The third sample period is between **January 2000 and December 2020**. As per Table 2.23, this period may be classified as a low inflation & low growth period. The dependent variable is the monthly percentage change in the S&P500 index.

Table 2.34: Regime Specific MV Regressions [Dep. Variable: Gold]

Asset	Sample Period	Obs	Regressors	
Gold	1970 - 1982	156	6	Full Sample

	Coefficients	Standard Error	P-value	Adjusted R Square
Intercept	0.0054	0.0034	0.119	
USDXY	-0.6722	0.1521	0.000	
Unemployment Claims	0.1437	0.0780	0.067	
Crude Oil	0.0485	0.0182	0.009	0.6547
Sugar	0.0572	0.0340	0.095	
Silver	0.3359	0.0427	0.000	
Platinum	0.1912	0.0790	0.017	

Asset	Sample Period	Obs	Regressors
Gold	1983 - 1999	204	11

	Coefficients	Standard Error	P-value	Adjusted R Square
Intercept	-0.0038	0.0047	0.410	
S&P500	-0.1654	0.0770	0.033	
USDXY	-0.1898	0.0868	0.030	
US Corp. Bond Index	-0.2835	0.1585	0.075	
Heavy Weight Trucks	-0.1006	0.0391	0.011	0.1889
M2 Velocity	1.1020	0.6203	0.077	
PPI Iron & Steel	-0.7008	0.3072	0.024	
CPI	1.9610	1.2110	0.107	
UM Sentiment Index	-0.1113	0.0567	0.051	
Rubber	0.1323	0.0409	0.001	
Aluminium	0.0627	0.0374	0.095	

Asset	Sample Period	Obs	Regressors
Gold	2000 - 2020	204	9

	Coefficients	Standard Error	P-value	Adjusted R Square
Intercept	0.0034	0.0014	0.0190	
S&P500	-0.1501	0.0435	0.0010	
USDXY	-0.1867	0.0642	0.0040	
HSE Pr Index	-0.3387	0.1873	0.0720	
Unemp Claims	0.0152	0.0055	0.0060	0.6636
Platinum	0.1604	0.0319	0.0000	
Silver	0.3229	0.0255	0.0000	
PPI Iron & Steel	-0.1319	0.0519	0.0120	
10 Year Treasury	0.1886	0.0688	0.0070	
Econ Uncert Index	0.0036	0.0020	0.0710	

Notes: The Table reports estimated coefficients for the three regime-specific sample periods as specified by the regime classification matrix. The first sample period is between **January 1970 and December 1982**. As per Table 2.21, this period may be classified as a high inflation & low growth period. The second sample period is between **January 1983 and December 1999**. As per Table 2.22, this period may be classified as a low inflation & high growth period. The third sample period is between **January 2000 and December 2020**. As per Table 2.23, this period may be classified as a low inflation & low growth period. The dependent variable is the monthly percentage change in the gold fixing price

Table 2.35: Regime Specific MV Regressions (Dep. Variable: 10 Year US Treasury Bond)

Asset	Sample Period	Obs	Regressors	
10 Year US Treasury	1970-1982	156	6	Full Sample

	Coefficients	Standard Error	P-value	Adjusted R Square
Intercept	0.0079	0.0033	0.020	
S&P500	0.0611	0.0320	0.059	
US Corp. Bond Index	0.7192	0.0622	0.000	
M1 Velocity	-0.7295	0.3054	0.018	**0.606**
CPI	-0.9143	0.5016	0.070	
Unemployment Rate	0.0957	0.0429	0.027	
Aluminium	-0.0552	0.0358	0.126	

Asset	Sample Period	Obs	Regressors	
10 Year US Treasury	1983-1999	204	5	Full Sample

	Coefficients	Standard Error	P-value	Adjusted R Square
Intercept	0.0010	0.0016	0.512	
S&P500	-0.0638	0.0338	0.060	
US Corp. Bond Index	1.2020	0.0727	0.000	
Treas 10Yr FF	-0.0003	0.0002	0.098	**0.5986**
PCE	-0.3988	0.1938	0.041	
Unemployment Claims	-0.0757	0.0463	0.104	

Asset	Sample Period	Obs	Regressors	
10 Year US Treasury	2000 - 2020	252	6	Full Sample

	Coefficients	Standard Error	P-value	Adjusted R Square
Intercept	0.0030	0.0011	0.006	
S&P500	-0.2634	0.0294	0.000	
US Corp. Bond Index	0.4504	0.1261	0.000	
PPIACO	-0.1993	0.0994	0.046	**0.5986**
AAA	-0.1843	0.0420	0.000	
Industrial Production Index	0.2733	0.1002	0.007	
Federal Funds Rate	-0.0152	0.0073	0.039	

Notes: The Table reports estimated coefficients for the three regime-specific sample periods as specified by the regime classification matrix. The first sample period is between **January 1970 and December 1982**. As per Table 2.21, this period may be classified as a high inflation & low growth period. The second sample period is between **January 1983 and December 1999**. As per Table 2.22, this period may be classified as a low inflation & high growth period. The third sample period is between **January 2000 and December 2020**. As per Table 2.23, this period may be classified as a low inflation & low growth period. The dependent variable is the monthly percentage change in the returns of the 10-Year Us Treasury Bond.

Table 2.36: Regime Specific Predictor Variables (S&P500)

ASSET	1970 - 1982	1983-1999	2000-2020
S&P500	Intercept	Intercept	Intercept
	Nikkei225**	Nikkei225	Nikkei225
	10 Year Treas**	10 Year Treasury	10 Year Treasury
	Heavy Weight Tr	US Corp. Bond Index*	US Corp. Bond Index
	M1 Velocity	USDXY*	USDXY
	Crude Oil	EconUncIndx*	EconUncIndx
	Iron Ore	UMSENT*	UMSENT
	AAA Yield	Gold*	Gold
	Personal Income*	PPIACO	Personal Income
		NFP	Copper
		M1V	Doll/ Yen
		Aluminium	

Notes: The Table reports the regime-specific predictor variables across each economic environment. The dependent variable is S&P500 returns. Variables denoted with one * appear twice across the three regimes whilst variables denoted with two * appear in each regime.

Table 2.37: Regime Specific Predictor Variables

ASSET	1970 - 1982	1983-1999	2000-2020
Gold	Intercept	Intercept	Intercept
	USDXY**	USDXY	USDXY
	Unemployment Claims*	US Corp. Bond Index	Unemployment Claims
	Crude Oil	S&P500*	S&P500
	Sugar	PPI Iron & Steel*	PPI Iron & Steel
	Silver*	Heavy Weight Trucks	Silver
	Platinum*	M2 Velocity	Platinum
		CPI	10 Year Treasury
		UM Sentiment Index	Econ Uncert Index
		Rubber	HSE Pr Index
		Aluminium	

Notes: The Table reports the regime-specific predictor variables across each economic environment. The dependent variable is gold returns. Variables denoted with one * appear twice across the three regimes whilst variables denoted with two * appear in each regime.

Chapter 3. Optimal Asset Allocation utilising a RBAA framework

Abstract

The 2008 Financial Crisis was a watershed moment for the practise of portfolio construction and the investment industry more broadly. Traditional asset allocation methods were over-reliant on an outdated mean-variance framework that failed to provide adequate tail-risk protection. Conventional risk-management practises neglected to recognise the tight positive correlations across assets linked to secular growth trends. This issue of ***Naïve diversification*** *epitomised a sense of false security amongst the professional investment community, institutional fund managers and retail investors. The contemporary prominence afforded to behavioural psychology in the context of asset management is an additional corollary of the 2008 financial crisis. This study has sought to assemble an objective, rules-based asset allocation process sustained by informationally efficient macroeconomic variables and a deeper awareness of the relationship between asset behaviour and state space regimes. Generally, our* ***regime-based asset allocation*** *approach provides promising results through blending leading market intelligence with a comprehensive understanding of economic regimes.*

3.1 Introduction

In chapter one we provided evidence to support the existence of regime specific economic environments. We also identified relationships between underlying assets and specific parameter estimates (most notably state space volatility). Our results reinforced the presence of a "low *volatility*" premium for investors with long-horizon investment mandates. We were also able to verify the theories that exposures to gold reduced risk exposure at the portfolio level. There was consistent evidence across all four individual sample periods of gold's ability to outperform in regimes of excessive volatility. The primary empirical findings from chapter one revealed that higher volatility equity regimes produce lower expected returns whilst higher volatility gold and fixed income regimes offered higher expected returns. In chapter 2, we created a regime classification framework encompassing four unique economic environments based on the explicit relationship between key economic variables[72]. Our four-quadrant economic regime framework allowed us to organise the 50-year sample period based on specific macro-economic developments. We sought to determine the relationship between financial assets and independent macroeconomic variables. The summary statistics produced for each economic regime classification proved to be consistent with the prevailing macroeconomic theory. The broader equity market exhibited optimal performance in an economic environment with increasing growth and subdued inflation dynamics. Gold outperformed the S&P500 during periods of rising inflation and US treasuries produced their strongest returns in deflationary regimes. As a robustness check, we cross-referenced the sample specific asset pricing data with the regime-dependent asset price. In general, we found consistency insofar as the annualised means and volatilities in both the sample specific and date-specific economic regimes produced remarkably similar results.

This thesis has questioned the traditional optimism based implicitly on the assumption that asset returns are identical and individually normally distributed. In this research we pose a straightforward question: "Does optimal asset allocation vary across different regimes or state spaces over time? The established consensus of expected annualised equity returns gravitates towards the historical mean. The constant expected return framework neglects to decipher the time-varying nature of asset returns. The empirical evidence gathered in Chapter's 1 and 2 advocate the benefits of focussing on time-varying

[72] The key economic variables included the rate of change in growth and inflation

expected returns. In Chapter 3, we use long-run historical data on asset prices to assess return predictability. In chapter 1,we utilised a regime-shifting Markov model to address our primary research question of whether "*asset pricing regime shifts exist?"*. The Markov regime-shifting framework allowed the states to be estimated by filtering state probabilities from return distributions. We observed the individual states through interpretation of the parameters. We also discovered robust evidence that regimes are ordered by the intrinsic nature of their volatility and of the existence of a negative risk-reward relationship between international equity markets and volatility[73]. Across all four of the individual study sample periods monthly gold returns outperform during periods of excess volatility. Our confirmation of the existence of regime-based economic environments led us towards additional research questions including whether we could classify these regimes based on an economic & policy framework and finally if we could forecast which assets are optimal from a risk-adjusted return basis in each regime? In chapter 2, regime classification is structured upon a combination of empirical evidence and established economic principles. Our 2 x 2 growth | inflation model characterised by a four-quadrant internal system attached statistical significance to the assertion that economic regimes are ordered by the specific dynamic inter-relationship of these important variables.

The main research question in chapter 3 is whether a model which utilizes these core inputs can consistently and accurately identify inflections in the performance of key factor exposures, across asset classes, 3-6 months ahead of the market consensus. The primary data signal relates to the rate of change of the underlying factor and whether it is either increasing or decreasing. The model is structured across a 2 x 2 factor model incorporating growth and inflation. This factor model captures four distinctive regimes. These regimes are determined by the prevailing economic conditions. There is a third latent factor relating to government policy which is mapped in second derivative terms. Dynamic asset allocation seeks to capture enhanced investment opportunities through profitable sector pivots, factor exposures and optimal asset allocation. The research seeks to identify if the model has the capacity to accurately forecast which sectors investors should be purchasing. We utilise a dynamic factor modelling approach through a Bayesian vector auto-regression model. If we can assume that all model parameters are random quantities, we can also suppose that prior knowledge be integrated in the model.

[73] This is commonly referred to as the "low-volatility" factor made famous through the works of Fama & French

This method contrasts with the classical, frequentist approach which presupposes that all parameters are unknown, fixed quantities. The Bayes rule provides a formulaic framework which captures historical or prior information and combines this with the data available. This posterior distribution is utilised to create model parameters including posterior means and interval estimates. In practical application, we have the data and need to identify our parameters. Through Bayesian inference we back-out the parameters from the data available. The relationship between the prior and the posterior is key. The former informs what the model knows about the parameters prior to using the information in the data. The latter describes what the model knows about the parameters after. We update prior distributions for parameters with sample information contained in the likelihood functions to form posterior distributions. The information in these prior distributions is not included in the estimation sample. This additional source of information therefore increases the granularity of the data inference. The estimations obtained through this Bayesian framework are enhanced as the likelihood function is reweighted by a prior density. By imposing priors on the AR parameters, BVAR models avoid collinearity and over-parameterization.

In this chapter, we develop a dynamic asset allocation framework that determines the optimal portfolio in a regime-shifting environment. Implicit in this framework is the conviction that a proactive, tactical approach to the macroeconomic environment produces outperformance. Robust portfolio risk management requires empirical investigation beyond the first two moments of the probability distribution. This study has focussed more attention on the 3rd (Skewness) and 4th (Kurtosis) moments of the return distribution. Following the work of *Wang, Sullivan & Ge* (2012), we have also focussed our attention on additional important concepts including volatility clustering and dynamic correlations. *Wang et al*. sought to implement a proactive, dynamic approach to active asset allocation. The individual asset weightings are determined by the prevailing market volatilities and covariances. They incorporate a two-state world conditioned on whether the prevailing market is classified under a "*normal risk*" regime or a "*high risk*" regime. The authors begin by applying extreme value theory (EVT) to capture fat-tailed return distributions. They also utilise a conditional value at risk or CVaR model. This enables them to produce forward-looking scenario-based outcomes

3.2 Literature Review

3.2.1 Risk premiums

Markowitz (1952) laid the groundwork for a more scientific approach to portfolio construction. Whilst his original research was ground-breaking for its time, the theory did also rely on several generous assumptions. These include the suppositions that investors are "*rational agents*", have homogenous expectations and markets are frictionless. Modern portfolio theory also assumes a constant risk-return framework whereby the underlying risk-premiums are static in nature. A vast amount of empirical research over the last seventy years has meant that investment professionals and academics alike recognise that investment markets are much more dynamic in nature and require a more flexible approach (*Li & Sullivan, 2011*). The investment environment is also constantly fluctuating. This phenomenon is best captured through the various growth, inflation and volatility cycles that often operate independently of the broader business cycle itself (*Achutan, L. 2016*). *Guidolin & Hyde*, (2010), *Hamilton*, J. (2016) and *Ang & Timmermann* (2012) all provide robust empirical evidence for the existence of market regimes. Our own research to date supports this hypothesis. The very existence of market regimes implies that asset pricing variables and parameters are time-varying in nature. If these underlying mean and volatility parameters are non-constant, then the risk-premiums associated with these assets can also fluctuate or shift. Investor psychology should also be recognised as a key determinant of fluctuating risk premiums. Often, innate investor bias and market sentiment drives market volatility [Kahneman, 2011 & Thaler, 2015]. Financial markets do not appear to exist in a constant environment of "*risk-on*" or "*risk-off*"[74] sentiment.

3.2.2 The Business Cycle

The investment industry is dominated by precarious "*rules of thumb*" style processes for analysing the business cycle. Prior to the technology bubble implosion at the start of the 21st century, the Julius Shiskin (1974) approach to the definition of recessions was commonly used[75]. Our research will show that what matters most is the cumulative directional change in the rate of growth and inflation and not some arbitrary, fixed definition. For instance, the 2000 dot-com bubble burst in an environment where GDP

[74] A "risk-on" market is one where the buyers are influencing the trend. A "risk-off" market is the opposite and the sellers are the dominant force.

[75] In 1974, Shiskin wrote an article in the New York Times noting that a recession can be framed into two successive quarterly declines in GDP.

traversed between positive and negative numbers. Instead of focussing narrowly on a GDP print, we recommend a broader approach focussing on the rate of change in important economic indicators including output, employment, income and sales. Cycles exist owing to the inter-relationships between their constituent parts – namely the expansion and contraction phases. The severity of the latter inevitably influences the trajectory (and speed) of the former. Mussa's (2009) work in this area supports the notion that the deeper the recession, the steeper the recovery. Banerji & Achuthan (2016) qualify this premise by adding that the steepness of the recovery is prominent in the "initial" phase of the recovery, and this does not always follow through to a persistent recovery. The authors support their general thesis of downward trending "initial phase" recovery since WWII. They use the analogy of a rubber ball that slowly loses its elasticity over time. The ball does bounce back. However, the force and height of the bounce reduces over time (Banerji & Achuthan (2009b). As such, the authors impose two restrictions on the ferocity of the rebound during the initial phase – the scale of the decline and the passage of the time. The latter is linked heavily to more persistent secular and structural changes.

3.2.3 Disinflation

Our research will reveal the sharp distinction between the benefits of forecasting recessions and cyclical slowdowns. Since 1990, there have been approximately ten cyclical slowdowns (NBER). However only three of these resulted in a recessionary environment. The *Economist* first published the term *disinflation* in an article two years after the end of WW2. We can describe disinflation as a reduction in the positive rate of change of inflation. Deflation is a reduction in prices which is not the same thing. The subtle difference between the two lies in the fact that disinflation may still encompass rising prices. However, the rate of change is negative and price rises occur at a slower and slower pace over time. The term disinflation became popular again during the early eighties after two decades of persistent inflation. During this period bond market yields were at record highs. During March 1980, the CPI inflation rate peaked at 14.8%[76]. Yardeni (2018) attributes much of the disinflationary pressures that emerged in the early 1980s to the new US political administration. Reagan had been elected on a four-pillar platform centred on lower government spending, marginal tax cuts, reduced regulation and inflation control. The latter was predominantly subdued through Fed chair Paul

[76] Yardeni, E. (20180

Volker. Additionally, Reagan sought to undermine the control of US labour unions. The PATCO[77] affair and diminishing inclusion of COLA[78] labour contract clauses had a noticeable impact upon wage inflation. Yardeni notes that union membership declined from 16.8% of workers during 1983 to less than 10% by the end of the 1990s.

3.2.4 Macroeconomics and Factors

Zhou & Jain (2014) examine the relationship between exogenous economic variables and alpha factors. They noted empirical evidence confirming factor return differences across different macroeconomic environments. These have been summarised in Table 3.1 below. A common trend appears as trade-offs and incentives drive the momentum behind different factors at various stages of the economic environment. For instance, the illiquidity premium (Ilmanen, 2011) during a stressed market event may lead investors to favour quality assets leading to outperformance during high volatility regimes. Alternatively, earnings yields are less pivotal for investors during high growth regimes in exchange for rapid capital appreciation expectations. This leads to an under-performance of earnings yield during a high-growth regime.

Table 3.1: Regime-based market signals

Market Signal	Economic environment	Performance
Earnings Yield	Slow earnings growth	Outperformed
Earnings Yield	High growth environment	Underperformed
Quality	High Market Volatility	Outperformed
Quality	Low market Volatility	Underperformed
Price	Strong Economic Growth	Outperformed
Momentum	Strong Economic Growth	Outperformed
Dividend	Bear Market	Outperformed
Non-Dividend	Bull Market	Outperformed

Source: Zhou & Jain (2014), Active Equity Management

3.2.5 Economic conditions

The existing economic environment as represented by prevailing interest rates, growth and inflation rates will have a varied and fluctuating impact on assets. For instance, rising inflation may force monetary policymakers to increase interest rates. The second order

[77] Reagan routinely fired over 11,000 air-traffic controllers in his first year of presidency for their role in an illegal strike action. Although PATCO union members were public-sector workers, the response sent a strong message to all workers in the US. It led to large numbers leaving their respective unions in the following years

[78] COLA or automatic "cost-of-living-adjustments" were routinely built into US workers employment contracts to protect workers from the rising cost of living. The inclusion of these clauses peaked in 1977. There was a sharp decline in the early eighties most notably in 1985.

implications of this policy will have contrasting consequences. Arnott et al (1992) noted that high dividend paying stocks underperformed in a rising inflationary environment. The rationale being that a rising rate environment would have negative implications for equities associated with a fixed payoff profile or stable cashflows. The assumption here then is that investors can enhance their marginal returns by incorporating pro-active, regime-based asset allocation strategies (RBBA). A distinction should be made between RBAA and pure market timing. The former process implies the use of a coherent economic scenario-based framework whereby market timing encompasses opportunity and a reactive trading approach. There is evidence that market-timing strategies have been successful[79]. The fundamental question however is are they persistent. O'Sullivan & Hutchinson (2000) have conducted extensive research on the distinction between investor manager "*luck*" and "*skill*" in the realm of asset allocation. Through a complex bootstrapping technique their results are consistent with the literature on market-timing. Successful market-timing does exist. It is rare however and when it does present much of the results are attributable to luck more so than skill. Arshanapalli et al. (2007) implemented a logistic regression model to analyse the comparative performance of "Value" and "Growth" based equity indices. Macroeconomic factors including the consumer price index and bond yields were utilised to construct a market timing strategy which outperformed all four passive indices in the sample. The outperformance was not insignificant resulting in a 46bps monthly outperformance between 1986 and 2000. Although the results appear significant, the sample period is short from a business cycle perspective and would not have encompassed enough cycles to have drawn huge inference.

3.2.6 Market Regimes

Zhou & Jain (2014) also examined the relationship between market regimes and factors. They noted empirical evidence confirming factor return differences across diverse macroeconomic environments. These have been summarised in Table 3.2 below.

[79] Arshanapalli, 2007

Table 3.2: Regime-based Factor signals

Factor	Asset| Factor	Market	Exposure
Market β	**Growth** Stocks		High
Market β	**Value** Stocks		Low
Market β	**High Momentum** Stocks	After a Bull Market	High
Market β	**High Momentum** Stocks	After a Bear Market	Low
	Low **earnings Variability** Stocks	Bear Market	Outperform
	High **earnings Variability** Stocks	Bear Market	Underperform

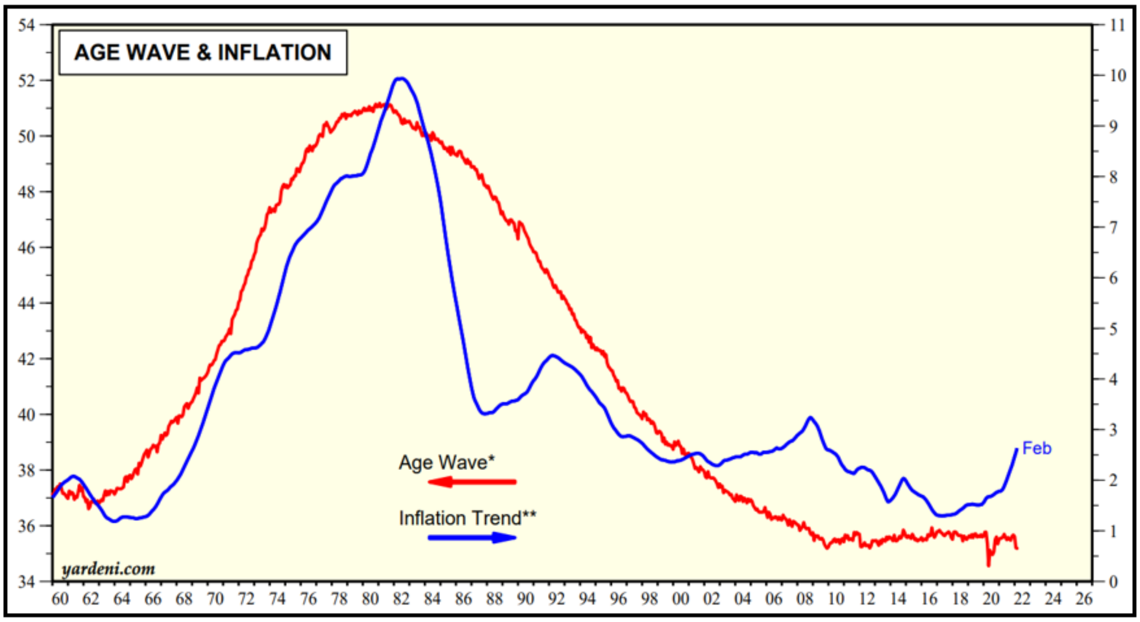
Source: Zhou & Jain (2014), Active Equity Management

3.2.7 Regime Classification

We can classify market regimes across multiple spectrums which encompass growth, inflation, policy and volatility cycles. Simple volatility regime classifications based on the realized daily market volatility can capture important regime shifts. An elevated volatility regime may encompass an economic scenario whereby the realised daily volatility in the past 6 months is higher than the 60-month average. We can classify this as a high volatility regime. Mandelbrot (1997) presented the multifractal model of asset returns and noted that market volatility exhibits much greater consistency because of this phenomenon of volatility clustering[80]. This persistence should ensure that volatility forecasting is easier to conduct. The global economy has experienced a consistent fall in inflation or disinflation since the early 1980s. There are numerous reasons for this decline, and these have been covered widely in the literature. Yardeni (2018) affirms that the "baby boomer" generation provided a strong tailwind for productivity growth. As this large cohort of the productive population settled into employment the view was that they would contribute a large portion of their annual income to domestic consumption. Yardeni emphasises this phenomenon through his "Age Wave Model" as indicated in Figure 3.1. He identified a strong correlation between the 16-34 age group and the five-year inflation trend. The red line shows the % change of 16–34-year-olds between 1960 and present day. For example, in 1982, this peaked at over 50%. The blue line represents the inflation trend over the same period.

[80] Volatility clustering describes the stylized behaviour of the dispersion of assets. In essence, high dispersion persists for a period and is followed by low dispersions which also persists. High volatility means high volatility and low volatility produces low volatility.

Figure 3.1: Age-Wave Model



Source: Bureau of Labour Statistics (Sourced from yardeni.com)

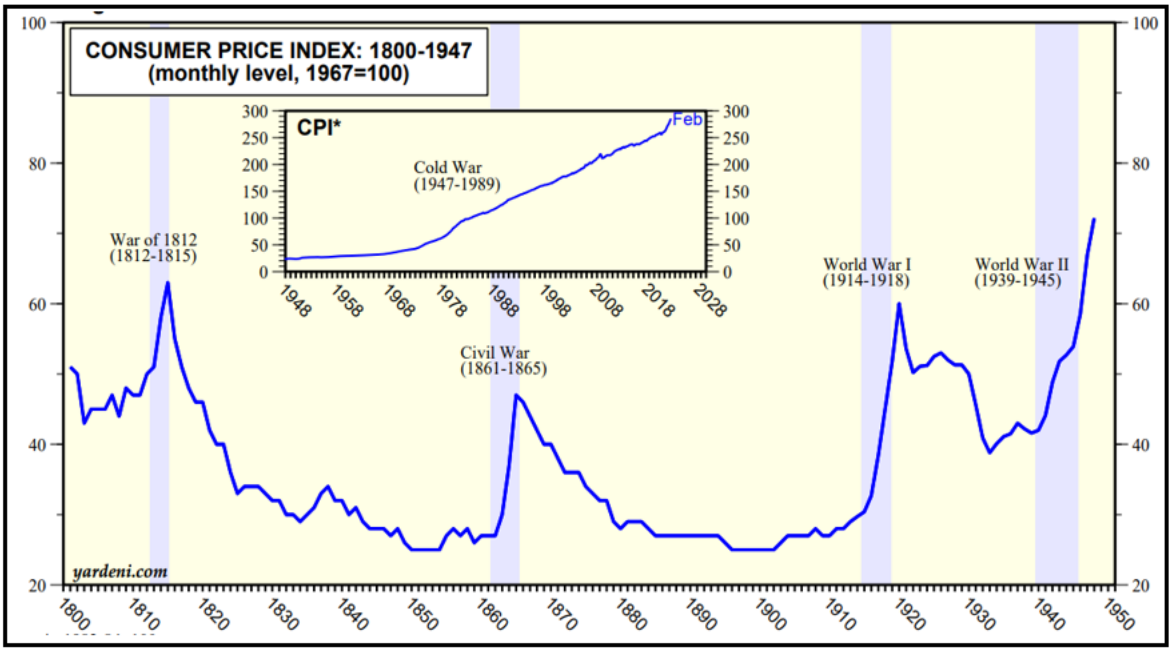
It is clear from figure 3.1 that the larger the proportional % of the labour force residing in the 16–34-year-old age cohort, the sharper the decline in the inflation trend. The persistence of the decline in the inflation trend since its peak in the early 1980s is most notable. There appears to have been some strong structural economic forces placing downward pressures on the inflation trend. Yardeni (2018) also points to the significance of technological advancement and the end of cold war hostilities at the end of the 1980s. The rapid increase of technological innovation in the early nineties and the intense competition between producers led to persistent reduction in the prices of these goods and services. The disintegration of the Soviet Union in 1989 paved the way for greater integration and unrestricted global trade. This led to greater assimilation between global markets, free trade and globalised competition – all disinflationary in nature. The next major event to deepen the trend towards disinflation was the decision by China to join the World Trade Organisation in 2001. The "China price" phenomenon further placed downward pressure on inflation as this new WTO member provided a huge source of young, disciplined, labour to manufacture cheap products for western multinational corporations. This new transmission of cheap global products from China to the US and western Europe filtered down to the domestic consumer leading to reduced overall costs for goods. Whilst consumers benefitted, western workers experienced wages declines as wage inflation was curtailed. The emergence of huge online shopping conglomerates may have further suppressed inflationary pressures.

3.2.8 Theories of Inflation

Tolstoy Model of Inflation

Edward Yardeni noted in his 1997 article "The Economic Consequences of the Peace"[81], that war is inflationary, and peace is deflationary. The basis of his arguments were that war and heightened geopolitical tensions obstruct economic competition. They create roadblocks and trade barriers. This is illustrated on a historical basis in figure 3.2 below. The grey shaded areas represent periods of significant historical military conflict.

Figure 3.2: Inflation & War



Source: Census Bureau, Historical Statistics of the United States (Sourced from yardeni.com)

There is clear evidence in figure 3.2 of positive correlation between the outbreak of military conflict and sharp rises in CPI. For instance, from 1939 through to 1947, the consumer price index rose by 72%. During the subsequent 40-year cold war period prices rose 415% (Yardeni, 2018). The Tolstoy model of inflation explains large spikes in inflationary trends through the prism of large international based military conflict. Wars appear to create an unconstructive, negative market environment whereby economic alliances are split among military alliances. Wars are also unproductive at the human level as labour participants may be forced into conscription. Businesses pause investment, research and innovation projects as uncertainty pervades. Commodity prices climb as competition between opposing forces for valuable, scarce resources soars. There is consensus among economists through the microeconomic model of perfect competition,

[81] The title was borrowed from the seminal work by John Maynard Keynes

that the larger the market and the less restrictions placed on free trade, the lower the prices ultimately faced by consumers.

3.2.9 A Bayesian approach

Sims (1990) initially utilised a flat set of prior beliefs. Later research focussed on informational efficiency with the inclusion of macroeconomic data and economic theory (Villani, 2009). In classical statistics our θ parameter in the population is referenced as a point value. Sampling error across multiple sample sets is inevitable given that this frequentist approach assumes that our parameter θ is fixed. Frequentists assume that the parameter of interest is fixed, and the data is varying or sample specific. Bayesian statistics proposes that a probability distribution govern the values of the specific parameter θ, the parameter varies, and the data is instead fixed. Bayesian analysis uses probability statements to address research questions about model parameters. The Bayesian approach assumes that parameters are random. We can incorporate prior knowledge into the model which differs from the traditionalist approach that assumes parameters are unknown, fixed quantities. The Bayes rule provides the framework from which we can combine historical information and current data to reveal the posterior distribution. Critical information such as credible intervals, means and medians are then obtained from this posterior distribution utilising the Bayesian approach. The practicality of Bayesian analysis is evident in the type of research questions addressed in the literature. Hoff (2009) sought to investigate the frequency of rare infectious disease in small urban area. Geweke & Amisano (2010) sought to quantify the distribution of future equity market returns placing particular importance on capturing the probability of extreme events. They produced multi-horizon Bayesian predictive distributions for returns on the S&P500 utilising five alternative models. Hoogerheide & Van Dijk (2010) focus their empirical research on the lower tail of the loss distribution whilst concentrating on the VaR framework. Beechey & Osterholm (2010) focus their attention on inflation-targeted regimes. Their work questions whether macroeconomic forecasting that focus on autoregressive models are enhanced through the incorporation of the underlying inflation targets. The authors conclude that inflation targets acting as *informative priors* provide an anchor for inflation expectations and improve forecasting in general. Our aim for this paper is to construct a forecasting model motivated by the ability to predict influential macroeconomic variables including GDP growth, consumer price index, personal consumption expenditures and the unemployment rate. The scale of the financial crisis of

2007/2008 was not accurately identified by traditional forecasting methods. Bialowolski et. al, (2012) claims that most forecasting models including dynamic simultaneous equation models, general equilibrium models, dynamic stochastic general equilibrium models and vector auto-regression models all failed to produce accurate short-run crisis predictions. Sargent & Sims (1977) and Sims (1980) pioneered the approach of atheoretical model construction. This method centres around the influence of consumer and business sentiment surveys as opposed to traditional prediction modelling focussing on (often) thin relationships between causality and economic theory. There has been a constant debate in the literature as to the optimal method of sourcing causal data. Should our forecasting model focus solely on the macroeconomic data or should it centre around business and consumer surveys. The latter obtained through direct consultation and recent engagements offer arguably a more prescient representation of the economic reality.

3.3 Models and Data

3.3.1 Data

For robustness, it was important to include a wide cross-section of dependent variables. This section provides a brief description of each variable. We included specific assets from the S&P500 equity market sector groupings, individual securities, a broad selection of unit-linked mutual funds and factor exposures. These have been listed below in Table 3.3.

Table 3.3: Dependent Variable Review

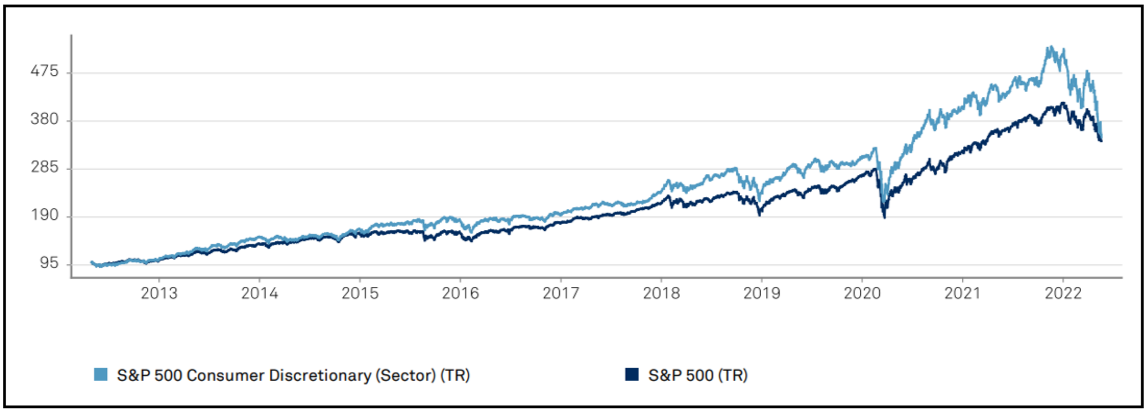
Asset Type	Sectors	Asset Type	Asset	Asset Type	Funds	Asset Type	Factors
S&P500 Equity Sectors	S&P500 Consumer Disc	Assets	S&P500	Funds	Managed Fund	Factors	Size
	S&P500 Consumer Staples		Nikkei 225		Agg. Global Equity Fund		Value
	S&P500 Financials		Gold		North Amer Equity Fund		Profitability
	S&P500 Energy		Commodities		Non-US Equity Fund		Investment Policy
	S&P500 Utilities		10 Yr Treas		Corp. Bond Fund		Momentum
	S&P500 Healthcare		Corp. Bonds		Commodity Fund		Market Factor
	S&P500 IT				Precious Metals Fund		Quality

3.3.2 Equity Market Sectors

1) S&P500 Consumer Discretionary Sector

This index comprises companies included in the S&P500 classified as members of the GICS^{R} Consumer Discretionary sector. It has a mean total market cap of $73.64bn with the top ten constituents accounting for approximately 75% of the index (as of 22/04/2022). These companies are well known consumer brands including Amazon, Tesla, Home Depot, McDonalds Corporation and Nike. The trailing Price to earnings and Price to Book of the index are 35.82 and 11.81 (as of 22/04/2022). The performance of the Consumer Discretionary Index since the Global Financial Recession has been noteworthy. Apart from 2018, the index produced returns well in excess of 10% gross per annum with exceptional returns of 43.08%, 27.94% and 33.3% in 2013, 2019 and 2020 respectively. Figure 3.3 highlights the divergence in performance from the main S&P500 Index most notably after 2018. We can see evidence also however of the cyclical sensitivity of the sector given the sharp moves negative from January 2022.

Figure 3.3: S&P500 Consumer Discretionary Sector

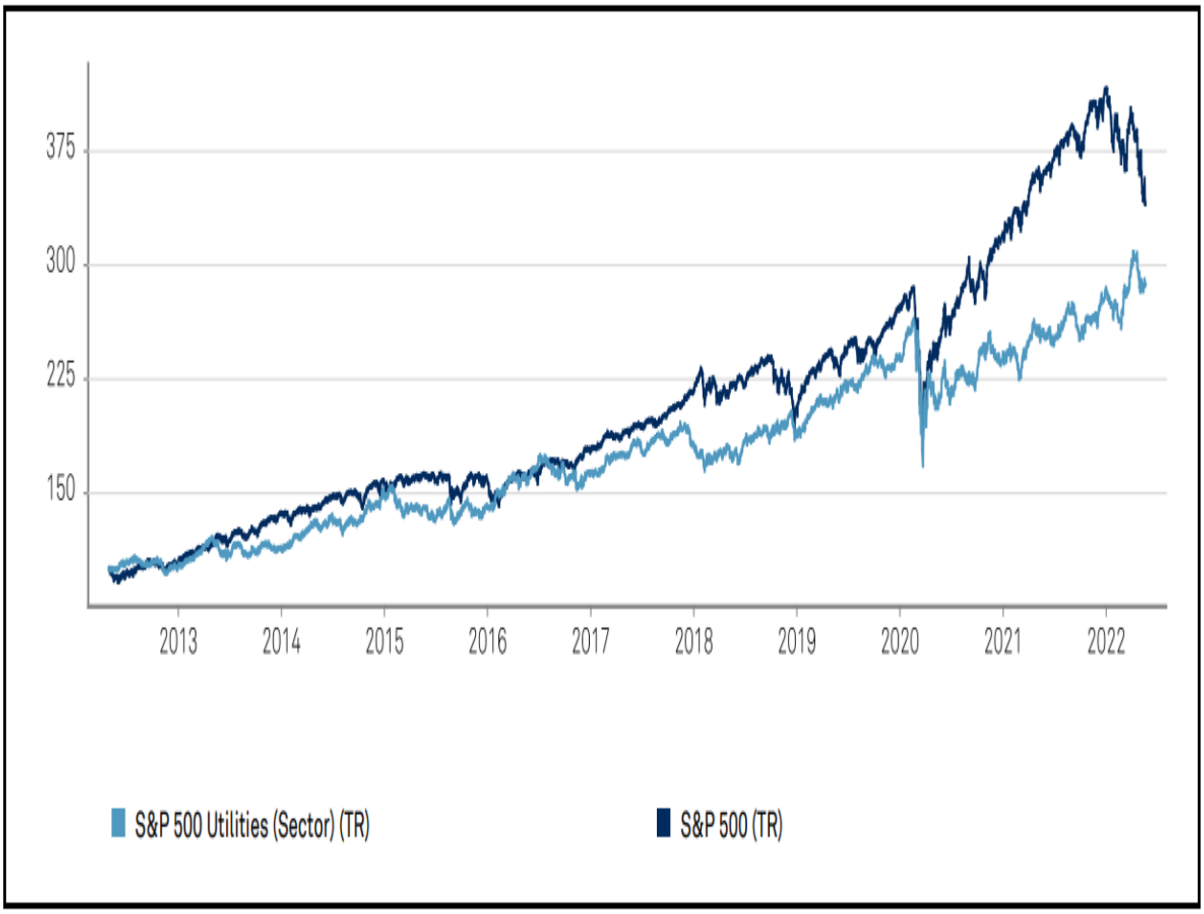


Source: S&P Dow Jones Indices

2) S&P500 Utilities

This index comprises companies included in the S&P500 classified as members of the GICS^R Utilities sector. It has a mean total market cap of $34.6bn with the top ten constituents accounting for approximately 62% of the index (as of 22/04/2022). The trailing Price to earnings and Price to Book of the index are noticeably lower than the more cyclical Consumer Discretionary sector at 28.44 and 2.37 (as of 22/04/2022). The under-performance of the Utilities Index since the Covid-19 pandemic has been noteworthy. The index returns have lagged the broader index significantly at periods. For instance, in 2012, 2015,2018 and 2020, the Utilities index produced returns of just 1.29%, -4.85%, 4.11% and 0.48% respectively. Figure 3.4 highlights the divergence in performance from the main S&P500 Index most notably post-Covid19. We can see evidence also however of the robustness of the utilities sector by maintaining a solid positive trend upwards from late 2021 whilst the main (S&P500) index was in a sharp decline.

Figure 3.4: S&P500 Utilities Sector

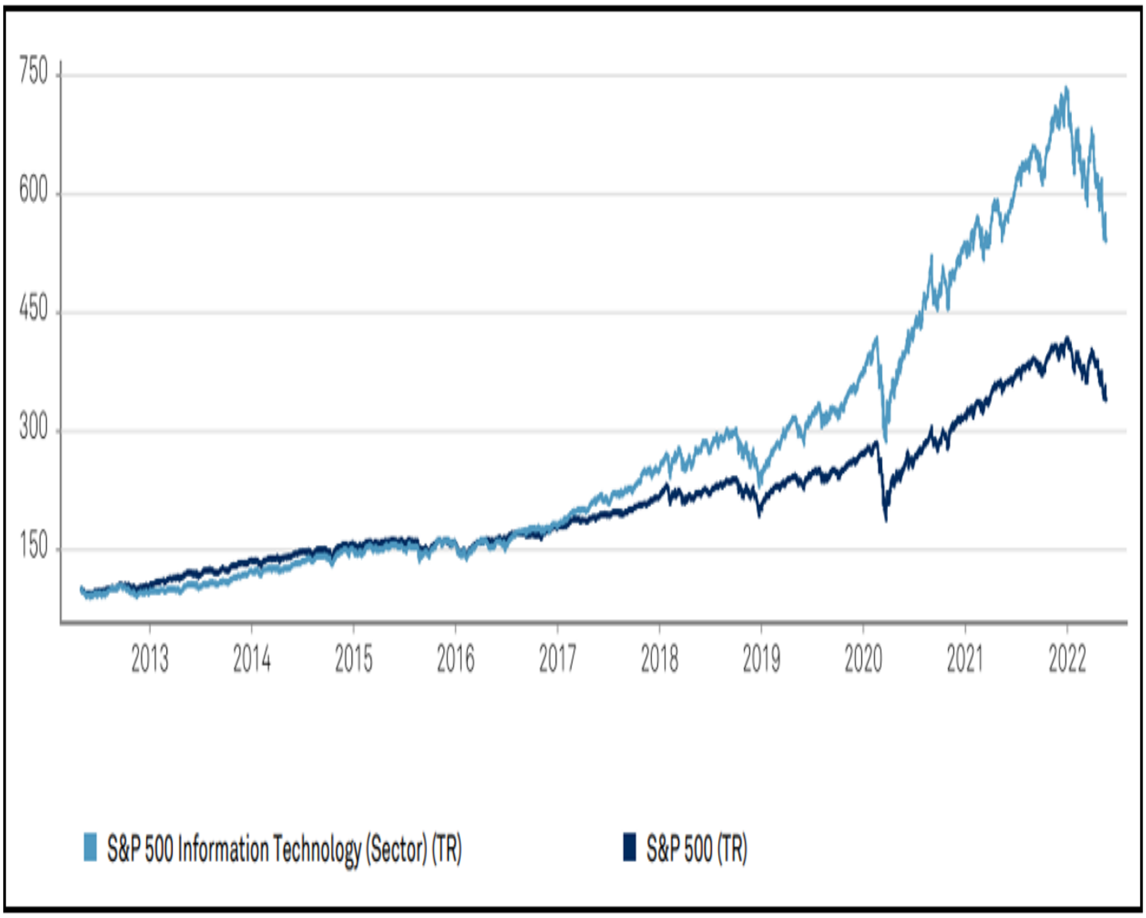


Source: S&P Dow Jones Indices

3) <u>S&P500 Information Technology</u>

This index comprises companies included in the S&P500 classified as members of the GICS® Information Technology sector. It has a mean total market cap of $130.74bn with the top ten constituents accounting for approximately 69.8% of the index (as of 29/04/2022). The trailing Price to earnings and Price to Book of the index are noticeably higher than the more defensive Utilities sector at 33.23 and 12.22 (as of 29/04/2022). The significant out-performance of the IT Index since 2010 appears to have been accelerated further by the "*work from home*" phenomenon of the Covid-19 pandemic. Like the Consumer Discretionary Index, the gross returns have been significantly higher than the main index at periods. For instance, in 2017, 2019, and 2020, the IT index produced returns of just 38.83%, 50.29%, and 43.89% respectively. Figure 3.5 highlights the divergence in performance from the main S&P500 Index most notably post-Covid19. We can see evidence also however of the inherent volatility of the sector with huge drawdowns experienced since the beginning of 2022. The top five constituent holdings by weight include Apple, Microsoft, Nvidia, Visa and Mastercard.

