How does the FTSE All-Share index respond to changes in U.K. macroeconomic variables?

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Abstract

The paper reports estimates of the relationships between the FTSE All Share Index *and the following macroeconomic variables using an Autoregressive Distributed Lag model applied to monthly data from January 1990 to January 2020 (inclusive). The bounds test suggested a lack of any long-run cointegrating relationships, allowing inference of the ARDL coefficients as short-run effects. The results show that contemporaneous changes in* Exchange Rate Index *have a statistically significant negative impact on changes in the* FTSE All Share Index. *However, the direction of the impact of a shock to the Exchange rate on the FTSE All Share Index appears to change from negative to positive for ERI by the third lag. A similar dynamic is evidenced for the effect of a shock from Oil Prices and the* Industrial Production Index. *However, the Consumer Price Index, Interest Rate and Money Supply (M1) coefficients lack statistical significance at 5%, which is also the case for the autoregressive effect. The researcher suggests the changes in coefficient signs may be caused by a statistical phenomenon such as overshooting and mean reversion, whereby the stock markets initial reaction to information regarding changes in macroeconomic variables is eventually absorbed over time. However, the researcher acknowledges that this may also be due to model misspecification following the Ramsay RESET test result, and that changes in the FTSE All Share Index may rely on other variables omitted from the model. Despite this, the diagnostic tests offer reasonable evidence to suggest the Gauss-Markov OLS assumptions are not violated, allowing credible inference of the model results to be made. The researcher also tests for one-way (unidirectional) causality, finding evidence to suggest that changes in the Industrial Production Index and Oil Prices Granger-cause changes in the share prices.*

1: Introduction

This paper asks the fundamental question, can changes in the prices of macro variables and key resource prices help predict Stock Market valuation? The work will focus on changes in Consumer Price Index (CPI), Interest Rate (INT), Exchange Rate Index (ERI), Money Supply (M1), Industrial Production Index (IPI) and Oil Prices (OP).

For several decades, market participants and policy makers have studied the extent to which stock markets respond to changes in various macroeconomic variables. A large proportion of the existing U.K. literature focuses on the FTSE 100 as the dependent variable, and for good reason. This paper aims to contribute to the debate by focusing on the FTSE All Share Index (ASX) as an alternative. Aggregating the FTSE 100, 250 and Small Cap indices, the ASX is a highly diversified measure of the equity market, accounting for 98-99% of the U.K.'s market capitalisation.

1.1 Research question

How does the FTSE All-Share index respond to changes in U.K. macroeconomic variables?

1.2 Main objectives

The main objectives of this research paper are as follows:

1. To identify correlation between dependent and independent variables.

2. To identify the presence of long and / or short-run dynamic relationships between dependent and independent variables, comparing the results against the hypotheses.

3. To identify the presence of one-way (unidirectional) causality from independent variables to the dependent variable.

2: Literature Review

An extensive literature exists on the relationship between macroeconomic variables and stock indices worldwide, spanning several decades and a variety of variables. This literature review focuses on those studies most aligned with the research paper's objective.

Earlier contributing works such as Fama's (1970) review on efficient capital markets and the efficient market hypothesis (EMH) suggested that stock prices reflect all available information, but findings on the impact of specific variables were mixed and, in some cases, inconclusive. Homa and Jaffe (1971) utilised a stock price equation in which stock price levels were dependent on past and present values of the money supply in both growth rates and levels, finding a positive relationship between the two. These findings aligned with Hamburger and Kochin (1972), who incorporated lagged variables into their methodology to uncover a significant link between money supply growth and changes in stock prices. Rozeff's (1974) regression analysis later showed a one directional relationship from equity prices to money supply, as opposed to the relationship being the other way around. As a result, his findings clashed with previous works by Homa and Jaffe (1971) and Hamburger and Kochin. Fama and Schwert (1977) later examined the effectiveness of assets as hedges against both expected and unexpected inflation. They built on concepts established by Fisher (1930) such as the Fisher equation and the Fischer effect. Their findings suggested evidence of a negative relationship between stock prices and inflation, a relationship later supported by Geske and Roll's (1983) study into stock market returns and inflation, and the inverse relationship evidenced in Omran & Pointon’s 2001 study of the Egyptian stock market. In contrast, Firth's (1979) study using the retail price index (RPI) in the U.K. suggested a positive relationship between the RPI and stock market returns.

Chen, Roll and Ross (1986) examined long and short interest rate spreads, expected and unexpected inflation, industrial production and the difference in spreads between low-grade and high-grade bonds and how these variables impacted stock market returns in the U.S. Their findings suggested cointegration was present and that risks associated with macroeconomic variables were "significantly priced" and therefore able to explain stock market returns. However, Poon and Taylor (1991) found that industrial production, short and long-term interest rate spreads, inflation, and spreads between low and high-grade bonds did not affect UK equity prices in the way described by Chen, Roll and Ross (1986). Asprem (1989) identified an inverse relationship between stock prices and interest rates, employment, imports, and inflation in ten European countries. A positive correlation was observed between the U.S. yield curve and local stock prices and between broader money supply measures and stock prices. The direction of the money supply relationship also agrees with the findings of Fama and Schwert (1977) with the study also showing that for some countries, a positive relationship existed between stock prices and exchange rates. Employing Johansen cointegration tests, Nasseh and Strauss (2000) also focused their study on European countries, finding that for the six countries examined, stock prices related significantly to short-term and long-term interest rates, industrial production and overseas stock prices. They also found that long-term interest rates exert a significant negative influence on stock prices, which was “*consistent with their role as a discount factor*”. Short-term interest rates, however, were shown to have a positive influence on stock prices.

Aggarwal (1981) conducted one of the earliest studies into the effect of exchange rates on stock prices in the U.S. His findings suggested a positive correlation existed between U.S. stock prices and the value of the U.S. dollar. This later clashed with the findings of Soenen and Hennigar (1988), who identified a negative relationship between the two variables, and Mukherjee and Naka (1995) who found a negative relationship between the Japanese stock market and the exchange rate when employing a Vector Error Correction Model (VECM) specification. Morley and Pentecost (2000) utilised time series modelling to analyse the relationship between spot exchange rates and stock prices for G-7 countries from 1982 to 1994. They found that exchange rates and the stock market were connected but only through common (cyclical) patterns and not through common trends.

Maysami, Howe, & Hamzah (2004) studied the long-term relationships between specific macroeconomic variables and Singapore’s stock market index (STI). In addition to assessing the composite index (STI), significant attention was given to sector indices – the property index, finance index and the hotel index. They found that the property index and the STI form a cointegrating relationship with inflation, exchange rate, money supply, industrial production, and short and long-term interest rates. Humpe and Macmillan (2009) later studied the influence of macroeconomic variables on stock prices in the U.S. and Japan. They found that stock prices are positively related to industrial production and negatively related to both the consumer price index and the long-term interest rate in the U.S. The relationship between stock prices and the money supply was positive but insignificant. For Japan, they found that stock prices are positively influenced by industrial production and negatively influenced by the money supply. Shawtari, Salem, Hussain, Hawariyuni, & Omer (2015) utilised a VECM approach when analysing South Africa's stock index and a set of macroeconomic variables, finding industrial production was the most important determinant of stock market prices. Other variables such as inflation, the exchange rate and money supply were also determinants of stock index movements but to a lesser extent. Lu, Metin IV, & Argac, (2010) focused their study on the Istanbul Stock Exchange (ISE) but found no evidence of a cointegrating relationship between the ISE and any of the variables included. They considered overnight interest rates, several definitions money supply (M1, M2 and currency in circulation), and foreign exchange rates of the U.S. dollar, German mark, British sterling and Japanese yen.

Sadorsky (1999) found that changes in oil prices had a significant and negative influence on stock market returns in the U.S. when using a Vector Auto-Regressive (VAR) specification. This negative impact was also observed by Papapetrou (2001), when analysing the relationship between oil prices, interest rates, employment, real activity, and stock prices in Greece using a multivariate VAR model. The results showed that oil prices (increases) had an immediate and negative impact on stock prices, industrial production, and employment. Later, Park and Ratti (2008) studied oil price shocks and the impact on stock markets in the U.S. and 13 European countries. They found that there was a "*statistically significant impact on real stock returns contemporaneously and/or within the following month in the U.S. and 13 European countries*". Interestingly, the findings showed that Norway, as a large oil exporter, experienced a positive stock market response to rises in oil prices. However, for the U.S. and ten of the thirteen European countries, an increase in the volatility of oil prices (price shock) was associated with a statistically significant (5%) negative impact on stock market returns. Lastly, Hosseini, Ahmad, and Lai (2011) examined the relationship between crude oil prices, industrial production, money supply, and inflation in China and India. They used a VECM approach and found both long-run and short-run relationships between the variables and stock indices in both countries. In the long-term, crude oil prices had a negative impact on the stock prices of both markets.

2.1 Relevant theory:

To provide a comprehensive analysis of the relationship between the FTSE All-Share index and macroeconomic variables, the researcher recognises the need to consider a range of relevant economic theories to supplement statistical findings.

The Efficient Market Hypothesis (Fama, 1970) states that financial markets are efficient in their ability to immediately reflect all publicly available (and new) information, making it very difficult for investors to consistently beat the market. This is relevant to the research question given the aim is to model how the ASX responds to changes in U.K. macroeconomic variables, which is publicly available information.

The Random Walk theory (Louis Bachelier, 1900) posits that prices of stocks and other financial assets move randomly, without any predictability. It also suggests that past values cannot be used as a means of predicting future prices. The relevance of this pertains to the robustness of the model estimates, which may be hampered by omitted variables or exogenous factors. These can include the human psychological and emotional influences on price movements, which can be difficult to measure quantitatively but might be accounting for a proportion of the change in the dependent variable.

