Department of Economics

Economic Analysis Research Group (EARG)

The Macroeconomy, Oil and the Stock Market: A Multiple Equation Time Series Analysis of Saudi Arabia

By Ruqayya Aljifri

Discussion Paper No. 2020-27

Department of Economics
University of Reading
Whiteknights
Reading
RG6 6EL
United Kingdom

www.reading.ac.uk

The Macroeconomy, Oil and the Stock Market: A Multiple Equation Time Series Analysis of Saudi Arabia

Ruqayya Aljifri*

Department of Economics, University of Reading

Abstract: This study investigates the existence of long-run relationship/s among the Saudi stock price index (TASI) and domestic macroeconomic variable of money supply (M2), the international variable of S&P 500 and global variable of oil prices, using quarterly data from 1988 quarter 1 to 2018 quarter 1. We also used local and global events dummy variables to control for the impact of local (the 2004 and 2005 TASI bubble that followed by the 2006 crash) and global (the 2008 financial crisis) events, making this paper the first study that takes into account the impact of the local and global financial crisis events when examining the relationship between TASI and macroeconomic variables. We applied the vector error correction model with dummy variables and variance decomposition for long-run analysis. We also applied the Indicator Saturation method to detect outliers and structural breaks. Findings show that there exists a long-run relationship between all of the variables in the system. The equilibrium relation between TASI and S&P 500 and oil prices is positive. However, the relationship between TASI and money supply is negative. Moreover, TASI is substantially driven by innovations in oil prices, and to a lesser extent, by money supply and S&P 500, respectively.

Keywords: TASI, macroeconomic variables, the TASI bubble and the crash, the global financial crisis, VECM, cointegration test, Indicator Saturation, variance decompositions.

JEL code: C22, E44, G

I would like to thank my supervisors Dr Simon Burke and Dr James Reade for their support and guidance. I would also like to thank Dr Carl Singleton for his helpful comments and suggestions.

*Correspondence concerning this article should be addressed to Ruqayya Aljifri, G78 Edith Morley Building, Department of Economics, University of Reading, Whiteknights, PO Box 218, Reading, Berkshire, RG6 6AA, United Kingdom. Email: r.m.a.aljifri@pgr.reading.ac.uk

1 Introduction

The stock market is an important segment of the financial system of any country because there is a positive linkage between financial development and economic prosperity (Levine, 2018). Interest in studying the link between the stock market and macroeconomic fundamentals has increased among researchers. Specifically, there is interest in whether stock prices are determined by local macroeconomic variables such as money supply, international factors such as a foreign stock price index, or global factors such as oil prices. Stock markets may channel funds between savers and borrowers by mobilising savings from diverse individual resources (Sohail & Hussain, 2009). Therefore, stock markets seem to encourage economic growth (Arestis, Demetriades, & Luintel, 2001). Also, stock markets may facilitate investments by minimising the savings mobilisation cost (Greenwood & Smith, 1997).

A linkage between stock markets and macroeconomic variables has been documented by pioneering empirical studies in the context of developed markets (Fama, 1981; Geske & Roll, 1983; Mukherjee & Naka, 1995) and emerging markets (Barakat, Elgazzar, & Hanafy, 2016; Jamaludin, Ismail, & Ab Manaf, 2017). Further, the interrelationships between the US stock market and various stock markets around the world have been documented. The US stock market was found to be interrelated with European and Australian stock markets (Meric, Lentz, Smeltz, & Meric, 2012), the Indian stock market (Samadder & Bhunia, 2018), the Chinese stock market (Bhatia, 2019) and the Saudi stock market (Khoj, 2017).

The current study contributes to the literature by adding some knowledge to the existing empirical works regarding the relationship between the Saudi stock market and the domestic variable of money supply, the international variable of S&P 500, and the global variable of oil prices. The findings of this study may be beneficial for researchers who desire to discover the connection between macroeconomic variables and stock markets. Findings of the degree of integration between the US and the Saudi stock markets is beneficial for investors. The Saudi stock market may provide attractive opportunities for international investors, who may benefit from diversification of their portfolio when investing in the Saudi stock market.

The Saudi Stock Exchange (Tadawul) is the largest among Gulf Cooperation Council (GCC) countries in the region, comprising 46% of total GCC market capitalisation (Cheikh, Naceur, Kanaan, & Rault, 2018), and is the largest, by capitalisation, in the Middle East and

North African (MENA) region (Sharif, 2019). Tadawul has recently implemented far-ranging reforms, some of which were technological market reforms that are aligned with the top procedures globally. In 2015, for example, Tadawul deployed NASDAQ'S X-Stream INET exchange framework, which is among the top trading platforms worldwide (Tadawul, 2017). Two additional reforms occurred in April 2017, when Tadawul moved transaction settlements from a T+0 cycle to a T+2 cycle and introduced short selling[1]. Thus, Tadawul became the first market in the region to implement a short-selling framework for all listed stocks to provide the market with additional depth (Tadawul, 2017).

Moreover, initially, foreign investors were not allowed to invest directly in the Saudi stock market "Tadawul". Foreign investment in Tadawul-listed securities was allowed indirectly, only through swap agreements with CMA-authorised persons. The stock market's accessibility was enhanced by opening up the Saudi Stock Market to qualified foreign investment (QFI) in 2015. Institutional investments are assumed to improve market stability by attracting long-term investments (Schuppli & Bohl, 2010). Moreover, recent significant developments have taken place that are related to the inclusion of Tadawul's shares in the prominent emerging market indices, namely the FTSE Russell Emerging Markets Index, the S&P Dow Jones Indices (S&P DJI), and the MSCI Emerging Markets Index (MSCI).

This paper contributes to the literature in that it is the first study to take into account the impact of the local event of the TASI bubble and crash and the global event of the 2008 financial crisis when modelling the relationship between TASI and macroeconomic variables. The Saudi Stock Exchange has experienced a bubble of 2004 and 2005, followed by an unexpected and sudden crash of 2006 (Aljloud, 2016; Alkhaldi, 2015). The crash of 2006 is the kingdom's first and worst local stock market collapse. The beginning of the Saudi stock market bubble dates back to 2003, when market capitalisation increased significantly from US $157 billion in 2003 to US $306 billion in 2004, and again, to US $650 billion in 2005. By the end of 2006, the market capitalisation of issued shares decreased 49.72% from the previous year to US $326.9 billion (Lerner, Leamon, & Dew, 2017). The Tadawul All

[1]T+0 settlement cycle means there is no difference between the and the settlement dates. T+2 settlement cycle means the settlement date occurs two business days after the transaction date. A T+2 cycle provides investors more time than T+0 cycle to verify transactions and/or address any problem that may occur, which aligns with global settlement practices.

Share Index (TASI) closed at 8,206.23 points in 2004, compared with 4437.6 points in 2003, increasing by 84 per cent. The TASI closed at 16,712.64 points in 2005, rising by 103.7 per cent. On February 2006, the TASI reached a peak of 20,634.86 points. By the end of 2006, the TASI reached a nadir of 7,933.29 points, falling by 52.53 per cent compared with 2005 (Alkhaldi, 2015).

The present paper fills a void in the existing literature by being the first study to consider the impact of local and global events. This point is particularly important, given that ignoring the effect of the TASI bubble and crash and the global financial crisis when estimating the empirical model may cause structural breaks and outliers in the model, which may invalidate inference, distort relationships and change distributions (Castle & Hendry, 2019). The main variable of interest "TASI" may capture an important determining mechanism, but ignoring it may lead results in model misspecification. This study uses a specialised technique to detect multiple outliers and structural breaks, such as the Indicator Saturation method, which is an essential practice. This procedure is simple, flexible, and efficient in the dynamic model (Marczak & Proietti, 2016). In this study, we included a group of macroeconomic variables, together with event dummy variables that control for the local and global events, in the vector error correction model (VECM) to achieve accurate conclusions. The choice of dummies is based on the domain knowledge that provides an economic explanation for the local and global events, which is supported by the findings of statistical methods of Indicator Saturation and Bai–Perron test (as an alternative robustness method). Results of the VECM with dummy variables are reportedly more accurate than conventional VECM (Jiang, Xu, & Liu, 2013).

In this paper, we provide a further understanding of the long-run relationship between the Saudi Stock Price Index (TASI) and the domestic variable of money supply (M2), the international variable of real S&P 500 and the global macroeconomic variable of real oil prices during the period 1988Q1–2018Q1. This study focuses on two research questions, namely:

1. Is there a long-run relationship between money supply, oil prices, S&P 500 variables, and the Saudi stock price index (TASI)?
2. Do the variations in money supply, oil prices, and S&P 500 variables influence the Saudi stock price index variations?

The paper is structured as follows. The next section presents theory and review of the literature. Section 3 offers data and model description. Section 4 explains methodology and Section 5 presents empirical analysis. Section 6 discusses long-run relationships. Section 7 provides a discussion, which is followed by Section 8, which concludes the paper.

2 Theory and Review of Literature

The existence of a relationship between macroeconomic variables and stock market performance has been documented theoretically and empirically. Theoretically, efficient market hypothesis (EMH), capital asset pricing model (CAPM), arbitrage pricing theory (APT), and the present value model (PVM) are the major theories suggesting the existence of a relationship between macroeconomic variables and stock market returns (Jacob Leal, 2015; Krause, 2001). Empirically, the connection between stock market performance and macroeconomic variables has been extensively studied in advanced countries. Developed countries have conducted most of the pioneering and preliminary research, for instance, in the United State, N. Chen, Roll, and Stephen (1986) and N.-F. Chen, Roll, and Ross (1986), in Japan, Mukherjee and Naka (1995). Also, there is a consensus among the results of most research findings on developed markets for most macroeconomic variables, providing strong evidence for the existence of a relationship between macroeconomic variables and the stock market (Awang, Hussin, & Zahid, 2017; Maysami, Howe, & Rahmat, 2005; Vejzagic & Zarafat, 2013). However, the nature of the relationship between stock prices and money supply has remained an open empirical question.

Lately, emerging countries have attracted more attention from, for example, Asaolu and Ogunmuyiwa (2011) in Nigeria, and Khan, Muttakin, and Siddiqui (2013) in Bangladesh. In fact, research on developing countries is still improving. However, few studies have been done in the Saudi context; the exceptions are Alkhudairy (2008), Alshogeathri (2011), Kalyanaraman and Tuwajri (2014), Samontaray, Nugali, Sasidhar, et al. (2014) and Almansour and Almansour (2016). Findings of emerging stock markets literature indicate that there has been no consensus among the researchers regarding the kind of connection between the performance of the stock market and macroeconomic variables. Findings for most macroeconomic variables, especially for the money supply, have been varying, conflicting, and uncertain.

Table 1 summarises the findings of researches that studied the impact of macroeconomic variables on the Saudi stock market. Following a review of the relevant Saudi literature, we found the following. Findings on money supply were conflicting; some studies found strong associations between stock prices and money supply and, in other studies, the relationships were found to be insignificant. The majority of Saudi studies that employed two measures of money supply have found contradictory results, in terms of the sign of money supply measures. For example, Alshogeathri (2011) and Khoj (2017) found that one measure of money supply has a positive impact on stock prices, whereas the other measure is negatively related to the Saudi stock market. Regarding the S&P 500, in some studies, there were positive relationships between TASI and S&P 500 and, in other studies, this relation was found to be negative. However, the majority of previous studies found a strong association between TASI and the S&P 500. These conflicting results may be because these studies did not account for structural breaks; they were conducted in different time period or/and have varying length time series. Moreover, the research study by Almansour and Almansour (2016) was conducted over a very short period from 2010 to 2014 and used the ordinary least squares (OLS) method, which is considered unpopular in time series analysis, because if the time series are non-stationary, OLS may generate a false regression and thus, may fail to address the intended academic target comprehensively.

Table 1: *Long-Run Impact of Selected Macroeconomic Variables on the Saudi Stock Market*

Macroeconomic variables	**Positive**	**Negative**	**Insignificant**
Money Supply	Alshogeathri (2011) Kalyanaraman and Tuwajri (2014) Khoj (2017)	Alshogeathri (2011) Khoj (2017)	Almansour and Almansour (2016)
Oil Price	Alshogeathri (2011) Samontaray et al. (2014) Kalyanaraman and Tuwajri (2014) Almansour and Almansour (2016) Khoj (2017)		
Standard and Poor 500 Index	Alkhudairy (2008)	Alshogeathri (2011) Khoj (2017)	Kalyanaraman and Tuwajri (2014)

By reviewing the relevant Saudi literature, the gap in the Saudi studies will be identified as follows. First, there exists few studies have considered TASI since its establishment, particularly to compare it to the volume of the Saudi economy. Hence, this study attempts to remedy the relative dearth of research on the relationship between the Saudi stock market and the macroeconomic variables. Moreover, the stock market and its relationship with macroeconomic variables may change from one period to the next, especially after the considerable economic and stock market reforms, which called out for new research. Moreover, the Saudi stock market studies are relatively short and did not adequately deal with a long time series. The current research covers a period of 1988Q1-2018Q1, which makes this study the most extended time-series study to be conducted on the Saudi stock market context, as none of the previous studies has exceeded 19 years.