Figure 3.5: S&P500 Information Technology

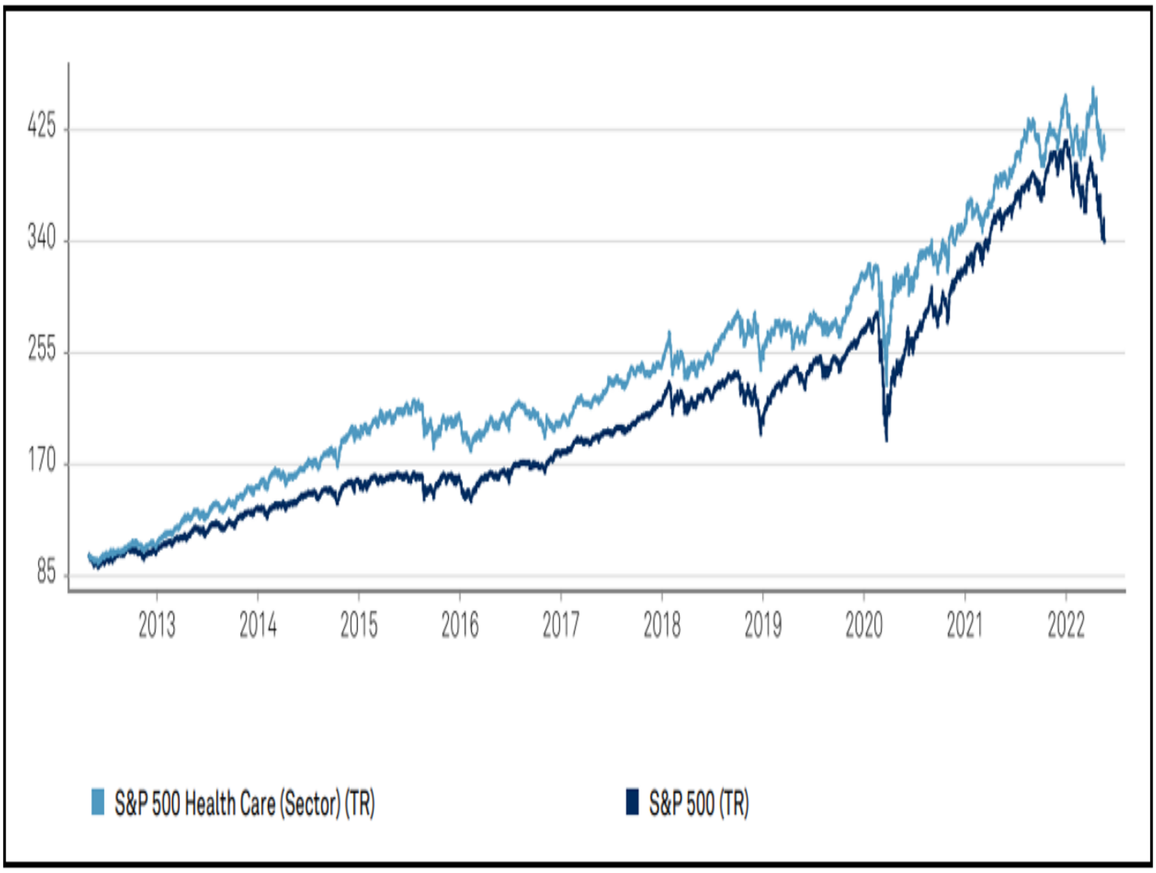


Source: S&P Dow Jones Indices

4) <u>S&P500 Healthcare</u>

This index comprises companies included in the S&P500 classified as members of the GICS^{R} Healthcare sector. It has a mean total market cap of $78.14bn with the top ten constituents accounting for approximately 54.2% of the index (as of 29/04/2022). The trailing Price to earnings and Price to Book of the index are noticeably lower than both the IT and Consumer Discretionary sectors at 24.2 and 5.48 respectively (as of 29/04/2022). The Healthcare index has outperformed the broader S&P500 index over the past decade. The range of outperformance has been much less volatile than the IT or Consumer Discretionary sector. Like Utilities, the Healthcare sector is viewed as a defensive option in volatile periods owing to the necessity of the services the sectors companies provide. Figure 3.6 highlights these defensive characteristics. We can assess the sharp downturns of the broader S&P500 both in Feb/ March 2020 and most recently since January 2022. It is noteworthy that the Healthcare sector is much less volatile during both of these bear market regimes. The top five constituent holdings by weight include United Health Group (UHG), Johnson & Johnson, Pfizer, AbbVie Inc. and Eli Lilly.

Figure 3.6: S&P500 Healthcare Sector

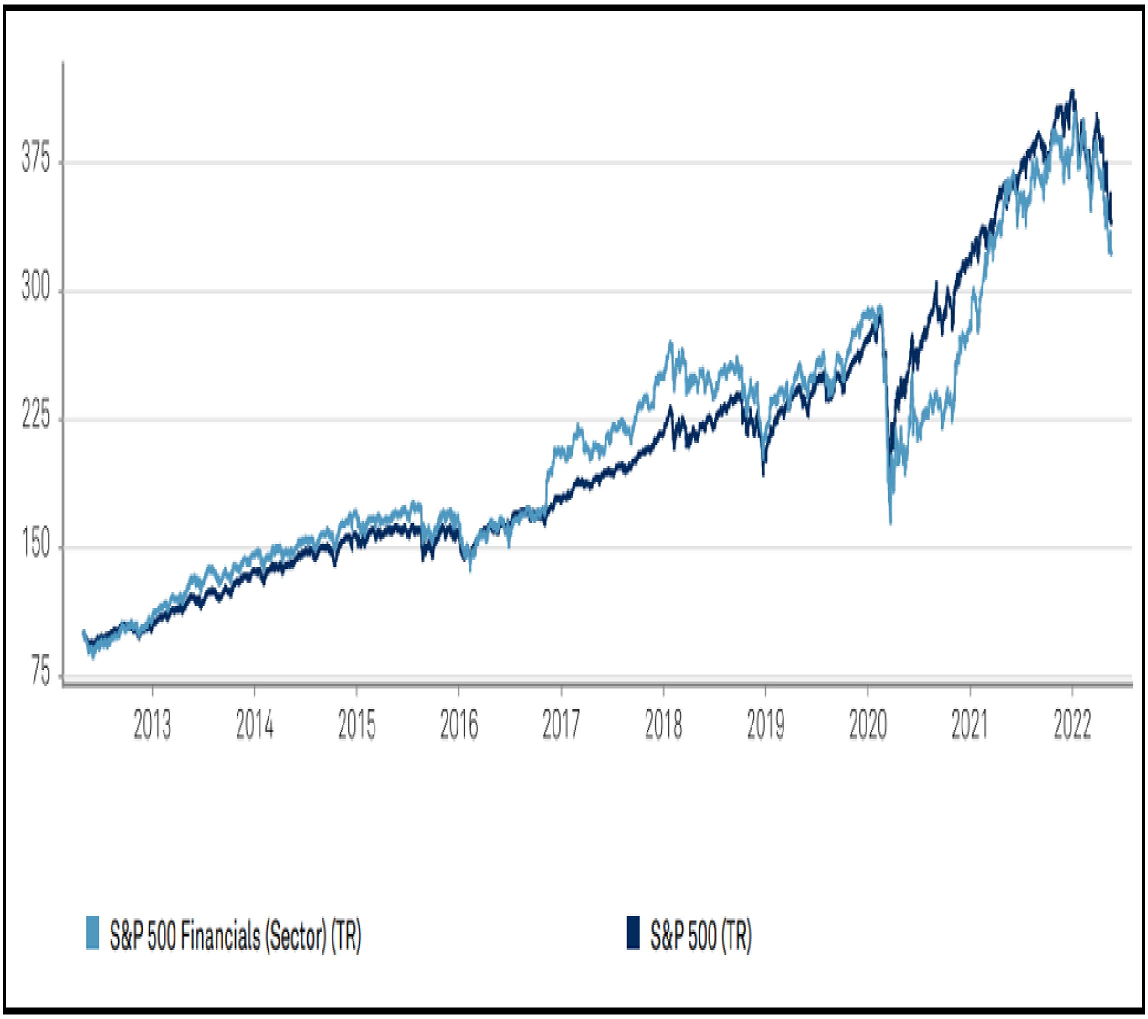


Source: S&P Dow Jones Indices

5) S&P500 Financials

This index comprises companies included in the S&P500 classified as members of the GICS[R] Financials sector. It has a mean total market cap of $62.61bn with the top ten constituents accounting for approximately 52.8% of the index (as of 29/04/2022). The trailing Price to earnings and Price to Book of the index are similar again to both the Utilities and Healthcare sectors at 11.08 and 1.74 respectively (as of 29/04/2022). The S&P500 Finance sector lagged the broader index for an 18-month period post Covid-19. In general terms the Finance sector has tracked the broad S&P500 market quite closely. This may be attributed to the pivotal role finance institutions play in the broader market. Banks and other financial institutions are particularly sensitive to interest rate risks and may fluctuate more with increased interest rate volatility. The top five constituent holdings by weight include the Berkshire Hathaway group, JP Morgan Chase, Bank of America, Wells Fargo and S&P Global Inc.

Figure 3.7: S&P500 Financial Sector



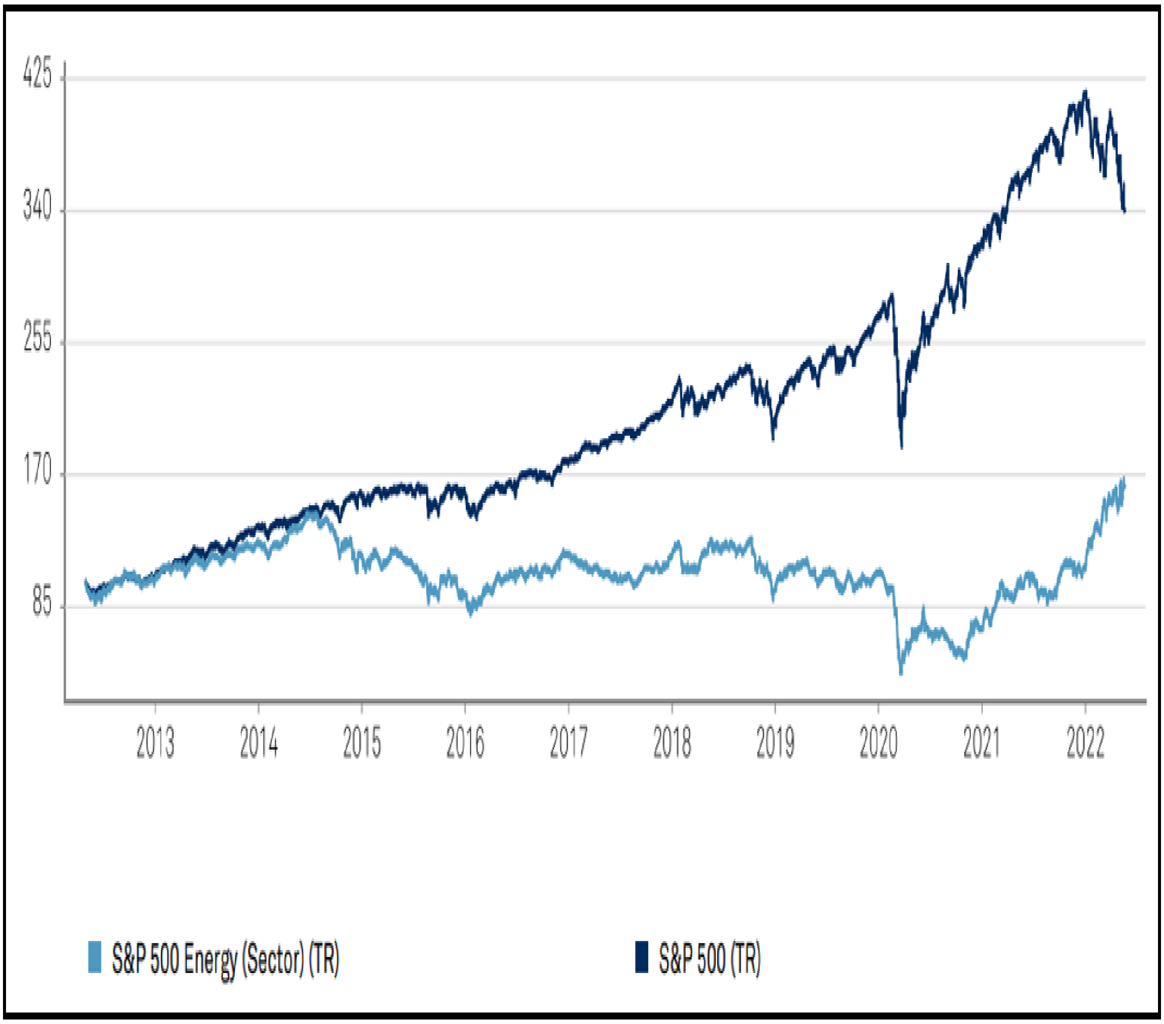
Source: S&P Dow Jones Indices

6) <u>S&P500 Energy</u>

This index comprises companies included in the S&P500 classified as members of the GICS^{R} Energy sector. It has a mean total market cap of $70.46bn with the top ten constituents accounting for approximately 78.8% of the index (as of 29/04/2022). The trailing Price to earnings and Price to Book of the index are similar again to both the Utilities and Healthcare sectors at 14.58 and 1.79 respectively (as of 29/04/2022). It is clear from Figure 3.8 that the Energy sector has been a clear laggard in terms of performance particularly since the middle of 2014. The rising political pressure on fossil fuel emittance, ESG mandates and structural under-investment has contributed to this underperformance. There have been multiple years of negative performance for the

Energy sector including -21.12%, -18.1% and -33.68% in 2015, 2018 and 2020 respectively. In contract 2021 produced a total gross return of 54.64%.

Figure 3.8: S&P500 Energy Sector



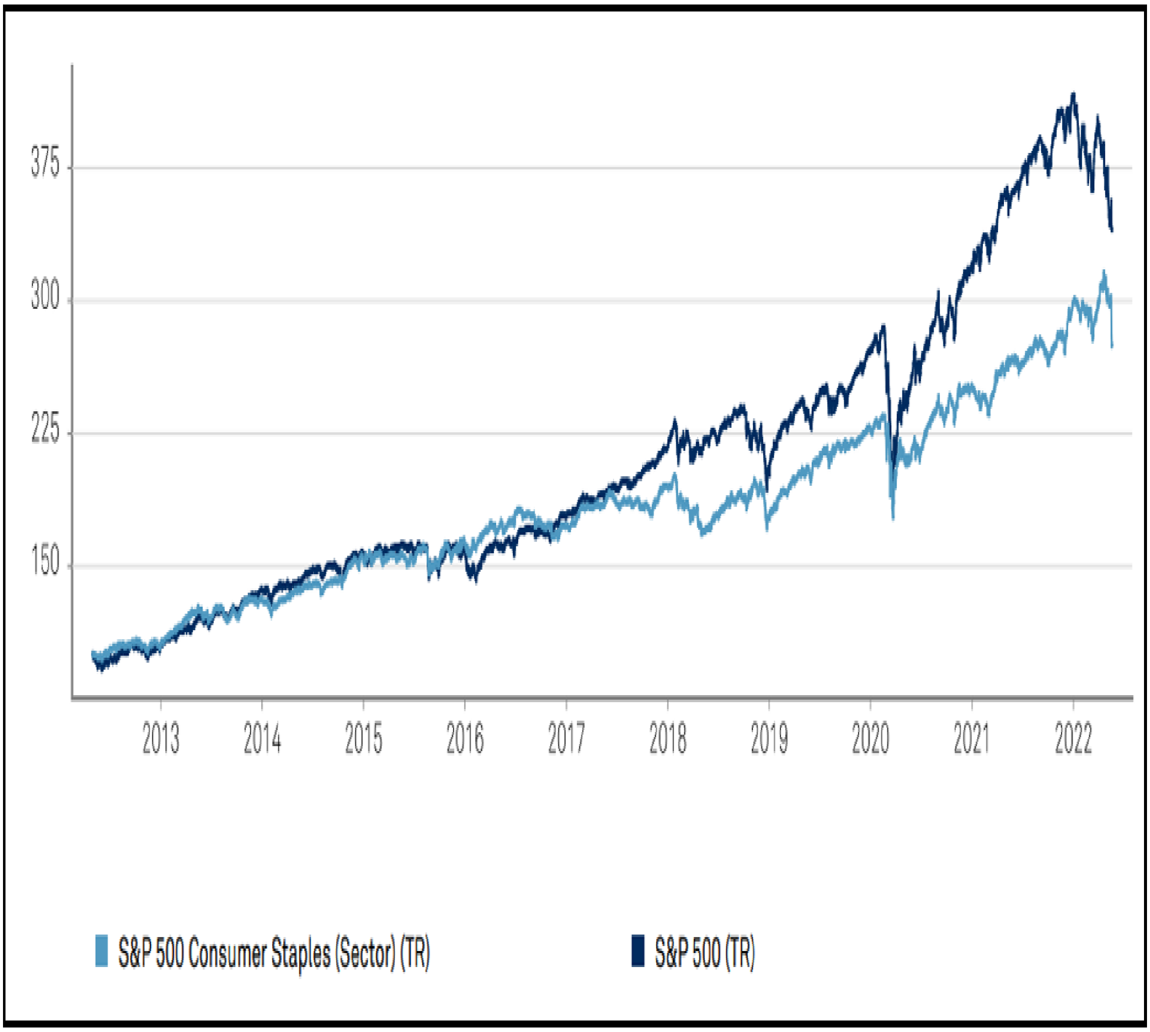
Source: S&P Dow Jones Indices

7) S&P500 Consumer Staples

This index comprises companies included in the S&P500 classified as members of the GICS^{R} Consumer Staples sector. It has a mean total market cap of $84.28bn with the top ten constituents accounting for approximately 78.8% of the index (as of 29/04/2022). The trailing Price to earnings and Price to Book of the index are similar again to both the Utilities and Healthcare sectors at 26.8 and 7.41 respectively (as of 29/04/2022). It is clear from Figure 3.9 that the Consumer Staples sector has consistently lagged the broader equity market. The relative under-performance may be attributable more to the large out-performance of particular segments of the equity market (IT & Consumer Discretionary).

Like the Utilities and Healthcare sectors, Consumer Staples are considered a defensive strategy given the pricing power associated with consumer goods companies (Food & Supplies are a staple).

Figure 3.9: S&P500 Consumer Staples Sector



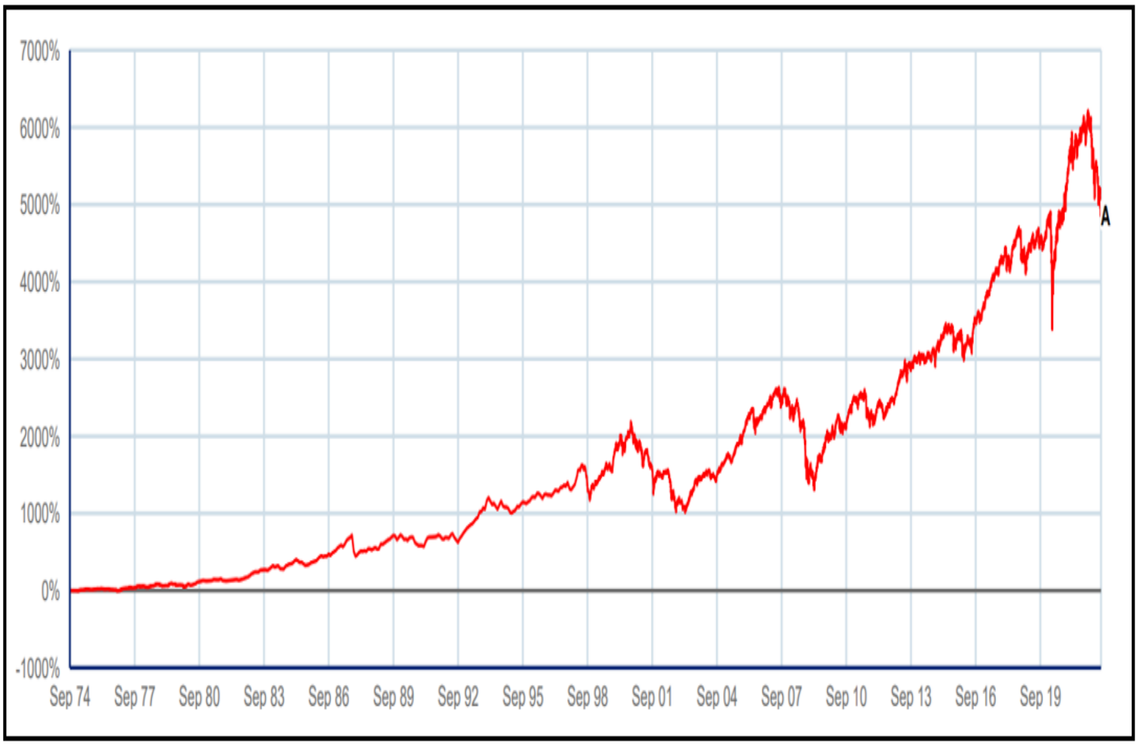
Source: S&P Dow Jones Indices

3.3.3 Asset-specific Mutual Funds

1) *Equity Fund: Aviva Life Investment Trust Portfolio*

The Aviva Life Investment Trust was launched in November 1968. The aim of the fund is to invest in UK closed end investment companies. The fund belongs to the global equities sector with both the unit and fund currency denominated in British pounds. Figure 3.10 displays the long-term performance of the fund since August 1974. We can extrapolate the performance of the fund from the cyclical movements in the business cycle during this period. For example, in the early 1990s we note a consistent rise in the positive performance of the fund up to the peak of the technology-bubble at the turn of the century. There then followed a sharp reversal until the business cycle recovered in the early 2000s. We note a continuation of the expansionary period right up until the peak of the Great Financial Recession in 2007 culminating in the collapse of the sub-prime housing bubble through 2008. Global equity markets found a bottom in March 2009 leading to the longest structural expansionary period in history until the Covid-19 induced economic slowdown and subsequent market sell-off. The NBER characterised this recession as the shortest in terms of duration in history. Massive government monetary and fiscal expansionism led to a recovery and subsequent boom-type period up to Q4 2021. The stock market decline between January 2022 and June 2022 has been the sharpest and largest negative initial 6-month performance period since records began. Table 3.10 provides evidence of the cumulative, discrete and annualised performance figures of the fund since launch.

Figure 3.10: Performance Chart/ Aviva Life Investment Trust



Source: Financial Express Fund Info

2) *Commodity Fund: JPMorgan Natural Resources*

The JP Morgan Natural Resources fund was launched in June 1965. The aim of the fund is to invest at least 80% of the fund's assets in the shares of global companies involved in the production and marketing of commodities. The fund has a total asset under management (AUM) of $926m (as of 22/06/2022). The primary commodity sectors include integrated oil & gas, diversified mining, base metals, oil and gas exploration and the gold & precious metals sector. Figure 3.11 displays the long-term performance of the fund since June 1974. We can extrapolate the performance of the fund from both cyclical movements in the business cycle and key energy-related volatility spikes during this period. For example, there appears to have been three significant rolling 5 to 7-year natural resource cycles between the late 1990s and the present day. In 1998, strong global demand more oil and commodities in general fuelled the large year on year increases in the underlying fund performance. This demand for global energy peaked in 2008 as the GFR led to large drawdowns. The natural resources market experienced a strong recovery in the three years post-GFR expanding higher than the previous market high in 2008. The subsequent collapse in oil prices specifically led the fund performance lower until its most recent recovery period in June 2016. Table 3.11 provides evidence of the cumulative, discrete and annualised performance figures of the fund since launch.

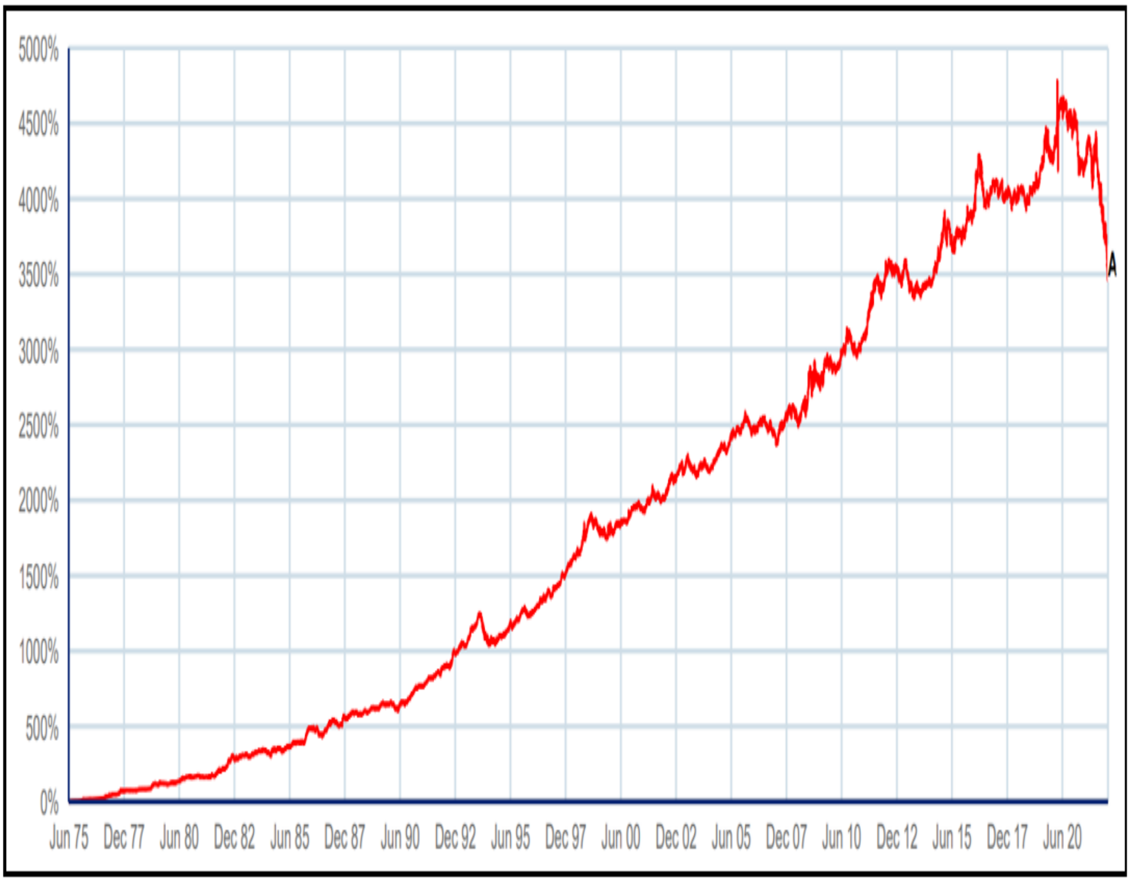
Figure 3.11: Performance Chart/ JP Morgan Natural Resources Fund

Source: Financial Express Fund Info

3) *Canada life Fixed Interest Pension Fund*

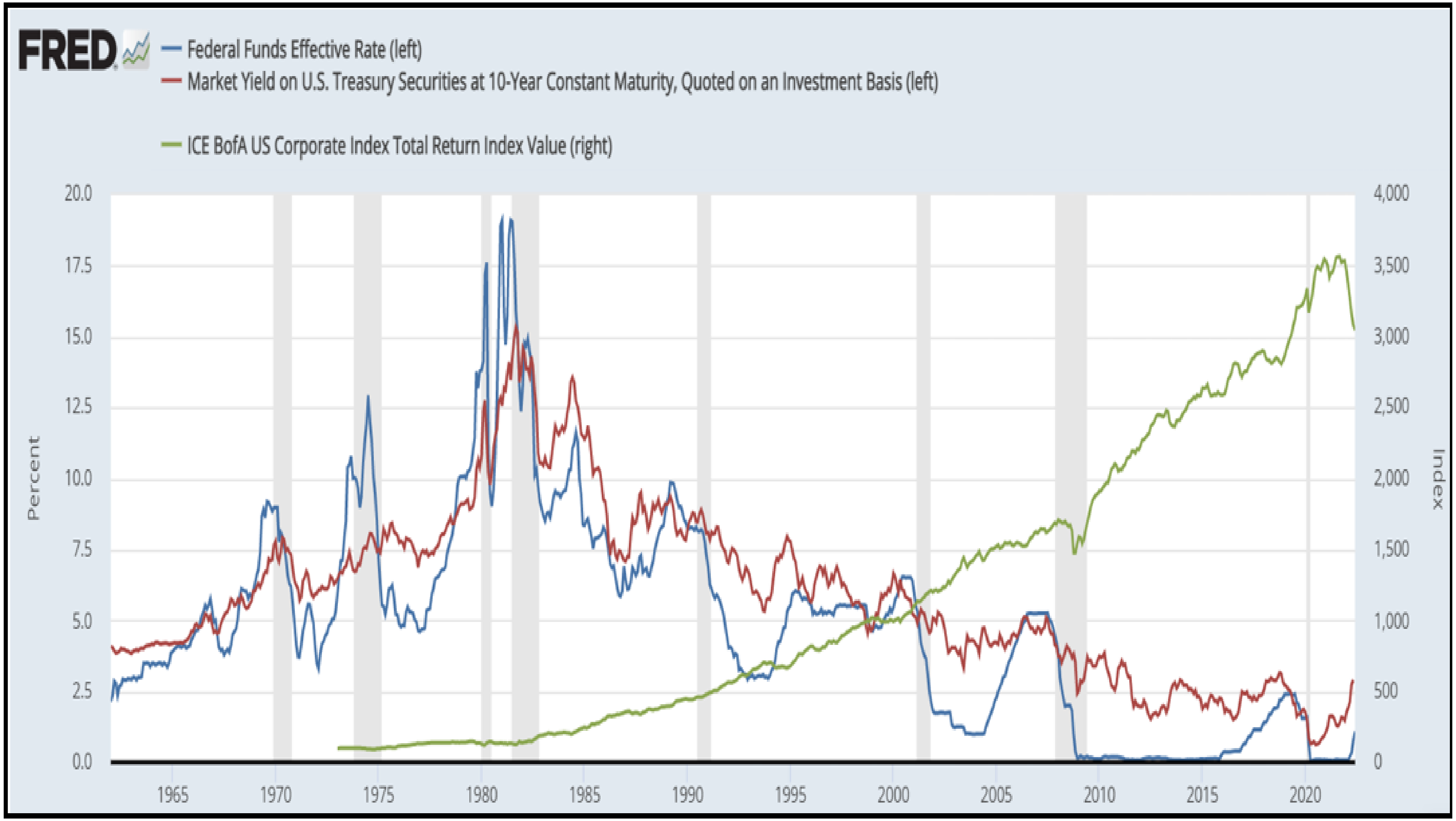
The Canada life Fixed Interest fund was launched in February1975. The aim of the fund is to invest primarily in UK Government bonds. The fund has a total asset under management (AUM) of £1.9bn (as of 22/06/2022). Figure 3.12 displays the long-term performance of the fund since June 1975. We can extrapolate the performance of this fixed income fund primarily from the secular decline in global interest rates from their peak in 1982. Figure 3.13 displays the decline in the effective federal funds rate mapped against the performance of US treasury yields and the price of US Corporate Bond index. The corporate index acts as a proxy for the price of bond holdings to display the strong inverse relationship between interest rates (yields) and bond prices. It would be reasonable to assume the identical relationship between UK monetary policy during this period and the performance trajectory of UK Gilts. Figure 3.12 also provides evidence of the cumulative, discrete and annualised performance figures of the fund since launch.

Figure 3.12: Performance Chart/ Canada Life Fixed Interest Pension Fund



Source: Financial Express Fund Info

Figure 3.13: Secular relationship between interest rates/ bond yields and bond prices



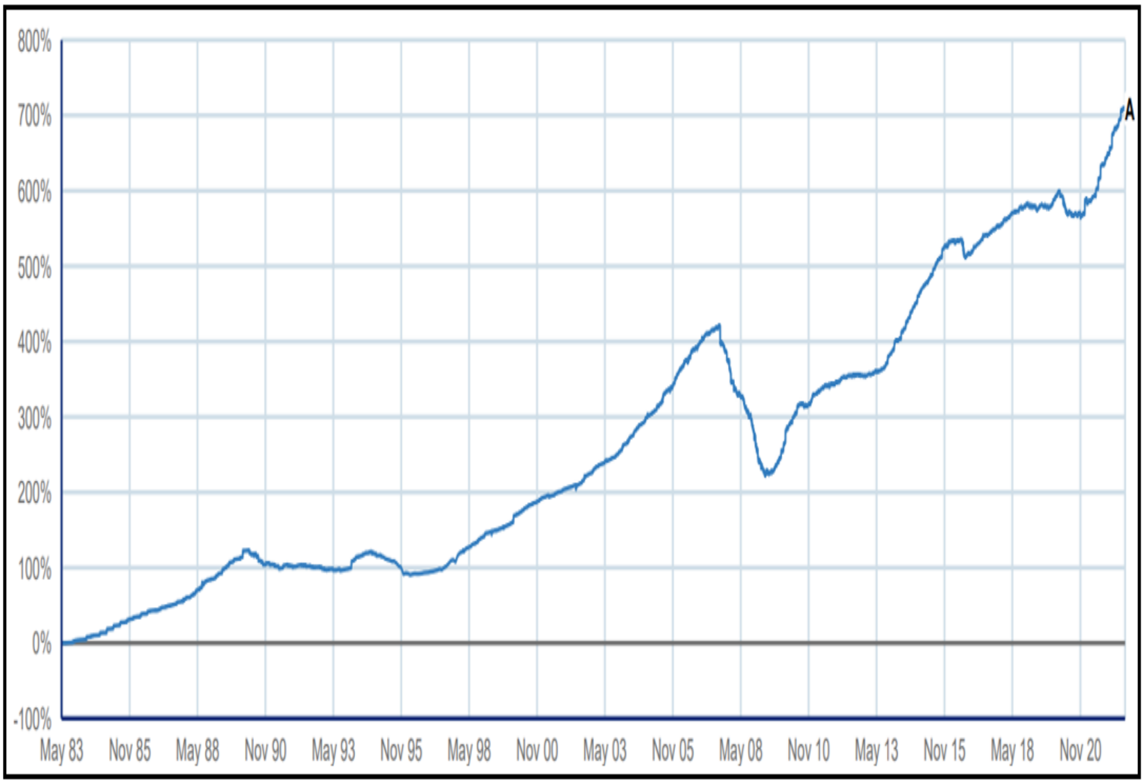
Source: Federal Reserve Economic Database

Figure 3.13 displays the inverse relationship between the long decline in the effective federal funds rate (blue line) since 1981 and the increasing price of the US Corporate Bond index (green line) during the same period. The corporate index acts as a proxy for the price of bond holdings to display the strong inverse relationship between interest rates (yields) and bond prices.

4) Aviva Life Property Fund

The Aviva life Property fund was launched in May 1983. The aim of the fund is to generate capital growth and income through investing in Commercial property in the UK. The fund is relatively small with approx. £93m assets under management (as of 31/05/2022). Figure 3.14 displays the long-term performance of the fund since May 1983. It is interesting to note the almost 450% return in the fund between 1995 and 2007. The GFR led to global collapses in property prices. There has been a notable recovery however since the lows of Q2 2009. The rate of change in price appreciation increased rapidly post-Covid 2020.

Figure 3.14: Performance Chart/ Aviva Life Property Fund



Source: Financial Express Fund Info

5) Aviva Life Mixed Investment Fund

The Aviva life Mixed Investment fund was launched in February 1986. The aim of the fund is to generate capital growth through investing in a wide range of assets including equities, fixed income, property and alternatives. The fund has assets under management of $1.25bn (as of 31/05/2022). The Aviva Life Mixed Investment fund was one of the first "multi-asset" type unit-linked/ pooled mutual funds made available to retail investors. The mandate is to provide investors with less concentrated portfolios, thereby decreasing investor risk. The fund managers have discretions to invest in global assets.

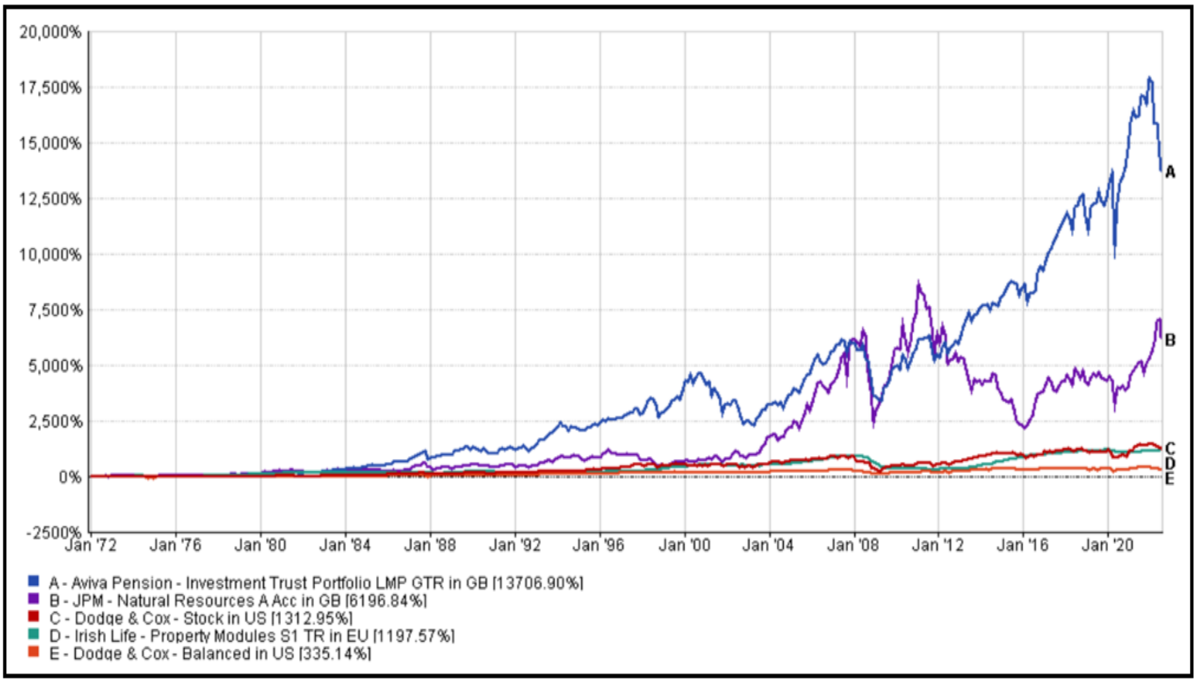
Traditionally, these multi-asset type portfolios have heavy weightings in both equities and fixed income instruments. The latter make up over 60% of the constituents of this fund with very low weightings in alternatives and property. Figure 3.15 displays the long-term performance of the fund since February 1986.

Figure 3.15: Performance Chart/ Aviva Life Mixed Investment

Source: Financial Express Fund Info

The relative performance of these mutual funds has been mapped out in Figure 3.16 below.

Figure 3.16: Relative Fund Performance



Source: Financial Express Fund Info

3.3.4 Fama & French Factors

Eugene Fama & Kenneth French produced extensive research in the early 1990s which challenged the prevailing consensus that the sensitivity to market volatility (through the Capital Asset Pricing Model) was the sole component in determining excess equity returns. This dominant paradigm inferred that market risk solely dictated future average returns. Fama & French, through their empirical analysis, identified that the CAPM failed to account for discrepancies when companies were sorted in terms of market capitalization, leverage and price to earnings multiples. They identified three dimensions of risk including the traditional exposure to the market. Two more risk factors were added to capture a dimension of systematic risk not catered for by market beta in the CAPM and describe how average returns differ from one another. The *size factor* differentiated between the returns of large companies and small companies (SMB). The *value factor* differentiated between the returns of high-book-to-market companies and low-book-to-market companies. (HML). Fama & French computed their SMB and HML factors using six portfolios formed using size and book-to-market-value. All stocks were initially ranked by the market value of equity and the median value of equity was calculated. All stocks below (above) the median value of equity were characterised as small (big) value. Next, the stocks were ranked by their book-to-market-value. Those stocks with a ranking above the 70th percentile were categorised as "value" stocks and stocks with a ranking below the 30th percentile were categorised as "growth" stocks. The SMB and HML factors are generated by identifying the returns on these portfolios. The SMB factor is calculated as follows:

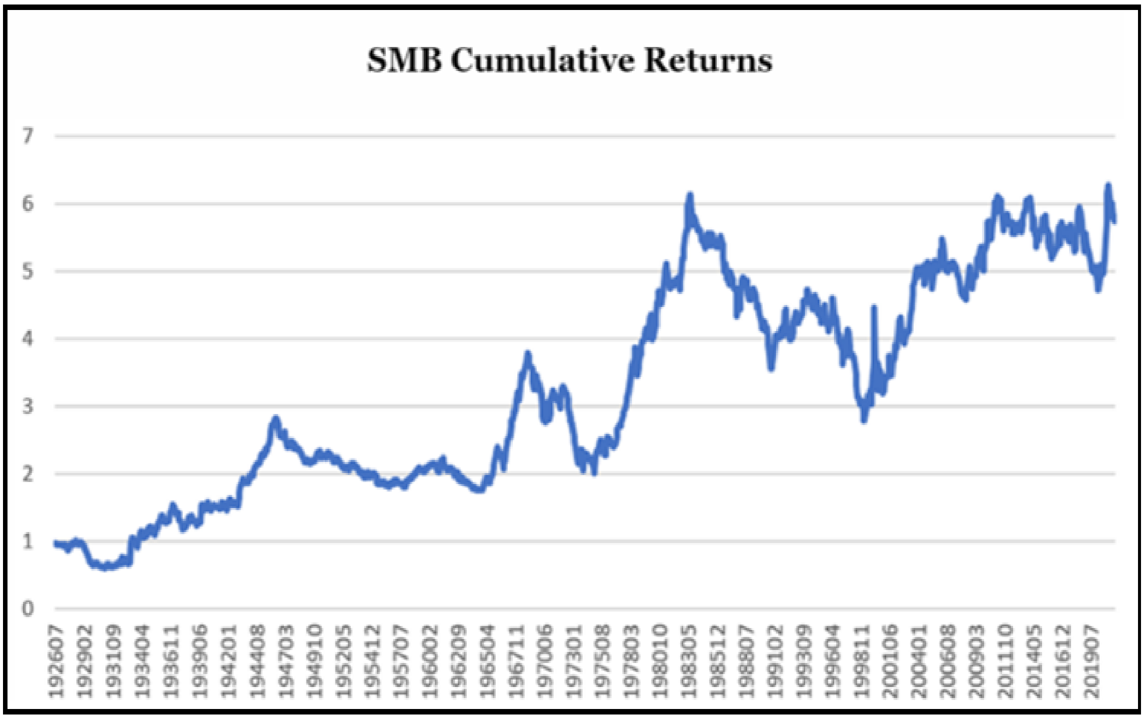
$$SMB = 1/3(Small\ Value + Small\ Neutral + Small\ Growth) \\ - 1/3(Big\ Value + Big\ Neutral + Big\ Growth)$$

$$HML = 1/2(Small\ Value + Big\ Value) \\ - 1/2(Big\ Growth + Big\ Growth)$$

1) **Size Factor** – (Small minus Big)

The starting point for Fama & French was the existence of two classes of stock that tended to outperform the market as a whole – (i) small market capitalization stocks and (ii) stocks with a high book-to-market-ratio or value stocks. In their seminal 1992 paper, Fama & French concluded that beta on its own did not explain average portfolio returns. The SMB factor measures the historical excess return of small cap companies versus large cap companies. The size factor attempts to capture the effects of size on portfolio returns. There is clear evidence for the cumulative returns in Figure 3.17 that this "size effect" did exist during the authors sample period of 1963 to 1990. Question marks remain however on whether the size factor remains influential.

Figure 3.17: SMB Cumulative returns

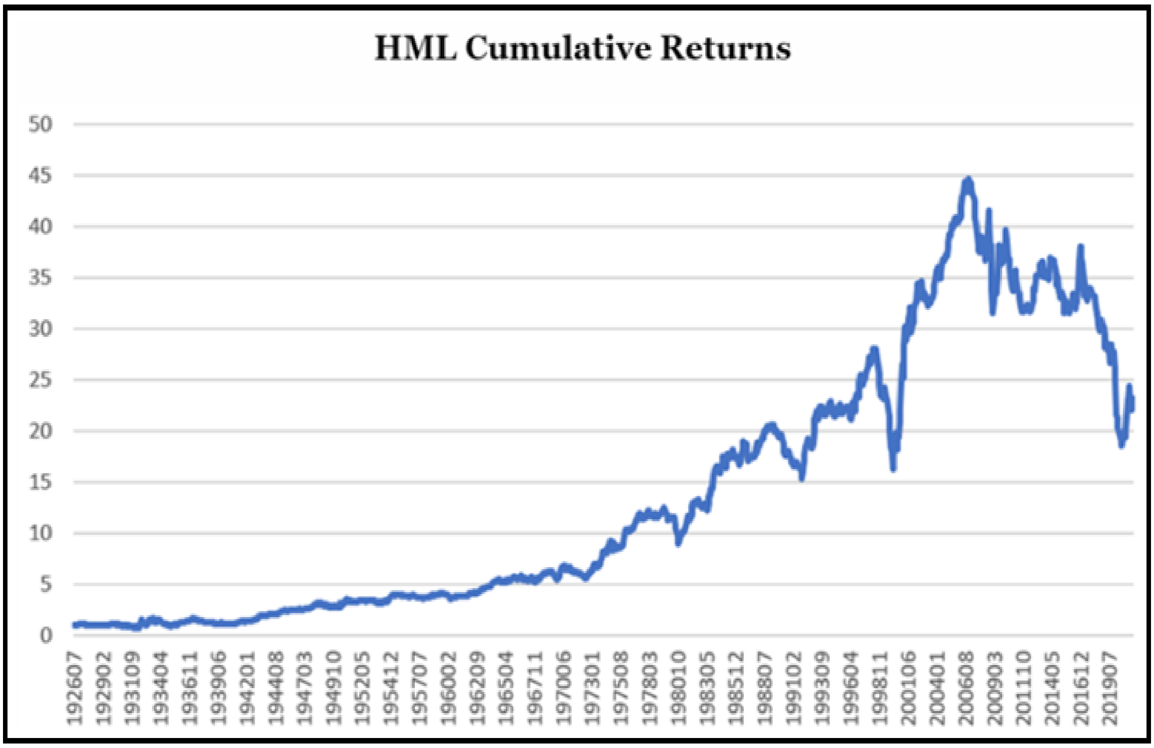


Source: Authors own excel calculation/ Data sourced from Kenneth French Website

2) **Value Factor** – (High minus Low/HML)

The HML factor organises stocks into two sub-sets of "*growth*" and "*value*". The former is defined by a company's ability to produce strong, consistent earnings into the future. Growth companies typically have larger P/E multiples in anticipation of future expectations on growth projections. In contrast, value companies have lower P/E multiples with more stable expected future earnings expectations. It is evident from Figure 19 that the practise of purchasing high-book-to-market companies and selling low-book-to-market companies had worked very well up until the GFR. This "value investing" approach has dramatically underperformed over the last 14 years as growth stocks have vastly outperformed.

