How do Changes in Key UK Macroeconomic Variables Influence Domestic Stock Market Prices?

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Abstract

The research aim in the following study is to analyse how changes in macroeconomic variables influence domestic stock prices within the UK, represented by the FTSE350 Index. The researcher obtained secondary data from the OECD, ONS, and Investing.com, to measure the independent variables and domestic stock prices over time from Jan 2003-Jan 2020. Initially, correlation matrices were utilised to investigate the surface relationships between the variables, GDP exhibited the strongest positive correlation, whereas short-term interest rates had the strongest negative correlation, with the FTSE350. A Vector Error Correction Model is employed to measure the short-run and long-run underlying relationships between the variables, measuring at the 5% significance level for statistical relevance. The findings indicate that in the short-run, there is a significant linear relationship between GDP growth rate increases lagged one period, and FTSE350 large growth rate increases in the current period, whereas CPIH exhibits a smaller, inverse, yet statistically significant relationship with the FTSE350. Other independent variables including money supply, unemployment, interest rates and oil prices, do not have significant relationships in the short-run. The long-run relationship between the variables is estimated via a cointegration equation but is evidently considered statistically irrelevant. Causality between the variables is determined via the Granger Causality test, The findings indicate that GDP, CPIH, and all other examined macroeconomic variables do not granger cause the FTSE350's share price, barring interest rates, which demonstrates a bidirectional causal relationship with the FTSE350. In addition, the study finds that the FTSE350 has a unidirectional causal relationship with GDP and Unemployment respectively. The overall model satisfies autocorrelation, multicollinearity, misspecification, and stability checks, but falls short in tests pertaining to residual normality and heteroskedasticity. Therefore, moderate caution is warranted when leveraging these findings due to the model's inability to meet certain diagnostic criteria.

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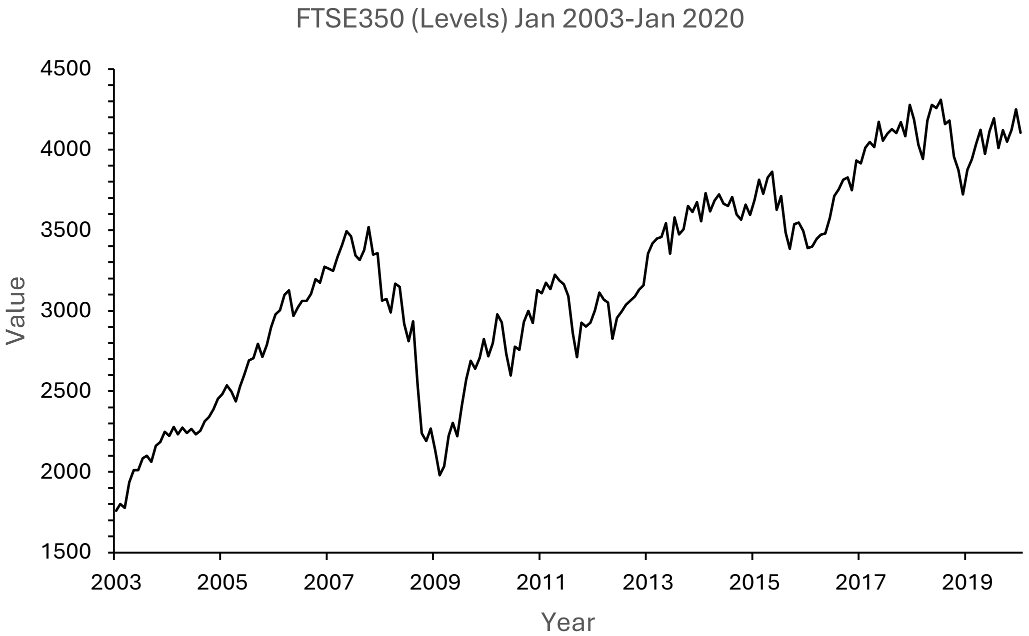
1: Introduction

Evidently, the stock market is a tempting investment and its importance spans across virtually every financial system in the world. However, it can also be daunting to place hard earned money in a system that isn't guaranteed to yield a profit. The Financial Times (2021) suggests that more than 70% of DIY investors lose money, highlighting the significance of understanding the underlying factors that influence stock market prices, thus unveiling the importance of this study.

The study explores the question of whether changes in key UK macroeconomic variables influence domestic stock market prices. The study will regress the Financial Times Stock Exchange 350 index fund on the Money Supply (M3), Gross Domestic Product (GDP), Consumer Price Index including Housing costs (CPIH), Labour Market Unemployment Rates (EMP), Short-term Interest Rates (INT), and Oil Prices (OIL).

Figure 1 Shows an overview of the price for the FTSE350 Index, across the period of investigation for this analysis:



The FTSE350 was launched by the London Stock Exchange (LSE, 2024) on the 30th of December 1983, five days before the launch of the FTSE100. This Index tracks the top 350 companies listed on the LSE by market capitalization, incorporating stocks from both the FTSE100 and FTSE250 indices. Combining both indices provides a much broader representation of the UK stock market, distinguishing the study's dependent variable.

1.1 Objectives of Study

The objective of this study is to examine the relationship between six macroeconomic variables and the FTSE350 Index for the period of January 2003-January 2020. Through this study, the researcher endeavours to inform policymakers with insights into the underlying relationships identified, reinforcing economic stability in future policy while also equipping individual firms and investors with informed strategies for keeping investments safe in any economic landscape. This will be done via 4 objectives:

1) Establish a hypothesis for each macroeconomic variable, based on the literature and economic theory available.
2) Utilise correlation matrices to establish correlations between macroeconomic variables and the FTSE350.
3) Utilise the Vector Error Correction Model to identify significant short-run and cointegrating long-run relationships between the variables.
4) Utilise the Granger Causality Test to identify one way causality from macroeconomic variables to the FTSE350.

2: Theoretical Framework

For this study, two essential theoretical frameworks have been employed that virtually every other study utilises to investigate the relationship between stock prices and macroeconomic variables: the Arbitrage Pricing Theory (APT) model introduced by Ross in 1976 and the Efficient Market Hypothesis (EMH) proposed by Fama in 1970. Utilizing these frameworks will not only sufficiently complement statistical results but will also ensure consistency and comparability for similar research on this topic.

2.1 Ross's Arbitrage Pricing Theory

Initially, the first fundamental framework for comprehending the connection between stock asset returns and systematic risk was proposed by William Sharpe (1964), this was known as the Capital Asset Pricing Model (CAPM). Though the CAPM served as a foundation for asset pricing theory, it did not account for multiple risk factors. Stephen A. Ross (1976) extended this framework and proposed an alternative model called Arbitrage Pricing Theory. APT offers a multi-factor model that explains asset returns via macroeconomic variables, with the key difference between the models lying in their approach to systemic risk factors.

Ross argued that the APT model allowed for the inclusion of multiple variables in his research both macroeconomic and non-macroeconomic. This flexibility will allow the researcher to use key UK macroeconomic variables in their analysis that could potentially affect asset returns and hence the FTSE350 if the asset is listed as a share within the index.

2.2 Fama's Efficient Market Hypothesis

The Efficient Market Hypothesis was created by Eugene Fama (1970), his theory states that financial markets are efficient at accessing all available information at any given time, this means all current information and any new information is immediately reflected in an asset's price. Because of this principle, the EMH states that it is impossible for an investor to time the market to generate returns above the average market return.

Fama identified three different types of market efficiency: weak form, semi-strong form, and strong form efficiency. This study is going to focus on the semi-strong form of EMH as it assumes stock prices reflect all publicly available information, both past and present, while private information is omitted from this form of definition. This framework is crucial as the inclusion of all public information implies that any UK macroeconomic data releases will be incorporated into stock prices and hence it's therefore possible that the chosen macroeconomic variables in this study will have an effect.

3: Literature Review

The following review will concentrate on the research that best aligns with the variables selected and the objectives of the study. The relationships between macroeconomic variables and stock prices have been extensively researched, the literature discussed within this study goes back over sixty years.

Some of the earliest research conducted on this topic was by Sprinkel (1964). He found that money supply changes were a good predictor of stock prices when using a simple quantity theory (SQT) model. Homa & Jaffee (1971) Found a similar relationship when investigating if common stock prices were dependent on the money supply using an EMH model. Stock prices was found to have a positive relationship with the money supply through the use of the risk-free rate of interest, this variable was a function of the money supply. This coincided with the research by Hamburger & Kochin (1972), and Keran (1971), which observed a strong positive relationship between money supply and the stock market.

Pesando (1974) questioned the validity of the findings in his evaluation of the three models proposed by Homa & Jaffee, Hamburger & Kochin, and Keran. He found that the models exhibited limited reliability in predicting stock prices when benchmarked against real-world data. Moreover, their structural stability proved inconsistent when adapting the specification. He concluded there is no assurance that money supply and stock prices are causally related. Cooper (1974) reviewed Sprinkel's findings and utilizing an SQT-EMH model, he identified an inverse relationship where stock prices accurately predicted changes in the money supply, directly opposing Sprinkel. As a result, he criticized Sprinkel's model for its misspecification and contended that SQT and EMH are complementary theories rather than contradictory.

Dimson et al. (2002) measured the cross-sectional effect of per capita economic growth on stock prices and concluded that there was a -0.27 correlation, a negative relationship between the two variables after adjusting for inflation. These results closely parallel Ritter's (2005) research, identifying a negative coefficient of -0.37, though he also found the association between the two variables was not statistically significant.