In contrast to the earlier studies reviewed above, this study will be the first study that controls for the effects of local (the TASI 2004 and 2005 bubble, followed by the 2006 crash) and global (the 2008 financial crisis) events when examining the relationship between macroeconomic variables and the Saudi stock market. Further, we are using, for the first time, the Indicator Saturation procedure to choose the most appropriate set of dummies regarding this topic in the Saudi context, as it is a relatively new procedure in the literature. This point is particularly important, given that the model may show severe misspecifications when fitting the data, ignoring outliers and structural breaks. Additionally, we adjusted the variables included in this study for inflation. Including the variables in real terms and excluding the effect of inflation may provide more accurate results.

2.1 Role of Money Supply (M2)

M1, M2 and M3 are the most commonly used measures of money supply (Jamaludin et al., 2017). On the one hand, a positive impact of money supply on the stock market may be due to the following explanations. First, increased money supply boosts liquidity, which means that there are more funds available for investors and more money for consumption. Second, an increase in money supply stimulates the economy, causing a rise in cash flows. Both circumstances result in higher stock prices. On the other hand, a negative impact of money supply on the stock market may be due to the following explanations. Changes in the money supply will have a negative influence on the stock prices only if these changes alter people's expectations about future monetary policy. For example, a positive shock of money supply will lead people to expect a tightening monetary policy in the future, which will cause people to demand more money and funds. As a result, the interest rate goes up, and consequently, the discount rates go up, resulting in a decline in the present value of future cash flows, and therefore a fall in stock market prices (Sellin, 2001).

Moreover, a higher interest rate may lead to decrease the economic activities, which would depress stock prices even more (Sellin, 2001). Furthermore, the risk premium hypothesis introduced by Cornell suggests that when money supply increased will increase money demand which indicates higher risk and as a result investors may demand higher risk premiums for holding their stocks that will make them less attractive (Sellin, 2001). However, the money supply may have no impact on stock prices. Fama (1981) argued that money growth might motivate the economy and boost cash flow, because of the corporate earnings effect; consequently, stock prices get higher. Therefore, the negative impact of the increased money supply may be balanced.

Regarding the findings of the previous studies, the nature of the relationship between stock prices and money supply is debatable and claimed to be an empirical question. The literature provided conflicting results regarding this relationship and was not able to provide a decisive answer on whether this relationship is significant or not. A significant negative impact was reported by Issahaku, Ustarz, and Domanban (2013) and Bala Sani and Hassan (2018). However, a significant and positive long-run nexus between money supply and the stock market was reported by Fama (1981), Mukherjee and Naka (1995) and Kotha and Sahu (2016). Finally, Humpe and Macmillan (2009), Islam and Habib (2016) and Jamaludin et al. (2017) found that there is no significant impact exist between money supply and stock prices. In this study, we used M2, which was used widely as a measure of money supply in previous studies, such as those by Hassan and Al Refai (2012) and Lawal, Somoye, Babajide, and Nwanji (2018).

2.2 Role of Oil Prices

It is crucial to consider including oil prices in the model to understand the stock market price movements (N.-F. Chen et al., 1986). Nowadays, oil has become a commodity of global importance and one of the most influential macroeconomic variables, especially in the case of Saudi Arabia. The Kingdom of Saudi Arabia is the number one oil exporter in the world. In 2018, for example, the total value of Saudi oil exports was US $182.5 billion, which accounted for 16.1% of total oil exports globally, with the world's largest reserves (OPEC, 2018). However, differentiating a net oil-exporting countries from net oil-importing countries is essential to determine the impact of oil prices on the stock market prices (Wang, Wu, & Yang, 2013). Wang et al. (2013) claimed that oil-exporting and importing countries respond differently to oil price changes. For example, the relationship between oil prices and stock market prices is positive in oil-exporting countries and negative in oil-importing countries. Most net oil-importing countries studies generally agree about the negative impact of oil price variations on stock returns, and therefore on the economy (Basher, Haug, & Sadorsky, 2012; Masih, Peters, & De Mello, 2011).

On the other hand, other studies have investigated the relationship between oil prices in net oil-exporting countries and stock market prices; this includes Park and Ratti (2008), who found a positive relationship between oil prices and the Norwegian stock market. Saudi Arabia is a net oil-exporting country, which means that when the prices of oil increase, the government revenue is expected to increase, and this has a positive effect on government expenditures and the aggregate demand in the Saudi economy, which raises corporate output and earnings, as well as stock prices (Kotha & Sahu, 2016). There is a consensus among the majority of the Saudi-related literature, such as Alshogeathri (2011) and Khoj (2017), regarding the nature of the relationship between oil prices and TASI, which has been found to be significant and positive. Hence, changes in oil prices are expected to play an important role in explaining the movements of the Saudi stock market.

2.3 Role of Standard and Poor's 500 Index (S&P 500)

We chose the US stock market to represent the international stock market, because the US stock market is one of the most influential stock markets, affecting stock markets all over the world (Eun & Shim, 1989). The S&P 500 is considered to be the best representative of the US stock market, as it tracks the value of 500 major companies listed on the New York Stock Exchange (NYSE) and the NASDAQ (Banton, 2020).

We expect that the relationship between the US and the Saudi stock markets is significant for the following reasons. First, globalisation may push stock markets all over the world to move towards integration. Additionally, the recent far-ranging reforms of the Saudi stock market, including technological market reforms and enhancement of the stock market's accessibility by opening up the Saudi stock market to qualified foreign investment (QFI) in 2015, may allow the two stock markets to become more integrated over time. Moreover, numerous financial events, including joining the Saudi stock market with the prominent emerging market indices, namely the FTSE Russell Emerging Markets Index and the Emerging Markets Index of Morgan Stanley Capital International (MSCI) may point to this increasing correlation. Finally, emerging stock markets have been identified as being partially integrated into international financial markets. As Tadawul has been upgraded officially to the status of an "emerging market", we expect it to have similar results to other emerging markets.

The relationship between the US stock market and various other stock markets has been documented widely in previous literature. Previous studies, such as that by Meric et al. (2012), have revealed an in the interrelation between the US stock market and developed stock markets and noted the existence of interrelation between the US stock market and emerging markets (Samadder & Bhunia, 2018). Several studies have suggested that integration exists between the Gulf Cooperation Council countries (GCC) countries and the US stock market, including that of Hatemi-j (2012), who revealed a degree of integration between the UAE and the US stock markets. However, Saudi studies that have examined the integration between the Saudi stock market and the US stock market are limited, and their findings are conflicting. Alshogeathri (2011) and (Khoj, 2017) reported a significant and negative long-run relationship between the Saudi stock market and the US stock market. By contrast, Alkhudairy (2008) found this relationship to be positive. However, Kalyanaraman and Tuwajri (2014) found no relationship between the US and the Saudi stock markets. Conflicting results among Saudi studies regarding the S&P 500 indicate a need for more investigation. We included the S&P 500 variable in this study to investigate whether the international stock price index contributed to Saudi stock price index movements.

3 Data and model

3.1 Data Description

We used quarterly data with a sample period of 1988Q1 to 2018Q1 for the Saudi stock price index (TASI), money supply (M2), oil prices and the US stock price index (S&P 500). The Saudi stock price index, oil prices and the US stock price index are in real term. We represent the data included in this study and its source in Table 2. For additional details on the deflation calculations, please see Appendix A.

Table 2: *Data Sources*

Variables	Source
Saudi Share Price Index (TASI) Tadawul All Share Index (TASI), the general share price index of the Saudi stock market	Database of Saudi Stock Exchange Company www.tadawul.com.sa
Money Supply (M2) M2: M1 (Currency outside banks + demand deposits) + time & savings deposits.	Saudi Arabia Monetary Agency (SAMA) http://www.sama.gov.sa
Oil Price Europe Brent Spot Price FOB (in dollars per barrel)	Thomson Reuters
Standard and Poor's (S&P 500) that represent the US stock price index which used as a proxy for the effect of the international stock market on the Saudi stock market	investing.com

3.2 Model Specifications

The current study focuses on investigating the long-run relationship between TASI and local, international and global macroeconomic variables. We followed a modified specification utilised by existent studies such as Bahmani-Oskooee and Hajilee (2013), which can be expressed as follows:

$$LNTASI = \beta_0 + \beta_1 LNM2 + \beta_2 LNOP + \beta_3 LNNSP500 + e_t \tag{1}$$

Where all of the variables are in the log of real terms. LNTASI is the log of Saudi Share Price Index (TASI), and it is a function of the local, international and global macroeconomic variables. LNM2 represent logs of money supply, LNOP and LNSP500 represent the Log of real oil prices and real S&P 500, respectively. Also, β_0 is an intercept and β_1, β_2, β_3 are the coefficients of the variables, which are expected to be more than zero, and e_t the stochastic error term, which represents the residual error of regression that includes any unmeasured factors.

4 METHODOLOGY

We use the cointegrated vector autoregressive method (CVAR) of Johansen et al. (1995), in common with many other papers (Brahmasrene & Jiranyakul, 2007; Kanjilal & Ghosh, 2017; Rafailidis & Katrakilidis, 2014; Shahrestani & Rafei, 2020). The VECM and cointegration analysis were among the most commonly used econometric methods to investigate the long-run association between the macroeconomic variables and the stock market (Perera & Silva, 2018). However, failing to model outliers and structural breaks may have a crucial impact on inferences and lead to the attainment of a misspecified model and deceptive conclusions (Castle & Hendry, 2019). Thus, for the model to be reliable, we must take into account outliers and structural breaks when modelling the model. Hence, we applied the vector error correction model with dummy variables. We used dummy variables to control for the impact of local (the TASI bubble of 2004 and 2005 and the TASI crash of 2006) and global (the 2008 financial crisis) events. For the local event, the dummy variable takes the value 1 in 2004Q1-2006Q1 intervals and 0 otherwise. For the financial crisis, the dummy variable takes the value 1 in 2008Q1-2008Q4 intervals and 0 otherwise. The choice of dummies is based on the domain knowledge, which is consistent with the findings of statistical methods such as Indicator Saturation, as we will discuss in more details in Section 5.2.

To answer the research questions, we used the Johansen cointegration test, the VECM with dummy variables and variance decomposition technique. This section presents unit root and stationarity tests, lag length selection, Johansen cointegration analysis, VECM, the Indicator Saturation (IS) method, which is employed to detect outliers and structural breaks in the model and the variance decomposition technique, which is used to assess the dynamic behaviour of the model.

4.1 Unit Root and Stationarity Tests

Although there is a common agreement that financial data (stock market indices) and macroeconomic variables are known to be non-stationary in levels, we start by checking the stationarity of the variables. If the variables found to be not stationary at the level and stationarity at the first difference, hence, variables are integrated of order one I (1). Then, we check the cointegration if the variables are found to be cointegrated, which means that the linear combination of the integrated variables is stationary I (0), we can proceed with the VECM. However, there is no agreement on a single test for stationarity and unit root that is regarded as the most powerful (Maddala & Kim, 1998). Therefore, to identify non-stationarity in the series, we employed formal tests: augmented Dickey-Fuller (ADF) (Dickey & Fuller, 1979, 1981) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (Kwiatkowski, Phillips, Schmidt, Shin, et al., 1992)[2].

4.2 Lag selection

Determining the optimal number of lags is a crucial step that must be taken before starting the estimation step. There is no clear-cut way to choose the optimal lag length. However, in the current study, we have selected the number of lags based on the information criteria[3].

4.3 Cointegration

A cointegration test is done to determine the number of long-run relationships the variables share among them. However, there are two pre-cointegration test steps required. First, all variables must be at most integrated of order one I (1). Second, the optimal lag length must be determined before the cointegration test is estimated. The general idea behind cointegration is that if a particular linear combination of non-stationary time series that are integrated of order one and have stationary long-run linear relationships integrated at Order 0. According to the cointegration concept, there are two forces. The pushing force is represented by exogenous shocks, which push the variables away from the long-run equilibrium. The pulling force is represented by short-run dynamic adjustments, known as the error correction mechanism, which pull the system back towards the long-run equilibrium. With this method, the researchers can exploit the most out of the long-run information of non-stationary series since there is no need to convert it by differencing or detrending series (Favero, 2001; Juselius, 2018).

