Energy Prices and Economic Activity in the US

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A thesis submitted in partial fulfilment of the requirements of a Master of Research Degree

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October 2018

Abstract

At least since the oil price shocks and the subsequent recessions of the 1970s, economists have been interested in the relationship between energy prices and economic activity. Economic theory and empirical literature over the last 40 years have suggested that this relationship has evolved over time. Controversy has arisen over the direction of causality, and even whether it is bidirectional or a decoupled relationship. The findings over the years have been equivocal. This thesis therefore strives to shed new light on the energy price–economic activity nexus through a time-varying Granger causality test, which is known to outperform other methods and to therefore provide a more credible conclusion.

The results of this study show that the crude oil price and industrial production have a bidirectional causal relationship between August 1998 and August 2005, and from November 2014 to September 2016. Both periods are initiated by innovations in economic activity. A causality running from economic activity to oil price is also detected from October 2008 to April 2010. These results confirm the literature findings that oil price is predominantly demand-driven post-1985. Since evidence in the literature for natural gas and coal prices is very limited, the finding of unidirectional causality running from industrial production to prices for natural gas in the late 80's, 90's and mid-2017, as well as a causality running in the opposite direction for coal in 2009 and more recently, advances our understanding of the overall energy price–economy nexus. In light of these findings, policy implications to promote alternative energy sources and extend energy price insurance markets are discussed.

Statement of Originality

This work has not previously been submitted for a degree or diploma in any university. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

(Signed)______________________________ Date: 18/10/2018

Acknowledgements

Special thanks to my supervisor Associate Professor Shuping Shi, to Dr Natalia Ponomareva, and to Master of Research Degree coordinator Associate Professor Tony Bryant for their support and guidance.

And to my Alicia, for giving me strength.

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1. Introduction

As the largest economies in the world, the United States (US) receives continual attention from academics around the world. According to the Energy Information Administration (EIA), the US consumed 18% of world energy in 2015 (EIA 2017). Its energy consumption comprises crude oil (37.1%), natural gas (28.7%) and coal (14.2%), followed by nuclear and renewables (EIA 2017). Energy price and crude oil price, in particular, have been at the centre of significant debate over their relationship with the US economy since the 1970s, with economists observing that nine out of ten recessions in the period since World War II were associated with a sudden rise in oil price (Hamilton 1996; Burbidge & Harrison 1984). Oil price shocks and recessions are illustrated in Figure 1.

It is generally agreed that, up until 1973, there was a negative relationship between oil prices and gross domestic product (GDP) growth (see e.g. Hamilton 1983, 2003; Hooker 1996; Mork 1989). After 1973, however, the relationship becomes more controversial, with arguments for oil price negatively affecting GDP growth (Hamilton 2003; Rodriguez & Sanchez 2005); for a reverse causality from GDP to oil prices (Benhmad 2013); and for a decoupling of the oil–GDP relationship (Hooker 1996; Darrat, Gilley & Meyer 1996). In recent years, there are new evidences showing that this causal relationship is time-varying and sample period-dependent (Hammoudeh, Bhar & Thompson 2010; Aguiar-Conraria & Soares 2011).

Such time-varying effects may have come about due to changes in energy market regulations, in the economic environment or in the composition of energy intensive goods production, and may be due to a time-varying energy consumption profile. The US energy consumption profile has been changing over time. Figure 2 illustrates the energy consumption (by resources) over time in the US. Up until 70 years ago, coal was the main energy source, with oil consumption subsequently increasing and peaking in 1980. Natural gas has become increasingly important as both oil and coal consumption decline (EIA 2017).

Energy plays a vital role in fuelling the economy and the world energy landscape is changing dramatically. There are many important questions being asked in regards to energy, such as the relationship between energy consumption and economic growth, as well as investigation of energy structural demand and supply channels. In this thesis, the question being addressed is: What is the time-varying causal relationship between energy price and economic activity for the period 1976–2018 in the US – is it a unidirectional, bidirectional or a decoupled relationship? Understanding this relationship has significant implications for policy design given increasing energy demand. This large body of research not only sheds light on the nexus between energy prices and economic performance, but also provides insights as the US economy transitions into renewables and other alternative energy sources.

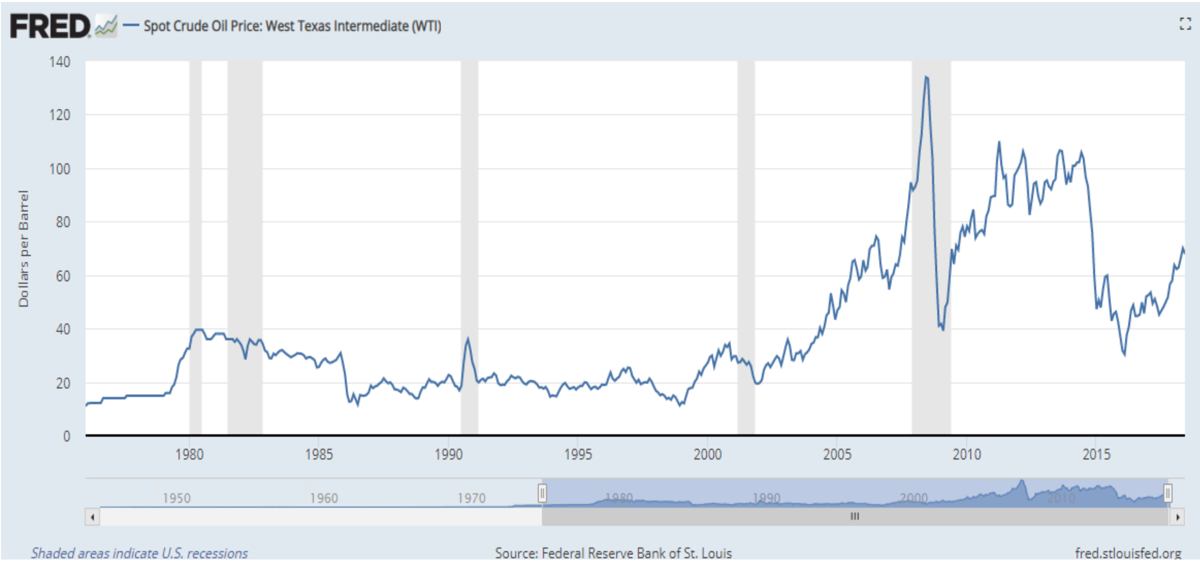


Figure 1. Oil price shocks and US recession

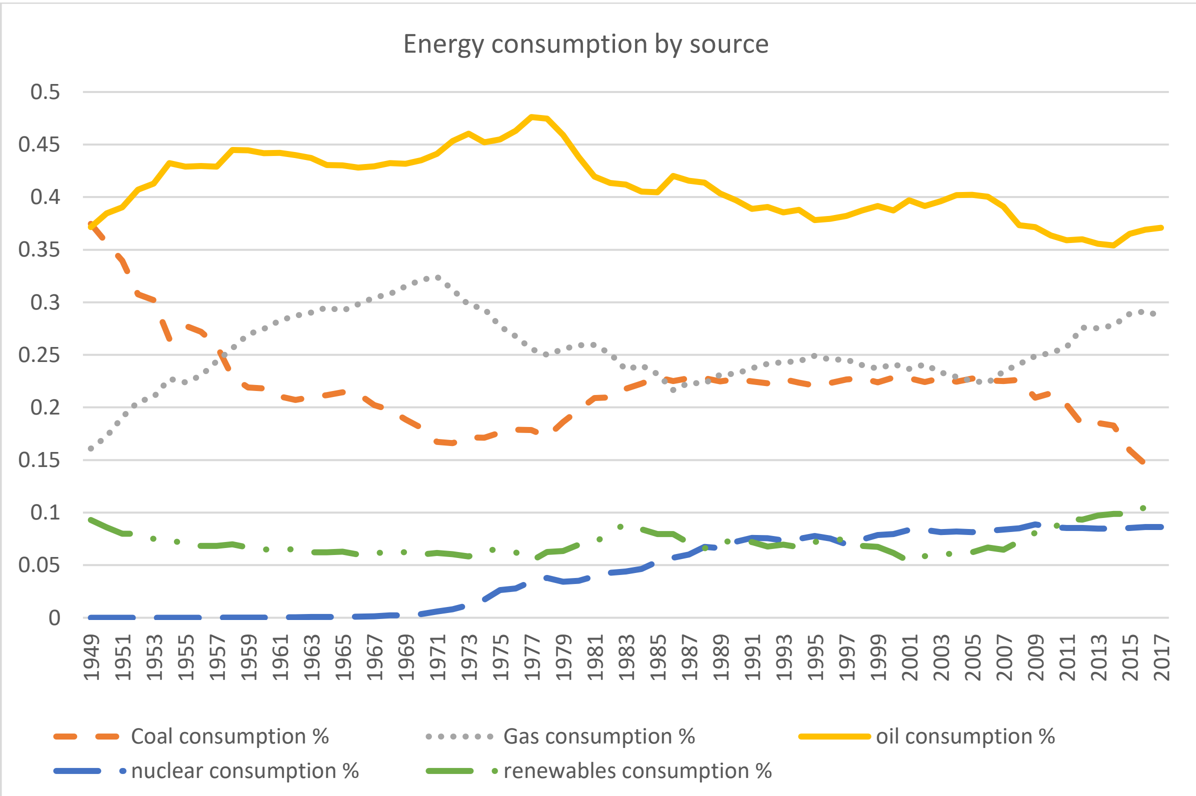


Figure 2. US energy consumption profile

2. Literature review

2.1 Economic theory

It is widely accepted that energy prices, and crude oil price in particular, are endogenous with respect to macroeconomic fundamentals dating back to the early 1970s. However, much of the early theoretical literature on oil price transmission channels dealt with exogenous oil price shocks. The traditional approach in dynamic stochastic general equilibrium (DSGE) models includes energy as a productive input and the relative price of energy as an exogenous random process (Kim & Loungani 1992).

The transmission of imported crude oil shocks directly affects GDP through various channels. An increase in the price of oil raises the marginal cost of production. If oil and capital are complements in the production process, then oil price increases can lead to a decrease in production capacity and a negative transitional output growth, as agents reduce both oil and capital usage in response to higher oil prices (Berndt & Wood 1979; Tatom 1988). Higher production costs lower domestic output to the extent up to which it is bounded by the shared cost of oil in gross domestic product. General equilibrium models predict that oil price shocks lead to increases in wages and prices, and decreases in real output (Bruno & Sachs, 1982; Harkness 1982). Neoclassical general equilibrium models show that seemingly small disruptions in the supply of primary commodities such as energy can have large effects on real output through reducing aggregate employment (Hamilton 1988).

Another main channel is through income transfer, after an increase in oil prices triggering a reduction in disposable income and consequently lowering the demand for goods and services. Firms' higher production costs increase unemployment, which also causes consumption to be adjusted downward (Mork 1985). It is a key mechanism through which energy prices affect the economy by altering consumers' and firms' discretionary spending on goods and services other than energy (Hamilton 2009). Reduction in expenditures may be further amplified through increases in the operating cost of energy-dependent durables (Hamilton 1988).

Exogenous oil price shocks indirectly affect GDP through inflation. Based on real balances, it has been posited that oil price increases lead to inflation, which lowers the quantity of real balances in the system. Lower real balances then produce recessions through monetary channels, where the central bank responds to inflation by raising interest rates, which dampens economic activity (Hall & Taylor 1991). Some have argued that counter-inflationary monetary policy responses to oil price increases are responsible for output losses after these oil price shocks (Darby 1982; Bohi 1991). Barsky and Kilian (2001), using an illustrative example that builds on Gordon (1984) and Rotemberg and Woodford

(1996), have verified that an oil price shock is indeed unambiguously inflationary for the price of gross output. Hence, following an oil price shock, one would expect stagflation in the form of a decline in industrial production and increased inflation. There is strong evidence of sharp changes in the CPI inflation rate only after major oil price changes (Barsky & Kilian, 2001). However, even if this results in an adverse shift of the aggregate supply curve and causes price levels to increase, in the absence of sticky wages it would not be expected to cause sustained inflation (Bruno & Sachs 1982).

Another indirect transmission mechanism of oil price changes is the uncertainty effect. In practice, oil price volatility is a proxy for uncertainty. An increase in real oil price that is large relative to recent volatility will result in reallocation of resources and a decrease in aggregate output. As implied by the real options theory, increased uncertainty about oil prices prompts firms to delay investments, which causes investment expenditure to decline, and as the level of oil price uncertainty increases, the option value rises and the incentive to invest declines (Bernanke 1983). Increased uncertainty also causes precautionary demand for oil to rise, leading to an immediate increase in the real oil price (Alquist & Kilian 2010). Furthermore, increased uncertainty about the prospect of unemployment in times of unexpected changes in oil prices could increase consumers' precautionary saving and thus decrease consumer expenditure (Edelstein & Kilian 2009). These shifts in consumer expenditure are likely to cause sectoral shifts throughout the economy, which indirectly affects GDP (Davis 1987; Hamilton 1988). Unemployment and cutbacks in output can result from capital and labour being unable to reallocate in the presence of frictions in capital and labour markets, thus further lowering consumption and amplifying the effect of higher energy price on the economy.

Oil price shocks can influence people's expectations about the future path of oil prices. Such expectations determine cash flow and net present value of future investment projects, as well as earlier investment decisions, both of which depend on the price of oil. These mechanisms are linked to macroeconomic variables including inflation, output and employment (Kilian 2008a).

Oil price also affects exchange rates through income transfer and changes in the domestic current account balance. Currencies of oil-exporting countries appreciate and those of oil importers depreciate after an oil price increase (Beckmann & Czudaj 2013). The US dollar may appreciate in the short run due to the wealth effect if oil-exporting countries reinvest their revenues in US dollar assets.

Empirical evidence within the theoretical literature is, however, equivocal in terms of explaining through what theoretical channel mechanisms this oil–GDP relationship arises. It is argued that contractionary monetary policy is responsible for the aggregate economic activity downturn in response to an oil price increase (Bernanke et al. 1997). This idea is challenged and it is argued that the monetary channel is, at best, a partial explanation for higher oil price adversely affecting output growth, while sectoral shocks and uncertainty channels over 1970–1990 period offer a partial solution to the asymmetric responses of the economy (Hamilton & Herrera 2004; Ferderer 1996; Balke, Brown & Yucel 2002). Some researchers support the view that underlying structural demand and supply shocks in the economy should be modelled since, depending on the sources of oil price perturbations, the economy responds differently to different types of shocks (Kilian 2009). In a later study of 16 Middle Eastern and North African countries, for net oil-importing countries, positive oil supply shocks lower the output whereas positive oil demand shocks increase the output. Oil price shocks do not impose significant effects on these countries when shocks are not differentiated. For the group of net oil-exporting countries, the output increases regardless of whether oil price increases are derived from oil demand shocks or supply shocks (Berument, Ceylan & Dogan 2010). Research has found that historical oil price shocks are driven mainly by a combination of global aggregate demand shocks and precautionary demand shocks, instead of oil supply shocks (Kilian 2009). This view helps explain the absence of recession following the sharp rise of crude oil prices in 2003, due to the fact that those oil price increases were driven by a global economic boom rather than oil supply disruptions (Kilian & Hicks 2013). Similar results are found for the US and China, for which oil demand plays a crucial role in oil price changes after 2000 (Liu et al. 2016). Typically for China, the effects of oil supply, oil aggregate demand and oil-specific demand shocks on its output are time-varying, with the direction of the effects changing over 1995–2015 (Gong & Lin 2018).