Klement (2015) utilised GDP per capita growth rates from a 50/50 ratio of developed and emerging economies in conjunction with a range of large, mid, and small cap stocks. Much like Ritter, Klement also failed to establish a significant relationship between GDP per capita and stock prices across all types of stock market indexes. This was similar to research conducted by Dimensional (2016), they investigated a mixture of developed and emerging market stock prices alongside short-term economic growth rates from 1995-2014, economies with lower growth rates produced higher stock returns. However, the relationship between the two variables was not significant: mirroring the outcomes of both Ritter and Klement. Hsu et al. (2022) built upon Dimson's work with a study sampling over 120 years' worth of data, they concluded: *"There is no theoretical basis for expecting a positive correlation between a country's stock returns and per capita income growth."*

Jaffe & Mandelker (1976) examined the relationship between inflation rates and stock prices, utilizing the Fisher hypothesis as a foundation to build on. The hypothesis states that nominal asset returns move with expected inflation, implying that the asset is a hedge against inflation. They regressed common stock price data from 1953-1971 on the Consumer Price Index (CPI). Ultimately, a significant negative relationship between rates of inflation and stock returns was found, contradicting the Fisher hypothesis. This matched findings by Nelson (1976), using a similar methodology but expanding the time frame an additional three years via the S&P 500 Index, he also generally found that there was a negative relationship between rates of inflation and stock returns for both anticipated and unanticipated rates of inflation. This finding was consistent with Geske & Roll's (1983) study on Inflation and Stock prices, moreover they offered a unique explanation of the data, proposing that an unanticipated increase in real inflation is a sign of a collapsing economy, which will inevitably affect stock prices.

Conversely, Firth (1979) used the monthly Index of Retail Prices (IRP) to lag the monthly measure of inflation in conjunction with the Ordinary FTSE, his results found a positive relationship between inflation and UK stock market returns, and therefore the stock market served as a partial hedge against inflation, a relationship that was also identified by Ang et al. (1979). Their work directly clashed with the findings of Jaffe & Mandelker, and Nelson, arguing that the studies did not prove nor disprove the existence of the Fisher Hypothesis. Using data from 1960-1975, they confirmed the existence of the hypothesis and established a positive relationship between inflation and stock prices.

Pearce & Roley (1985) measured real economic activity by utilizing the unemployment rate and industrial production data, they found that unemployment, industrial production, and CPI had no significant effect on prices from 1977-1982. McQueen & Roley (1993) built on this initial research and extended the sample period to 1988. They concluded that broadening the sample period increased the variety of business cycle stages captured, and hence a strong positive relationship between unemployment rates and stock prices was found, this aligns with the research produced by Boyd et al. (2005), they on average found that an unemployment increase announcement had a positive effect on stock prices. A shared finding by Gonzalo & Taamouti (2017), their rationale behind this effect is rooted in the anticipation that rising unemployment signals forthcoming interest rate reductions. Boyd et al. further explains that the size of this relationship is influenced by economic conditions, for example, they found interest rate fluctuations play a more significant role during economic booms.

Campbell & Ammer (1993), used a Vector Autoregressive Model (VAR) to identify which macroeconomic variables move stock prices. In particular, they found that short-term real interest rates were found to have little to no impact on stock returns. Zhou (1996) regressed stock returns against interest rates over an 8-year period, he found that for long-term investment horizons, there was a significant and positive relationship between interest rates and stock returns, a relationship that clashes with work by Ratanapakorn & Sharma (2007). They investigated six different macroeconomic variables between 1975-1999 and observed a negative relationship between long-term interest rates and stock prices. However, they also simultaneously found that short-term interest rate increases were associated with higher stock returns. Alam & Uddin (2009), using both time-series and panel regressions for investigating the relationship between interest rates and stock prices for fifteen countries. They found for all countries, a significant negative relationship between interest rates and share price.

Gjerde & Saettem (1999), and Sadorsky (1999) produced some of the earliest research on the relationship between oil prices and stock prices, both using a VAR model. Gjerde & Saettem focused on Norwegian data, a country notably dependent on oil exports for its economy. As anticipated, they found that oil prices shared a significant and positive relationship with stock market returns in Norway. In contrast, Sadorsky sourced relevant data from the U.S., his estimated model suggested that fluctuations in oil prices had a significant and negative impact on stock prices, this observation was further supported by Driesprong et al. (2008). Utilizing a world market index and market indices from 18 different countries, they found that an increase in oil prices lead to a significant drop in stock market returns. Their results could not be explained by time-varying risk premia (TVRP). To conclude this section, Park & Ratti (2008) utilised a multivariate VAR model and included data from both the U.S. and 13

European countries to investigate oil prices and stock returns over a 20-year period. They found that within Norway, oil prices had a significant and positive relationship with stock market returns, aligning with Gjerde & Saettem's findings on the oil exporter. On the other hand, Park & Ratti also determined that fluctuations in oil prices contribute to 6% of the variability observed in real stock returns, they subsequently concluded by suggesting that increased volatility of oil prices significantly reduced stock returns for European countries.

4: Hypotheses, Data & Methodology

4.1 Hypotheses

Table 1 Summarises the hypotheses for this analysis, determined by the combination of economic theory and the extensive overview of literature that points to a general consensus among researchers regarding the significant influence of various macroeconomic variables on the dynamics of stock prices:

Variable	Abbreviation	Hypothesis	Supporting Literature
Money Supply	M3	Despite the criticisms of the proposed models, the most common result and hypothesis for this study will be that there is a **positive relationship** between stock prices and M3.	Sprinkel (1964), Homa & Jaffee (1971), Hamburger & Kochin (1972), Keran (1971)
Gross Domestic Product	GDP	Mixed significancy results but typically with a negative relationship, this study will hypothesize that there is a **negative relationship** between stock prices and GDP.	Dimson et al. (2002) Ritter's (2005) Dimensional (2016) Hsu et al. (2022)
Consumer Price Index Inc. Housing costs	CPIH	The review yields mixed results, though economic theory suggests higher inflation signals interest rate hikes, therefore this study will hypothesize that there is a **negative relationship** between stock prices and CPIH.	Jaffe & Mandelker (1976) Nelson (1976) Geske & Roll's (1983)
Unemployment Rate	EMP	General consensus among literature as well as supporting economic theory suggests unemployment rate increases signal interest rate decreases, therefore the hypothesis for this study will be that there is a **positive relationship** between stock prices and EMP.	McQueen & Roley (1993), Boyd et al. (2005), Gonzalo & Taamouti (2017)

Short-Term Interest Rates	INT	Mixed results from the review, though in order to stay consistent with economic theory and preceding variables, this study will hypothesize that there is a **negative relationship** between stock prices and INT.	Ratanapakorn & Sharma (2007) Alam & Uddin (2009)
Oil Prices	OIL	Results were highly dependent on the context of the country's reliance of exporting oil, given this trend, this study will hypothesize that there is a **negative relationship** between stock prices and OIL.	Sadorsky (1999) Driesprong et al. (2008) Park & Ratti (2008)

4.2 Variable Descriptions

The variables selected for the analysis are chosen based on their potential to exert significant influence over stock market prices and their extensive coverage in the public domain. This section offers insights into these selected variables, shedding light on their importance in the price of the UK's domestic stock market.

Dependent, FTSE Index (FTSE350): The FTSE350 is a highly diversified index which includes the top 350 UK companies listed on the LSE by market capitalization. Providing the researcher with a huge range of companies to represent domestic stock prices while also excluding the volatility of penny stocks from the analysis.

Independent [1], Money Supply (M3): M3 money supply encompasses a broad scope of financial assets. It includes physical currency, demand deposits, repurchase agreements, institutional money market funds, etc. It's a key indicator of an economy's monetary base and it mirrors overall financial health and stability.

Independent [2], Gross Domestic Product (GDP): GDP is a globally recognised standard of economic performance, it delineates the total monetary value of all goods and services produced by an economy within a specific timeframe. GDP encapsulates consumption, investment, government spending, and net exports, therefore, it can track whether an economy at a given point is either growing or contracting.

Independent [3], Consumer Price Index Inc. Housing costs (CPIH): CPIH mirrors the average price of a basket of goods and services consumed by households in the UK and is virtually identical to CPI but with the added costs of housing and council tax. The rationale behind using this alternative measure of inflation is due to its accurate reflection of real-world inflationary pressures on households.

Independent [4], Unemployment Rate (EMP): The Unemployment Rate identifies the proportion of the labour force actively seeking employment for at least a period of four weeks. It reflects workforce participation and hence the economy's health. Changes in the unemployment rate have an effect on government spending, consumer confidence, and as rationalised by Gonzalo & Taamouti (2017), unemployment rate fluctuations signal interest rate changes.

Independent [5], Short-Term Interest Rates (INT): Short-term interest rates reflect the immediate cost of borrowing and lending in financial markets, a short-term measurement was selected based on its ability to capture rapid effects on financial markets, prime example of this in the UK is the treasury bill rate, also known as the “money market rate” or “risk-free rate”.

Independent [6], Oil Prices (OIL): Oil prices have profound effects on practically every business sector, and especially on manufacturing, energy, and transportation. For example, a rise in oil prices will typically drive-up costs for firms, thus reducing profit margins. This domino effect has the potential to reduce consumer confidence in a company's financial outlook, thereby influencing stock prices. Although oil is categorised as a commodity, it has been included in this research owing to its significant influence on the stock market. The chosen measurement for oil prices is the Brent crude benchmark, as it serves as the pricing mechanism for more than three-quarters of the world's traded oil (Wittner, 2020)

4.3 Data Collection

This study focuses on a monthly time-series for the FTSE350 Index and six independent variables using secondary data, suggesting that the researcher themselves did not obtain/survey this data but instead collected it from reputable information sources. The period for the measurement is from January 2003 to January 2020, comprised of 205 observations. This period has been selected based on data availability and avoidance of economic shocks where possible such as the covid pandemic.

Stock market index data and Brent oil prices were collected from Investing.com, a reputable financial market platform that provides real-time price data for stock indices and commodities. Both Short-term interest rates and M3 Money supply data were collected from the highly regarded Organization for Economic Cooperation and Development (OECD). The remaining three variables; GDP, CPIH and Unemployment Rates, have been sourced from the Office of National Statistics (ONS).