Figure 3.18: HML Cumulative returns

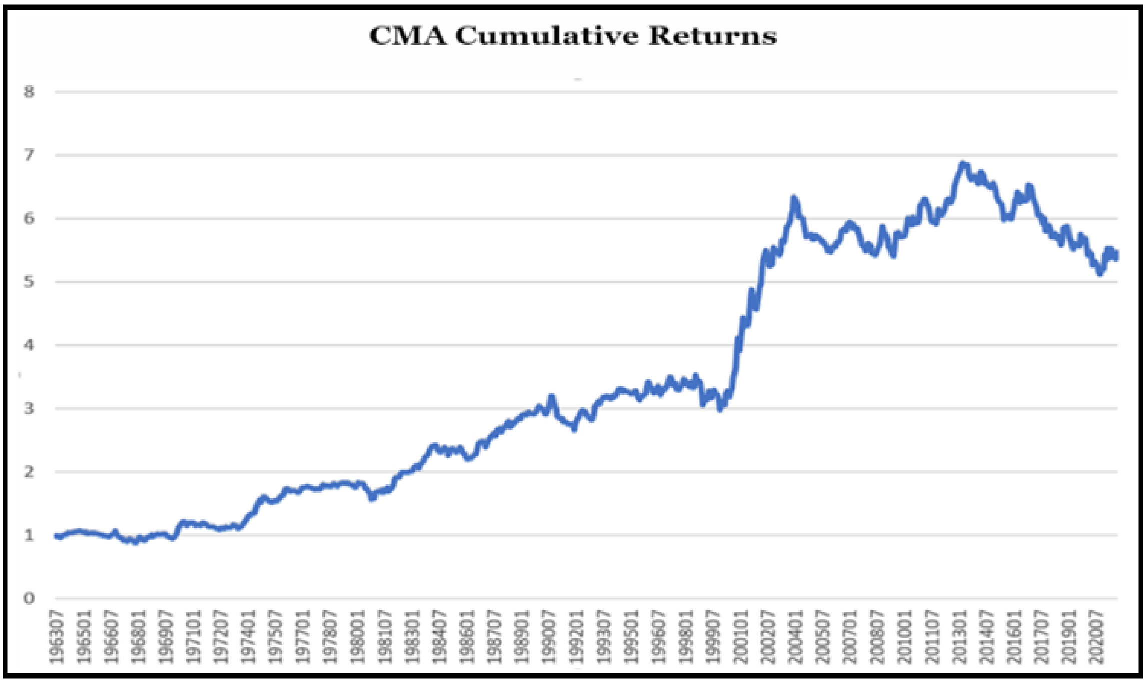


Source: Authors own excel calculation/ Data sourced from Kenneth French Website

3) **Investment Policy** – (Conservative minus Aggressive/CMA)

Fama & French (2015) updated their three-factor model as it became evident from academic investigation that additional factors were necessary to fully explain the cross-section of stock returns. Numerous studies had reported 3-factor alphas that were statistically significantly different from zero. Fama & French added a *profitability* and *investment* factor in their 2015 paper. The CMA factor focussed on the investment policy of companies sorting stocks by reference to whether they had conservative or aggressive investment policy procedures. It is interesting to note that the CMA factor is quite similar to the HML factor as represented by Figure 3.19 below. Capitalizing companies with a conservative investment mandate would have been a highly profitable investment strategy between 1963 and 2013. The returns in recent years have been much more muted and actually declined in significance.

Figure 3.19: CMA Cumulative returns

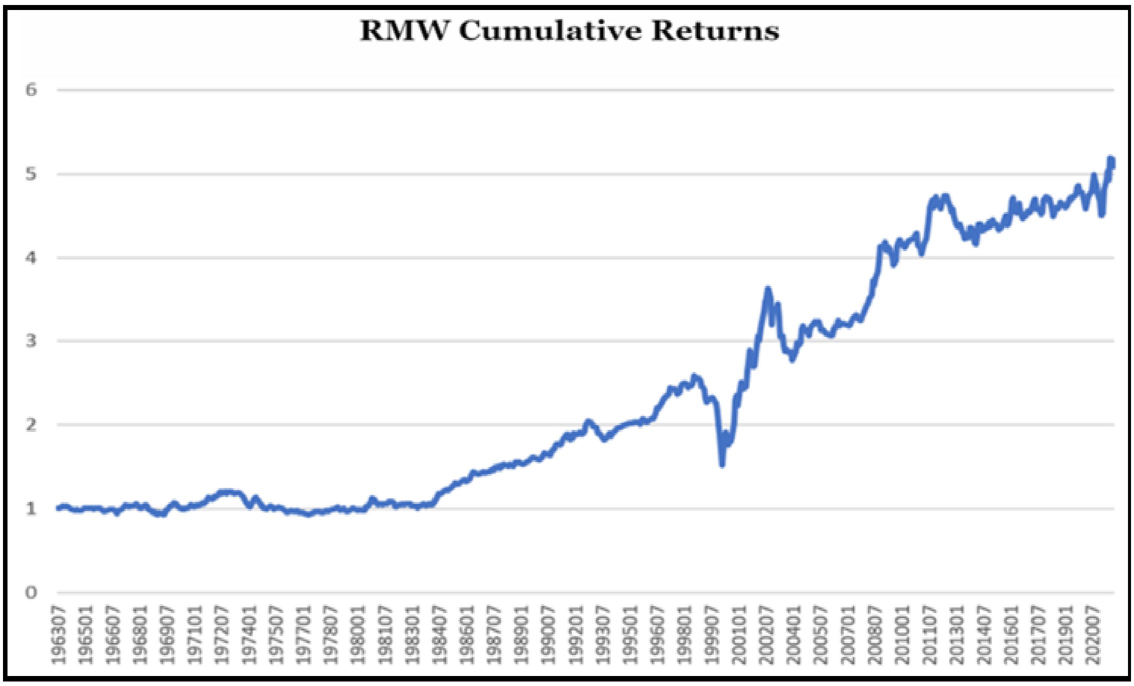


Source: Authors own excel calculation/ Data sourced from Kenneth French Website

4) RMW

The robust minus weak (RMW) factor compares the returns of companies with high or robust operational profitability with those of weak or low operational profitability. This Quality factor has consistently provided superior returns as illustrated in Figure 3.20. The strategy involved investing in companies that have a track record of profitability and shorting their un-profitable counterparts.

Figure 3.20: RMW Cumulative returns



Source: Authors own excel calculation/ Data sourced from Kenneth French Website

3.3.5 Causal Predictors

In this section the core macroeconomic variables, sentiment/ leading indicators are described and differentiated with reference to their ability to forecast unique economic regimes. Table 3.4 summarises the relevant predictors with brief commentary in the rest of this section.

Table 3.4:Causal Predictors – Brief descriptions

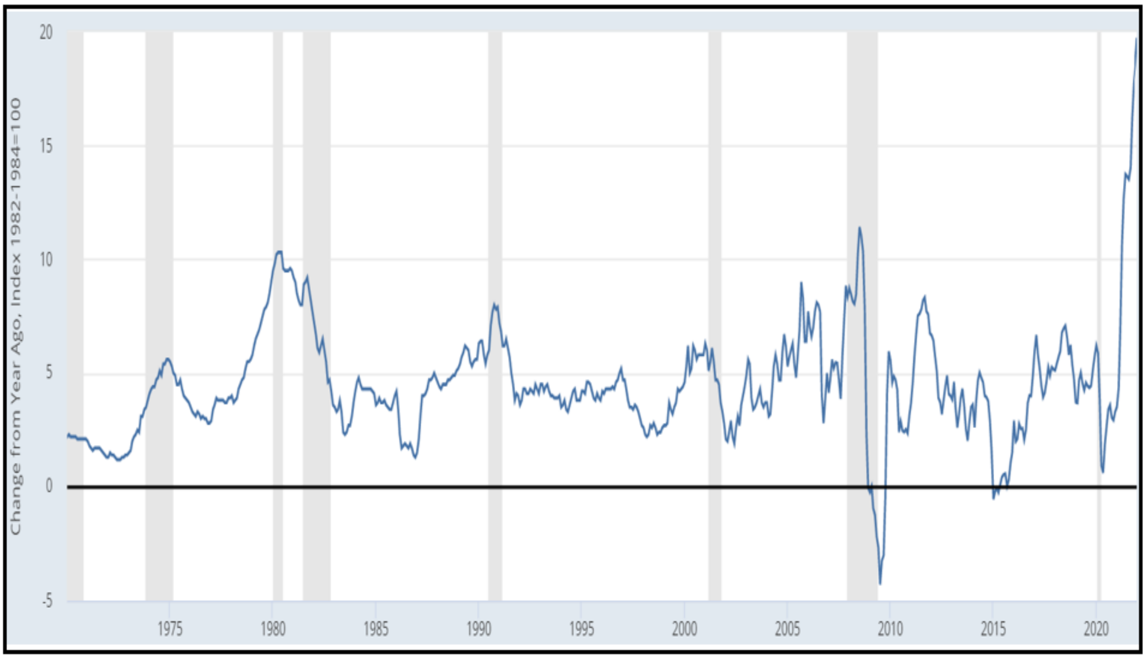
Macroeconomic Variables	Information	Sentiment Indicators	Information	Leading Indicators	Information
Consumer Price Index (CPI)	Inflation	University of Michigan	Consumer Sentiment	Composite Leading Indicator	Business Cycle Identification
Personal Consumption Expenditures (PCE)	Inflation	ISM Purchasing Manager Index	Business Sentiment	Business Confidence Index	Business confidence
Unemployment	Economic Growth	House Price Index	Consumer Sentiment	Consumer Confidence Index	Consumer confidence
Federal Funds Rate	Economic Growth			ISM Purchasing Manager Index	Business confidence
Total Reserve Requirement				House Price Index	Consumer confidence

3.3.5.1 Macroeconomic Variables

Consumer Price Index (CPI)

The CPI data for this study was sourced from the Bureau of Labor statistics via the Federal Reserve Economic Database. For ease of interpretation, we transformed the unit scale on the vertical axis from a seasonally adjusted index to a measure of the index change on an annual basis. This makes Figure 3.21 more analytically intuitive. The CPI for all urban consumers calculates the average monthly change in the price for goods and services. According to the Federal Reserve Economic Database (FRED), the index accounts for 88% of the total population including wage earners, self-employed, short-term workers, those unemployed and retirees. The consumer prices information is collated each month from approx. 4000 US households and 26,000 retailers, The price index captures the rate of change across common household expenditure items including housing, food, fuel, clothing, service fares, utility costs and travel outlays. Price changes are allocated weightings dependent upon their significance. It is commonly accepted that inflation is a lagging economic indicator. It is also a statistical measurement and prone to sampling error.

Figure 3.21: Consumer Price Index (1970-2020)



Source: Federal Reserve Economic Database
Notes: Figure 3.21 illustrates the seasonally adjusted Consumer Price Index (CPI) measured as the Index change from one year previous. The lightly grey shaded areas represent official recession periods as dated by the NBER.

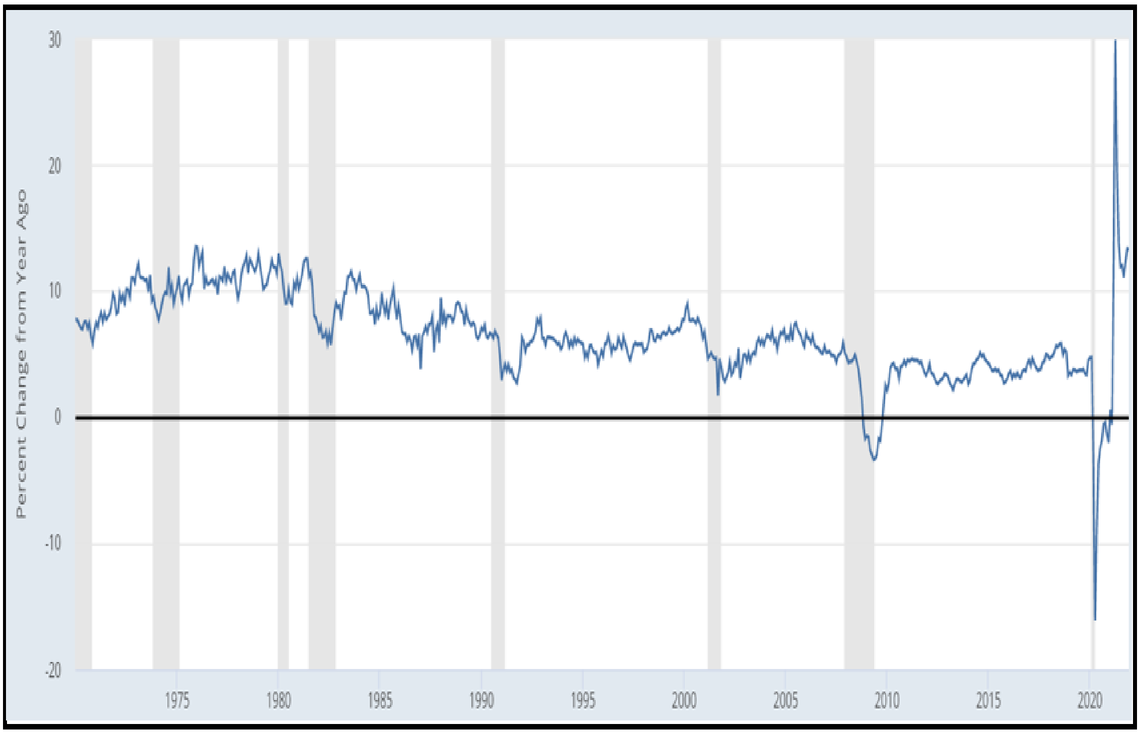
Anderson (2011) studied the relationship between money growth, economic growth and the consumer price index in eight developed countries. He found evidence of positive correlation between money growth and financial asset price inflation across most time periods (short, medium and long term). There was evidence of positive correlation between money growth and consumer inflation only over longer sample periods. Economists have struggled with the task of forecasting inflation. The federal reserve relies on an alternative measure of inflation – Personal Consumption Expenditures (PCE). McNulty et al (2007) highlights four distinct differences between the two measures. Both measures are derived using different index level formulas[82]. The relative weightings for the individual item prices are based on different data sources with CPI focussing on household surveys and PCE relying on business surveys. Thirdly, CPI focuses primarily on expenditure at the household level while PCE concentrates on the goods and services that are purchased. Lastly, there are seasonal and price adjustments that differ across both measures.

[82] CPI uses a modified formula whilst PCE is calculated using the Fisher-ideal formula

Personal Consumption Expenditure (PCE)

The PCE data for this study was sourced from the US Bureau of Economic Analysis (BEA) via the Federal Reserve Economic Database. For ease of interpretation, we transformed the unit scale on the vertical axis from a seasonally adjusted index to a measure of the index change on an annual basis.

Figure 3.22: Personal Consumption Expenditures (1970-2020)



Source: Federal Reserve Economic Database
Notes: Figure 3.22 illustrates the seasonally adjusted Personal Consumption Expenditure Index (PCE) measured as the Index change from one year previous.

Battistin, E. (2003) identifies some potential data quality issues associated with the PCE measure of inflation. He is critical of the over-reliance on this survey-based approach which relies on numerous data points that may ultimately enhance the error distribution. Battistin recommends that an overlapping questionnaire approach focussing on a reduced sample of consumption behaviour may produce more accurate results.

Unemployment claims

Continued claims of unemployment insurance are sourced from the US Employment and Trading administration. The data is released on a weekly basis and measures the number of people that have filed an initial claim and who have also experienced a week of unemployment leading to a continued claim. Common sense dictates that periods of positive economic growth should be associated with lower unemployment figures.

Eychenne et al. (2011) refer to the positive output gap whereby economic productivity exceeds its potential. Okun's law captures a situation where workers become scarcer due to a maximum requirement for all available resources.

Figure 3.23: Unemployment Claims (1970-2020)

Source: Federal Reserve Economic Database

Notes: Figure 3.23 illustrates the seasonally adjusted number of weekly continued claims filed in the United States dating back to 1968.

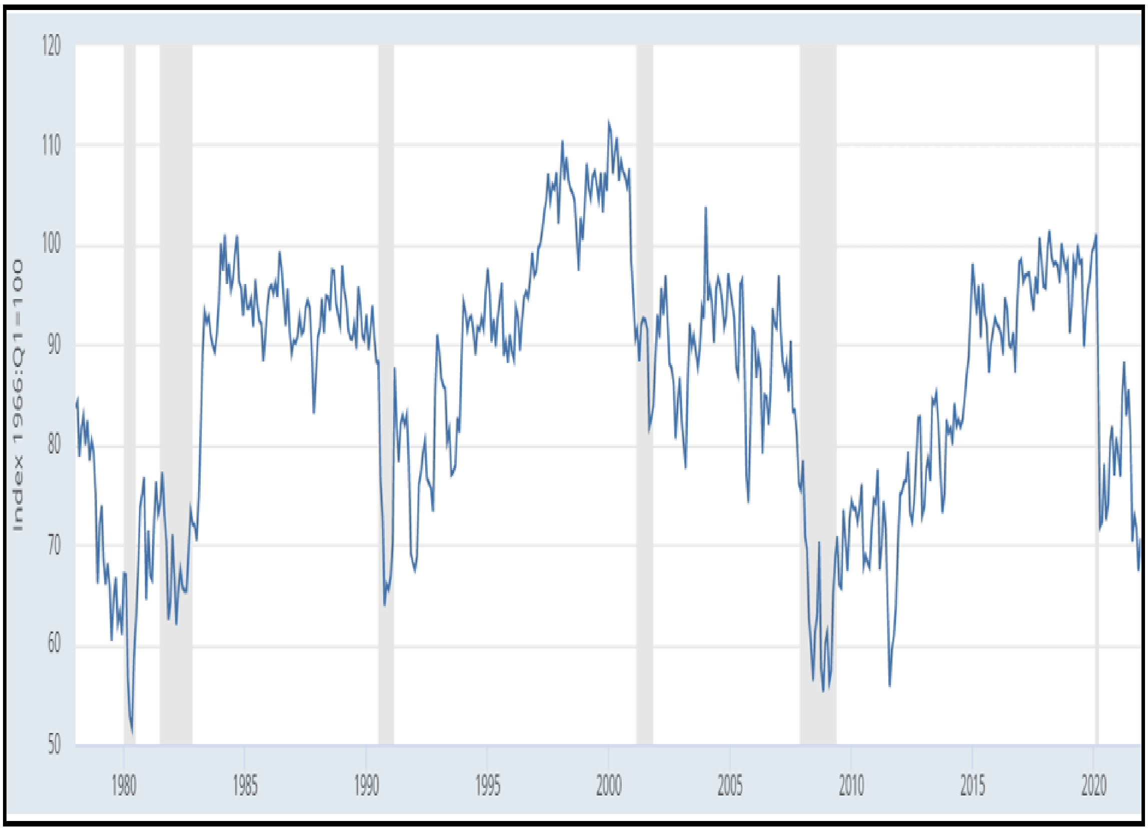
Epstein & Yelden (2008) undertake global analysis of the relationship between the central adoption of a new inflation-targeting (IT) approach and employment. They find evidence that countries adopting an inflation-targeting approach have not produced excess economic growth or improved the employment numbers. As per Figure 3.23, Unemployment claims does provide some useful information in anticipating recessionary periods.

3.3.5.2 Sentiment Indicators

University of Michigan Consumer Sentiment Survey (UM Sent)

The UM Sentiment survey seeks to capture important information from both an economic growth and inflation perspective. The survey is a monthly gauge of consumer confidence in the United States and conducted by the University of Michigan. Qualitative information is gathered through telephone exchanges with consumers. Short and longer-term confidence in consumers personal economy and the broader economy are analysed.

Figure 3.24: University of Michigan Consumer Sentiment (1978-2020)



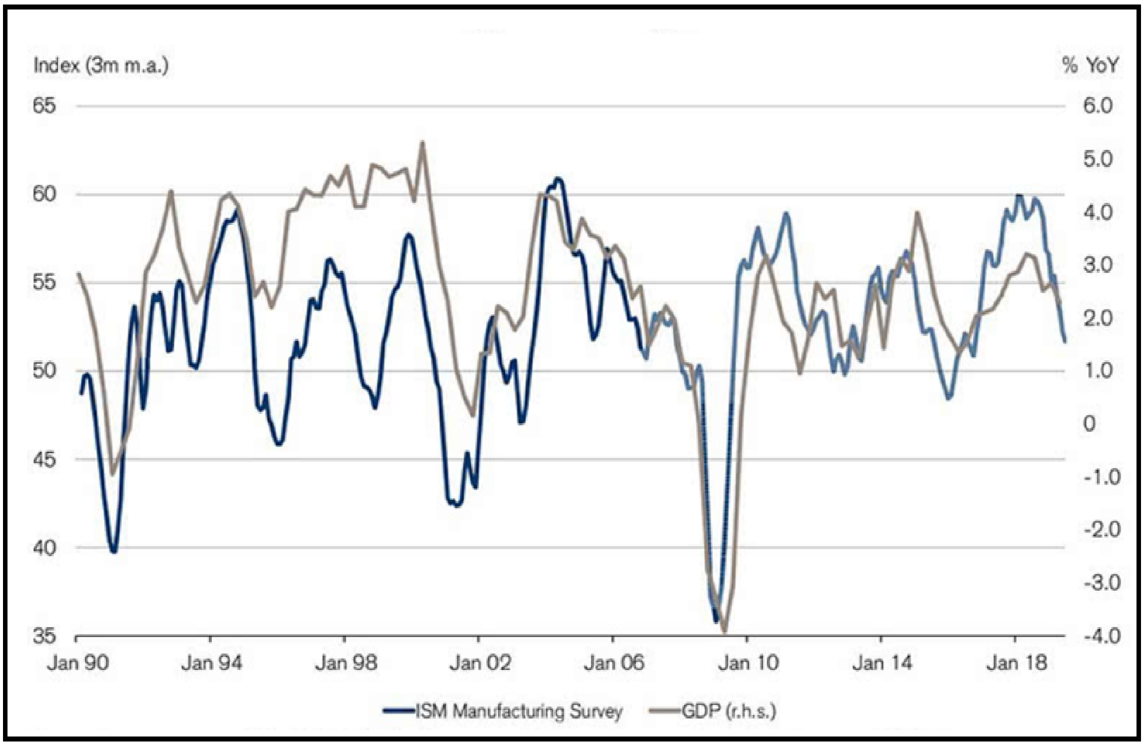
Source: Federal Reserve Economic Database
Notes: Figure 3.24 illustrates the non-seasonally adjusted UM sentiment survey of consumer confidence (Index level). The lightly grey shaded areas represent official recession periods as dated by the NBER.

It appears that this predictor acts as a leading indicator of economic growth. The survey index appears to decline sharply approx. 6 to 12 months in advance of the start of an economic recessionary period. It may also act as a useful indicator of the bottom of the business cycle as evident most notably in March 2009. The survey results appear volatile over shorter periods. However, it may be useful to identify longer-term trends in the data.

Institute of Supply Management Purchasing Managers Index (ISM)

The Institute of Supply Management publishes the Manufacturing ISM Report on Business each month. The survey is based on data compiled from purchasing and supply executives of major US corporations. The Purchasing Managers Index (PMI) refers to the actual data point that is released at the beginning of each month. The survey respondents are polled on the performance of their businesses in the current month. Whilst the questions appears to capture coincident or lagging information, the PMI data has a strong historical track record of leading economic activity. We note this from Figure 3.25 below. The executive respondents are asked a selection of questions relating to the performance of their businesses. These include whether production levels, new orders, employment levels and inventories are contracting or growing. Each question receives a rating, and the combined output produces the PMI result. The PMI score or % has historically ranged predominantly between 30% and 60%. In general terms, a reading of 50% or higher is indicative of expansion whilst a reading below 50% is indicative of a contraction in the broader economy.

Figure 3.25: ISM Manufacturing report & Economic growth (1990-2018)



Source: DataStream, Credit Suisse

The ISM survey results (via the PMI) is recorded on the left-hand side of the chart. A PMI above 50 is generally viewed by economic commentators as positive and expansionary whereas a PMI release below 50 is viewed as negative. We can identify a consistent leading relationship between the ISM survey and our economic growth proxy of choice, Gross Domestic Product (GDP). We note, for instance that the ISM consistently fell sharply before broader economic slowdowns of the early 1990s, the technology bubble of 2000 and the Great Financial Recession of 2007/2008.

3.3.5.3 Leading Indicators

Composite Leading Index (CLI)

To gain a greater understanding of the business cycle, we are interested in identifying short- and medium-term trends in economic activity. The Organization for Economic, Cooperation and Development (OECD) developed the Composite Leading Index to capture important turning points in the business cycle through combining influential economic indicators into a single composite. The CLI was first introduced in the 1980s. The CLI framework is designed to predict fluctuations between the level of GDP and its underlying trend. A leading indicator often pre-empts the change in the direction of the underlying economy (positive or negative) six to nine months in advance. The standard indicators in the CLI include orders & inventory changes, market indicators (share price information), business confidence surveys and economic sector specific performance trends. The CLI data is released monthly. We may interpret the CLI data in the same way that we decipher the business cycle. In general terms the business cycle captures fluctuations in economic activity. The upward slope from an economic trough to peak level indicates growth above normal whereas the downward slope between a peak and a trough captures growth below normal. When both the CLI rate of change is positive and the released number is greater than 100, economic growth indicator (via GDP) tends to be increasing. This is indicative of an *expansion* period colour coded blue in Table 3.5 below. In contrast, a negative CLI rate of change release associated with a number below 100 is associated with a *slowdown* in economic activity.

Table 3.5: Composite Leading Indicator Framework

		CLI is below/above 100	
		Below	Above
Change in month-on-month CLI	Up	Real **GDP levels remaining below long-term trend** *Negative GDP-gap expected to narrow* Real GDP growth anticipated above long-term growth	Real **GDP levels remaining above long-term trend** *Positive GDP-gap expected to widen* Real GDP growth anticipated above long-term growth
	Down	Real **GDP levels remaining below long-term trend** *Negative GDP-gap expected to widen* Real GDP growth anticipated below long-term growth	Real **GDP levels remaining above long-term trend** *Positive GDP-gap expected to narrow* Real GDP growth anticipated below long-term growth

Composite Leading Indicator Framework

There follows a detailed explanation of our composite leading indicator framework. We model turning points in the business cycle through anticipation of the level of the CLI and its rate of change. A CLI reading above 100 is indicative of GDP levels above the longer-term trend whereas a CLI reading below 100 is suggestive of GDP levels below the longer-term trend. The CLI rate of change (via monthly increases/ decreases) indicate important information re the velocity of GDP growth/declines. Table 3.6 provides a visual guide to how turning points in expected GDP are determined by the simultaneous relationships between the changes in monthly CLI and the reported level of the CLI. Table 3.6 provides the framework from which to classify four individual economic regimes linked to the expected rate of future economic growth. We have built upon the GDP turning point guidelines in Table 3.5 to develop our economic regime model in Table 3.6 below.

Table 3.6: Economic Regime

	Positive Change in CLI	Negative Change in CLI
CLI is above 100	Expansion	Downturn
CLI is below 100	Recovery	Slowdown

An economic *expansion* is one defined by positive changes in the CLI month on month and a CLI release above 100. A recovery in growth exhibits a positive change in the CLI. However, the level of the CLI is rising from below a previous high of 100. This is consistent with the trough to peak movement of a typical business cycle *recovery* period described previously. During a slowdown in economic activity, the rate of change in the CLI matters more than the absolute level. For instance, during a *downturn* the CLI may be above 100 but a negative change in the CLI is indicative of a trending move lower as economic growth declines. An economic *slowdown* emerges when the persistent downturn results in an absolute level of the CLI returning below 100 and an acceleration in the negative rate of change of the CLI. This economic framework was used to develop the regime filtering coding necessary as part of our regime-based asset allocation experiment. We have coded each of the four business cycle regimes from 1 to 4 depending upon the prevailing economic environment as detailed in Table 3.7. Each regime is profiled with a unique coding arrangement depending upon whether the CLI is above/below 100 or if there is a positive/ negative change. For instance, our economic recovery regime is coded 1|1 as per Table 3.7 and the excel coding formula below.

IF(AND(CLI Below 100=1,Positive Change in CLI=1),1,0)

A full mapping of the 52-year sample from 1970 to 2022 is included in the appendices. Our aim is to utilise this leading index footprint to optimally allocate assets six to nine months in advance of turning points in the business cycle. The results of this analysis are detailed in Section 4.

Table 3.7: Economic Regime coding framework

GrRegime		CLI is below 100	Positive Change in CLI
1	Recovery	1	1
2	Expansion	0	1
3	Downturn	0	0
4	Slowdown	1	0

Business Confidence Index (BCI)

Like the Composite leading Indicator, the BCI sources information on future economic changes from surveying industry. Each industry sector is surveyed on the inventory of finished goods, orders, and developments in production. These inputs are utilised to monitor output growth and economic turning points. A data release above 100 is indicative of increasing business confidence with a release below 100 suggesting negative business sentiments. We have applied the same economic turning point framework used with the CLI for the BCI. We model turning points in the business cycle through anticipation of the level of the BCI and its rate of change. A BCI reading above 100 is indicative of business confidence levels above the longer-term trend whereas a BCI reading below 100 is suggestive of business confidence levels below the longer-term trend. The BCI rate of change (via monthly increases/ decreases) indicate important information re the velocity of business confidence growth/declines. Table 3.8 provides a visual guide to how turning points in expected business confidence are determined by the simultaneous relationships between the changes in monthly BCI and the reported level of the BCI. Table 3.8 provides the framework from which to classify four individual regimes linked to the expected outcome of future business confidence.

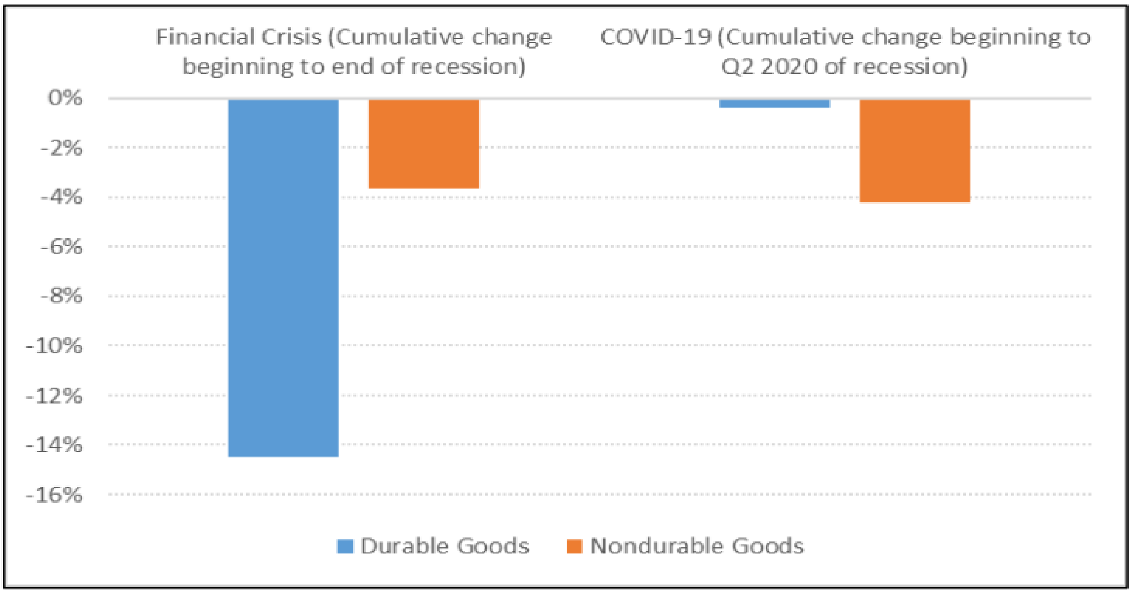
Table 3.8: Business Confidence Regime coding framework

	Positive Change in BCI	Negative Change in BCI
BCI is above 100	Positive Future Business Confidence	Declining Future Business Confidence
BCI is below 100	Growing Future Business Confidence	Negative Future Business Confidence

Consumer Confidence Index (CCI)

Consumer spending is defined by the Bureau of Economic Analysis (BEA) as the value of the goods and services purchased by persons living in the United States. In 2022, Personal Consumption Expenditures (PCE) accounts for approximately 66% of US GDP. There is an abundance of academic literature[83] pointing to the significant role that PCE plays in driving short-run economic growth. More granular analysis of "durable" versus "non-durable" goods is instructive when assessing the dynamic relationship between consumer spending behaviours and the business cycle. An economic regime characterised by growing consumer confidence should experience a noticeable boon in durable goods purchases owing to their cyclicality. Alternatively, a less than robust economic outlook should produce weaker consumer sentiment towards durable goods in favour of necessity-based non-durable goods. There was evidence of this consumer-led behaviour most recently during the Covid-19 pandemic and the Great Financial Recession of 2008.

Figure 3.26: Consumer-led behaviour | Covid-19



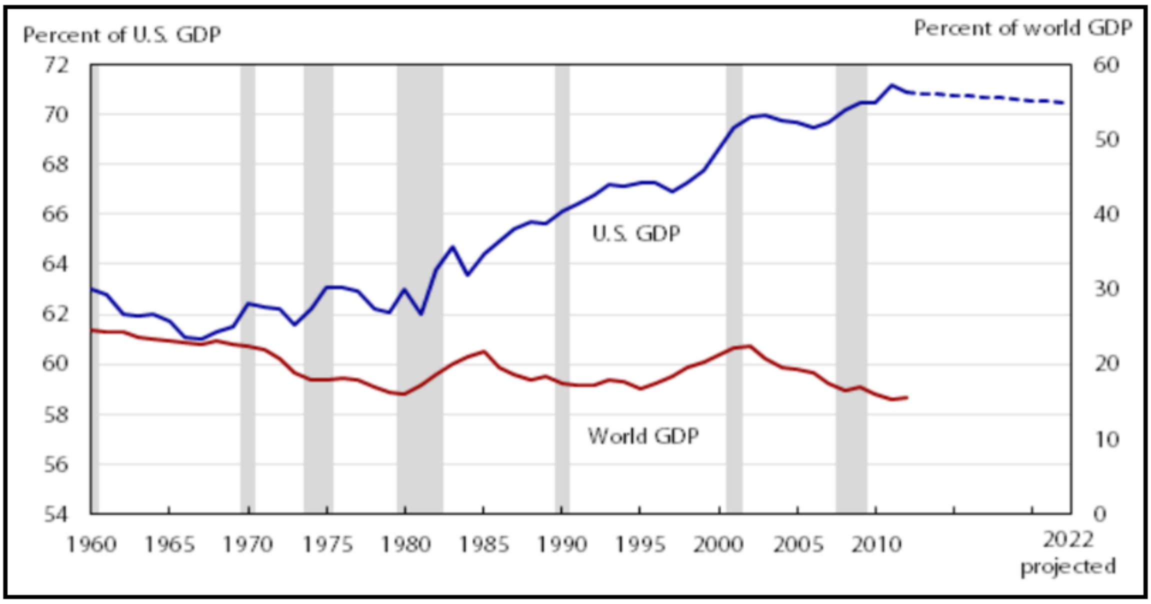
Source: Bureau of Economic Analysis

There has been a noticeable increase in the influence of personal consumption expenditure as a percent of Gross Domestic Product since the 1980s in the United States. Figure 3.27 displays this trend upwards since 1980. We can hypothesize that the growing influence of personal consumption expenditures on GDP arose from looser interest rate policy in the US following the two short, sharp recessions of January-July 1980 and July 1981-November 1982. A lower cost of capital and decreasing fiscal taxation policies may

[83] Beaton, K. (2009), Fornell, C. et al (2010)

have contributed to the growing trend in greater volumes of disposable income. This emerging influence of consumer expenditures appears to have been a US phenomenon and not represented through global GDP data.

Figure 3.27: Consumer spending (%/GDP)



Source: Bureau of Economic Analysis, World Bank (Actual data)
Bureau of Labour Statistics (Projected)

The Consumer Confidence Index (CCI) provides valuable insights to the future trajectory of consumer spending sourced from personal surveys. These focus on financial circumstances, employment levels, consumer expectations, savings rates and confidence in general. A release above 100 signals consumer confidence, decreased focus on accumulating savings and increased spending behaviour. If the CCI reports a number below 100, this may represent consumer pessimism about the outlook and increased savings.

3.3.6 Factor descriptions

Our factor model consists of several primary drivers of economic growth and inflation. Inflation is captured by the rate of change in the consumer price index on a monthly basis. We experienced a challenge in mapping economic growth (via gross domestic product (GDP) into our monthly timeseries dataset given that the GDP numbers are released on a quarterly basis. One reasonable solution would be to generate a proxy variable for economic growth which closely correlated with GDP. Several correlation tests were conducted using the house price index, US vehicle sales, the industrial production index, building permits and non-farm payrolls. The US House price index exhibits strong positive correlation with GDP which in turn has a strong track record of statistical correlation with economic growth. Table 3.9 sets out both the average and rolling correlations between the various growth proxies chosen for this model. We note that the US house price index average correlation to GDP is very close to 1 and its rolling correlations are very high also.

Table 3.9: Economic Growth Proxy variables

	GDP/US Hse Price Index	US Vehicle Sales	Ind Prod Index	GDP/Bldg Permits	GDP/Total NFP
Average Correlation	0.98	0.41	0.93	-0.18	0.94
Avg. Rolling 5 Year Correlation	0.80	0.16	0.64	0.30	0.73
Avg. Rolling 10 Year Correlation	0.84	0.15	0.68	0.30	0.78

3.3.7 Economic considerations

One of the primary research questions of this paper is to identify a framework that anticipates directional changes in economic growth. We will also show that the optimal approach to the construction of this framework is to isolate the cyclical behaviour of the three main aspects of economic activity: *growth*, *inflation* and *employment*. We have summarised the individual variables below in Table 3.10.

Table 3.10: Economic Framework variables

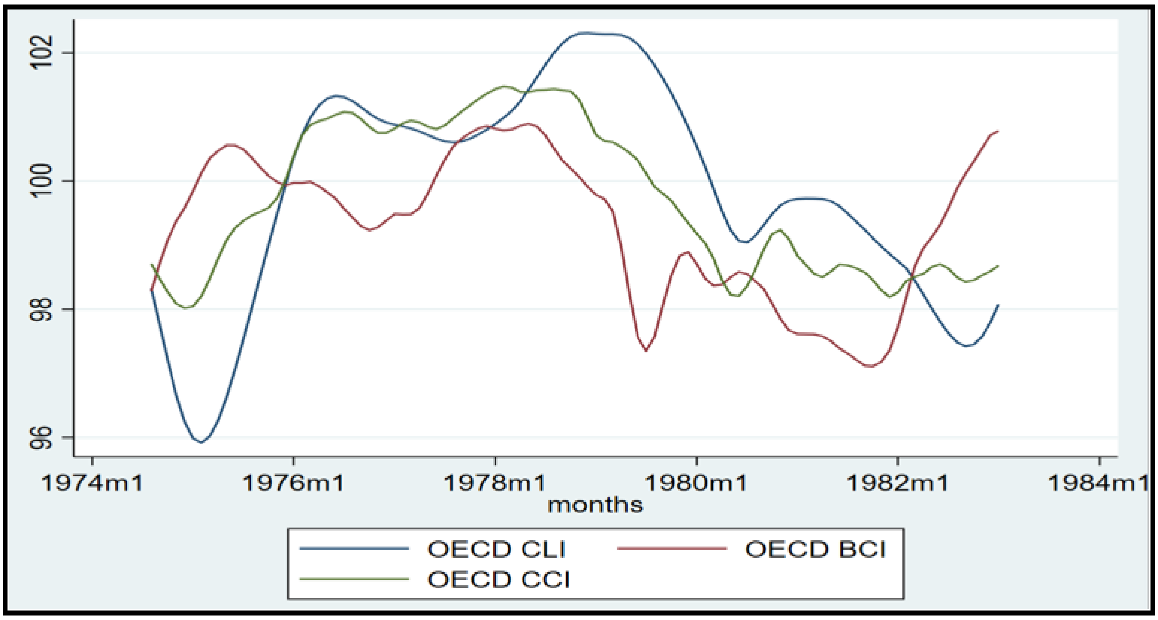
Economic Growth	Inflation	Employment
- Domestic economy	- Consumer Prices	- Aggregate employment
- Foreign Trade	- House Prices	- Manufacturing
- Services sector	- Commodity Prices	- Non Manufacturing
- Manufacturing sector		
- Construction sector		
- Financial sector		
- Non Financial sector		
- Exports		
- Imports		

Growth rate cycle downturns

If we can identify periods of economic growth deceleration, we can position portfolios accordingly. There have been eight significant corrections in the S&P500 since the recovery of that index in March 2009. For the purposes of this paper, we have defined a "significant" correction as encompassing a decline of -10% or more. There have in fact been three corrections of -20% which should dispel the notion of zero equity market volatility post Great Financial Crisis. We will show that equity market drawdowns are linked to growth rate cycle downturns. We will show that the conditional probability of a severe equity market drawdown has a high correlation with economic growth decelerations. Our approach is to distinguish between long, medium and short leading indicators. The longer leading index should capture directional changes in economic growth first. The subsequent medium- and shorter-term leading indicators are designed to provide confirmation of this longer-leading index. The coincident indicator is the final mover confirming what the actual live data is doing. This sequential approach creates a systematic early warning framework whereby conviction around the asset allocation decision is confirmed in a sequence over time. Figures 3.28-3.30 convey this progressive analysis via our OECD indicators visually across each of the study sample periods.

The purpose of this approach is to impound the marginal benefits of a proactive, dynamic asset allocation strategy. For instance, the correlation between rising/falling inflation and the movements of US Treasury yields has been well covered in the academic literature to date. Rising inflation tends to drag treasury yields higher as investors require higher yields as a hedge against the inflation risk premium. Conversely, a dis-inflationary environment places downward pressure on bond yields. Conventional inflation forecasting concentrate on model-based metrics.

Figure 3.28: OECD Indicators (1974 – 1983)

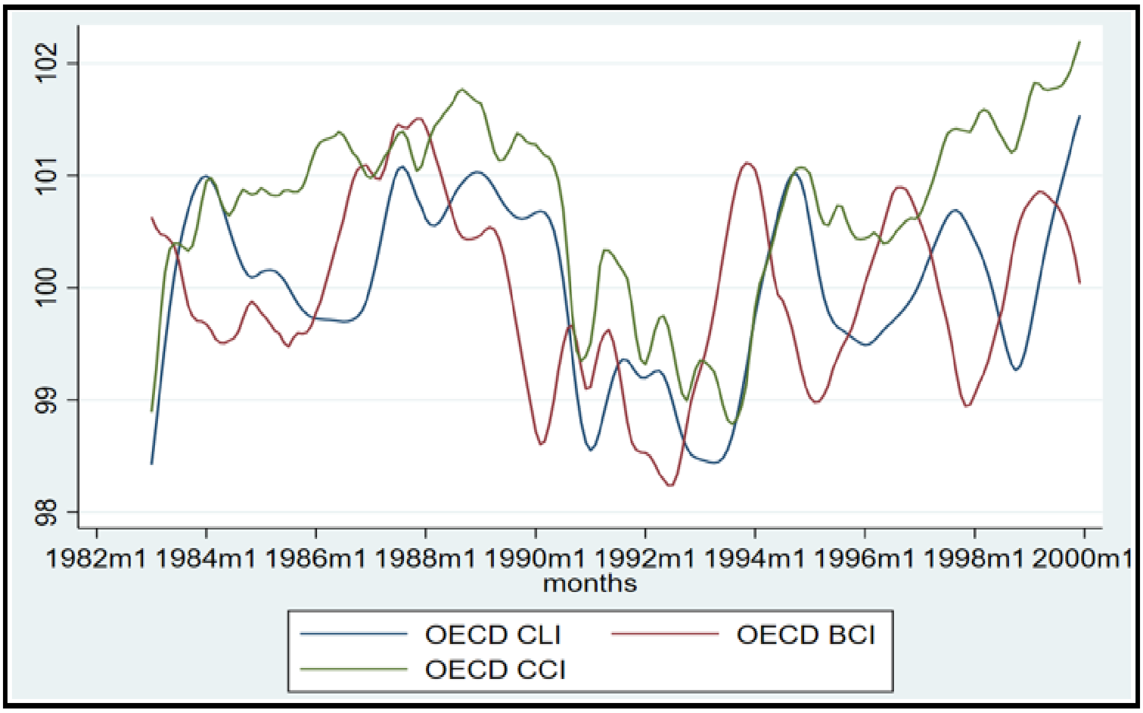


Source: Authors own charts/ Data sourced from OECD

It is evident from Figure 1 that the OECD Business Confidence indicator (**red** line) acts as the early warning signal in this data timeseries. The BCI turns sharply negative a full four months before the OECD Consumer Confidence Indicator (**green** line) and seven months before the broader OECD Composite Leading Indicator (**blue** line). Given our 50-year research sample, it may be interesting to assess whether this sequential relationship between these leading indicators is consistent.

This study has produced evidence supporting the literature (Guidolin & Hyde, 2008; Ang & Bekaert, 1999; Ang & Timmerman 2012) that macroeconomic regimes influence the behaviour of investible securities. If assets are dynamic in nature and dependent upon the underlying economic state space for their direction, there should be value in identifying consistent relationships among macroeconomic leading indicators. It appears in Figure 3.29 that the BCI continues to act as an early warning signal during the 1983-1999 regime. It is interesting to note that the lag-time between the various indicators appears consistent also. For instance, we note that in 1989 the BCI drops sharply followed by its confidence indicator counterpart and eventually the composite CLI. The broad nature of the composite index has previously been underscored as the primary reason for its lagging nature.