[2] There are three reasons we employed the ADF over Phillips-Perron test (PP) (Phillips & Perron, 1988) to represent the unit root test in this study. First, ADF and PP are unit root tests, and they share the same null hypothesis. Second, we ADF is one of the earliest pioneering works for a unit root test in time series. Third, the ADF test performs better than the PP test in a finite sample (Davidson, MacKinnon, et al., 2004).

[3] We also we considered the frequency of the data, such that we have included more than four lags to capture any seasonal effects. Moreover, took into account the misspecification tests and the behaviour of the residuals when determining the optimal lag length.

4.4 Vector Error Correction (VEC) model

The vector error-correction model (VEC) is a restricted VAR, and the variables are restricted to converge to their long-run relationship; hence, the error-correction term (ECT_{t-1}) that represents the long-run relationship between the variables is included in the model.

4.5 Indicator Saturation (IS)

It is important to take into account outliers and structural breaks when modelling the empirical model to avoid obtaining a misspecified model and deceptive conclusions (Castle & Hendry, 2019). The domain knowledge provided an economic explanation for the local and global dummy variables included in this study. However, employing statistical procedure such as Indicator Saturation Santos, Hendry, and Johansen (2008) is an essential practice to detect the existence of outliers and structural breaks and their timing. Robustness of statistical and automated methods such as Indicator Saturation is employed to support the choice of dummy variables that are based on the domain knowledge. Indicator saturation method has proven to be flexible and efficient in the dynamic model (Marczak & Proietti, 2016). The idea behind this procedure is to start with a general model that allows for outliers or location-shifts. This is done by creating a dummy for every observation such that T indicators are included for T observations. The statistical software R R Core Team (2013), specifically the package Gets Pretis, Reade, and Sucarrat (2017), was used to search for any possible outliers and location shifts and to keep only significant ones (Castle & Hendry, 2019; Pretis, Reade, & Sucarrat, 2018).

4.6 Variance Decomposition

Variance decomposition is used to display the percentage of changes in the dependent variables caused by its own shock, in comparison to shocks to the remaining variables in the model. It shows the related significance of every individual shock to the variables included in the model (Stock & Watson, 2001).

5 Empirical Analysis

5.1 Ocular analysis

We will initiate the analysis by gaining knowledge and insight to variables in the model by eyeballing and analysing the time series figures carefully and also have an idea about the variable occurrences/behaviour over time. We will graphically check both stationarity and co-movements among the variables. Regarding stationarity, all of the variables have a clear downward or upward trend over time with varying mean and variance. There is neither clear nor constant long-run mean. Hence, the variables are expected to be non-stationary; however, we will check this properly by unit root and stationary tests.

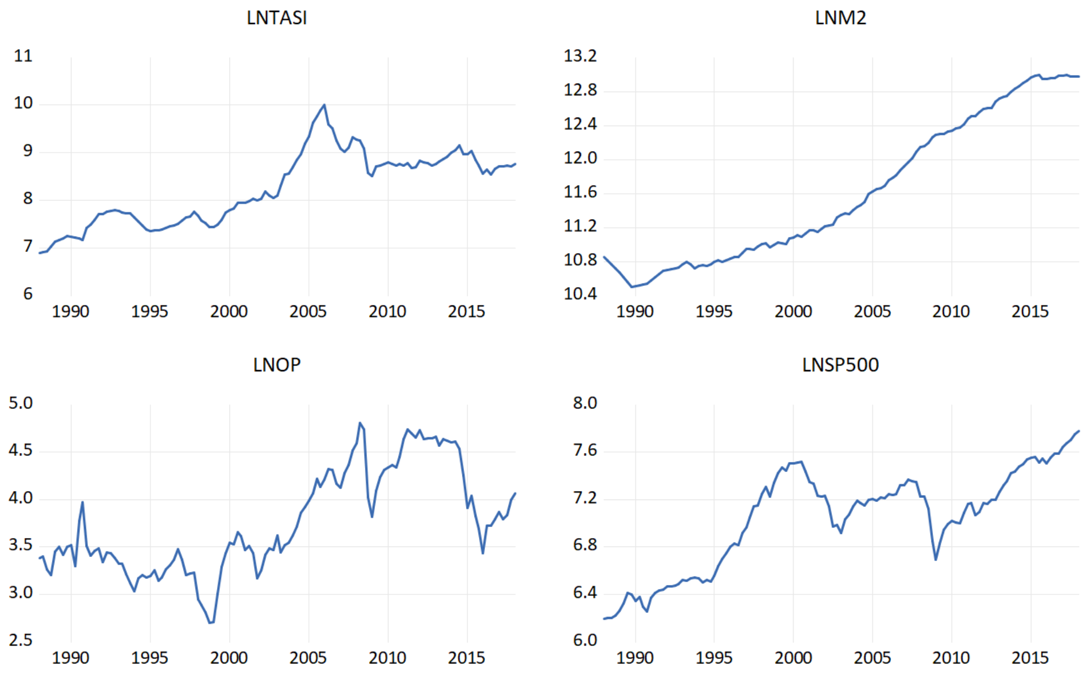
Regarding the co-movements, we will focus on the co-movements between the variable of interest ”TASI” and each variable in the system, since we are trying to explain the movement of ”TASI” by the movements of the other variables in the system, Figure 1 illustrates the plotted data. We will start with the TASI and the global and international variables of oil prices and S&P 500 since there are obvious co-movement examples compared to the local variable of M2. Regarding the TASI, oil prices and S&P 500 co-movements, we have noticed that TASI, oil prices and S&P 500 variables reached a high point in 2008 that followed by a sharp decrease until reaching a low point in 2009Q1. Also, the variables share low points of 2009Q1 and 2016Q1. Graphical analysis findings are consistent with the long-run analysis findings. Regarding the local variable, we have noticed that the flattening of M2 coincides with the 2015Q2 stock market fall.

5.2 Statistical Analysis

5.2.1 Detecting structural breaks and outliers

We applied the Indicator Saturation method, which saturates the linear regression with dummies to detect structural breaks, retaining only the statistically significant ones (Castle & Hendry, 2019). As illustrated in Figure 2, trend breaks are detected in 1988Q2, 2003Q1 and 2006Q1. In 2003Q1, the trend becomes steeper, which marks the beginning of the TASI bubbles. The trend changed in 2006Q1 when the Saudi stock market reached its peak. Two sequential downward step-shifts are detected in 2006Q4 and 2008Q4. Similarly, the three

Figure 1: *Time series figures of the variables*



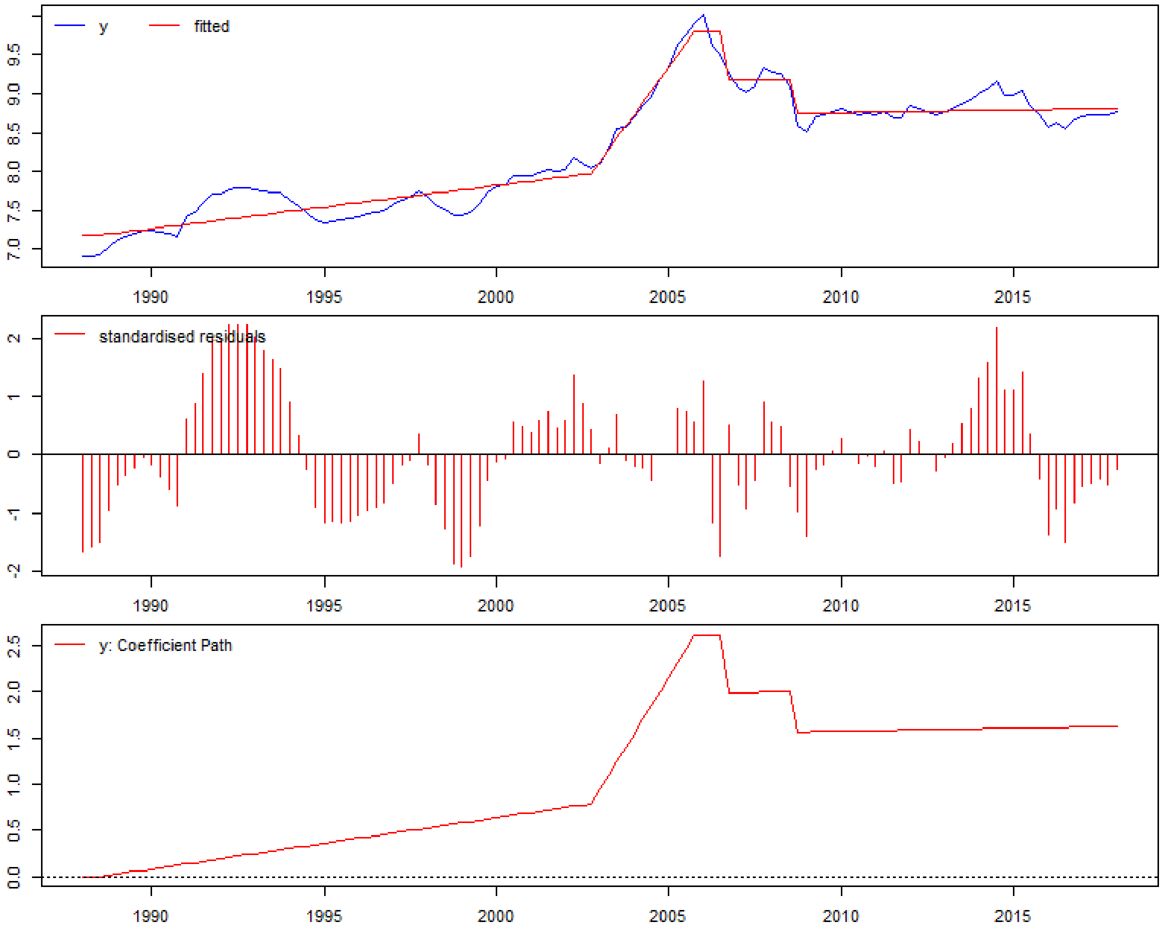
Note. LN is the log of the variable, TASI is the real Saudi stock price index, M2 is money supply, OP is real oil prices, and SP500 is the real S&P's 500 stock price index.

panels are provided for each variable in Appendix B. We also applied the Bai–Perron test Bai and Perron (1998), an alternative statistical method to detect break dates, as a robustness method. According to the Bai–Perron Test, breaks were detected in the TASI time series in 1997Q2, 2004Q1, and 2008Q4. The statistical findings are consistent with the domain knowledge and support the choice of event dummies. The event dummy variables are included in the model to control for the impacts of local (the 2004 and 2005 TASI bubble that followed by the 2006 crash) and global (the 2008 financial crisis) events. For the local event, a dummy was used for the period 2004Q1–2006Q1. For the financial crisis event, a dummy was used for the period of 2008Q1–Q4.

5.2.2 Linking domain knowledge with statistical methods

In this sub-section, we compare the output of Indicator Saturation method with the domain knowledge of the history and major events of the Saudi stock market. Table 3 shows multiple detected step-shifts in the time series of the main variable of interest, TASI, where sis and tis represent the step and trend dummies, respectively. We noticed that break dates selected based on the Indicator Saturation method reflect the historical development stages and the main events of the Saudi stock market, which is consistent with the domain knowledge of

Figure 2: *Log of quarterly the real Saudi stock price index "TASI"*



Note. The output from R version 4.0.1. The top panel shows the observed (blue) and fit (red) values. The middle panel shows the standardised residuals, while the bottom panel shows the coefficient path relative to the intercept and its approximate 95% confidence interval.

the Saudi stock market history. The break date of 1988 reflects one stage of the Saudi stock market, which started in 1985 when the Saudi Stock Exchange (Tadawul) was established under the supervision of the SAMA. This stage is usually referred to as the establishment stage (1985–2003); (Alshogeathri, 2011; Khoj, 2017). However, the data started in 1988; hence, the data (1988–2003) represent this stage. Also, the year 2003 marks a more advanced and developed stage of the Saudi stock market, which started with the CMA's establishment in 2003 (Khoj, 2017). Moreover, 2006Q1 may reflect when the TASI market reached a record high of 20,634.86 points before it crashed at the beginning of 2006[4]. In addition, 2006Q4 reflects a TASI crash, when the market capitalisation had dropped by 49.72% from the previous year, and the TASI lost nearly 65% of its value by the end of 2006[4]. Finally,

[4]Tadawul. (2006). Annual Review. Retrieved from https://www.tadawul.com.sa/static/pages/en/Publication/PDF/Annual_Report_2006_English.pdf

2008 represents the effect of the financial crisis on the TASI.