The Capital Asset Pricing Model (CAPM - Sharpe, 1964) and Arbitrage Pricing Theory (APT – Ross, 1976) both offer frameworks for understanding how asset prices and their expected returns are determined by a range of risk factors. They use the "risk-free rate", often represented by an asset carrying zero risk such as a government bond, to determine the expected return on investments. Three-month LIBOR, a variable used in this study, could be used as a close (but not exact) proxy for the risk-free rate. These models are relevant to the research question because expected returns are reflected in an assets price. If the asset is a listed company share, this will ultimately influence the wider index.

3: Hypotheses

The hypotheses set out below are influenced by both economic theory and empirical evidence from the literature review[1]. Barring Lu, Metin IV, & Argac, (2010) and Morley and Pentecost (2000) (exchange rates), most researchers find a variety of key macroeconomic variables do influence the stock market.

- **Interest Rates**: The research hypothesis will be that a **negative** relationship exists between stock prices and interest rates - *Asprem (1989), Nasseh and Strauss (2000) and Chen, Roll and Ross (1986).*

- **Consumer Price Index:** The empirical findings were mixed and, in some instances, conflicting. However, a **negative** relationship between stock prices and inflation was more commonly observed, forming the basis of this hypothesis - *Fama and Schwert (1977), Geske and Roll (1983), Omran & Pointon (2001).*

- **Money Supply:** The research hypothesis will be that a **positive** relationship exists between stock prices and money supply - *Homa and Jaffe (1971), Asprem (1989) and Humpe and Macmillan (2009).*

- **Exchange Rates:** Existing evidence is mixed, with some finding a positive relationship *Aggarwal (1981) and Asprem (1989)* but others finding either little correlation *(Morley and Pentecost, 2000)* or a negative relationship *(Mukherjee and Naka, 1995)*. It appears the impact on stock prices depends largely on the economy's level of trade and international exposure. As over half of the ASX market capitalisation is comprised of Oil and Gas companies (whose business tends to prosper when sterling is weak) the hypothesis will be a **negative** relationship.

- **Industrial Production Index:** The research hypothesis will be that a **positive** relationship between stock prices and the industrial production index - *Geske and Roll (1983), Nasseh and Strauss (2000), Humpe, A. and Macmillan, P., (2009) and Shawtari, Salem, Hussain, Hawariyuni, & Omer (2015).*

[1] Authors in italics refer to studies in which the findings supported the chosen hypothesis.

- **Oil Prices:** The research hypothesis will be a **negative** relationship between stock prices and oil prices - *Sadorsky (1999), Papapetrou (2001), Hosseini, Ahmad and Lai (2011) and Park and Ratti (2008).*

4: Methodology & Data

4.2 Data Collection

The data sample has been collected in the form of monthly time series, from January 1990 to January 2020 inclusive, totalling 356 observations.

The researcher gathered secondary market data from Bloomberg (five variables) and the OECD (two variables); both regarded as highly credible sources of historical economic and financial data. A greater number of data points were available for certain variables, however uniformity meant aligning all observations to the year 1990. The researcher also decided to exclude data from February 2020 onwards due to outliers caused by the COVID-19 pandemic.

1.3 Variable Descriptions

The macroeconomic variables selected for examination in the paper will now be explained in more detail below. Selection is based on those deemed most likely to influence share prices.

FTSE All-Share Index (ASX) [dependent]: The FTSE All-Share Index (ASX) is a highly diversified index, representing 98-99% of the UK equity market by incorporating the FTSE 100, 250 and SmallCap indices. This broad representation was the reason behind its selection as the dependent variable over the more widely acknowledged FTSE 100. The variable represents monthly closing prices.

Consumer Price Index (CPI) [independent]: The Consumer Price Index (CPI) is one of the most prominent measures of inflation in the UK, calculated as the average weighted price of a basket of commonly purchased household goods and services. Moderate inflation indicates healthy consumer spending levels, benefitting company earnings and share prices (*ceteris paribus*). However, persistently high inflation can have the reverse effect, eroding real income and consumer spending power. Recent high inflation in the U.K. (10.1% annual in March 2023) prompted the Bank of England to raise interest rates from 0.10% in March 2020 to 4.25% as of March 2023, in attempts to bring inflation back towards its 2% target.

Short-term Interest rates (INT) [independent]: A popular and highly sensitive measure of short-term interest rates in the U.K. is the British pound three-month London Interbank Offered Rate (LIBOR). This is a benchmark rate calculated for several currencies and maturities, published daily by the Intercontinental Exchange (ICE)[2]. As it represents the cost of borrowing, an inverse relationship is often observed with the stock market. Another measure is the three-month UK Treasury Bill rate, known as the "risk-free" rate[55], however data limitations meant this variable wasn't included.

[2] LIBOR has now almost entirely been phased out and replaced by SONIA (Sterling Overnight Index Average)

Sterling Exchange Rate Index (ERI) [independent]: The Sterling Exchange Rate Index (ERI) represents the price of one country's currency (U.K.) in terms of another's. It's published by the Bank of England on a daily basis and calculated by weighting together bilateral exchange rates. The countries included and associated weights are determined by the significance of their trade flows. Exchange rate volatility can be heavily influenced by other macroeconomic factors such as interest rates and inflation, both at home and abroad. This exchange rate exposure can negatively impact a firm's profitability and the value of their shares when revenues are derived internationally, or their raw materials are imported.

Money Supply (M1) [independent]: The money supply refers to the quantity of money in the economy, also known as the monetary base. It's monitored and controlled by the central bank through monetary policy tools like interest rates, reserve requirements, and quantitative easing. There are various categories of "money" range from "narrow" to "broad" (M0 to M4). This study uses M1 as the measure, which represents the narrow money supply in the UK; it includes physical notes, coins, and operational deposits at the central bank.

Industrial Production Index (IPI) [independent]: The Industrial Production Index (IPI) measures a country's production output from sectors such as mining, manufacturing, energy supply, and waste management. Data on turnover and volume is gathered to calculate the index by adjusting for the impact of price changes. The IPI is closely monitored by market participants as a leading indicator of GDP and wider economic health. The researcher originally intended to use GDP data; however quarterly data releases meant this wasn't possible - the IPI is often used as a suitable proxy.

Oil Prices (OP) [independent]: Oil prices (OP) are determined by global supply and demand. Although oil is classified as a commodity as opposed to an economic indicator, its direct or indirect use as a raw material is ubiquitous in our everyday lives. As a result, higher oil prices can increase production costs, which in turn, can adversely affect the cost of living at a micro level. Through this mechanism, a fall in consumer spending may negatively impact revenues and the value of company shares. This study focuses on Brent Crude prices[3], with "Brent" being the most universal benchmark used for oil pricing in Africa, Europe, and the Middle East.

Table 1 below summarises the data source for each variable:

Variable	**Abbreviation**	**Data Source**
FTSE All Share index	ASX	Bloomberg
Consumer Price Index	CPI	Bloomberg
Short-term Interest rates	INT	OECD
Sterling Exchange Rate Index	ERI	Bloomberg
Money Supply	M1	OECD
Industrial Production Index	IPI	Bloomberg
Oil Prices	OP	Bloomberg

[3] Prices are quoted in U.S. Dollars per barrel (USD / BBL)

4.3 Visual Inspection and Descriptive Statistics

The data was visually inspected to identify persistent trends, drift or anomalies. Figures 1 – 7 (appendix A) graph data in levels from January 1990 to January 2020, with descriptive statistics (appendix B) and accompanying histogram plots in appendix C (Figures 8 – 14). Notable outliers can be observed in some of the raw series, specifically around times of economic crisis such as 2008. Skewness and Kurtosis values, as well as accompanying histogram plots, offer an insight into the distribution of each variables data points. Figure 8 – 12 & 14 (ASX, CPI, INT, ERI and M1) all evidence moderately platykurtic (flatter) distributions, with slight to moderate positive skew. Figure 6 (IPI) evidences a relatively flat but negatively skewed distribution.

4.4 Correlation

Tests for correlation were carried out to further understanding the relationships between variables (appendix D), with accompanying scatter plots in appendix E (figures 15 – 20). The correlation matrix results are as follows:

- ASX and CPI have a strong positive correlation (0.8978), suggesting that they move in a similar direction.
- ASX and INT have a strong negative correlation (-0.7625), suggesting an inverse relationship.
- ASX and ERI have a weak negative correlation (-0.0351), indicating a weak inverse relationship.
- ASX and M1 have a strong positive correlation (0.8701), suggesting that they move in the same direction.
- ASX and IPI have a moderate positive correlation (0.6634), indicating a moderate positive relationship.
- ASX and OP have a moderate positive correlation (0.6012), suggesting a slightly positive relationship between the two.

4.5 Research Model: Autoregressive Distributed Lag (ARDL)

The researcher used an ARDL (Autoregressive Distributed Lag) model to test the hypotheses, employing an ordinary least square (OLS) estimation method. First introduced by Pesaran and Smith (2001), the ARDL model is a popular and flexible approach to estimating both short and long-run dynamics in a single equation. The ARDL model can also be efficient in the case of smaller sample size, as in this study.

The generalised ARDL (*p, q*) model is specified below (Brooks, 2008):

$$Y_t = \gamma_{0i} + \sum_{i=1}^{p} \delta_i \, Y_{t-i} + \sum_{i=0}^{q} \beta'_i \, X_{t-i} + \varepsilon_{it}$$

Where Y_t is the dependent variable, X_{t-i} is an *I*(0), *I*(1) or cointegrated independent variable, β and δ are coefficients, γ is the constant (i =1…*k*), p, q are optimal lag orders of the dependent and exogenous variables respectively and ε_{it} is a white noise error term. In this specification, the dependent variable is a function of its own lagged values (autoregressive) and the current and lagged values of the independent variables.