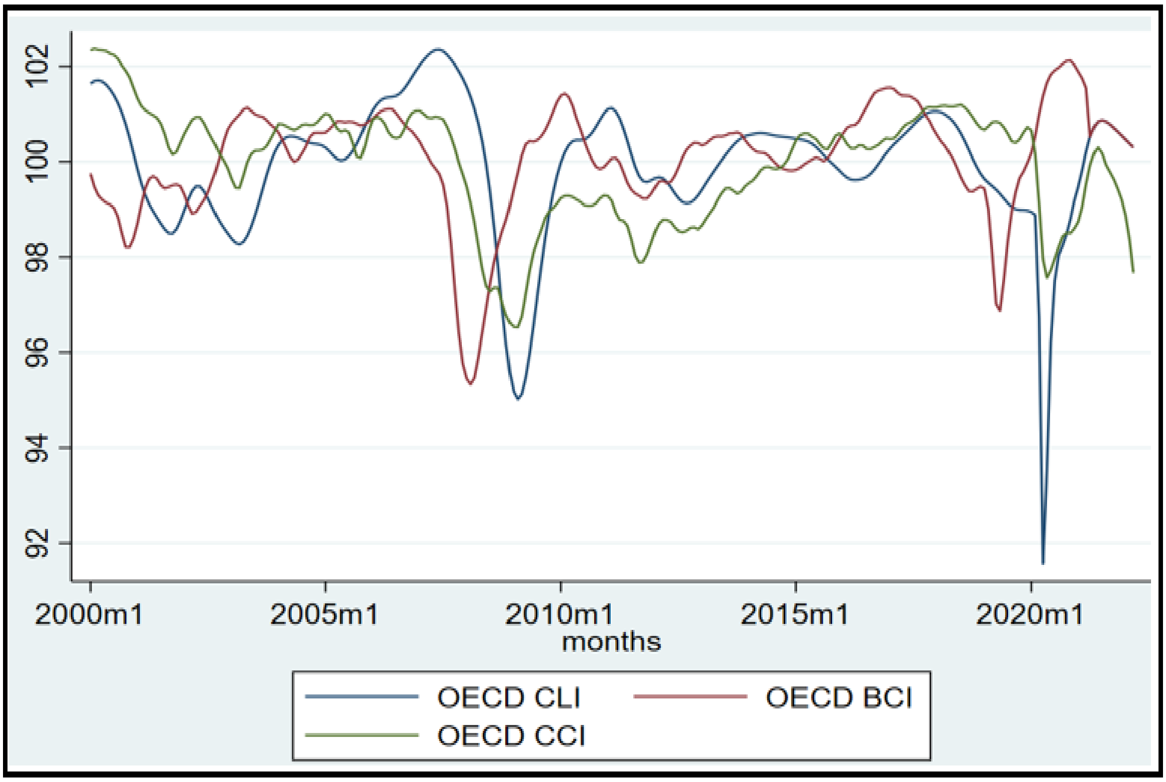
Figure 3.29: OECD Indicators (1983 – 1999)



Source: Authors own charts/ Data sourced from OECD

Figure 3.30 confirms that the BCI consistently forewarns of economic recession with approximately 3 to 5 months lead in advance of the CCI and CLI. We note that the Business Confidence Indicator turned sharply negative well before the last three major economic recessions (2000 Technology bubble, 2008 Financial Crisis, Covid-19). Although it would be difficult to assign predictive power to the BCI with regards forecasting the Covid-19 pandemic of 2020, the global economy has produced evidence of slowdown in late 2019 as indicated by a steeping yield curve in Q4 2019. Whilst these leading indicators appear useful in forewarning of economic declines, they also appear to provide strong indications of market bottoms as evidenced by the steep recover of the BCI in both 2001 and 2009.

Figure 3.30: OECD Indicators (2000 – 2020)



Source: Authors own charts/ Data sourced from OECD

3.3.8 Econometric Framework /Dynamic Forecasting

Quinn et al. (1997) were critical of the dominance of economic theory-based analysis of inflation expectations. They recommended a multivariate time series model focussed on forecasting. Leaning on the work of Doan, Litterman and Sims (1984), the authors assert the need for a transition away from rigid, structural modelling to an alternative VAR framework. The transition may be framed as the transition from inflexible simultaneous equations to a more dynamic set of linear equations which sourced their explanatory power from each variable in the model. A Vector Auto-Regression or VAR model is a generalization of univariate autoregressive (AR) models based on the basic premise of interdependency between the lagged values of all variables. The primary uses of VAR models focussed upon forecasting methodology (Koop, 2013 & Clark, 2011) and monetary policy examination (Bernanke, Boivin and Eliasz, 2005). Del Negro & Schorfheide (2011) described vector-autoregression models as one of the key empirical tools in modern macroeconomics. In general terms, VAR models are a series of multivariate linear time-series models constructed to capture the joint dynamics of multiple time series. Each endogenous variable in the system is treated as a function of lagged values of all endogenous variables. The seminal work of Christopher Sims (1980) criticized the traditional empirical modelling framework of macro-econometricians. Large, simplistic models with highly restrictive assumptions failed to address the complex incentive and utility mechanisms that drive a dynamic ecosystem. Sims argued that exogenous variables should not dominate in a social environment of rational, forward-looking agents. Sims model was pioneering as it provided a systematic framework to allow economists to gather complex dynamics in multiple time series. The general problem associated with VAR models relates to over-parametrization owing to the large number of coefficients involved. $N + N^2p$ coefficients imply dense parameterization or what has generally become regarded in the literature as the curse of dimensionality.

Our research requires the use of a VARX model with exogenous variables as specified below.

$$y_t = \alpha + A_1 y_{t-1} + \ldots + A_p y_{t-p} + B_0 x_t + B_1 x_{t-1} + \ldots\ldots + B_s x_{t-s} + \mu_t \qquad \textit{Eq. 1}$$

Where

y_t is a K x 1 vector of random variables,

A_1 through A_p are a K x K matrix of parameters,

x_t is a K x 1 vector of exogenous variables

B_0 through B_s are a K x M matrix of coefficients,

α is a K x 1 vector of parameters,

μ_t is a white noise process

This research seeks to identify whether the regime identification offers optimal asset allocation benefits to the portfolio construction process. There is evidence that varying economic environments produce consistent and repeatable investment opportunities. If we can identify alpha or specific asset class outperformance associated with a regime classification process, then a logical initial step may be to discover the factors driving the regime-shifting framework. Our research shifts to a focus on isolating the key determinants of inflation and growth. We are interested in identifying what fraction of the variation in inflation and growth in the past 50 years is due to changes in our sentiment and business indicators. In the next section, we look quantitatively at this research question using multi-variable VARs estimated using monthly US data on the growth rate (Ψ_t), rate of price inflation (λ_t), government monetary policy (Π_t), consumer sentiment (π_t), business demand (ω_t) and the business cycle (φ_t) from 1970 to 2020. Given our study includes independent or exogenous variables, we extend the basic VAR model to a VARX model with exogenous variables (Hamilton, 1994; Tsay, 2005).

We utilise a simple VAR model of the following form:

$$Y_t = \alpha_0 + A_1Y_{t-1} + \ldots + A_pY_{t-p} + B_1X_{t-1} + \ldots + B_qX_{t-q} + E_t$$

where,

A_p represents the matrices of parameters of endogenous variables (of vector Y_p)

B_q represents the matrices of parameters of exogenous variables (of vector X_q)

E_t is a vector of random disturbance terms

α_0 is a constant term

3.3.9 Methodology

Bayesian Forecasting

We sought to scale back the over-parameterization problem by applying greater structure on our model. Could for instance, relevant historical information form part of our model? The Bayesian VAR approach allows us to incorporate informative prior beliefs. Whilst the inclusion of these priors addresses the overparameterization issue, there are new issues relating to the selective process of these prior beliefs. Our task in this chapter is to develop these unknowns with a probabilistic model. Bayesian forecasting utilises this conditional probability approach to express uncertainty about all unknowns. We have experienced several empirical challenges in this paper whilst attempting to forecast the direction of financial assets. Attempts at capturing unobservable dynamic randomness including asset volatility whilst simultaneously dealing with the non-linearity of asset pricing proved challenging. Bayesian inferences seeks to use probability to represent uncertainty in all parts of a statistical model. Our study incorporates a Bayesian VAR model comprising of data, a generative model and prior information. A generative model may be defined as a mathematical expression where you feed fixed parameter values and produce simulated data. We are trying to identify how much the data varies given the parameters. Through Bayesian inference we work our way backwards from the data that's known to learn about the parameter values that we don't know.

Updating Procedure

We used a Markov-Chain Monte-Carlo [MCMC] simulation with the Metropolis-Hastings algorithm to generate a sample from the Posterior distribution of θ. Our next step was to use this sample to estimate the mean of the posterior distribution. Closer inspection of this methodology is instructive. Monte-Carlo simulation is a method for generating random numbers from a normal distribution [$\theta_t \sim N(\mu, \sigma)$]. A Markov-Chain process is a sequence of numbers where each number is dependent upon the previous number in the sequence. Our acceptance | rejection threshold for each value of θ is controlled by the Metropolis-Hastings algorithm. Our newly generated value of θ allowed us to calculate the posterior probability and also calculated the Posterior probability using the previous value of θ. We assumed that the proposal distribution was a normal distribution with this distribution shifting to the right each time a value of θ is drawn. Once we have generated over 10,000 samples, the resulting density looks very like the proposal distribution. Utilising a MCMC process our trace plot of θ resembled a random walk process. Having calculated the posterior probability using the newly generated value of θ, we calculate the posterior probability using the previous value of θ. The Metropolis-Hastings algorithm states that if the Posterior probability is greater for the new value of θ, the ratio of the probabilities will be greater than 1 and we will always accept the new value of θ. The end-product of this process is a sample from the posterior distribution

3.3.10 Sampling procedure

Step 1: We fit the VAR model using the bayes: var command. The default model prior is a conjugate Minnesota Prior for both regression coefficients and the error covariance

Step 2: We specify the rseed () option and run the Markov Chain Monte-Carlo chains. Our simulation is performed using Gibbs Sampling. The problems of parameter uncertainty is naturally addressed by the Bayesian approach through treating the model parameters Θ as probability distributions instead of constants. The Bayesian portfolio approach proceeds as follows:

I. The probability distribution of the returns (Likelihood) and
II. Parameter Prior distributions are defined
III. The Posterior probability distributions are then obtained through Markov Chain Monte-Carlo simulations

MCMC refers to a set of algorithms which allow us to draw samples from the Posterior probability distribution of our Bayesian model. A Bayesian based portfolio optimization approach is attractive for several reasons. Firstly, we had the ability to incorporate prior knowledge into our model using an informative prior distribution. Secondly, model parameters Θ were treated as probability distributions instead of constants and finally there is a convenience associated with numerical algorithms. We identified two key issues *with the MCMC Metropolis Hastings algorithm*. Firstly, auto-correlation may be an issue arising from the persistent structure associated with Markov chains. Also, MCMC-MH is heavily dependent upon the starting values. We dealt with the latter issue trough extension of the burn-in period for our samples. The Bayesian VAR inference approach offers flexible priors, reliable lag-selection criteria and efficient algorithm sampling techniques. To overcome computation issues and improve efficiency our BVAR utilises both the default Minnesota prior and a conjugate Normal-inverse-Wishart prior during this study. Our goal is to use Markov Chain Monte-Carlo to estimate a target distribution (Posterior distribution). Our initial challenge is to discern for how long the sampler should run to produce a decent approximation after the chain has started sampling from the target distribution. The Gelman-Rubin diagnostic has been developed to assist in this task and is one of the most widely used diagnostics used to decide when to terminate a Markov chain. The Gelman-Rubin process runs independent chains over dispersed starting points aiming to target multiple points of our target distribution. $\hat{R}$ is calculated once it reaches a pre-determined threshold and the process stops. $\hat{R}$ is equal to the square root of the sum of two ratios as set out in Eq.3. The second ratio with the *between chain variance* in the numerator and *within chain variance* in the denominator is the primary ratio of importance. The inevitable consequence of the statistical relationship between these two variances means that the fraction of the second ratio will be large. Therefore, $\hat{R}$ will start out large and the second ratio will reduce as the chains explore more of the target distribution. The first ratio will converge to 1 and as the second ratio shrinks further our $\hat{R}$ will minimize to our designated threshold close to 1[84]. The question remains whether this threshold is low enough to produce reliable results.

$$\hat{R} = \sqrt{\frac{chain\ length - 1}{chain\ length} + \frac{between\ chain\ variance}{within\ chain\ variance}} \qquad \text{Eq.3}$$

We start by fitting the model in Eq. 1 utilising the bayes: var command. We initially use the default model prior – conjugate Minnesota prior for our regression coefficients and error covariance estimates. In Stata, we specified the quantity for reproducibility and ran three MCMC chains to compute the Gelman-Rubin convergence diagnostic.

[84] Gelman et al (2004) stated that for most studies, values below 1.1 are acceptable

Our simulation is performed using Gibbs sampling. Modern Bayesian inferences resorts to two basic algorithms to develop Markov chains that converge to f(Θ|Data). These include the Hastings-Metropolis algorithm and Gibbs sampling. We are forced to use these simulation algorithms because we have models for which it is exceedingly difficult to identify closed-form solutions for the parameters. Gibbs sampling is applied when it is impossible to simulate from the joint posterior distribution of the parameters. However, this joint posterior distribution may be divided into a series of simpler conditional distributions from which it may be easier to generate the samples required. The Gibbs sampling procedure used is set out in Appendix 2.

The Gibbs sampler constructs a Markov chain whose values converge towards some target distribution. The sampling method is a specific case of the Metropolis-Hastings algorithm. If we are unable to identify the joint distribution of our multivariate distribution, Gibbs sampling is convenient when the conditional distribution of each variable is known and therefore easier to sample from. The core idea of Gibbs sampling is to split our multi-dimensional θ into blocks and sample each block separately, conditional on the most recent values of the other blocks. We are transforming complex, high-dimensional problems into more digestible, low-dimensional problems.

3.3.11 Markov Chain Monte Carlo (MCMC)

MCMC allows us to sample randomly high-dimensional probability distributions. We utilise Monte Carlo integration with Markov Chains. We draw samples from the required distribution and form averages to approximate the expectations. Gibbs sampling is the most common form of MCMC algorithm. The Gibbs sampler uses an approach to constructing a Markov Chain whereby the conditional probability of the initial sample determines the probability of the following sample distribution. Having an ability to sample from the posterior distribution is crucial to the practise of Bayesian methods. As direct sampling from the posterior distribution is restricted, we need to investigate the Gibbs sampling and H-M algorithms which facilitate sampling when a direct approach is not possible.

A Markov chain is a sequence of random variables x^0, x^1, x^2, if the distribution of $x^{(t+1)}$ depends only on the previous draw,

$$P(x^{(t+1)} = x) = t(x|X^{(t)})$$

and is independent of $x^0, x^1, \dots, x^{t-1}$. The transition probability is governed by a Markov property whereby $t(x|X^{(t)})$ governs the transition probabilities. With the Metropolis-

Hastings algorithm, if we suppose that a Markov chain is in position x; the Metropolis Hastings algorithm is as follows.

We propose a transition to y with probability q(y|x)

We calculate the ratio

$$r = \frac{p(y)q(x|y)}{p(x)q(y|x)}$$

We accept the proposed move with probability $\alpha = \min\{1, r\}$;

otherwise, remain at x $[x^{(t+1)} = x^{t}]$

Our simulation is performed using Gibbs sampling. This method provides a high sampling efficiency. The maximum Gelman-Rubin statistic is 99% and this suggest that we experienced no convergence issues.

Minnesota Prior

This mathematical expression about the belief of our parameter is called the Prior distribution. Bayesian analysis allows us to update our belief about the parameter. The Posterior distribution will usually be equivalent to the likelihood function when we use a completely uninformative prior. More informative priors will relay greater influence upon the Posterior distribution. Similarly larger data samples will give the likelihood function greater influence on the Posterior distribution. Litterman (1980) noted that variables follow random walks with parameters as follows:

- **λ** governing tightness
- **Ψ** shrinks lags of variables other than the dependent variables
- **α** shrinks lags of more remote observations

The common issue cited with the Minnesota prior is its deterministic component owing to its readying of the model based on the initial values.

Bayesian VAR modelling is attractive owing to the flexible nature of the prior beliefs. For illustration, equation 1 is highlighted with both the asset specific returns r_t and the predictor variables y_t listed below.

$$\begin{pmatrix} r_t \\ y_t \end{pmatrix} = \begin{pmatrix} \mu \\ \mu_{yt} \end{pmatrix} + A \begin{pmatrix} r_{t-1} \\ y_{t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_t \\ \varepsilon_{yt} \end{pmatrix}$$

r_t: **Asset returns**

5. r_{t} **SP500**
6. r_{t} **NIK225**
7. r_{t} **Gold**
8. r_{t} **10 YrTrs**

y_t: **Predictor variables**

6. φ: CPI y_t^{φ}
7. β: PPI $y_{t\beta}$
8. φ: UNP $y_{t\varphi}$
9. θ: INDPRD $y_{t\theta}$
10. λ : CFNAI $y_{t\,\lambda}$

3.3.12 Model Specification

Bayesian inference relies upon the observed data and some prior information to create a probability distribution of all model parameters known as the Posterior distribution. This posterior distribution is a combination of a likelihood whereby the model parameters observed in the data is captured and historical information or the prior. Model inputs are sourced therefore both after [Likelihood] and before [Prior] we observe the data. We can combine the likelihood and prior models using the Bayes rule producing our posterior distribution in equation 4.

$$\text{Posterior distribution} \propto \text{Likelihood x Prior} \qquad \text{Eq.4}$$

The model specification of our Bayesian inference may be distilled in the following example. If we wish to model the prevalence of disease in an urban setting, we first assume that a certain fraction of that population have this disease. The parameter which governs this probability is θ. The question for us to answer is what posterior distribution we can assign to θ from this sample population. For the purposes of this example, we assume a sample size of 100 with 5 confirmations of the disease.

N: 100

x: 5

If we use a binomial distribution for our likelihood

$$P(\text{data}|\ \theta) = \binom{100}{5}\theta^{1}(1\text{-}\theta)^{95}$$

If we have an uninformative prior given our lack of understanding of the prevalence of the disease in the population, we can specify the prior as a beta distribution

$$P(\theta) = \text{Beta}\ (1,1)$$

We are interested in finding the probability of θ given our data x. The Posterior distribution is a function of the likelihood and the prior

$$P(\theta|x) = \frac{P(x|\theta)xP(\theta)}{P(X)}$$

Our beta prior and binomial likelihood allow us to derive the posterior distribution quite quickly as the beta prior is conjugate to the binomial. The posterior will also be a beta distribution.

Conjugate Priors

If the study assumes that our likelihood function P(x|θ) is normally distributed, then we can also assume a normal distribution for our prior as set out below.

$$\text{If the } P(\theta|\text{data}, \mu) \sim \text{Normal}$$

$$P(\theta|\mu) \sim \text{Normal}$$

then

$$P(\theta|\text{data}, \mu) \sim \text{Normal}$$

Our choice of Prior distribution such that it is conjugate to the Likelihood, then the Posterior will have the same form as the Prior. There are options available for our prior distribution. For instance, a Beta distribution is conjugate to a Bernoulli prior producing a Beta Posterior distribution.

If we have a Bernoulli form likelihood and a beta Prior as set out below, then the Posterior distribution is also a Beta distribution. Therefore, the Beta distribution is conjugate to a Bernoulli Prior ultimately producing a Beta Posterior distribution.

$$\text{Likelihood} \propto \theta^{Z}(1-\theta)^{N-Z} \quad \text{Bernoulli Likelihood}$$

$$\text{Prior} \propto \theta^{a-1}(1-\theta)^{b-1} \sim \quad \text{Beta}$$

$$\text{Posterior} \sim \text{Beta Distribution}$$

In summary, we can opt for convenient parametric forms for our priors, such that the Posterior remains feasible. If the priors parametric form is consistent to the posterior, this is called a conjugate prior. As the Posterior distribution belongs to the same distribution family as the prior distribution, the beta distribution is called a conjugate prior for the binomial likelihood function. Both the prior and posterior have beta distributions. Bayesian analysis allows us to draw inference from the existing data and historical data. The latter or the *prior* will have a varying impact upon the posterior distribution depending upon the nature of your prior. For instance, the Posterior distribution will usually be equivalent to the likelihood function when we use an uninformative prior. On the contrary, a more informative prior will have greater influence upon the posterior distribution. Unsurprisingly, large sample sizes will ensure that the Likelihood function has greater influence on the posterior distribution. Once we estimated our Posterior distribution, we were in a position to calculate the mean of the probability distribution, the probability that our parameters lie within certain intervals

3.4 Discussion of Results

3.4.1 VAR model and Preliminary tests

We construct a multivariate VARX model incorporating endogenous and exogenous variables. Our endogenous variables include the Consumer Price Index (CPI), Personal Consumer Expenditures (PCE), Unemployment rate (UNEMP) and the House Price Index (HPI). Our exogenous variables include a range of leading indicators. These have been listed below and covered in more detail in the next section.

$$Y_t = \alpha_0 + A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + B_1 X_{t-1} + \ldots + B_q X_{t-q} + E_t \qquad \textit{Eq. 5}$$

<u>Endogenous variables</u>

- Y_{t1}: Consumer Price Index [CPI]
- Y_{t2}: Personal Consumption Expenditures [PCE]
- Y_{t3}: Unemployment
- Y_{t4}: House Price Index
- Y_{t5}: Federal Funds rate

<u>Exogenous variables</u>

- X_{t1}: University of Michigan Consumer sentiment indicator
- X_{t2}: Total Reserve requirement
- X_{t3}: ISM Purchasing Managers Index
- X_{t4}: Federal Funds rate
- X_{t5}: Composite Leading Indicator
- X_{t6}: Business Confidence Index
- X_{t7}: Consumer Confidence Index

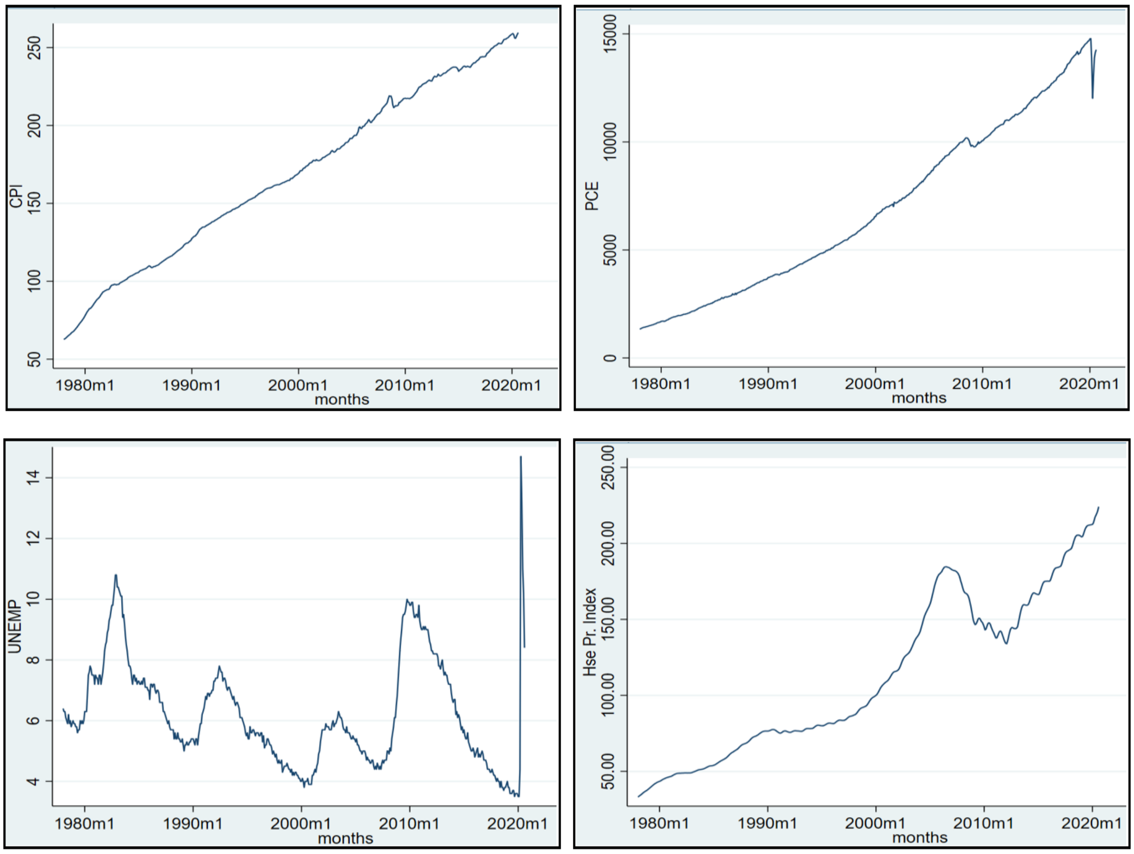
We can represent this VAR model in matrix form as follows:

$$\binom{yt}{xt} = \binom{\alpha y}{\alpha x} + \begin{pmatrix} b11 & \cdots & b1n \\ \vdots & \ddots & \vdots \\ bn1 & \cdots & bnn \end{pmatrix} \begin{bmatrix} yt-1 & \cdots & yt-n \\ \vdots & \ddots & \vdots \\ xt-1 & \cdots & xt-n \end{bmatrix} + \binom{\mu t}{\upsilon t}$$

3.4.2 Unit Root Tests

Our model assumes that variables y_t and x_t are stationary. The first step was to check for the presence of unit roots in the raw data. We identified clear evidence of trending across most of the variables as evidenced in Figure 3.31 & 3.29 below. Augmented Dickey-Fuller and Phillip Perron tests were conducted to test for the presence of unit roots in the data. The results indicated that the data was non-stationary.

Figure 3.31: Tests for stationarity (CPI/PCE/UNEMP/HSE PRICE/ISM/UM SENT)



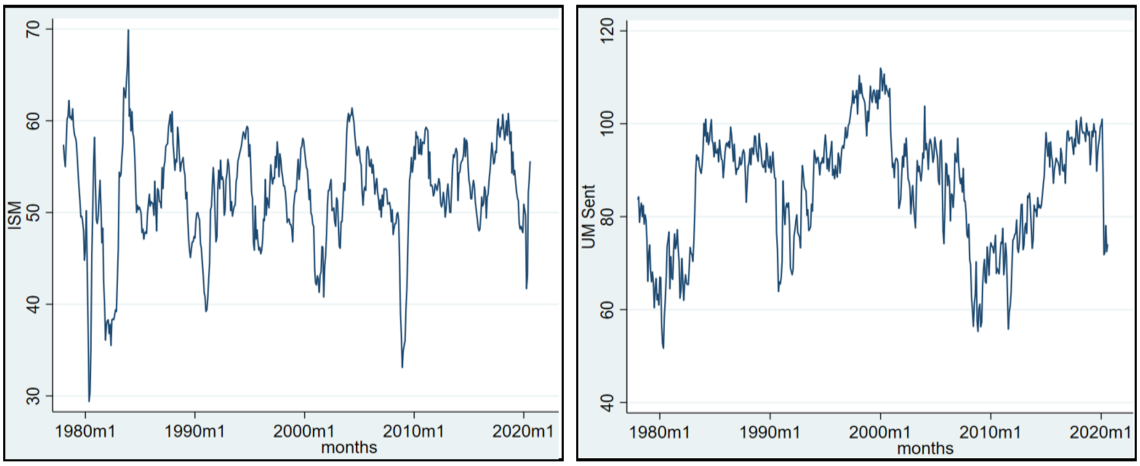


Figure 3.31 displays the timeseries plots of consumer price inflation, personal consumption expenditures, unemployment, house price index, the ISM and the University of Michigan sentiment index. The presence of a unit root is visible through obvious trending in the data for the first four tables. There is less evidence of trending in the sentiment and ISM data.

Figure 3.32: **Tests for stationarity (Leading Indicators)**

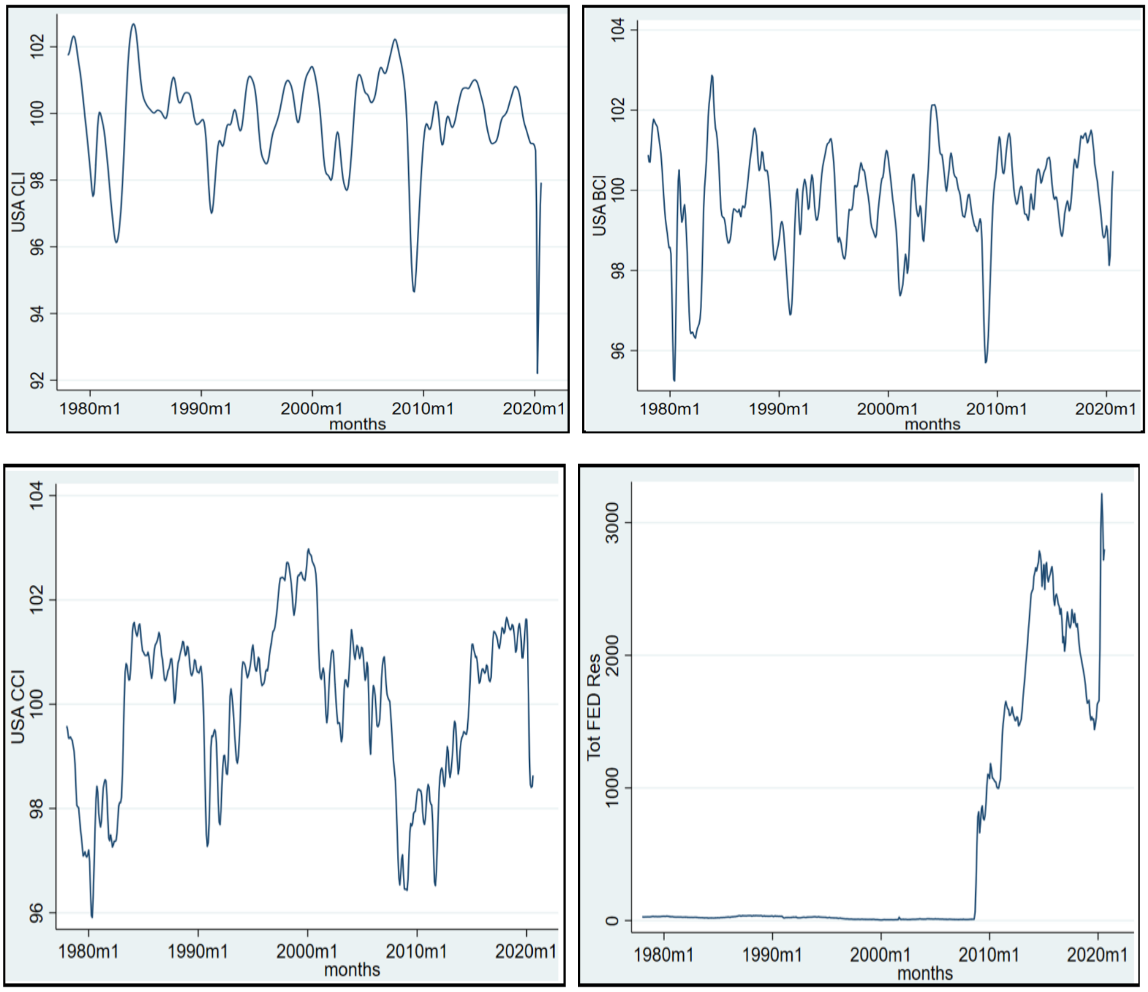


Figure 3.32 displays the timeseries plots of the main leading indicators of our study. The presence of a unit root is visible through obvious trending in the data for the first four tables. There is less evidence of trending in the business confidence indicator. Following our visual inspection and confirmation of non-stationarity, the variables were first differenced to correct for the presence of a unit root process. The Philip Perron and augmented-Dickey Fuller tests for the presence of stationarity were completed with the results confirming that the data is stationary. The results have been detailed below.

Figure 3.33: ADF Tests (CPI/PCE)

```
. dfuller CPI

Dickey-Fuller test for unit root          Number of obs  = 510
Variable: CPI                             Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic           1%           5%          10%
─────────────────────────────────────────────────────────────
 Z(t)           -10.400       -3.430       -2.860       -2.570
─────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

```
. dfuller PCE

Dickey-Fuller test for unit root          Number of obs  = 510
Variable: PCE                             Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic           1%           5%          10%
─────────────────────────────────────────────────────────────
 Z(t)           -20.710       -3.430       -2.860       -2.570
─────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

Figure 3.34: ADF Tests (House Pr. Index & Unemployment)

```
. dfuller HsePrIndex

Dickey-Fuller test for unit root          Number of obs  = 510
Variable: HsePrIndex                      Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic           1%           5%          10%
─────────────────────────────────────────────────────────────
 Z(t)            -4.942       -3.430       -2.860       -2.570
─────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

```
. dfuller UNEMP

Dickey-Fuller test for unit root          Number of obs  = 510
Variable: UNEMP                           Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic           1%           5%          10%
─────────────────────────────────────────────────────────────
 Z(t)           -20.998       -3.430       -2.860       -2.570
─────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

Figure 3.33/3.34 displays the results of our ADF and PP tests **post-differencing** our variables. The data is now stationary.

Exogenous Variables

Tests for stationarity and the presence of unit root were also carried out on the [differenced] exogenous leading indicator variables. The results of these stationarity tests are listed below.

Figure 3.35: ADF Tests (ISM & University of Michigan)

```
. dfuller ISM

Dickey-Fuller test for unit root                   Number of obs  = 510
Variable: ISM                                      Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ──────── critical value ────────
              statistic            1%           5%          10%
──────────────────────────────────────────────────────────────────────
 Z(t)           -18.682         -3.430       -2.860       -2.570
──────────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

```
. dfuller UMCons

Dickey-Fuller test for unit root                   Number of obs  = 510
Variable: UMCons                                   Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ──────── critical value ────────
              statistic            1%           5%          10%
──────────────────────────────────────────────────────────────────────
 Z(t)           -22.485         -3.430       -2.860       -2.570
──────────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

Figure 3.36: ADF Tests (FED Reserves & Composite Leading Indicators)

```
. dfuller TotFEDRes

Dickey-Fuller test for unit root                   Number of obs  = 510
Variable: TotFEDRes                                Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ──────── critical value ────────
              statistic            1%           5%          10%
──────────────────────────────────────────────────────────────────────
 Z(t)           -14.795         -3.430       -2.860       -2.570
──────────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

```
. dfuller USACLI

Dickey-Fuller test for unit root                   Number of obs  = 510
Variable: USACLI                                   Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ──────── critical value ────────
              statistic            1%           5%          10%
──────────────────────────────────────────────────────────────────────
 Z(t)           -12.748         -3.430       -2.860       -2.570
──────────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

Figure 3.37: ADF Tests (Business Confidence Index & Consumer Confidence Index)

```
. dfuller USABCI

Dickey-Fuller test for unit root                   Number of obs  = 510
Variable: USABCI                                   Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ──────── critical value ────────
              statistic            1%           5%          10%
──────────────────────────────────────────────────────────────────────
 Z(t)            -6.836         -3.430       -2.860       -2.570
──────────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

```
. dfuller USACCI

Dickey-Fuller test for unit root                   Number of obs  = 510
Variable: USACCI                                   Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ──────── critical value ────────
              statistic            1%           5%          10%
──────────────────────────────────────────────────────────────────────
 Z(t)            -8.357         -3.430       -2.860       -2.570
──────────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

Figure 3.35/3.36/3.37 display the results of our ADF and PP tests **post-differencing** our variables. The data is now stationary.

VARX estimation

Step 1: We estimates our VARX model of the form

$Y_{t1} = \alpha_0 + A_1Y_{1,t-1} + \ldots + A_pY_{t-p} + B_1X_{t-1} + \ldots + B_qX_{t-q} + E_t$
$Y_{t2} = \alpha_0 + A_1Y_{2t-1} + \ldots + A_pY_{t-p} + B_1X_{t-1} + \ldots + B_qX_{t-q} + E_t$
$Y_{t3} = \alpha_0 + A_1Y_{3,t-1} + \ldots + A_pY_{t-p} + B_1X_{t-1} + \ldots + B_qX_{t-q} + E_t$
$Y_{t4} = \alpha_0 + A_1Y_{4,t-1} + \ldots + A_pY_{t-p} + B_1X_{t-1} + \ldots + B_qX_{t-q} + E_t$
$Y_{t5} = \alpha_0 + A_1Y_{5,t-1} + \ldots + A_pY_{t-p} + B_1X_{t-1} + \ldots + B_qX_{t-q} + E_t$

Endogenous variables

- Y_{t1}: Consumer Price Index [CPI]
- Y_{t2}: Personal Consumption Expenditures [PCE]
- Y_{t3}: Unemployment
- Y_{t4}: House Price Index
- Y_{t5}: Federal Funds rate

Exogenous variables

- X_{t1}: University of Michigan Consumer sentiment indicator
- X_{t2}: Total Reserve requirement
- X_{t3}: ISM Purchasing Managers Index
- X_{t4}: Federal Funds rate
- X_{t5}: Composite Leading Indicator

3.4.3 VAR Stability Tests

We conducted some initial stability and residual diagnostic checks. The stability of the VAR system implies stationarity. If all inverse roots of the characteristic auto-regressive polynomial have modulus < 1 and lie inside the unit circle, the estimate VAR is stable. We cannot use an instable VAR as future diagnostic tests and impulse response standard errors will not be valid. We test the Eigenvalue stability conditions in Table 3.11 below.

Table 3.11: Test for Stability

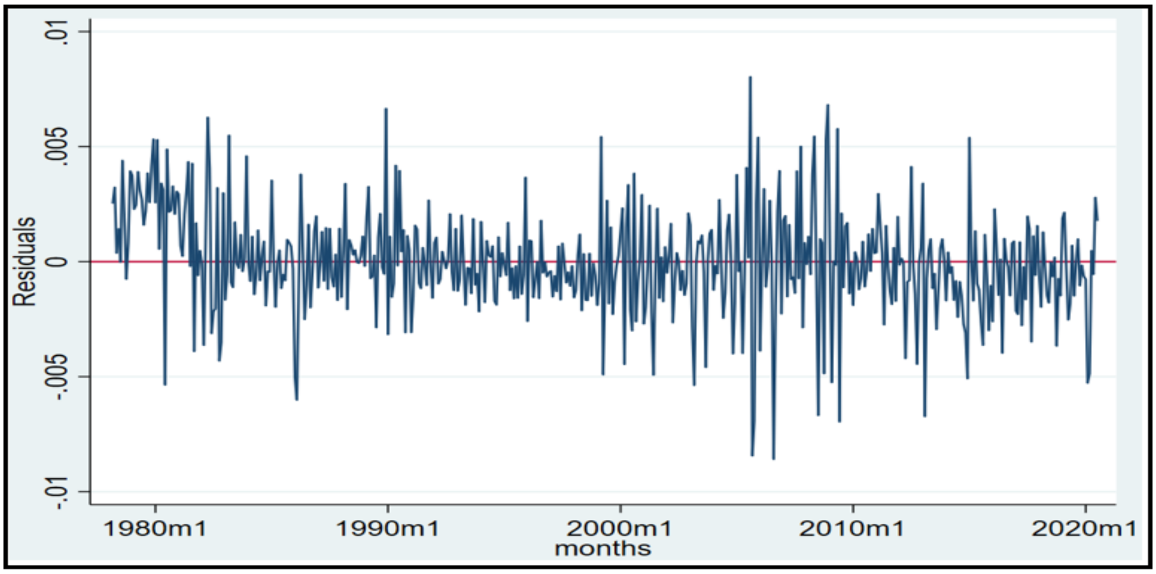
Eigenvalue	Modulus
.7139925 + .2645517i	.761428
.7139925 - .2645517i	.761428
.6405635	.640564
-.5513751	.551375
.5424158	.542416
-.05153793 + .3005471i	.304934
-.05153793 - .3005471i	.304934
.0157619	.015762

As per Table 3.11 we note that all the roots lie inside the unit circle so we can conclude that our model is stable.

3.4.4 Tests for Autocorrelation

We need to identify whether autocorrelation is present in the residuals. We generated our residuals and then graphed these around our mean value as per Figure 3.38 below. One of the most important diagnostic tests is to check the model residuals. In Figure 3.38 we have plotted the residual series. Once we have generated the residuals from our estimated model, we generate the mean value. The initial visual inspection indicates that the residuals are behaving as they should around our mean estimate.

Figure 3.38: Initial estimated residual plot around mean



Formal Test for **Autocorrelation**

The original VAR model included many parameters resulting in problems with autocorrelation among the error terms as per Table 3.12 below. The null hypothesis of the Lagrange Multiplier test is zero autocorrelation for 2 lags. As our p-value of the Box-Pierce Q-statistic at the second lag is < 0.05, this confirms the presence of autocorrelation in our model.

Table 3.12: Lagrange Multiplier test

lag	chi2	df	Prob > chi2
1	331.7664	64	0.00000
2	239.7564	64	0.00000

We revised our VAR model to address the autocorrelation issues:

$$Y_t = \alpha_0 + A_1Y_{t-1} + \ldots + A_pY_{t-p} + B_1X_{t-1} + \ldots + B_qX_{t-q} + E_t$$

or in matrix form

$$\binom{yt}{xt} = \binom{\alpha y}{\alpha x} + \begin{pmatrix} b11 & \cdots & b1n \\ \vdots & \ddots & \vdots \\ bn1 & \cdots & bnn \end{pmatrix} \begin{bmatrix} yt-1 & \cdots & yt-n \\ \vdots & \ddots & \vdots \\ xt-1 & \cdots & xt-n \end{bmatrix} + \binom{\mu t}{vt}$$

Given the evidence of autocorrelation, it was a requirement to adjust the lag-lengths. We completed numerous re-calculations involving the inclusion and exclusion of variables. It was noted that the *House Prices Index* was driving the strong autocorrelation in our model. There was additional concerns that this variable is highly correlated with CPI. A decision was taken to replace this growth variable for another growth proxy. Additional regressions were completed excluding the House Price Index along with additional checks for evidence of autocorrelation among the residuals.

We re-estimated our VAR model of the form in equation 3 with 4 lags specified

$$Y_{t1} = \alpha_0 + A_1Y_{1,t-1} + \ldots + A_pY_{t-p} + B_1X_{t-1} + \ldots + B_qX_{t-q} + E_t \qquad \textit{Eq. 3}$$

Endogenous variables

- Y_{t1}: Consumer Price Index [CPI]
- Y_{t2}: Unemployment
- Y_{t3}: Federal Funds rate

Exogenous variables

- X_{t1}: University of Michigan Consumer sentiment indicator
- X_{t3}: ISM Purchasing Managers Index

3.4.5 Lag selection

Proper specification of the lag length is crucial. Model misspecification occurs if the lag-length is too small. Alternatively, degrees of freedom are wasted if the lag-length is too large. To determine the length of our VAR model we utilised the Akaike, Schwartz and Hannan-Quinn criteria. As set out in Table 3.13, all three criteria suggest that the optimal lag length is for three lags.

Table 3.13: Lag Selection

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	6636.36				5.9e-17	-26.0132	-25.961	-25.8802
1	7285.47	1298.2	16	0.000	4.9e-18	-28.5009	-28.3965	-28.2348
2	7466.57	362.2*	16	0.000	2.6e-18*	-29.1496*	-28.9931*	-28.7505*

3.4.6 Empirical Findings

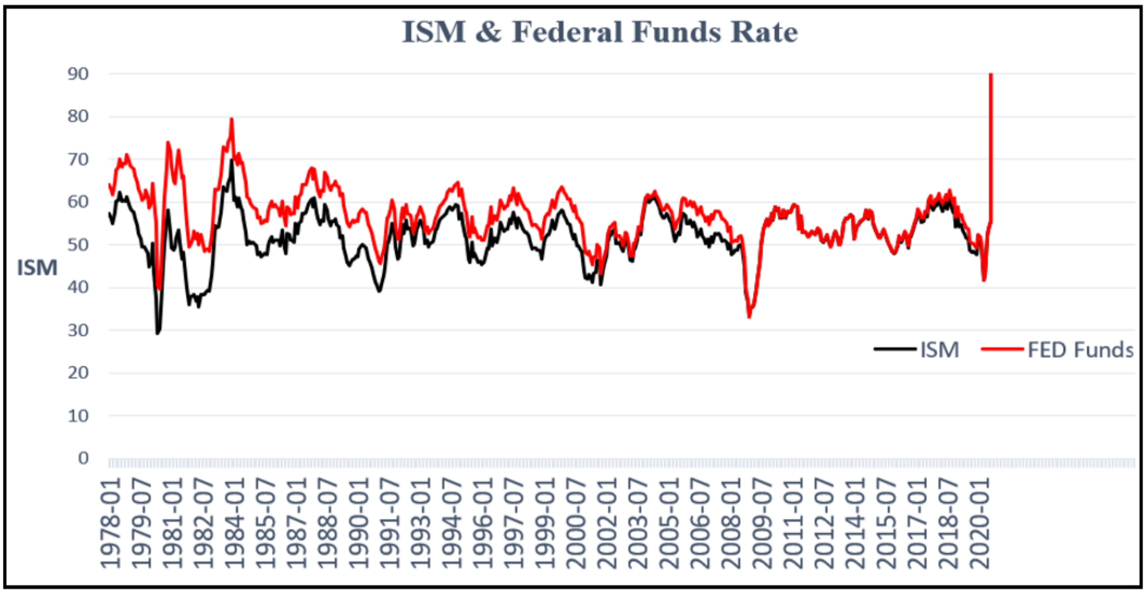
In Table 3.14 we note that the federal funds rate does assist in predicting the unemployment rate at the 5% significance level. The Institute of Supply management (ISM) leading indicator is also significant at the 5% level in predicting the federal funds rate. In fact, the University of Michigan consumer sentiment survey indicator is useful in predicting the key federal funds rate at a 1% statistically significant level. The unemployment rate is strongly statistically significant in predicting the ISM. This is an important result owing to the influence of second-order effects which will be covered in the next section. Finally, the consumer price index is statistically significant (at the 10% level) in predicting consumer sentiment.