Table 3: *The output of the Indicator Saturation Method*

	Mean Results				
	Break Dates *(year and quarter)*	*Coef*	*SE*	*t-stat*	*p-value*
LNTASI	mconst	7.182	0.041	177.340	<.001
	sis:2006 Q4	-0.632	0.088	-7.158	<.001
	sis:2008 Q4	-0.438	0.087	-5.010	<.001
	tis:1988 Q4	0.014	0.001	11.668	<.001
	tis:2003 Q1	0.134	0.007	18.833	<.001
	tis:2006 Q1	-0.150	0.007	-21.020	<.001

Note. The output from R version 4.0.1.

5.3 Unit Root and Stationarity Tests

The order of integration of the variables will be determined in this section. This is the first step that must be checked before proceeding with any long-run analysis. This study employed the augmented Dickey-Fuller (ADF) test and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. There are two reasons for applying these two tests. First, the null hypothesis of a unit root test such as the ADF test is that the series has a unit root, whereas the null hypothesis of stationarity tests such as the KPSS test is that the series is stationary. Hence, applying the two tests provides a robustness check for stationarity and generates a precise conclusion, which is essential before proceeding with any statistical analysis.

Second, the main criticism of the ADF test that it has low power (Brooks, 2019). The idea behind this criticism is that if a series has a root close to 1, such as 0.95 or 0.99, then the null hypothesis that the unit root exists should be rejected. Hence, the ADF test is unable to distinguish between the unit root and near–unit root process, especially with a finite sample. Therefore, one way to deal with this issue is to use a stationarity test to complement the unit root test. However, two approached were used to decide whether to include the intercept, the trend and intercept, or neither of them. The first approach, followed by many researchers, is to conduct the test with the three options mentioned above and come to a clear conclusion when the results do not contradict. A complementary criterion is to run the ADF test and check the significance of the intercept versus the intercept and trend, to exclude the insignificant component. Regarding the 10% of ΔM2 when we included only the intercept, the trend was significant when we ran the model with the trend and intercept. Hence, we can say that the results of using the trend and intercept were 1% more reliable because they met the two criteria. Similarly, the trend was insignificant when we ran 10% of the ΔOil model with the trend and intercept. Hence, the results of using only the intercept were 1% more reliable because they met the two criteria. Based on the ADF and KPSS tests, the variables were I (1) at the 1% and 5% levels for two reasons.

Table 4: *Results of the ADF and KPSS Tests*

Variables	ADF (t-statistic) H_0 : Variable is non-stationary			KPSS (LM statistic)	Order of integration
	None	Intercept	Trend and Intercept	H_0 : Variable is stationary	
TASI	-1.084	-2.262	-2.654	0.692**	
ΔTASI	-7.908***	-7.886***	-7.860***	0.053	I (1)
M2	4.084	2.243	-1.650	1.169***	
ΔM2	-1.929**	-2.759*	-7.822***	0.783	I (1)
OIL	-0.801	-2.222	-2.824	0.503**	
ΔOIL	0.001***	-3.378***	-3.353*	0.079	I (1)
SP500	1.804	-0.301	-1.258	0.921***	
ΔSP500	5.582***	-5.777***	-5.761***	0.093	I (1)

Note. ***: Significant at the 1% level. **: Significant at the 5% level. *: Significant at the 10% level. Δ represents the first difference.

Table 4 indicates that the variables were non-stationary at the level since the t-statistic of the ADF test was not significant and the LM statistic of the KPSS test was significant at the 1% and 5% levels. Second, the variables became stationary at the first difference since the t-statistic of the ADF test was significant, and the LM statistic of the KPSS test was not significant at the 1% and 5% levels. Hence, all six variables in the system were integrated at the same order: Order 1.

6 Long-run relationships

The estimation of the long-run analysis is based on the Johansen cointegration test and the VECM. This study will follow the following main steps. The first step was to check for stationarity using unit root and stationarity tests. If the variables are non-stationary at the level and stationary at the first difference, then the variables are I (1). If the variables are I (1), then we would move to the next step: to choose the lag length using several criteria as a pre-cointegration test requirement. The third step is to conduct a Johannsen cointegration test to check the existence of long-run relationships among the variables. After satisfying the three steps above, we proceeded with the VECM.

6.1 Model Validation

Checking the residuals is crucial to ensure that we generate accurate conclusions from the analysis. The results show that residuals of each variable are normally distributed and that the series are jointly normal distributed, homoscedastic, and not serially correlated at Lag 7 and Lags 1 to 7. Table 5 summarises misspecification tests results at the 5% level, and it shows that the model is well-specified.

Table 5: *Summary of the Misspecification Tests' Results*

Residual test	Results	Description
White VEC residual heteroskedasticity tests	$p = .15 > .05$	Cannot reject the null hypothesis that residuals are homoscedastic.
VEC residual serial correlation Lagrange multiplier (LM) tests	$p = .09 > .05$ (checked up to seven lags)	Cannot reject the first null hypothesis that there is no serial correlation at Lag 7. Cannot reject the second null hypothesis that there is no serial correlation at Lags 1 to 7.
VEC residual normality Tests	$p = .14$ (Jarque–Bera) $> .05$	Cannot reject the null hypothesis that the residuals of each variable are normally distributed. Cannot reject the null hypothesis that the residuals are jointly normally distributed.

Note. To check the estimated residual plots of the VECM, please see Figure D1, Appendix D.

6.2 Choosing the optimal lag length

We will choose seven lags for estimating VECM for the following reasons. First, information criteria suggest seven lags for estimating the VECM. Second, the residuals' behaviour and diagnostic tests are crucial factors that must be considered when choosing the optimal lag length, mainly because the information criteria are based on the likelihood function, which does not allow for serial correlation (Wood, 2011). The model with seven lags provides residuals that are normally distributed individually (for each variable) and jointly, homoscedastic, and not serially correlated. Finally, according to the Johansen cointegration test, no cointegration existed in the four-lag model, but one cointegrating equation existed in the seven-lag model. Hence, we chose seven lags as the optimal lag length for the model.

6.3 Number of cointegration relations

Cointegration test is done to determine the number of long-run relationships the variables share. The Johansen cointegration test must be conducted with lagged differences up to (p-1), which is the same number of lags as that used in the VECM model. We put the Johansen cointegration test into practice, which is one of the most commonly used tests for cointegration. Unlike the Engle-Granger approach, this test can find multiple cointegrating stationary long-run relationships among the non-stationary variables.

Table 6: *Johansen Cointegration Test (Trace test) assuming only an intercept*[5]

H_0	H_1	**Likelihood ratio**	**5% critical value**
$r = 0$	$r > 0$	54.409*	47.856
$r \leq 1$	$r > 1$	20.879	29.797
$r \leq 2$	$r > 2$	6.886	15.495
$r \leq 3$	$r > 3$	$< .001$	3.841

Note. *: Denotes the rejection of the hypothesis at the 5% level.

Table 7: *Summary of different assumptions of Trace and Maximum eigenvalue tests*

Data Trend	**Linear**	**Linear**
Test type	Only intercept	Intercept and trend
Trace	1	1
Maximum eigenvalue	1	1

Table 6 represents the results of Trace test and Table 7 reporting the findings on cointegrating rank with different assumptions of both tests Trace and Maximum eigenvalue. Table 7 compares the cointegration results of the trace and Max-eigenvalue tests and shows whether the trend is included. At the 5% level, the trace and Max-eigenvalue tests indicate one significant cointegrating vector, whether we included the trend or not. Therefore, the variables in the system share one long-run relationship and there only seem to be a single

[5] H_0 represents the null hypothesis of r cointegrating relations against the alternative hypothesis H_1 of k cointegrating relations, where k is the number of endogenous variables. r : the number of cointegrating relations assuming only an intercept.

long-run relationship. The cointegration relation is a linear combination of variables in the system such that each of the variables is I (1) but their linear combination, which represents the long-run relationship, is I (0).

6.4 The Vector Error Correction Model (VECM)

Because the variables are I (1) and have one cointegration relation, we can proceed with the VECM to estimate the long-run results. The hypothesis of long-run weak exogeneity is testable via zero restrictions on the coefficient of the cointegration equation (Hendry & Mizon, 1993). For example, a variable z_t is said to be weakly exogenous for the long-run with respect to a cointegrating vector when we accept the null that $\alpha_z = 0$. In other words, when we accept the null of a zero raw in α_z, where α_z is the coefficient of the cointegration equation, which represents the adjustment coefficients. Weak exogeneity means that the weakly exogenous variable does not react to disequilibrium errors (Johansen, 1992). Therefore, it is not reasonable to normalise on variables that are weakly exogenous as the long-run relation does not appear in that short-run equation. We applied the likelihood ratio (LR) test, distributed as $\chi^2(1)$, with the null hypothesis that the variable is weakly exogenous with respect to the cointegrating vector, as shown in Table 8. The weak exogeneity test for M2 and the S&P 500 indicates that we cannot reject the null hypothesis. We found that M2 and S&P 500 have $\chi^2(1)$ value of 3.33 and 2.12 with a corresponding p-value of 0.07 and 0.14 respectively. Moreover, the joint hypothesis of the two variables (M2 and the S&P 500) also cannot be rejected. We found that the test statistic, distributed as $\chi^2(2)$, is 4.45 with a p-value 0.11 and we cannot reject that both variables are jointly weakly exogenous in the TASI equation. However, the weak exogeneity test for TASI and oil prices indicates that we can reject the zero-restrictions on the adjustment coefficients. We found that TASI and oil prices have $\chi^2(1)$ value of 6.57 and 4.61 with a corresponding p-value of 0.01 and 0.03 respectively.

We conclude that TASI and oil prices are non-exogenous variables, whereas money supply and S&P 500 are found to be weakly exogenous with respect to the cointegrating vector. By finding money supply and S&P 500 are weakly exogenous variables for the long-run parameters, then the cointegrating relation can be defined either in terms of TASI or oil prices, and either normalisation is valid. Hence, the choice of normalisation on TASI is valid.

Table 8: *LR Test for weak exogeneity*[6]

Variable	Chi-square χ^2(1)	Probability
LNTASI	6.57*	0.01
LNM2	3.33	0.07
LNOIL	4.61**	0.03
LNSP500	2.12	0.14

Note. *: Significant at the 1% level; **: Significant at the 5% level.

Table 9: *Long-Run Results (normalised on LNTASI)*

Estimated long-run elasticity dependent variable: TASI			
Variable	Coefficient	*SE*	*t*
LNM2 (-1)	0.55**	0.246	2.2475
LNOIL (-1)	-1.52***	0.324	-4.6703
LNSP500 (-1)	-1.13 ***	0.301	-3.7688

Note. *: Significant at the 1% level; **: Significant at the 5% level.

Table 9 represents the output based on normalising the cointegrating vector on the Saudi stock market index "TASI", which is the main variable of interest. We identified the cointegrating vector by imposing a single restriction of a unit coefficient of TASI. A correct normalisation is on a non-exogenous variable (Johansen, 1992), but is the non-unique as we have two non-exogenous variables, naming TASI and oil prices. However, we chose to normalise on TASI for the flowing reasons. First, TASI is the variable of interest. Also, based on the LR test, TASI is a non-exogenous variable with a high significance level of 1% versus oil prices which is non-exogenous at 5% level. Furthermore, it does not seem sensible that the global variable of oil prices is caused by TASI and the local M2 of Saudi Arabia. Hence, the choice of normalisation on TASI is valid and most sensible. The normalised cointegrating vector that represents the long-run equilibrium can be represented as follows:

$$
\begin{aligned}
LNTASI_t = 1.01 &- 0.55LNM2_t + 1.52LNOP_t + 1.13LNNSP500_t \\
&\quad (0.24612) \qquad (0.32445) \qquad (0.30065) \\
&\quad [2.24750] \qquad [-4.67034] \qquad [-3.76877]
\end{aligned}
\tag{2}
$$

[6]LR stands for the Likelihood Ratio; Chi-square stands for the theoretical value of $\chi^2(1)$; The null hypothesis (H_0: α_z=0) is that the variable is weakly exogenous with respect to the cointegrating vector; The null hypothesis is a linear restriction on α and is discussed in Johansen and Juselius (1990).