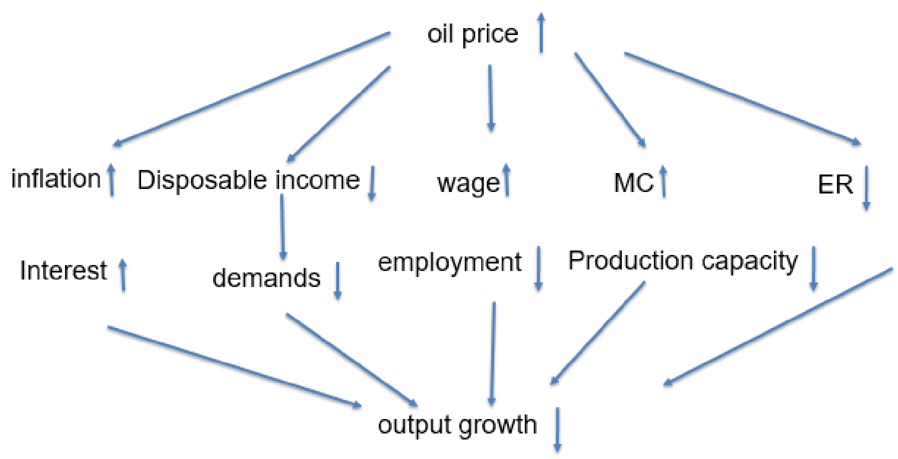


Figure 3. Summary of transmission channels of oil price

2.2 Empirical methods

There have been numerous econometric developments and various methodologies applied in the literature to explore the energy price–economic growth relationship since the 1980s. Single-equation models are applied in a few studies where GDP growth is regressed on its own lags and lags of oil price changes for the US and Japan (Hamilton 2005; Zhang 2008). In another study, the macroeconomic aggregate of interest is regressed on its lags, exogenous oil supply shock series and lags (Kilian 2008b). Regression analysis is extended for panel data on groups of countries using an error correction-based panel cointegration and panel autoregressive distributed lag approach within a two-sector endogenous growth model (Berk & Yetkiner 2014). In another panel study, Hamilton's (2001) time-series methodology is extended with a Bayesian parametric approach (Kim 2012).

A number of studies utilise structural vector autoregression (VAR) models to study underlying mechanisms from which energy prices derives their impact on the economy and the correlation between energy prices and macroeconomic variables (Abeysinghe 2001; Blanchard & Gali 2007; Lippi & Nobili 2008). In order to further investigate the causal relationships between energy price and macroeconomic variables, a large number of studies have been applying the Granger causality test for single countries and for groups of countries (e.g. Hamilton 1983; Burbridge & Harrison 1984; Lee, Ni & Ratti 1995; Costantini & Martini 2010).

2.3 Empirical evidence

The empirical literature is largely devoted to the relationship of crude oil price and macroeconomic fundamentals. It is led by a group of researchers who find significant effects of energy supply shocks on economic activity. It has been found that higher oil price is recessionary for the oil-importing US economy. It has been shown that over the period 1948–1972, the correlation between dramatic increases in the price of crude oil and subsequent downturns in US gross national product (GNP) growth is statistically significant (Hamilton 1983). This supports the idea that oil price shocks are a contributing factor to at least some of the US recessions prior to 1972. A parallel study of the period 1961–1982 corroborated Hamilton's findings, showing that crude oil price has a significant impact on US real GNP, price level, unemployment and real investment (Gisser & Goodwin 1986). Later research extended the data from previous studies to 1988, to include the oil market collapse with the oil price measure adjusted to account for price increases and decreases separately (Mork 1989). The results were in line with Hamilton's finding that oil price increases are negatively correlated to US GNP growth. The later research also found a significant asymmetric response, whereby oil price decreases, unlike oil price increases, are not correlated to GNP growth. Mork later updated the data to 1992 in a study of six other OECD countries in addition to the US. The results supported previous findings on the negative relationship of oil price increase and GDP growth, as well as the evidence of asymmetric responses (Mork, Olsen & Mysen 1994). The asymmetric real GNP responses to oil price shocks was also confirmed in a following study showing that positive oil shocks have a powerful effect on growth while negative oil shocks do not (Lee, Ni & Ratti 1995). Additionally, oil price changes were found to have a greater impact on real GNP and unemployment in a stable environment than when oil price movement has been erratic. Oil price volatility as measured by monthly standard deviations of daily oil prices has also been found to forecast aggregate output movements in the US over the period 1970–1990 (Ferderer 1996).

In contrast to the findings above, results from other studies are less than straightforward. There is evidence showing that the relationship is time-varying and not always significant. For example, the oil price shocks in 1979–1980 for the US and four other OECD countries was found to have a minimal impact, while the influence of the oil shocks in 1973–1974 appears to be strong (Burbidge & Harrison 1984). Although the recession in the mid-70s began before oil price rises occurred, it seems the shock made matters worse. Another study of the period 1948–1994 suggests oil prices only Granger cause macroeconomic indicator variables up to 1973, and not after (Hooker 1996). Hamilton responded to this result by introducing a different measure of oil price changes, NOPI (net oil price increase). This approach restored the correlation between oil price shocks and recession over the period 1948–1994, the reason being that since 1985 many of the oil price increases are corrections to price decreases in the previous quarter (Hamilton 1996). Hamilton later refined this approach, but until then it was accepted by a group of researchers that the oil price–growth relationship is non-linear: oil price increases affect the economy whereas oil price decreases do not (Hamilton 2003; Lee, Ni & Ratti 1995; Hamilton 1996; Jimenez-Rodriguez & Sanchez 2005; Jimenez-Rodriguez 2009). In contrast to this view, some researchers argue that the relationship is linear (Kilian & Vigfusson 2011). Kilian criticised conventional VAR models using censored oil prices, such as NOPI, and stated that a linear model is better at rationalising the US data as there is no significant asymmetry in the responses (Kilian & Vigfusson 2011; Herrera & Karaki 2015).

In recent years, more evidence has emerged showing this relationship is time-varying and sample period-dependent. It has been found that the relationship between oil prices and the US industrial production is not clear-cut. Three structural breaks have been found: mid-1970s, mid-1980s and the end of 1995. Before 1985, oil price influenced industrial production; after 1985, a reverse causality occurs (Aguiar-Conraria & Soares 2011). This research concludes that demand-driven oil price shocks became important around 1985 and more important around 1995, which is broadly in line with the argument of Kilian (2009) and Baumeister and Peersman (2013). Another study finds similar results; before 1984, oil prices Granger cause US GDP, and after 1984 there is a reverse causality (Benhmad 2013). More recently, a positive impact from oil prices on economic activity over 1979–2013 has been posited, with a feedback effect between the two (Raza et al. 2018). The sharp oil price decline over 2014–2016 is found to have no stimulus effect on the economy (Baumeister & Kilian 2016).

In some earlier studies, the attempt to get around relationship instability rests on enforcing structural breaks on the data and estimating VAR models on subsamples separately (Hamilton 1983; Gisser & Goodwin 1986; Cuñado & de Gracia 2003). Other approaches include Markov regime-switching models on univariate time series and rolling window impulse response in VAR models which allows for gradual changes in the estimates without imposing discrete breaks in a single period (Raymond & Rich 1997; Cologni & Manera 2009; Gronwald 2012; Blanchard & Gali 2007; Arora & Lieskovsky 2014). Additionally, a Bayesian time-varying parameter structural VAR model with stochastic volatility is used to estimate the effects of oil supply and demand shocks in the world oil market and for the US economy and for China (Baumeister & Peersman 2013; Gong & Lin 2018).

Results from countries other than the US is also equivocal. Oil prices are found to have permanent short-run and asymmetric effects on industrial production growth, and the results are significantly different among a group of European countries over 1960–1999 (Cuñado & de Gracia 2003). Oil prices are found to have significant effects on economic activity in the short run for a group of Asian countries over 1975–2002 (Cuñado & de Gracia 2005). The correlations with oil price increases are negative for a group of OECD countries except Norway, and oil-price decreases are positive but only significant for the US and Canada (Mork et al. 1994). Furthermore, no evidence is found for oil price shocks in 1973–74 and 2002–03 having impact on real growth in any G7 country, whereas 1978–79, 1980 and 1990–91 oil price shocks contributed to lower growth in some G7 countries (Kilian 2008b). In another study, no long-run relationships between energy prices and industrial production is found for most OECD, GCC and OPEC countries, but a unidirectional causality runs from oil prices to industrial production and no causal relationship is found between natural gas price and industrial production from 1998–2014 (Karacaer-Ulusoy & Kapusuzoglu 2017).

In comparison to crude oil, very little is known about how natural gas prices and other energy sources affect the economy. Available information identifies no relationship between natural gas prices and US industrial production and a modest positive impact on the economy at regional levels after a shale gas boom (Kliesen 2006; Weber 2012). It is found that natural gas does affect US economic activity through changes in supply, more so after the shale gas boom in 2008 (Arora & Lieskovsky 2014). A long-run relationship exists between natural gas prices and industrial production, with gas price impacting industrial production growth for some European countries (Acaravci et al. 2012). Furthermore, crude oil and natural gas interact with each other in the US energy market as competitive substitutes and are cointegrated over the 1989–2005 period (Villar & Joutz 2006). It has also recently been found that a bidirectional causality exists between changes in renewable energy consumption and economic growth, and a dependence from changes in oil prices to changes in renewable energy consumption (Troster et al. 2018).

To conclude, it is important to revisit the energy prices–economic activity relationship in the current economic environment due to its time-varying nature. This time-varying effect arises from multiple factors, including policy changes in the energy market and the changing energy intensity of the economy among others. Clarifying and renewing understanding of this relationship has significant implications for policy design to achieve a higher energy efficiency and economic growth. In this thesis, I will be analysing the US aggregate economic data from the 1976–2018 period using a time-varying Granger causality test with a bootstrap recursive evolving window method, which is shown to outperform other methods in causal change detection within possibly integrated systems (Shi, Hurn & Phillips 2018).

3. Methodology

To investigate the time-varying relationship between US energy prices and industrial production, this thesis adopts a methodology developed in Shi, Hurn & Phillips (2018). It is a recursive evolving window Granger causality test based on a lag-augmented VAR system. The test uses bootstrapped 5% critical values to control family-wise size in the recursive hypothesis testing.

3.1 Granger causality

A variable y_{2t} is said to Granger cause y_{1t}, if the past values of y_{2t} help predict the current level of y_{1t} given all other relevant information is unchanged. The simplest Granger causality test requires estimating a bivariate VAR:

$$y_{1t} = \beta_{10} + \sum_{i=1}^{p} \beta_{11,i}\, y_{1t-i} + \sum_{i=1}^{p} \beta_{12,i}\, y_{2t-i} + \varepsilon_{1t} \ , \qquad (1)$$

$$y_{2t} = \beta_{20} + \sum_{i=1}^{p} \beta_{21,i}\, y_{1t-i} + \sum_{i=1}^{p} \beta_{22,i}\, y_{2t-i} + \varepsilon_{2t} \ , \qquad (2)$$

where p is the number of lags that adequately models the structure, so that the coefficients of further lags of the variables are insignificant and the error terms are white-noise processes. Assuming error terms are uncorrelated, there is a unidirectional causality from y_2 to y_1 if the lagged y_2 coefficients are jointly significant in (1) and the lagged y_1 coefficients are not jointly significant in (2). There is a feedback causality when the lagged coefficients are jointly significant in both (1) and (2). Multivariate Granger causality tests are identical to bivariate test except for more variables and their lags in each regression. By including additional variables that may be responsible for causing y_1 or y_2 , or whose effects might obscure the effect of y_1 on y_2 and vice versa, multivariate Granger causality can help avoid spurious correlation and uncover indirect channels of causation (Lütkepohl 1982; Stern 1993).

When some or all of the variables are non-stationary, as is often the case for macroeconomic time series, the standard Granger causality test in levels is invalid (Ohanian 1988; Park & Phillips 1989). If variables are known to be *I*(1) (integrated of order 1) with no cointegration, then VAR is estimated in first-order differences of the variables. If the variables are *CI*(1,1) (cointegrated of order 1,1), then a vector error correction model (VECM) is specified. In order to avoid possible pre-test biases arising from unit root and cointegration tests, Toda and Yamamoto (1995) modified the standard Granger causality test on the variables in levels by adding additional lags. The test statistics are constructed from Wald statistics, which follow standard chi-squared distribution under the null hypothesis of non-causality. This lag-augmented VAR model is suitable for systems with *I*(1) and *I*(2) variables. It outperforms the fully modified VAR and VECM approach in size stability, although it has a comparatively lower power ((Phillips 1995; Yamada & Toda 1998).

3.2 Lag augmented VAR (LA-VAR) Granger causality test

In a bivariate system y_{1t} and y_{2t} , where variables are integrated at most *I*(d) around a linear trend, the Granger causality test is conducted by estimating a lag-augmented VAR (Toda & Yamamoto 1995):

$$y_{1t} = \gamma_{10} + \gamma_{11}t + \sum_{i=1}^{k} J_{11,i}y_{1t-i} + \sum_{i=k+1}^{k+d} J_{11,i}y_{1t-i} + \sum_{i=1}^{k} J_{12,i}\, y_{2t-i} + \sum_{i=k+1}^{k+d} J_{12,i}\, y_{2t-i} + \varepsilon_{1t} \quad ,$$

$$y_{2t} = \gamma_{20} + \gamma_{21}t + \sum_{i=1}^{k} J_{21,i}\, y_{1t-i} + \sum_{i=k+1}^{k+d} J_{21,i}y_{1t-i} + \sum_{i=1}^{k} J_{22,i}\, y_{2t-i} + \sum_{i=k+1}^{k+d} J_{22,i}\, y_{2t-i} + \varepsilon_{2t} \quad ,$$

where $\varepsilon_{1t}, \varepsilon_{2t}$ are a white-noise process, $t = 1, 2, \ldots, T,\ d$ is the maximum order of integration in the variable y_t , and k is the lag order selected using the Bayesian information criterion (BIC) with a maximum lag length of 12 for the VAR model (without the lag-augmented component).

A bivariate or a multivariable system can be simplified as:

$$\begin{aligned} y_t &= \gamma_0 + \gamma_1 t + \textstyle\sum_{i=1}^{k} J_i y_{t-i} + \sum_{i=k+1}^{k+d} J_i y_{1t-i} + \varepsilon_t \\ &= \Gamma\tau_t + \Phi x_t + \Psi z_t + \varepsilon_t \quad , \qquad (3) \end{aligned}$$

where $\Gamma = (\gamma_0, \gamma_1)_{n\times 2}\,, \tau_t = (1, t)'_{2\times 1}\,,\ x_t = (y'_{t-1}, \ldots, y'_{t-k})'_{nk\times 1}\,, z_t = (y'_{t-k-1}, \ldots, y'_{t-k-d})'_{nd\times 1}\,,$

$\Phi = (J_1, \ldots, J_k)_{n\times nk}\,,\ \Psi = (J_{k+1}, \ldots, J_{k+d})_{n\times nd}\,,\ y_t$ is a column vector containing, in this study, macroeconomic variables for the US and energy prices. n is the number of variables in the system.

The null hypothesis of Granger non-causality is given by restrictions on the non-augmented variables and their lags, such that

$$H_0 : \mathrm{R}\varphi = 0, \tag{4}$$

where $\varphi = vec(\Phi)$ using row vectorisation and R is a $m \times n^2k$ matrix. The OLS estimator is

$$\widehat{\Phi} = Y'QX(X'QX)^{-1}$$

where $\mathrm{Y} = (y_1, y_2, \dots, y_T)'_{T\times n}$, $X = (x_1, \dots, x_T)'_{T\times nk}$, $Q = Q_\tau - Q_\tau Z(Z'Q_\tau Z)^{-1}Z'Q_\tau$ with $Q_\tau = I_T - \tau(\tau'\tau)^{-1}\tau'$, $Z = (z_1, \dots, z_T)'_{T\times nd}$, $\tau = (\tau_1, \dots, \tau_T)'_{T\times 2}$.

Let $\hat{\varphi} = vec(\widehat{\Phi})$, $\widehat{\Sigma}_\varepsilon = \frac{1}{T}\hat{\varepsilon}'\hat{\varepsilon}$, and $\varepsilon = (\varepsilon_1, \dots, \varepsilon_T)'_{T\times n}$. The standard homoscedasticity Wald statistic, denoted by W, for testing the null hypothesis H_0 is

$$W = (R\hat{\varphi})'[R\{\widehat{\Sigma}_\varepsilon \otimes (X'QX)^{-1}\}R']^{-1}R\hat{\varphi}.$$

It has χ^2_k asymptotic distribution with k number of zero restrictions being tested under the null.

3.3 Time-varying Granger causality test based on LA-VAR

A recent econometric development in handling causal relationship instability is the time-varying recursive evolving window Granger causality test. The recursive evolving algorithm was originally developed for monitoring financial bubbles and then adapted to detect Granger causality and causal direction change between money and income (Shi, Hurn & Phillips 2018). The fact that it is based on the lag-augmented VAR model makes it suitable for potentially integrated systems. This method has been shown through a simulation study to outperform rolling window and forward recursive algorithms (Shi, Hurn & Phillips 2018). This thesis will apply this methodology for a subsample causal change detection between energy prices and economic activity for the US, as described below.