ARDL is advantageous when modelling time series data with variables integrated of different orders, as in this paper. A series' order of integration is determined by the minimum number of times it needs to be differenced to become stationary (Wooldridge, 2019). If a series has no unit root in levels, it is integrated of order zero (I(0)); if a series becomes stationary upon taking the first difference, it's integrated of order one (I(1)). However, an ARDL specification is not suitable for an I(2) series.

5: Time Series Procedures

5.1 Augmented-Dickey Fuller test for unit roots.

Before estimating the ARDL model, it's important to check for data imperfections that could lead to bias and inconsistent results. Time series data, especially macroeconomic data, often suffers from non-stationarity, stochastic trends and unit roots, meaning its statistical properties (mean and variance) change over time due to economic shocks or cyclical influences. For a time series y_t to be stationary, the following conditions must be met:

1) Constant μ (mean), for all periods of time (*t*)

2) Constant σ (variance) for all periods of time (*t*)

3) Constant autocovariance i.e. $Cov(y_{t,}y_{t-i}) = \sigma^2$ where y_t and y_{t-i} are two observations of y at i periods apart, and σ^2 represents the constant covariance between them.

The Augmented Dickey-Fuller (ADF) test was used to assess the presence of a unit root on variables in levels and percentage levels (INT) first. The method is designed to handle autocorrelation and serial correlation in the data (often present in time series datasets). The ADF test is a revised version of the original Dickey-Fuller (DF) equation, which was augmented to include autoregressive terms of the dependent variable.

The ADF specification with a constant is:

$$\Delta Y_t = \ aY_{t-1} + \sum_{p=1}^{p} \theta_p \, \Delta Y_{t-p} + \mu_t$$

Where p is the number of is lags (autoregressive terms) i.e.,($\Delta Y_{t-1} = \Delta Y_{t-1} - \Delta Y_{t-2}$) and $y_{t-2} = (y_{t-2} - \ y_{t-3})$ etc. $\sum_{p=1}^{p} \theta_p \, \Delta Y_{t-p}$ are additional autoregressive terms and μ_t is the uncorrelated white noise error term. The null hypothesis (H_0) is that the series contains a unit root and is non-stationary, whilst the alternative (H_1) is no unit root and a stationary series. The ADF results (appendix F) show that INT achieved stationarity in percentage levels, implying that the series was integrated of order zero (I(0)). However, this wasn't the case for the remaining variables.

5.2 Variable transformations.

In an attempt to remove the unit roots present in the remaining variables, the series were transformed into natural logarithms (visible representation in appendix G, figures 21 – 27). This can make trends more linear by reducing the magnitude and stabilising the variance[4]. The researcher conducted a second round of ADF tests on the log-transformed variables (appendix F) but could only reject the null hypothesis of a unit root for LnCPI.

The next step was to compute the difference between consecutive observations for each variable, known as first differencing. This can achieve "difference stationarity" by removing remaining trends or seasonality, an effective method of making an integrated process weakly dependent and reducing autocorrelation. See appendix H (figures 28 – 34) for visual representations of the differenced variables, as well as ADF test results in appendix F.

Following these transformations, the ADF results allowed the researcher to reject the null hypothesis of a unit root for the remaining variables in log-differenced form (ASX, ERI, M1, IPI and OP). With this, the researcher concludes that the ARDL model will be handling variables integrated of different orders e.g. I(0) and I(1), a scenario the specification can adequately accommodate.

5.3 Optimal lag length selection

A further advantage of the ARDL approach is the flexibility in optimal lag length selection, allowing the researcher to specify different lag lengths for each variable. This was determined based on the Akaike Information Criterion (AIC) - with lower AIC values suggesting greater model accuracy. A maximum number of twelve lags was chosen for the test given the nature of the data i.e., monthly time series. **Table 2** below present the results.

Table 2 - Optimal lag order (AIC)

Variable	Lag length
ASX (ln, differenced)	1
CPI (ln, level)	3
INT (level)	1
ERI (ln, differenced)	3
M1 (ln, differenced)	1
IPI (ln, differenced)	6
OP (ln, differenced)	1

5.4 Bounds test for cointegration

The next stage of the process involved cointegration analysis. Cointegration refers to when a long-run equilibrium relationship exists between two or more variables, despite experiencing divergence in the short-run. The ARDL model allows for the possibility of long-run cointegrating relationships when re-parametrised into an Error Correction Model (ECM)

[4] Logarithmic transformations were deemed unsuitable for "INT" due to negative values being returned. Fortunately, the variable had already achieved stationarity in levels.

specification that includes both the difference operator (short-run) and the error correction term (long-run) - Hassler and Wolters (2005, 2006). Once re-specified, the researcher conducted the bounds test for cointegration, which is the appropriate method when handling variables of mixed orders of integration (Pesaran, Shin and Smith (2001). This test is conducted on data in level form, using critical values as derived from asymptotic distribution theory. The null and alternative hypotheses are as follows:

$H_0: b_{1i} = b_{2i} = b_{3i} = 0,$ (where $i = 1,2,3$) i.e., No cointegration

$H_1: b_{1i} \neq b_{2i} \neq b_{3i} \neq 0$ i.e., Cointegration exists

The results (appendix I**)** show that the Bounds F-statistic (1.750) falls below all critical values for the [I_0] series, implying no evidence of cointegration. This allows the researcher to conclude no re-parameterisation to ECM form is necessary and that an ARDL model is the appropriate specification for the data.

Chapter 6: Interpretation and discussion of results

The researcher will now present, interpret and discuss the ARDL model results (appendix J), with a condensed summary presented in table 3 for convenience.

The overall significance of the model is assessed using the F-statistic (2.52) and the probability of F-statistic (0.0002), indicating that the model is statistically significant at conventional levels (0.05). The R-squared value (0.1733) and adjusted R-squared value (0.1184) indicate that the model explains approximately 17.33% and 11.84% of the variation in the dependent variable (ASX), respectively. However, these ought to be interpreted in context of the functional form. In models including differenced variables, a lower R-squared isn't necessarily representative of poor model fit. This is because differencing can reduce the level of correlation between variables by representing their change over time, rather than level specifications where a high R-square may be capturing a common trend.

The coefficients require careful interpretation due to the highly dynamic nature of the model estimated. Six of the seven variable series were transformed into natural logarithms, with five variables then being first differenced and optimal lags introduced.

ASX: The estimated coefficients for variables represented as first differences of natural logarithms approximate growth rates, as taking first differences of the natural logarithm is equivalent to computing the period-on-period percentage change. The coefficient for the first lag (**L1**) of ASX is 0.0732616, implying that a 1% increase in the growth rate of the dependent variable one period ago, leads to a 0.0732616% increase in its growth rate in the current period (*t*), all else equal. However, the corresponding p-value (0.239) suggests a lack of statistical significance for the positive autoregressive effect observed.

CPI: This variable was estimated in natural log-level form. Given the dependent variable is specified in first differences of natural logarithms, this implies that a 1% increase in CPI in e.g., the current period **(--.),** causes a 0.815777% increase in ASX in the next period, controlling for other variables. However, the p-value for the current period (0.254) lacks statistical significance at 5%, which is also the case for lags one (**L1**) and three (**L3**), when the coefficient changes sign. The positive coefficient for lag two (**L2**) is significant at the 10% level (p-value of 0.090).

Table 3 – ARDL estimates of final model.

First difference of the natural logarithm of ASX	**Coefficient**	**P >|t|**
Lag 1	0.073	0.239
First difference of the natural logarithm of CPI		
Current period	0.816	0.254
Lag one	-1.357	0.130
Lag two	1.558	0.090
Lag three	-1.076	0.156
First difference of INT		
Current period	-0.020	0.074
Lag one	0.017	0.143
First difference of the natural logarithm of ERI		
Current period	-0.366	0.001
Lag one	0.157	0.200
Lag two	0.084	0.467
Lag three	0.244	0.033
First difference of the natural logarithm of M1		
Current period	-0.055	0.827
Lag one	0.265	0.139
First difference of the natural logarithm of IPI		
Current period	0.172	0.403
Lag one	0.449	0.019
Lag two	0.187	0.321
Lag three	0.146	0.541
Lag four	-0.264	0.182
Lag five	-0.304	0.158
Lag six	-0.581	0.009
First difference of the natural logarithm of OP		
Current period	0.053	0.052
Lag one	-0.059	0.043
Constant	0.273	0.057

INT: The coefficient for INT in the current period **(--.)** is -0.0202612. The interpretation is slightly different again, implying that a 1 unit increase in INT in the current period, causes a decrease of 0.0202612 units in the growth rate of ASX in the next period[5] - this coefficient is significant at 10% (p-value of 0.074). The **L1** coefficient (0.0166533) changes sign, implying that a one unit increase in INT one period ago, causes an increase of 0.0166533 units in the growth rate of the ASX in the current period. However, this coefficient is not statistically significant (p-value of 0.143).

[5] As this variable (INT) represents a percentage rate in its raw form (3M GBP LIBOR), a one-unit change is equivalent to implying a 1% change in the LIBOR rate.

The coefficient interpretation for the following variables will be as per ASX interpretations above, given their "first differences of natural logarithm" form.