The t-statistics are in square brackets, and the standard errors are in parentheses. The coefficients are significant at the 1% level except for M2, which is significant at the 5% level. The normalised coefficients reflect the long-run elasticity for M2, OP, and S&P 500. Oil prices and the S&P 500 had large influences on the Saudi stock price index, while money supply had a relatively minor influence. The equilibrium relationship among TASI; the international stock price index, as proxied by the S&P 500; and the global variable, as represented by oil prices, was positive. However, the relationship between TASI and the local macroeconomic variable M2 was negative. The coefficient of the error-correction term ECT_t represents the cointegrating/long-run relationship between the variables, which is specified as follows:

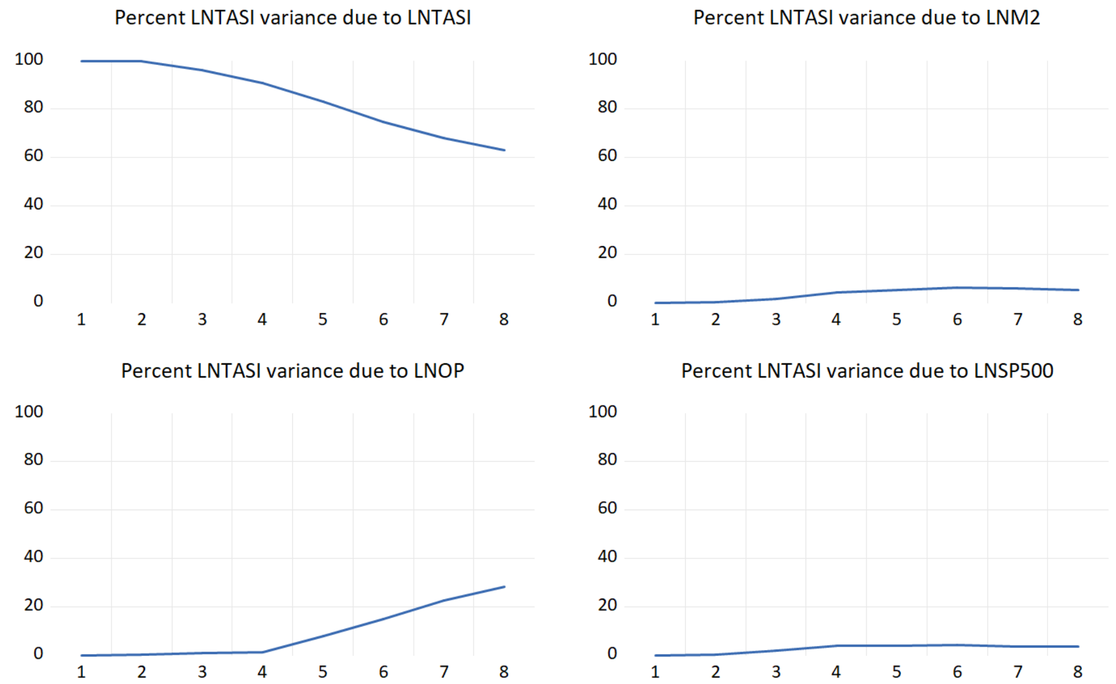
$$ECT_t = LNTASI_t + 0.55LNM2_t - 1.52LNOP_t - 1.13LNNSP500_t \tag{3}$$

The coefficient of the error-correction term measures the speed of the variables' adjustment towards the equilibrium, and it found to be negative and significant. Therefore, we can conclude that the Saudi stock price index, M2, oil prices, and S&P 500 adjusted to correct the disequilibrium each quarter. The coefficient of the error-correction term was -0.078 and highly significant, p = 0.008, implying that approximately half a disequilibrium will occur in about two and a quarter years. The coefficient is significant, but it is small, which means it may take a relatively long time for the disequilibrium to be halved.

6.5 Dynamic behaviour of the VECM

We applied variance decomposition to analyse the model's dynamic behaviour. It provides a quantitative sense of what percentage of the variation in one variable in the system is explained by its own shocks, as compared to shocks in other variables (Enders, Sandler, & Gaibulloev, 2011). This enabled us to see how one variable reacted to different shocks to the model. Table 10 summarises the variance decomposition results of forecasts one to eight quarters ahead for each variable. The Saudi stock price index was substantially driven by innovations in oil prices and, to a lesser extent, by M2 and the S&P 500[7]. As illustrated in Figure 3, the movements in TASI that are due to the shocks of the other variables increase gradually in the first year. However, the role of oil prices continues to increase significantly starting from the fifth quarter, reaching more than 28% of TASI changes are due to oil prices shocks, by the end of the second year. The money supply is dominated by innovations in oil prices. Oil prices variable is largely influenced by the Saudi stock price index and, to lesser degrees, by the S&P 500 and money supply. The S&P 500 seems to be the most exogenous variable but was still influenced by the TASI.

Figure 3: *Variance decomposition using Cholesky decomposition*



[7] As illustrated in Table 10, in the first year the movements in TASI are due to its own shocks, versus the shocks of the other variables. We find that changes in TASI is mainly due to changes in itself, M2 and S&P 500 respectively to the comparison of oil prices variable in the model. However, starting from the fifth quarter, we found that TASI was substantially driven by innovations in oil prices. The role of oil prices continues to increase, it can be seen that more than 28% of TASI changes are due to oil prices shocks, by the end of the second year.

Table 10: *Variance decomposition using Cholesky decomposition*

	SE	Quarters	LNTASI	LNM2	LNOP	LNSP500
LNTASI	0.081	1	100.000	0.000	0.000	0.000
	0.124	2	99.734	0.128	0.124	0.015
	0.155	3	96.012	1.439	0.815	1.734
	0.185	4	90.908	4.026	1.304	3.762
	0.208	5	83.015	5.185	7.809	3.991
	0.228	6	74.824	6.203	14.925	4.048
	0.242	7	67.965	5.776	22.635	3.624
	0.255	8	62.968	5.253	28.111	3.667
LNM2	0.022	1	0.004	99.996	0.000	0.000
	0.034	2	0.006	96.963	2.782	0.249
	0.042	3	0.023	91.001	8.809	0.168
	0.050	4	0.016	85.051	14.365	0.567
	0.062	5	0.015	80.710	17.753	1.523
	0.071	6	0.079	77.255	21.353	1.313
	0.078	7	0.155	72.560	25.912	1.373
	0.085	8	0.436	68.877	29.467	1.221
LNOP	0.127	1	8.734	0.005	91.261	0.000
	0.198	2	16.499	1.784	81.713	0.004
	0.236	3	18.907	1.864	77.905	1.324
	0.272	4	21.692	1.404	74.040	2.864
	0.310	5	18.753	1.729	77.103	2.415
	0.332	6	16.862	1.931	79.006	2.200
	0.350	7	15.294	2.080	80.523	2.103
	0.369	8	14.243	2.100	81.586	2.070
LNSP500	0.057	1	7.833	0.585	0.688	90.894
	0.086	2	11.210	0.854	0.892	87.044
	0.104	3	11.740	1.240	1.262	85.759
	0.122	4	11.455	2.648	2.905	82.992
	0.140	5	9.532	6.628	3.340	80.499
	0.157	6	7.951	8.944	3.158	79.948
	0.177	7	6.384	9.776	3.171	80.670
	0.194	8	5.459	9.275	4.088	81.178

Note. Variables ordering: LNTASI, LNM2, LNOP, and LNSP500.

7 Discussion

The findings of the long-run equation show that the global variable of oil prices and the international variable of S&P 500 included in the model had highly significant positive longrun relationships with TASI at 1% level; however, the local macroeconomic variable of the money supply had a negative relationship with TASI, at a 5% significance level.

The current findings indicate a negative relationship between M2 and TASI at the 5% level. Overall, there was no consensus among the researchers regarding the nature of the relationship between stock prices and money supply is debatable and claimed to be an empirical question. This result is consistent with some of those studies on the developed stock markets such as Olomu (2015) and on the emerging stock market such as Issahaku et al. (2013) and Bala Sani and Hassan (2018). Regarding the relevant Saudi literature, most of the findings of the previous studies were not able to provide a decisive answer regarding this relationship. Some studies found strong associations between stock prices and money supply and, in other studies, the relationships were found to be insignificant. The majority of Saudi studies that employed two measures of money supply have found contradictory results, in terms of the sign of money supply measures. For example, Alshogeathri (2011) and Khoj (2017) found that one measure of money supply has a positive impact on stock prices, whereas the other measure is negatively related to the Saudi stock market.

The relationship between stock prices and money supply is an empirical question for developed markets, emerging markets and the Saudi stock markets. Hence, there is a need to establish more studies in emerging markets context to clarify this relationship. Keynesian economists support this relationship, arguing that people will demand more money if they expect that increasing the money supply will result in a tightened monetary policy in the future. As a result, increased interest rates will raise the discount rate, resulting in a decline in the present value of future cash flows, hence leading to decreased stock market prices (Sellin, 2001). Another explanation of this relationship might be a liquidity trap operating where people choose to avoid bonds and prefer to keep their money in the form of cash savings. According to Keynes (1936), this behaviour is due to the popular belief that interest rates may rise soon, which may push bond prices down, Making monetary policy ineffective. Because of the negative relationship exist between bonds and interest rates, consumers prefer not to hold an asset with a price that may decrease.

Another explanation is related to the Saudi economy; it might be that interest rate does not consider as an alternative investment of stocks in Saudi Arabia. Investors in Saudi Arabia do not focus on the level of interest rates (Al-Jasser, Banafe, et al., 2002). The Saudi economy is not sensitive to changes in interest rate (Al-Jasser & Banafe, 1999). This means that the argument that links money supply and stock market through interest rate may not work as expected in the case of the Saudi stock market. For example, many argue that an increase in money supply and resulting fall in interest rates would increase the attractiveness of stocks. However, in the case of Saudi, when the money supply increases, stock prices may not increase, since the interest rate does not seem to be an alternative investment of stocks. Thus, risk-free assets are not the primary alternative for the majority of investors in Saudi Arabia. The limited the role of interest rates in the Saudi economy may be due to the following facts. First, the Saudi riyal is pegged to the US Dollar since the 1980s, resulting in riyal interest rates to closely follow dollar interest rates (Al-Darwish et al., 2015). Second, the dual system of the Saudi Arabian banking sector of conventional and Islamic banks, where conventional banks are affected by changes in interest rates but Islamic banks are not because interest is forbidden in Islam.

The relationship between stock prices and oil prices was positive and highly significant at the 1% level, which met the previous expectations of the current study. The findings were consistent with those from all of the previous Saudi studies included in the current study, such as Alshogeathri (2011), Samontaray et al. (2014), Kalyanaraman and Tuwajri (2014) and Almansour and Almansour (2016). A strong positive relationship was expected between Saudi stock prices and oil prices since the Kingdom of Saudi Arabia is an oil-based economy, and the top oil exporter globally. Unlike the economies of oil-importing countries, the economy of Saudi Arabia, as an oil-exporting country, is expected to have a positive relationship with oil prices (Wang et al., 2013).

Standard and Poor's 500 (S&P 500) represented the US stock price index and was used as a proxy for the effect of the international stock market on the Saudi stock market. A majority of previous researchers confirmed a significant relationship between the S&P 500 and TASI. However, while Alkhudairy (2008) found a significant and positive association, which is consistent with our findings, Alshogeathri (2011) and Khoj (2017) found this relationship to be significant and negative. A significant influence of the international stock index, as measured by the S&P 500, implies that the Saudi stock market is partially integrated toward the international financial markets. Some of the previous studies have found this relationship to be significant and negative, while the current study found the S&P 500 to have a significant and positive impact on TASI.

The current study's findings of this positive association are maybe due to several factors. Firstly, these results might reflect the inclusion of the Saudi stock market as an emerging stock market; the results are more consistent with those from studies on emerging stock markets. For example, the majority of the emerging markets literature found a positive and significant relationship between the S&P 500 and emerging stock markets such as Arshanapalli, Doukas, and Lang (1995), Berument and Ince (2005) and Bhunia and Yaman (2017). Additionally, this study is the most recent study regarding this topic; hence, it may capture all recent economic and stock market events in Saudi Arabia. Empirical evidence from the current study shows that Saudi Arabia has strong global and international links. Global factors, as proxied by oil prices, and international factors, as proxied by the S&P 500, had highly significant positive relationships with the domestic stock price index of TASI at the 1% level. These findings imply a gradual integration of the Saudi stock market into the world capital markets and the global economy. This study focused on those factors due to the trend of globalisation.

The highly significant relationships between the TASI and both global and international factors may be due to several factors. Globalisation is pushing stock markets worldwide to move towards integration. The stock market's accessibility was also enhanced after it was opened up to qualified foreign investment in 2015. Moreover, significant financial events, including the Saudi stock market joining prominent emerging market indices, namely the FTSE Russell Emerging Markets Index and the MSCI Emerging Markets Index, may point to this increasing correlation. Finally, in the long-run, the partial explanatory power of oil prices and the S&P 500 indicates the higher relative importance of global and international factors than that of the domestic variable of the money supply.