3.3.1 Recursive evolving window regressions

Wald statistics from subsamples of the data are calculated from recursive Granger causality tests. It is convenient to use sample fractions in the following illustration. Let f be the (fractional) observation of interest and f_0 be the minimum (fractional) window size required to estimate the VAR model. Let f_1 and f_2 be the starting and ending points of the subsample regression; and f_w the size of the regression window, such that $f_w = f_2 - f_1$. Wald statistics calculated for this sample is $W_{f_2}^{f_1}$. Let $\tau_1 = [f_1T]$, $\tau_2 = [f_2T]$, $\tau_w = [f_wT]$, where T is the total number of observations, and $\tau_0 = [f_0T]$ be the minimum number of observations needed to estimate the VAR. [.] is a floor function that returns the largest integer less than or equal to the number inside the bracket.

In order to correct for heteroscedasticity in the data, a subsample heteroscedastic consistent Wald statistic is defined as:

$$W_{f_2}^{f_1} = \tau_w \left(R\, \hat{\varphi}_{f_1,f_2}\right)'[R\left(\hat{V}_{f_1,f_2}^{-1}\, \hat{\Sigma}_{f_1,f_2}\, \hat{V}_{f_1,f_2}^{-1}\right) R']^{-1} \left(R\, \hat{\varphi}_{f_1,f_2}\right), \quad (5)$$

where $\hat{V}_{f_1,f_2}^{-1} \equiv I_n \otimes \hat{Q}_{f_1,f_2}$ with $\hat{Q}_{f_1,f_2} \equiv \frac{1}{\tau_w} \sum_{t=[Tf_1]}^{[Tf_2]} x_t x_t'$ and $\hat{\Sigma}_{f_1,f_2} \equiv \frac{1}{\tau_w} \sum_{t=[Tf_1]}^{[Tf_2]} \hat{\epsilon}_t \hat{\epsilon}_t'$, with $\hat{\epsilon}_t \equiv \hat{\varepsilon}_t \otimes x_t$.

For the recursive evolving window procedure, the end point of the regression is $f_2 \in \{f_0, \dots, 1\}$, the starting point f_1 varies from 0 to $f_2 - f_0$. For each observation f, there exists a sequence of Wald statistics $\{W_{f_1,f_2}\}_{f_2 = f}^{f_1 \in [0,\, f_2 - f_0]}$. The test statistic is defined as the supremum of the Wald statistic sequence

$$SW_f(f_0) = \sup_{f_2 = f,\ f_1 \in [0, f_2 - f_0]} \{W_{f_1,\, f_2}\} \quad .$$

It is upon this supreme Wald statistic $SW_f(f_0)$ that the Granger non-causality inference for observation $[fT]$ is based.

The subsample Wald statistic has a limit distribution of

$$W_{f_2}^{f_1} \Rightarrow \left[\frac{W_m(f_2) - W_m(f_1)}{f_w^{\frac{1}{2}}}\right]' \left[\frac{W_m(f_2) - W_m(f_1)}{f_w^{\frac{1}{2}}}\right],$$

where W_m is a vector standard Brownian motion with covariance matrix I_m with m number of restrictions under the null. The supreme Wald statistic converges to

$$SW_f(f_0) \Rightarrow \sup_{f_2 = f,\ f_1 \in [0, f_2 - f_0]} \left[\frac{W_m(f_2) - W_m(f_1)}{f_w^{\frac{1}{2}}}\right]' \left[\frac{W_m(f_2) - W_m(f_1)}{f_w^{\frac{1}{2}}}\right],$$

as $T \to \infty$ (Shi, Hurn & Phillips 2018).

3.3.2 Bootstrapping method in recursive testing

A bootstrap method is used to solve the multiplicity issue in recursive testing. The multiplicity issue is caused by multiple hypotheses tests, which can lead to size distortion. Since the test of causality starts from $\tau_0 = [Tf_0]$ to T , the number of hypotheses tests over the sample period is $T - \tau_0 + 1$. A bootstrap method (Shi, Hurn & Phillips 2018) is proposed to control the family-wise size distortion. The details are described below using an example of bivariate VAR(1) for the causality from y_2 to y_1 , which can be extended to multivariable systems.

1. Imposing null hypothesis of no-Granger causality from y_2 to y_1 , i.e., lagged y_2 coefficients are set to 0 in equation (1). Estimate the restricted model and obtain the residuals.
2. Bootstrapped residuals are randomly drawn with replacement from estimated residuals in step 1. A sample is generated using bootstrapped residuals and coefficient estimates of step 1. Initial values used are y_{1i} and y_{2i} for the first k observations. The number of observations in the window for which size is to be controlled is τ_b . The sample size of the bootstrapped sample is $\tau_0 + \tau_b - 1$.
3. Compute the bootstrapped test statistic sequences $\{SW_t^b(\tau_0)\}_{t=\tau_0}^{\tau_0+\tau_b-1}$ and the maximum values of the test statistic sequences
$$SM^b(\tau_0) = \max_{t\in[\tau_0,\tau_0+\tau_b-1]}(SW_t^b(\tau_0)). \qquad (6)$$
4. Repeat steps 2–3 499 times.
5. The critical value is the 95% percentiles of the $\{SM(\tau_0)^b\}_{b=1}^{499}$ sequence. The probability of having at least one false positive detection is 5% over the sample period τ_b. Thus, any potential size distortion due to multiplicity is controlled.

4. Empirical results

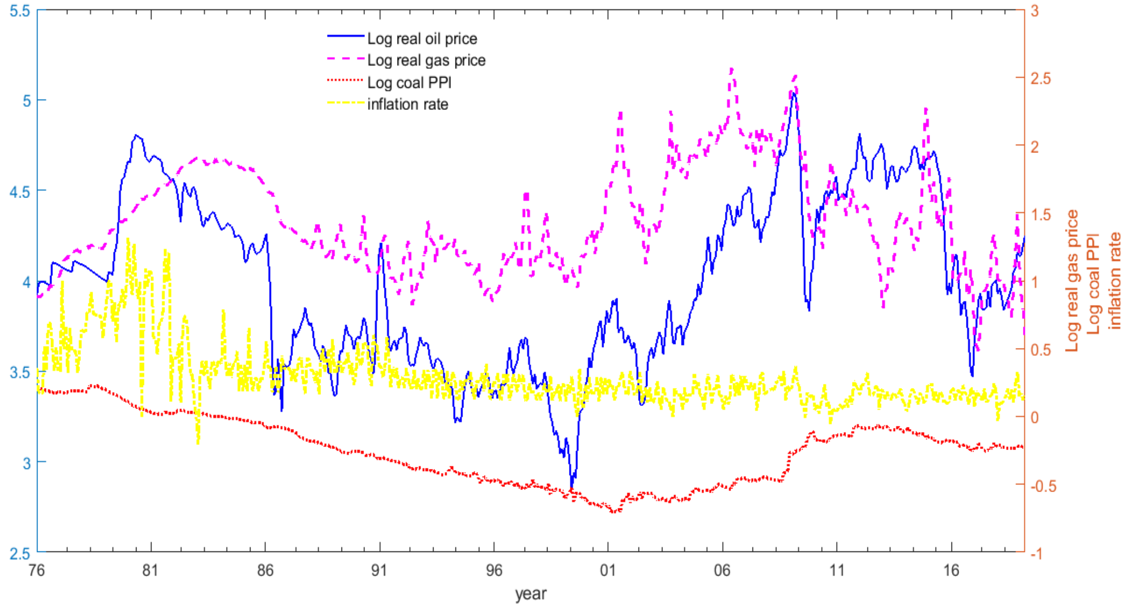
4.1 Variables included in the VAR

Many early studies adopt a multivariable model, which represents a compact approximation to macroeconomic reality (Sims 1980; Hamilton 1983; Burbidge & Harrison 1984; Mork 1989; Lee, Ni & Ratti 1995). In particular, analysis of the oil price–economic growth relationship is carried out through a seven-variable VAR framework. These variables include real GNP/GDP growth or industrial production; unemployment rate; short-term interest rate; currency and demand deposits (M1); average manufacturing wage rate; consumer price index (CPI); and real/nominal oil price changes. Other studies differ from this model by adding real investment and fiscal activity variables in the VAR, or a Federal funds rate measuring the stance of monetary policy, or oil price volatility measured by a monthly standard deviation (Gisser & Goodwin 1986; Ferderer 1996). There are also studies that use fewer variables. In a five-variable VAR, an indicator of the state of the oil market is used to identify exogenous movement in the price of oil, monetary policy and oil price shocks (Bernanke et al. 1997). In another study, either real GDP or unemployment rate is used as macro-indicator variable while M1 is omitted (Hamilton 1996). M1 and unemployment rate are omitted and real exchange rate and long-term interest rate are included in a study of OECD countries (Jimenez-Rodriguez & Sánchez 2005). A four-variable structural VAR with real exchange rate, inflation, GDP growth and oil prices, from Cushman & Zha (1997) is used for Middle Eastern and North African countries under the assumption that these countries are a small enough not to affect world oil prices (Berument et al. 2010). There are studies that only include inflation on top of real GDP and oil prices or use bivariate VAR to study the oil price and growth relationship (Cavalcanti & Jalles 2013; Kilian & Vigfusson 2011). In terms of oil price variables, the censored oil price measures such as net oil price increase (NOPI) and scaled oil price increase (SOPI) are challenged for giving inconsistent parameter estimates (Kilian & Vigfusson 2011). These oil price measures were originally developed to accommodate the asymmetric evidence observed in the relationship (Hamilton 1996, 2003; Lee, Ni & Ratti 1995; Mork 1989). A summary of variables is provided in Appendix Table A(1).

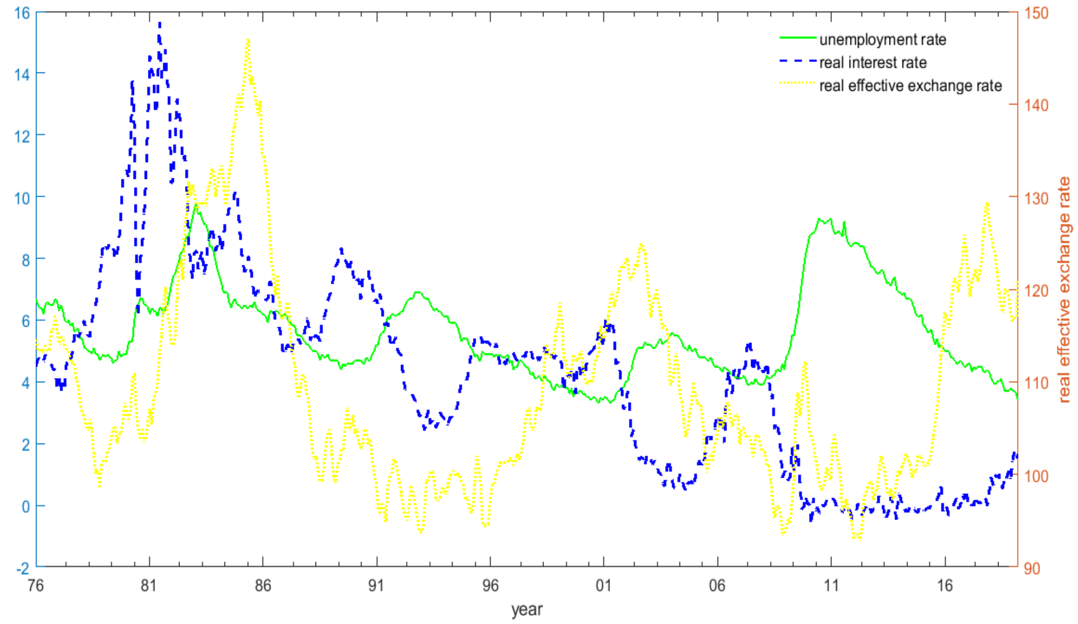
According to economic theories which has been discussed in the literature review chapter of this thesis, energy prices affect the economy through various channels. Higher energy prices can increase inflation, wage rate and unemployment and affect exchange rates. By affecting macroeconomic variables, energy prices exert an influence on economic activity. Taking into consideration of these channels, a nine-variable VAR system is adopted in this thesis to approximate macroeconomic reality. The nine variables are (i) log of industrial production index (ip_t); (ii) log of real price of oil (oil_t); (iii) log of real price of natural gas (gas_t); (iv) log of coal producer price index ($coal_t$) ; (v) inflation rate (pi_t) (CPI less energy based); (vi) log of real wage rate ($wage_t$) ; (vii) real effective exchange rate (er_t); (viii) real interest rate (i_t); and (ix) unemployment rate (emp_t).

4.2 Data and preliminaries

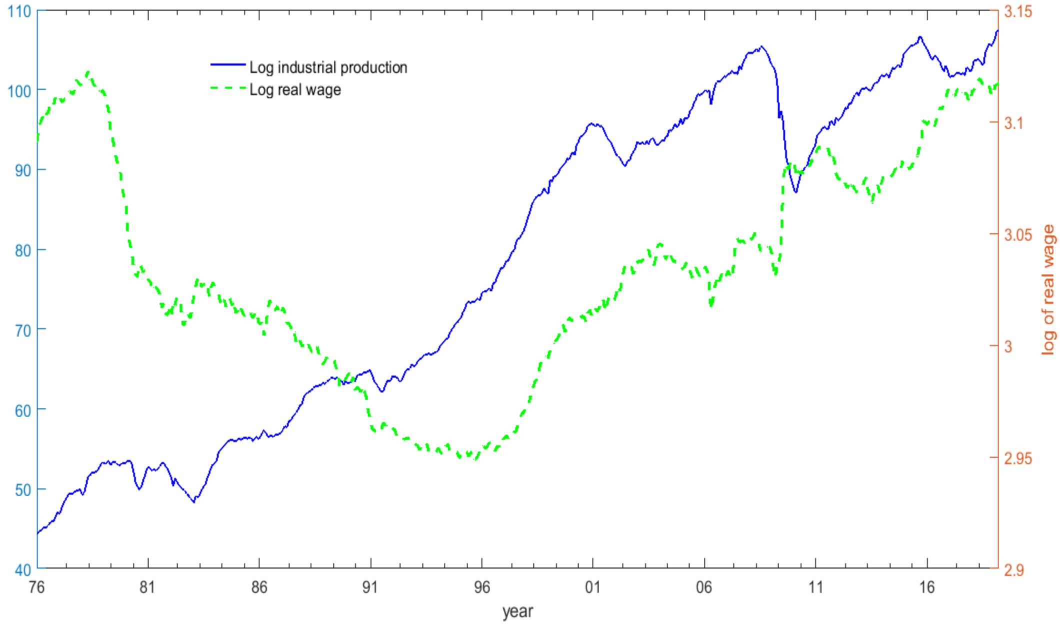
Data is sourced from the Federal Reserve Bank of St Louis and the EIA (US Energy Information Administration). Real interest rate is the secondary market rate of the three-month Treasury bills adjusted by inflation rate. Inflation is based on CPI for all urban consumers less energy (seasonally adjusted). Real effective exchange rate is CPI-based narrow index (comprising 27 economies). Real wage rate is average hourly earnings of production (total private), CPI and seasonally adjusted. Real oil prices is spot crude oil prices WTI (West Texas Intermediate, CPI adjusted), and real natural gas price is wellhead price from 1976 to 2012 extended with import price to 2018. Coal producer price index is for fuels, related products and power and adjusted by CPI. Industrial production index and US unemployment rate are seasonally adjusted. All data included are monthly observations for the period January 1976–May 2018. Data is plotted in Figure 4 (a), (b) and (c). All data series look non-stationary. Energy price moves radically through economic boom and recessions. According to NBER (National Bureau of Economic Research), the recession periods are: 1980:M01–M07, 1981:M07–1982:M11, 1990:M07–1991:M03, 2001:M03–M11 and 2007:M12–2009:M06.



(a) Log of energy prices and inflation



(b) Unemployment, real interest rate and real effective exchange rate



(C) log of industrial production and real wage

Figure 4. Time series plots of data

In order to find the maximum number of integration for the estimation of the LA-VAR model, an augmented Dickey-Fuller test is applied to all variables with a constant and with or without a time trend (Dickey & Fuller 1979). Test results are displayed in Table 1. Lag orders of all tests are selected using BIC with maximum lag order of 12.