Table 3.14: Granger causality Wald Test: All variables

UNEMP	CPI	1.6382	4	0.802
UNEMP	FEDFunds	33.85	4	0.000
UNEMP	ISM	4.9484	4	0.293
UNEMP	UMCons	5.9457	4	0.203
UNEMP	ALL	48.78	16	0.000
FEDFunds	CPI	11.129	4	0.025
FEDFunds	UNEMP	38.945	4	0.000
FEDFunds	ISM	10.222	4	0.037
FEDFunds	UMCons	16.371	4	0.003
FEDFunds	ALL	70.63	16	0.000
ISM	CPI	3.6131	4	0.461
ISM	UNEMP	24.307	4	0.000
ISM	FEDFunds	2.6506	4	0.618
ISM	UMCons	16.404	4	0.003
ISM	ALL	57.797	16	0.000
UMCons	CPI	9.2791	4	0.054
UMCons	UNEMP	4.9643	4	0.291
UMCons	FEDFunds	2.2124	4	0.697
UMCons	ISM	13.226	4	0.010
UMCons	ALL	28.256	16	0.029

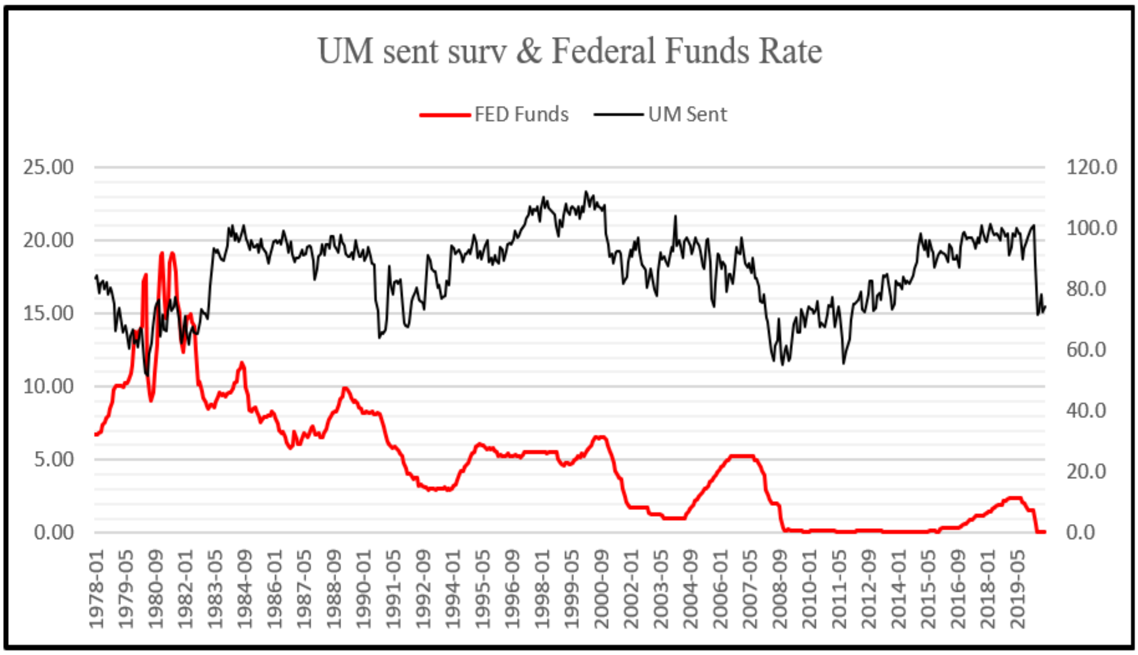
These results appear sensible. A fluctuating federal funds rate is a key determinant of economic activity. A primary monetary policy tool of central banks globally is to raise (lower) rates when the economy is late (early) cycle. The unemployment rate is a key barometer of the health of any economy. With the federal funds rate playing such a pivotal role, we can identify why the relationship between unemployment and interest rates is statistically significant. The ISM appears influential also over the federal funds rate. The ISM surveys are leading indicators. They may influence a lagging relationship between their release and subsequent monetary policy. A persistent set of negative ISM data releases (below 50) appears to influence the trajectory of the federal funds rate. We see evidence of this relationship in figure 3.39 below.

Figure 3.39: Relationship between the ISM & Federal Funds Rate



Between January 1978 and January 1981, the ISM survey releases were persistently negative and below 50. The federal fund rate appears to follow the ISM down after a short lag. The federal funds rate (red line) appears to lag the ISM (black line). Accordingly, the low of the ISM also appears to place a floor under the fall in the federal funds rate. This relationship appears consistent over the decade's most notably again in January 1981, February 1984 and January 1990. The correlation between the two variables appears to have grown more positive in recent decades. There was greater divergence evident in the 1970s & 1980s. However, the leading influence of the ISM on the federal funds rate appears to be consistent also. In this study we are trying to identify the variables that provide informative, consistent and leading intelligence about the movement of investable assets**.** Our thesis states that if we can identify the structural drivers of important macroeconomic variables including the federal funds rate and CPI, we can assign some additional conditional probabilities to the forecasted outcomes. Our Granger-causality reports in Table 3.14 indicate that the University of Michigan consumer sentiment survey indicator is accurate in predicting the key federal funds rate at a 1% statistically significant level. The link between consumer sentiment and the key monetary policy rate has been noteworthy in the literature. Debes et. al (2014) utilise a behavioural DSGE model in their investigation of the role of consumer confidence in the diffusion of monetary policy shocks. They find that consumer sentiment drops significantly post central bank monetary tightening. Acemoglu & Scott (1994), Matsusaka & Sbor-done (1995) and Barsky & Sims (2012) have written extensively on the impact of consumer confidence on the macroeconomy. Carroll, Fuhrer and Wilcox (1994) noted in their work that consumer sentiment indicators such as the University of Michigan consumer sentiment survey contained valuable information not necessarily present in the existing macro-economic data. What kind of relationship should we expect to see if the theoretical relationship detailed in the literature holds? Figure 3.40 provides the historical evidence.

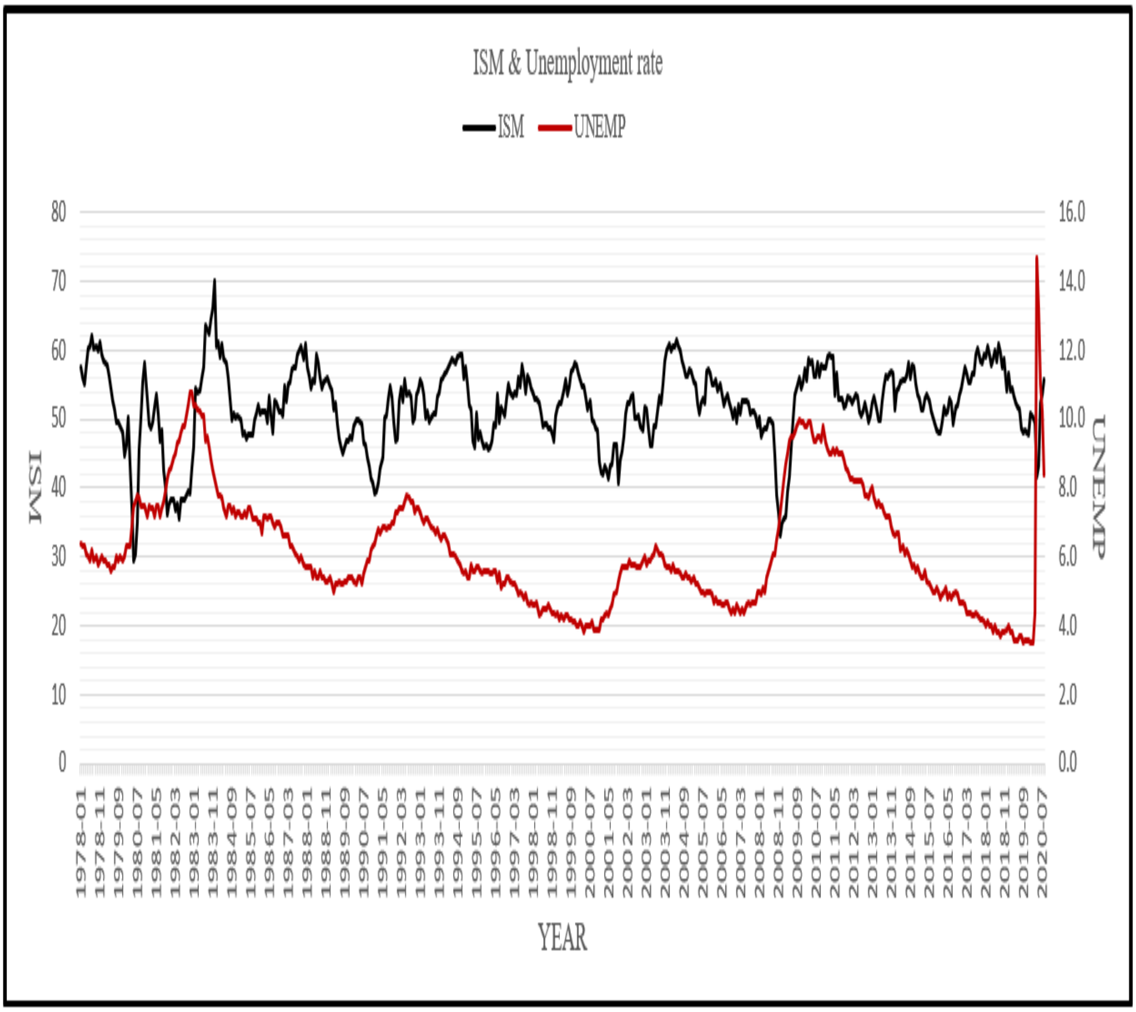
Figure 3.40: Relationship between the UM sentiment survey & Federal Funds Rate



The late 1970s and early 1980s were turbulent economic periods in the United States with two short, sharp recessions arising from a combination of exogenous energy supply shocks and aggressive Federal Reserve monetary policy to quell inflationary pressures. The early 1980s witnessed a revival in consumer confidence, and sentiment rose (as evidenced by the UM sentiment survey black line moving up from 1982). Consequently, Federal Reserve policy loosened, and interest rates began to fall rapidly for the next five years. The Federal Reserve raised the federal funds rate in 1988. There was a sharp decline in the University of Michigan sentiment survey in early 1990 and the federal fund rate reversed trend quickly. There is clear visual evidence from figure 3.40 along with the statistical confirmation from our granger-causality test of a positive relationship between consumer sentiment and the federal funds rate. As the University of Michigan consumer sentiment indicator falls, the federal funds rate follows with a lag thereafter arising from a policy response to loosen or ease financial conditions thereby stimulating demand in the economy.

The unemployment rate is strongly statistically significant in predicting the ISM. This is an important result owing to the influence of second-order effects which will be covered in the next section. Finally, the consumer price index is statistically significant (at the 10% level) in predicting consumer sentiment

Figure 3.41: Relationship between the ISM & the Unemployment rate



3.4.7 Impulse response Functions

The Impulse Response Function (IRF) informs us about the dynamics and economics of what predictability means. Impulse response functions assist in characterising what the dynamics of our VAR model imply. If we reconsider our reduced form VAR model:

$$Y_t = \alpha_0 + A_1Y_{t-1} + \dots + A_pY_{t-p} + B_1X_{t-1} + \dots + B_qX_{t-q} + \varepsilon_t$$

where $e_t | I_{t-1} \overset{d}{=} N(0, \Omega)$

The contemporaneous effects in the VAR model are captured in our Ω matrix or the covariance matrix of the error vector. Unlike other standard linear regression models, the model parameters A_p and B_q are difficult to interpret directly via the vector autoregressive model. We therefore use impulse response analysis to interpret these coefficients. We are attempting to ascertain what occurs to the variables in our model Y_t if there is a shock to the error term ε_t. We recognise that this shock to the error term may have instantaneous and more time-varying responses. We can analyse the shock to ε_t through the moving average representation

$$Y_t = \varepsilon_t + \varphi_1\varepsilon_{t-1} + \varphi_2\varepsilon_{t-2} + \ldots + \varphi_t\varepsilon_{t-p} + \varphi_0 \qquad \text{Eq.4}$$

We are next interested with determining what happens to our Y_t variable if there is a shock to our error term. We can differentiate Eq.4 with respect to ε_t to reveal our identity matrix

$$\frac{\partial Yt}{\partial \varepsilon t} = I_p, \frac{\partial Yt+1}{\partial \varepsilon t} = \varphi_1, \frac{\partial Yt+2}{\partial \varepsilon t} = \varphi_2, \ldots.$$

Our gamma matrices are complicated functions of the original parameters in our model equation 1 and the derivative functions may be represented visually through our impulse response functions. These IRFs allow us to sketch out the time route of both the current and future values of the variables in our model to a one unit increase in the current value of one of the VAR errors. We are generally interested in determining the impact a one-unit shock on the x variable has on the y variable. We impose a restriction on the main matrix to identify the impulse responses. The *Cholesky Decomposition* is utilised to determine the identity of the impulse response. We utilise a Cholesky decomposition to orthogonalize the disturbances to assist in obtaining structurally interpretable IRFs. Impulse-response functions trace the effects of structural shocks on the endogenous variables whereby each response contains the effect of a specific shock on one of the variables of the system at shock time t, shock time t+1 and so on.

The process requires the transformation of our SVAR into a Wold representation:

$$X_t = \mu + \sum_{i=0}^{\infty} C_i\mu_{t-i}$$

It is widely recognised that knowledge of the forecast errors is useful in analysing the relationship among our model variables. The variance decomposition provides the proportion of those movements due to shocks to itself and shocks to other variables in the system. The residuals in our model take on recursive ordering whereby a sequential chain is arranged with variables arranged in decreasing order of exogeneity. The causal priority changes the order of the coefficients in B^{-1} matrix and therefore the Cholesky decomposition. Economic meaning is attached to our choice of restrictions. The ordering of the variables plays an important role given that the restriction on the matrix implies some shocks have no contemporaneous effects on some of the variables in the system.

Cholesky Decomposition

We will specify the following VAR model:

$$Y_{t1} = \alpha_0 + A_1Y_{1,t-1} + \ldots + A_pY_{t-p} + B_1X_{t-1} + \ldots + B_qX_{t-q} + \varepsilon_t \qquad \textit{Eq. 5}$$

<u>Endogenous variables</u>

- *Y_t: Consumer Price Index [CPI]*
- *I_t: Unemployment*
- *P_t: Federal Funds rate*
- *X_t: University of Michigan Consumer sentiment indicator*
- *V_t: ISM Purchasing Managers Index*

We can specify this in long form as (with 2 lags)

$$Y_t = \alpha_1 + A_{11}Y_{t-1} + A_{12}I_{t-1} + A_{13}P_{t-1} + A_{14}V_{t-1}\ A_{15}X_{t-1} + B_{11}Y_{t-2} + B_{12}I_{t-2} + B_{13}P_{t-2} + B_{14}V_{t-2} + B_{15}X_{t-2} + \varepsilon_t$$

$$I_t = \alpha_2 + A_{21}Y_{t-1} + A_{22}I_{t-1} + A_{23}P_{t-1} + A_{24}V_{t-1}\ A_{25}X_{t-1} + B_{21}Y_{t-2} + B_{22}I_{t-2} + B_{23}P_{t-2} + B_{24}V_{t-2} + B_{25}X_{t-2} + \mu_t$$

$$P_t = \alpha_3 + A_{31}Y_{t-1} + A_{32}I_{t-1} + A_{33}P_{t-1} + A_{34}V_{t-1}\ A_{35}X_{t-1} + B_{31}Y_{t-2} + B_{32}I_{t-2} + B_{33}P_{t-2} + B_{34}V_{t-2} + B_{35}X_{t-2} + \upsilon_t$$

$$V_t = \alpha_4 + A_{41}Y_{t-1} + A_{42}I_{t-1} + A_{43}P_{t-1} + A_{44}V_{t-1}\ A_{45}X_{t-1} + B_{41}Y_{t-2} + B_{42}I_{t-2} + B_{43}P_{t-2} + B_{44}V_{t-2} + B_{45}X_{t-2} + \varphi_t$$

$$X_t = \alpha_5 + A_{51}Y_{t-1} + A_{52}I_{t-1} + A_{53}P_{t-1} + A_{54}V_{t-1}\ A_{55}X_{t-1} + B_{51}Y_{t-2} + B_{52}I_{t-2} + B_{53}P_{t-2} + B_{54}V_{t-2} + B_{55}X_{t-2} + \lambda_t$$

We can represent this in Matrix form

$$\begin{bmatrix} Y_t \\ I_t \\ P_t \\ V_t \\ X_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \end{bmatrix} + \begin{pmatrix} A_{11} & A_{12} & A_{13} & A_{14} & A_{15} \\ A_{21} & A_{22} & A_{23} & A_{24} & A_{25} \\ A_{31} & A_{32} & A_{33} & A_{34} & A_{35} \\ A_{41} & A_{42} & A_{43} & A_{44} & A_{45} \\ A_{51} & A_{52} & A_{53} & A_{54} & A_{55} \end{pmatrix} \begin{bmatrix} Y_{t-1} \\ I_{t-1} \\ P_{t-1} \\ V_{t-1} \\ X_{t-1} \end{bmatrix} + \begin{pmatrix} B_{11} & B_{12} & B_{13} & B_{14} & B_{15} \\ B_{21} & B_{22} & B_{23} & B_{24} & B_{25} \\ B_{31} & B_{32} & B_{33} & B_{34} & B_{35} \\ B_{41} & B_{42} & B_{43} & B_{44} & B_{45} \\ B_{51} & B_{52} & B_{53} & B_{54} & B_{55} \end{pmatrix} \begin{bmatrix} Y_{t-2} \\ I_{t-2} \\ P_{t-2} \\ V_{t-2} \\ X_{t-2} \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ \mu_t \\ \upsilon_t \\ \varphi_t \\ \lambda_t \end{bmatrix}$$

3.4.8 Granger-Causality Test

The central question that our VAR model seeks to answer is whether the variables in the model help to predict each other. We utilised the Granger causality test to assess whether the lagged values of one variable helps to predict other variables within the model. The null hypothesis sets out that the independent variable does not granger cause the dependent variable whilst the alternative hypothesis states that the dependent variable granger causes y.

$$H_0 : \text{x does not Granger cause y}$$

$$H_1 : \text{x does Granger cause y}$$

The parameters of the decision rule relating to the Granger Causality test states that if the p-value < 0.05 then we can confirm that x Granger causes y at the 5% significance level. If the p-value is > 0.05, we confirm that x does not Granger cause y at the 5% significance level. For *Equation 5*, we may pose the following questions:

- *Does the unemployment rate assist us in predicting future fed rates?*
- *Does the University of Michigan sentiment survey influence consumer price inflation?*
- *Does the ISM help us to forecast unemployment?*

This study has indicated in Chapter 2 that macroeconomic variables including the *federal funds rate*, *consumer price index* and *unemployment* have statistical significance in determining the underlying economic regime. This was evident from the classification of each of the four individual regimes in chapter 2. If these macroeconomic variables provide informational efficiency, then optimal asset allocation should develop from our ability to forecast these macro variables with preceding sources of market information captured through leading indicators including the ISM, University of Michigan survey and others. In Table 3.15 we can assess the results of our Granger-Causality tests. We note that none of the variables are statistically significant at the 5% level in predicting CPI. Additional variables were reviewed and found to be significant. The results are discussed in section 3.4.

Table 3.15: Granger causality Wald Test: CPI

Equation	Excluded	chi2	df	Prob > chi2
CPI	UNEMP	5.4707	4	0.242
CPI	FEDFunds	2.3615	4	0.670
CPI	ISM	3.9382	4	0.414
CPI	UMCons	5.9141	4	0.206
CPI	ALL	17.281	16	0.368

We used the Granger causality tests to identify both the most exogenous variables in our model to assist with the ordering of our variables and to determine the impulse and response variables for our Impulse response functions. Our study is focussed on determining the structural drivers of key macroeconomic variables including inflation, unemployment and the policy rate. Therefore, our response variables include CPI, the Unemployment rate and the Federal Funds rate. The impulse variables include the ISM, University of Michigan consumer sentiment survey and the Federal funds rate

Table 3.16: Granger Causality Test results

Granger Causality Tests

H0: x does <u>not</u> Granger cause y

H1: x does Granger cause y

Response Variable **Consumer Price Inflation**

Question	Yes	No	**Statistical significance level**
Does unemployment help to predict future values of CPI			
Does the FFR help to predict future values of CPI			
Does the ISM help to predict future values of CPI			
Does the Univ. Mich Survey help to predict future values of CPI			

Response Variable **Unemployment**

Question	Yes	No	**Statistical significance level**
Does the CPI help to predict future values of unemployment			
Does the FFR help to predict future values of unemployment			**0.01**
Does the ISM help to predict future values of unemployment			
Does the Univ. Mich Survey help to predict future values of unemployment			

Response Variable **Federal Funds Rate**

Question	Yes	No	**Statistical significance level**
Does the CPI help to predict future values of FFR			**0.05**
Does the unemp rate help to predict future values of FFR			**0.01**
Does the ISM help to predict future values of FFR			**0.05**
Does the Univ. Mich Survey help to predict future values of unemployment			**0.01**

Response Variable **ISM**

Question	Yes	No	**Statistical significance level**
Does the CPI help to predict future values of the ISM			
Does the unemp rate help to predict future values of the ISM			**0.01**
Does the FFR help to predict future values of the ISM			
Does the Univ. Mich Survey help to predict future values of the ISM			**0.01**

Response Variable **Univ Mich Consumer Sentimet**

Question	Yes	No	**Statistical significance level**
Does the CPI help to predict future values of the UMCS			**0.1**
Does the unemp rate help to predict future values of the UMCS			
Does the FFR help to predict future values of the UMCS			
Does the ISM Survey help to predict future values of the ISM			**0.01**

3.4.9 Postestimation IRF Analysis

Our postestimation analysis (Table 3.16) revealed further evidence of statistical significance between our macroeconomic variables. We have summarised some of these relationships briefly.

(i) Federal funds shock on Unemployment

We note that a one standard deviation shock on the federal funds rate has a negative effect on the unemployment rate for an initial two-month period. After approximately three months the unemployment rate recovers to neutral. A federal funds rate shock means that interest rates rise leading to a tightening in monetary conditions which has initial implications for business and consumer spending. A more hawkish policy stance will negatively impact also upon sentiment leading to less job security and inevitable employment losses.

(ii) ISM shock on the Federal funds rate

We note that a one standard deviation shock on the ISM has a positive impact on the federal funds rate for an initial three-month period and then turns slightly negative for the next three months. After approximately eight months the federal funds rate recovers to neutral. An ISM shock means that a positive ISM sentiment survey is released. The marginal response from rates may reveal initial levels of uncertainty.

(iii) ISM shock on the Unemployment rate

We note that a one standard deviation shock on the ISM has no immediate effect on the unemployment rate for an initial two-month period and then turns slightly negative for the next month. A positive shock in the ISM should lead to a positive (reducing) unemployment response. However, the IRF is inconclusive. The initial Impulse Response Functions have been detailed below.

Table 3.17: Impulse Response Functions

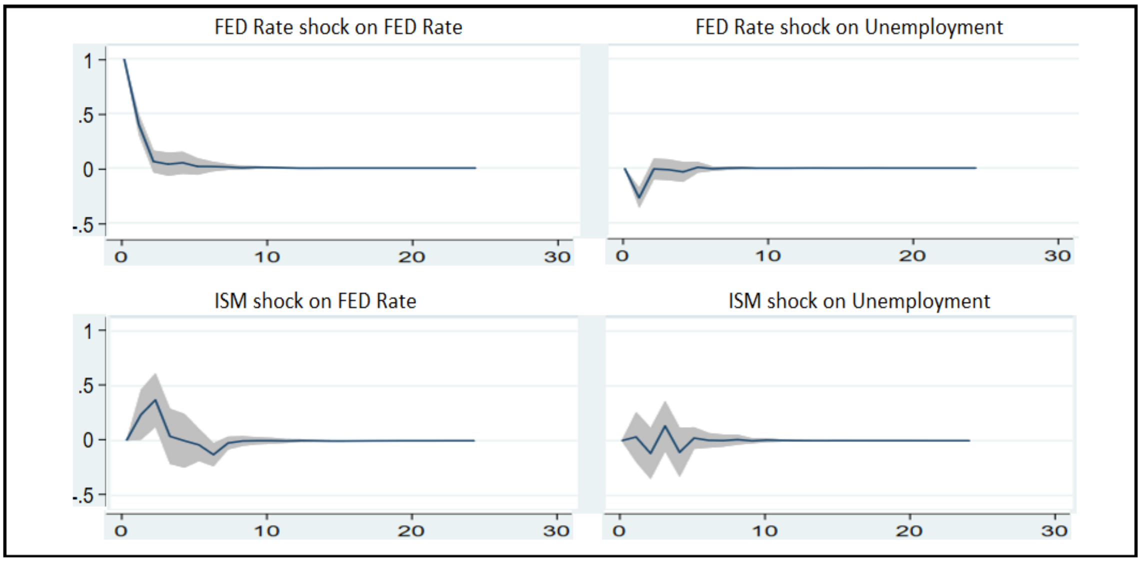
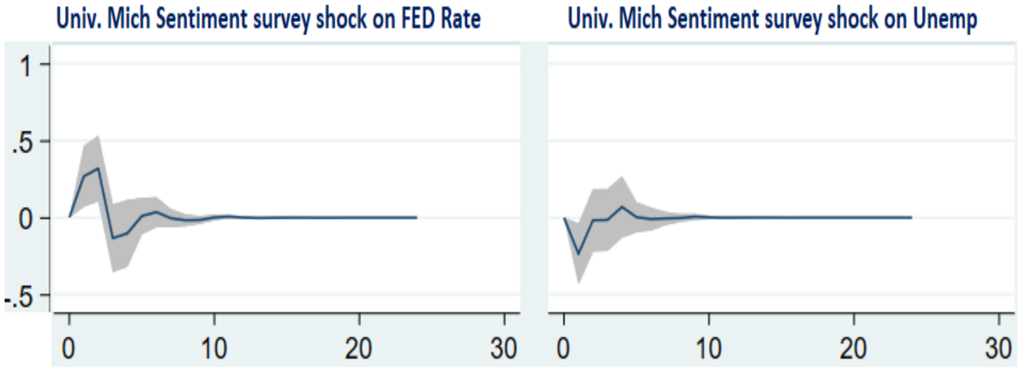


Table 3.17: Impulse Response Functions (Cont'd)



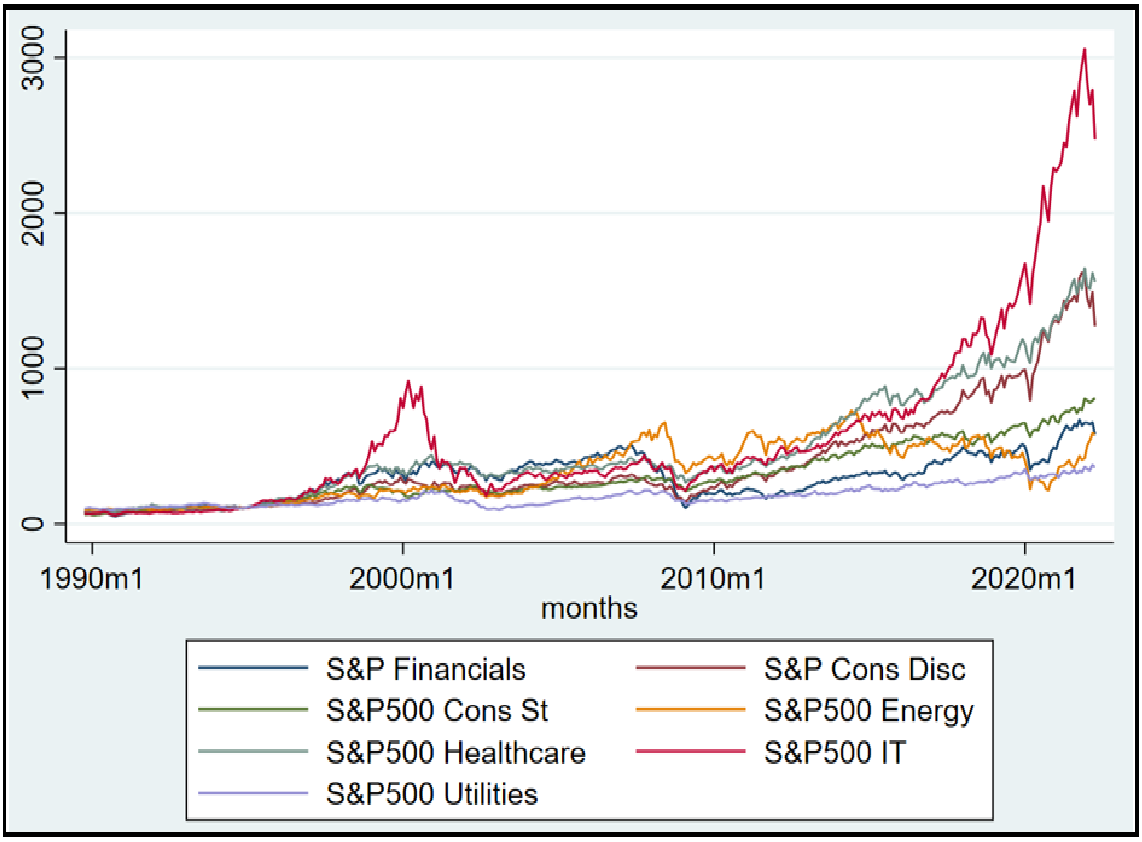
We are interested in determining whether the unemployment rate assists us in forecasting inflation rates. Granger-causality statistics examine whether lagged values of one variable assist in predicting another variable. We may utilise a three-variable reduced form VAR set out as follows. We allow y_t to be a vector with the value of n variables at time t: y_t = [y_1, y_2, y_3 . . . . y_n] where y_1 references *GDP*, y_2 captures *unemployment rate* and y_3 measures *inflation*. A lack of economic restrictions on the data and the non-orthogonal nature of the residuals means that we have a reduced-form VAR.

We compute several IRF statistics associated with our Bayesian VAR model. We compute the effects of shocks for up to 9 months into the future. These have been visually represented in Tables 3.18 to 3.49 in section seven (refer to Appendices). The IRF command draws the posterior mean estimates of impulse response function coefficients along with 95% Crls. We start by inspecting the effect of a shock on the fed funds rate.

3.4.10 Equity Sector-based analysis

There are nine different sectors of the S&P500 classified according to the underlying company constituents/ sector. This study sought to differentiate the underlying market regime through interpreting the individual responses of these equity sectors to shocks in our underlying macroeconomic variables. Initially, we analysed each sector visually to aid with interpretation. Figure 3.42 displays the sector-specific constituents of the S&P500.

Figure 3.42: S&P500 Sector specific indices

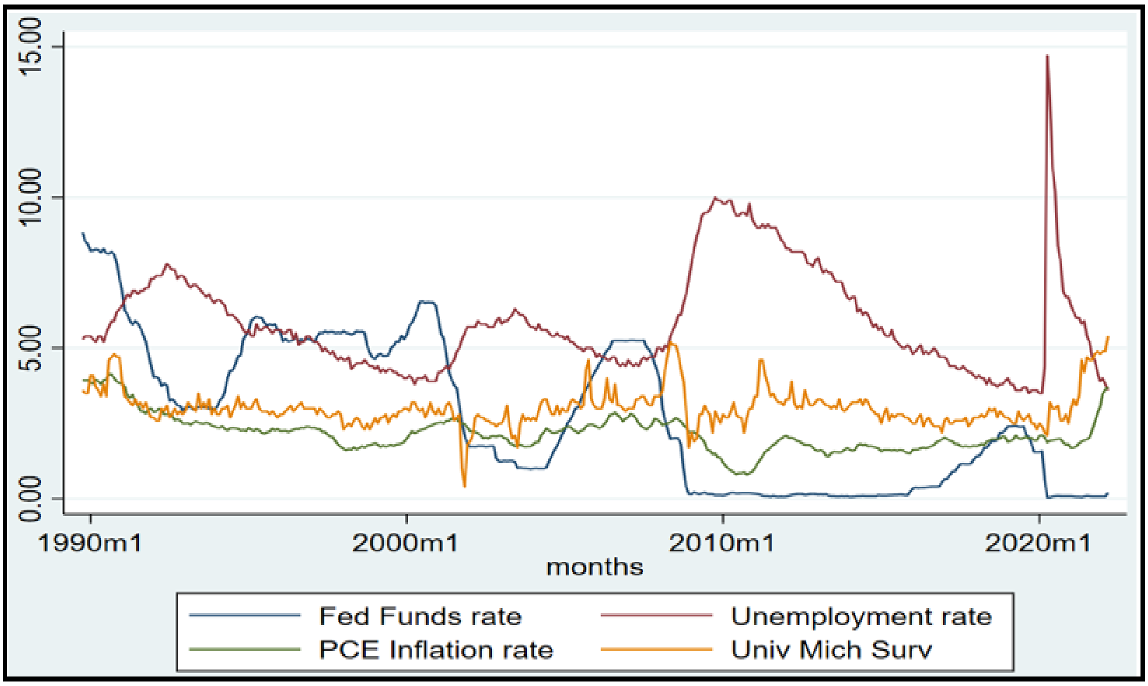


Source: Authors own chart/ Figure 3.42 displays the sector-specific constituents of the S&P500.

The divergence in performance becomes quite noticeable post Great Financial Recession. The spread in performance increases considerably during the Covid-19 pandemic. For instance, healthcare, consumer discretionary and information technology are strong outperformers arising from key policy decisions relating to vaccines, fiscal policy and remote working respectively. Figure 3.43 displays the corresponding macroeconomic variables between the late 1980s and present day. The consistently downward trend in the Federal Funds rate is notable particularly when mapped against the strong general equity market performance across all S&P500 equity sectors for this period. We note that the unemployment rate is particularly vulnerable to economic shocks as evident from the

2008 financial crisis and the Covid emergency. Large upward spikes in unemployment during these stressed periods contrasted with sharp declines in the Federal Funds rate as policy makers sought to manage the monetary response. We note the short-term dips in consumer sentiment during recession periods as evidenced through the University of Michigan consumer sentiment survey. The stability of the PCE rate is noteworthy until recent months. The leading nature of the University of Michigan sentiment survey in advance of the inflation spike should also be noted.

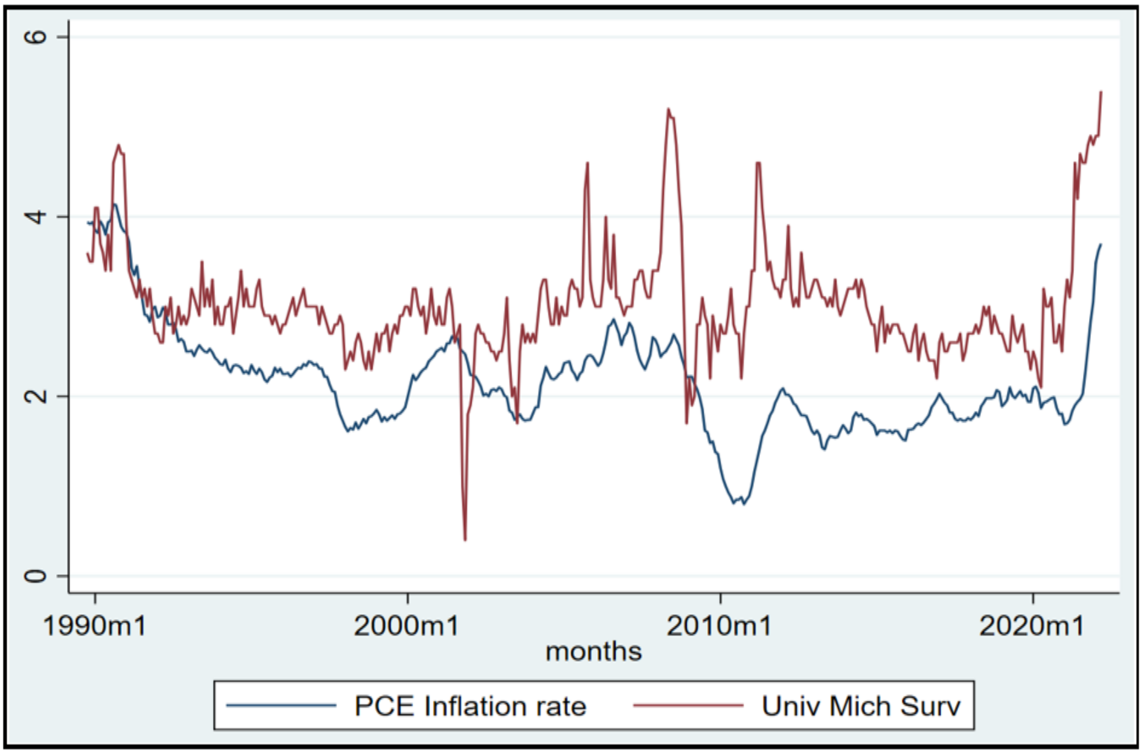
Figure 3.43: Predictor Variables



Source: Authors own chart/Figure 3.43 displays the corresponding macroeconomic variables between the late 1980s and present day.

Figure 3.44 displays the relationship between an established leading economic indicator (University of Michigan sentiment survey) and the Federal Reserve's inflation indicator of choice, Personal Consumption Expenditures. Clearly, the leading indicator is more volatile with sharp movements typically 1-month prior to the move in the PCE variable. Whilst the relationship is not always constant, there does appear to be consistency in the ability of the sentiment indicator to provide an element of "early warning".

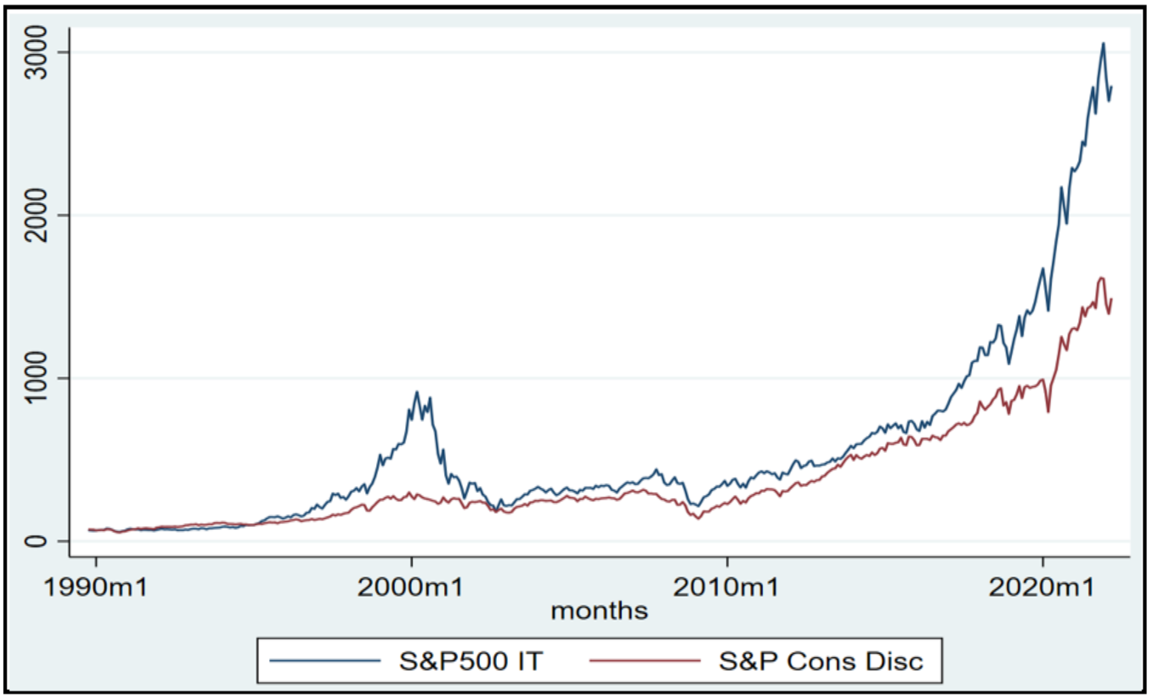
Figure 3.44: Inflation-related predictor variables



Source: Authors own chart/Figure 3.44 displays the relationship between the University of Michigan sentiment survey and Personal Consumption Expenditures

Figure 3.45 displays the trajectory of interest rate sensitive sectors of the S&P500. There was a sharp move upwards for these sectors post the Great Financial Recession as interest rates were pushed to the lower bound globally by Central Banks.

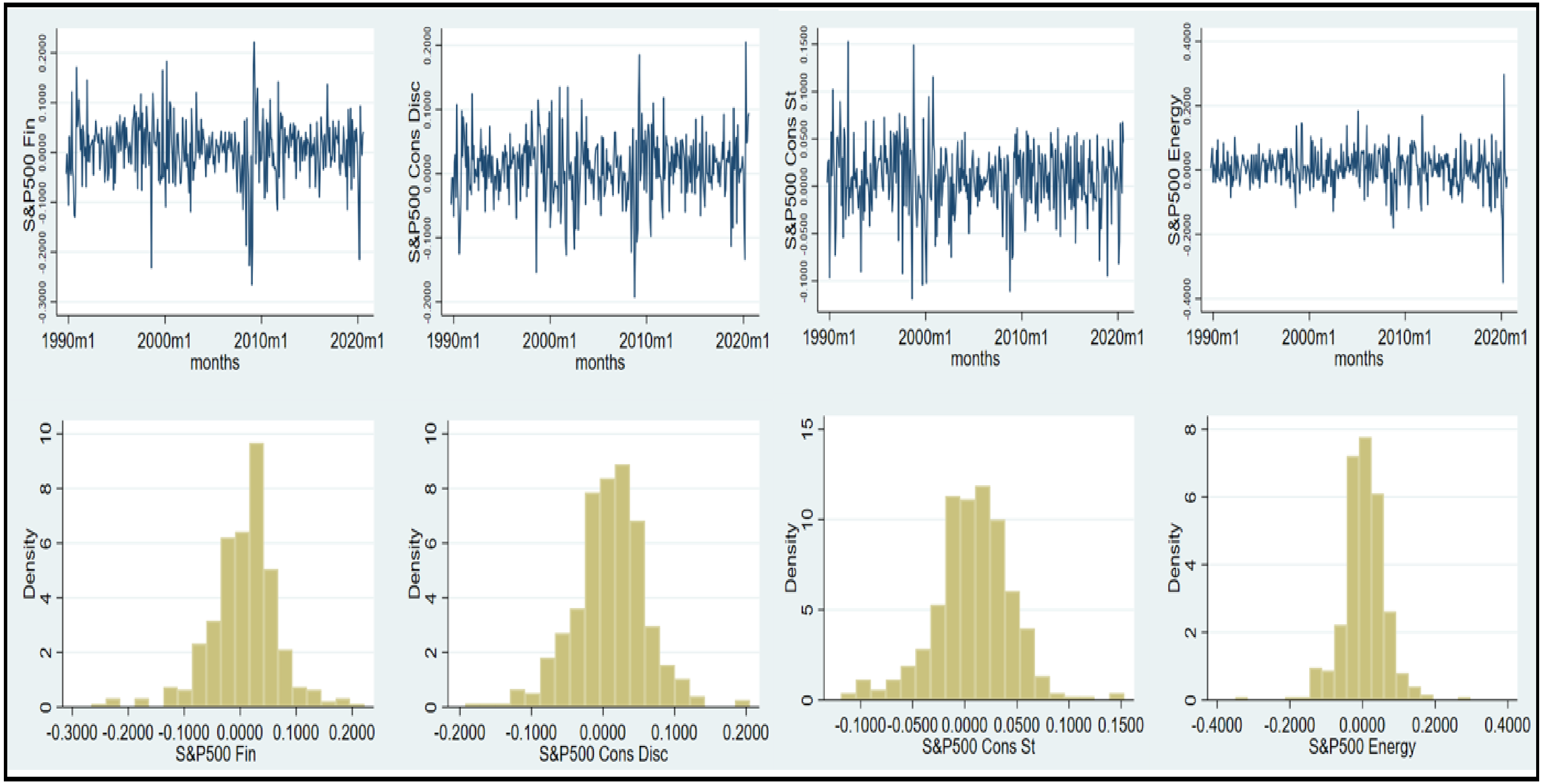
Figure 3.45: Interest rate sensitive cyclical stocks



Source: Authors own chart/Figure 3.45 displays the relationship between the University of Michigan sentiment survey and Personal Consumption Expenditures

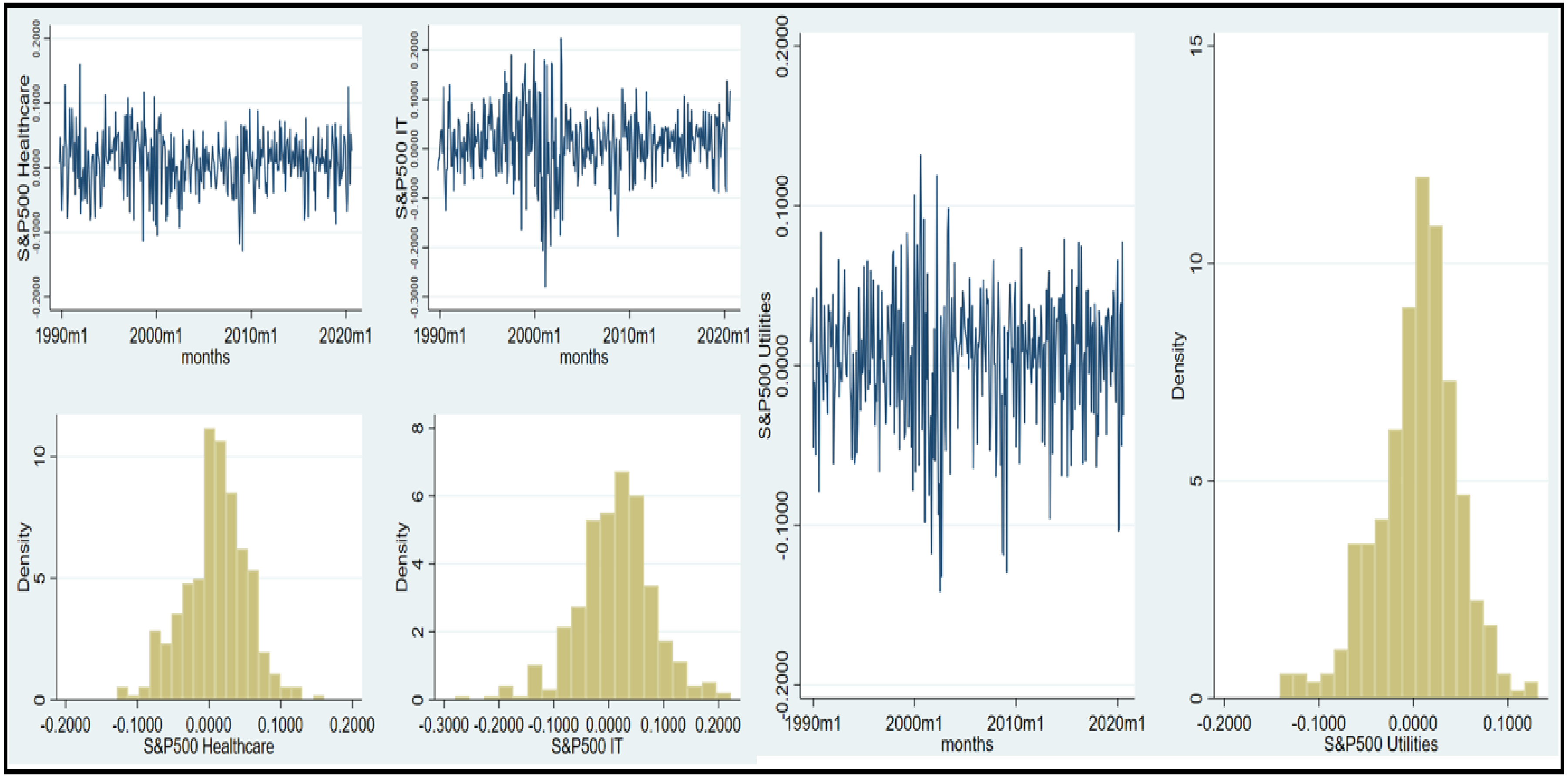
Figure 3.46 displays the volatility and density plots of four sectors of the S&P500 including Financials, Consumer Discretionary, Consumer Staples and Energy. It is interesting to note the stylized features of each individual sector. For instance, consumer discretionary stocks have much greater cyclical sensitivity to the broader business cycle and encapsulate much greater market volatility. This is evidenced through the wider bands of return volatility in Consumer Discretionary versus Consumer Staples with the latter ranging between +10% & -10% and the former bands ranging between +20% & -20%. The price change plots appear to also confirm the presence of volatility clustering across all sectors. Finally, we notice that certain equity sectors such as Energy are prone to idiosyncratic volatility shocks which are captured by very large spikes. The most recent example of this was the huge volatility in oil prices during the initial Covid-19 period. The same sector-specific volatility spike is evidenced through the behaviour of Financials during the Great Financial Recession. The density plots provide useful confirmation of general equity market negative skewness and the extreme volatility associated with those idiosyncratic equity sector such as Energy & Finance. The obvious representation of this is the extreme left tail distribution of Energy (-36%) and Financial (-27%). Figure 3.47 displays the volatility and density plots of an additional three sectors of the S&P500 including Healthcare, Information Technology, and Utilities. It is interesting to note the stylized features of each individual sector. For instance, Information Technology stocks encompass greater cyclical sensitivity to the broader business cycle and encapsulate much greater market volatility. This is evidenced through the wider bands of return volatility in Information Technology versus the more defensive sectors of the S&P500. The price change plots appear to also confirm the presence of volatility clustering across all three sectors. Finally, we notice that certain equity sectors such as IT are prone to idiosyncratic volatility shocks which are captured by very large spikes. The most recent example of this was the huge volatility (+/- 20%) in the IT sector during the 2000 “technology bubble”. In contrast, during this period of the sample, defensive sectors including Utilities and Healthcare were confined to a much narrower volatility range (+/- 10%). The density plots provide additional confirmation of the extreme volatility associated with those idiosyncratic equity sector such as Information Technology. The obvious representation of this is the extreme left tail distribution of the IT sector (-27%) versus positive skew in the Healthcare sector.