Regarding the dummy variables, the domain knowledge provided an economic explanation for the local and global dummy variables included. A statistical method of Indicator

Saturation is also included to detect outliers and shifts. The statistical findings of Indicator Saturation and Bai-Perron methods were consistent with the domain knowledge and support the choice of event dummy variables. As a robustness check, we took into account an alternative method of choosing dummies. Specifically, we run the model with Bai-Perron test dummies, which provided residuals that are serially correlated and not normally distributed. Moreover, the model showed severe misspecification when the data was fit, ignoring outliers and structural breaks. The residuals were serially correlated, heteroscedastic and not normally distributed. However, when dummies of the local and global events were accounted for, residuals' behaviour substantially improved because they become normally distributed, homoscedastic and not serially correlated.

8 Conclusion

The current study aimed to explore the existence of long-run equilibrium relationships among Saudi stock price index (TASI) and selected domestic, international and global macroeconomic variables to explain the movement of the Saudi stock market. In contrast to the earlier studies reviewed in the current study, this study will be the first study that controls for the effects of local (the TASI 2004 and 2005 bubble that followed by the 2006 crash) and global (the 2008 financial crisis) events on the Saudi stock market when examining this relationship. Moreover, this study is the most extended time-series study that examines the relationship between TASI and macroeconomic variables. The Johansen cointegration test, VECM with dummy variables, and variance decomposition were applied to the long-run analysis of quarterly data from 1988Q1 to 2018Q1. The Indicator Saturation method was employed to detect outliers and structural breaks.

Findings of this study are based on normalising the cointegrating vector on the Saudi stock market index ”TASI”, which is the main variable of interest. The choice of normalisation is supported by LR test. Based on the LR test, LNTASI and LNOIL are non-exogenous variables in the model. However, the LNTASI variable is most highly significant at 1% level, followed by LNOIL variable, which is significant at 5% level. Moreover, it does not seem sensible that the global oil prices variable is caused by TASI and the local M2 of Saudi Arabia. Hence, the choice of normalisation on TASI is valid and most sensible. The findings show a long-run relationship between all of the variables in the system. The equilibrium relationships between the TASI and both the S&P 500 and oil prices were positive. However, the relationship between the TASI and M2 was negative. Variance decompositions indicated that the Saudi stock prices are substantially driven by innovations in oil prices, and to a lesser extent, by M2 and S&P 500. In the long-run, the Saudi stock market is driven more by the global variable of oil prices and the international variable of the S&P 500 than by the domestic macroeconomic variable of the money supply.

With the exception of oil prices, selected Saudi previous studies have not considered global macroeconomic variables that are common to the entire world. For example, none of the previous Saudi studies has examined the influence of global macroeconomic variables that are common to the entire world such as global inflation and global output (proxied by world GDP) on the Saudi stock market. Ideas for future researches could be to incorporate a wider range of macroeconomic variables, especially global Macroeconomic variables. Moreover, employing different econometrics techniques such as ARDL, ARCH and GARCH models to evaluate the association between macroeconomic variables and the Saudi stock market.

References

Al-Darwish, M. A., Alghaith, N., Behar, M. A., Callen, M. T., Deb, M. P., Hegazy, M. A., ... Qu, M. H. (2015). *Saudi Arabia:: Tackling Emerging Economic Challenges to Sustain Strong Growth*. International Monetary Fund.

Al-Jasser, M., & Banafe, A. (1999). Monetary policy instruments and procedures in Saudi Arabia. *BIS Policy Papers*, *5*, 203–17.

Al-Jasser, M., Banafe, A., et al. (2002). The development of debt markets in emerging economies: the Saudi Arabian experience. *BIS Papers*, *11*, 178–182.

Aljloud, S. A. (2016). *The law of market manipulation in Saudi Arabia: a case for reform* (Doctoral dissertation, Brunel University London).

Alkhaldi, B. A. (2015). The Saudi capital market: The crash of 2006 and lessons to be learned. *International Journal of Business, Economics and Law*, *8*(4), 135–146.

Alkhudairy, K. S. (2008). *Stock prices and the predictive power of macroeconomic variables: The case of the Saudi Stock Market*. Colorado State University.

Almansour, A. Y., & Almansour, B. Y. (2016). Macroeconomic Indicators and Saudi Equity Market: A Time Series Analysis. *British Journal of Economics, Finance and Management Sciences 12 (2)*, 59–72.

Alshogeathri, M. A. M. (2011). *Macroeconomic determinants of the stock market movements: empirical evidence from the Saudi stock market.* (Doctoral dissertation, Kansas State University).

Arestis, P., Demetriades, P. O., & Luintel, K. B. (2001). Financial development and economic growth: the role of stock markets. *Journal of money, credit and banking*, 16–41.

Arshanapalli, B., Doukas, J., & Lang, L. H. (1995). Pre and post-October 1987 stock market linkages between US and Asian markets. *Pacific-Basin Finance Journal*, *3*(1), 57–73.

Asaolu, T., & Ogunmuyiwa, M. (2011). An econometric analysis of the impact of macroecomomic variables on stock market movement in Nigeria. *Asian journal of business management*, *3*(1), 72–78.

Awang, N. A., Hussin, S. A. S., & Zahid, Z. (2017). The Relationship between Macroeconomic Variables and FTSE Bursa Malaysia Kuala Lumpur Composite Index. *Indian Journal of Science and Technology*, *10*, 12.

Bahmani-Oskooee, M., & Hajilee, M. (2013). Exchange rate volatility and its impact on domestic investment. *Research in Economics*, *67*(1), 1–12.

Bai, J., & Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *Econometrica*, 47–78.

Bala Sani, A., & Hassan, A. (2018). Exchange rate and stock market interactions: Evidence from Nigeria. *Arabian Journal of Business and Management Review*, *8*(1), 334.

Banton, C. (2020). *An Introduction to U.S. Stock Market Indexes.* Retrieved from `https://www.investopedia.com/insights/introduction-to-stock-market-indices/`

Barakat, M. R., Elgazzar, S. H., & Hanafy, K. M. (2016). Impact of macroeconomic variables on stock markets: Evidence from emerging markets. *International journal of economics and finance*, *8*(1), 195–207.

Basher, S. A., Haug, A. A., & Sadorsky, P. (2012). Oil prices, exchange rates and emerging stock markets. *Energy Economics*, *34*(1), 227–240.

Berument, H., & Ince, O. (2005). Effect of S&P500's return on emerging markets: Turkish experience. *Applied Financial Economics Letters*, *1*(1), 59–64.

Bhatia, P. (2019). Impact of US on Chinese and Indian Stock Markets Post Asian Financial Crisis. *Global Journal of Enterprise Information System*, *11*(4), 24–28.

Bhunia, A., & Yaman, D. (2017). Is There a Causal Relationship Between Financial Markets in Asia and the US? *The Lahore Journal of Economics*, *22*(1), 71.

Brahmasrene, T., & Jiranyakul, K. (2007). Cointegration and causality between stock index and macroeconomic variables in an emerging market. *Academy of Accounting and Financial Studies Journal*, *11*(3), 17–30.

Brooks, C. (2019). *Introductory econometrics for finance*. Cambridge university press.

Castle, J. L., & Hendry, D. F. (2019). *Modelling our changing world*. Springer Nature.

Cheikh, N. B., Naceur, M. S. B., Kanaan, M. O., & Rault, C. (2018). *Oil prices and GCC stock markets: New evidence from smooth transition models*. International Monetary Fund.

Chen, N., Roll, R., & Stephen, A. (1986). Ross, 1986, Economic forces and the stock market. *Journal of business*, *59*(3), 383–403.

Chen, N.-F., Roll, R., & Ross, S. A. (1986). Economic forces and the stock market. *Journal of business*, 383–403.

Davidson, R., MacKinnon, J. G., et al. (2004). *Econometric theory and methods* (Vol. 5). Oxford University Press New York.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, *74*(366a), 427–431.

Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica: journal of the Econometric Society*, 1057–1072.

Enders, W., Sandler, T., & Gaibulloev, K. (2011). Domestic versus transnational terrorism: Data, decomposition, and dynamics. *Journal of Peace Research*, *48*(3), 319–337.

Eun, C. S., & Shim, S. (1989). International transmission of stock market movements. *Journal of financial and quantitative Analysis*, *24*(2), 241–256.

Fama, E. F. (1981). Stock returns, real activity, inflation, and money. *The American economic review*, *71*(4), 545–565.

Favero, C. A. (2001). *Applied macroeconometrics*. Oxford University Press on Demand.

Geske, R., & Roll, R. (1983). The fiscal and monetary linkage between stock returns and inflation. *The journal of Finance*, *38*(1), 1–33.

Greenwood, J., & Smith, B. D. (1997). Financial markets in development, and the development of financial markets. *Journal of Economic dynamics and control*, *21*(1), 145–181.

Hassan, G. M., & Al Refai, H. M. (2012). Can macroeconomic factors explain equity returns in the long run? The case of Jordan. *Applied Financial Economics*, *22*(13), 1029–1041.

Hatemi-j, A. (2012). Asymmetric causality tests with an application. *Empirical Economics*, *43*(1), 447–456.

Hendry, D., & Mizon, G. (1993). *Evaluating dynamic econometric models by encompassing the VAR. Chapter 18 in Phillips PCB (ed.) Models, methods, and applications of econometrics: Essays in honor of AR Bergstrom.* Blackwell Publishers, Cambridge, Massachusetts.

Humpe, A., & Macmillan, P. (2009). Can macroeconomic variables explain long-term stock market movements? A comparison of the US and Japan. *Applied Financial Economics*, *19*(2), 111–119.

Islam, K. U., & Habib, M. (2016). Do macroeconomic variables impact the Indian stock market. *Journal of Commerce & Accounting Research*, *5*(3).

Issahaku, H., Ustarz, Y., & Domanban, P. B. (2013). Macroeconomic variables and stock market returns in Ghana: Any causal link?

Jacob Leal, S. (2015). Fundamentalists, chartists and asset pricing anomalies. *Quantitative Finance*, *15*(11), 1837–1850.

Jamaludin, N., Ismail, S., & Ab Manaf, S. (2017). Macroeconomic variables and stock market returns: Panel analysis from selected ASEAN countries. *International Journal of Economics and Financial Issues*, *7*(1).

Jiang, H., Xu, Y., & Liu, C. (2013). Construction price prediction using vector error correction models. *Journal of Construction Engineering and Management*, *139*(11), 04013022.

Johansen, S. (1992). Testing weak exogeneity and the order of cointegration in UK money demand data. *Journal of Policy modeling*, *14*(3), 313–334.

Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration—with appucations to the demand for money. *Oxford Bulletin of Economics and statistics*, *52*(2), 169–210.

Johansen, S., et al. (1995). *Likelihood-based inference in cointegrated vector autoregressive models*. Oxford University Press on Demand.

Juselius, K. (2018). The cointegrated VAR methodology. In *Oxford research encyclopedia of economics and finance.*

Kalyanaraman, L., & Tuwajri, B. (2014). Macroeconomic forces and stock prices: some empirical evidence from Saudi Arabia. *International journal of financial research*, *5*(1).

Kanjilal, K., & Ghosh, S. (2017). Dynamics of crude oil and gold price post 2008 global financial crisis–New evidence from threshold vector error-correction model. *Resources Policy*, *52*, 358–365.

Keynes, J. M. (1936). *The General Theory of Employment, Interest, and Money: Interest and Money*. Harcourt, Brace and company.

Khan, A., Muttakin, M. B., & Siddiqui, J. (2013). Corporate governance and corporate social responsibility disclosures: Evidence from an emerging economy. *Journal of business ethics*, *114*(2), 207–223.

Khoj, H. (2017). *The Behavior of the Saudi Stock Market* (Doctoral dissertation, The Claremont Graduate University).

Kotha, K. K., & Sahu, B. (2016). Macroeconomic factors and the Indian stock market: Exploring long and short run relationships. *International Journal of Economics and Financial Issues*, *6*(3).

Krause, A. (2001). An overview of asset pricing models. *University of Bath School of Management. UK*.

Kwiatkowski, D., Phillips, P. C., Schmidt, P., Shin, Y., et al. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of econometrics*, *54*(1-3), 159–178.

Lawal, A. I., Somoye, R. O., Babajide, A. A., & Nwanji, T. I. (2018). The effect of fiscal and monetary policies interaction on stock market performance: Evidence from Nigeria. *Future Business Journal*, *4*(1), 16–33.