Table 1. ADF test for unit root

Variables	Test statistics		Variables	Test statistics	
	Constant	Constant&Trend		Constant	Constant&Trend
$Log\ (ip_t)$	-1.43	-1.77	$\Delta Log\ (ip_t)$	-8.32***	-8.37***
$Log\ (oil_t)$	-2.63*	-2.58	$\Delta Log\ (oil_t)$	-16.70***	-16.69***
$Log\ (gas_t)$	-2.90**	-2.83	$\Delta Log\ (gas_t)$	-17.57***	-17.61***
$Log\ (coal_t)$	-2.00	-0.84	$\Delta Log\ (coal_t)$	-26.92***	-27.22***
$Log\ (wage_t)$	-0.56	-1.52	$\Delta Log\ (wage_t)$	-17.40***	-17.82***
pi_t	-1.55	-2.35	Δpi_t	-16.18***	-16.16***
er_t	-2.08	-2.01	Δer_t	-16.51***	-16.51***
u_t	-3.10**	-3.16*	Δu_t	-7.80***	-7.81***
i_t	-1.52	-3.22*	Δi_t	-18.07***	-18.06***

Note: *** significant at 1%, ** at 5%, * at 10%

For all data series, the ADF tests indicate *I*(1) at 5% level of significance. Therefore, the maximum order of integration in LA-VAR system is set at one and $d_{max} = 1$. Sensitivity analysis with $d_{max} = 2$ is provided as a robustness check.

The LA-VAR model specification includes a constant and a time trend because of the apparent rise for some of the variables shown in Figure 4. The existence of causal relationships from energy prices to industrial production, and vice versa, are investigated. In the baseline model, the minimum window size is set to 108 (9 years; a window size of 96 is used in the robustness check). The choice of window size is to make sure that there are enough observations to initiate the regression, and a sensitivity analysis is included for window size 96. The lag length is selected with BIC with a maximum lag order of 12 and assumed to remain the same for all subsample regressions (the Akaike information criterion (AIC)-based result is included in the robustness check). The selected lag order is one. The overall size over a one-year period is controlled to be 5% with 499 repetitions (a three-year period is included in the robustness check). The sample size of the bootstrapped data series is $T_b = \tau_0 + 11$ ($T_b = \tau_0 + 35$ for the three years) and the maximum value in (6) is taken over a sequence of 12 (36 for the three-years) test statistics.

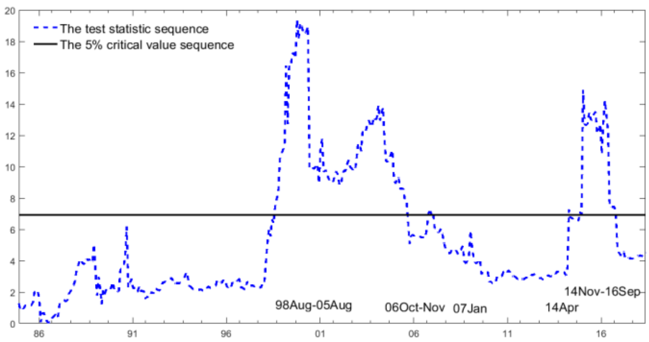
4.3 Recursive Granger causality test

4.3.1 Energy Prices to Industrial Production

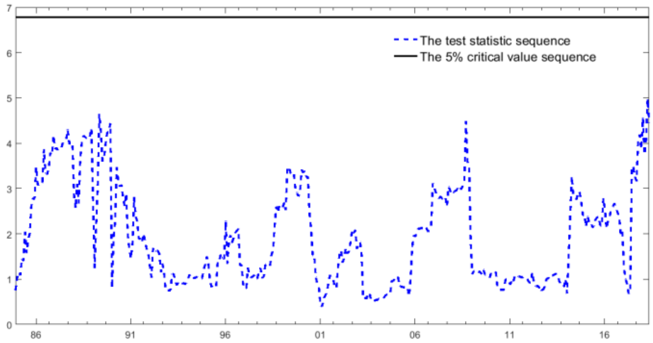
A recursive Granger causality test is carried out using the baseline model specifications. Heteroscedastic consistent time-varying Wald test statistics for causal relation from energy prices to industrial production, together with the bootstrapped 5% critical vales (controlled over a one-year period), are displayed in Figure 5 for real price of oil (a), real price of natural gas (b) and coal producer index (c). The minimum window size is set to 108. The lag length is selected with BIC with a maximum lag order of 12 and assumed to remain the same for all subsample regressions for the whole sample period. The selected lag order is one and it is applied to all subsample regressions. The size over a one-year period is controlled to be 5% with 499 repetitions. The sample size of the bootstrapped data series is $T_b = \tau_0 + 11$ and the maximum value in (6) is taken over a sequence of 12 test statistics.

For the real price of oil, causality is detected from August 1998 to August 2005, October to November 2006, January 2007, April 2014, and from November 2014 to September 2016. The first three causal episodes correspond to a steady increase in real prices of oil and the last two episodes to a drastically decreasing price of oil. For coal producer index, causality is detected for July 2009, from November to December 2009, March 2017 and April 2018. The first two periods correspond to a peaking coal index while the latter two periods correspond to index at a trough. It seems oil price has more predictive power for industrial output during expansions than in recessions. Notice that the Wald statistic for oil price increases dramatically and peaks just ahead of industrial production towards the end of an economic expansion period in 2000, then drops quickly to a trough for the recession of 2001. It then increases again for the next economic expansion period, then drops to insignificance through the global financial crisis (GFC) and remains low afterwards. Not until April 2014 does causality from oil price to industrial production peak again, after which it remains significant for the next two years.

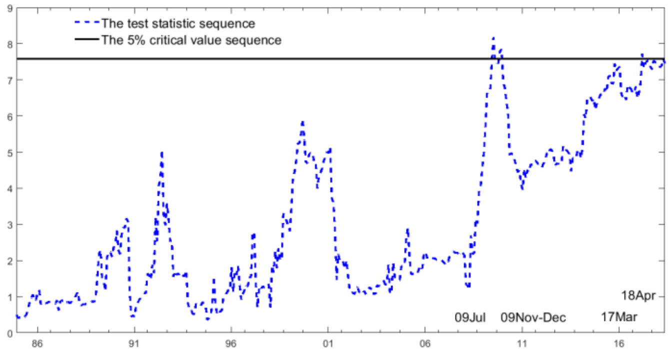
Structural shifts are present within the coal index–industrial production relationship over time and the coal index is also more powerful for predicting industrial output in expansion periods than recessions. Observe that the Wald statistics for coal index increase rapidly at the end of GFC and peaks immediately in July 2009 after the recession ends. During recessions, the coal index rises dramatically while industrial production falls. The index level stays high while the Wald statistic drops quickly and then peaks again, whereas the coal index decreases for the expansion period after the GFC. As illustrated in Figure 6, the US is a coal net-exporting country since 2009; after the GFC, its coal exports increase rapidly while at the same time the causality running from coal price to industrial production strengthens. Between 2012 and 2016 exports decline, which sees the Wald statistic decreasing to a trough, and then increasing as exports pick up from 2017. An additional observation is that, since the mid-80s, oil price and industrial production more or less move together in the same direction. In contrast, the coal index moves in the opposite direction from industrial production until after the 2001 recession, after which they move in the same direction until the onset of the GFC. During the recession their movement is opposite, then more or less parallel again afterwards. These time-varying shifts highlight the importance of carrying out causal relationship detection in a time-varying framework. No causality is detected from natural gas price to industrial production under this specification setting.



(a) Oil



(b) gas



(c) coal

Figure 5. Causality direction: Energy prices to industrial production

Heteroscedastic consistent Wald test statistics are obtained from VAR(1) model in the logs of $y_t = (ip_{t,} \, oil_t, gas_t, coal_t, pi_t, wage_t, er_t, i_t, u_t)'$ and augmented lag d=1. Test sequences are for the real oil price, gas price and coal index from January 1976 to May 2018 with 108 observations for the minimum window size. The 5% bootstrapped critical values are obtained from (6) with 499 repetitions and controlled over a one-year period. Lag orders are selected using BIC with a maximum length of 12 for the whole sample period, and are assumed to be constant.

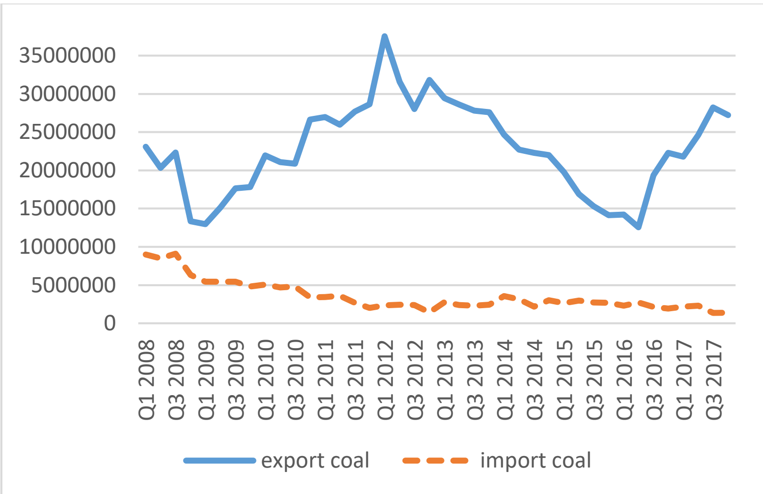


Figure 6. US coal export and import quantity (short tons)

4.3.2 Industrial Production to Energy Prices

Heteroscedastic consistent time-varying Wald test statistics for causal relation from industrial production to energy prices, together with the bootstrapped 5% critical vales (controlled over a one-year period) are displayed in Figure 7. This illustrates the sequences of test statistics for the log of real oil (a) price, natural gas price (b) and coal producer price index (c).

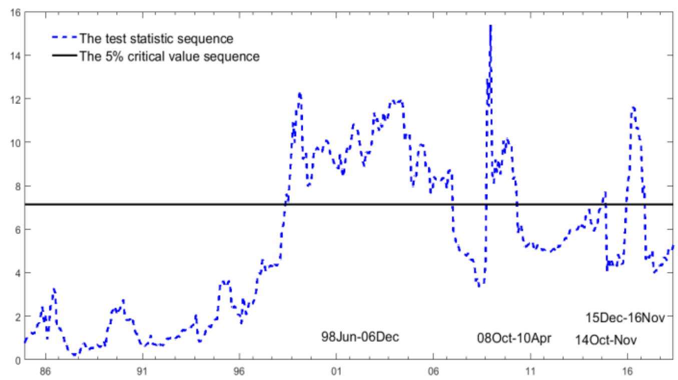
For the real price of oil, causality is detected from June 1998 to December 2006, October 2008 to April 2010, October to November 2014, and from December 2015 to November 2016. In the first episode (starts: June 1998), causality runs from industrial production to oil price, preceding causality running from oil to industrial production (starts: August 1998) two months later, which means the bidirectional relationship is initiated by economic activity; after that, causality runs in both directions until August 2005, and then from October to November 2006. From October 2008, decreasing industrial production drives oil price downwards during the GFC, and then upwards during recovery until April 2010. For the last two episodes tested, causality from industrial production to oil (starts: October 2014) precedes that in the reverse direction (starts: November 2014) one month later, when decreasing economic activity drives oil prices downward and initiates a feedback relationship lasting until September 2016, after which increasing economic activity drives oil prices upward until November 2016.

For the two major episodes between August 1998 and August 2005, and from November 2014 to September 2016 when a feedback relationship occurs, both episodes are initiated by innovations in economic activity (measured by industrial production). Historically, the great surge of oil price between 2002 and 2008 when WTI climbed from $28 to $134 per barrel, was caused by oil demand shifts associated with the expansion of the global economy around 2001, driven particularly by strong oil demand from emerging Asia (Hamilton 2009; Kilian & Hicks 2013). The sharp drop in oil prices from 2014 is explained by a weakening of the global economy and increased oil production in Canada and Russia (Baumeister & Kilian 2016). The bidirectional causal relationship episodes initiated by the economic activity are consistent with the historical explanation of oil prices' rise and fall being demand-driven during those periods. Note that the oil price–industrial production relationship decouples between May 2010 and March 2014, when the oil price is volatile. This is consistent with the findings of Lee, Ni & Ratti (1995) that a stable oil price environment has a greater impact on economy than when oil price movement has been erratic.

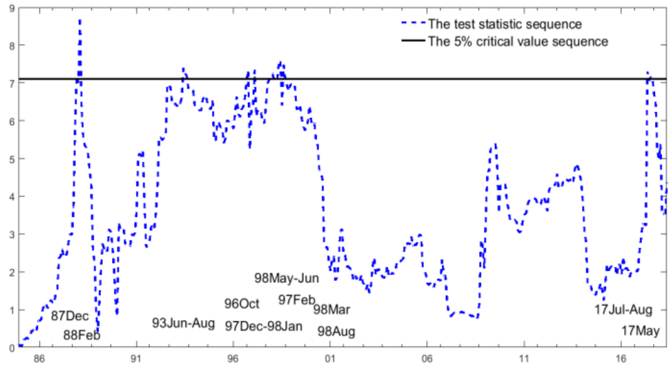
The typical findings of the earlier literature are that oil price increases negatively affect economic growth, but that oil price decreases do not have much effect (Mork 1989; Lee, Ni & Ratti 1995; Hamilton 1996; Jimenez-Rodriguez 2009). More recent literature finds that the relationship is time-varying and sample period dependent. Some of the findings suggest a feedback relationship between 1979 and 2013 (Raza et al. 2018), or a unidirectional causality running from oil prices that reverses after 1985 (Benhmad 2013), or that after 1995 the oil price is predominantly demand-driven (Aguiar-Conraria & Soares 2011). This result is consistent with the literature in finding a bidirectional causal relationship between 1998 and 2005. The second episode of bidirectional relationship between 2014 and 2016 is a new finding in this literature.

For natural gas, industrial production causes price increases at the end of the 1980s, then on-and-off in the 1990s and in mid-2017; all episodes occur during economic expansion periods when industrial production is on the way up. As illustrated in Figure 8, during these periods, the energy consumption of natural gas (measured as a percentage) is on the rise while oil and coal are in decline. Between 2009 and 2014, the relationship gets stronger (although it is not detected at 5%), when natural gas consumption increases. This result shows that when natural gas consumption increases relative to oil and coal, the causality from industrial production to natural gas price becomes stronger. Literature on the subject of US natural gas has been sparse and equivocal; for example, no relationship is found between gas price and industrial production (Kliesen 2006) or modest positive impacts on the economy after shale gas boom at regional level are suggested (Weber 2012). This finding of a unidirectional causal relationship running from industrial production to natural gas price adds to the scarce evidence in the literature.

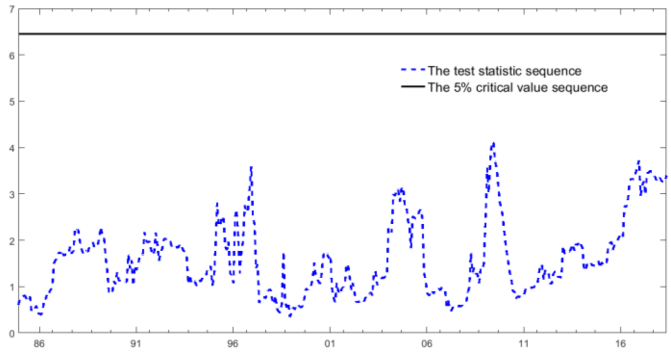
No causality is detected from industrial production to coal producer price index under this specification setting. Although economic activity does not have a causal impact on the coal producer index, the finding of a unidirectional causal relationship running from coal producer price index to industrial production in 2009, 2017 and 2018 adds to the scarce literature on this topic. The conclusion that a causal relationship can be detected need to be checked for robustness against alternative test specification settings, which is delivered in the next section.



(a) oil



(b) gas



(c) coal

Figure 7. Causality direction: Industrial production to energy prices

The heteroscedastic consistent Wald test statistics are obtained from VAR(1) model in the logs of: $y_t = (ip_{t,}\, oil_t, gas_t, coal_t, pi_t, wage_t, er_t, i_t, u_t)'$ and augmented lag d=1. Test sequences are for the real oil price, gas price and coal index from January 1976 to May 2018 with 108 observations for the minimum window size. The 5% bootstrapped critical values are obtained from (6) with 499 repetitions and controlled over a 1-year period. Lag orders are selected using BIC with a maximum length of 12 for the whole sample period, and are assumed to be constant.