4.4 Vector Error Correction Model

The chosen model for the time-series analysis is the Vector Error Correction Model (VECM), also known as the equilibrium correction model, similar to a standard Vector autoregression (VAR) model but for non-stationary variables with cointegrating relationships, developed by Sargan (1964). The model was selected due to its unique ability to measure both short-run relationships and long-run stochastic trends between cointegrating variables while also aligning with the APT framework. Brooks (2008) defines a VECM with two variables and constant terms as the following equation:

Equation 1:

$$\boldsymbol{\Delta y_t = \beta_0 + \beta_1 \Delta x_1 + \beta_2 (y_{t-1} - \alpha - \gamma x_{t-1}) + u_t}$$

Where variables $\boldsymbol{y_t}$ and $\boldsymbol{x_t}$ are cointegrated, $\boldsymbol{y_{t-1}}$ represents the lagged value of the dependent variable, $\boldsymbol{\gamma}$ is the cointegration coefficient that describes the long-run relationship between $\boldsymbol{x_t}$ and $\boldsymbol{y_t}$, and $(\boldsymbol{y_{t-1} - \alpha - \gamma x_{t-1}})$ is known as the error correction term (ECT). The ECT can be separated into its own equation to isolate the long-run model, this is known as the cointegrating equation:

Equation 2:

$$\boldsymbol{ect_{t-1} = y_{t-1} - \alpha - \gamma x_{t-1}}$$

Additional parameters such as $\boldsymbol{\beta_2}$ represent the speed of adjustment within a period for variables to tend back towards their long-term equilibrium if they deviate from it, $\boldsymbol{\beta_1}$ represents the impact of a unit change in $\boldsymbol{x_t}$ on the change in $\boldsymbol{y_t}$ in the short-run relationship,

$\boldsymbol{\beta}_0$ & $\boldsymbol{\alpha}$ represent the constant terms for the short run and long-run equilibrium relationships respectively and $\boldsymbol{u_t}$ is the residual term. Integrating the study's dependent and macroeconomic variables, into the standard VECM model, as well as including lag and log transformations into the final equation, yields:

Equation 3:

$$\Delta lnFTSE350_t = \beta_0 + \beta_1 \Delta lnFTSE350_{t-1} + \beta_2 \Delta lnM3_{t-1} + \beta_3 \Delta lnGDP_{t-1} + \beta_4 \Delta lnCPIH_{t-1} + \beta_5 \Delta lnEMP_{t-1} + \beta_6 \Delta lnINT_{t-1} + \beta_7 \Delta lnOIL_{t-1} + \beta_8 (lnFTSE350_{t-1} - \alpha - \gamma_1 lnM3_{t-1} - \gamma_2 lnGDP_{t-1} - \gamma_3 lnCPIH_{t-1} - \gamma_4 lnEMP_{t-1} - \gamma_5 lnINT_{t-1} - \gamma_6 lnOIL_{t-1}) + u_{t-1}$$

5: Analysis & Time-Series Prerequisites

In this section, the researcher will perform a comprehensive analysis of the 17-year time-series dataset. The use of correlation matrices and descriptive statistics are employed as well as pre-emptive variable changes and tests, which will ultimately allow the researcher to run the final VECM model. This includes standard non-stationary data prerequisites including Dickey-Fuller tests for unit roots, VAR lag selection and the Johansen test for potential cointegrating relationships.

5.1 Descriptive Statistics

Appendix A shows the table of descriptive statistics for each variable, encompassing measures such as the mean, variance, kurtosis, skewness, and additional relevant metrics. The levels of variables are showcased in **Appendix B,** as well as their natural logarithms in **Appendix D**, offering valuable insights into the behaviour of the variables over time. Notably, **Figure 1** shows a clear upward bias observed in the FTSE350 (akin to most index funds), reaching a peak price of 4,311 in July 2018. All variables, with the exception of CPIH, possess a positive kurtosis value, this implies they are distributed with thinner tails and less extreme values than a normal distribution, this known as a platykurtic distribution. CPIH possesses a positive kurtosis figure of 0.35, suggesting that the distribution has a heavier tail and more extreme values, known as a Leptokurtic distribution.

Distributive histogram plots have been utilised in **Appendix C** to visualize the variability and frequency of distribution to spot abnormalities; this has aided the choice to exclude covid-19 data from the period analysed to reduce noise and multicollinearity. **Figures 8,10 & 11** (FTSE350, GDP & CPIH) convey relatively normal bell-shaped distributions with most data points falling around the mean value accompanied by a low spread. Whereas **Figures 9 & 12-14** (M3, EMP, INT & OIL) have a bimodal nature, likely as a result of the 2007-2009 financial crisis. As exemplified by **Figures 6 & 13** describing the values and distribution of interest rates, a large frequency of extremely low interest rates is observed after 2008. All variables apart from the FTSE350 and M3 have a slight positive skew figure, indicating an asymmetric distribution (longer right-side tail). While the researcher recognizes platykurtic distribution and positive skew doesn't necessarily require immediate action, these characteristics could affect the reliability of the VECM analysis, requiring thorough diagnostic checks for the final model.

5.2 Correlation

A correlation matrix was employed to further understand the surface relationships between the macroeconomic variables and FTSE350.

Table 2 Shows the summary correlation matrix:

Variable	FTSE350	Correlation
FTSE350	**1.000**	**Perfect Positive**
M3	**0.790**	**Very Strong Positive**
GDP	**0.930**	**Very Strong Positive**
CPIH	**-0.085**	**Very Weak Negative**
EMP	**-0.308**	**Moderate Negative**
INT	**-0.511**	**Strong Negative**
OIL	**0.238**	**Weak Positive**

M3: The FTSE350 & M3 had a very strong positive correlation of 0.79 implying that they move together in an upward direction.

GDP: The FTSE350 & GDP had a very strong positive correlation of 0.93 implying that they move together in an upward direction.

CPIH: The FTSE350 & M3 had a very weak negative correlation of -0.085 implying that they move in opposing directions.

EMP: The FTSE350 & M3 had a moderate negative correlation of -0.308 implying that they move in opposing directions.

INT: The FTSE350 & M3 had a strong negative correlation of -0.511 implying that they move in opposing directions.

OIL: The FTSE350 & M3 had a weak positive correlation of 0.238 implying that they move together in an upward direction.

5.3 Augmented Dickey-Fuller Test

One major challenge encountered in a time-series analysis arises from the presence of non-stationarity data or unit roots causing stochastic trends. These characteristics could introduce the possibility of random walk behaviour which may lead to spurious regressions. Using the Augmented Dickey-Fuller (ADF) test, the researcher can determine whether a unit root is present in the time-series, which helps determine whether to implement first order differences within the data. The Augmented Dickey-Fuller mirrors the original Dickey & Fuller (1979) test but allows for more complex models which potentially includes more parameters, lagged differences and the ability to account for trends/seasonality. The test the researcher is going to use includes a constant (drift term), this decision stems from the recognition that the macroeconomic variables are likely not purely stochastic and instead exhibit influences from underlying economic fundamentals. Thus, rather than testing for a pure random walk, the researcher will test for a random walk with drift which yields this ADF specification:

Equation 4:

$$\Delta Y_t = \alpha + \gamma Y_{t-1} + \sum_{j=1}^{p} (\delta_j \Delta Y_{t-j}) + e_t$$

Where α is the intercept constant, also known as the drift term which represents the baseline of the time-series, p specifies the number of lagged differences, γ is the parameter of interest which signifies the magnitude of root, $\sum_{j=1}^{p} (\delta_j \Delta Y_{t-j})$ denotes additional autoregressive terms and e_t is the residual term at time t.

Three data conditions must be met to satisfy the **weakly** stationary requirement for the regression:

[1] The mean (μ) remains constant across all periods (t).

[2] The variance (σ) remains constant across all periods (t).

[3] The autocovariance function $\gamma(h) = Cov(X_t, X_{t-h})$ which measures the covariance between two observations of the series at different time lags, remains constant. This is represented by: $\gamma(h) = \gamma(0)$ where $\gamma(h)$ is the autocovariance at lag h and $\gamma(0)$ is the autocovariance at lag 0.

The null hypothesis H_0 for this test is that a unit root is present, the null hypothesis will be rejected if the value of the T-Statistic is **lower** than that of the critical value, if the null hypothesis is rejected at the critical values of 10%, 5% and 1%, a unit root is not present. **Appendix F** shows the first initial results using pre-emptive natural logarithm transformations of the variables, the ADF test revealed that out of the seven variables examined, a unit root was present in six, with only M3 displaying an absence of unit roots at the 10% significance level. Based on these results, the researcher will take first differences of the data, represented in **Appendix E,** and rerun the ADF test, this should satisfy the stationarity requirement after subtracting the previous value of a variable from the current value, denoted as: $\Delta y_t = y_t - y_{t-1}$, this is known as the difference-stationary process.

Table 3 Summarises Second Augmented Dickey-Fuller Test (With a Constant) on the First Difference of Natural Logs:

Variable	Test Statistic (Critical Value)	Critical Value (1%)	Critical Value (5%)	Critical Value (10%)	P-Value (ADF Test)	Unit Root (UR) Result
D_LN_FTSE	**-14.185**	**-3.457**	**-2.873**	**-2.573**	**0.000**	UR is Not Present at 1% Significance
D_LN_M3	**-4.002**				**0.001**	UR is Not Present at 1% Significance
D_LN_GDP	**-3.757**				**0.003**	UR is Not Present at 1% Significance
D_LN_CPIH	**-11.693**				**0.000**	UR is Not Present at 1% Significance
D_LN_EMP	**-3.247**				**0.017**	UR is Not Present at 5% Significance
D_LN_INT	**-4.378**				**0.000**	UR is Not Present at 1% Significance
D_LN_OIL	**-11.086**				**0.000**	UR is Not Present at 1% Significance

The table above breaks down the seven variables with a critical value as well as the p-value and the resulting hypothesis of the ADF test, all variables possess a T-statistic lower than the 5% critical value threshold, this means that the null hypothesis $\boldsymbol{H}_0$ is rejected, none of the variables possess a unit root and all are considered weakly stationary at I(1). This means the researcher can now move onto identifying the necessary lag specification to perform a cointegration test.

5.4 VAR Lag Order Selection

Time-series data frequently has temporal dependencies, which means that the FTSE350 value at a given point in time is likely dependent on both its historical values and the historical values of macroeconomic variables; incorporating delays into the model is a procedure that will account for this phenomenon. To determine the lag specification for the cointegration test, a maximum number of lags must be selected. Given that the researcher is using monthly data, a maximum of 6 lags will be sufficient for the lag order selection test. The test was initially conducted with 5 different lag criteria; however, the chosen criteria will be the Akaike (1974) information criterion (AIC) due to the limited sample size available for this analysis, and its ability to determine risk for both overfitting and underfitting a model.