Lerner, J., Leamon, A., & Dew, S. (2017). The CMA and the Saudi stock market crash of 2006. *BELLA Research Group, Saudi Capital Market Authority (CMA)*.

Levine, R. (2018). Finance, growth and economic prosperity. *Macroeconomic Review*, 82–88.

Maddala, G. S., & Kim, I.-M. (1998). *Unit roots, cointegration, and structural change* (No. 4). Cambridge university press.

Marczak, M., & Proietti, T. (2016). Outlier detection in structural time series models: The indicator saturation approach. *International Journal of Forecasting*, *32*(1), 180–202.

Masih, R., Peters, S., & De Mello, L. (2011). Oil price volatility and stock price fluctuations in an emerging market: evidence from South Korea. *Energy Economics*, *33*(5), 975–986.

Maysami, R. C., Howe, L. C., & Rahmat, M. A. (2005). Relationship between macroeconomic variables and stock market indices: Cointegration evidence from stock exchange of Singapore's All-S sector indices. *Jurnal Pengurusan (UKM Journal of Management)*, *24*.

Meric, G., Lentz, C., Smeltz, W., & Meric, I. (2012). International evidence on market linkages after the 2008 stock market crash. *The International Journal of Business and Finance Research*, *6*(4), 45–57.

Mukherjee, T. K., & Naka, A. (1995). Dynamic relations between macroeconomic variables and the Japanese stock market: an application of a vector error correction model. *Journal of financial Research*, *18*(2), 223–237.

Olomu, E. (2015). *Impact of macroeconomic variables on UK stock market: A case study of FTSE100 index.* (Doctoral dissertation, University of East London).

OPEC. (2018). *Annual Statistical Bulletin* (Rep.) Retrieved from `https://www.opec.org/opec_web/en/press_room/5027.htm`

Park, J., & Ratti, R. A. (2008). Oil price shocks and stock markets in the US and 13 European countries. *Energy economics*, *30*(5), 2587–2608.

Perera, W., & Silva, S. (2018). Macroeconomic Influence on the Stock Market: A Review Influence on the Stock Market: A Review.

Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, *75*(2), 335–346.

Pretis, F., Reade, J., & Sucarrat, G. (2017). gets: General-to-Specific (GETS) Modelling and Indicator Saturation Methods [Computer program]. Retrieved from `http://CRAN.R-project.org/package=gets` (R package version 0.26)

Pretis, F., Reade, J., & Sucarrat, G. (2018). Automated General-to-Specific (GETS) regression modeling and indicator saturation methods for the detection of outliers and structural breaks. *Journal of Statistical Software*, *86*(3).

R Core Team. (2013). R: A Language and Environment for Statistical Computing [Programming language]. Vienna, Austria. Retrieved from `http://www.R-project.org/`

Rafailidis, P., & Katrakilidis, C. (2014). The relationship between oil prices and stock prices: a nonlinear asymmetric cointegration approach. *Applied Financial Economics*, *24*(12), 793–800.

Samadder, S., & Bhunia, A. (2018). Integration between Indian Stock Market and Developed Stock Markets. *Journal of Commerce and Accounting Research*, *7*(1), 13.

Samontaray, D. P., Nugali, S., Sasidhar, B., et al. (2014). A study of the effect of macroeconomic variables on stock market: Saudi Perspective. *International Journal of Financial Research*, *5*(4), 120–127.

Santos, C., Hendry, D. F., & Johansen, S. (2008). Automatic selection of indicators in a fully saturated regression. *Computational Statistics*, *23*(2), 317–335.

Schuppli, M., & Bohl, M. T. (2010). Do foreign institutional investors destabilize China's A-share markets? *Journal of International Financial Markets, Institutions and Money*, *20*(1), 36–50.

Sellin, P. (2001). Monetary policy and the stock market: theory and empirical evidence. *Journal of economic surveys*, *15*(4), 491–541.

Shahrestani, P., & Rafei, M. (2020). The impact of oil price shocks on Tehran Stock Exchange returns: Application of the Markov switching vector autoregressive models. *Resources Policy*, *65*, 101579.

Sharif, S. (2019). How foreign investors influence stock markets? The Saudi Arabian experience. *Middle East Development Journal*, *11*(1), 105–123.

Sohail, N., & Hussain, Z. (2009). Long-run and short-run relationship between macroeconomic variables and stock prices in Pakistan: The case of Lahore Stock Exchange. *Pakistan Economic and Social Review*, 183–198.

Stock, J. H., & Watson, M. W. (2001). Vector autoregressions. *Journal of Economic perspectives*, *15*(4), 101–115.

Tadawul. (2017). *Annual Report* (Rep.) Retrieved from `https://www.tadawul.com.sa/wps/wcm/connect/7ea9ab40-5d5a-4f6c-a200-c18f849e913f/Tadawul+AR2017-English.pdf?MOD=AJPERES&CONVERT_TO=url&CACHEID=ROOTWORKSPACE-7ea9ab40-5d5a-4f6c-a200-c18f849e913f-mjHc2WS`

Vejzagic, M., & Zarafat, H. (2013). Relationship between macroeconomic variables and stock market index: Cointegration evidence from FTSE Bursa Malaysia Hijrah Shariah index. *Asian journal of management sciences & education*, *2*(4).

Wang, Y., Wu, C., & Yang, L. (2013). Oil price shocks and stock market activities: Evidence from oil-importing and oil-exporting countries. *Journal of Comparative Economics*, *41*(4), 1220–1239.

Wood, S. N. (2011). Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *73*(1), 3–36.

Appendices

Appendix A Deflation calculations

1. Oil prices ($ per barrel): quarterly the US CPI index.

   The process for oil prices. Step 1 is to calculate the average of the deflator for the base year (2015), as shown in the fourth column of Table A1. Step 2 is to calculate the deflator at the base year 2010 by dividing the deflator by the average year 2010 and then the multiplying by 100, as shown in the fifth column of Table A1. Step 3 is to apply the deflator to current prices divided by the deflator, as shown in the sixth column of Table A1.

Table A1: *An example of the deflation steps*

	Current Prices ($ per barrel)	US Inflation (quarterly index, base 2015)	CPI for the US (the average year 2010)	US Inflation (quarterly index, base 2010) (P[t] deflator)	Constant Prices ($ per barrel, base 2010)
			Step 1	Step 2	Step 3
1989Q1	17.587	51.332	92.009	55.791	31.522
1989Q2	18.873	52.162	92.009	56.693	33.291
1989Q3	17.387	52.570	92.009	57.136	30.430
1989Q4	19.160	53.104	92.009	57.717	33.197
1990Q1	19.817	54.019	92.009 = (99.712 + 99.680 + 9.949 + 92.693) / 4	58.710 = 100 x (54.019/92.009)	33.753 = 100 x (19.817 /58.710)
1990Q2	16.020	54.553	92.009	59.291	27.019
1990Q3	26.413	55.495	92.009	60.315	43.792
1990Q4	32.453	56.438	92.009	61.339	52.908

2. Saudi stock prices: quarterly Saudi CPI index.
3. US stock prices: quarterly ”US” CPI index.

   The process for series 2 and 3 is identical. Step 1 is to calculate the annual percentage from the base index (2013 for Saudi, 2015 for the US) by dividing the current quarter by the previous quarter as shown in the fourth column of Table A2. Step 2 is to calculate the base 2010 deflator from the quarterly percentage by using the formulas:

$$\begin{cases} P(t) = P(t+4)/(1+INF(t+4) & if\ \ t < 2010 \\ 100 & if\ \ t = 2010(BasePrice) \\ P(t) = P(t-4)x(1+INF(t)) & if\ \ t > 2010 \end{cases}$$

Where *P(.)* is the price deflator, *INF(.)* is the annual percentage of inflation, and *t* is the current year, which accumulates the annual percentages year on year as shown in the fifth column of Table A2. As they are quarters, the formula is applied individually for each quarter, that means current Q1 with the previous Q1, current Q2 with the previous Q2, and so on. Step 3 is to apply the deflator, so current prices divided by the deflator, as shown in the sixth column of Table A2.

Table A2: *An example of the deflation steps*

	The stock price index for the US (current prices)	CPI for the US (base 2015)	CPI for the US (Annual %)	CPI for the US; base 2010 (P[t] deflator)	The stock price index for the US (constant 2010 prices)
			Step 1	Step 2	Step 3
1989Q1	293.73	51.34	4.67	55.97	524.79
1989Q2	316.05	52.19	5.16	56.90	555.48
1989Q3	348.89	52.57	4.71	57.17	610.24
1989Q4	346.58	53.06	4.63	57.29	604.96
1990Q1	333.64	54.03	5.23 = (54.03 / 51.34 – 1) x 100	58.90 = 62.00 / (1 + 5.26 / 100)	566.45 = 100 x (333.64 /58.90)
1990Q2	350.02	54.58	4.58	59.50	588.23
1990Q3	328.25	55.51	5.58	60.35	543.87
1990Q4	293.73	51.34	4.67	60.89	523.62
1991Q1	362.07	56.86	5.26	62.00	584.01

Appendix B The Indicator Saturation method

Tables show multiple detected step-shifts in the time series of the main variable of interest, TASI, where sis and tis represent the step and trend dummies, respectively. For all figures, the top panel shows the observed (blue) and fit (red) values. The middle panel shows the standardised residuals, while the bottom panel shows the coefficient path relative to the intercept and its approximate 95% confidence interval.

Table B1: *Break dates based on Indicator Saturation*

	Mean Results				
	Break Dates *(year and quarter)*	*Coef*	*SE*	*t-stat*	*p-value*
LNTASI	mconst	7.182	0.041	177.340	<.001
	sis:2006 Q4	-0.632	0.088	-7.158	<.001
	sis:2008 Q4	-0.438	0.087	-5.010	<.001
	tis:1988 Q4	0.014	0.001	11.668	<.001
	tis:2003 Q1	0.134	0.007	18.833	<.001
	tis:2006 Q1	-0.150	0.007	-21.020	<.001
LNM2	mconst	10.858	0.026	413.270	<.001
	tis:1988 Q2	-0.048	0.004	-11.082	<.001
	tis:1990 Q1	0.061	0.004	13.786	<.001
	tis:2002 Q4	0.025	<.001	34.620	<.001
	tis:2011 Q1	-0.018	0.001	-16.980	<.001
LNOP	mconst	3.348	0.028	118.868	<.001
	sis:1998 Q1	-0.505	0.078	-6.480	<.001
	sis:1999 Q3	0.644	0.083	7.766	<.001
	sis:2004 Q3	0.760	0.053	14.222	<.001
	sis:2010 Q4	0.360	0.056	6.437	<.001
	sis:2015 Q1	-0.784	0.066	-11.946	<.001
LNS&P 500	mconst	6.414	0.026	244.562	<.001
	sis:1995 Q3	0.440	0.057	7.705	<.001
	sis:1997 Q3	0.423	0.059	7.221	<.001
	sis:2003 Q3	-0.132	0.037	-3.551	<.001
	sis:2013 Q2	0.404	0.040	10.237	<.001

	Diagnostics		
	χ^2	*df*	*p-value*
LNTASI			
Ljung-Box AR(1)	84.468	1	<.001
Ljung-Box ARCH(1)	74.062	1	<.001
LNM2			
Ljung-Box AR(1)	82.493	1	<.001
Ljung-Box ARCH(1)	62.117	1	<.001
LNOP			
Ljung-Box AR(1)	35.991	1	<.001
Ljung-Box ARCH(1)	26.065	1	<.001
LNS&P 500			
Ljung-Box AR(1)	79.500	1	<.001
Ljung-Box ARCH(1)	56.474	1	<.001

Note. sis indicates step Indicator Saturation, and tis indicates trend Indicator Saturation