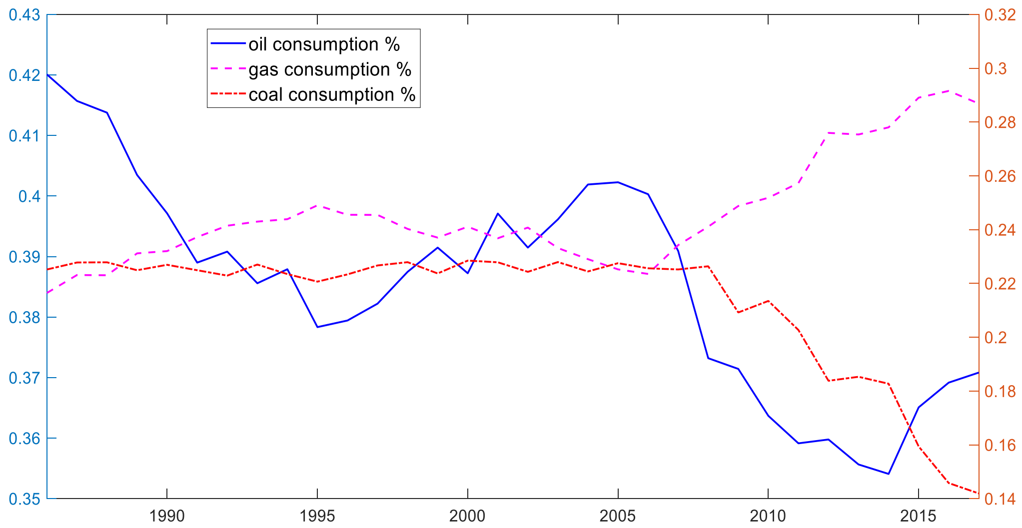


Figure 8. Energy consumption by source (percentage)

4.3.3 Sensitivity analysis

In order to investigate the robustness of the conclusions on Granger causality from energy prices to industrial production and vice versa, sensitivity analysis is carried out. The baseline specifications used to obtain the main result in the previous section (minimum window size of 108, 5% critical value controlled over one-year period, augmented lag being one (d=1), lag selection using BIC, heteroscedastic consistent statistics and data in logs), are replaced using alternative specifications one at a time with the rest of the specifications unchanged. The alternative specifications are: a minimum window size of 96 (eight years) observations is used to search for local variability in more detail in the test statistics; 5% bootstrapped critical values controlled over a three-year period are used; the regression model is augmented with two lags (d=2) to cover potentially higher levels of integration in the sample; lags are selected using AIC; homoscedastic consistent test statistics are estimated; and data in levels are used in estimation. Various scenarios are discussed in section below and graphs are included in the Appendix.

4.3.3.1 Minimum window size of 96

Figure A(1) displays heteroscedastic consistent time-varying Wald test statistics for causal relations from energy prices to industrial production, together with the bootstrapped 5% critical vales (controlled over a one-year period). It illustrates the sequences of test statistics for the log of real oil price, natural gas price and coal producer price index.

For oil price statistic, a smaller minimum window size of 96 picks up an extra earlier episode. Other episodes are also longer than those seen at window size 108, i.e. they start earlier and end later. Similarly, an extra earlier episode for natural gas price is detected. For the coal index, the episodes are identical for both window sizes. Causality from energy prices to industrial production is robust to change of minimum window size.

In Figure A(2), heteroscedastic consistent time-varying Wald test statistics for causal relation from industrial production to energy prices, together with the bootstrapped 5% critical vales (controlled over a one-year period) are displayed. It illustrates the sequence of test statistics for the log of real oil price, natural gas price and coal producer price index.

For oil price statistic, the first episode starts two months later and the last episode starts a few months earlier on the timeline compared to the episodes from window size 108, with two extra episodes detected in between. For natural gas price, the first episode is the same, while the last episode starts and ends earlier, and lost five on-and-off episodes in between. For the coal index, test statistics remains insignificant under the new setting. Causality from industrial production to energy prices is robust to change of minimum window size.

4.3.3.2 Controlled over three years (yr=3)

Figure A(3) displays the heteroscedastic consistent time-varying Wald test statistics for causal relation from energy prices to industrial production, together with the bootstrapped 5% critical vales. The probability of drawing at least one false positive conclusion is controlled at 5% over a three-year period instead of a one-year period. The critical values are obtained from (6) with 499 repetitions with bootstrap sample size $T_b = \tau_0 + 35$. A lower chance of making false positive conclusion is expected with this stricter rejection criterion; therefore, a lower power of causality detection is also expected. For oil price statistic, only the two main episodes remain detected, and their durations become shorter (start later and end sooner) compared to the baseline setting of yr=1. For natural gas price, the relationship remains insignificant and for the coal index the episodes detected under yr=1 setting are lost, due to a higher critical value under the yr=3 specification.

In Figure A(4), causality runs from industrial production to energy prices; the rest of the settings are the same as Figure A(3). For oil price statistic, since critical value increased under the yr=3 setting, the first episode is cut through and disintegrated into a series of short episodes compared to the yr=1 setting. Nonetheless, the causality period again starts earlier and ends sooner than yr=1 setting, thus episodes are shorter. For natural gas price, only the first episode remains, while the coal index test statistic remains insignificant.

4.3.3.3 Maximum order of integration is set as two (d=2)

In Figure A(5), heteroscedastic consistent time-varying Wald test statistics for causal relation from energy prices to industrial production, together with the bootstrapped 5% critical vales (controlled over a one-year period) are displayed. It illustrates the sequence of test statistics for the log of real oil price, natural gas price and coal producer price index. The potential maximum order of integration is set at d=2.

For oil price, the higher integration setting (d=2) does not change the shape of the test statistic significantly. Causality becomes slightly stronger from the late 1980s, but the two main episodes stay roughly the same with small variations. Natural gas price test statistics pick up an early episode in 1987, while the coal index test also picks up three episodes in 1990 where causality is stronger; for recent years, however, it is weaker compared to the d=1 setting.

In Figure A(6), causality runs from industrial production to energy price and the rest of the settings are the same as for Figure A(5). For oil price, the causality increases in the late 1980s but is weaker towards the end of the sample. The episode from 1998 to 2010 does not vary significantly. Under the d=2 setting, natural gas episodes are similar to the d=1 setting and results are same for the coal index. Causality detection is robust to different integration settings.

4.3.3.4 VAR lag selection using AIC

In Figure A(7), heteroscedastic consistent time-varying Wald test statistics for causal relation from energy prices to industrial production, together with the bootstrapped 5% critical vales (controlled over a one-year period) are displayed. Lag orders are selected using AIC with a maximum length of 12 for the whole sample period, and are assumed to be constant. The selected lag order is 3. The figure illustrates the sequence of test statistics for the log of real oil price, natural gas price and coal producer price index.

For oil price statistic, causality is detected earlier in 1995 compared to the baseline result, and the episode during 1998 and 2005 is still present and is later extended to 2008. The episode between 2014 and 2016 is missed and a causality in mid-2018 is picked up instead. For the coal index, test statistics remain high in recent years and natural gas is still insignificant.

Figure A(8) shows causality from industrial production to energy prices; the rest of settings are the same as for Figure A(7). For oil price, the first episode becomes much shorter and the other episodes commence earlier and are also shorter. Natural gas causality is detected only for recent years, and coal index causality detected in 2000 and 2001. The causality result seems to be sensitive to the VAR lag length selection, which suggests caution in this causality test; using different lag length selection criteria produces different results.

4.3.3.5 Data estimated in levels

In Figure A(9), heteroscedastic consistent time-varying Wald test statistics for causal relation from energy prices to industrial production, together with the bootstrapped 5% critical vales (controlled over a one-year period) are displayed. The figure illustrates the sequence of test statistics for real oil price, natural gas price and coal producer price index in levels. This alternative setting is tested because in the literature some studies use data in the levels and others use data in logs (Mork 1989; Bernanke et al. 1997; Naccache 2010).

For oil price, the first large episode becomes shorter and is divided into two series, while towards the end of sample a short episode between 2016 and 2018 is detected. Natural gas price’s test statistics remain insignificant, while for the coal index, test statistics are lower towards the end compared to data in logs setting.

Figure A(10) shows causality from industrial production to energy prices; the rest of settings are the same as for Figure A(9). For oil price, the first main episode is delayed slightly and test statistics during the middle period are higher, with extra causality detected towards the end of the sample period. Causality for natural gas during the late 1980s and for most of the 1990s is still detected, while the test statistics towards the end of the sample period are lower compared to data in the levels setting; the coal index statistics remain insignificant. The causality result is robust under data settings in logs versus in levels.

4.3.3.6 Estimation under assumption of homoscedasticity

In Figure A(11), homoscedastic time-varying Wald test statistics for causal relation from energy prices to industrial production, together with the bootstrapped 5% critical vales (controlled over a one-year period) are displayed. The figure illustrates the sequence of test statistics for the log of real oil price, natural gas price and coal producer price index. This test criterion is examined due to the fact that heteroscedasticity is likely to be present within monthly data (Bollerslev 1987).

For oil price, the homoscedastic test statistic is detected later than the heteroscedastic consistent test sequences, the episode is shorter, and causality in 2006 and 2007 is not detected. Natural gas causality is magnified during the GFC, while the coal index is not amplified towards the end of sample as it is in the heteroscedastic consistent test sequences.

Figure A(12) shows causality running from industrial production to energy prices; the rest of the settings are the same as for Figure A(11). For oil price, the homoscedastic test statistic detected causality in 2013 but not in 2015. Causality for natural gas is still detected for the end of the 1980s and most of the 1990s but the episode in 2017 is missed. The coal index remains insignificant.

In summary, the detection of causal episodes appears to be robust to changes in setting with minor variations in start and/or end dates for the episodes, expect for AIC lag selection and homoscedastic statistic.

4.4 Whole sample LA-VAR Granger causality test

The existence of causal relationships from energy prices to industrial production and vice versa is investigated for the whole sample period. The lag length is selected using BIC with a maximum lag order of 12 and assumed to remain the same for all subsample regressions for the whole sample period. The selected lag order is one. The 5% critical values are obtained from residual bootstrapping with 499 repetitions. Results are shown in Table 2.

Table 2. Whole sample Granger causality test

Causality direction	Test statistics	5% Critical value
$Log\ (oil_t)$ to $Log\ (ip_t)$	11.81	3.78
$Log\ (gas_t)$ to $Log\ (ip_t)$	6.69	3.94
$Log\ (coal_t)$ to $Log\ (ip_t)$	22.12	4.06
$Log\ (ip_t)$ to $Log\ (oil_t)$	16.48	4.05
$Log\ (ip_t)$ to $Log\ (gas_t)$	13.02	4.27
$Log\ (ip_t)$ to $Log\ (gas_t)$	9.14	4.39

As shown above, all test statistics are higher than 5% bootstrapped critical value. The null hypothesis of no-Granger causality is rejected in all cases and the conclusion is that, for whole sample LA-VAR test, causality runs from oil, gas and coal to industrial production and vice versa. Being completely different from the subsample causality test, this whole sample result highlights the danger of using Granger causality Wald tests over the full sample period. Since the economic structure of the US has changed over the sample period (i.e. there are multiple structural breaks), the assumption of a constant relationship between US industrial production and energy prices is invalid.

5. Conclusion

This thesis studies the time-varying causal relationships between energy prices (oil, gas and coal) and industrial production in the US from 1976 to 2018, applying a subsample recursive evolving Granger causality test based on a LA-VAR system.

Results for oil price mostly confirm the findings in the literature, namely that a bidirectional relationship exists between the real price of oil and industrial production between August 1998 and August 2005, and that oil price is predominantly demand-driven in the post-1995 period. This is reflected in the two major bidirectional causal episodes detected, which are initiated by innovations in economic activity, and the unidirectional causality running from industrial production to oil price.

Since the literature for natural gas–economy and coal price–economy relationships is both sparse and equivocal, the results from this study enhance the understanding of the energy price–economy nexus. A unidirectional causality running from economic activity to natural gas prices in the late 1980s and 1990s seems to be consumption-driven as the US switches away from coal, while a unidirectional causality running from coal producer index to economic activity in the post-2009 period appears to be driven by demand from abroad through export.

The strengths of this study are that it used long-range data from 1976 to 2018 (over 40 years), incorporated most of the transmission channels recognised by economics theory literature into the

VAR model, and applied a new econometric approach that has been proven to outperform other methods in regards to the time-varying Granger causality test.

It is arguable that the observed fluctuations in the price (for reasons of supply and demand variations), introduce uninsurable uncertainties into production plans. The following policy recommendations are suggested: (a) promote the development of energy sources that do not demonstrate such high price volatility (such as renewables and nuclear energy); and (b) extend the coverage of insurance markets.

As to the limitations of this study, failure to reject the null hypothesis of no-Granger causality does not necessarily mean there is no actual causality. The policy inferences from this study are limited to the US economy using the variables chosen; omitted variables may have produced different results. Future studies can explore the specific economic responses to energy price increases versus energy price decreases accordingly.

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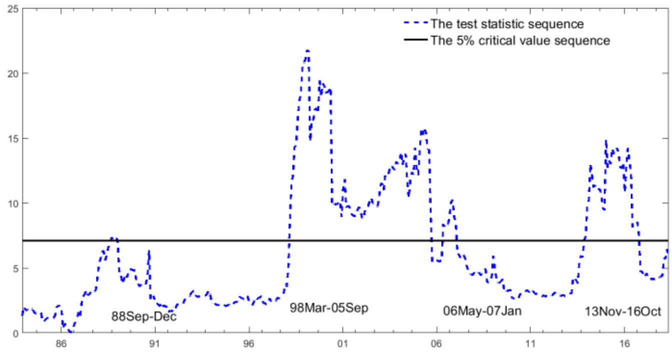
Appendix

Sensitivity Analysis results



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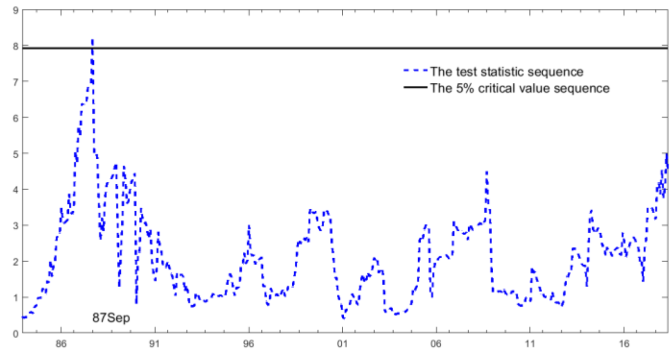
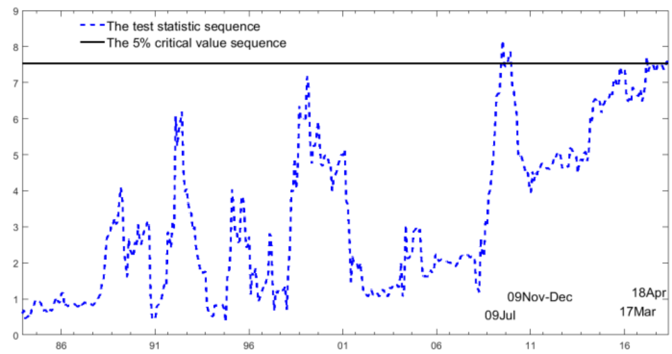


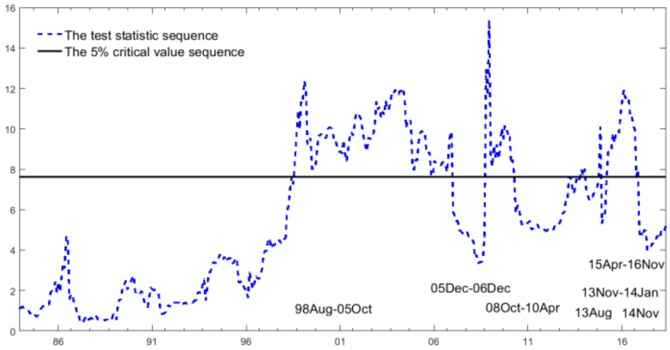
(b) gas



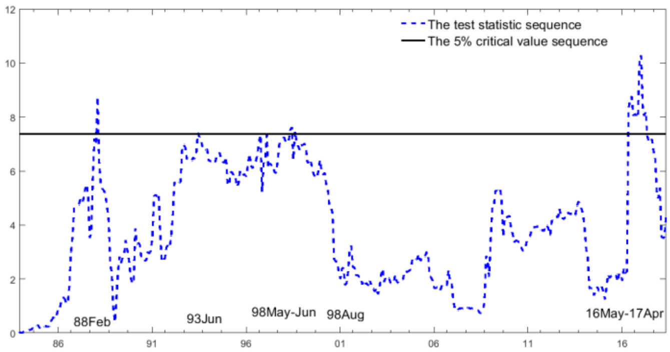
(c)coal

Figure A(1). Causality direction: Energy prices to industrial production

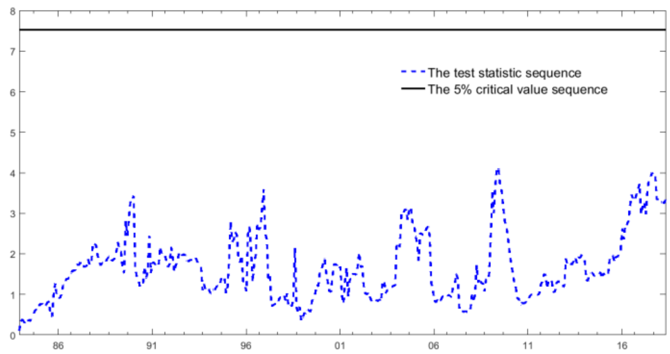
The heteroscedastic consistent Wald test statistics obtained from VAR(1) model in the logs of: $y_t = \left(ip_{t,} \, oil_t, gas_t, coal_t, pi_t, wage_t, er_t, i_t, u_t\right)'$ and augmented lag d=1. Test sequences are for the real oil price, gas price and coal index from January 1976 to May 2018 with 96 observations for the minimum window size. The 5% bootstrapped critical values are obtained from (6) with 499 repetitions and controlled over a 1-year period. Lag orders are selected using BIC with a maximum length of 12 for the whole sample period, and are assumed to be constant.