Table 4 summarises the results from the VAR Lag Order Selection Criteria for AIC:

Lag	LogLik	AIC	Optimal Lag Order
0	**573.208**	**-5.691**	No
1	**3082.163**	**-30.327**	No
2	**3182.287**	**-30.928***	**Yes**
3	**3224.019**	**-30.854**	No
4	**3257.485**	**-30.698**	No
5	**3306.631**	**-30.700**	No
6	**3345.838**	**-30.601**	No

The table denotes the optimal lag via the asterisk. The test utilizes the natural log levels rather than the first difference because the VECM model planned for use automatically takes the first difference of the variables. The lower AIC values indicate better-fit models; hence lag 2 is selected as the optimal lag order for cointegration.

5.5 Johansen Cointegration Test

Time-series data can possess long-run equilibrium relationships between two or more non-stationary variables, cointegration captures the relationship of the variables that move together over time, this implies that even if there is a short-term shock, the series is expected to converge in the long-run. In order to run a VECM, the researcher needs to determine the cointegration rank, utilizing the Johansen (1991) test, ideal for a time-series with more than one cointegrating relationship equation. There are two forms of the test that identify what rank of cointegration is present within a time-series, the first form is the trace test, the second form is the maximum eigenvalue test (Lmax test). The null hypothesis $\boldsymbol{H}_0$ for this test is that there is no cointegrating equation, the alternative hypothesis $\boldsymbol{H}_1$ is that there is a cointegrating equation, **Appendix G,** discloses the Johansen Cointegration Test results for 6 different ranks, for ranks 3-6 of cointegration, the p-value yielded a result above the 5% significance level for each test, hence the researcher does not reject the null hypotheses, there is no cointegration at the 3rd-6th rank.

Table 5 summarises the results from the Johansen Cointegration test:

Cointegration Rank	Eigenvalue	Trace Test P-value	Lmax Test P-Value
None*	0.339	**0.000**	**0.000**
At most 1	0.170	**0.004**	**0.111**
At most 2	0.132	**0.031**	**0.230**

The table contains mixed results regarding the conclusion for the cointegration rank, the trace test indicates there are potentially **over two** cointegrating equations for the time-series, this is clear from the p-value's that are below the 5% significance level, hence the null hypothesis is rejected. However, according to the Lmax test, only the "None" rank's p-value is below the 5% significance level, hence the researcher can only reject the null hypothesis for the 0th rank. As the null cannot be rejected for both tests for the first and second rank, the overall result indicates that there is **one** cointegration equation for the time-series analysis. Now that the lag order has been determined and cointegration has been found within the time-series data, the appropriate specification for the regression is a vector error correction model.

6: Results

In this section, the researcher will present and interpret the findings and the statistical relevance of each variable from the final model utilizing the VECM methodology discussed in **4.4**. These results will determine the short-term and long-term significant relationships between the variables, measuring at the 5% significance level. Results will also undergo additional validation by utilizing the Granger-Causality test to determine whether a variable granger causes another in a unidirectional or bidirectional relationship.

6.1 Final Models Interpretation & Discussion

All variables were transformed into the first differenced, natural logarithm of their level, determined by the Dickey-Fuller Test. The VAR lag selection process identified the ideal final model to have two lags, however, a VECM model output will have one lag of difference, denoted by **(-1)** in the final tables. This is due to the fact that the variables in the VECM are in their first difference form, but the underlying VAR is specified for original variables. Finally, the model assumes there is one cointegrating equation, determined by the Johansen test.

The overall model has an **R^2** value of 8.21%, the adjusted **R^2** value falls to 4.43%, suggesting that only 4.43% of the FTSE350's price variation is explained by the macroeconomic variables. However, **R^2** is a measure of explanatory power rather than fit, meaning that although the value itself is quite low, the model can still possess statistically significant explanatory power, exemplified by the F-statistic for the model, yielding a value of 2.17. The p-value for the F-statistic is 0.03, this suggests that the model is significant at the 5% significance level. Furthermore, one possible rationale for a lower R^2 value is the first-difference transformations reducing the variation and correlation within the data.

Table 6 presents the estimated results from the cointegrating (long-run) equation:

Variable	Coefficient [γ]
LN_FTSE350(-1)	**1.000**
LN_M3(-1)	**-0.041**
LN_GDP(-1)	**-3.560**
LN_CPIH(-1)	**0.003**
LN_EMP(-1)	**-0.360**
LN_INT(-1)	**-0.078**
LN_OIL(-1)	**-0.038**
C (Intercept) [α]	**8.866**

When interpreting the coefficient values of a cointegrating equation, it is imperative that the positive and negative signs are reversed as the equation subtracts the coefficient as seen in equation 3, hence substituting the values from the table yields the final cointegrated long-term equation:

Equation 5:

$$ect_{t-1} = 1.00\boldsymbol{lnFTSE}350_{t-1} - 8.87 + 0.041\boldsymbol{lnM}3_{t-1} + 3.56\boldsymbol{lnGDP}_{t-1} - 0.003\boldsymbol{lnCPIH}_{t-1} + 0.36\boldsymbol{lnEMP}_{t-1} + 0.078\boldsymbol{lnINT}_{t-1} + 0.038\boldsymbol{lnOIL}_{t-1}$$

This equation implies that for the following variables, assuming ceteris paribus:

M3: A 1% increase in M3 lagged one period, will result in a 0.041% increase in the FTSE350 in the long-run.

GDP: A 1% increase in GDP lagged one period, will result in a 3.56% increase in the FTSE350 in the long-run.

CPIH: A 1% increase in CPIH lagged one period, will result in a 0.003% decrease in the FTSE350 in the long-run.

EMP: A 1% increase in EMP lagged one period, will result in a 0.36% increase in the FTSE350 in the long-run.

INT: A 1% increase in INT lagged one period, will result in a 0.078% increase in the FTSE350 in the long-run.

OIL: A 1% increase in OIL lagged one period, will result in a 0.041% increase in the FTSE350 in the long-run.

To determine whether the long-run relationship for the variables is statistically relevant, the researcher must analyse the coefficient $\boldsymbol{\beta}_8$ output.

Table 7 presents the estimated results for the final VECM:

Variable	$\boldsymbol{\beta}_2$ $\boldsymbol{\beta}_3$ Coefficient	Estimated Value	P-Value
d_lnFTSE350(-1)	$\boldsymbol{\beta}_4$	**0.006**	**0.938**
d_lnM3(-1)	$\boldsymbol{\beta}_5$	**0.332**	**0.354**
d_lnGDP(-1)	$\boldsymbol{\beta}_6$	**1.374**	**0.011**
d_lnCPIH(-1)	$\boldsymbol{\beta}_7$	**-0.041**	**0.022**
d_lnEMP(-1)	$\boldsymbol{\beta}_8$	**-0.245**	**0.2**
d_lnINT(-1)	$\boldsymbol{\beta}_0$	**0.002**	**0.945**
d_lnOIL(-1)		**0.008**	**0.797**
COINTEQ1		**-0.042**	**0.245**
C (Intercept)		**0.0002**	**0.943**

COINTEQ1($\boldsymbol{\beta}_8$) is associated with a coefficient of -0.042, this is an encouraging indication as this conveys there is long-run convergence, it also implies the previous period's deviation from the long-run equilibrium is corrected in the current period at an adjustment speed of 4.2%, however the p-value is above the 5% significance level at 0.245; this suggests that the long-run relationship estimated is not significant.

The remaining coefficients from $\boldsymbol{\beta}_1$ to $\boldsymbol{\beta}_7$ represent the short run relationship between the macroeconomic variables and the FTSE350, this yields the final short-run equation:

Equation 6:

$$\boldsymbol{FTSE}350_{\boldsymbol{t}} = 0.0002 + 0.006\boldsymbol{\Delta lnFTSE}350_{\boldsymbol{t-1}} + 0.332\boldsymbol{\Delta lnM}3_{\boldsymbol{t-1}} + 1.374\boldsymbol{\Delta lnGDP}_{\boldsymbol{t-1}} - 0.041\boldsymbol{\Delta lnCPIH}_{\boldsymbol{t-1}} - 0.245\boldsymbol{\Delta lnEMP}_{\boldsymbol{t-1}} + 0.002\boldsymbol{\Delta lnINT}_{\boldsymbol{t-1}} + 0.008\boldsymbol{\Delta lnOIL}_{\boldsymbol{t-1}} - 0.042\boldsymbol{ect}_{\boldsymbol{t-1}} + \boldsymbol{u}_{\boldsymbol{t-1}}$$

All variables are in their natural log form and are of their first difference, this means that the difference between two periods is being calculated, which measures their approximate per period growth rates as a percentage (%) change. Given this information, this equation implies that for the following variables, assuming ceteris paribus:

FTSE350: A 1% increase in the growth rate of the FTSE350 lagged one period, will result in a 0.006% increase in the growth rate for the FTSE350 in the current period. The P-value for the FTSE350 is 0.938, this is not statistically significant.

M3: A 1% increase in the growth rate of M3 lagged one period, will result in a 0.332% increase in the growth rate for the FTSE350 in the current period. The P-value for M3 is 0.354, this is not statistically significant.

GDP: A 1% increase in the growth rate of GDP lagged one period, will result in a 1.374% increase in the growth rate for the FTSE350 in the current period. The P-value for GDP is 0.011, this is statistically significant at the 5% significance level.

CPIH: A 1% increase in the growth rate of CPIH lagged one period, will result in a 0.041% decrease in the growth rate for the FTSE350 in the current period. The P-value for CPIH is 0.022, this is statistically significant at the 5% significance level.

EMP: A 1% increase in the growth rate of EMP lagged one period, will result in a 0.245% decrease in the growth rate for the FTSE350 in the current period. The P-value for EMP is 0.200, this is not statistically significant.

INT: A 1% increase in the growth rate of INT lagged one period, will result in a 0.002% increase in the growth rate for the FTSE350 in the current period. The P-value for INT is 0.945, this is not statistically significant.

OIL: A 1% increase in the growth rate of OIL lagged one period, will result in a 0.008% increase in the growth rate for the FTSE350 in the current period. The P-value for OIL is 0.797, this is not statistically significant.