Figure 3.46: S&P500 Sector specific volatility & histogram charts



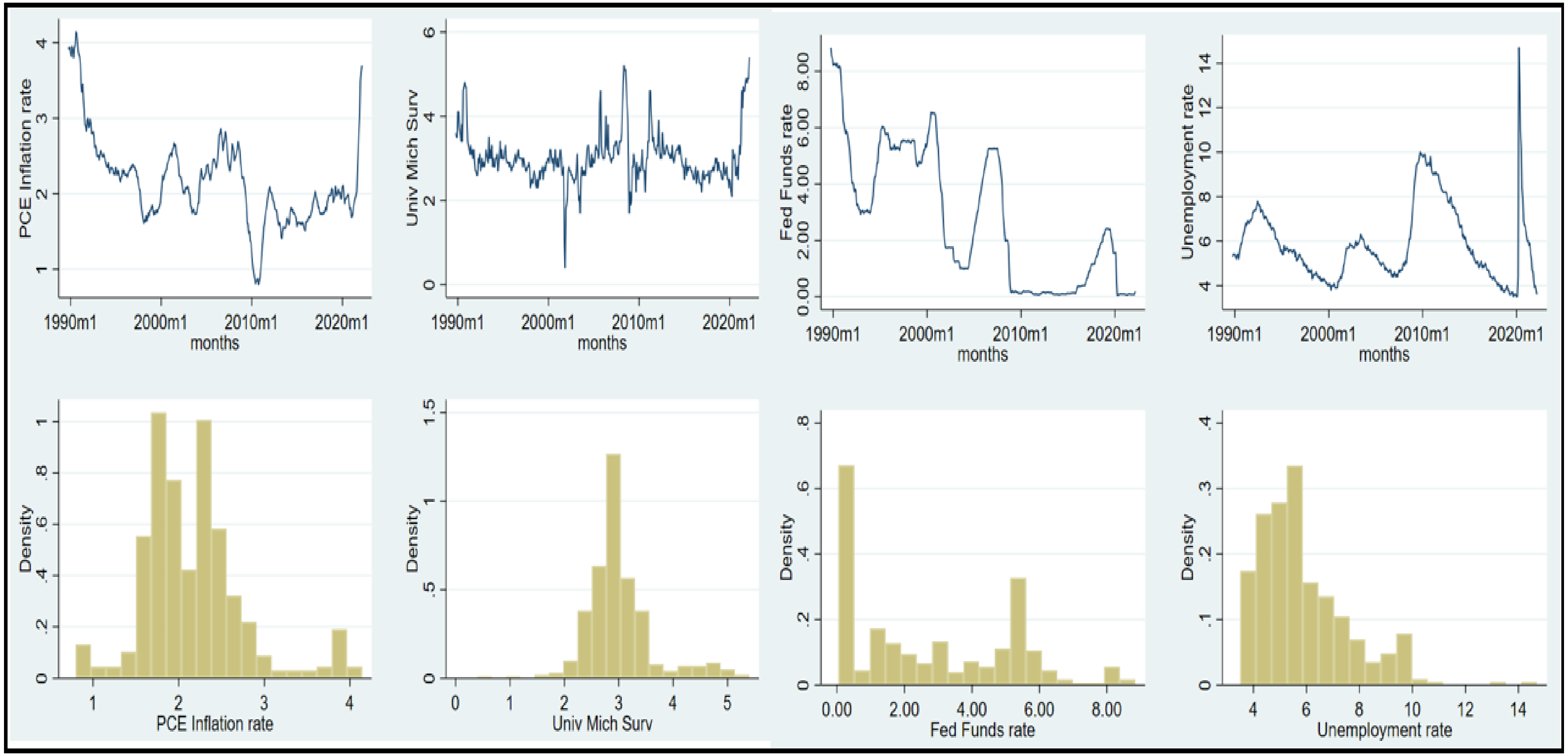
Source: Authors own chart /Figure 3.46 displays the volatility and density plots of four sectors of the S&P500 including Financials, Consumer Discretionary, Consumer Staples and Energy.

Figure 3.47: S&P500 Sector specific volatility & histogram charts



Source: Authors own chart /Figure 3.47 displays the volatility and density plots of an additional three sectors of the S&P500 including Healthcare, Information Technology, and Utilities.

Figure 3.48: Timeseries plots of PCE, Univ. Michigan, Fed Funds & Unemployment



Source: Authors own chart /Figure 3.48 displays the volatility and density plots of our key macroeconomic variables

3.4.11 Bayesian Analysis of S&P Equity Sectors

Our empirical results to date favour a probabilistic approach that endorses the inclusion of subjective, informationally efficient data. In chapter 1, we have produced evidence confirming the existence of economic regimes clearly delineated by altering state space characteristics. In chapter 2, we constructed an economic regime classification framework whose inputs are determined by a dynamic, fluid structure. Consistency requires that we utilise an econometric model that captures the non-linearities and unpredictable dynamics of financial markets. The Bayesian approach to statistical analysis looks upon model parameters in a very different way to traditional statisticians. The parameters are not viewed as fixed, unknown quantities but instead as random variables that may be described with a probability distribution. We can then attach belief to these probabilities. Bayesian inference relies on conditional probability. We are interested in finding the value of theta given the data available [P(θ|data)]. Bayes rule allows us to modify this as

$$\text{P}(\theta|\text{data}) = \frac{P(data|\theta)xP(\theta)}{P(data)}$$

where,

P(θ|data) is our parameter probability distribution or Posterior

P(data|θ) is the likelihood that given a particular value of theta, what would be the probability

of generating this data sample

P(θ) is a marginal probability capturing our belief of the historical prior data

P(data) is the probability of the data

3.5.2 Philosophical Methodology

Our focus on Bayesian inference rests on the assumption that prior information matters. Any study of financial time series recognises that economic data incorporates intrinsic, heuristic characteristics including volatility clustering, trending and regime-based economic environments dominated by a persistent, common set of market variables. In short, the prior or historical experience is significant. Bayesian inference supposes that the posterior distribution is proportional to the product of the likelihood function and the prior distribution of theta. The origins of Bayesian inference stem from the fundamental difference between traditional frequentist and Bayesian statistics. The classical approach or so-called "*frequentists*" treat the model parameters as unknown and fixed whereas "*Bayesians*" treat parameters as random and unknown. There have been philosophical debates about the true meaning of probability for centuries. Frequentist and Bayesian inference take a divergent look at what probability is. How do we define probability? Traditional statistical analysis places more emphasis upon the frequencies of data generation. Implicit in this approach is the traditional law of large numbers theory of frequency. This is both objective and mechanical in nature. Bayesian inference builds in some element of subjective experiences to the model. If the philosophical interpretation varies between these approaches, then the individual analysis must also differ. Frequentists analyse the variations of data by reference to fixed model parameters whereas Bayesians analyse the variation of beliefs about parameters by reference to fixed observed data. The data is observed and therefore fixed whilst the model varies around this fixed data. Frequentists use fixed models and state that the data varies around these fixed models. In the Bayesian approach what we are interested in fundamentally is a *Probability*.

Bayes Theorem allows us to generate the Posterior, or the probability of the model value given the data that has been observed. The theorem allows us to produce this posterior through identification of additional parameters including the likelihood, the prior belief and the model observables. The frequentist approach forms part of our Bayesian inference through the maximum likelihood. The prior gives us the probability distribution of our posterior "prior" to including the data. We can make assumptions about the information level of this prior. If we declare little knowledge, then we must utilise a non-informative prior. As the scale of uncertainty relating to the parameters increase so does the differences that exist between Bayesian and Frequentist approaches. Bayes theorem is a conditional probabilities deduction whereby the probability of the hypothesis B given the data A is equal to the product of the probability of the data A given the hypothesis B times the probability of the hypothesis B, all divided by the probability of the data A. Our hypothesis is some unknown or unobserved probability. Put simply, Bayes theorem gives us the probability of our hypothesis given the data.

$$\Pr(B|A) = \frac{\Pr(A|B)\,\Pr(B)}{\Pr(A)} \qquad \text{Eq.2}$$

Bayes theorem oversees this updating procedure, and we can decompose Eq. 2 further. The $\Pr(\theta|\text{data})$ or our Posterior distribution represents what we know after having reviewed the data. It is the product of the "*updating*" procedure of bayes theorem. In essence we incorporate the prior, collect the data and update the prior with this data. The $\Pr(\text{data}|\theta)$ is our likelihood, and the $\Pr(\theta)$ is our prior distribution or what we know before looking at the data. The Pr(data) is the integral of this term with respect to θ. Bayesian analysis is the preferred approach for this study owing to its robustness.

3.4.12 Impulse Response Function Testing

We compute several IRF statistics associated with our Bayesian VAR model. We compute the effects of shocks for up to 9 months into the future. These have been visually represented in Table 3.18 to Table 3.48 (refer to Appendix). The IRF command draws the posterior mean estimates of impulse response function coefficients along with 95% Crls. We start by inspecting the effect of a shock on the fed funds rate on the S&P500 IT and Consumer Discretionary sectors. Tables 3.56-3.59 have summarised the observations from these tests. We can summarise them succinctly as follows:

- Cyclically sensitive sectors of the S&P500 including IT and Consumer Discretionary appear to behave similarly to shocks in both the federal funds rate and consumer price inflation
- The durations of each reversion are also quite similar with consistency of reaction by independent response variables to a one standard deviation shock evident.
- Inflation sensitive sectors of the S&P500 including Energy and the JP Morgan natural resources fund appear to behave similarly to shocks in both the federal funds rate and consumer price inflation.
- Unlike the more cyclically sensitive response variables, positive shocks in the CPI lead to sharp positive increases in both the S&P500 Energy sector and the JP Morgan natural resources fund.
- There is evidence that independent response variables appear to behave in a consistent manner driven by the underlying economic regime.

Table 3.56: Impulse Response Functions – Summary Table 1

Impulse variable	Response variable	Regime	Growth	Inflation	Duration	Observation
Federal Funds rate	S&P500 IT	Regime 1	High	Low	2 months	Positive shock in fed funds results in initial decline in the S&P500 IT sector
Federal Funds rate	S&P500 Cons. Disc	Regime 1	High	Low	2 months	Positive shock in fed funds results in initial decline in the S&P500 Cons. Disc sector
Federal Funds rate	S&P500 IT	Regime 3	Low	High	4 months	Positive shock in fed funds results in initial rise in the S&P500 IT sector
Federal Funds rate	S&P500 Cons. Disc	Regime 3	Low	High	4 months	Positive shock in fed funds results in initial rise in the S&P500 Cons. Disc sector
Consumer Price Infl	S&P500 IT	Regime 1	High	Low	4 months	Positive shock in CPI results in initial rise in the S&P500 IT sector
Consumer Price Infl	S&P500 Cons. Disc	Regime 1	High	Low	2 months	Positive shock in CPI has no response/ Followed by initial rise in the S&P500 Cons. Disc sector for 2 months
Consumer Price Infl	S&P500 IT	Regime 3	Low	High	4 months	Positive shock in CPI results in sharp initial rise in the S&P500 IT sector, decl rapidly and flat after 3 months
Consumer Price Infl	S&P500 Cons. Disc	Regime 3	Low	High	4 months	Positive shock in CPI results in initial slight decline in the S&P500 Cons. Disc sector
Consumer Price Infl	S&P500 Energy	Regime 1	High	Low	3 months	Positive shock in CPI results in sharp initial rise in the S&P500 Energy sector, decl rapidly and flat after 3 months
Consumer Price Infl	JP Morgan Nat. Res	Regime 1	High	Low	3 months	Positive shock in CPI results in very sharp initial rise in the JPM Nat. res fund, decl rapidly and flat after 3 months
Consumer Price Infl	S&P500 Energy	Regime 3	Low	High	4 months	Positive shock in CPI results in initial rise in the S&P500 Energy sector, decl rapidly and flat after 4 months
Consumer Price Infl	JP Morgan Nat. Res	Regime 3	Low	High	3 months	Positive shock in CPI results in very sharp initial rise in the JPM Nat. res fund, decl rapidly and flat after 3 months

Upon observing the consistency of the underlying behaviour of our response variables to shocks in the macroeconomic impulses, we conducted further analysis across the independent assets. We have classified the response variables by their commonalities. For instance, the *S&P500* is closest aligned to both the "*Market*" & "*Small minus Big*" factors. Similarly, the "*Dox & Cox Equity Fund*" best captures the stylized behaviour of the S&P500. In contrast *Gold* is bracketed with a combination of the "*JP Morgan Natural Resources*" fund, "*commodities*" and the "*Conservative minus Aggressive*" factor. The response variables have been categorised based on reasonable assumptions relating to their behaviour during various stages of the business cycle. We have produced evidence supporting the thesis that the broader equity and the precious metals markets are inversely correlated through various stages of the business cycle. Table 3.57 appears to support the argument that this segmentation of assets may incorporate a broader sub-set of assets/ response variables.

Table 3.57: Impulse Response Functions – Summary Table 2

Impulse variable	Response variable	Regime	Growth	Inflation	Observation
Federal Funds rate	S&P500	Regime 1	High	Low	Initial slight decline flattening out after 3 months
Federal Funds rate	Market Factor	Regime 1	High	Low	Initial slight decline flattening out after 3 months
Federal Funds rate	SMB Factor	Regime 1	High	Low	Very slight decline flattening out after 3 months
Federal Funds rate	Dox & Cox Equity Fund	Regime 1	High	Low	Initial slight decline flattening out after 3 months
Federal Funds rate	S&P500	Regime 2	High	High	Flat | No response
Federal Funds rate	Market Factor	Regime 2	High	High	Slight rise and flattens after 1 month
Federal Funds rate	SMB Factor	Regime 2	High	High	Flat | No response
Federal Funds rate	Dox & Cox Equity Fund	Regime 2	High	High	Initial slight decline flattening out after 3 months
Federal Funds rate	S&P500	Regime 3	Low	High	Initial sharp decline for first month, rising rapidly and flattening off by month 4
Federal Funds rate	Market Factor	Regime 3	Low	High	Initial sharp decline for first month, rising rapidly and flattening off by month 4
Federal Funds rate	SMB Factor	Regime 3	Low	High	Initial sharp decline for first month, rising rapidly and flattening off by month 4
Federal Funds rate	Dox & Cox Equity Fund	Regime 3	Low	High	Initial sharp decline for first month, rising rapidly and flattening off by month 4

Impulse variable	Response variable	Regime	Growth	Inflation	Observation
Consumer Price Infl.	RMW Factor	Regime 1	High	Low	Initial sharp decline flattening out after 5 months
Consumer Price Infl.	S&P500	Regime 1	High	Low	Initial sharp increase flattening out after 5 months
Consumer Price Infl.	Market Factor	Regime 1	High	Low	Initial increase flattening out after 5 months
Consumer Price Infl.	Dox & Cox Equity Fund	Regime 1	High	Low	Initial increase flattening out after 5 months
Consumer Price Infl.	RMW Factor	Regime 2	High	High	Very slight rise with Flat | No response
Consumer Price Infl.	S&P500	Regime 2	High	High	Slight decrease and flattens after 5 months
Consumer Price Infl.	Market Factor	Regime 2	High	High	Slight decrease and flattens after 5 months
Consumer Price Infl.	Dox & Cox Equity Fund	Regime 2	High	High	Slight decrease and flattens after 5 months
Consumer Price Infl.	RMW Factor	Regime 3	Low	High	Initial sharp decline for first month, rising rapidly and flattening off by month 5
Consumer Price Infl.	S&P500	Regime 3	Low	High	Initial sharp decline for first month, rising rapidly and flattening off by month 4
Consumer Price Infl.	Market Factor	Regime 3	Low	High	Initial sharp decline for first month, rising rapidly and flattening off by month 4
Consumer Price Infl.	Dox & Cox Equity Fund	Regime 3	Low	High	Initial slight decline for first month, rising and flattening off by month 3

Tables 3.57 has summarised the observations from these tests. We can summarise them succinctly as follows:

- Cyclically sensitive assets including S&P500, the equity factors and equity fund appear to behave similarly to shocks in both the federal funds rate and consumer price inflation
- The durations of each reversion are also quite similar with consistency of reaction by independent response variables to a one standard deviation shock evident.
- We observe a generally muted/ subdued response in regimes 1 & 2 to a federal funds shock. A fed funds shock in regime 3 produces a sharp decline across all observable assets.
- The "growth" proxies in Table 3.57 appear to be much more sensitive to a CPI driven shock with sharp responses in regimes 1 and 3 most noticeably.

- Inflation sensitive sectors of the S&P500 including Energy and the JP Morgan natural resources fund appear to behave similarly to shocks in both the federal funds rate and consumer price inflation.
- Unlike the more cyclically sensitive response variables, positive shocks in the CPI lead to sharp positive increases in both the S&P500 Energy sector and the JP Morgan natural resources fund.
- There is evidence that independent response variables appear to behave in a consistent manner driven by the underlying economic regime.

Table 3.58: Impulse Response Functions – Summary Table 3

Impulse variable	Response variable	Regime	Growth	Inflation	Observation
Consumer Price Infl.	Gold	Regime 1	High	Low	Initial very sharp rise flattening out after 3 months
Consumer Price Infl.	JP Morgan Nat. Res	Regime 1	High	Low	Initial very sharp rise flattening out after 3 months
Consumer Price Infl.	CMA Factor	Regime 1	High	Low	Initial slight increase flattening out after 5 months
Consumer Price Infl.	Commodities	Regime 1	High	Low	Initial very sharp rise flattening out after 6 months
Consumer Price Infl.	Gold	Regime 2	High	High	Initial rise flattening out after 3 months
Consumer Price Infl.	JP Morgan Nat. Res	Regime 2	High	High	Initial rise flattening out after 3 months
Consumer Price Infl.	CMA Factor	Regime 2	High	High	Initial rise flattening out after 3 months
Consumer Price Infl.	Commodities	Regime 2	High	High	Slight decrease and flattens after 5 months
Consumer Price Infl.	Gold	Regime 3	Low	High	Initial sharp decline for first month, rising rapidly and flattening off by month 6
Consumer Price Infl.	JP Morgan Nat. Res	Regime 3	Low	High	Initial sharp rise for first month, declining slowly and flattening off by month 6
Consumer Price Infl.	CMA Factor	Regime 3	Low	High	Initial sharp decline for first month, rising rapidly and flattening off by month 6
Consumer Price Infl.	Commodities	Regime 3	Low	High	Slight decrease and flattens after 5 months

Tables 3.58 has summarised the observations from these tests. We can summarise them succinctly as follows:

- Inflation sensitive assets including "*Gold*", the "*JP Morgan natural resources fund*", the "*CMA*" factor and "*Commodities*" appear to behave similarly to shocks in both the federal funds rate and consumer price inflation.
- Unlike the more cyclically sensitive response variables, positive shocks in the CPI lead to sharp positive increases across the assets
- There is evidence that independent response variables appear to behave in a consistent manner driven by the underlying economic regime

Table 3.59provides evidence of the varying nature of the behaviour of our response variables dependent upon the underlying economic regime and the impulse function. We have included the foremost leading indicators of this research to support our analysis including the OECD Composite Leading Indicator (CLI) and the University of Michigan consumer sentiment index.

Table 3.59: Impulse Response Functions – Summary Table 4

Impulse variable	Response variable	Regime	Growth	Inflation	Observation
CLI	S&P500	Regime 1	High	Low	Initial very sharp rise flattening out after 6 months
CLI	Gold	Regime 1	High	Low	Initial very sharp rise flattening out after 3 months
CLI	JP Morgan Nat. Res	Regime 1	High	Low	Initial very sharp rise flattening out after 9 months
CLI	S&P500	Regime 2	High	High	Initial rise flattening out after 3 months
CLI	Gold	Regime 2	High	High	Initial sharp decline for first month, rising rapidly and flattening off by month 5
CLI	JP Morgan Nat. Res	Regime 2	High	High	Initial very sharp rise flattening out after 3 months
CLI	S&P500	Regime 3	Low	High	Initial slight rise flattening out after 1 month
CLI	Gold	Regime 3	Low	High	Very slight fall with Flat | No response
CLI	JP Morgan Nat. Res	Regime 3	Low	High	Initial very sharp rise flattening out after 5 months
Impulse variable	**Response variable**	**Regime**	**Growth**	**Inflation**	**Observation**
University of Michigan	S&P500	Regime 1	High	Low	Initial very sharp rise flattening out after 3 months
University of Michigan	Gold	Regime 1	High	Low	Initial rise and rapid decline flattening out after 3 months
University of Michigan	S&P500	Regime 2	High	High	Initial very sharp rise flattening out after 3 months
University of Michigan	Gold	Regime 2	High	High	Initial slight rise for first month and flattening off by month 3
University of Michigan	S&P500	Regime 3	Low	High	Initial very sharp rise flattening out after 3 months
University of Michigan	Gold	Regime 3	Low	High	Initial very sharp rise flattening out after 3 months

3.5 Dynamic Asset Allocation using Historical returns

In the previous section, we provided further evidence of the regime-dependent relationship between specific assets. We posed one final question: whether we could optimise investment portfolios utilising the leading indicators with the greatest informational efficiency in this study to date. Several hypothetical portfolios were constructed using historical asset performance. Table 3.60 provides some useful insights into the time-varying nature of asset returns. An equally weighted gold and equity portfolio (Portfolio Nr. 4) produced strong positive returns between January 1970 and December 1982. The returns for the preceding decades were much lower producing half the expected returns of the earlier period. The primary benefit of diversification is to enhance risk-adjusted returns. We note that the equally weighted portfolio numbers 1-3 are relatively consistent which appears to support this premise. The anthesis of diversification is concentrated holdings in single assets and market timing appears to be very important in this respect. We can see this through the performance of the gold portfolio numbers 16 &18 with concentrated holdings in gold producing large positive gains between 1970 & 1982 and again between 2000 & 2020. The returns during the intervening period (1983-1999) were vastly inferior however reinforcing the concept of mean reversion among asset returns.

Table 3.60 Portfolio-based Historical Returns

Portfolio Nr.	Group	Sample Period	Portfolio Return	Portfolio Nr.	Group	Sample Period	Portfolio Return
1	Equal Weight	1970-1982	€332,663 [9.7%]	4	Eq| Gold	1970-1982	€551,645 [14%]
2	Equal Weight	1983-1999	€384,600 [8.3%]	5	Eq| Gold	1983-1999	€311,921 [6.9%]
3	Equal Weight	2000-2020	€299,157 [5.6%]	6	Eq| Gold	2000-2020	€364,764 [6.7%]
Portfolio Nr.	Group	Sample Period	Portfolio Return	Portfolio Nr.	Group	Sample Period	Portfolio Return
7	Eq| Commod	1970-1982	€217,900 [6.2%]	10	Eq| Corp. B	1970-1982	€215,345 [6%]
8	Eq| Commod	1983-1999	€336,800 [7.4%]	11	Eq| Corp. B	1983-1999	€541,025 [10%]
9	Eq| Commod	2000-2020	€195,396 [3.4%]	12	Eq| Corp. B	2000-2020	€262,686 [4.95%]
Portfolio Nr.	Group	Sample Period	Portfolio Return	Portfolio Nr.	Group	Sample Period	Portfolio Return
13	Eq| 10 Yr. Treas	1970-1982	€254,169 [7.4%]	16	Gold	1970-1982	€862,218 [18%]
14	Eq| 10 Yr. Treas	1983-1999	€531,343 [10.3%]	17	Gold	1983-1999	€56,553 [-3.31%]
15	Eq| 10 Yr. Treas	2000-2020	€251,183 [4.7%]	18	Gold	2000-2020	€552,970 [8.5%]

Observations

It is immediately observable that portfolio returns vary widely depending upon the underlying economic regime. We have already classified regime 1 (1970-1983) as a low-growth and high inflationary regime. The portfolio performance confirms the evidence suggested in chapters 1 & 2 that extra allocation to traditional inflation hedges including gold outperforms equally weighted portfolios. We note that the equally weighted portfolio nr. 1 produces a positive annualised gross return of 9.7% between 1970 & 1982. A combination of equities and gold over the same period produced annualised returns of

14% per annum. It is interesting to note that a combination of equities and commodities (Portfolio 7) underperformed both the equally weighted portfolio (Portfolio 1) and the split portfolio of equities and bonds (Portfolio 7) during the same period. This finding would support the literature in evidence of equities providing a long-term inflation hedge. Ely & Robinson (1997) are critical of the traditional modelling used to capture the relationship between equities and inflation stating that their appears to be too much emphasis on the short-run relationships. Using a reduced-form approach, they find evidence supporting the thesis that stock prices maintain their value relative to goods prices during periods of rising inflation. We have produced evidence that regime 2 (1983-199) may be classified as a high growth and low inflation regime. It is interesting to observe that both the equity/gold portfolio selection (Portfolio 5) and the equity/commodities portfolio selection (Portfolio 8) underperformed the equally weighting portfolio (Portfolio 2) during this period. These asset allocation results are consistent with the evidence produced in chapters 1 & 2 suggesting that "growth" assets such as equities and corporate bonds should outperform inflation assets (Gold/ commodities) during a high growth| low inflation environment. The substantial underperformance of a concentrated holding in gold (Portfolio 17) during this period is also notable given the strong track record in the preceding decades of 18% annualised returns. We have already classified regime 3 (2000-2020) as a low-growth and low inflationary regime. Despite strong positive equity market returns during this two-decade period, we immediately identify a noticeable decline in portfolio performance across most portfolios from the preceding regimes. We could argue that the process of diversification largely underperformed during this period as all portfolios (excl. concentrated gold holdings) were less than the previous regime. Further research is warranted on the influence of global monetary policy expansion during this period and possible distortionary impacts of government policy on public markets.

The NBER have officially registered seven unique recessionary periods since 1970. These are listed in Table 3.50 below. Evidence has been produced already to support the relationship between leading indicators including the ISM, University of Michigan sentiment survey and Composite Leading Indicator and key macroeconomic variables. This study now seeks to identify whether each of these leading indicators are consistent in predicting key recessionary turning points. Each leading indicator has been mapped across a four-quadrant economic regime framework including recovery, expansion, downturn and slowdown. There is evidence that our leading indicators are consistent across the full sample period.

Table 3.61: Recessionary Periods since 1970

Peak month (Peak Quarter)	Trough month (Trough Quarter)	Contraction	Expansion	Cycle	
		Duration, peak to trough	*Duration, trough to peak*	*Duration, trough to trough*	*Duration, peak to peak*
December 1969 (1969Q4)	November 1970 (1970Q4)	11	106	117	116
November 1973 (1973Q4)	March 1975 (1975Q1)	16	36	52	47
January 1980 (1980Q1)	July 1980 (1980Q3)	6	58	64	74
July 1981 (1981Q3)	November 1982 (1982Q4)	16	12	28	18
July 1990 (1990Q3)	March 1991 (1991Q1)	8	92	100	108
March 2001 (2001Q1)	November 2001 (2001Q4)	8	120	128	128
December 2007 (2007Q4)	June 2009 (2009Q2)	18	73	91	81
February 2020 (2019Q4)	April 2020 (2020Q2)	2	128	130	146

The behaviour of each leading indicator is mapped out in greater detail in Appendix 2. The summary details are covered here across each of the seven official recessionary periods. We have summarised the optimal portfolio tilts based on the behaviour of these leading indicators in Table 3.62.

1. Peak to Trough recession period: <u>December 1969 – November 1970</u>

Institute of Supply Management (ISM)

- ISM entered a *slowdown* phase in April 1970
- Negative ISM releases lasted 20 months ending in November 1971

2. Peak to Trough recession period: <u>November 1973 – March 1975</u>

Institute of Supply Management (ISM)

- ISM entered a *downturn* phase in November 1973
- Negative ISM releases lasted 9 months
- ISM entered a *slowdown* phase in August 1974
- Slowdown phase lasted until November 1975

Composite Leading Indicator (CLI)

- CLI entered a *downturn* phase in September 1973
- Negative CLI releases lasted 7 months
- CLI entered a *slowdown* phase in April 1974
- Slowdown phase lasted until September 1974

University of Michigan, Consumer Expectations TBC

- UMCS entered a *downturn* phase in September 1973
- Negative UMCS releases lasted 7 months
- UMCS entered a *slowdown* phase in April 1974

- Slowdown phase lasted until September 1974

3. Peak to Trough recession period: <u>January 1980 – July 1980</u>

Institute of Supply Management (ISM)

- ISM entered a *downturn* phase in March 1979
- Negative ISM releases lasted 19 months until September 1980

Composite Leading Indicator (CLI)

- CLI entered a *downturn* phase in March 1979
- Negative CLI releases lasted 12 months until March 1980

University of Michigan, Consumer Expectations

- Inflation expectations increased in January 1979
- Positive UMCS releases lasted until February 1981

4. Peak to Trough recession period: <u>July 1981 – November 1982</u>

Institute of Supply Management (ISM)

- ISM entered a *downturn* phase in May 1981
- Negative ISM releases lasted 14 months until November 1982

Composite Leading Indicator (CLI)

- CLI entered a *downturn* phase in October 1980
- Negative CLI releases lasted 12 months until October 1981
- Negative CLI releases reappeared in January 1982 until April 1982

University of Michigan, Consumer Expectations

5. Peak to Trough recession period: <u>July 1990 – March 1991</u>

Institute of Supply Management (ISM)

- ISM entered a *downturn* phase in October 1989
- Negative ISM releases lasted 16 months until January 1991

Composite Leading Indicator (CLI)

- CLI entered a *downturn* phase in February 1990
- Negative CLI releases lasted 8 months until September1990
- A full-blown slowdown emerged in June 1991 and lasted until December 1991

University of Michigan, Consumer Expectations

- Inflation expectations increased in November 1987
- Positive UMCS releases lasted until April 1991

6. Peak to Trough recession period: <u>March 2001 – November 2001</u>

Institute of Supply Management (ISM)

- ISM entered a *downturn* phase in June 2000
- Negative ISM releases lasted 20 months until April 2002

Composite Leading Indicator (CLI)

- CLI entered a *downturn* phase in November 1999
- Negative CLI releases lasted 15 months until January 2001
- A full-blown slowdown emerged in March 2002 and lasted until August 2002

University of Michigan, Consumer Expectations

- Inflation expectations increased in January 2000
- Positive UMCS releases lasted until June 2002

7. Peak to Trough recession period: <u>December 2007 – June 2009</u>

Institute of Supply Management (ISM)

- ISM entered a *downturn* phase in May 2007
- Negative ISM releases lasted 26 months until July 2009

Composite Leading Indicator (CLI)

- CLI entered a *downturn* phase in January 2007
- Negative CLI releases lasted 17 months until May 2008
- A full-blown slowdown emerged in June 2008 and lasted until October 2008

University of Michigan, Consumer Expectations

- Inflation expectations increased in March 2005
- Positive UMCS releases lasted until July 2008

Table 3.62: Leading Indicator Summary results

Regime	ISM	CLI	UMICH	Observations
1. Peak to Trough recession period: December 1969 – November 1970	Apr-70 Nov-71		*No Data*	The ISM turned negative in April 1970 until November 1971
2. Peak to Trough recession period: November 1973 – March 1975	Nov-73 Aug-74 Nov-75	Sep-73 Apr-74 Sep-74	*No Data*	Both the ISM and the CLI turned negative in Q3 1973. Both indicators also forecasted a slowdown in August & April of 1974 respectively.
3. Peak to Trough recession period: January 1980 – July 1980	Mar-79 Sep-80	Mar-79 Mar-80	Jan-79 Jun-80	All three indicators forecasted a growth slowdown in Q1 1979 with various turning pt forecasts between March & September 1980
4. Peak to Trough recession period: July 1981 – November 1982	May-81 Nov-82	Oct-80 Oct-81 Jan-82 Apr-82	Sep-81 Sep-82	The CLI was the first indicator to turn negative in Ocotber 1980 followed in May 1981 by the ISM and the Univ. Michigan consumer sentiment index in September 1981
5. Peak to Trough recession period: July 1990 – March 1991	Oct-89 Jan-91	Feb-90 Jun-91 Dec-91	May-89 May-91	All three indicators forecasted a growth slowdown before the peak in July 1990
6. Peak to Trough recession period: March 2001 – November 2001	Jun-00 Apr-02	Nov-99 Jan-01 Mar-02 Aug-02	Dec-00 Jan-02	All three indicators forecasted a growth slowdown before the peak in March 2001
7. Peak to Trough recession period: December 2007 – June 2009	May-07 Jul-09	Jan-07 May-08 Jun-08 Oct-08	Sep-07 Mar-09	All three indicators forecasted a growth slowdown before the peak in December 2007

Legend
Negative Data Print
Positive Data Print

3.5.1 Asset allocation utilising leading indicators

In the following section, we assess the accuracy and ability of our shortlisted selection of leading indicators to forecast key turning points in the macroeconomic environment. We have already established in Chapter 2 that leading indicators including the ISM, CLI and University of Michigan sentiment survey index produce consistent evidence of forecasting macroeconomic turning points. The main aim of this research is to identify asset allocation strategies that optimise portfolio construction through a regime-based asset allocation approach. We test the accuracy of these leading indicators in the following section by analysing their behaviour across each of our three sample periods.

i. Regime 1: 1970-1982

This period was a disorderly time in global financial markets borne out by the fact that four out of the seven official recession periods since 1970 were recorded during this initial 12-year period. In September 1973, our Composite Leading Indicator (CLI) indicated a downturn in growth expectations. The subsequent negative growth would persist for several months transitioning into a full slowdown in April 1974. The slowdown would persist for six months. We sought to test the optimality of making portfolio adjustments in advance of this challenging growth period. Table 3.63 illustrates the portfolio performance differential if a proactive tactical decision was taken to reduce the equity holdings and reallocate to gold. From this point, the strike date will describe the specific date at which the asset allocation changes were made. Table 3.63 captures two individual strike dates. The initial portfolio adjustment on the 1st of February 1972 involves a full liquidation of the equity holdings and purchase of gold. This results in a significant performance improvement over the duration of the regime (47.92%). The second-strike date of November 1976 represents a rebalancing of the strategy back into equities (albeit at lower levels of 15.26%). The rebalancing is driven by positive behaviour of the leading indicators suggesting a return to positive economic environment. Although the final portfolio differential performance is reduced from 47.92% to 21.52%, the regime-based asset allocation approach incorporating leading indicators has optimised returns.

Table 3.63: Dynamic allocation 1 (1972-1983)

Date	Starting Capital	€16,666.67	€16,666.67	€16,666.67	€16,666.67	€16,666.67	€16,666.67	Portfolio Return	Differential
	Asset	SP500	Nikkei225	Gold	Non-Energy	US CorpB Indx	10 Year Treas		
01/01/1970	EQUAL WEIGHT	16.67%	16.67%	16.67%	16.67%	16.67%	16.67%	€332,663.15	
01/02/1972	PORT ADJ.	0%	0%	52.26%	14.50%	14.38%	18.86%	€492,090.62	47.92%
01/11/1976	PORT ADJ.	15.26%	15.26%	30.51%	15.32%	10.21%	13.45%	€404,268.84	21.52%

In this section, we test several other key economic turning points as defined by our set of leading indicators to ascertain whether the identification of *regime shifts* results in optimal portfolio construction. In Quarter 1 1979, all three leading indicators forecasted a growth slowdown. The various turning point forecasts would last until between March & September 1980. It is interesting to note both the consistency of indicator behaviour (i.e., negative) and the proximity of forecasts. The official recession would commence a full 10 months later in January 1980. As per Table 3.64, the equally weighted portfolio held continuously from January 1970 to December 1982 produces a final portfolio figure of €332,663.15.

Table 3.64 Dynamic allocation **2** (1972-1983)

DATE	Starting Capital	€16,666.67	€16,666.67	€16,666.67	€16,666.67	€16,666.67	€16,666.67	Portfolio Return	Differential
	Asset	SP500	Nikkei225	Gold	Non-Energy	US CorpB Indx	10 Year Treas		
01/01/1970	EQUAL WEIGHT	16.67%	16.67%	16.67%	16.67%	16.67%	16.67%	€332,663.15	
01/03/1979	PORT ADJ.	0%	0%	62.25%	16.02%	9.58%	12.16%	€340,011.00	2.21%
01/06/1980	PORT ADJ.	25.61%	25.61%	25.61%	10.15%	5.60%	7.42%	€450,238.65	35.34%

Table 3.64 also captures the initial portfolio adjustment on the 1st of March 1979. This encompassed a full liquidation of the equity holdings and re-purchase of gold given the consistent negative sentiment across our indicators. The median expectation of recovery is June 1980. We utilised this date for our second-strike date and rebalancing of equity exposures given the recovery in growth expectations and sentiment. This results in a significant performance improvement over the duration of the regime (35.34%). The second-strike date of June 1980 represents a rebalancing of the strategy back into equities (at higher levels of 25.61%). The rebalancing is driven by positive behaviour of the leading indicators suggesting a return to positive economic environment. Although the final portfolio differential performance is increased from just 2.21% to 35.34%, the

regime-based asset allocation approach incorporating leading indicators has optimised returns through active asset allocation.

ii. Regime 2: 1983-1999

The NBER list of officially recognised recessionary cycles appears to validate the ordering of this study's economic regimes. Recessions are most closely associated with prolonged periods of growth slowdown. In chapter two, we classified the period between 1983 & 1999 as a high-growth and low inflation regime. Consistent with our approach we note that the NBER include a single recessionary episode during this 18-year period – *July 1990 to March 1991*. Whilst our leading indicators identified additional periods of below average growth during this regime, the study assesses the optimality of an RBAA approach within the confines of the NBER designated recessionary periods.

It is interesting to note that all three leading indicators forecasted a growth downturn well before the peak of the economic cycle in July 1990. The ISM released negative data publications in October 1989. This was seven months before the official slowdown in July the following year. The University of Michigan consumer sentiment index forecasted negative consumer sentiment in May 1989 and the CLI numbers turned negative in February 1990. Both the ISM and UM indicators forecast better economic conditions in January 1991 and May 1991 respectively. The CLI had a shorter lead-time of five months, so the recovery was not forecasted until December of 1991. The latter had forecasted a full-blown slowdown in June 1991. It is interesting to note that the NBER designated recessionary period lasted just nine months. In contrast the average duration of peak to trough negative to positive sentiment range from the three leading indicators was eighteen months. One could reasonably hypothesise that the sequencing of the individual leading indicators is better understood through the framework of the *economic machine thesis*[85]. For instance, we observe that the earliest leading indicator to turn negative is the University of Michigan consumer sentiment index. The ISM follows five months later followed by the broader (perhaps more diluted) composite leading index four months later. We see a logical flow of negative sentiment from the consumer (UM) through to business and industry (ISM) and finally into the broader market (CLI).

[85] Ray Dalio (2017) proposed a mechanical framework for understanding the underlying processes that drive global financial markets. His work focusses on the inter-relationships between consumers, workers and business. He asserts that the economic machine continues to produce positive economic growth through a combination of entrepreneurial innovation and productivity growth over the long-term and credit availability over the short-term.

We sought to test the optimality of making portfolio adjustments in advance of this challenging growth period. Table 3.65 illustrates the portfolio performance differential if a proactive tactical decision was taken to reduce the equity holdings and reallocate to gold. Table 3.65 captures two individual strike dates. The initial portfolio adjustment on the 1st of October 1989 involves a full liquidation of the equity holdings and purchase of gold. The second-strike date of May 1991 represents a rebalancing of the strategy back into equities (albeit at slightly higher levels of 17.77%). The rebalancing is driven by positive behaviour of the leading indicators suggesting a return to positive economic environment. It is interesting to note that on this occasion, the regime-based asset allocation approach incorporating leading indicators has failed to significantly optimise returns. The differential of just 1.2% in portfolio performance is likely to have been reduced further by the inclusion of trading and transaction costs.

Table 3.65: Dynamic allocation 3 (1983-1999)

DATE	Starting Capital	€16,666.67	€16,666.67	€16,666.67	€16,666.67	€16,666.67	€16,666.67	Portfolio Return	Differential
	Asset	SP500	Nikkei225	Gold	Non-Energy	US CorpB Indx	10 Year Treas		
01/01/1983	EQUAL WEIGHT	16.67%	16.67%	16.67%	16.67%	16.67%	16.67%	€384,600.18	
01/10/1989	PORT ADJ.	0%	0%	56.36%	9.36%	17.14%	17.14%		
01/05/1991	PORT ADJ.	17.77%	17.77%	17.77%	8.39%	19.37%	18.92%	€389,205.44	1.20%

Does this result weaken our research findings to date? In fact, the regime-based asset class performance data uncovered in chapter 2 should have guided us away from allocations to gold in a dis-inflationary regime. The period 1983-1999 is a dis-inflationary regime. Therefore, despite the strong evidence uncovered in chapter 1 of the ability of gold to protect portfolios during stress events, the underlying economic regime appears to have significance. To reinforce this point, we repeated the portfolio adjustment exercise utilising the exact economic turning point dates as indicated by our leading indicators. Traditionally fixed income securities have been utilised in portfolio construction owing to the negative correlation with stocks. When we included the 10-year treasury returns as a defensive portfolio allocation adjustment displayed in Table 3.66, the overall improvement in portfolio returns is significant. An important conclusion here therefore is that defensive assets such as gold and fixed income securities will behave differently irrespective of the degree of market stress dependent upon the underlying economic regime. The underperformance of gold appears to have had less to do with the assets ability to hedge out systemic risk and more with its intrinsic relationship to the underlying inflationary regime.

Table 3.66: Dynamic allocation 4 (1983-1999)

DATE	Starting Capital	€16,666.67	€16,666.67	€16,666.67	€16,666.67	€16,666.67	€16,666.67	Portfolio Return	Differential
	Asset	SP500	Nikkei225	Gold	Non-Energy	US CorpB Indx	10 Year Treas		
01/01/1983	EQUAL WEIGHT	16.67%	16.67%	16.67%	16.67%	16.67%	16.67%	€384,600.18	
01/10/1989	PORT ADJ.	0%	0%	5.87%	9.40%	17.23%	67.51%		
01/05/1991	PORT ADJ.	25.45%	25.45%	4.01%	5.94%	13.71%	25.45%	€621,171.44	61.51%

Source: Authors own production

iii Regime 3: 2000-2020

As noted previously recessionary periods are most closely associated with an economic growth downturn and eventual slowdown. In chapter 2, we classified the period between January 2000 and December 2019 as a low growth| low inflation regime. As is consistent with the evidence to date, low growth regimes produce more instances of recessionary periods. If we had extended our sample by a further six months to June 2020, this period would have captured three officially recognised NBER recessions. It is interesting to note that all three leading indicators forecasted a growth downturn well before the peak of the economic cycle in March 2001. It should be noted that although the official recession period commenced in March of 2001 (according to the NBER), the US stock market peaked a full 12 months earlier in March 2000. There is an abundance of academic literature supporting the thesis that the stock market itself is an accurate leading indicator of the economic cycle[86]. The ISM released negative data publications in June 2000 just two months after the US technology index the Nasdaq peaked. Unlike previous downturns, the consumer sentiment indicator lagged the ISM by six months reporting negative sentiment in December 2000. We may hypothesise that a common phenomenon known as the wealth effect[87] may have influenced the sequencing of our indicators. Case, Quigley & Shiller (2005) examined the linkages between household wealth, consumer behaviour and financial wealth. In their international study, they found a strong statistical relationship between positive household wealth and consumer confidence. This may explain why the University of Michigan sentiment index lagged the ISM during this period as investors felt the pain of wealth destruction after six months of market declines. Both the ISM and UM indicators forecasted better economic conditions in Q1/Q2 2002. As with other periods we have studied the CLI appears to produce more elongated periods

[86] Comincioli, B., (1996) & Broome, S. and Morley, B., (2004)
[87] Case, K.E, Quigley, J.M & Schiller, R.J. (2005)

of negative growth prospects. The composite nature of the index means that it may be less concentrated by construction and therefore not as agile to market turning points. The CLI recovery was not forecast until August of 2002 with a full-blown slowdown projected just five months previously.

We sought to test the optimality of making portfolio adjustments in advance of this challenging growth period. We have illustrated the portfolio performance differential if a proactive tactical decision was taken to reduce the equity holdings and reallocate to gold. Table 3.67 captures two individual strike dates. The initial portfolio adjustment on the 1st of June 2000 involves a full liquidation of the equity holdings and purchase of gold. The second-strike date of April 2002 represents a rebalancing of the strategy back into equities (albeit at slightly lower levels of 15.69%). The rebalancing is driven by positive behaviour of the leading indicators suggesting a return to positive economic environment. The figure of €319,742.57 represents the total portfolio performance excluding any regime-based tactical allocation during the global financial crisis of 2008. The performance differential is a modest 6.88%. It is important to highlight however that in this example, we are reallocating into a balanced, well diversified portfolio. Therefore, due to a lack of concentrated holdings for much of the regime the variance of portfolio returns is relatively stable. It is interesting to note however that the regime-based asset allocation positioning during the GFR has a substantial positive impact on the portfolio returns (44.65%).