ERI: The coefficient for ERI in the current period **(--.)** is -0.3655747. This coefficient is statistically significant at the 1% level (p-value of 0.001). The coefficients for lags one (**L1**) and two (**L2**) change sign but lack statistical significance, while the coefficient for **L3** (0.2443878) achieves significance at the 5% level (p-value of 0.033).

M1: The coefficient for M1 in the current period **(--.)** (-0.0552284) and one period ago (**L1)** (0.2646096) both lack statistical significance (p-value of 0.827 and 0.139 respectively) and change sign between periods.

IPI: The current **(--.)**, **L2, L3, L4** and **L5** coefficients for IPI are all statistically insignificant (p-values, 0.403, 0.321, 0.541, 0.182 and 0.158 respectively). However, the positive **L1** coefficient (0.4489091) and negative L6 coefficient (-0.580544) are statistically significant at 5% (**L1** p-value of 0.019) and 1% level (**L6** p-value of 0.009) respectively.

OP: The coefficient for OP in the current period **(--.) (**0.0532646) and one period ago (**L1**) (-0.0586527) change sign and are statistically significant at the 10% (p-value of 0.052) and 5% (p-value of 0.043) respectively.

_cons: the coefficient value for the intercept term (_cons) is 0.2731275 statistically significant at 10% (p-value of 0.057).

6.1 Granger Causality

The coefficients that OLS estimation yields (as above) only offer insight into whether a statistically significant linear relationship exists between variables, which may not imply causality. The Granger Causality test (C.W. J. Granger, 1969) on the other hand, allows the researcher to determine whether past values of one variable contain any statistical power in forecasting future values of another (both assumed to be stationary). With this, inference regarding any causal relationships can be made. The two-way Granger causality test in levels (Granger, 1969) is stated as:

1)

$$Y_t = \sum_{i=1}^{n} a_i\, Y_{t-i} + \sum_{j=1}^{n} \beta_j\, X_{t-j} + \mu_{1(t)}$$

2)

$$X_t = \sum_{i=1}^{n} \lambda_i\, Y_{t-i} + \sum_{j=1}^{n} \sigma_i\, X_{t-j} + \mu_{2(t)}$$

Where a, β, λ and σ are coefficients, $\mu_{1(t)}$ and $\mu_{2(t)}$ are the error terms and n represents optimal number of lagged observations as determined by the appropriate Information Criterion (AIC or BIC).

Drawing on the concept of causal ordering, equation 1 implies that the present value of Y (Y_t) is related to past values of itself and those of X (X_t) and vice versa. Unidirectional causality $(X_t \rightarrow Y_t)$ and the rejection of the null, is evidenced when the lagged coefficients on X_t are collectively statistically different from zero $(\sum \beta_j \neq 0)$ and the collective lagged coefficients estimated on Y_t aren't $(\sum \lambda_i \neq 0)$[6]. Bilateral causality or feedback is present when the coefficients for both X_t and Y_t are statistically different from zero $(\neq 0)$ in both (1) and (2) above.

Given the interest of this paper pertains to the impact of macroeconomic variables on the ASX, only one-way (unidirectional) Granger causality has been tested on the current (t) value of ASX. The results, (appendix K) show that most of the null hypotheses are accepted, i.e., the independent variable does not Granger-cause the dependent variable, implying no significant causal relationship from one to the other. However, for some variables, the null hypothesis is rejected at varying levels of significance. Note: the interpretation differs to the level interpretation due to the "differenced log" specification of the following variables. Specifically, at 10%, the null hypotheses that the change or growth rate in the IPI one period ago does not Granger-cause the current change in the ASX is rejected, suggesting evidence of a significant causal unidirectional relationship. This is also the case at the sixth lag of the IPI, rejecting the null at 1% (p-value of 0.003). There is also evidence of a unidirectional causal relationship from the change in OP at one lag (p-value of 0.015) and the current change in ASX, rejecting the null of no causality at 5%.

6.2 Model Diagnostics (appendix L)

The post-estimation Durbin Watson (Durbin and Watson, 1950) test for autocorrelation (serial correlation) in the residuals produced a "d-statistic" of 1.94798, allowing the researcher to conclude no presence of autocorrelation (accompanying residual histogram in Figure 35, appendix M). This was further supported by the Breusch-Godfrey test, with results for up to four lags all being greater than the 5% critical value. The White's test results for heteroscedasticity yields a p-value of 0.0966, meaning the null hypothesis (homogeneity of error variance) cannot be rejected at 5%. This offers little evidence to suggest heteroscedasticity in the residuals, which was also considered through the use of robust standard errors. Additionally, the fitted versus residual plot (figure 36, appendix M) shows a relatively random distribution of residuals around zero. The null hypothesis of normally distributed residuals was not rejected by the Jarque-Bera p-value (0.5895), implying the residuals approximate a normal distribution. The accompanying histogram of residuals (figure 35 - appendix M) supports this to some extent, with the longer left tail suggesting the presence of outliers on the left side of the distribution. The CUSUM (Cumulative Sum) plot (figure 37, appendix N) facilitates a visual assessment of the stability of a series and whether there is evidence to suggest structural breaks or changes in the variables' relationships over the period. In earlier observations of the series, the cumulative sum of residuals tends towards the expected value of the cumulative sum under a null hypothesis of no structural break. From the middle of the sample onwards, there is visible deviation from this line, however the cumulative residuals

[6] The opposite is also the case for unidirectional causality from $(Y_t \rightarrow X_t)$

remain within the pre-defined 5% significance bounds, indicating the model fits the data well and is consistent with the null hypothesis. Detection of multicollinearity was determined using VIF (variance inflation factor) values. The results range from 1.01 to 5.85, indicating low to moderate levels of multicollinearity in the model, however this isn't severe enough to cause issues in relation to coefficient estimates. Lastly, the null hypothesis of no misspecification as per the Ramsay RESET test is rejected at 5% (p-value of 0.0178).

7: Conclusion

The researcher now evaluates how the findings align with the hypotheses, objectives and overarching research question. The first objective of identifying correlation was achieved through the correlation matrices **(appendix D)**, which evidence correlation between the ASX and independent variables ranging from strongly negative (INT) to strongly positive (CPI). The second objective of identifying short and / or long-run dynamic relationships was achieved firstly by conducting the bounds test. With this result, the researcher ruled out evidence of long-run cointegrating relationships and estimated an appropriate short-run ARDL model. The results (**appendix J**) were compared to the original hypotheses. When assessed in terms of statistical significance at 5%, the hypotheses for the relationships between CPI, INT and M1 and the dependent variable (ASX), were not supported by results for any lag length. However, results for ERI in the current period and IPI and OP at one lag do align with the original hypothesis i.e., negative, positive and negative, respectively. Lastly, the third objective of identifying one-way causality from independent to dependent variables was achieved using Granger causality tests **(appendix K),** with results suggesting unidirectional Granger-causality from IPI and OP to the ASX.

To determine the credibility of any inference, the statistical strength of the model was assessed using post-estimation diagnostic tests (**appendix L**). These tests allowed the researcher to conclude that the Gauss-Markov OLS BLUE assumptions (Best Linear Unbiased Estimator) were reasonably satisfied. However, failure to reject the null hypothesis for the Ramsay RESET test implies the possibility of functional form misspecification. This indicates that the model may be failing to account for important features of the data, in addition to the possibility of omitted variables. This may also be contributing to the change in coefficient signs observed across different lag lengths.

Overall, the researcher concludes that the estimated results are dependable enough to suggest that changes in several of the studied macroeconomic variables are likely to influence changes in the ASX. With this, the researcher hopes their findings make a credible contribution to the existing literature, providing insights to policy makers, investors, and market participants alike. The researcher recommends further analysis to address potential issues of misspecification and to explore alternative models, particularly those pertaining to mean reversion and impulse response functions. This avenue may produce higher degrees of estimation power and yield results that help to explain observed changes in coefficient signs.