6.2 Granger Causality test

The final step to determine the relationship between macroeconomic variables and the FTSE350 is to identify causality rather than just a significant linear relationship. This can be done via the Granger (1969) Causality test which identifies whether a variable is *"granger caused"* by another via Granger's defined equations:

Equation 7:

$$Y_t = \sum_{i=1}^{n} \alpha_i Y_{t-i} + \sum_{j=1}^{n} \boldsymbol{\beta}_j X_{t-j} + u_{1t}$$

Equation 8:

$$X_t = \sum_{i=1}^{n} \lambda_i Y_{t-i} + \sum_{j=1}^{n} \sigma_j X_{t-j} + u_{2t}$$

Equation 7 conveys that $\boldsymbol{Y_t}$ is related to past values of itself as well as past values of $\boldsymbol{X_t}$ and vice versa for equation 8. In other words, the equations identify whether past values of one variable help predict future values of another variable, this relationship can be bidirectional, meaning that both macroeconomic variables could granger cause domestic stock prices and vice versa. Thus, answering the objective of whether a unidirectional causal relationship can be identified. In addition, n conveys the optimal number of lags within the model determined by the Dickey-Fuller test and $\alpha, \beta, \lambda, \& \sigma$ are the coefficients for the lagged values, If the coefficient is 0, it indicates that a lagged value does not have an effect on the target variable.

Table 8 presents the results from the Granger Causality test:

Null Hypothesis Ho**: Variable 1 Does not Granger Cause Variable 2**			
Variable 1 (first difference and Natural log)	Variable 2 (first difference and Natural log)	P-Value	Result for *Ho*
M3	FTSE350	**0.476**	Accept
FTSE350	M3	**0.157**	Accept
GDP	FTSE350	**0.112**	Accept
FTSE350	GDP	**0.004**	**Reject**
CPIH	FTSE350	**0.113**	Accept
FTSE350	CPIH	**0.792**	Accept
EMP	FTSE350	**0.884**	Accept
FTSE350	EMP	**0**	**Reject**
INT	FTSE350	**0.011**	**Reject**
FTSE350	INT	**0.001**	**Reject**
OIL	FTSE350	**0.079**	Accept
FTSE350	OIL	**0.877**	Accept

The results in the table indicate that for all macroeconomic variables, there is no unidirectional causal relationship with the FTSE350, as the null hypothesis has not been rejected in most cases. The only macroeconomic variable that granger causes the FTSE350 is short-term interest rates, rejecting $\boldsymbol{H}_0$ at the 5% significance level. Therefore, the change in growth rate of INT lagged one period granger causes the FTSE350's growth rate in the current period. However, this relationship is bidirectional as indicated by the p-value at 0.001 for FTSE350→ INT, this is significant at the 1% significance level. Furthermore, there are two significant unidirectional relationships from FTSE350→ EMP/GDP, this implies that the change in growth rate of the FTSE350 lagged one period granger causes GDP/EMP's growth rate in the current period.

6.3 Diagnostics

Appendix H summarises the diagnostic tests for the model, firstly the researcher employed a Breusch-Godfrey Serial Correlation LM Test, the model yielded a 0.549 p-value, this indicates there is no autocorrelation within the data, this is further reinforced by the initial Durbin-Watson test for the model, measured at 2.015, as this is very close to the expected value of 2, this indicates that autocorrelation is not present within the data. Variance Inflation Factor (VIF) measurements were employed to test for multicollinearity within the data, the maximum value determined from the variables was 1.164, implying that there is very low multicollinearity. Stability diagnostics were investigated using a CUSUM plot in **Figure 29**, this tests the cumulative sum of deviations for the model, identifying any abnormalities in the variable's relationship over time. The blue trend line stays within the 5% significance boundary, this suggests that the model is dynamically stable. To test for the normality of residuals, the researcher chose the Cholesky of covariance (Lutkepohl) orthogonalization method and utilised the Jarque-Bera value to investigate both Kurtosis and Skewness. The test investigated all seven coefficients of the short-run relationships within the model, all variables except OIL had a p-value below the 5% significance, indicating that their residuals are not normally distributed. Furthermore, White's test was employed to examine the variance of the residuals (heteroskedasticity), this yielded a p-value of 0.000, strongly suggesting that the variance is not constant. On the other hand, Ramsey's RESET test was employed to determine whether the specification of the model was adequate, this yielded a p-value of 0.161, this is above the 5% significance level hence we do not reject the null hypothesis, the test implies that the model is correctly specified.

7: Conclusion

The study aimed to analyse the influence of macroeconomic variables on domestic stock prices for both short and long-term perspectives. The research question utilised two theoretical foundations which were the Arbitrage Pricing Theory (APT) and the Efficient Market Hypothesis (EMH) to give credibility and significance to the research question. The researcher formulated four objectives for the analysis, the first objective involved an extensive review of relevant literature pertaining to each independent variable's relationship with various stock markets, deriving the study's hypotheses as outlined in **Table 1**. The second objective involved the examination of correlative relationships revealing (**Table 2**) that GDP exhibited the strongest positive correlation, while INT exhibited the strongest negative correlation with the FTSE350.

Addressing the third objective required multiple time-series procedures such as the use of the Dickey-Fuller Test, Johansen cointegration test and VAR lag selection (**Appendix F, G, Table 4**) before estimating the Vector Error Correction Model (VECM). The results (**Table 7**) show that in the short-run, there is a significant linear relationship between GDP growth rate increases lagged one period and large FTSE350 growth rate increases in the current period, Inconsistent with the study's initial hypothesis. In contrast, CPIH shows a smaller, inverse, but statistically significant relationship with the FTSE350, aligning with the initial hypothesis but inconsistent with the fisher hypothesis. Short-term correlations between other independent variables are not significant at the 5% level. The cointegration equation was constructed in **Equation 5**, this established the long-term relationships between macroeconomic variables and stock prices, however the equation was statistically insignificant.

Finally, the fourth objective was achieved by utilizing the granger causality test, the findings (**Table 8**) indicated that all macroeconomic variables other than INT do not granger cause the FTSE350's share price. INT demonstrated a bidirectional causal relationship with the FTSE350, and the FTSE350 demonstrated a unidirectional causal relationship with GDP and EMP respectively.

7.1 Closing Remarks

The overall model satisfies the Breusch-Godfrey test, Durbin-Watson test, VIF test, Ramsey RESET test and dynamic stability checks, but falls short in tests pertaining to residual normality and heteroskedasticity, violating some of the Gauss-Markov OLS assumptions. The researcher recommends utilizing a larger sample period in future work to alleviate residual normality issues.

Overall, the researcher concludes that although a portion of the explanatory findings are statistically significant, moderate caution is warranted to policymakers, firms and individual investors when leveraging these findings due to the model's inability to meet residual normality and heteroskedastic diagnostic criteria.

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Appendices

Appendix A, Descriptive Statistics (Levels):

Descriptive Stat	FTSE350	M3	GDP	CPIH	EMP	INT	OIL
Mean	3,191.15	89.91	87.80	2.11	5.83	2.17	72.16
Standard Error	45.12	1.60	0.46	0.06	0.10	0.15	1.89
Sample Variance	417,282.56	524.69	43.58	0.81	2.00	4.37	728.82
Kurtosis	-0.85	-0.87	-0.89	0.35	-1.21	-1.18	-0.85
Skewness	-0.22	-0.54	0.41	0.26	0.51	0.76	0.33
Minimum	1,760.30	45.37	76.31	0.20	3.86	0.30	23.68
Maximum	4,310.96	122.30	100.82	4.80	8.47	6.60	139.83
Count	**205**						

Appendix B, FTSE 350 and Macroeconomic Variables Levels Over Time:

Figure 1 - FTSE350 (Levels) Jan 2003-Jan 2020

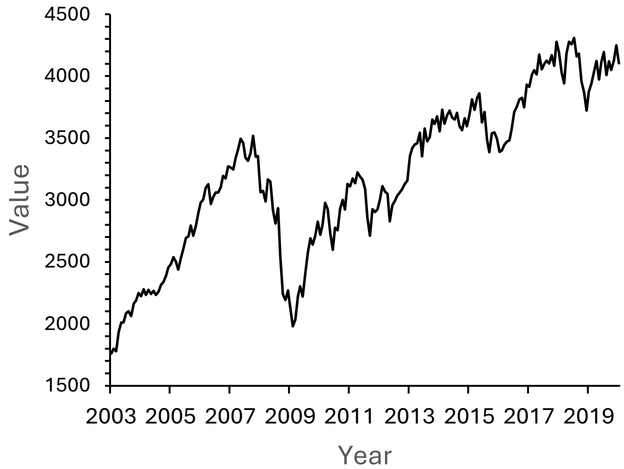


Figure 2 - M3 Chain Index 2015=100 (Levels) Jan 2003-Jan 2020

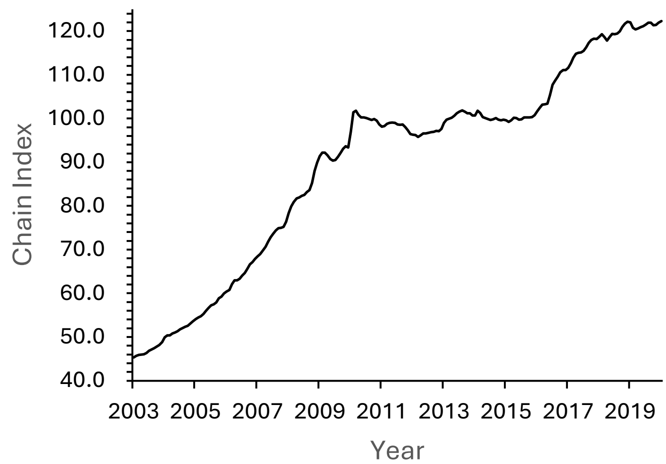


Figure 3 - GDP Chain Index 2019=100 (Levels) Jan 2003-Jan 2020

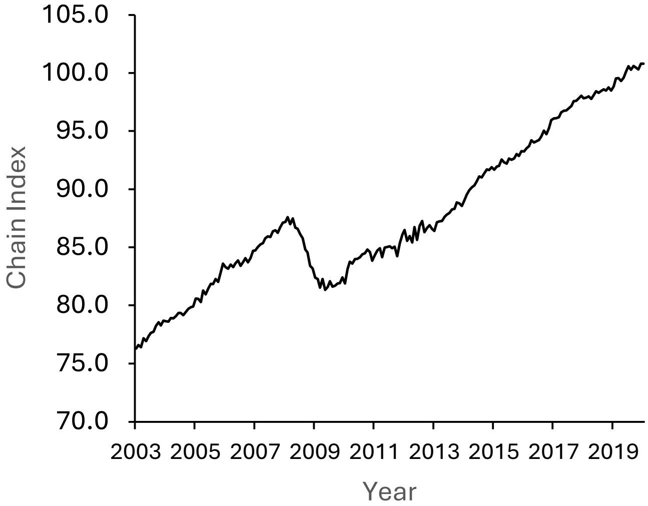


Figure 4 - CPIH (%) Jan 2003-Jan 2020

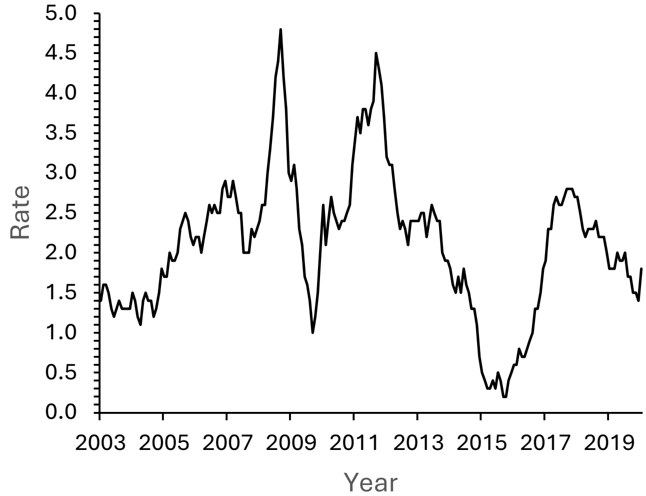


Figure 5 - Unemployment Rate (%) Jan 2003-Jan 2020

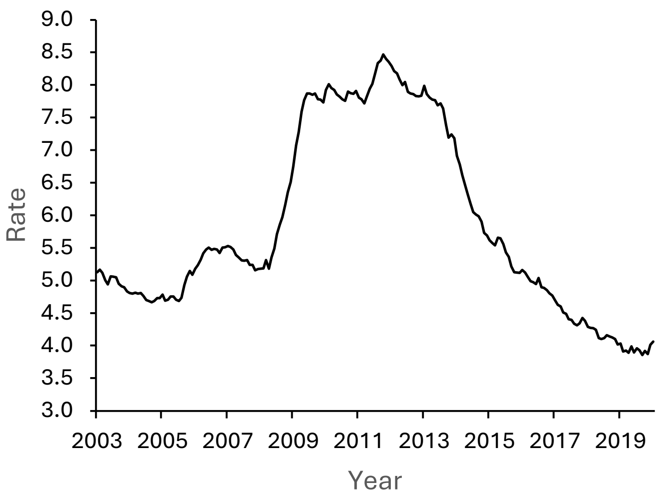


Figure 6 - Interest Rate (%) Jan 2003-Jan 2020

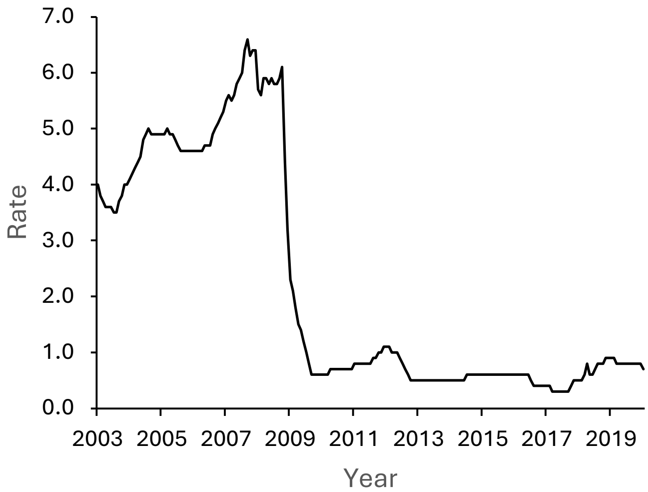
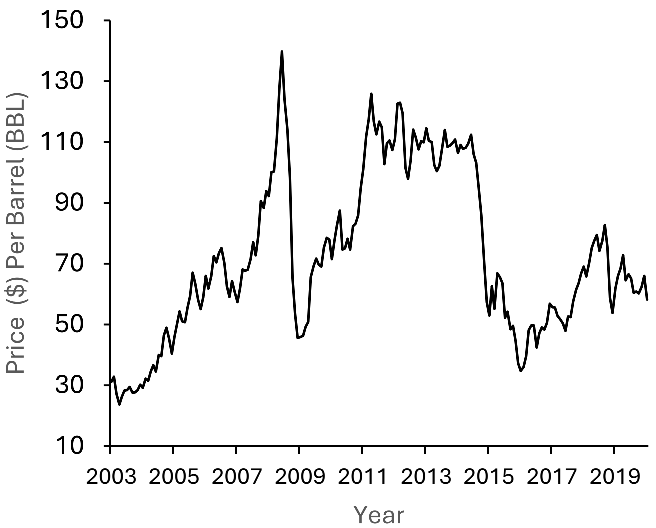


Figure 7 - Oil Prices (Levels) Jan 2003-Jan 2020



Appendix C, Distribution Histogram Plots (Levels):