Table 3.67: Dynamic allocation 5 (2000-2020)

DATE	Starting Capital	€16,666.67	€16,666.67	€16,666.67	€16,666.67	€16,666.67	€16,666.67	Portfolio Return	Differential
	Asset	SP500	Nikkei225	Gold	Non-Energy	US CorpB Indx	10 Year Treas		
01/01/2000	EQUAL WEIGHT	16.67%	16.67%	16.67%	16.67%	16.67%	16.67%	€299,157.35	
01/06/2000	**PORT ADJ.**	0%	0%	48.48%	16.64%	16.99%	17.89%		
01/04/2002	**PORT ADJ.**	15.69%	15.69%	15.69%	14.62%	18.76%	19.56%	€319,742.57	**6.88%**
DATE	Asset	SP500	Nikkei225	Gold	Non-Energy	US CorpB Indx	10 Year Treas		
01/05/2007	**PORT ADJ.**	0%	0%	48.59%	19.44%	16.16%	15.81%		
01/07/2009	**PORT ADJ.**	17.91%	17.91%	17.91%	15.71%	14.51%	16.05%	**€432,737.97**	**44.65%**

Global Financial Crisis (2008)

As is consistent with our study to date, all three leading indicators forecasted a growth downturn well before the peak of the economic cycle in December 2007. The ISM released negative data publications in May 2007. Like the so-called "technology bubble" in 2000, the consumer sentiment indicator lagged the ISM by four months reporting negative sentiment in September 2007. This is further evidence is support of the wealth effect. Both the ISM and UM indicators forecasted better economic conditions in Q3/Q1 2002 respectively. Unlike other periods we have studied, the CLI appears to produce much shorter forecast of negative growth prospects with encouraging data emerging in October 2008.

3.6 Conclusion

We have produced evidence which is consistent with the literature that economic regimes influence asset prices. Our unique approach focuses on testing this relationship across multiple regimes using both contiguous and non-contiguous sampling methods. We used a distinctive macroeconomic factor model incorporating the key variables growth and inflation to inform the dynamics of these individuals state spaces. Additionally, we adopted a novel forecasting methodology to identify important turning points in the business cycle and included multiple assets ranging from individual securities to investment factors as part of our robustness checks. We have established through our empirical investigations that financial asset behaviour is determined by the inherent volatility of economic regimes. If assets do not exist in a vacuum, then a deeper understanding of the drivers of these economic forces is required. Whilst we have focussed primarily on the relationship between financial assets and regimes, an important question for further research relates to the "drivers of economic regimes". We have utilized an original regime classification framework (informed by established economic theory) in subsequent chapters to identify these drivers. Additional research is warranted in uncovering the "behavioural biases" embedded in the classification of these unique state spaces. Importantly, we have confirmed both the existence of a low-volatility equity premium and a portfolio risk reduction factor through allocating to precious metals. The primary research question in chapter 3 was whether portfolio optimization is attainable by implementing a leading indicator macroeconomic framework. The initial econometric modelling focussed on identifying these influential leading indicators through a Bayesian VAR set up. If causal inference could be established through recurrent impulse response function testing, then this information could prove effective in the design of our "early warning" dynamic asset allocation model. For robustness, there is a requirement to utilise a broad range of asset specific instruments to test the statistical significance of our findings. Unique to this study, multiple sources of investible securities were sourced ranging from mutual funds, physical holdings, equity-linked instruments and factor-based investments. The consistency of the results, irrespective of the underlying investible security, provided further evidence of the considerable influence of macroeconomic regimes. Having secured a short-list of consistently significant leading indicators, the study sought to assess the capacity of these to forecast key turning points in the macroeconomy. In the interest of avoiding data mining issues, our ex-post portfolio construction analysis focussed strictly on the official recession dates published by the NBER since 1970. We develop a unique macroeconomic leading indicator framework which constantly update our "beliefs" and is consistent with the Bayesian approach to statistical inference adopted in this research. The results support the primary contention of this research. Optimal portfolio construction is enhanced through the incorporation of a regime-based asset allocation approach. Our core research findings are in conflict with a traditional mean-variance framework of portfolio construction. The latter expresses the relationship between expected return and risk linearly whereas our model incorporates non-linearity and time-invariance. Further research in optimal asset allocation may incorporate more dynamic models including the Black-Litterman portfolio optimisation model which has much in common with the key findings of this paper.

Our empirical analysis provides an important contribution to the existing literature on dynamic portfolio construction. In the following section we feature five specific areas of the research which offer a unique perspective to the existing literature. Firstly, our study uses a novel leading indicator framework informed by the inter-relationship between macroeconomic variables and leading (consumer, business and sentiment) indexes. This sequential "*early warning*" process offers distinctive improvements in the practical implementation of portfolio construction within the regime-shifting literature. Much of the existing research focuses primarily on the identification of regimes. The *identification* and *classification* of unique state spaces in chapters *one* and *two* respectively provides the foundation from which our forecasting model develops. Our approach is novel in the manner that we dissect the full fifty-year sample into individual sub-periods and conduct additional empirical analysis. This supports the linkages between the contiguous and non-contiguous data sampling. The research provides novel contributions to the literature with the consistency with which all four sub-regimes are classified. We capture four individual samples covering four assets per sample resulting in 16 sets of parameter estimates. It is noteworthy that 87.5% of our observations are consistent with both the low-volatility equity premium and portfolio risk reduction factor. We have also identified key trends and consistencies associated with economic regimes and their duration not captured previously in the literature. Additionally, the integration of a wide array of assets[88] to assess consistency is novel within the literature. Assets were categorised based on their behaviour during low and raised volatility periods. Most of the existing literature focussed its analysis on individual asset classes. This study is unique in its inclusion of characteristically comparable assets. For instance, those assets closely positively correlated with economic growth including the *S&P500*, the *market factor, SMB* factor, *cyclically sensitive equity sectors*[89] and individual equity funds formed one cohort. Alternatively, *gold*, the *commodity* sector and the *JP Morgan natural resources mutual fund* formed a different subset for analysis. The consistency in behaviour of the constituent's subset to shocks in macroeconomic variables offered unique "category" evidence as opposed to individual "asset" based evidence in the existing literature. Finally, the economic classification model adopted in chapter two offers a unique framework in the regime-shifting literature. Our two-factor model is primarily informed by the dynamic nature of the independent and inter-dependent relationship between economic growth and inflation. A more novel aspect to this approach however is the implied monetary policy implications associated with the regime classification process. As detailed in Chapter two, and absent in the current literature, our classification process incorporates the reaction function of Central Banks to shifts in the rate of change in growth and inflation.

[88] including *equity sectors*, *mutual funds*, *factors* and *securities*
[89] Consumer discretionary and Information technology stocks.

3.7 Tables & Figures

Table 3.18: FED funds shock/ S&P500 IT & S&P500 Consumer Disc

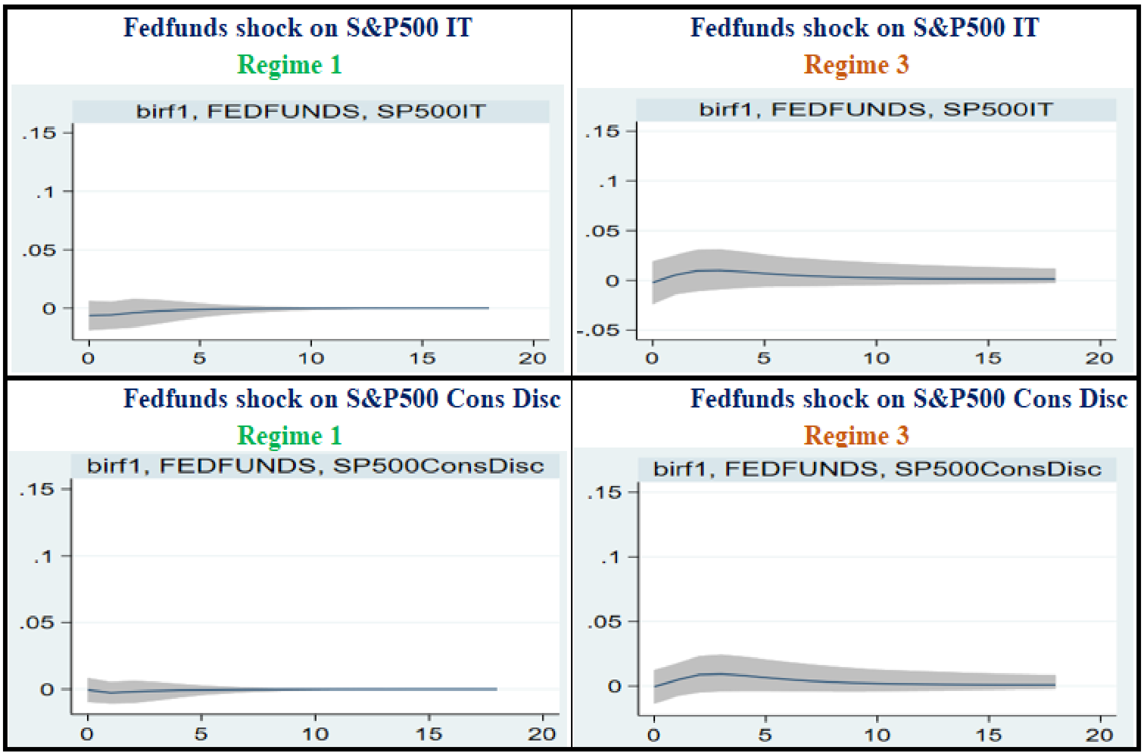


Table 3.19: CPI shock/ S&P500 IT & S&P500 Consumer Disc

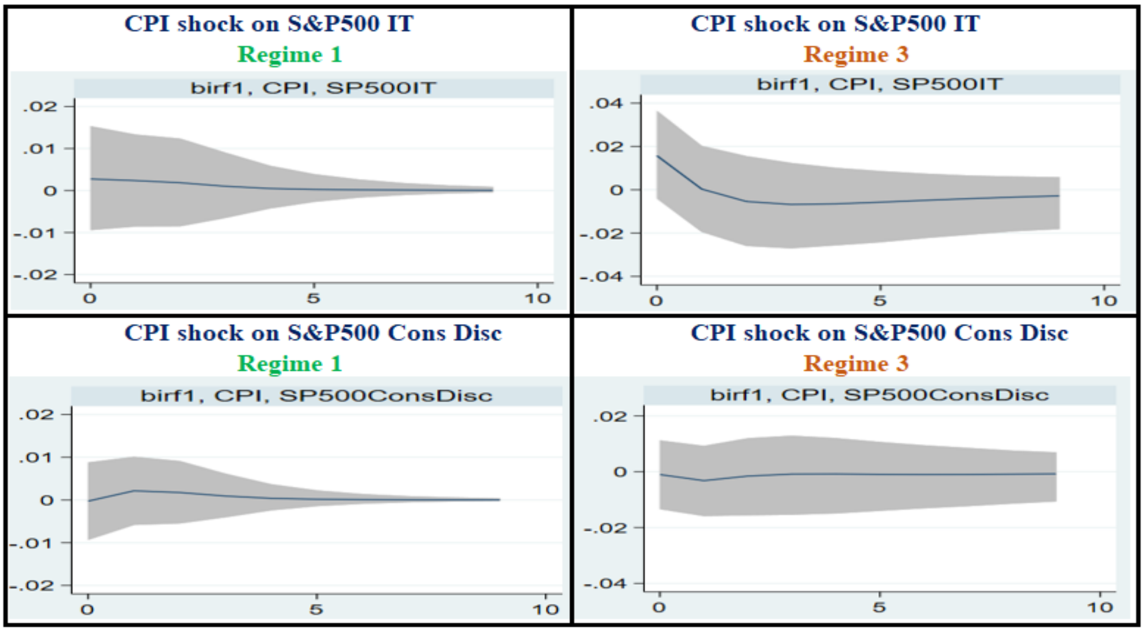


Table 3.20: CPI shock/ S&P500 Energy & JPM Natural Resources

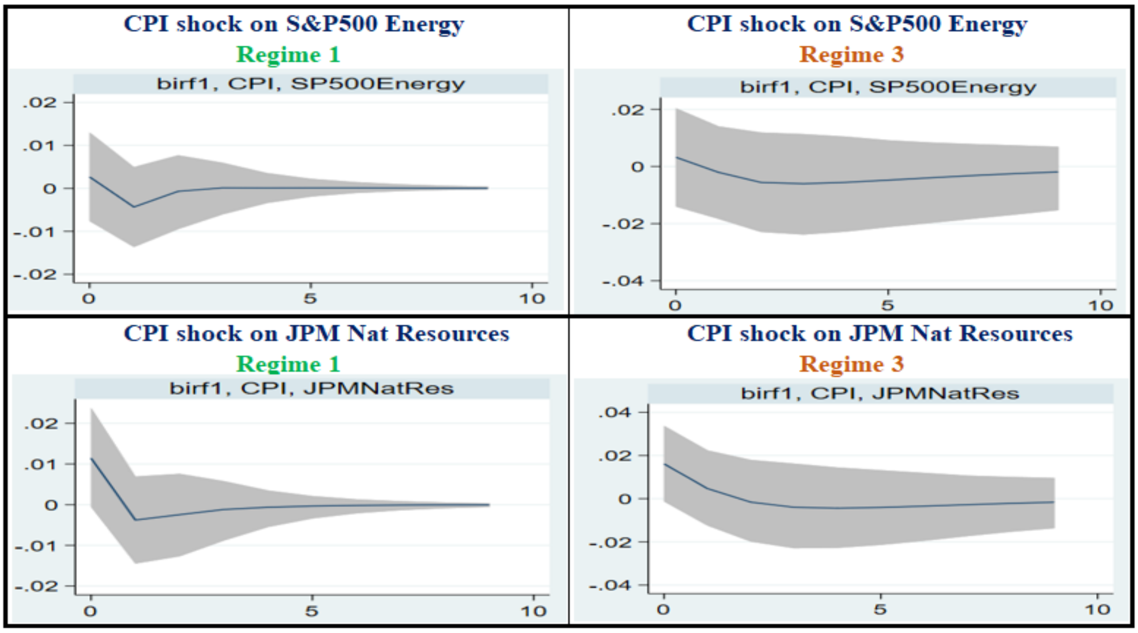


Table 3.21: Fed funds shock on S&P500

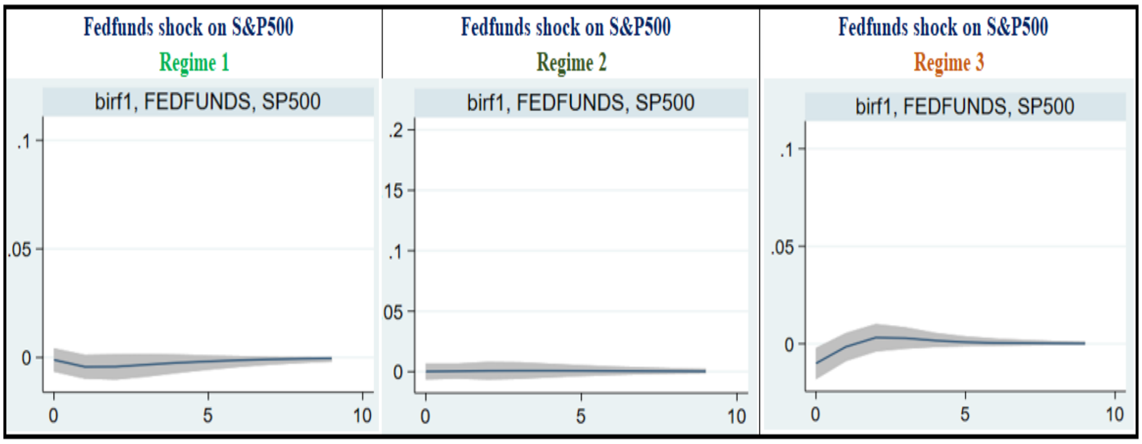


Table 3.22: Fed funds shock on the Market Factor

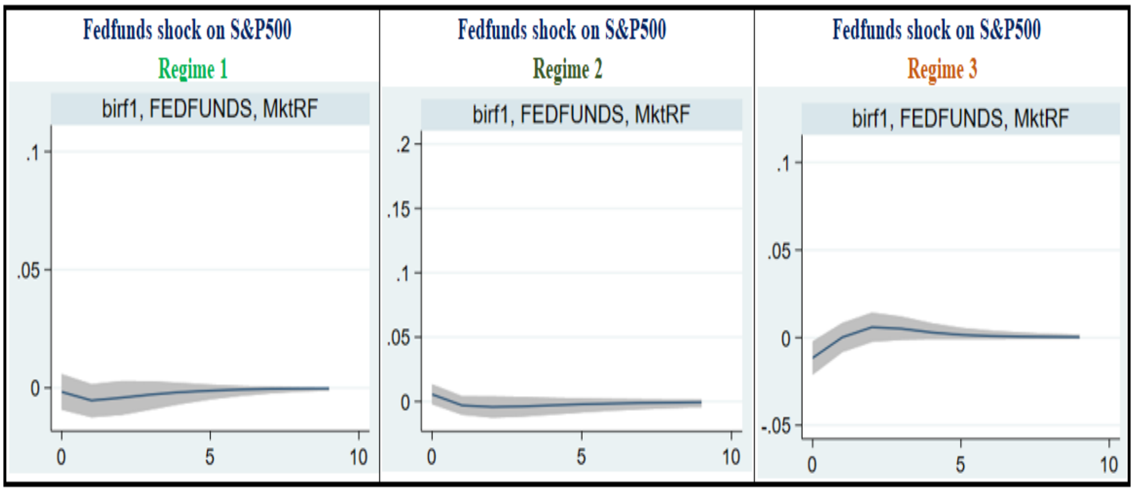


Table 3.33: Fed funds shock on the SMB Factor

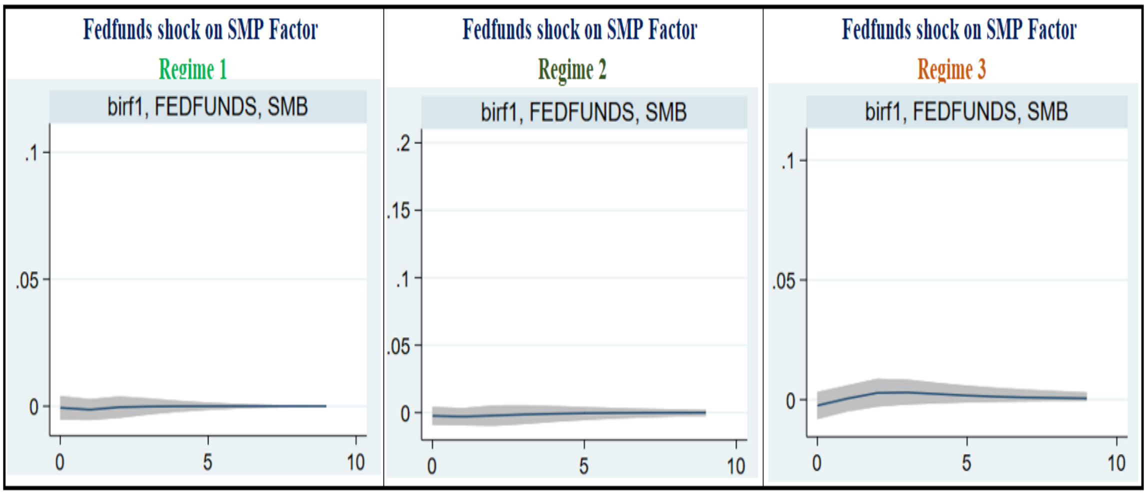


Table 3.34: Fed funds shock on D&C Equity Fund

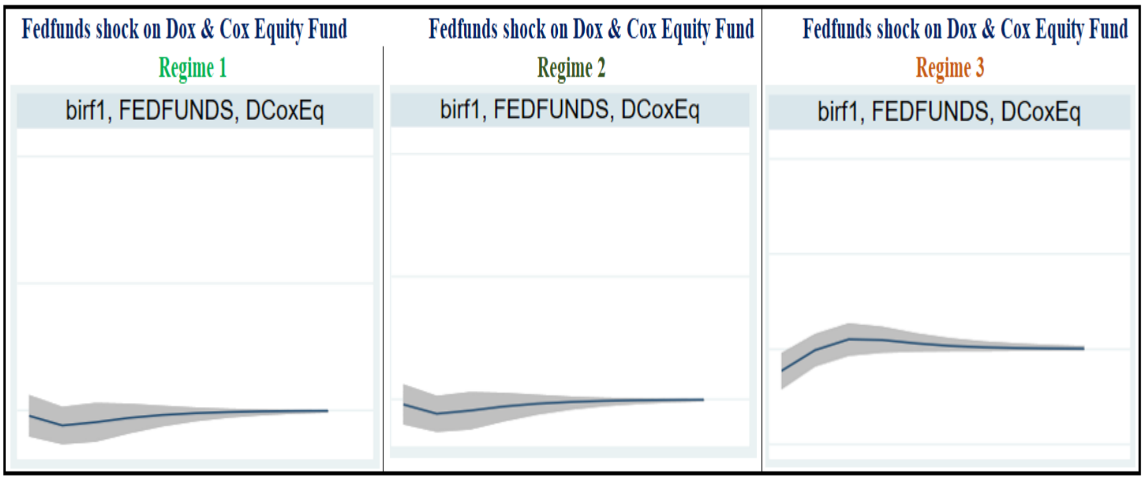


Table 3.35: CPI shock on RMW Factor

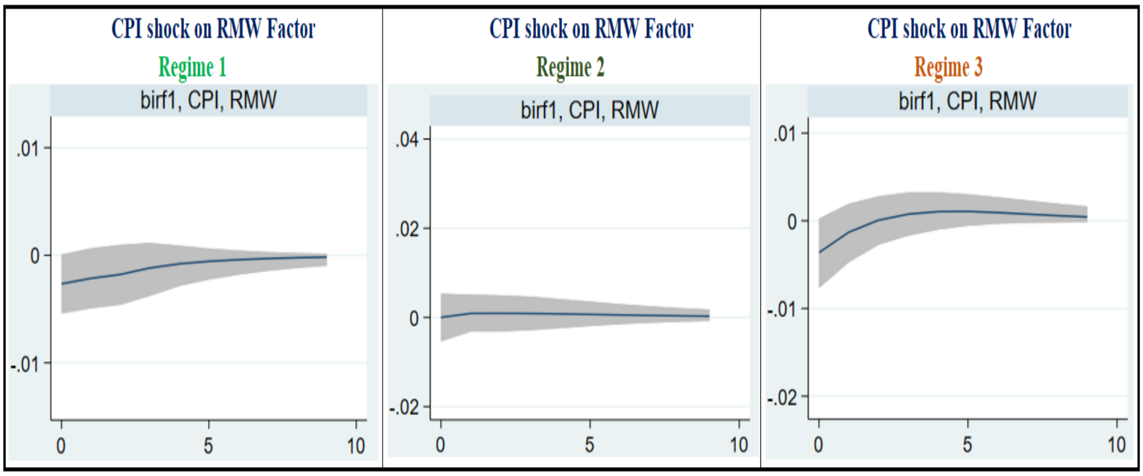


Table 3.36: Fed funds shock on Gold

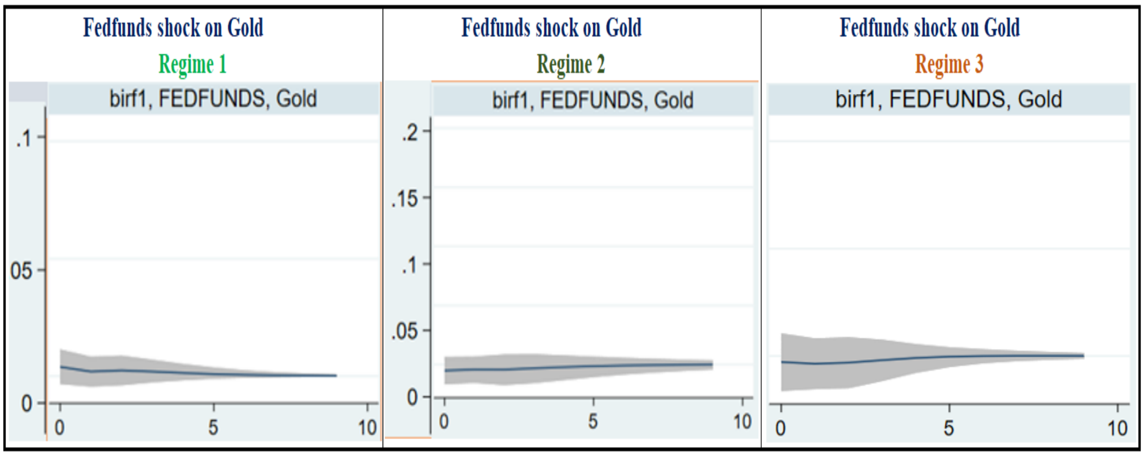


Table 3.37: Fed funds shock on JPM Nat. Resources

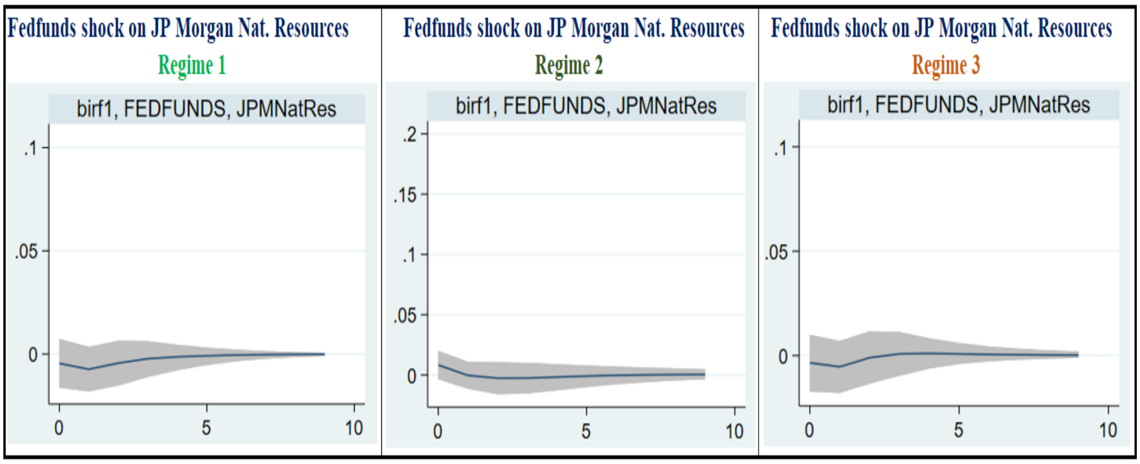


Table 3.38: CPI shock on S&P500

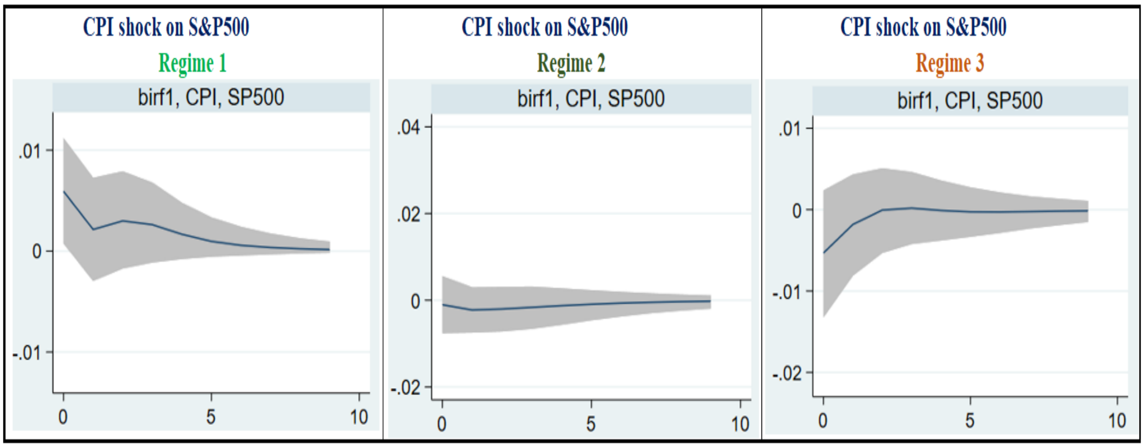


Table 3.39: CPI shock on Market Factor

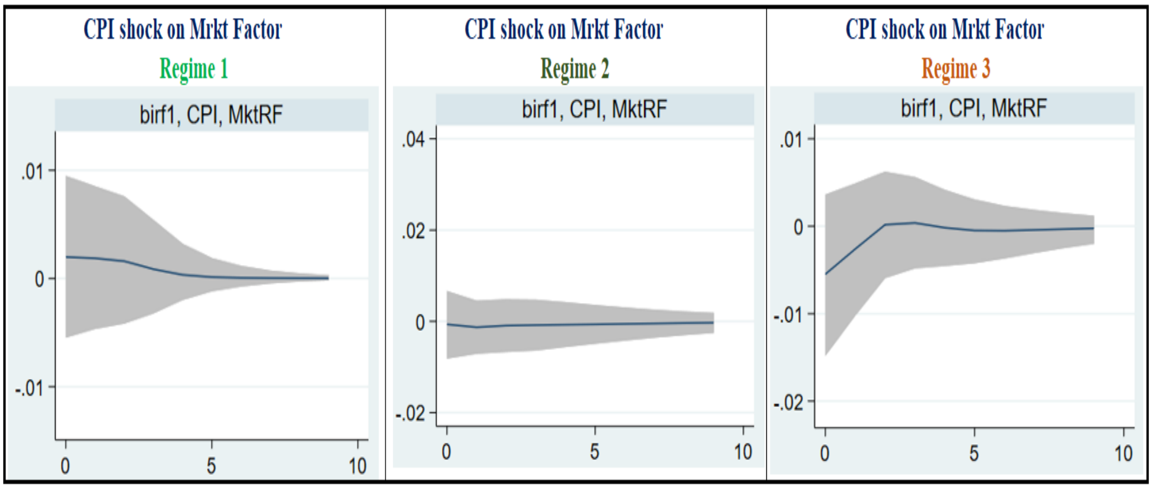


Table 3.40: CPI shock on Market Factor

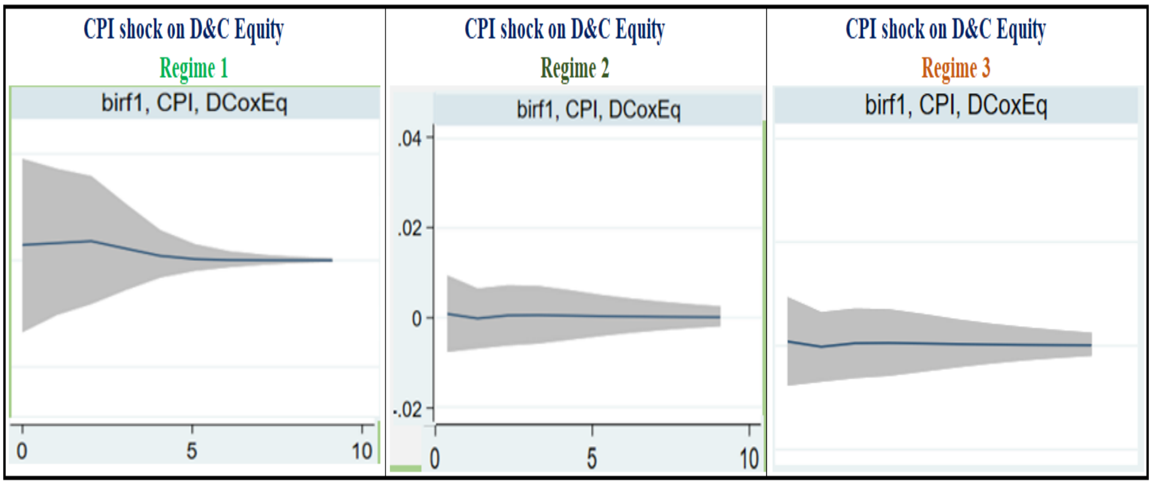


Table 3.41: CPI shock on Gold

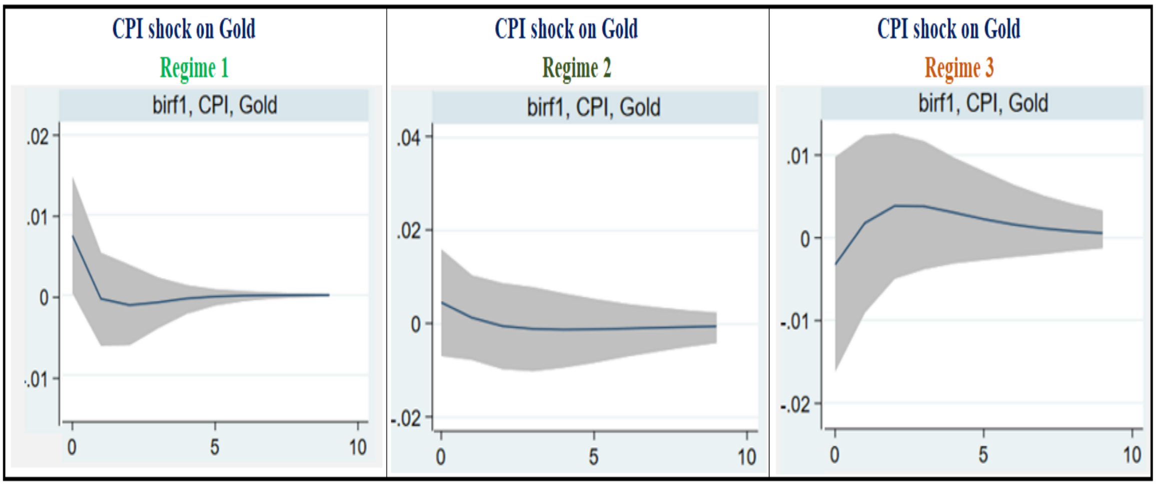


Table 3.42: CPI shock on JP Morgan Nat. Resources Fund

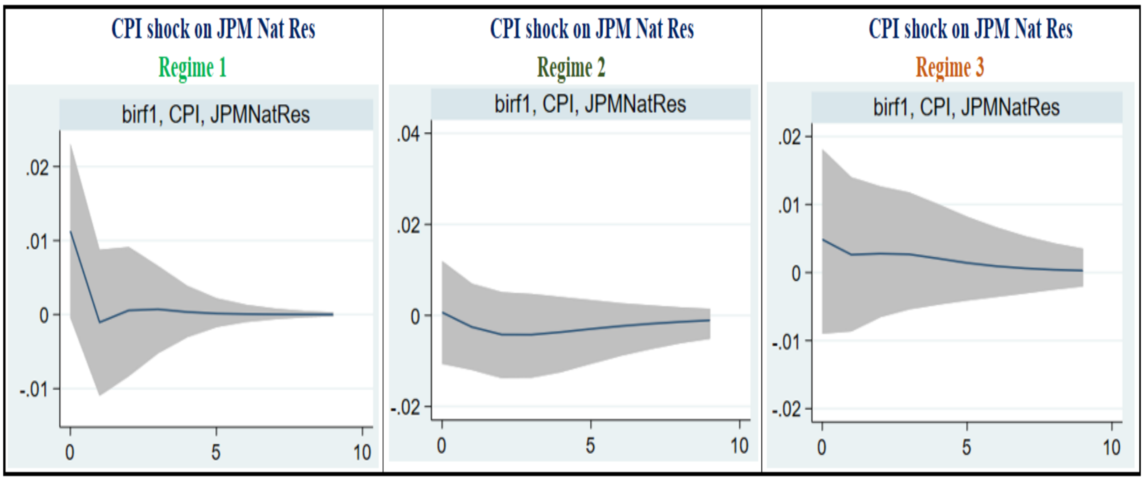


Table 3.43: CPI shock on CMA Factor

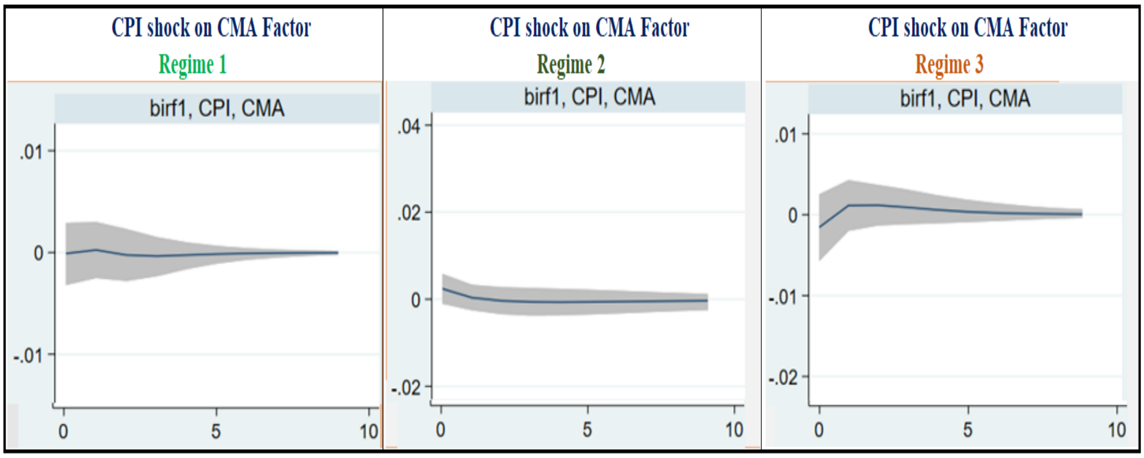


Table 3.44: CPI shock on (Non-Energy) Commodities

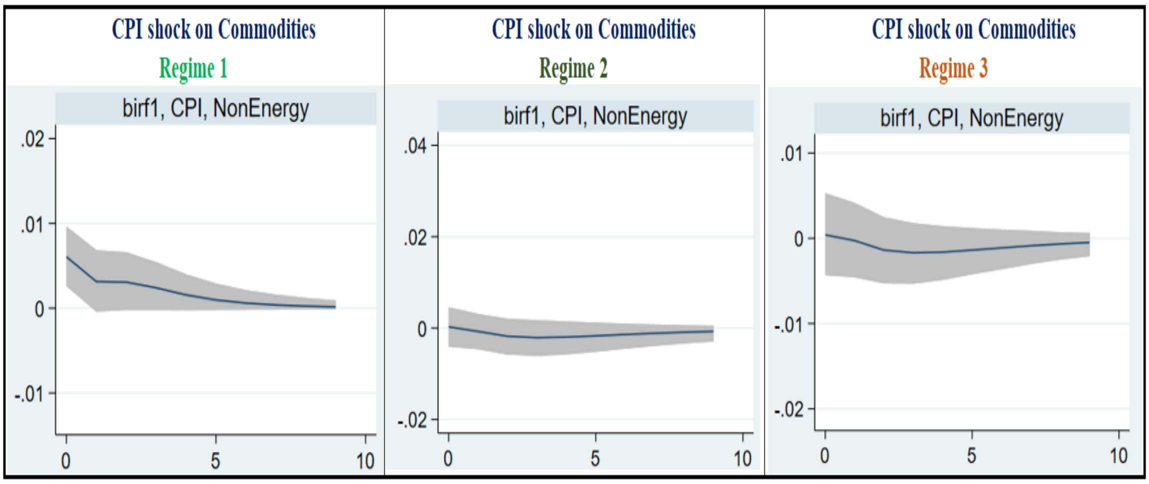


Table 3.45: OECD CLI shock on S&P500

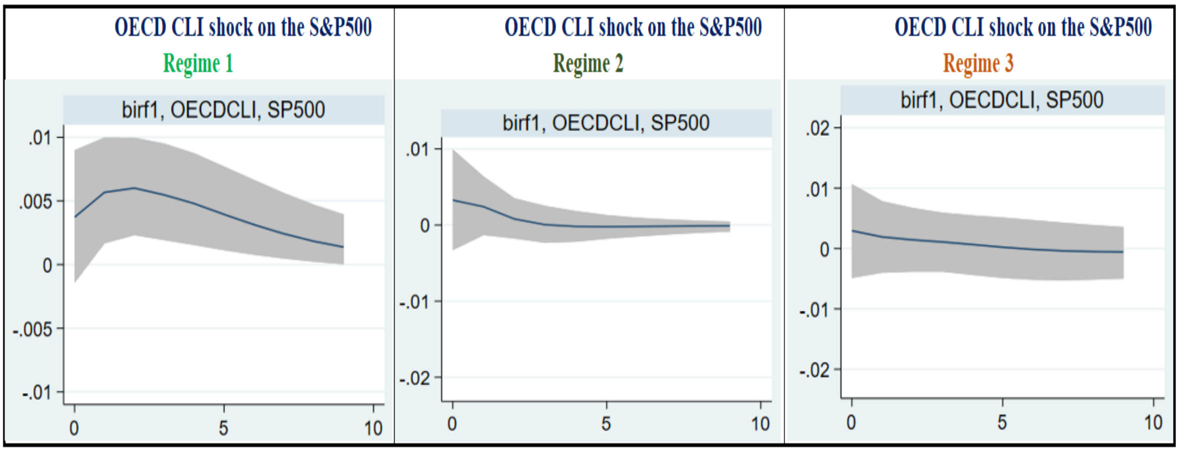


Table 3.46: OECD CLI shock on Gold

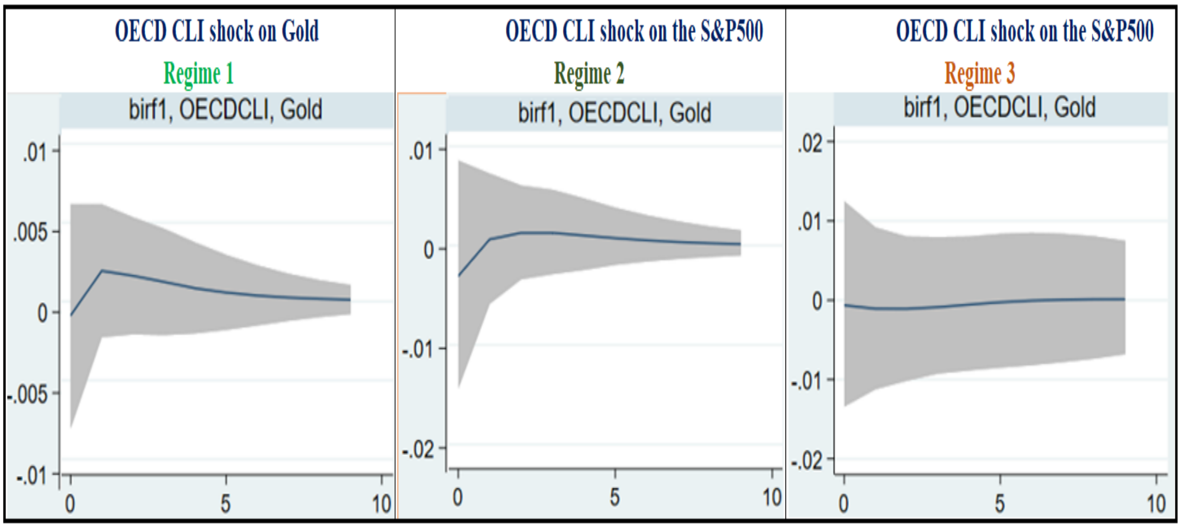


Table 3.47: CPI shock on JP Morgan Nat. Resources Fund

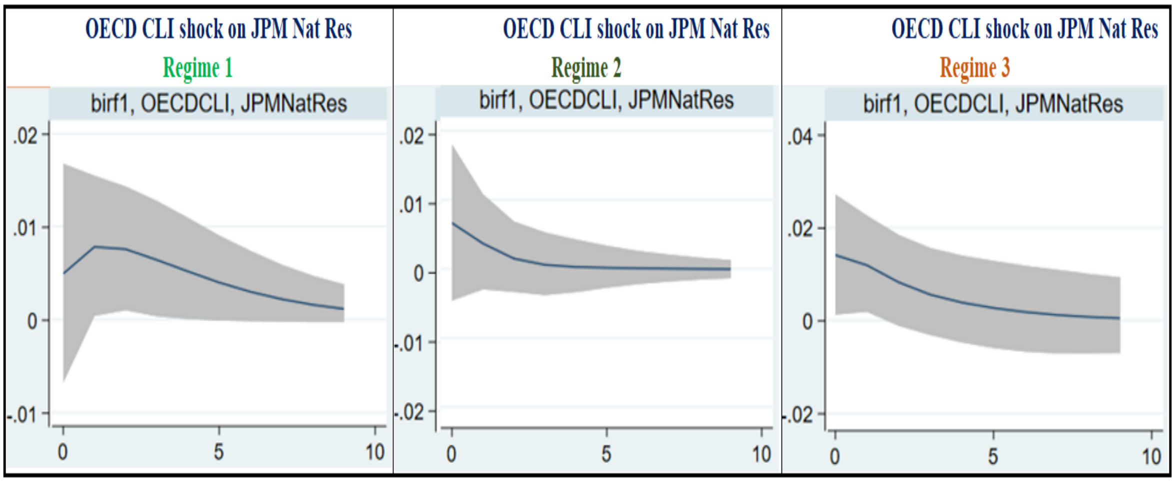


Table 3.48: Univ. Michigan shock on S&P500

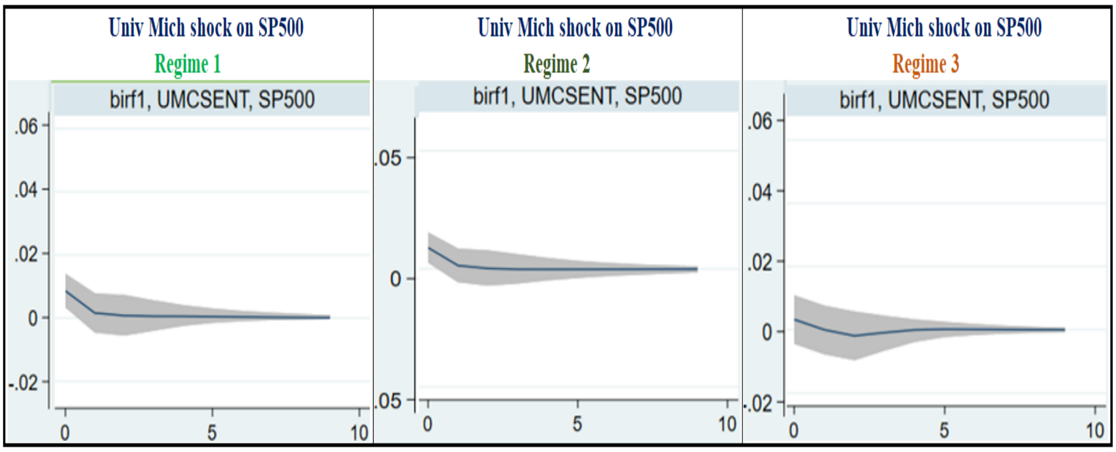


Table 3.49: Univ. Michigan shock on Gold

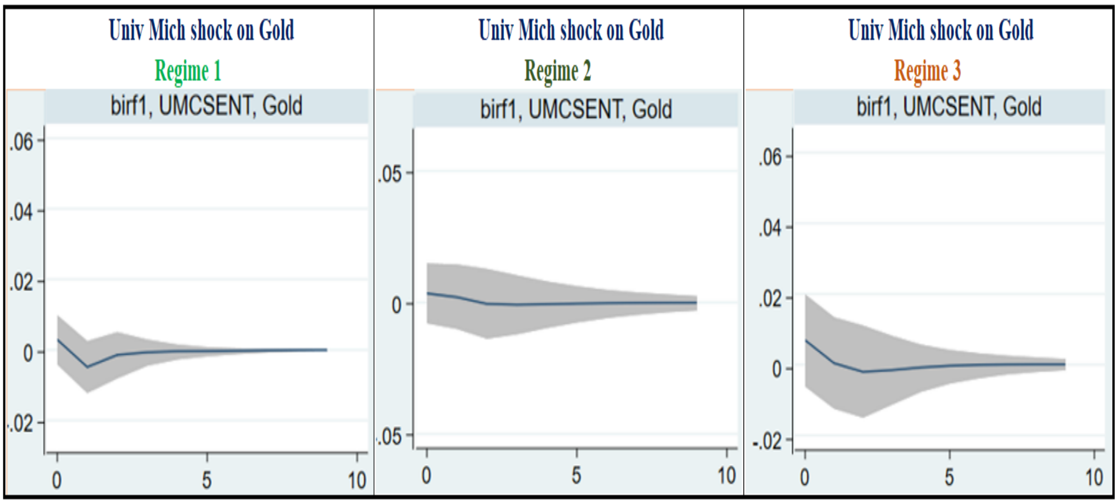


Table 3.50 : Composite Leading Indicator Framework (1970-2004)