(a) oil



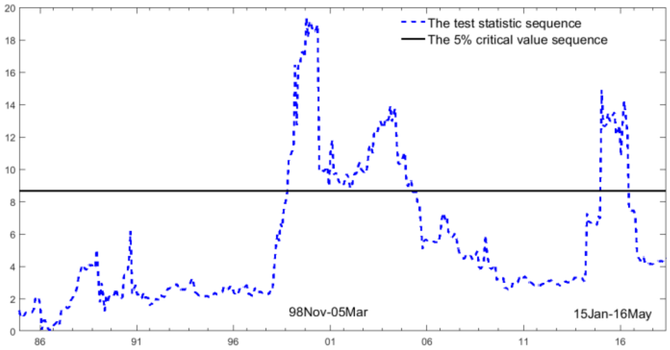
(b) gas



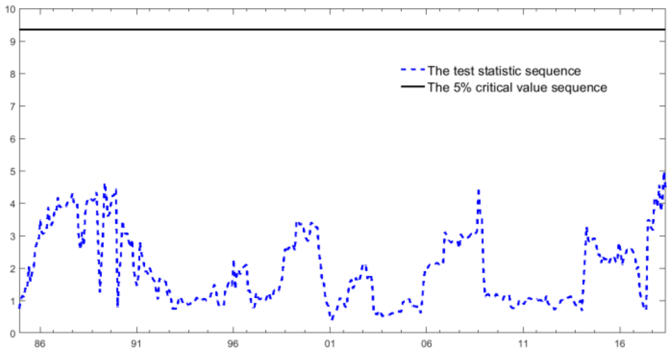
(c)coal

Figure A(2). Causality direction: Industrial production to energy prices

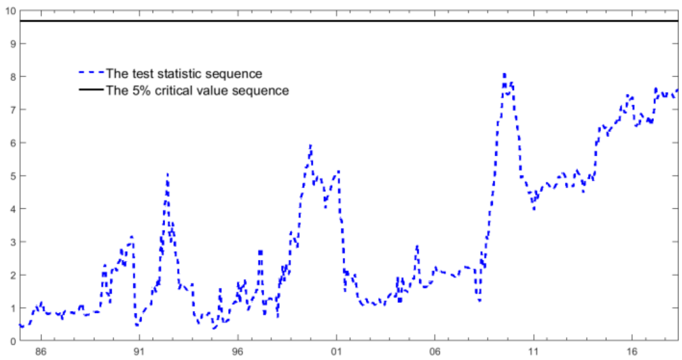
The heteroscedastic consistent Wald test statistics obtained from VAR(1) model in the logs of: $y_t = (ip_{t,} oil_t, gas_t, coal_t, pi_t, wage_t, er_t, i_t, u_t)'$ and augmented lag d=1. Test sequences are for the real oil price, gas price and coal index from January 1976 to May 2018 with 96 observations for the minimum window size. The 5% bootstrapped critical values are obtained from (6) with 499 repetitions and controlled over a 1-year period. Lag orders are selected using BIC with a maximum length of 12 for the whole sample period, and are assumed to be constant.



(a) oil



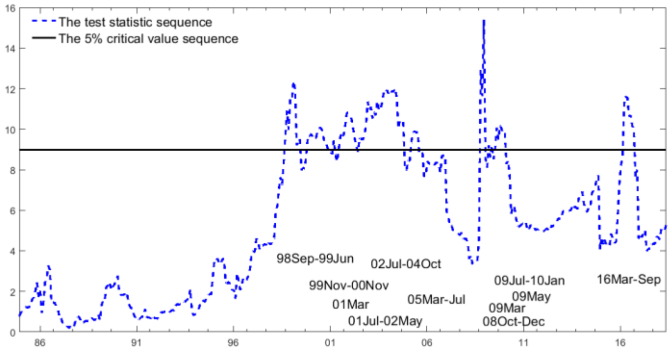
(b) gas



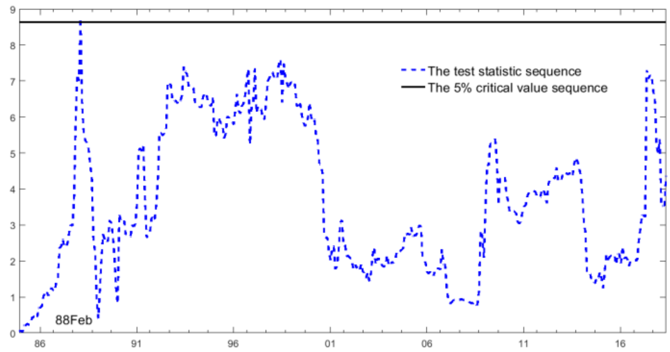
(c)coal

Figure A(3). Causality direction: Energy prices to industrial production

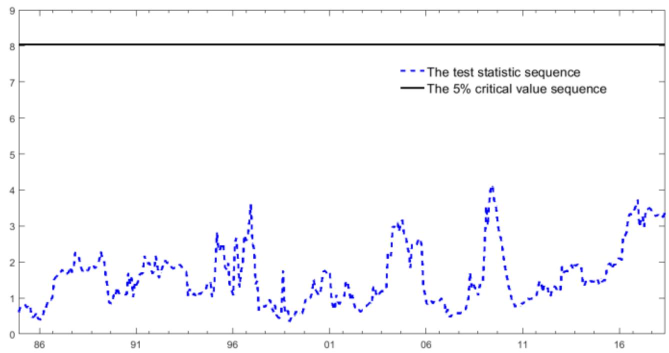
The heteroscedastic consistent Wald test statistics obtained from VAR(1) model in the logs of: $y_t = (ip_{t,} \, oil_t, gas_t, coal_t, pi_t, wage_t, er_t, i_t, u_t)'$ and augmented lag d=1. Test sequences are for the real oil price, gas price and coal index from January 1976 to May 2018 with 108 observations for the minimum window size. The 5% bootstrapped critical values are obtained from (6) with 499 repetitions and controlled over a 3-year period. Lag orders are selected using BIC with a maximum length of 12 for the whole sample period, and are assumed to be constant.



(a) oil



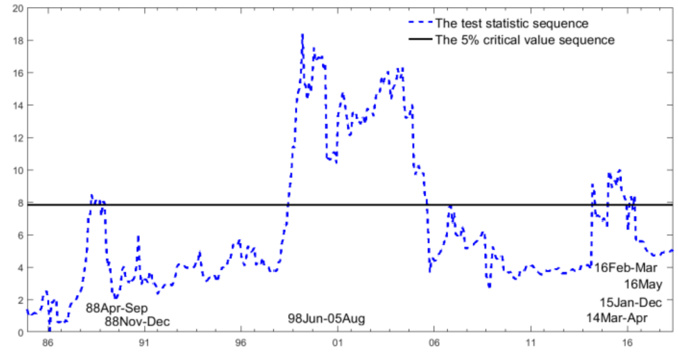
(b) gas



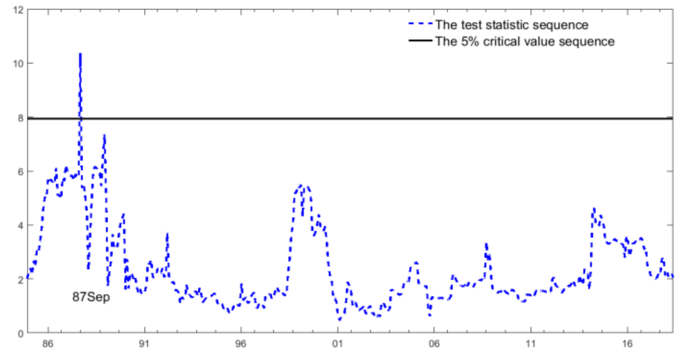
(c) coal

Figure A(4). Causality direction: Industrial production to energy prices

The heteroscedastic consistent Wald test statistics is obtained from VAR(1) model in the logs of: $y_t = \left(ip_{t,} \, oil_t, gas_t, coal_t, pi_t, wage_t, er_t, i_t, u_t\right)'$ and augmented lag d=1. Test sequences are for the real oil price, gas price and coal index from January 1976 to May 2018 with 108 observations for the minimum window size. The 5% bootstrapped critical values are obtained from (6) with 499 repetitions and controlled over a 3-year period. Lag orders are selected using BIC with a maximum length of 12 for the whole sample period, and are assumed to be constant.



(a) oil



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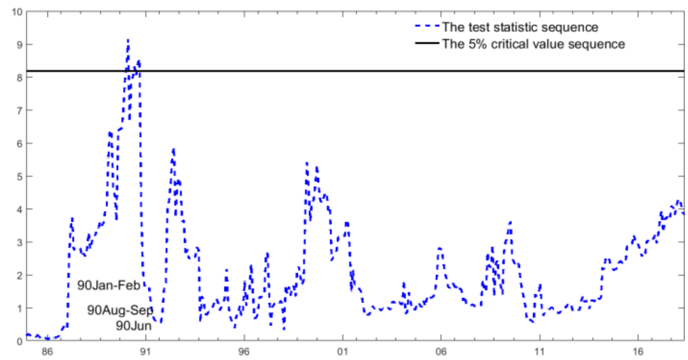
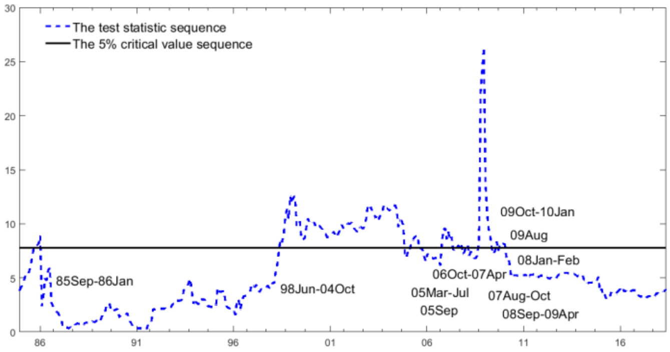


(c)coal

Figure A(5). Causality direction: Energy prices to industrial production

The heteroscedastic consistent Wald test statistics is obtained from VAR(1) model in the logs of: $y_t = (ip_{t,}\ oil_t, gas_t, coal_t, pi_t, wage_t, er_t, i_t, u_t)'$ and augmented lag d=2. Test sequences are for the real oil price, gas price and coal index from January 1976 to May 2018 with 108 observations for the minimum window size. The 5% bootstrapped critical values are obtained from (6) with 499 repetitions and controlled over a 1-year period. Lag orders are selected using BIC with a maximum length of 12 for the whole sample period, and are assumed to be constant.



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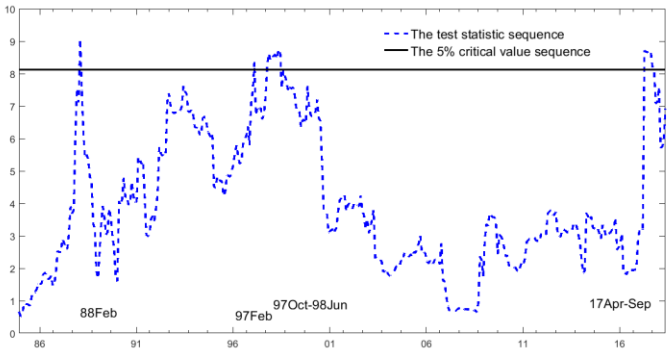

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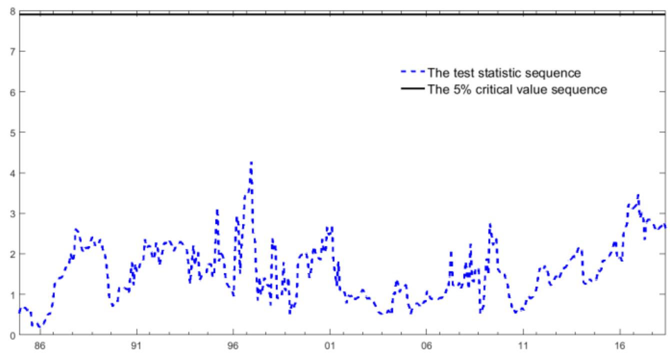
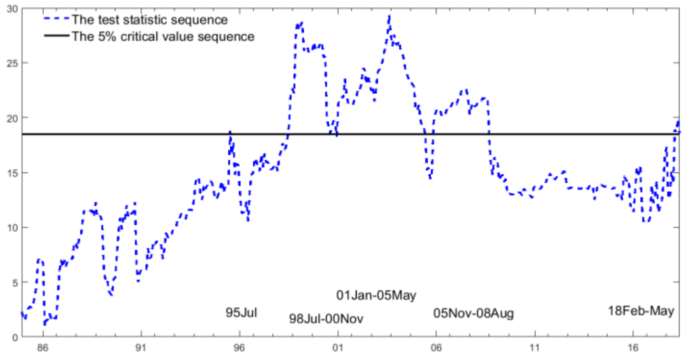


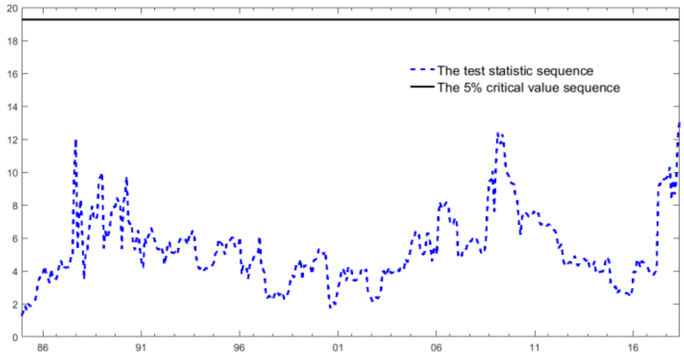
(c) coal

Figure A(6). Causality direction: Industrial production to energy prices

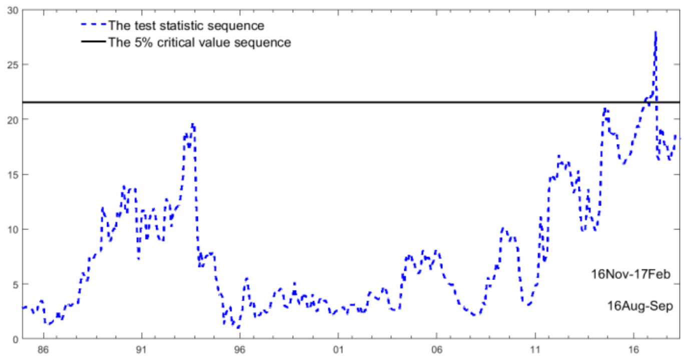
The heteroscedastic consistent Wald test statistics is obtained from VAR(1) model in the logs of: $y_t = (ip_{t,} \, oil_t, gas_t, coal_t, pi_t, wage_t, er_t, i_t, u_t)'$ and augmented lag d=2. Test sequences are for the real oil price, gas price and coal index from January 1976 to May 2018 with 108 observations for the minimum window size. The 5% bootstrapped critical values are obtained from (6) with 499 repetitions and controlled over a 1-year period. Lag orders are selected using BIC with a maximum length of 12 for the whole sample period, and are assumed to be constant.