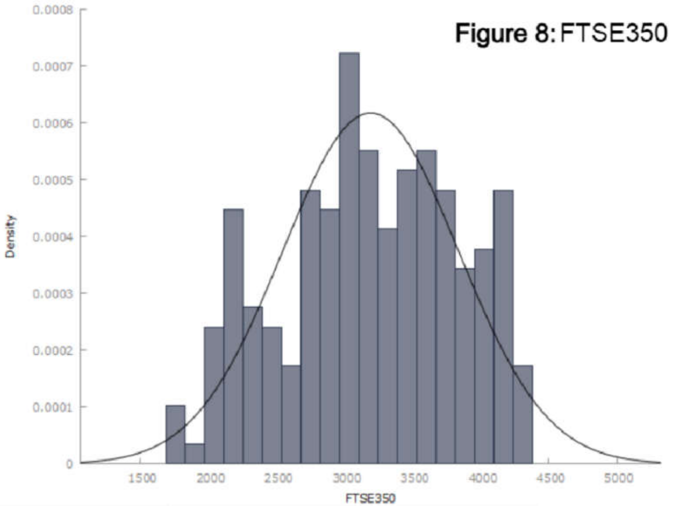


Figure 8: FTSE350

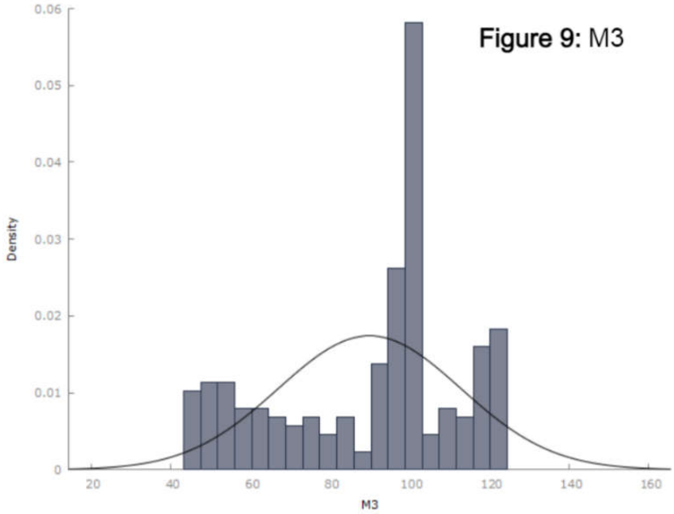


Figure 9: M3

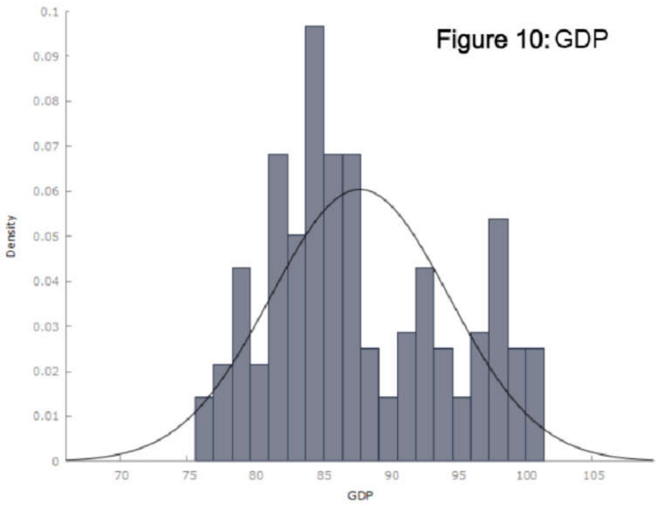


Figure 10: GDP

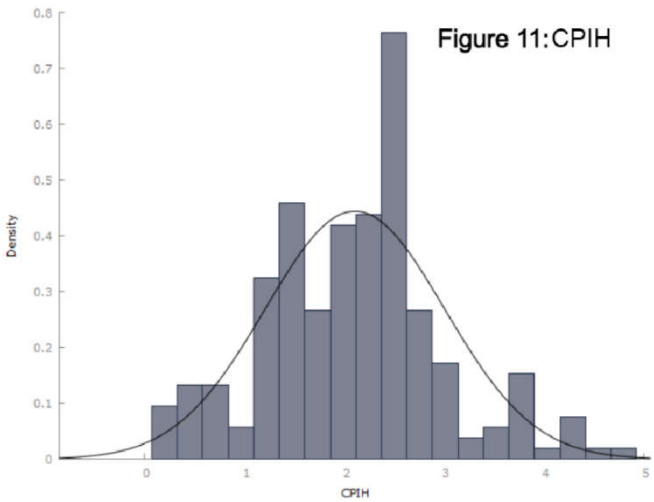


Figure 11: CPIH

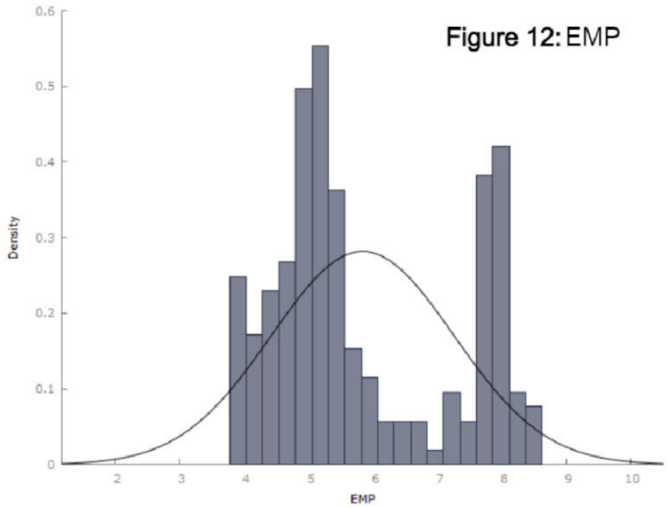


Figure 12: EMP

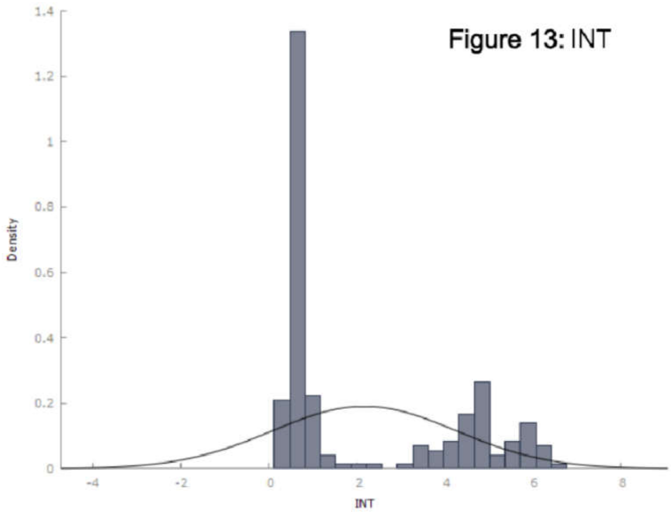
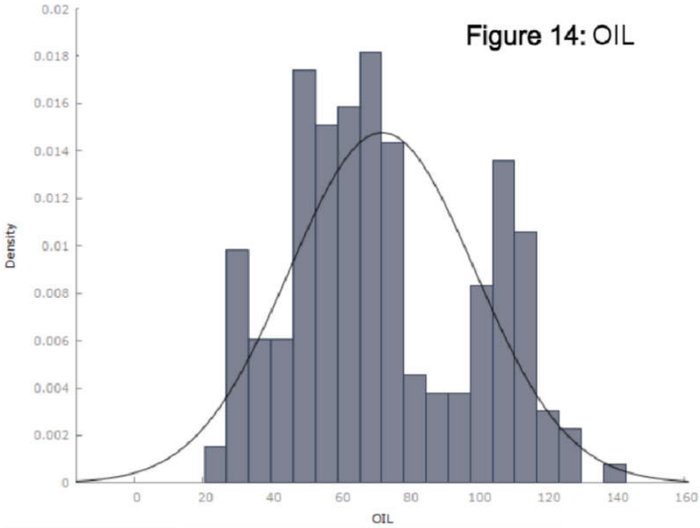
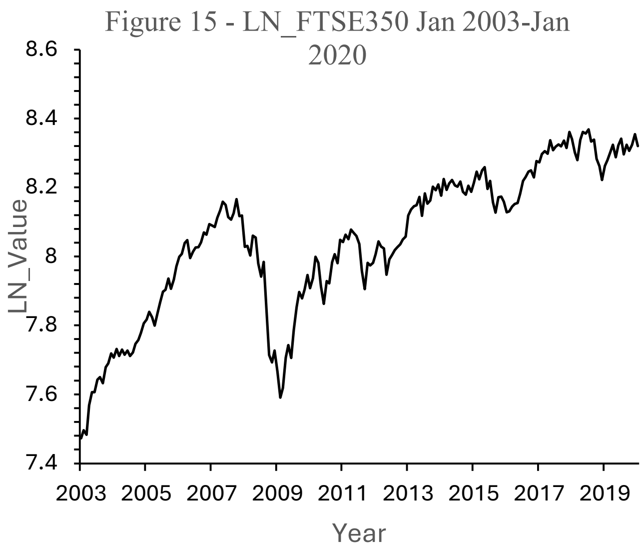


Figure 13: INT



Appendix D, Natural Logarithms of FTSE 350 and Macroeconomic Variables Over Time:



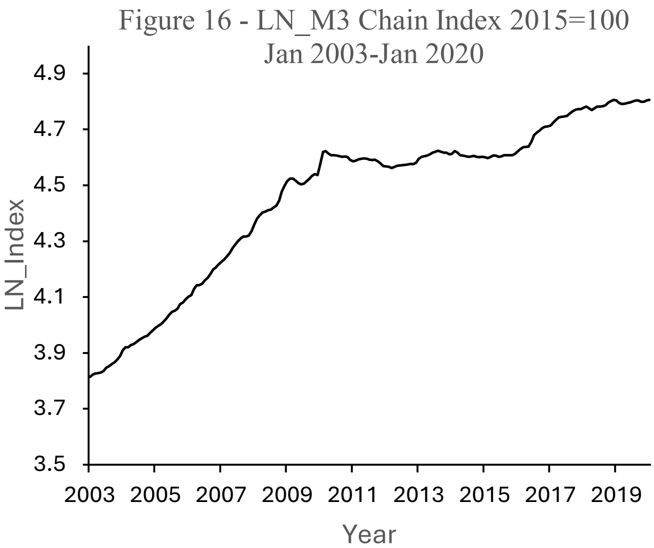


Figure 17 - LN_GDP Chain Index 2019=100 Jan 2003-Jan 2020

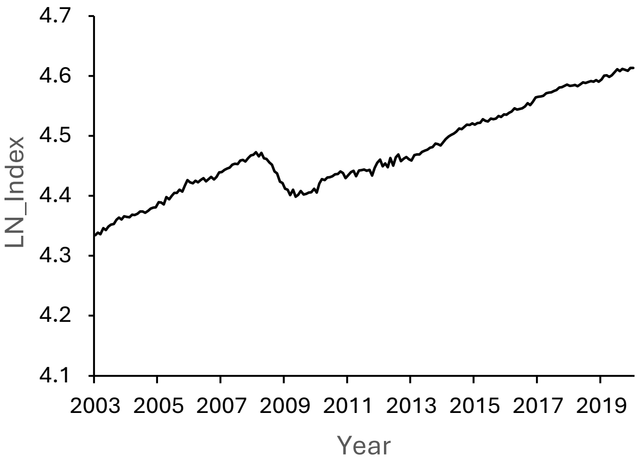


Figure 18 - LN_CPIH Jan 2003-Jan 2020

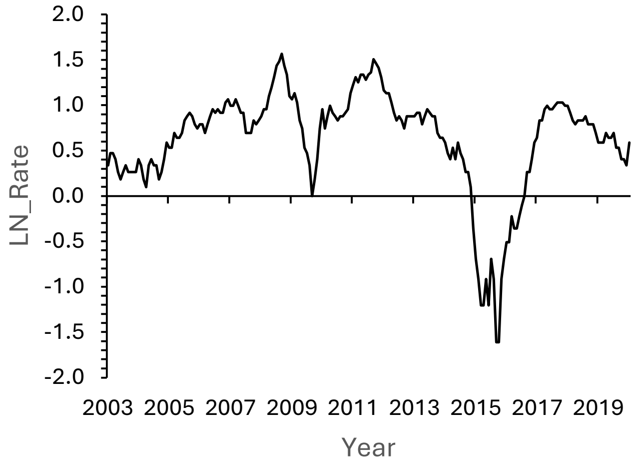


Figure 19 - LN_Unemployment Rate Jan 2003-Jan 2020

Figure 20 - LN_Interest Rate Jan 2003-Jan 2020

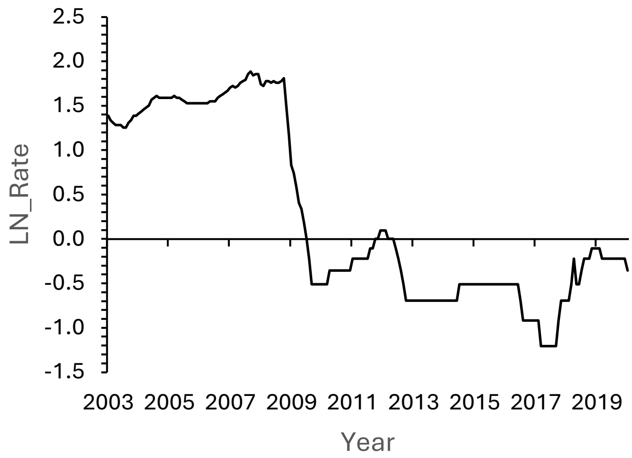
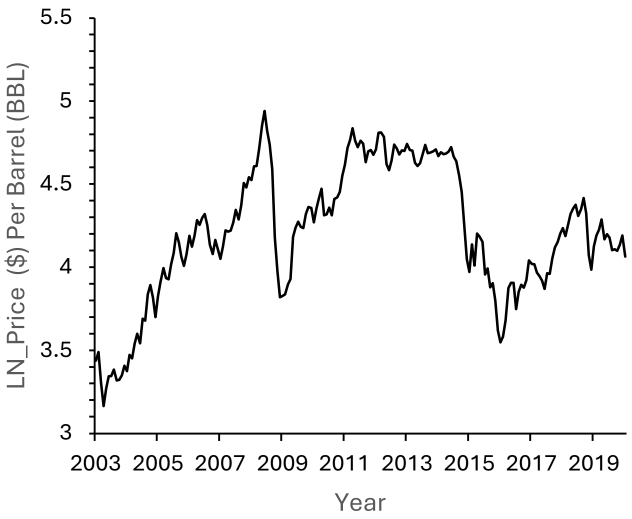