1970-01	1970-02	1970-03	1970-04	1970-05	1970-06	1970-07	1970-08	1970-09	1970-10	1970-11	1970-12	1971-01	1971-02	1971-03	1971-04	1971-05	1971-06
		1	1	1	1	1	1	1	1	1	1	1	4	4	4	4	4
1971-07	1971-08	1971-09	1971-10	1971-11	1971-12	1972-01	1972-02	1972-03	1972-04	1972-05	1972-06	1972-07	1972-08	1972-09	1972-10	1972-11	1972-12
4	1	1	1	2	2	2	2	3	3	3	3	3	2	2	3	3	3
1973-01	1973-02	1973-03	1973-04	1973-05	1973-06	1973-07	1973-08	1973-09	1973-10	1973-11	1973-12	1974-01	1974-02	1974-03	1974-04	1974-05	1974-06
3	3	3	3	3	3	3	2	3	3	3	3	3	3	3	4	4	4
1974-07	1974-08	1974-09	1974-10	1974-11	1974-12	1975-01	1975-02	1975-03	1975-04	1975-05	1975-06	1975-07	1975-08	1975-09	1975-10	1975-11	1975-12
4	4	4	1	1	1	1	1	1	1	1	1	1	1	4	4	4	3
1976-01	1976-02	1976-03	1976-04	1976-05	1976-06	1976-07	1976-08	1976-09	1976-10	1976-11	1976-12	1977-01	1977-02	1977-03	1977-04	1977-05	1977-06
3	3	3	3	3	3	3	3	3	2	2	2	2	3	3	3	2	2
1977-07	1977-08	1977-09	1977-10	1977-11	1977-12	1978-01	1978-02	1978-03	1978-04	1978-05	1978-06	1978-07	1978-08	1978-09	1978-10	1978-11	1978-12
2	2	2	2	2	2	2	2	2	2	2	2	3	3	3	3	3	3
1979-01	1979-02	1979-03	1979-04	1979-05	1979-06	1979-07	1979-08	1979-09	1979-10	1979-11	1979-12	1980-01	1980-02	1980-03	1980-04	1980-05	1980-06
2	2	3	3	3	3	3	3	3	3	3	3	3	4	4	1	1	1
1980-07	1980-08	1980-09	1980-10	1980-11	1980-12	1981-01	1981-02	1981-03	1981-04	1981-05	1981-06	1981-07	1981-08	1981-09	1981-10	1981-11	1981-12
1	1	1	4	4	4	4	4	4	4	4	4	4	4	4	1	1	1
1982-01	1982-02	1982-03	1982-04	1982-05	1982-06	1982-07	1982-08	1982-09	1982-10	1982-11	1982-12	1983-01	1983-02	1983-03	1983-04	1983-05	1983-06
4	4	4	4	1	1	1	1	1	1	1	1	1	1	1	4	4	3
1983-07	1983-08	1983-09	1983-10	1983-11	1983-12	1984-01	1984-02	1984-03	1984-04	1984-05	1984-06	1984-07	1984-08	1984-09	1984-10	1984-11	1984-12
3	3	3	3	3	3	3	3	3	3	3	3	2	2	2	2	2	2
1985-01	1985-02	1985-03	1985-04	1985-05	1985-06	1985-07	1985-08	1985-09	1985-10	1985-11	1985-12	1986-01	1986-02	1986-03	1986-04	1986-05	1986-06
2	3	3	3	3	3	3	4	1	1	1	1	1	1	1	1	4	4

Table 3.50 : Composite Leading Indicator Framework (1970-2004) **Con'td**

1986-07	1986-08	1986-09	1986-10	1986-11	1986-12	1987-01	1987-02	1987-03	1987-04	1987-05	1987-06	1987-07	1987-08	1987-09	1987-10	1987-11	1987-12
4	1	1	1	1	1	2	2	2	2	3	3	3	3	3	3	3	2
1988-01	1988-02	1988-03	1988-04	1988-05	1988-06	1988-07	1988-08	1988-09	1988-10	1988-11	1988-12	1989-01	1989-02	1989-03	1989-04	1989-05	1989-06
3	2	2	2	2	2	3	3	3	3	3	3	3	3	3	3	3	2
1989-07	1989-08	1989-09	1989-10	1989-11	1989-12	1990-01	1990-02	1990-03	1990-04	1990-05	1990-06	1990-07	1990-08	1990-09	1990-10	1990-11	1990-12
2	2	2	2	2	2	2	3	3	3	3	3	3	4	4	1	1	1
1991-01	1991-02	1991-03	1991-04	1991-05	1991-06	1991-07	1991-08	1991-09	1991-10	1991-11	1991-12	1992-01	1992-02	1992-03	1992-04	1992-05	1992-06
1	1	1	1	1	4	4	4	4	4	4	1	1	1	1	4	4	4
1992-07	1992-08	1992-09	1992-10	1992-11	1992-12	1993-01	1993-02	1993-03	1993-04	1993-05	1993-06	1993-07	1993-08	1993-09	1993-10	1993-11	1993-12
4	4	1	1	1	1	1	1	4	1	1	1	1	1	1	1	1	1
1994-01	1994-02	1994-03	1994-04	1994-05	1994-06	1994-07	1994-08	1994-09	1994-10	1994-11	1994-12	1995-01	1995-02	1995-03	1995-04	1995-05	1995-06
4	4	3	3	3	3	3	3	3	3	3	3	3	3	2	1	1	1
1995-07	1995-08	1995-09	1995-10	1995-11	1995-12	1996-01	1996-02	1996-03	1996-04	1996-05	1996-06	1996-07	1996-08	1996-09	1996-10	1996-11	1996-12
1	1	4	4	1	1	1	1	1	1	1	4	4	1	1	1	1	1
1997-01	1997-02	1997-03	1997-04	1997-05	1997-06	1997-07	1997-08	1997-09	1997-10	1997-11	1997-12	1998-01	1998-02	1998-03	1998-04	1998-05	1998-06
2	2	2	2	3	3	3	3	3	3	3	3	3	2	3	3	4	4
1998-07	1998-08	1998-09	1998-10	1998-11	1998-12	1999-01	1999-02	1999-03	1999-04	1999-05	1999-06	1999-07	1999-08	1999-09	1999-10	1999-11	1999-12
4	1	1	1	1	1	1	1	3	3	3	3	3	3	3	2	3	3
2000-01	2000-02	2000-03	2000-04	2000-05	2000-06	2000-07	2000-08	2000-09	2000-10	2000-11	2000-12	2001-01	2001-02	2001-03	2001-04	2001-05	2001-06
3	3	3	3	3	3	3	3	3	3	3	3	4	1	1	1	1	1
2001-07	2001-08	2001-09	2001-10	2001-11	2001-12	2002-01	2002-02	2002-03	2002-04	2002-05	2002-06	2002-07	2002-08	2002-09	2002-10	2002-11	2002-12
1	1	1	1	1	1	1	1	4	4	4	4	4	4	1	1	1	1
2003-01	2003-02	2003-03	2003-04	2003-05	2003-06	2003-07	2003-08	2003-09	2003-10	2003-11	2003-12	2004-01	2004-02	2004-03	2004-04	2004-05	2004-06

Table 3.50 : Composite Leading Indicator Framework (1970-2004) **Con'td**

2004-07	2004-08	2004-09	2004-10	2004-11	2004-12	2005-01	2005-02	2005-03	2005-04	2005-05	2005-06	2005-07	2005-08	2005-09	2005-10	2005-11	2005-12
3	3	2	2	2	3	3	3	3	2	2	2	2	2	2	2	2	3
2006-01	2006-02	2006-03	2006-04	2006-05	2006-06	2006-07	2006-08	2006-09	2006-10	2006-11	2006-12	2007-01	2007-02	2007-03	2007-04	2007-05	2007-06
3	3	3	3	3	3	2	2	2	2	2	2	3	3	3	3	3	3
2007-07	2007-08	2007-09	2007-10	2007-11	2007-12	2008-01	2008-02	2008-03	2008-04	2008-05	2008-06	2008-07	2008-08	2008-09	2008-10	2008-11	2008-12
3	3	3	3	3	3	3	3	3	3	3	4	4	4	4	4	1	1
2009-01	2009-02	2009-03	2009-04	2009-05	2009-06	2009-07	2009-08	2009-09	2009-10	2009-11	2009-12	2010-01	2010-02	2010-03	2010-04	2010-05	2010-06
1	1	1	1	1	1	1	4	4	4	4	4	4	3	3	3	3	3
2010-07	2010-08	2010-09	2010-10	2010-11	2010-12	2011-01	2011-02	2011-03	2011-04	2011-05	2011-06	2011-07	2011-08	2011-09	2011-10	2011-11	2011-12
2	2	2	2	2	3	3	3	3	3	3	3	3	1	1	1	1	1
2012-01	2012-02	2012-03	2012-04	2012-05	2012-06	2012-07	2012-08	2012-09	2012-10	2012-11	2012-12	2013-01	2013-02	2013-03	2013-04	2013-05	2013-06
1	4	4	4	4	4	1	1	1	1	1	1	1	1	4	4	4	3
2013-07	2013-08	2013-09	2013-10	2013-11	2013-12	2014-01	2014-02	2014-03	2014-04	2014-05	2014-06	2014-07	2014-08	2014-09	2014-10	2014-11	2014-12
3	3	3	3	3	3	3	3	3	3	3	3	3	2	2	2	3	3
2015-01	2015-02	2015-03	2015-04	2015-05	2015-06	2015-07	2015-08	2015-09	2015-10	2015-11	2015-12	2016-01	2016-02	2016-03	2016-04	2016-05	2016-06
2	3	3	3	3	3	3	3	2	1	1	4	1	1	1	1	1	1
2016-07	2016-08	2016-09	2016-10	2016-11	2016-12	2017-01	2017-02	2017-03	2017-04	2017-05	2017-06	2017-07	2017-08	2017-09	2017-10	2017-11	2017-12
1	1	1	1	2	3	3	3	3	3	2	2	2	2	3	3	3	3
2018-01	2018-02	2018-03	2018-04	2018-05	2018-06	2018-07	2018-08	2018-09	2018-10	2018-11	2018-12	2019-01	2019-02	2019-03	2019-04	2019-05	2019-06
3	3	3	3	3	3	3	3	3	3	1	1	1	1	1	4	4	4
2019-07	2019-08	2019-09	2019-10	2019-11	2019-12	2020-01	2020-02	2020-03	2020-04	2020-05	2020-06	2020-07	2020-08	2020-09	2020-10	2020-11	2020-12
1	1	1	1	1	4	4	4	4	4	1	1	4	4	4	1	1	1
2021-01	2021-02	2021-03	2021-04	2021-05	2021-06	2021-07	2021-08	2021-09	2021-10	2021-11	2021-12	2022-01	2022-02	2022-03			
4	1	2	3	3	3	3	3	3	3	3	3	3	2	2			

Table 3.51: Cumulative/ Discrete/ Annualised Performance of **Aviva Life Inv Trust Portfolio**

Cumulative performance	1m	3m	6m	1y	3y	5y	10y	Start of Data
A Aviva Life Investment Trust Portfolio LML Acc	-4.7%	-10.9%	-19.7%	-16.5%	6.4%	18.6%	108.0%	4040.8%

Discrete performance	0-12m	12-24m	24-36m	36-48m	48-60m
A Aviva Life Investment Trust Portfolio LML Acc	-16.5%	22.5%	4.0%	1.6%	9.7%

Annualised Performance	1y	3y	5y	10y	Start of Data
A Aviva Life Investment Trust Portfolio LML Acc	-16.5%	2.1%	3.5%	7.6%	7.2%

Source: Financial Express Fund Info

Table 3.52: Cumulative/ Discrete/ Annualised Performance of ***JP Morgan Natural Resources Fund***

Cumulative performance	1m	3m	6m	1y	3y	5y	10y	Start of Data
A JPM Natural Resources C Acc	-13.1%	-10.6%	14.3%	20.2%	35.1%	69.2%	31.2%	6663.4%

Discrete performance	0-12m	12-24m	24-36m	36-48m	48-60m
A JPM Natural Resources C Acc	20.2%	29.9%	-13.4%	0.5%	24.6%

Annualised Performance	1y	3y	5y	10y	Start of Data
A JPM Natural Resources C Acc	20.2%	10.6%	11.1%	2.7%	8.7%

Source: Financial Express Fund Info

Table 3.53: Cumulative/ Discrete/ Annualised Performance of ***Canada Life Fixed Interest Fund***

Cumulative performance	1m	3m	6m	1y	3y	5y	10y	Start of Data
A Canlife Fixed Interest Pn PS4 Acc	-4.7%	-7.3%	-15.9%	-15.3%	-15.0%	-12.7%	0.9%	3698.9%

Discrete performance	0-12m	12-24m	24-36m	36-48m	48-60m
A Canlife Fixed Interest Pn PS4 Acc	-15.3%	-7.6%	8.5%	4.4%	-1.6%

Annualised Performance	1y	3y	5y	10y	Start of Data
A Canlife Fixed Interest Pn PS4 Acc	-15.3%	-5.3%	-2.7%	0.1%	8.0%

Source: Financial Express Fund Info

Table 3.54: Cumulative/ Discrete/ Annualised Performance Aviva Life Property

Cumulative performance	1m	3m	6m	1y	3y	5y	10y	Start of Data
A Aviva Life Property FPL	0.1%	2.9%	6.8%	15.1%	19.1%	25.9%	77.6%	708.9%

Discrete performance	0-12m	12-24m	24-36m	36-48m	48-60m
A Aviva Life Property FPL	15.1%	4.8%	-1.3%	1.0%	4.7%

Annualised Performance	1y	3y	5y	10y	Start of Data
A Aviva Life Property FPL	15.1%	6.0%	4.7%	5.9%	5.5%

Source: Financial Express Fund Info

Table 3.55: Cumulative/ Discrete/ Annualised Performance Aviva Life Mixed Investments

Cumulative performance	1m	3m	6m	1y	3y	5y	10y	Start of Data
A Aviva Life Mixed Investment (40-85% Shares) (PM) Ini	-3.9%	-6.3%	-9.3%	-7.1%	-4.9%	-6.3%	24.0%	162.4%

Discrete performance	0-12m	12-24m	24-36m	36-48m	48-60m
A Aviva Life Mixed Investment (40-85% Shares) (PM) Ini	-7.1%	7.1%	-4.3%	-0.6%	-0.9%

Annualised Performance	1y	3y	5y	10y	Start of Data
A Aviva Life Mixed Investment (40-85% Shares) (PM) Ini	-7.1%	-1.6%	-1.3%	2.2%	2.7%

Source: Financial Express Fund Info

Table 3.68: Coding Framework: Institute of Supply Management Index

		ISM is below/above L/T trend	
		Below	**Above**
Change in month on month ISM	Up	ISM levels remaining below long-term trend ISM growth above L/T trend	ISM levels remaining above long-term trend ISM growth above L/T trend
	Down	ISM levels remaining below long-term trend ISM growth below L/T trend	ISM levels remaining above long-term trend ISM growth below L/T trend

Source: Authors own Table

Table 3.69: Coding Framework: University of Michigan Sentiment Index

	MICH Sentiment is Declining/ Increasing	
Mich Sentiment Positive or Negative	**Declining**	**Increasing**
Positve	Positive Univ Michigan Sentiment **4** Rate of change declining	Positive Univ Michigan Sentiment **3** Rate of change increasing
Negative	Negative Univ Michigan Sentiment **1** Rate of change declining	Negative Univ Michigan Sentiment **2** Rate of change increasing

Source: Authors own Table

Technical Appendix: Review of Estimation Methodology

Appendix 1: Likelihood function with latent states

The conditional density of our dependent variable(s) is assumed to rely only on the prevailing economic regime s_t and is conveniently summarised as $f(y_t|s_t = i, y_{t-1}; \theta)$. There are k conditional densities for k states and θ represents a vector of parameters. We estimate θ by updating the conditional likelihood utilising a nonlinear filter. Following the Hamilton [1989] approach (as detailed in Appendix 1) we weigh the conditional densities by their individual probabilities to determine the marginal density of y_t.

$$f(y_t|\theta) = \sum_{i=1}^{k} f(y_t|s_t = i, y_{t-1}; \theta)\, \Pr(s_t = i; \theta)$$

Let η_t denote a k x 1vector of conditional densities given by

$$\eta_t = \begin{bmatrix} f(y_t|s_t = 1, y_{t-1}; \theta) \\ f(y_t|s_t = 2, y_{t-1}; \theta) \\ \\ \\ f(y_t|s_t = k, y_{t-1}; \theta) \end{bmatrix}$$

We estimate the probability that st takes on values utilizing the historical data at $_{t-k}$ along with the model parameters θ. If we allow the $\Pr(s_t = i|y_t; \theta)$ to denote the conditional probability of observing $s_t = i$ based on data until time t.

Then

$$\Pr(s_t = i|y_{t-1}; \theta) = \frac{f(y_t|s_t = i, y_{t-1}; \theta)\, \Pr(s_t = i|y_{t-1}; \theta)}{f(y_t|y_{t-1}; \theta)}$$

where $f(y_t|y_{t-1}; \theta)$ is the likelihood of y_t and $\Pr(s_t = i|y_{t-1}; \theta)$ is the forecasted probability of st = i given observation until t – 1. Then

$$\Pr(s_t = 1|y_{t-1}; \theta) = \sum_{i=1}^{k} \Pr(s_t = i|s_{t-1} = j, y_{t-1}; \theta)\, \Pr(s_{t-1} = j|y_{t-1}; \theta)$$

We follow the procedure adopted by Hamilton (1994) and allow $\psi_{t|t}$ and $\psi_{t|t-1}$ to denote k x 1 vectors of conditional probabilities $Pr(s_t = i|y_t; \theta)$ and $Pr(s_t = i|y_{t-1}; \theta)$. We find the likelihood by iterating on the following equations:

$$\psi t|t = \frac{(\psi_{t|t-1} \, \Theta \, \eta_t)}{1'(\psi_{t|t-1} \, \Theta \, \eta_t)}$$

$$\psi_{t+1|t} = P \, \psi_{t|t}$$

where 1is a k x 1 vector of 1s. The log-likelihood function is attained as

$$L(\theta) = \log f(y_t|y_{t-1}; \theta)$$

where

$$f(y_t|y_{t-1}; \theta) = 1'(\psi_t|_{t-1} \, \Theta \, \eta_t)$$

We follow the algorithmic approach of Kim (1994) in calculating the smoothed probabilities. We let $\psi_t|T$, where $t < T$, denote the k x 1 vector of conditional probabilities $Pr(st = i|y_T; \theta)$. This represents the probability of $st = i$ using information available through time T.

$$\psi_t|_T = \psi_t|_t \, \Theta \, \{P' \, (\psi_{t+1}|T(\div)\psi_{t+1}|_t)\}$$

where (÷) element by element division. The smoothed probabilities are sourced by iterating backwards from t = T, T – 2. . . 1.

Appendix 2: Gibbs Sampling procedure

Our starting point for the Gibbs sampling algorithm is to suppose that we have a vector of parameters Θ, with k elements

$$\Theta = (\theta_1, \ldots, \theta_k)$$

We recognise that it may be impossible to draw samples from

$$f(\Theta|\text{Data}) = f(\theta_1, \theta_2, \ldots, \theta_k|\text{Data})$$

We break down the joint posterior distribution into a series of conditional distributions:

$$f(\Theta|\text{Data}) = f(\theta_1|\theta_2, \ldots, \theta_k, \text{Data})$$
$$\times \quad f(\theta_2|\theta_1, \theta_3 \ldots, \theta_k, \text{Data}) \ldots \times$$
$$f(\theta_k|\theta_1, \ldots, \theta_{k-1}, \text{Data})$$

We commence the process by sampling from some initial uninformed values of the parameters

$$\theta^0: \theta_1^0, \theta_2^0, \ldots, \theta_k^0$$

We next draw samples

$$\theta_1^1 \sim f(\theta_1^1|\ \theta_2^0, , \theta_k^0, \text{Data})$$
$$\theta_2^1 \sim f(\theta_2|\ \theta_1^1, , \theta_3^0, \ldots, \theta_k^0, \text{Data})$$
$$\ldots$$
$$\theta_k^1 \sim f(\theta_k|\ \theta_1^1, , \theta_2^1, \ldots, \theta_{k-1}^1, \text{Data})$$

We can repeat the second step above t times to obtain the values

$$\theta_k^t \sim f(\theta_k|\ \theta_1^t, \ldots, \theta_{k-1}^t, \ldots, \theta_k^{t-1}, \text{Data})$$

at each iteration t = 2, ... , t of the algorithm

References

Acemoglu, D. and Scott, A., 1994. Consumer confidence and rational expectations: Are agents' beliefs consistent with the theory? *The Economic Journal*, *104*(422), pp.1-19.

Akcay, S. (2011) "The causal relationship between producer price index and consumer price index", Empirical evidence from selected European countries, International Journal of Economics & Finance, 3.6 pp:227-232

Akram, T. and Das, A., 2019. An analysis of the daily changes in US treasury security yields.
Levy Economics Institute Working Paper No. 934

Anderson, F. (2011) "Monetary Policy, Asset price Inflation and Consumer Price Inflation", Economics Bulletin, 31.1

Ang, A. and Bekaert, G., 1999. International asset allocation with time-varying correlations.

Ang, A. and Bekaert, G., 2002. International asset allocation with regime shifts. *The review of financial studies*, *15*(4), pp.1137-1187.

Ang, A. and Bekaert, G., 2007. Stock return predictability: Is it there? *The Review of Financial Studies*, *20*(3), pp.651-707.

Ang, A. and Chen, J., 2002. Asymmetric correlations of equity portfolios. *Journal of financial Economics*, *63*(3), pp.443-494.

Ang, A. and Timmermann, A., 2012. Regime changes and financial markets. *Annu. Rev. Finance. Econ.*, *4*(1), pp.313-337.

Arshanapalli, B.G., Switzer, L.N. and Panju, K., 2007. Equity-style timing: A multi-style rotation model for the Russell large-cap and small-cap growth and value style indexes. *Journal of Asset Management*, *8*(1), pp.9-23.

Arnott, R.D., Li, F. and Warren, G.J., 2013. Clairvoyant discount rates. *The Journal of Portfolio Management*, *40*(1), pp.109-123.

Backus, D.K. and Gregory, A.W., 1993. Theoretical relations between risk premiums and conditional variances. *Journal of Business & Economic Statistics*, *11*(2), pp.177-185.

Baur, D.G and Lucey, B.M. "Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold, The Financial Review 45 (2010) 217–229

Baker, M., Bradley, B. and Wurgler, J., 2011. Benchmarks as limits to arbitrage: Understanding the low-volatility anomaly. *Financial Analysts Journal*, *67*(1), pp.40-54.

Baker, N.L. and Haugen, R.A., 2012. Low risk stocks outperform within all observable markets of the world. *Available at SSRN 2055431*

Banerji, A., Layton, A. P. and Achuthan, L. (2008), 'Dating the 'World Business Cycle,' ECRI Working Paper
Battistin, E. (2003) "Errors in survey reports of consumption expenditures", No. 03/77, IFS Working Papers

Barsky, R.B. and Sims, E.R., 2012. Information, animal spirits, and the meaning of innovations in consumer confidence. *American Economic Review*, *102*(4), pp.1343-77.

Baele, L., Bekaert, G., Inghelbrecht, K., 2010. The determinants of stock and bond return comovements. Review of Financial Studies 23 (6), 2374-2428.

Beaton, K., 2009. *Credit constraints and consumer spending* (No. 2009-25). Bank of Canada.

Beechey, M. and Österholm, P., 2010. Forecasting inflation in an inflation-targeting regime: A role for informative steady-state priors. *International Journal of Forecasting*, *26*(2), pp.248-264.

Bernanke, B.S., Boivin, J. and Eliasz, P., 2005. Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach. *The Quarterly journal of economics*, *120*(1), pp.387-422.

Bhansali, V., 2011. Beyond risk parity. *The Journal of Investing*, *20*(1), pp.137-147.

Białowolski, P., Kuszewski, T. and Witkowski, B., 2012. Macroeconomic forecasts in models with Bayesian averaging of classical estimates. *Contemporary Economics*, *6*(1), pp.60-69.

Blitz, D.C. and Van Vliet, P., 2007. The volatility effect. *The Journal of Portfolio Management*, *34*(1), pp.102-113.

Blitz, D.C. and Van Vliet, P., 2008. Global tactical cross-asset allocation: applying value and momentum across asset classes. *The Journal of Portfolio Management*, *35*(1), pp.23-38.

Brandt, M.W., 1999. Estimating portfolio and consumption choice: A conditional Euler equations approach. *The Journal of Finance*, *54*(5), pp.1609-1645.

Brennan, M.J., Schwartz, E.S. and Lagnado, R., 1997. Strategic asset allocation. *Journal of Economic dynamics and Control*, *21*(8-9), pp.1377-1403.

Broome, S. and Morley, B., 2004. Stock prices as a leading indicator of the East Asian financial crisis. *Journal of Asian Economics*, *15*(1), pp.189-197.

Brinson, G.P., Hood, Beebower, G.L. (1986), "Determinants of Portfolio Performance", Financial Analysts Journal, Vol. 42(4), pp:39:44

Brinson, G.P., Singer, B.D. and Beebower, G.L. (1991), "Determinants of Portfolio Performance II: An Update", Financial Analysts Journal, Vol. 47(4), pp:40:48

Busse, J.A., 1999. Volatility timing in mutual funds: Evidence from daily returns. *The Review of Financial Studies*, *12*(5), pp.1009-1041.

Cai, J., 1994. A Markov model of switching-regime ARCH. *Journal of Business & Economic Statistics*, *12*(3), pp.309-316
Campbell, J.Y. and Vuolteenaho, T., 2004. Inflation illusion and stock prices. *American Economic Review*, *94*(2), pp.19-23.

Campbell, J., Sunderam, A. and Viceira, L.M., 2013. Inflation bets or deflation hedges.

Capie, F., Mills, T.C. and Wood, G., 2005. Gold as a hedge against the dollar. *Journal of International Financial Markets, Institutions and Money*, *15*(4), pp.343-352.

Carhart, M.M., 1997. On persistence in mutual fund performance. *The Journal of finance*, *52*(1), pp.57-82.

Carvalho, L. & Rezai, A. (2016) "Personal Income Inequality and aggregate demand", Cambridge Journal of Economics.

Case, K.E., Quigley, J.M. and Shiller, R.J., 2005. Comparing wealth effects: the stock market versus the housing market. *Advances in macroeconomics*, *5*(1).

Carroll, C.D., Fuhrer, J.C. and Wilcox, D.W., 1994. Does consumer sentiment forecast household spending? If so, why? *The American Economic Review*, *84*(5), pp.1397-1408.

Chow, T.M., Hsu, J.C., Kuo, L.L. and Li, F., 2014. A Study of Low-Volatility Portfolio Construction Methods. *The Journal of Portfolio Management*, *40*(4), pp.89-105.

Chu, C.S.J., Santoni, G.J. and Liu, T., 1996. Stock market volatility and regime shifts in returns. *Information Sciences*, *94*(1-4), pp.179-190.

Clark, T.E., 2011. Real-time density forecasts from Bayesian vector autoregressions with stochastic volatility. *Journal of Business & Economic Statistics*, *29*(3), pp.327-341.

Cutler, D.M., Poterba, J.M. and Summers, L.H., 1989. What moves the stock market. *Journal of Portfolio Management*, *15*(3), pp.4-11.

Comincioli, B., 1996. The stock market as a leading indicator: An application of granger causality. *University avenue undergraduate journal of economics*, *1*(1), p.1.

Cole, C. 2016 "Allegory of the Hawk and the Serpent", Artemis Capital.

CRS [Congressional Research Service], 2020 "Introduction to US Economy: Personal Income", Congressional research service paper on Personal Income, 30th November 2020.

Dalio, R., 2019. Why and how capitalism needs to be reformed. *Economic Principles*, p.2021.

Debes, S., Gareis, J., Mayer, E. and Rüth, S., 2014. *Towards a consumer sentiment channel of monetary policy* (No. 91). WEP-Würzburg Economic Papers.

Del Negro, M. and Schorfheide, F., 2011. Bayesian macro econometrics. *The Oxford handbook of Bayesian econometrics*, *293*, p.389.

De Grauwe, P. & Polan, M. 2001 "Is Inflation always and everywhere a Monetary Phenomenon", Discussion Paper Series, Nr. 2481, Centre for Economic Policy Research.
Dimson, E., Marsh, P. and Staunton, M., 2009. Triumph of the Optimists. In *Triumph of the Optimists*. Princeton University Press.

Doan, T., Litterman, R. and Sims, C., 1984. Forecasting and conditional projection using realistic prior distributions. *Econometric reviews*, *3*(1), pp.1-100.

Eraker, B., 2008. Affine general equilibrium models. *Management Science*, *54*(12), pp.2068-2080.

Epstein, G. & Yelden, E. (2008) "Inflation Targeting, Employment creation and economic development: assessing the impacts and policy alternatives, International review of Applied Economics, Vol. 22(2), 131-144

Evans, C.L & Marshall, D.A (2004) "Economic Determinants of the Nominal Treasury Yield Curve, Federal Reserve Bank of Chicago, Journal of Monetary Economics, 54(7), pp:1986:2003

Ely, D.P. and Robinson, K.J., 1997. Are stocks a hedge against inflation? International evidence using a long-run approach. *Journal of International Money and Finance*, *16*(1), pp.141-167.

Eychenne, K., Martinetti, S. & Roncalli, T. (2011) "Strategic Asset Allocation", *Available at SSRN 2154021* (2011).

Fama, E.F., 1965. The behaviour of stock-market prices. *The journal of Business*, *38*(1), pp.34-105.

Fama, E.F. and French, K.R., 1988. Permanent and temporary components of stock prices. *Journal of political Economy*, *96*(2), pp.246-273.

Fama, E.F. and French, K.R., 1989. Business conditions and expected returns on stocks and bonds. *Journal of financial economics*, *25*(1), pp.23-49.

Fama, E.F. and French, K.R., 1992. The cross-section of expected stock returns. *the Journal of Finance*, *47*(2), pp.427-465.

Fama, E.F. and French, K.R., 2015. A five-factor asset pricing model. *Journal of financial economics*, *116*(1), pp.1-22.

Farrell, H. and Quiggin, J., 2017. Consensus, dissensus, and economic ideas: economic crisis and the rise and fall of Keynesianism. *International studies quarterly*, *61*(2), pp.269-283.

Ferson, W.E. & Schadt, R.W "*Measuring Fund Strategy and Performance in Changing Economic Conditions*", Journal of Finance, 1996, vol. 51, issue 2, 425-61

Foran, J. & O'Sullivan, N. (2017) "Mutual fund skill in timing market volatility and liquidity", International Journal of Finance & Economics, 22(4), PP:257-273.

Foran, J. and O'Sullivan, N., 2017. Mutual fund skill in timing market volatility and liquidity. *International Journal of Finance & Economics*, *22*(4), pp.257-273.

Fornell, C., Rust, R.T. and Dekimpe, M.G., 2010. The effect of customer satisfaction on consumer spending growth. *Journal of Marketing Research*, *47*(1), pp.28-35.

French, K.R., Schwert, G.W. and Stambaugh, R.F., 1987. Expected stock returns and volatility. *Journal of financial Economics*, *19*(1), pp.3-29.

Friedman, M., 1963. Price determination in the United States treasury bill market: A comment. *The Review of Economics and Statistics*, pp.318-320.

Garcia, R. and Perron, P., 1996. An analysis of the real interest rate under regime shifts. *The review of economics and statistics*, pp.111-125.

Geweke, J. and Amisano, G., 2010. Comparing and evaluating Bayesian predictive distributions of asset returns. *International Journal of Forecasting*, *26*(2), pp.216-230.

Giambona, E. and Golec, J.H., 2007. Incentive fees and mutual fund volatility timing. *Available at SSRN 820264*.

Gray, S.F., 1996. Modelling the conditional distribution of interest rates as a regime-switching process. *Journal of Financial Economics*, *42*(1), pp.27-62.

Guidolin, M. and Timmermann, A., 2003. Option prices under Bayesian learning: Implied volatility dynamics and predictive densities. *Journal of Economic Dynamics and Control*, *27*(5), pp.717-769.

Guidolin, M. and Timmermann, A., 2007. Asset allocation under multivariate regime switching. *Journal of Economic Dynamics and Control*, *31*(11), pp.3503-3544.

Guidolin, M. and Hyde, S., 2008. Equity portfolio diversification under time-varying predictability: Evidence from Ireland, the US, and the UK. *Journal of Multinational Financial Management*, *18*(4), pp.293-312.

Guidolin, M. and Hyde, S., 2012. Can VAR models capture regime shifts in asset returns? A long-horizon strategic asset allocation perspective. *Journal of Banking & Finance*, *36*(3), pp.695-716.

Guidolin, M. and Hyde, S., 2012. Simple VARs cannot approximate Markov switching asset allocation decisions: An out-of-sample assessment. *Computational Statistics & Data Analysis*, *56*(11), pp.3546-3566.

Hamilton, J.D., 1989. A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica: Journal of the econometric society*, pp.357-384.

Hamilton, J.D. and Susmel, R., 1994. Autoregressive conditional heteroskedasticity and changes in regime. *Journal of econometrics*, *64*(1-2), pp.307-333.

Hamilton, J.D., 2010. Regime switching models. In *Macroeconometrics and time series analysis* (pp. 202-209). Palgrave Macmillan, London.

Hamilton, J.D., 2016. Macroeconomic regimes and regime shifts. *Handbook of macroeconomics*, *2*, pp.163-201.

Henriksson, R.D., 1984. Market timing and mutual fund performance: An empirical investigation. *Journal of business*, pp.73-96.

Hossain, A. (2005) "*The Granger-Causality between Money Growth, Inflation, Currency Devaluation And Economic Growth in Indonesia: 1954-2002*", International Journal of Applied Econometrics and Quantitative Studies. Vol. 2-3.

Hoff, P.D., 2009. *A first course in Bayesian statistical methods* (Vol. 580). New York: Springer.

Hommes, C., Sonnemans, J., Tuinstra, J. and Van de Velden, H., 2008. Expectations and bubbles in asset pricing experiments. *Journal of Economic Behavior & Organization*, *67*(1), pp.116-133.

Hood, M. and Malik, F., 2013. Is gold the best hedge and a safe haven under changing stock market volatility?. *Review of Financial Economics*, *22*(2), pp.47-52.

Hoogerheide, L. and van Dijk, H.K., 2010. Bayesian forecasting of value at risk and expected shortfall using adaptive importance sampling. *International Journal of Forecasting*, *26*(2), pp.231-247.

Huang, J., Sialm, C. and Zhang, H., 2011. Risk shifting and mutual fund performance. *The Review of Financial Studies*, *24*(8), pp.2575-2616.

Ibbotson, R.G. and Kaplan, P.D., 2000. Does asset allocation policy explain 40, 90, or 100 percent of performance? *Financial Analysts Journal*, *56*(1), pp.26-33.

Illmanen, A. (2011) "Expected Returns: An Investor's guide to harvesting market rewards, John Wiley & Sons

Ibbotson, G.L., (2010) "Importance of Asset Allocation", Financial Analysts Journal, vol. 66(2), pp: 18-20

Jorion, P., 2003. The long-term risks of global stock markets. *Financial Management*, pp.5-26.

Johnson, R.R., Buetow, G.W., Jensen, G.R. and Reilly, F.K., 2003. Monetary policy and fixed income returns. *The Quarterly Review of Economics and Finance*, *43*(1), pp.133-146.

Joy, M., 2011. Gold and the US dollar: Hedge or haven? *Finance Research Letters*, *8*(3), pp.120-131.

Kahneman, D. (2016) "Thinking Fast and Slow", Farrar, Strauss & Giro

Kandel, S. and Stambaugh, R.F., 1996. On the predictability of stock returns: an asset-allocation perspective. *The Journal of Finance*, *51*(2), pp.385-424.

Kaminski, K.M., 2012. In Search of Crisis Alpha.
Keim, D.B. and Stambaugh, R.F., 1986. Predicting returns in the stock and bond markets. *Journal of financial Economics*, *17*(2), pp.357-390.

Keynes, J.M., 2017. *The economic consequences of the peace*. Routledge.

Kollar, M. (2013) "A sketch of Macro-based asset allocation", International Journal of Economic Sciences, 2(3), pp: 101-120

Koop, G.M., 2013. Forecasting with medium and large Bayesian VARs. *Journal of Applied Econometrics*, *28*(2), pp.177-203.

Kritzman, M. & Page, S. (2003) "The Hierarchy of investment choice: a normative interpretation, Journal of Portfolio Management, Vol. 29, pp: 11-23

Lawrence, C., 2003. Why is gold different from other assets? An empirical investigation. *London, UK: The World Gold Council*.

Le, TH. & Chang, Y. (2011) "Oil and Gold: Correlation or Causation", Munich Personal RePEc Archive

Litterman, R.B., 1980. *Bayesian procedure for forecasting with vector autoregressions*. Massachusetts Institute of Technology.

Li, X. and Sullivan, R.N., 2011. A dynamic future for active quant investing. *The journal of portfolio management*, *37*(3), pp.29-36.

Mark, N.C., Cecchetti, S.G. and Lam, P.S., 1990. Mean Reversion in Equilibrium Asset Prices.[electronic resource] Stephen G. Cecchetti, Pok-sang Lam, Nelson C. Mark.

Markowitz, H. (1954) "Portfolio Selection", Journal of Finance, American Finance Association, vol. 7(1), pp: 77-91

Markowitz, H., 1952. The utility of wealth. *Journal of political Economy*, *60*(2), pp.151-158.

Mandelbrot, B.B., Fisher, A.J. and Calvet, L.E., 1997. A multifractal model of asset returns.

Matsusaka, J.G. and Sbordone, A.M., 1995. Consumer confidence and economic fluctuations. *Economic Inquiry*, *33*(2), pp.296-318.
Meyler, A., Kenny, G. and Quinn, T., 1998. Forecasting Irish inflation using ARIMA models.

Merton, R.C., 1973. An intertemporal capital asset pricing model. *Econometrica: Journal of the Econometric Society*, pp.867-887.

McNulty, P., Moyer, B. & Stewart, K. (2007) "Comparing the Consumer Price Index and the Personal Consumption Expenditures Price Index", Survey of Current Business, 87(1).

Mukherjee, T.K. and Naka, A., 1995. Dynamic relations between macroeconomic variables and the Japanese stock market: an application of a vector error correction model. *Journal of financial Research*, *18*(2), pp.223-237.

Mussa, M. and Savastano, M., 1999. The IMF approach to economic stabilization. *NBER macroeconomics annual*, *14*, pp.79-122.

Pagan, A.R. and Schwert, G.W., 1990. Alternative models for conditional stock volatility. *Journal of econometrics*, *45*(1-2), pp.267-290.

Pagan, A.R. and Sossounov, K.A., 2003. A simple framework for analysing bull and bear markets. *Journal of applied econometrics*, *18*(1), pp.23-46.

Page, S. and Taborsky, M.A., 2011. Invited Editorial Comment: The Myth of Diversification: Risk Factors versus Asset Classes. *The journal of portfolio management*, *37*(4), pp.1-2.

Pan, Z., Pettenuzzo, D. and Wang, Y., 2020. Forecasting stock returns: A predictor-constrained approach. *Journal of Empirical Finance*, *55*, pp.200-217.

Pástor, Ľ. and Stambaugh, R.F., 2001. The equity premium and structural breaks. *The Journal of Finance*, *56*(4), pp.1207-1239.

Park, D.K., Gelman, A. and Bafumi, J., 2004. Bayesian multilevel estimation with poststratification: State-level estimates from national polls. *Political Analysis*, *12*(4), pp.375-385.

Perez-Quiros, G. and Timmermann, A., 2000. Firm size and cyclical variations in stock returns. *The Journal of Finance*, *55*(3), pp.1229-1262.

Pesaran, M.H. and Timmermann, A., 2002. Market timing and return prediction under model instability. *Journal of Empirical Finance*, *9*(5), pp.495-510.

PIMCO, 2010 "Viewpoints Discussion Paper", June 2010, Pacific Investment Management Company LLC

Poterba, J.M. and Summers, L.H., 1988. Mean reversion in stock prices: Evidence and implications. *Journal of financial economics*, *22*(1), pp.27-59.

Reboredo, J.C., 2013. Is gold a safe haven or a hedge for the US dollar? Implications for risk management. *Journal of Banking & Finance*, *37*(8), pp.2665-2676.

Sargent, T.J. and Sims, C.A., 1977. Business cycle modelling without pretending to have too much a priori economic theory. *New methods in business cycle research*, *1*, pp.145-168.

Samuelson, P.A., 1965. A theory of induced innovation along Kennedy-Weisäcker lines. *The Review of Economics and Statistics*, pp.343-356.

Schooley, D.K. and Worden, D.D., 1996. Risk aversion measures: Comparing attitudes and asset allocation. *Financial services review*, *5*(2), pp.87-99.

Sharpe, W.F., 1965. Risk-aversion in the stock market: Some empirical evidence. *The Journal of Finance*, *20*(3), pp.416-422.

Sharpe, W.F (1998) "The Sharpe Ratio", Streetwise – the Best of the Journal of Portfolio Management, pp: 169-185

Sheikh, A.Z. and Sun, J., 2012. Regime change: Implications of macroeconomic shifts on asset class and portfolio performance. *The Journal of Investing*, *21*(3), pp.36-54.

Shiller, R.J., 2000. Measuring bubble expectations and investor confidence. *The Journal of Psychology and Financial Markets*, *1*(1), pp.49-60.

Shiskin, J., 1974. Updating the consumer price index—an overview. *Monthly Labor Review*, pp.3-20.

Schooley, D.K. and Worden, D.D., 1996. Risk aversion measures: Comparing attitudes and asset allocation. *Financial services review*, *5*(2), pp.87-99.

Siegel, L.B., Kroner, K.F. and Clifford, S.W., 2001. The greatest return stories ever told. *The Journal of Investing*, *10*(2), pp.91-102

Sirucek, M., 2012. Macroeconomic variables and stock market: US review.

Sims, C.A., Stock, J.H. and Watson, M.W., 1990. Inference in linear time series models with some unit roots. *Econometrica: Journal of the Econometric Society*, pp.113-144.

Swinkels, L. (2019) Treasury Bond Return Data Starting in 1962

Taleb, N.N. and Raju, P.V.L., 2011. Fooled by Randomness.

Thaver, R.L & Lopez, J. (2016) "Unemployment as a determinant of Gold Prices: Empirical evidence", The International Journal of Business and Finance Research, Vol.10(4), pp: 43-52

Thaler, R.H. and Ganser, L.J., 2015. Misbehaving: The making of behavioural economics.

Treynor, J.L & Mazuy, K.K 1966 "Can Mutual Funds Outguess the Market", Harvard Business Review, 4, 131-136.

B. Tuckman and A.Serrat (2011) "Fixed Income Securities. Tools for Today's Markets", Third Edition, 2011, Wiley Finance (FIS)

Turner, C.M., Startz, R. and Nelson, C.R., 1989. A Markov model of heteroskedasticity, risk, and learning in the stock market. *Journal of Financial Economics*, *25*(1), pp.3-22.

Tumarkin, R., and R. Whitelaw. 2001. "News or Noise? Internet Postings and Stock Prices."
Financial Analysts Journal 57: 41–51.

Villani, M., 2009. Steady-state priors for vector autoregressions. *Journal of Applied Econometrics*, *24*(4), pp.630-650.

Wang, P., Sullivan, R.N. and Ge, Y., 2012. Risk-Based Dynamic Asset Allocation with Extreme Tails and Correlations. *The Journal of Portfolio Management*, *38*(4), pp.26-42.

Welch, I. and Goyal, A., 2008. A comprehensive look at the empirical performance of equity premium prediction. *The Review of Financial Studies*, *21*(4), pp.1455-1508.

Whitelaw, R.F., 2000. Stock market risk and return: An equilibrium approach. *The Review of Financial Studies*, *13*(3), pp.521-547.

Yardeni, E.E., 2018. *Predicting the Markets: A Professional Autobiography*. YRI Press.

Zhou, X. and Jain, S., 2014. *Active equity management*.