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Appendices

Appendix A: variables in levels

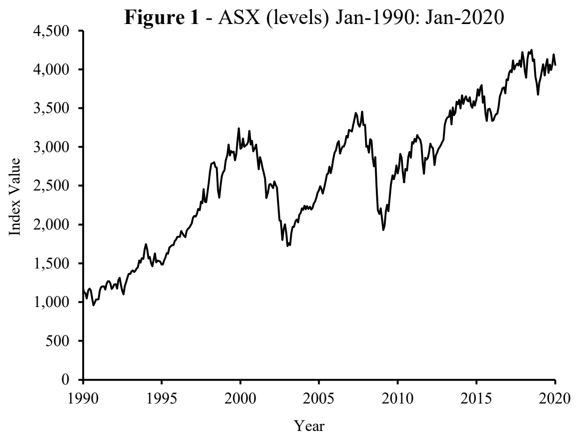


Figure 1 - ASX (levels) Jan-1990: Jan-2020

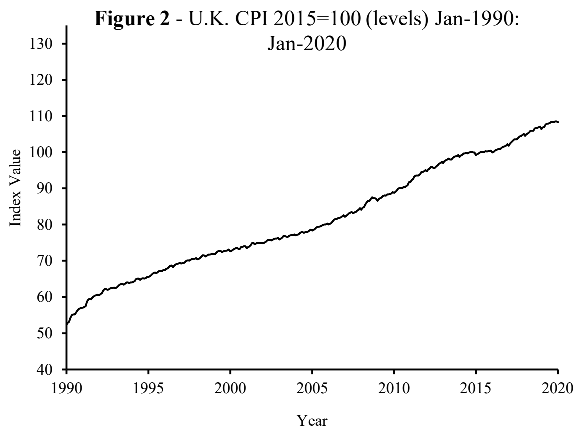


Figure 2 - U.K. CPI 2015=100 (levels) Jan-1990: Jan-2020

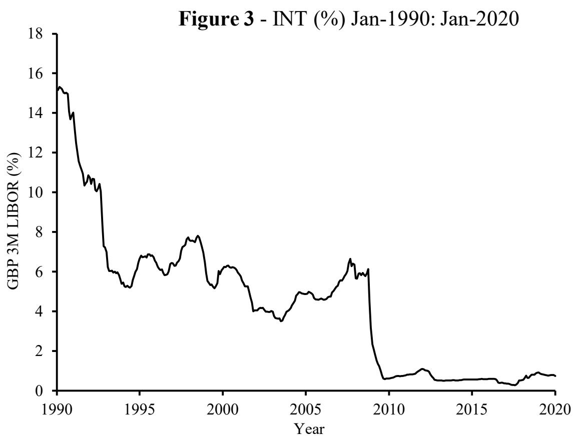


Figure 3 - INT (%) Jan-1990: Jan-2020

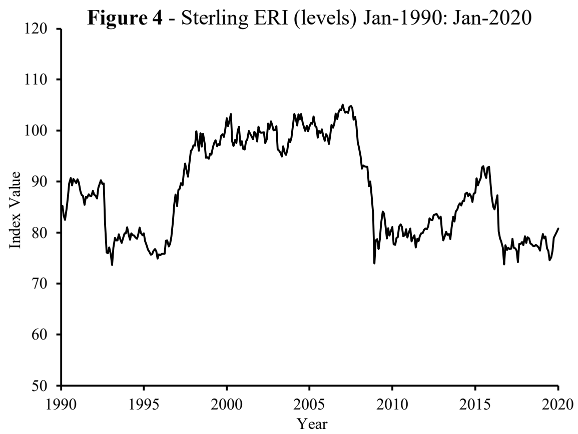


Figure 4 - Sterling ERI (levels) Jan-1990: Jan-2020

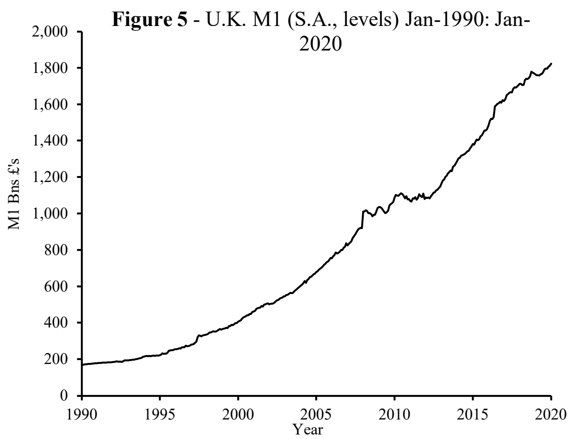


Figure 5 - U.K. M1 (S.A., levels) Jan-1990: Jan-2020

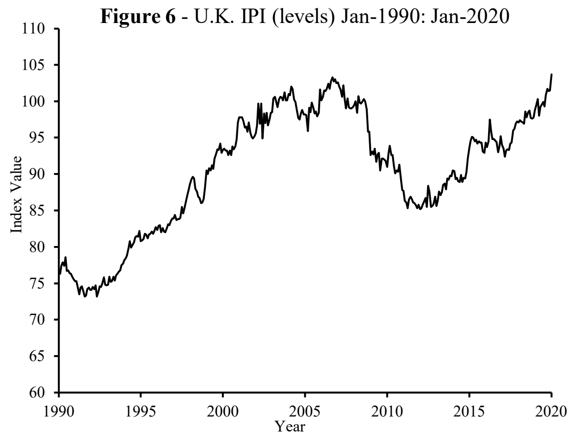
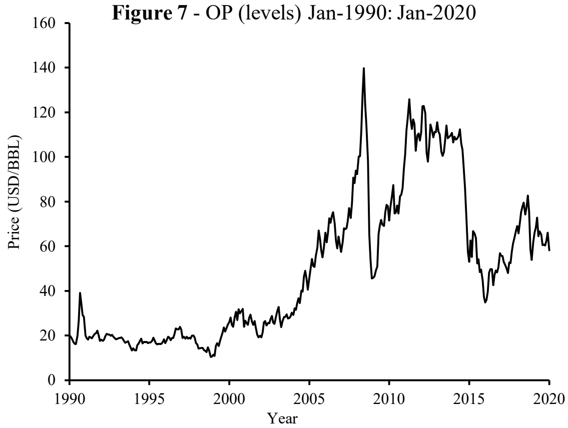


Figure 6 - U.K. IPI (levels) Jan-1990: Jan-2020

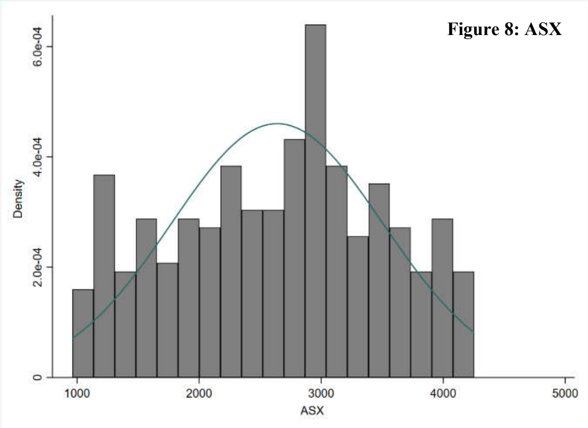
Figure 7 - OP (levels) Jan-1990: Jan-2020

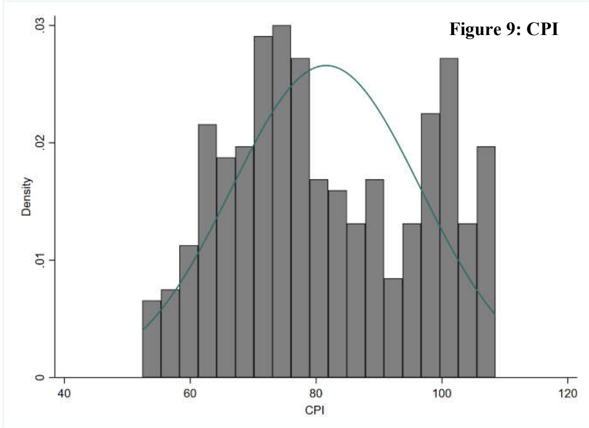


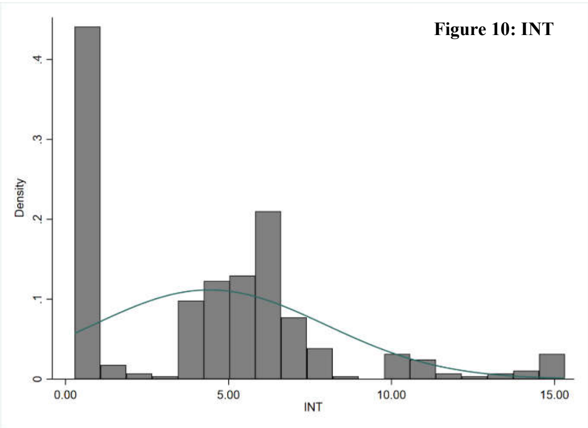
Appendix B: descriptive Statistics

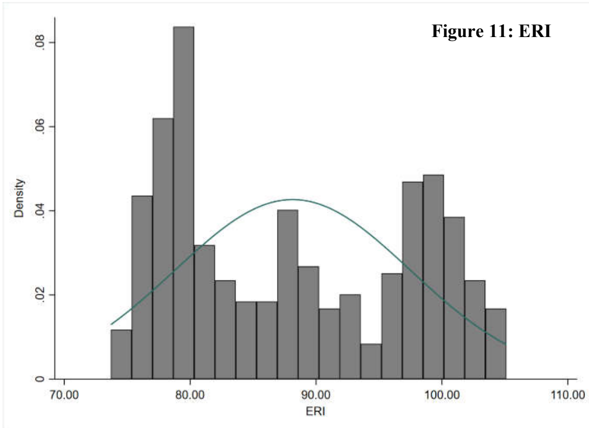
Statistic	ASX	CPI	INT	ERI	M1	IPI	OP
Mean	2,639.36	81.60	4.42	88.14	788.94	90.48	49.71
Standard Error	45.62	0.79	0.19	0.49	27.09	0.44	1.74
Standard Deviation	866.82	15.01	3.58	9.35	514.69	8.41	33.04
Sample Variance	751,379.79	225.25	12.79	87.46	264,908.64	70.76	1,091.87
Kurtosis	(0.93)	(1.12)	0.77	(1.44)	(1.04)	(0.88)	(0.67)
Skewness	(0.12)	0.16	0.88	0.22	0.48	(0.49)	0.73
Count	361	361	361	361	361	361	361

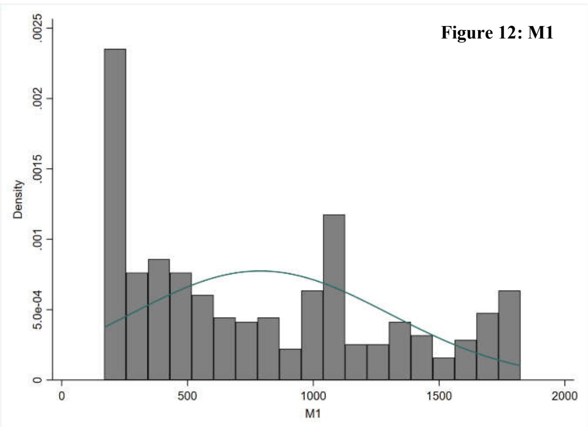
Appendix C: histogram plots of distribution