Figure 21 - LN_Oil Prices Jan 2003-Jan 2020



Appendix E, First Difference, Natural Logarithms of FTSE350 and Macroeconomic Variables Over Time:

Figure 22 - d_LN_FTSE350 Jan 2003-Jan 2020

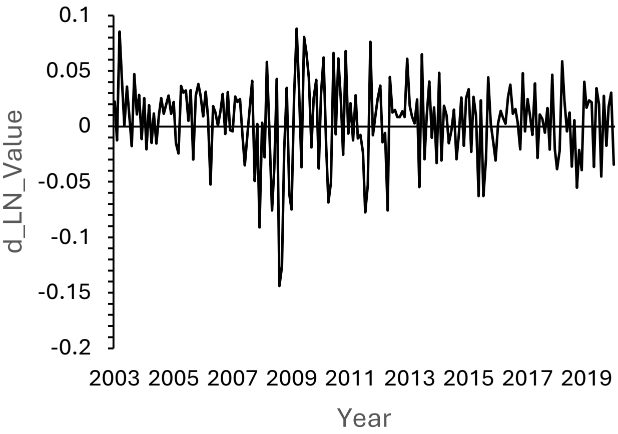


Figure 23 - d_LN_M3 Chain Index 2015=100 Jan 2003-Jan 2020

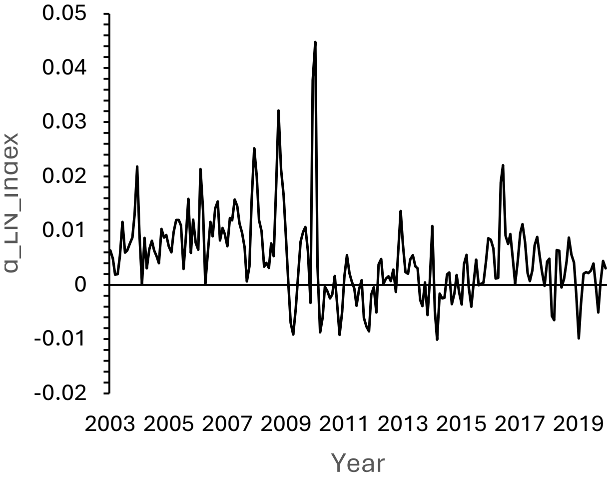


Figure 24 - d_LN_GDP Chain Index 2019=100 Jan 2003-Jan 2020

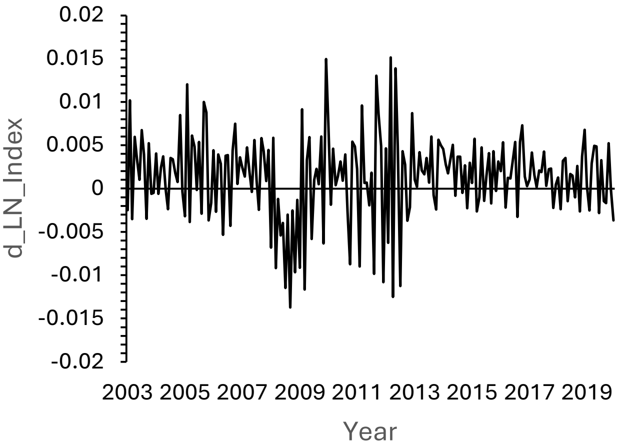


Figure 25 - d_LN_CPIH Jan 2003-Jan 2020

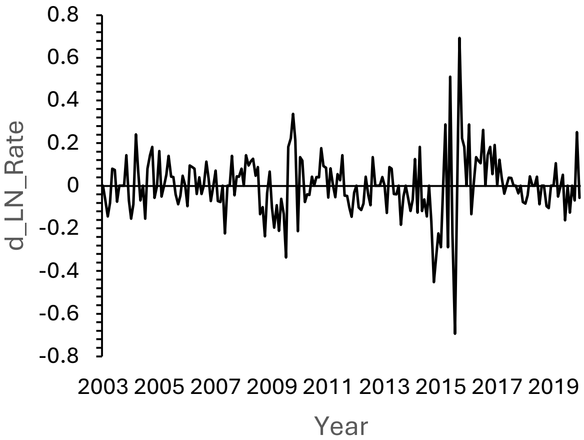


Figure 26 - d_LN_Unemployment Rate Jan 2003-Jan 2020

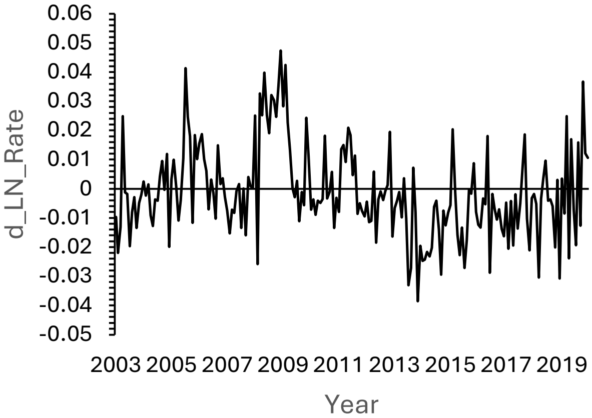


Figure 27 - d_LN_Interest Rate Jan 2003-Jan 2020

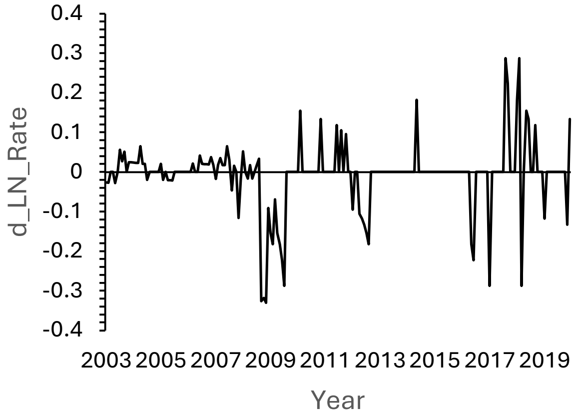
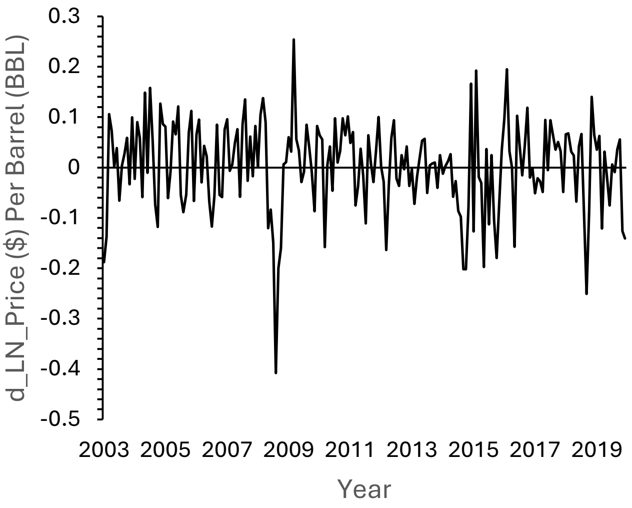


Figure 28 - d_LN_Oil Prices Jan 2003-Jan 2020



Appendix F, Initial Augmented Dickey-Fuller Test (With Constant) on Natural Logs:

Variable	T-Stat (Critical Value)	Critical Value (1%)	Critical Value (5%)	Critical Value (10%)	P-Value (ADF Test)	Unit Root (UR) Result
LN_FTSE	**-2.376**	**-3.457**	**-2.873**	**-2.573**	**0.149**	**UR is Present**
LN_M3	**-2.747**				**0.066**	UR is Not Present at 10% Significance
LN_GDP	**-0.295**				**0.923**	**UR is Present**
LN_CPIH	**-2.165**				**0.220**	**UR is Present**
LN_EMP	**-1.183**				**0.684**	**UR is Present**
LN_INT	**-1.372**				**0.598**	**UR is Present**
LN_OIL	**-2.397**				**0.143**	**UR is Present**

Appendix G, Johansen Cointegration test, Lag order = 2, Restricted Constant:

Endogenous variables: LN_FTSE350, LN_M3, LN_GDP, LN_CPIH, LN_EMP, LN_INT, LN_OIL					
Cointegration Rank	Eigenvalue	Trace Test	**Trace Test P-Value**	Lmax test	**Lmax Test P-Value**
None	0.33893	201.180	**0.0000**	84.021	**0.000**
At most 1	0.16951	117.150	**0.0043**	37.704	**0.111**
At most 2	0.13196	79.450	**0.0305**	28.729	**0.230**
At most 3	0.099506	50.722	**0.0959**	21.277	**0.334**
At most 4	0.068958	29.445	**0.1844**	14.504	**0.430**
At most 5	0.048734	14.940	**0.2349**	10.142	**0.333**
At most 6	0.023359	4.798	**0.3170**	4.7982	**0.316**

Appendix H, Model Diagnostic Test Summary:

Test	F-Test	P-Value	H_0
Breusch-Godfrey	0.360235	0.549	Accept
	Value	**Expected Value**	**Difference**
Durbin-Watson	2.015479	2.000	+0.015479
VIF (Variance Inflation Factor)	**VIF Value**	**1/VIF**	**Multicollinearity (if VIF>10)**
d_lnM3	1.134	0.882	**No Multicollinearity**
d_lnGDP	1.104	0.906	
d_lnCPIH	1.020	0.980	
d_lnEMP	1.164	0.859	
d_lnINT	1.085	0.922	
d_lnOIL	1.026	0.975	
Residual Normality Test (Lutkepohl)	**Jarque-Bera**	**P-Value**	**H_0**
d_lnFTSE350	21.82	0.000	**Reject**
d_lnM3	377.673	0.000	
d_lnGDP	16.619	0.000	
d_lnCPIH	382.897	0.000	
d_lnEMP	10.519	0.005	
d_lnINT	150.307	0.000	
d_lnOIL	1.396	0.4975	Accept
	Chi-sq	**P-Value**	**H_0**
White's Test	687.9608	0.000	**Reject**
	F-Test	**P-Value**	**H_0**
Ramsey RESET	1.845473	0.161	Accept

Figure 29: CUSUM plot