Figure B1: *LNM2*

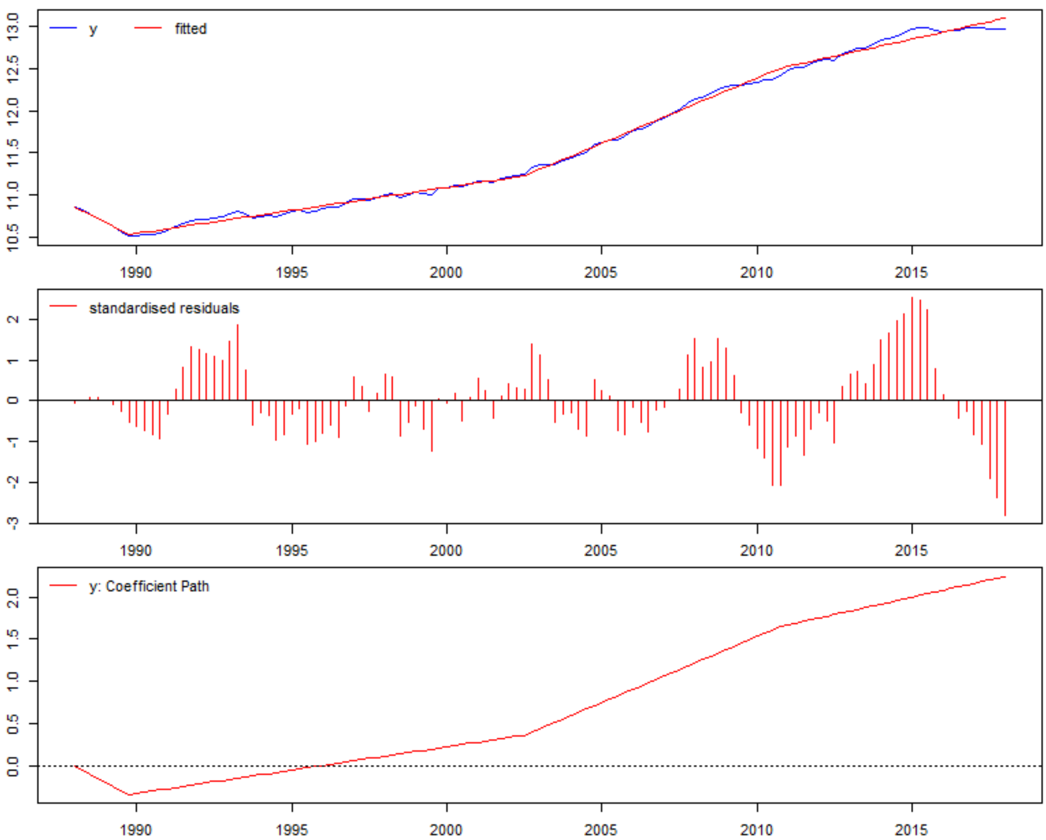


Figure B2: *LNOP*

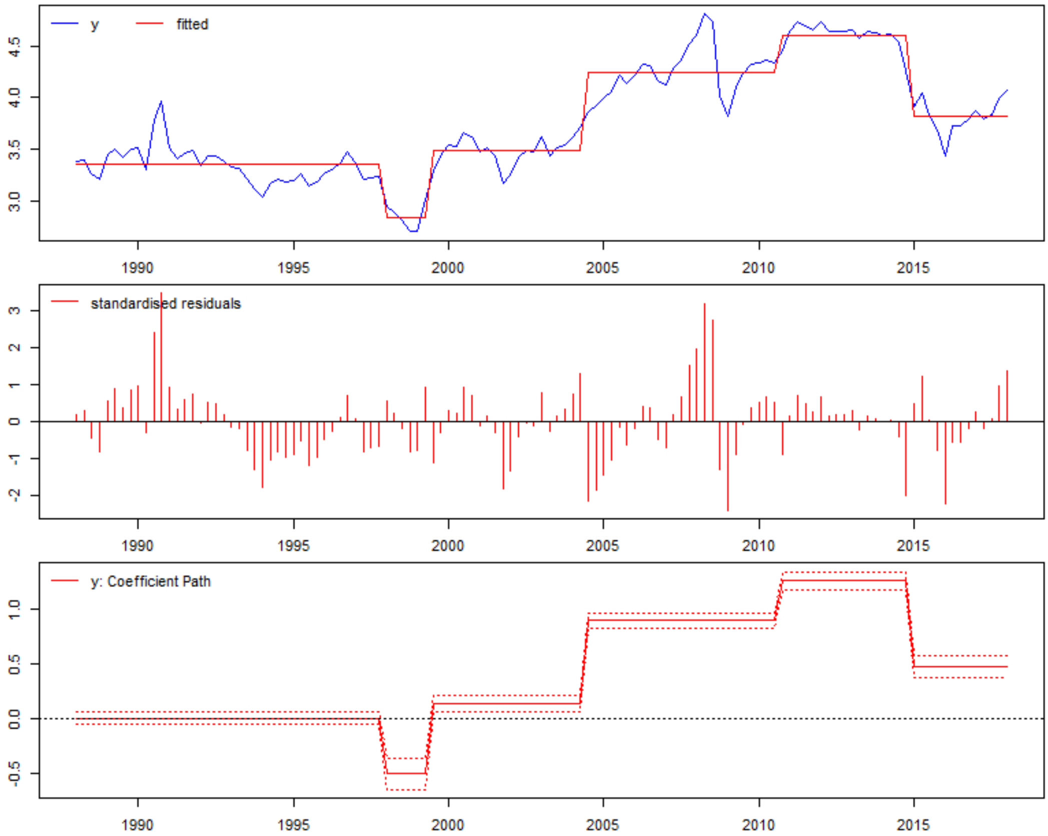
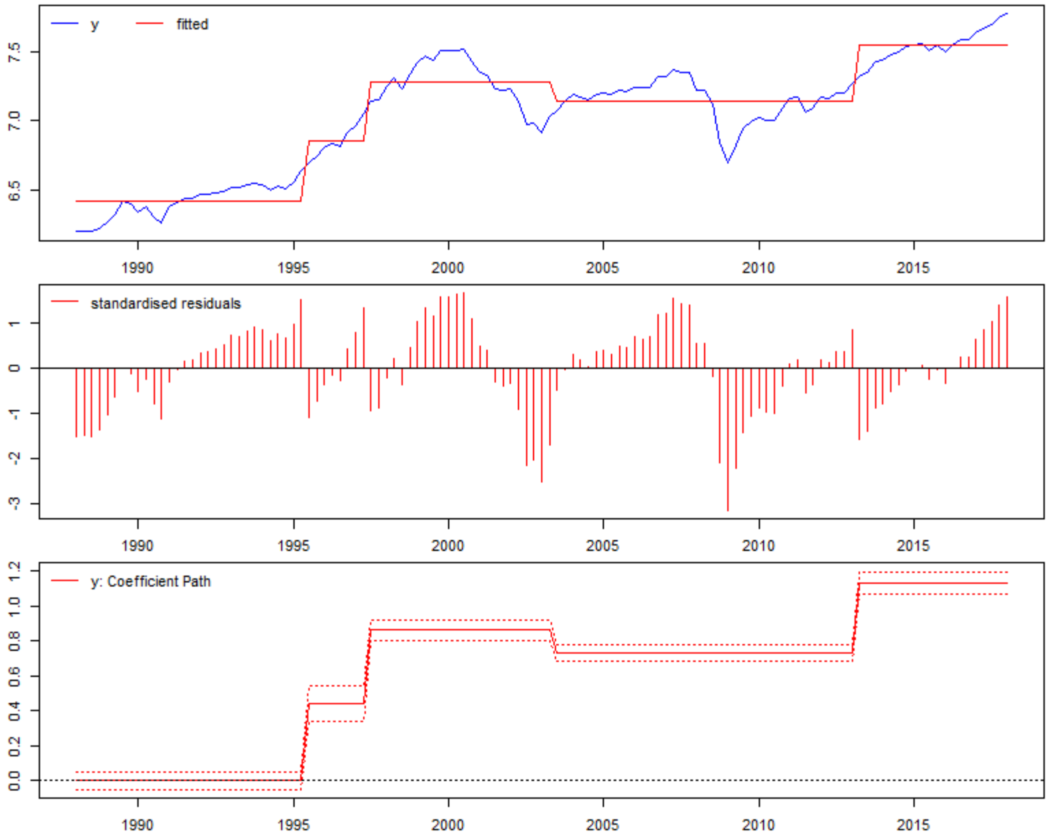


Figure B3: *LNS&P 500*



Appendix C Unit Root and Stationarity Tests

Table C1: *Dickey–Fuller test*

	At the level		At the first difference	
	t-statistic	*P**	*t-statistic*	*P**
Panel A: Model with intercept only				
TASI				
ADF test statistic	-2.262	0.186	-7.886	$<$.001
1% critical value	-3.485		-3.485	
5% critical value	-2.885		-2.885	
10% critical value	-2.579		-2.579	
M2				
ADF test statistic	2.243	1.000	-2.759	0.067
1% critical value	-3.485		-3.486	
5% critical value	-2.885		-2.886	
10% critical value	-2.579		-2.580	
Oil prices				
ADF test statistic	-2.222	0.200	-3.378	0.014
1% critical value	-3.488		-3.488	
5% critical value	-2.887		-2.887	
10% critical value	-2.580		-2.580	
S&P 500				
ADF test statistic	-0.301	0.920	-5.777	$<$.001
1% critical value	-3.484		-3.485	
5% critical value	-2.885		-2.885	
10% critical value	-2.579		-2.580	
Panel B: Model with intercept and trend				
TASI				
ADF test statistic	-2.654	0.258	-7.860	$<$.001
1% critical value	-4.035		-4.035	
5% critical value	-3.447		-3.447	
10% critical value	-3.149		-3.149	
M2				
ADF test statistic	-1.650	0.767	-7.822	$<$.001
1% critical value	-4.035		-4.035	
5% critical value	-3.447		-3.447	
10% critical value	-3.149		-3.149	

Oil prices				
ADF test statistic	-2.824	0.192	-3.353	0.063
1% critical value	-4.040		-4.040	
5% critical value	-3.450		-3.449	
10% critical value	-3.150		-3.150	
S&P 500				
ADF test statistic	-1.258	0.893	-5.761	<.001
1% critical value	-4.034		-4.036	
5% critical value	-3.447		-3.447	
10% critical value	-3.148		-3.149	
Panel C: Neither intercept nor trend				
TASI				
ADF test statistic	-1.084	0.251	-7.907	<.001
1% critical value	-2.584		-2.584	
5% critical value	-1.943		-1.943	
10% critical value	-1.615		-1.615	
M2				
ADF test statistic	4.084	1.000	-1.929	0.052
1% critical value	-2.584		-2.585	
5% critical value	-1.943		-1.944	
10% critical value	-1.615		-1.615	
Oil prices				
ADF test statistic	-0.801	0.367	-3.395	<.001
1% critical value	-2.585		-2.585	
5% critical value	-1.944		-1.944	
10% critical value	-1.615		-1.615	
S&P 500				
ADF test statistic	1.804	0.983	-5.582	<.001
1% critical value	-2.584		-2.584	
5% critical value	-1.943		-1.943	
10% critical value	-1.615		-1.615	

Table C2: *Kwiatkowski-Phillips-Schmidt-Shin test*

	At the level	At the first difference
	LM stat.	*LM stat.*
Panel A: Model with intercept only		
TASI		
KPSS test statistic	0.692	0.053
1% critical value	0.739	0.739
5% critical value	0.463	0.463
10% critical value	0.347	0.347
M2		
KPSS test statistic	1.169	0.783
1% critical value	0.739	0.739
5% critical value	0.463	0.463
10% critical value	0.347	0.347
Oil prices		
KPSS test statistic	0.503	0.079
1% critical value	0.739	0.739
5% critical value	0.463	0.463
10% critical value	0.347	0.347
S&P 500		
KPSS test statistic	0.921	0.093
1% critical value	0.739	0.739
5% critical value	0.463	0.463
10% critical value	0.347	0.347
Panel B: Model with intercept and trend		
TASI		
KPSS test statistic	0.128	0.043
1% critical value	0.216	0.216
5% critical value	0.146	0.146
10% critical value	0.119	0.119
M2		
KPSS test statistic	0.330	0.123
1% critical value	0.216	0.216
5% critical value	0.146	0.146
10% critical value	0.119	0.119

Oil prices		
KPSS test statistic	0.135	0.079
1% critical value	0.216	0.216
5% critical value	0.146	0.146
10% critical value	0.119	0.119
S&P 500		
KPSS test statistic	0.123	0.082
1% critical value	0.216	0.216
5% critical value	0.146	0.146
10% critical value	0.119	0.119

Appendix D Misspecification tests

Table D1: *VEC Residual Normality Test*

Component	Jarque–Bera	*df*	*p*
1	3.622	2	0.164
2	2.144	2	0.342
3	4.961	2	0.084
4	1.493	2	0.474
Joint	12.221	8	0.142

Table D2: *VEC Residual Serial Correlation LM Test*

Null hypothesis: No serial correlation at lag h			
Lag	LRE* stat	*df*	*p*
1	3.622	2	0.164
2	2.144	2	0.342
3	4.961	2	0.084
4	1.493	2	0.474
Joint	12.221	8	0.142

Table D3: *VEC Residual Serial Correlation LM Test*

Joint test		
χ^2	*df*	*p*
635.156	600	0.155

Figure D1: *Estimated Residuals Figures of the VEC Model*