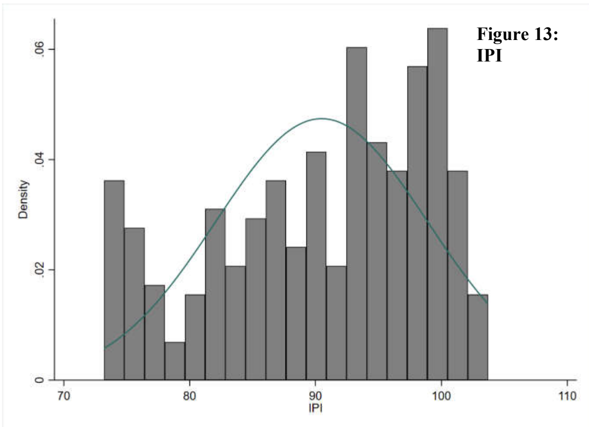












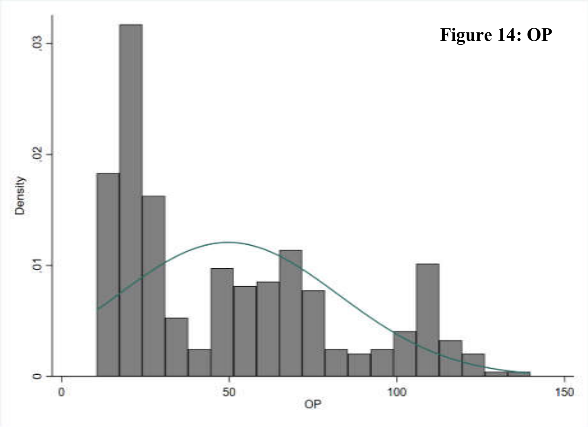


Figure 14: OP

Appendix D: correlation matrices

	ASX	CPI
ASX	1.0000	
CPI	0.8978	1.0000

	ASX	INT
ASX	1.0000	
INT	-0.7625	1.0000

	ASX	ERI
ASX	1.0000	
ERI	-0.0351	1.0000

	ASX	M1
ASX	1.0000	
M1	0.8701	1.0000

	ASX	IPI
ASX	1.0000	
IPI	0.6634	1.0000

	ASX	OP
ASX	1.0000	
OP	0.6012	1.0000

Appendix E: scatter plots of linear relationships

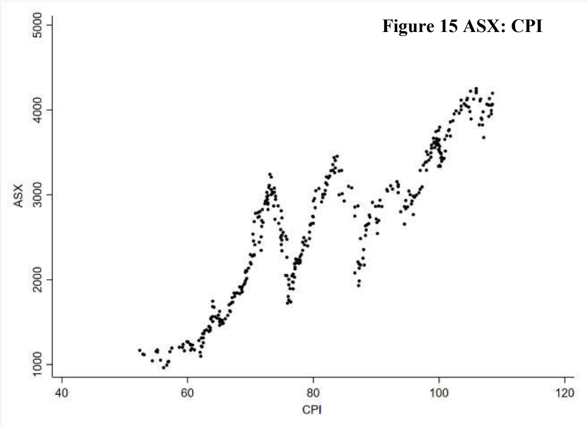


Figure 15 ASX: CPI

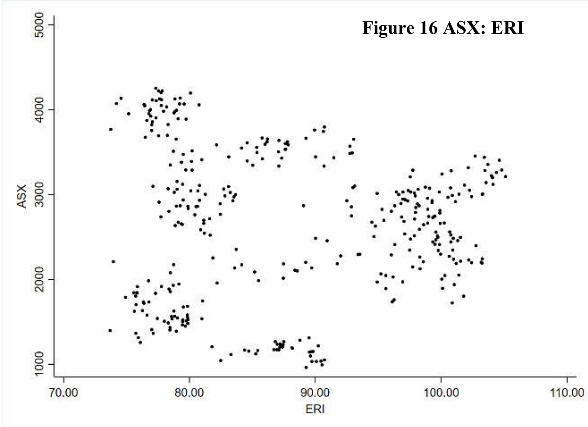


Figure 16 ASX: ERI

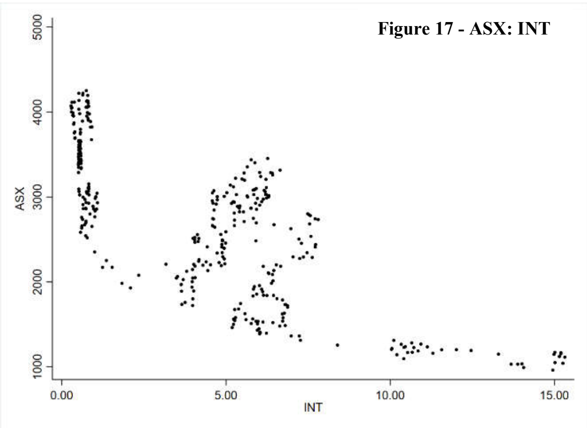


Figure 17 - ASX: INT

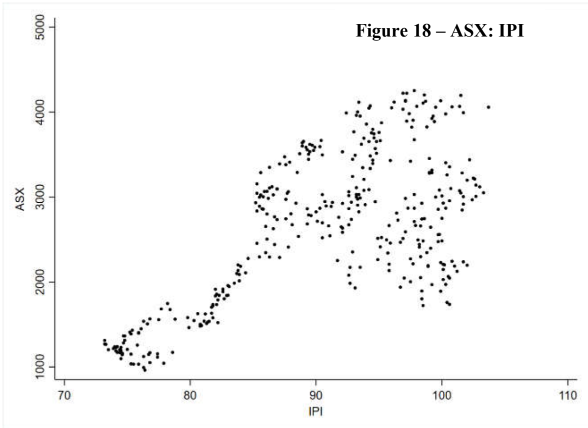


Figure 18 – ASX: IPI

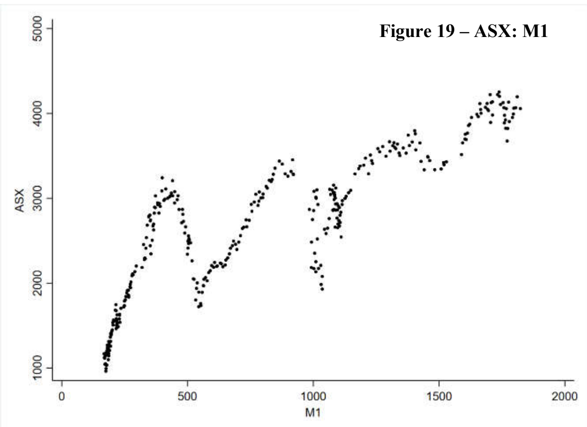


Figure 19 – ASX: M1

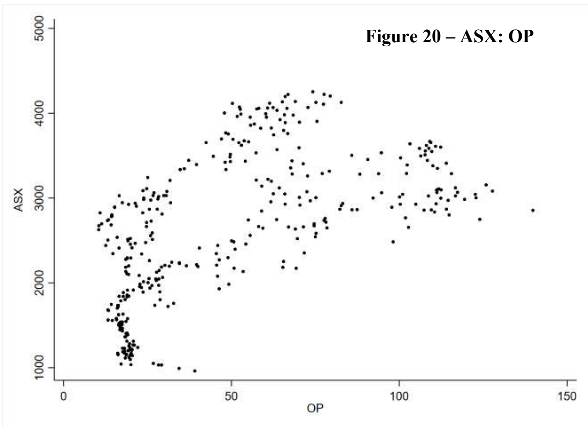


Figure 20 – ASX: OP

Appendix F: augmented-Dickey Fuller tests

	p-value for Z(t)		Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
ASX	0.6975	Z(t)	-1.143	-3.451	-2.876	-2.570
CPI	0.7092		-1.115			
INT	0.0013		-4.018			
ERI	0.4566		-1.651			
M1	1.0000		3.857			
IPI	0.6835		-1.177			
OP	0.5063		-1.555			
Ln_ASX	0.4867	Z(t)	-1.594	-3.451	-2.874	-2.570
Ln_CPI	0.0015		-3.982			
Ln_ERI	0.4275		-1.707			
Ln_M1	0.4583		-1.648			
Ln_IPI	0.6657		-1.218			
Ln_OP	0.5941		-1.375			
d_Ln_ASX	0.0000	Z(t)	-18.120	-3.451	-2.874	-2.570
d_Ln_ERI	0.0000		-18.820			
d_Ln_M1	0.0000		-18.689			
d_Ln_IPI	0.0000		-24.469			
d_Ln_OP	0.0000		-15.573			