(a) oil



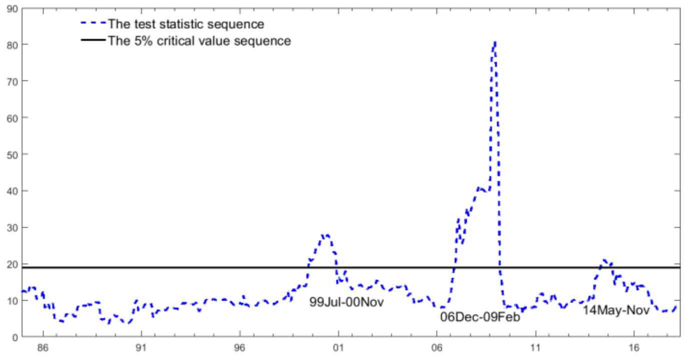
(b) gas



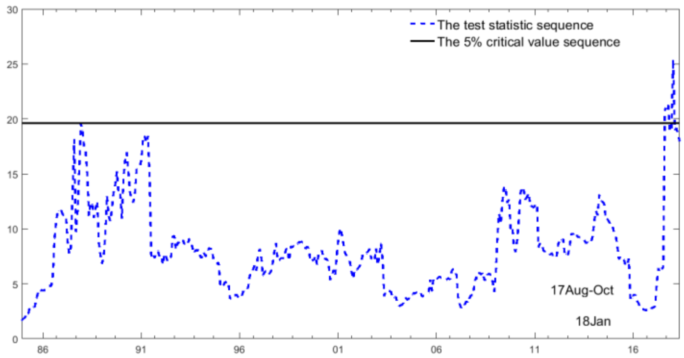
(c) coal

Figure A(7). Causality direction: Energy prices to industrial production.

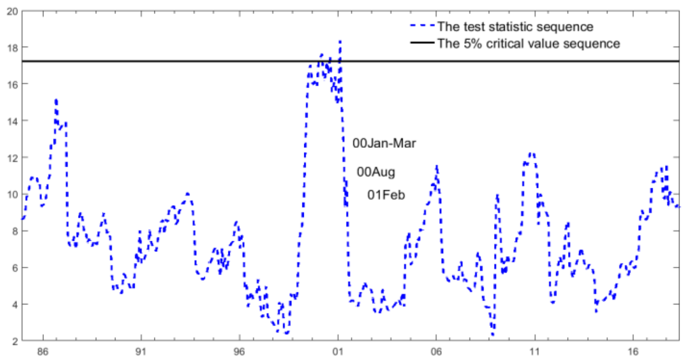
The heteroscedastic consistent Wald test statistics is obtained from VAR(3) model in the logs of: $y_t = (ip_{t,}\, oil_t, gas_t, coal_t, pi_t, wage_t, er_t, i_t, u_t)'$ and augmented lag d=1. Test sequences are for the real oil price, gas price and coal index from January 1976 to May 2018 with 108 observations for the minimum window size. The 5% bootstrapped critical values are obtained from (6) with 499 repetitions and controlled over a 1-year period. Lag orders are selected using AIC with a maximum length of 12 for the whole sample period, and are assumed to be constant.



(a) oil



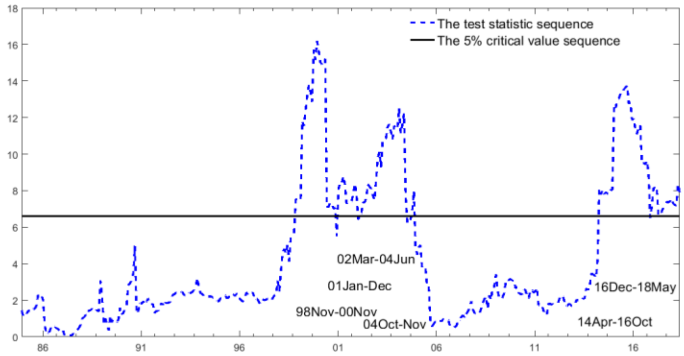
(b) gas



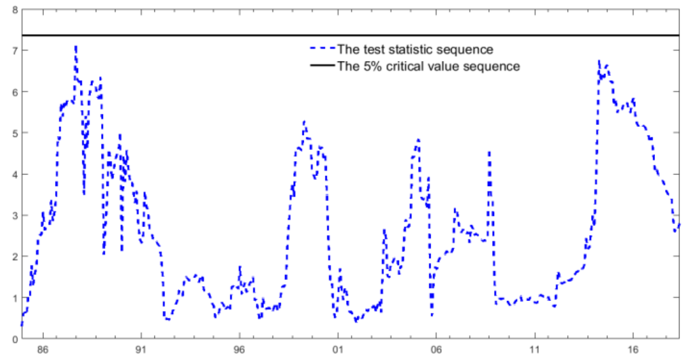
(c) coal

Figure A(8). Causality direction: Industrial production to energy prices

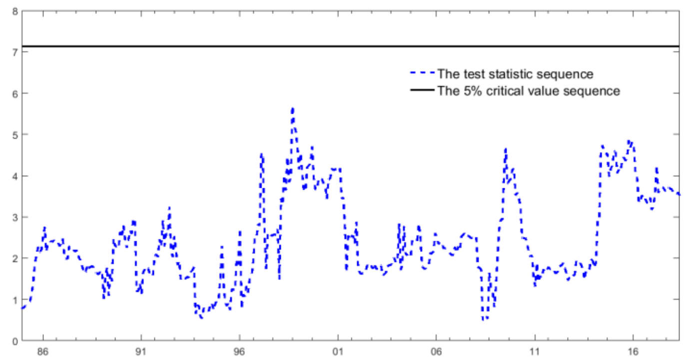
The heteroscedastic consistent Wald test statistics is obtained from VAR(3) model in the logs of: $y_t = (ip_{t,} oil_t, gas_t, coal_t, pi_t, wage_t, er_t, i_t, u_t)'$ and augmented lag d=1. Test sequences are for the real oil price, gas price and coal index from January 1976 to May 2018 with 108 observations for the minimum window size. The 5% bootstrapped critical values are obtained from (6) with 499 repetitions and controlled over a 1-year period. Lag orders are selected using AIC with a maximum length of 12 for the whole sample period, and are assumed to be constant.



(a) oil



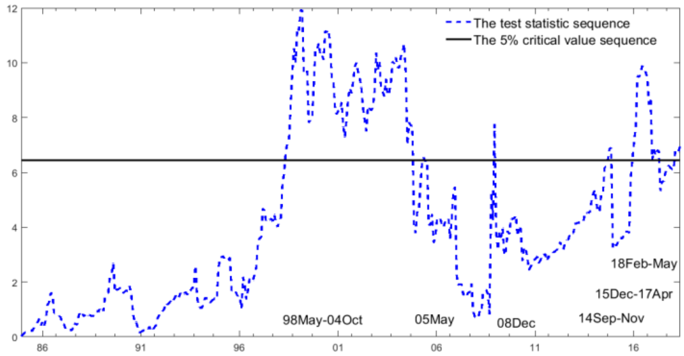
(b) gas



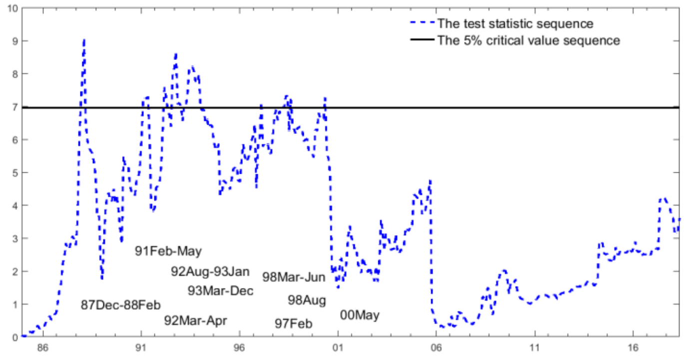
(c) coal

Figure A(9). Causality direction: Energy prices to industrial production

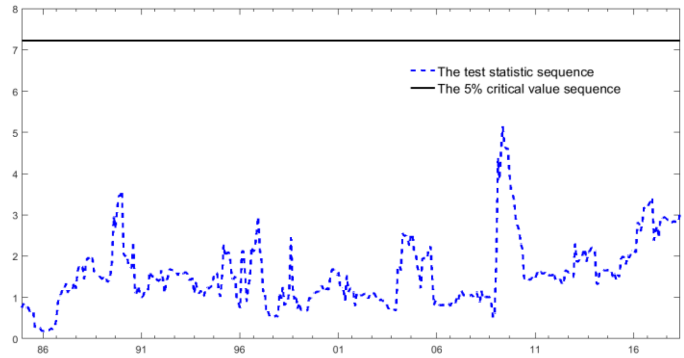
The heteroscedastic consistent Wald test statistics is obtained from VAR(1) model in the levels of: $y_t = (ip_{t,} \, oil_t, gas_t, coal_t, pi_t, wage_t, er_t, i_t, u_t)'$ and augmented lag d=1. Test sequences are for the real oil price, gas price and coal index from January 1976 to May 2018 with 108 observations for the minimum window size. The 5% bootstrapped critical values are obtained from (6) with 499 repetitions and controlled over a 1-year period. Lag orders are selected using BIC with a maximum length of 12 for the whole sample period, and are assumed to be constant.



(a) oil



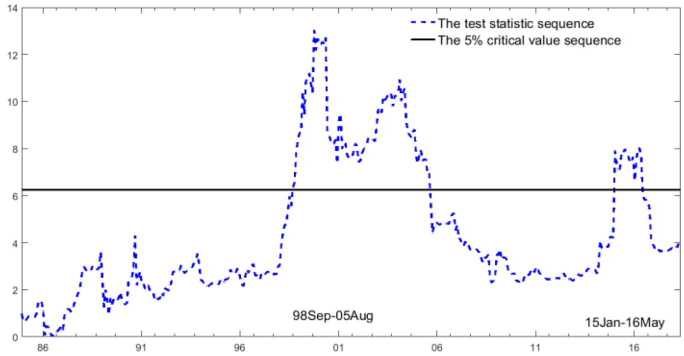
(b) gas



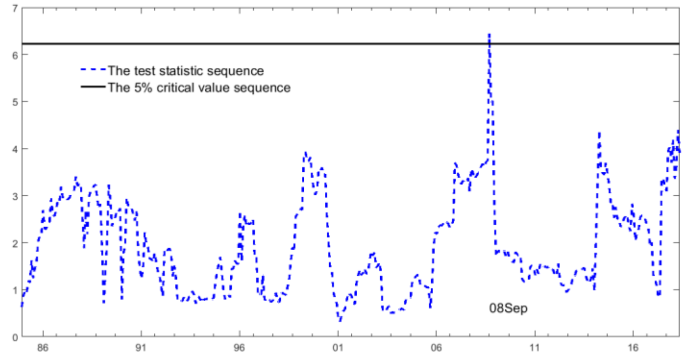
(c) coal

Figure A(10). Causality direction: Industrial production to energy prices

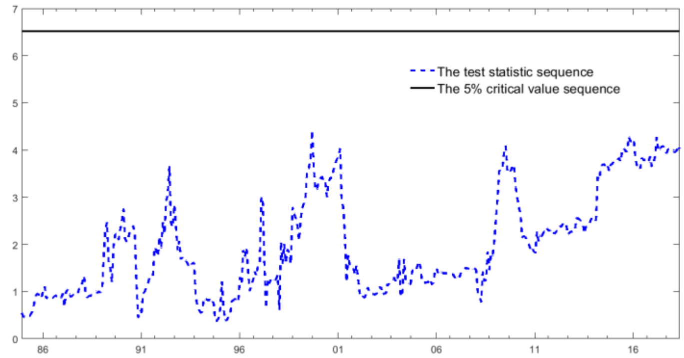
The heteroscedastic consistent Wald test statistics is obtained from VAR(1) model in the levels of: $y_t = (ip_{t,} oil_t, gas_t, coal_t, pi_t, wage_t, er_t, i_t, u_t)'$ and augmented lag d=1. Test sequences are for the real oil price, gas price and coal index from January 1976 to May 2018 with 108 observations for the minimum window size. The 5% bootstrapped critical values are obtained from (6) with 499 repetitions and controlled over a 1-year period. Lag orders are selected using BIC with a maximum length of 12 for the whole sample period, and are assumed to be constant.



(a) oil



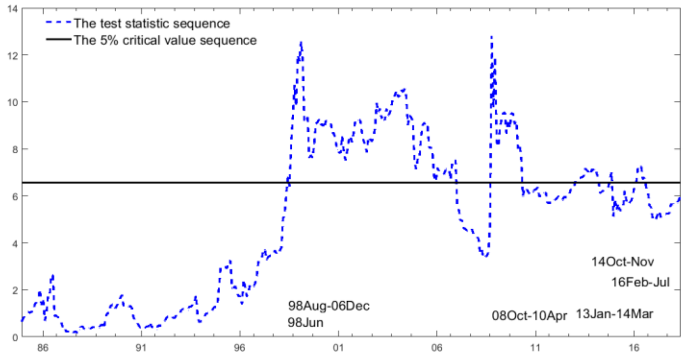
(b) gas



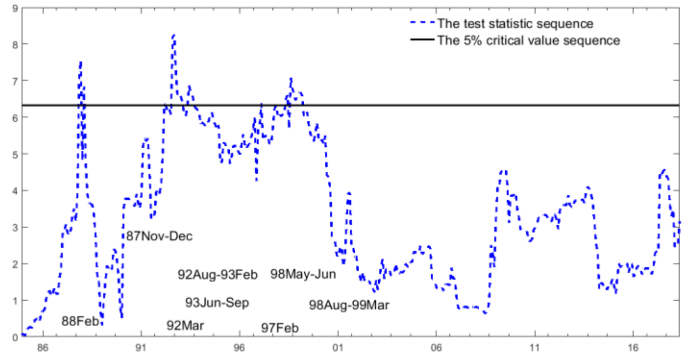
(c) coal

Figure A(11). Causality direction: Energy prices to industrial production

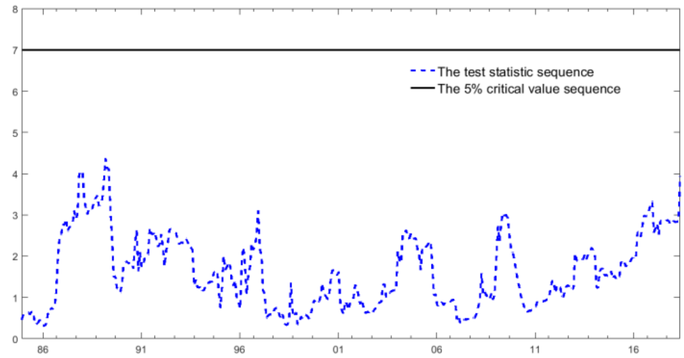
The homoscedastic Wald test statistics is obtained from VAR(1) model in the logs of: $y_t = (ip_{t,}\, oil_t, gas_t, coal_t, pi_t, wage_t, er_t, i_t, u_t)'$ and augmented lag d=1. Test sequences are for the real oil price, gas price and coal index from January 1976 to May 2018 with 108 observations for the minimum window size. The 5% bootstrapped critical values are obtained from (6) with 499 repetitions and controlled over a 1-year period. Lag orders are selected using BIC with a maximum length of 12 for the whole sample period, and are assumed to be constant.