Appendix G: natural logarithm transformations

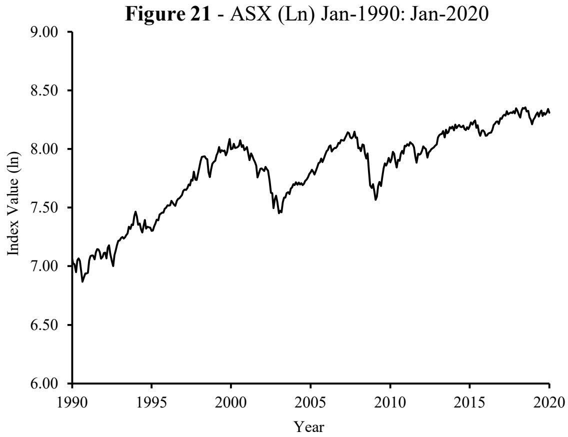


Figure 21 - ASX (Ln) Jan-1990: Jan-2020

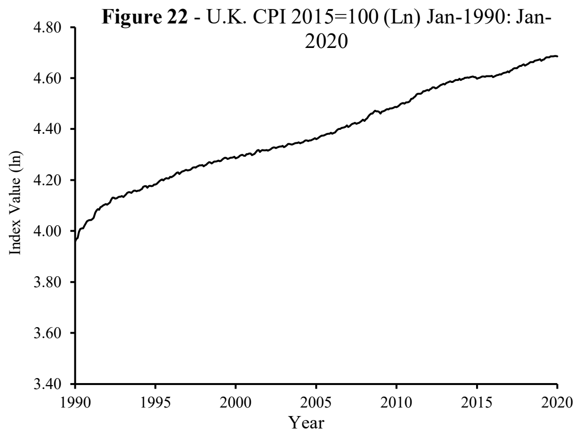


Figure 22 - U.K. CPI 2015=100 (Ln) Jan-1990: Jan-2020

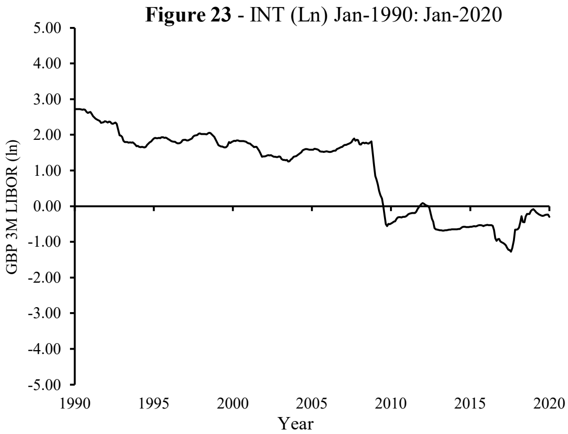


Figure 23 - INT (Ln) Jan-1990: Jan-2020

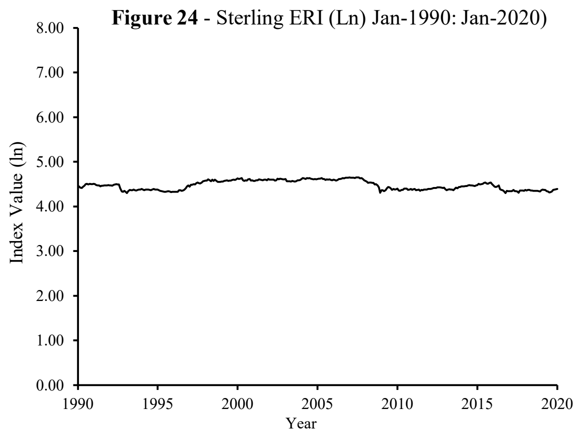


Figure 24 - Sterling ERI (Ln) Jan-1990: Jan-2020)

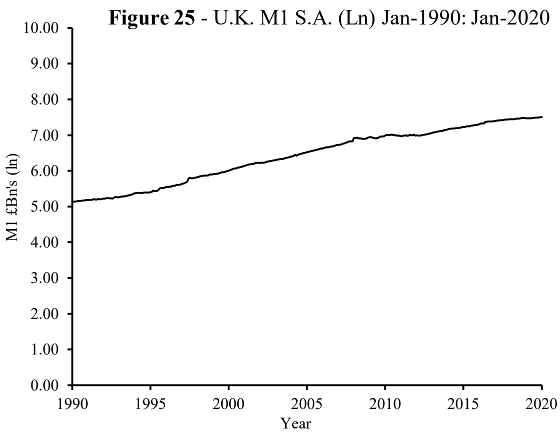


Figure 25 - U.K. M1 S.A. (Ln) Jan-1990: Jan-2020

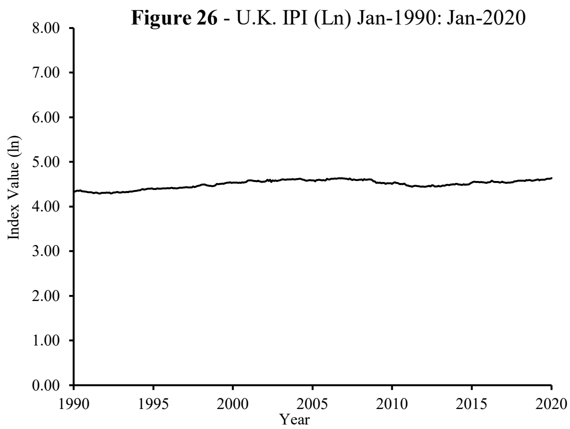


Figure 26 - U.K. IPI (Ln) Jan-1990: Jan-2020

Appendix H: first differenced variables

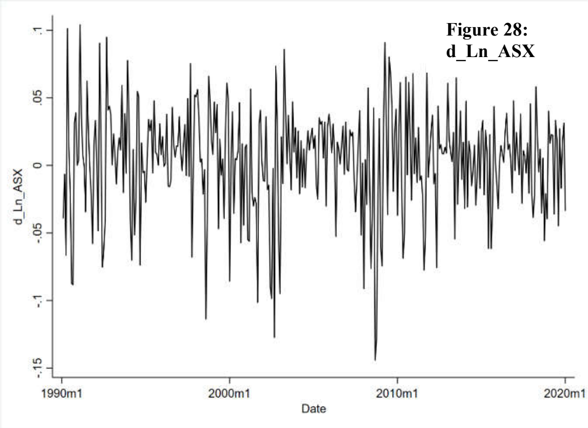


Figure 28: d_Ln_ASX

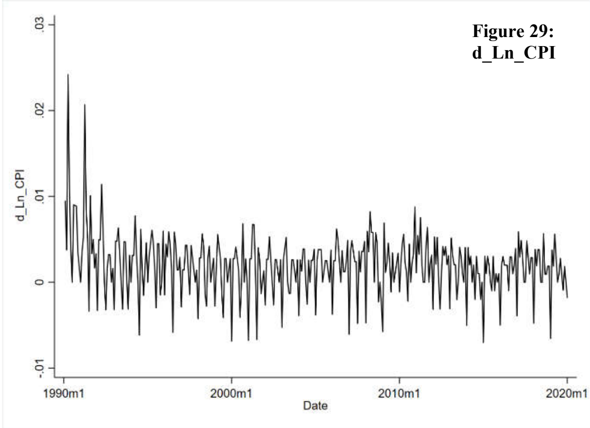


Figure 29: d_Ln_CPI

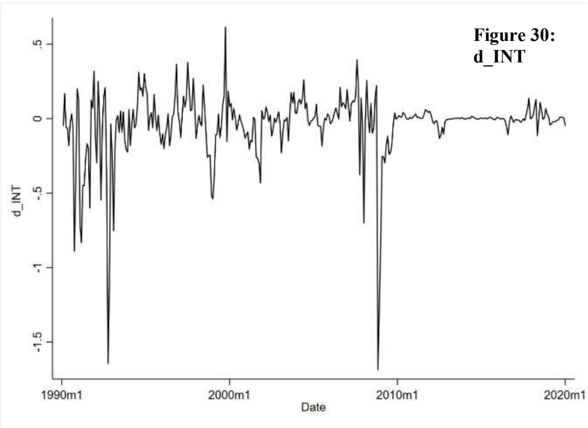


Figure 30: d_INT

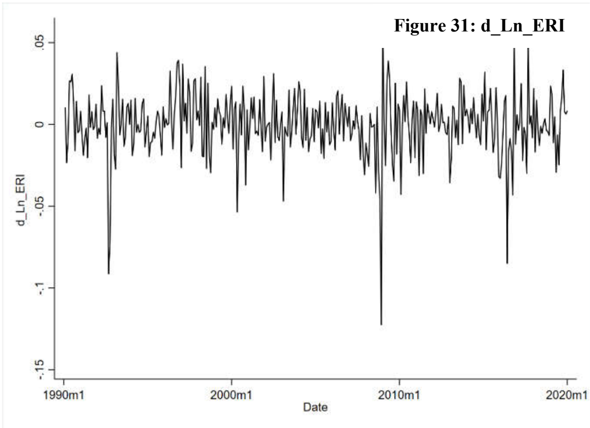


Figure 31: d_Ln_ERI

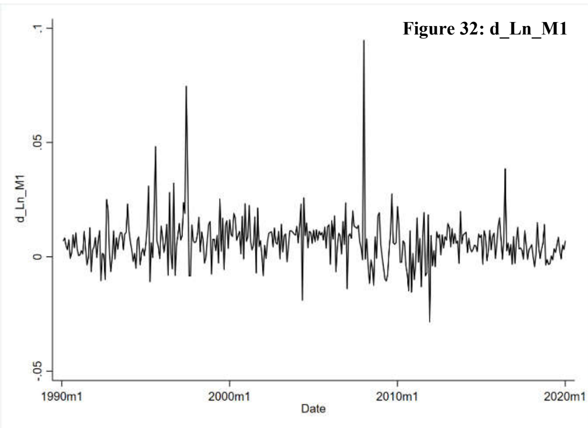


Figure 32: d_Ln_M1

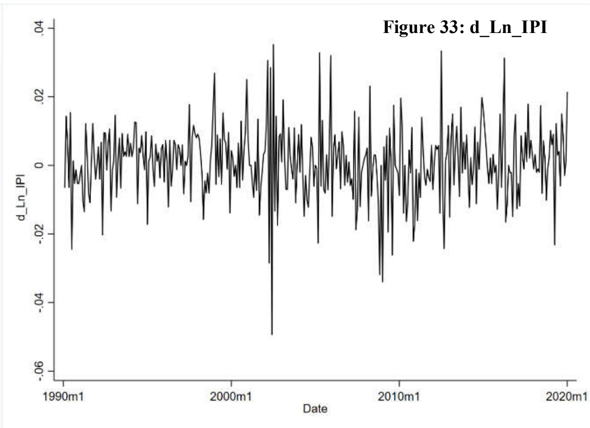


Figure 33: d_Ln_IPI

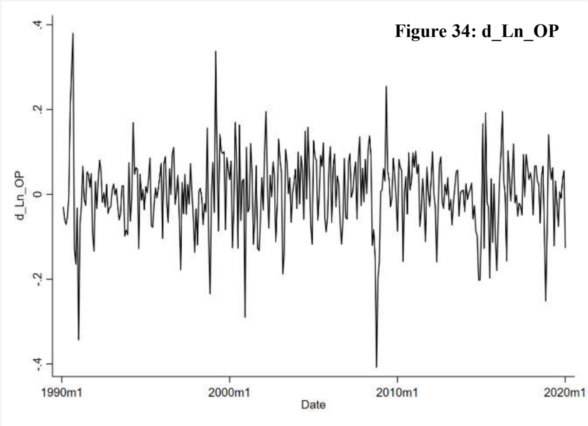


Figure 34: d_Ln_OP

Appendix I: Bounds test for cointegration

Pesaran/Shin/Smith (2001) H0: no levels relationship								
Critical Values (0.1-0.01), **F-statistic**			F = 1.750 t = -1.520					
	[I_0] L_1	**[I_1] L_1**	**[I_0] L_1**	**[I_1] L_1**	**[I_0] L_1**	**[I_1] L_1**	**[I_0] L_1**	**[I_1] L_1**
k_6	2.12	3.23	2.45	3.61	2.75	3.99	3.15	4.43
accept if F < cv for I(0) regressors								
reject if F > cv for I(1) regressors								
Critical Values (0.1-0.01), **t-statistic**								
	[I_0] L_1	**[I_1] L_1**	**[I_0] L_1**	**[I_1] L_1**	**[I_0] L_1**	**[I_1] L_1**	**[I_0] L_1**	**[I_1] L_1**
k_6	-2.57	-4.04	-2.86	-4.38	-3.13	-4.66	-3.43	-4.99
accept if t > cv for I(0) regressors								
reject if t < cv for I(1) regressors								

Appendix J: ARDL regression results, optimal lags (1 3 1 3 1 6 1)

Sample: 1990m8 - 2020m1				Obs	=	354
				F(22, 331)	=	2.52
				Prob > F	=	0.0002
				R-squared	=	0.1733
				Adj R-squared	=	0.1184
Log likelihood = 676.34199				Root MSE	=	0.0370
d_Ln_ASX	**Coefficient**	**Robust Std. Err.**	**t**	**P >|t|**	**95% Confidence Interval**	
d_Ln_ASX						
L1.	0.0732616	0.0620909	1.18	0.239	-0.048881	0.1954042
d_Ln_CPI						
--.	0.8157777	0.713508	1.14	0.254	-0.5878045	2.21936
L1.	-1.356895	0.89387	-1.52	0.130	-3.115277	0.4014877
L2.	1.55771	0.9156253	1.70	0.090	-0.2434685	3.358889
L3.	-1.075636	0.7573558	-1.42	0.156	-2.565473	0.414202
d_INT						
--.	-0.0202612	0.0113002	-1.79	0.074	-0.0424904	0.001968
L1.	0.0166533	0.0113299	1.47	0.143	-0.0056344	0.038941
d_Ln_ERI						
--.	-0.3655747	0.1099018	-3.33	0.001	-0.5817689	-0.1493806
L1.	0.1569357	0.1220892	1.29	0.200	-0.0832329	0.3971044
L2.	0.084269	0.1156954	0.73	0.467	-0.1433221	0.31186
L3.	0.2443878	0.1143057	2.14	0.033	0.0195306	0.469245
d_Ln_M1						
--.	-0.0552284	0.2531159	-0.22	0.827	-0.553147	0.4426903
L1.	0.2646096	0.1785962	1.48	0.139	-0.086717	0.6159363
d_Ln_IPI						
--.	0.1720397	0.2053838	0.84	0.403	-0.2319825	0.5760618
L1.	0.4489091	0.1909284	2.35	0.019	0.073323	0.8244952
L2.	0.1870444	0.1881024	0.99	0.321	-0.1829825	0.5570712
L3.	0.1462237	0.238690	0.61	0.541	-0.323317	0.6157644
L4.	-0.263556	0.1971717	-1.34	0.182	-0.6514236	0.1243117
L5.	-0.3036055	0.2148165	-1.41	0.158	-0.7261832	0.1189723
L6.	-0.580544	0.2215367	-2.62	0.009	-1.016342	-0.1447465
d_Ln_OP						
--.	0.0532646	0.0272589	1.95	0.052	-0.000358	0.1068871
L1.	-0.0586527	0.0288808	-2.03	0.043	-0.1154657	-0.0018396
_cons	0.2731275	0.1431728	1.91	0.057	-0.0085158	0.5547708

Appendix K: Granger Causality Wald results

Null hypothesis: ⌐ used as notation for “does not Granger-cause”			chi2	Prob>chi2	Decision
L.d_Ln_ASX	⌐	d_Ln_ASX	0.64184	0.423	Accept
L.LnCPI	⌐	d_Ln_ASX	0.42389	0.515	Accept
L2.LnCPI		d_Ln_ASX	1.7822	0.410	Accept
L3.LnCPI	⌐	d_Ln_ASX	3.0642	0.382	Accept
L.INT	⌐	d_Ln_ASX	0.00468	0.945	Accept
L.d_Ln_ERI	⌐	d_Ln_ASX	0.39937	0.527	Accept
L2.d_Ln_ERI	⌐	d_Ln_ASX	0.82731	0.661	Accept
L3.d_Ln_ERI	⌐	d_Ln_ASX	3.9462	0.267	Accept
L.d_Ln_M1	⌐	d_Ln_ASX	1.2024	0.273	Accept
L.d_Ln_IPI	⌐	d_Ln_ASX	3.2846	0.070	Reject @10%
L2.d_Ln_IPI	⌐	d_Ln_ASX	3.4383	0.179	Accept
L3.d_Ln_IPI	⌐	d_Ln_ASX	5.7621	0.124	Accept
L4.d_Ln_IPI	⌐	d_Ln_ASX	7.3929	0.117	Accept
L5.d_Ln_IPI	⌐	d_Ln_ASX	8.1197	0.150	Accept
L6.d_Ln_IPI	⌐	d_Ln_ASX	19.86	0.003	Reject @1%
L.d_Ln_OP	⌐	d_Ln_ASX	5.8753	0.015	Reject @5%

Appendix L: Diagnostic tests

Durbin-Watson d-statistic (23, 354)	= 1.94798

Breusch-Godfrey LM test for Autocorrelation H0: no serial correlation			
lags(p)	**chi2**	**df**	**Prob > chi2**
1	1.305	1	0.2533
2	2.093	2	0.3512
3	2.361	3	0.5009
4	3.716	4	0.4458

White's Test for Heteroscedasticity			
Heteroscedasticity	305.94	275.00	0.0966
Skewness	37.08	22.00	0.0232
Kurtosis	2.86	1.00	0.0907
Total	345.89	298.00	0.0292

Jarque-Bera test for residual normality H0: Normality	1.057		0.5895
Ramsay RESET for model misspecification H0: model has no misspecification / ov			
F(3, 328) = 3.41			
Prob > F = 0.0178			

VIF (variance inflation factor)

Variable	**VIF**	**1/VIF**
LnCPI	5.85	0.170864
INT	5.83	0.171549
d_Ln_M1	1.05	0.955390
d_Ln_ERI	1.04	0.958490
d_Ln_OP	1.02	0.978443
d_Ln_IPI	1.01	0.993720
Mean VIF	2.63	

Appendix M: Histogram of residuals

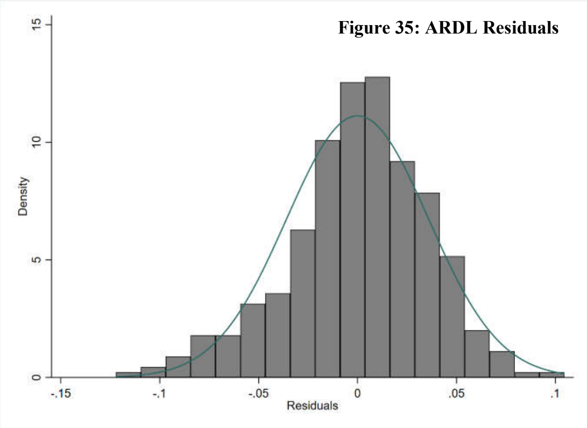


Figure 35: ARDL Residuals

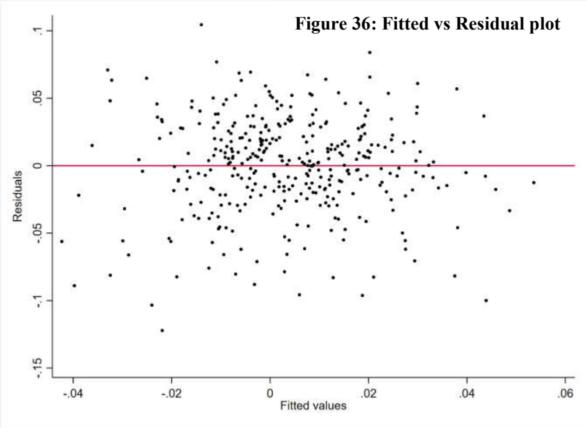


Figure 36: Fitted vs Residual plot

Appendix N: Figure 37 - CUSUM plot