(a) oil



(b) gas



(c) coal

Figure A(12). Causality direction: industrial production to energy prices

The homoscedastic Wald test statistics is obtained from VAR(1) model in the logs of: $y_t = (ip_{t,} oil_t, gas_t, coal_t, pi_t, wage_t, er_t, i_t, u_t)'$ and augmented lag d=1. Test sequences are for the real oil price, gas price and coal index from January 1976 to May 2018 with 108 observations for the minimum window size. The 5% bootstrapped critical values are obtained from (6) with 499 repetitions and controlled over a 1-year period. Lag orders are selected using BIC with a maximum length of 12 for the whole sample period, and are assumed to be constant.

Table A(1). Variable choices in literature.

Author/title	**Scope**	**Summary**
Hamilton (1983) *Oil and the macroeconomy since World War II*	US 1948–80 quarterly Divided into 1948–72 and 1973–80 subsamples	7-variable VAR (Sims 1980): real GNP, unemployment, implicit price deflator, hourly compensation per worker, import prices, M1, change in oil price.
Burbidge & Harrison (1984) *Testing for the effects of oil-price rises using vector autoregressisons*	US, Japan, Germany, UK, Canada 1961:1–1982:6 monthly Subsamples	7 variable VAR (Sims 1980): relative price of oil, total industrial production in OECD countries other than country involved, industrial production in domestic economy, short-term interest rate, currency and demand deposits, average hourly earnings in manufacturing, CPI.
Gisser & Goodwin (1986) *Crude oil and the macroeconomy: Tests of some popular notions*	US 1961:1–1982:4, quarterly Pre- and post-1973 subsamples	Reduced form (St Louis model): real GNP, price level P, unemployment, real investment, money supply, federal expenditures measure of fiscal policy, nominal crude oil price.
Mork (1989) *Oil and the macroeconomy when prices go up and down: An extension of Hamilton's results*	US 1949:1–1988:2, quarterly Full sample	7-variable VAR (Sims 1980): real GNP growth, inflation (GNP deflator), 3-month Treasury bill rate, unemployment rate, wage rate, import price inflation, real oil price changes.
Mork et al. (1994) *Macroeconomic responses to oil price increases and decreases in 7 OECD countries*	US, Canada, Japan, France, Germany, UK, Norway. 1967:3–1992:4, quarterly Full sample	Bivariate and multivariate. GDP growth, oil price increases and decreases as separate variables, contemporaneous changes in oil price, inflation, interest rate, unemployment, real wage, industrial production, oil import ratio.
Lee, Ni & Ratti (1995) *Oil shocks and the macroeconomy: The role of price variability*	US 1949.1–1992.3, quarterly Full sample	(Sims 1980): same as Mork (1989), plus oil price changes/shocks. Univariate GARCH error process augmented VAR.
Ferderer (1996) *Oil price volatility and the macroeconomy*	US 1.1.1970–31.12.1990 Full sample	Ordering: monetary policy variable (federal funds rate), real oil price level, oil price volatility, log of industrial production.
Hooker (1996) *What happened to the oil price–macroeconomy relationship?*	US 1948:1–1994:2, quarterly Full sample and subsamples	Granger causality VAR: oil price, 3-month Treasury bill, GDP deflator, import price deflator, real GDP/unemployment rate.
Hamilton (1996) *This is what happened to the oil price–macroeconomy relationship*	US 1948:1–1994:2, quarterly Full sample and subsample	Replicates method of Hooker (1996) as above.

Darrat, Gilley & Meyer (1996) *US oil consumption, oil prices and macroeconomy*	US 1960–1993, quarterly	6-variable VAR ordering: real price of oil, federal budget deficit, monetary base, industrial production, domestic crude oil consumption, short-term interest rate.
Bernanke et al. (1997) *Systematic monetary policy and the effects of oil price shocks*	US 1965:1–1995:12, monthly Full sample, GDP interpolated	5-variable system: log of real GDP; log of GDP deflator; log of an index of spot commodity prices; an indicator of the state of the oil market; and the level of the federal funds rate.
Carruth, Hooker & Oswald (1998) *Unemployment equilibria and input price: Theory and evidence from the US*	US 1954:2–1995:2 Full and subsample	Granger causality. Bivariate and trivariate (including real long-term interest rates).
Hooker (1999) *Oil and the macroeconomy revisited*	US 1948:2–1998:4, quarterly On Mork's (1989) oil price Full and subsample	Granger causality. See previous studies: Hamilton (1983), Mork (1989).
Sadorsky (1999) *Oil price shocks and stock market activity*	US 1947:1–1996:4, monthly	GARCH VAR Order: 3-month T-bill rate, oil prices/GARCH measure, industrial production, stock returns.
Davis & Haltiwanger (2001) *Sectoral job creation and destruction responses to oil price changes*	US 1972–1988, quarterly	7 variable: oil shock index, absolute change, manufacturing job creation and destruction rates, interest rate quality spread, sectoral job creation and destruction rates.
Jimenez-Rodriguez & Sanchez (2005) *Oil price shocks and real GDP growth: Empirical evidence for some OECD countries*	US, EA (euro-area), Japan, Canada, France, Italiy, Germany, Norway, UK. 1972:2–2001:4 Full sample	VAR ordering: real GDP, real oil price, inflation, short-term interest rate, long-term interest rate, real wage, real effective exchange rate.
Kilian (2008) *A comparison of the effects of exogenous oil supply shocks on output and inflation in the G7 countries*	US, Canada, Japan, France, Germany, Italy, UK. 1971.1–2004.3, quarterly Full sample	Real GDP, CPI, GDP deflator, real wage, short-term interest rate, exchange rate.
Kilian (2009) *Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market*	US 1973.1–2007.12, monthly Full sample	Reduced Structural VAR: percentage change in global crude oil production, real economic activity, real price of oil.
Edelstein & Kilian (2009)	US 1970.2–2006.7, monthly	Bivariate VAR.

How sensitive are consumer expenditures to retail energy prices?		
Berument et al. (2010) *Impact of oil price shocks on the economic growth of selected MENA countries*	16 MENA countries 1952–2005, annual Full sample	4-variable model of Cushman & Zha (1997) ordering: real exchange rate, inflation, output growth. Exogenous oil prices.
Naccache (2010) *Slow oil shocks and the weakening of the oil price-macroeconomy relationship*	US 1974:2–2010	Log change in real GDP, log change of GDP deflator, log change of wage rate, log change of oil price specification, unemployment rate, 3-month Treasury bill rate.
Kilian & Vigfusson (2011) *Are the responses of the US economy asymmetric in energy price increases and decreases?*	US 1973.2–2007.4 Full sample	Bivariate.
Cavalcanti & Jalles (2013) *Macroeconomic effects of oil price shocks in Brazil and in the US*	US, Brazil (polar cases on oil import dependence rate) 1975:1–2008:2 Subsample at 1985:1	Average oil price, real GDP, CPI-based inflation rate.
Kilian & Hicks (2013) *Did unexpectedly strong economic growth cause the oil price shock of 2003–2008?*	Brazil, Russia, India, China, US, Germany, Japan 2000.11–2008.12 Full sample	Killian model (2008, 2009).
Karacaer-Ulusoy & Kapusuzoglu (2017) *The dynamics of financial and macroeconomic determinants in natural gas and crude oil markets*	34 OECD, 6 GCC, 12 OPEC countries 1998–2014	Granger causality. Monthly oil, gas prices, IP, liquidity level, stock market.
Nguyen & Tatuyoshi (2017) *Asymmetric reactions of the US natural gas market and economic activity*	US 1980–2016	Smooth-transition STVAR. 4-variable recursive VAR: change in US gas production, change in real economic activity, real oil price, real gas price.
Gronwald (2012) *Oil and US macroeconomy: A reinvestigation using rolling impulse responses*	US 1962-2010, monthly	VAR ordering: industrial production, CPI, short-term interest rate, long-term interest rate, money supply and oil prices.

Table A(2). Empirical findings of reference paper.

Author/title	**Findings**
Hamilton (1983) *Oil and the macroeconomy since World War II*	Oil shocks between 1948 and 1980 are contributing factor to US recessions. The correlation of preceding price shocks and recession is significant. (In this period all the large oil price movements were upward. Also there were price controls in 1970s which distorted variables. Nominal oil price.)
Burbidge & Harrison (1984) *Testing for the effects of oil-price rises using vector autoregressisons*	Significant impact of oil on real activity. Impact on industrial production was larger for US and UK than other countries.
Gisser & Goodwin (1986) *Crude oil and the macroeconomy: Tests of some popular notions*	Crude oil prices had significant impact on broad range of macro indicators. Oil prices have both real effects and inflationary effects. No dramatic break after 1973, although prior to that inflation was strongly informative about future oil prices. Later is weak. Oil-GDP was stable in past 25 yrs.
Mork (1989) *Oil and the macroeconomy when prices go up and down: An extension of Hamilton's results*	Extends Hamilton's data to 1988, oil price measure is adjusted to account for increases and decreases separately. Oil price increases are negatively correlated to GNP which is in line with Hamilton. Asymmetric response is significant, oil price decreases found to have little/zero correlation to GNP growth. Real oil prices.
Mork et al. (1994) *Macroeconomic responses to oil price increases and decreases in 7 OECD countries*	Oil-price increases are negative and significant for most countries, but positive for Norway (oil-producing sector is large). Oil-price decreases are mostly positive, but only significant for US and Canada. Most countries show evidence of asymmetry, except for Norway. Bivariate results show a general pattern of negative correlations between GDP& oil. Significant at 10% except Canada. Oil–GDP correlation stands out more significant in multivariate model than bivariate.
Lee-Ni-Ratti (1995) *Oil shocks and the macroeconomy: the role of price variability*	Review Hamilton's and Mork's results, updated till 1992. Oil shock variable is normalised to account for general variability of real oil prices. It is found that in stable environments, oil price changes have a more pronounced effect on real GNP growth and unemployment than in times of erratic oil price movements. Asymmetry exists. Only positive oil shocks were significant. For 8-variable system, oil price increase, oil price decrease.
Ferderer (1996) *Oil price volatility and the macroeconomy*	Oil market disruptions may affect the macro economy through two channels: changing the level of oil prices; raising oil price volatility.

	Monetary tightening in response to oil price increases explain part of the output–oil price correlation. Oil price volatility has a negative and significant impact on output growth that occurs immediately and then again beginning at eleventh months. Oil price volatility has higher predictive power than oil price level.
Hooker (1996) *What happened to the oil price–macroeconomy relationship?*	Contradicting Hamilton and Mork on more recent data: Oil prices Granger cause a variety of US macroeconomic indicator variables in data up to 1973, but not from then to the present.
Hamilton (1996) *This is what happened to the oil price–macroeconomy relationship*	Proposes a new measure of real oil price changes that accounts for a phenomenon observed after 1986 (net oil price increase): almost all increases of real oil prices are corrections to declines in the preceding quarters. Increases are negatively related to GDP growth for full sample 1948-1994, weaker but significant from 1973 to 1994. (NOPI oil price transformation: the percentage change in Mork's levels series from the past four quarters' high if that is positive, and zero otherwise)
Darrat, Gilley & Meyer (1996) *US oil consumption, oil prices and the macroeconomy*	Oil prices are not major cause of US business cycles.
Bernanke et al. (1997) *Systematic monetary policy and the effects of oil price shocks*	Monetary policy could be used to eliminate any recessionary consequences of an oil price shock. Majority of the impact of an oil price shock on the real economy is attributable to the central bank's response to the inflationary pressures engendered by the shock. 1 per cent oil price shock leads only to a 0.02 per cent response of the price level and a 0.025 per cent output response at the peak of the responses.
Balke, Brown & Yucel (2002) *Oil price shocks and US economy:Where does the asymmetry originate?*	Monetary policy alone cannot account for asymmetry.
Cuñado & de Gracia (2003) *Do oil price shocks matter? Evidence for some European countries*	The main results suggest that oil prices have permanent effects on inflation and short run but asymmetric effects on production growth rates. Significant differences are found among the responses of the countries to these shocks.
Hamilton (2003) *What is an oil shock?*	Measurement is adjusted from Hamilton (1996). Using current and lagged values of Qt in place of oil prices.

	Both 3-year net increase and Lee, Ni & Ratti 1995. measure seem to capture the relation adequately. Possibly it is events associated with the military conflicts themselves, rather than the specific changes in oil prices, that leads the economy into recession.
Hamilton & Herrera (2004) *Oil shocks and aggregate macroeconomic behaviour: The role of monetary policy*	Challenges Bernanke (1997), suggests Federal Reserve doesn't have the power to implement such a policy; and that the policies they proposed would not succeed in averting a downturn. However, it could have made difference for inflation (Barsky & Kilian 2001; Hooker 1999).
Cuñado & de Gracia (2005) *Oil prices, economic activity and inflation: Evidence for some Asian countries*	Oil prices have a significant effect on both economic activity and price indexes, although the impact is limited to the short term and more significant when oil price shocks are defined in local currencies.
Jimenez-Rodriguez & Sanchez (2005) *Oil price shocks and real GDP growth: Empirical evidence for some OECD countries*	Ordering assumes: real output does not react contemporaneously on impact to the rest of the variables. Oil price is exogenous. It has immediate impact on inflation, which then feed into changes in interest rates, two relative prices (wage and exchange rate) close the system. Used non-linear transformation. Scaled model performed best. Evidence of non-linear effects of oil price on real economic activity is found. Paper studies effects of oil price shocks on real economic activity of main OECD countries, net oil importing and exporting countries. Real GDP growth of oil importing economies is negatively affected by higher oil prices.
Kliesen (2006) *Rising natural gas prices and real economic activity*	Output is responsive to natural gas prices in some manufacturing sectors. When the analysis is extended to the macroeconomy (real GDP growth), increases in crude oil prices significantly predict real GDP growth, but natural gas prices do not.
Villar & Joutz (2006) *The relationship between crude oil and natural gas prices*	WTI crude oil and Henry Hub natural gas prices have a long-run cointegrating relationship. Oil price influence long-run development of gas but not vice versa. Crude oil price weakly exogenous to gas, short-run response of gas to changes in oil is significant. Gas grows slightly faster than oil. Narrow the gaps between the two over time.
Kilian (2008b) *A comparison of the effects of exogenous oil supply shocks on output and inflation in the G7 countries*	Distinguishing between supply and demand shocks. Similarity in real growth responses: exogenous oil shock cause temporary reduction in real GDP growth, typically in the second year after shock. Median CPI inflation response peaks after 3–4 quarters. It need not be sustained. Typical responses included fall in real wage, higher short-term interest rate, depreciating currency.
Kilian (2009) *Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market*	Highlights the importance of including structural demand and supply shocks in modelling any relationship to the GDP as they have different impact on US economy. Also, the assumption of exogenous oil price is misleading. Oil price increases may have very different effects on the real price of oil. Depending on underlying cause of the price increase.

Jimenez-Rodriguez (2009) *Oil price shocks and real GDP growth: Testing for non-linearity*	Find existence of non-linearity earlier than 1984, even before 1977.
Berument et al. (2010) *Impact of oil price shocks on the economic growth of selected MENA countries*	First shock in oil price has significant positive effect on the growth of mostly net oil-exporting economies. Other countries output decreases with positive oil supply shocks and output increases with positive oil demand shocks.
Kilian & Vigfusson (2011) *Are the responses of the US economy asymmetric in energy price increases and decreases?*	Challenge the assumption of censored oil price measures (such as the NOPI or any other ex-ante asymmetric data manipulation to that end): censored energy price VAR models are invalid; suggest an encompassing VAR model Results suggest that oil price shocks are only one of many factors that contribute to recessions.
Aguiar-Conraria & Soares (2011) *Oil and the macroeconomy: Using wavelets to analyse old issues*	The relationship between oil prices and industrial production is not clear-cut. There are periods and frequencies where the causality runs from one variable to the other and vice versa, justifying some instability in the empirical evidence about the macroeconomic effects of oil price shocks. The volatility of both the inflation rate and the industrial output growth rate started to decrease in the decades of 1950 and 1960.
Weber (2012) *The effects of a natural gas boom on employment and income in Colorado, Texas, and Wyoming*	Colorado, Texas, and Wyoming are three states where natural gas production expanded substantially since the late 1990s. A large increase in the value of gas production caused modest increases in employment, wage and salary income, and median household income.
Acaravci (2012) *Natural gas prices and stock prices: Evidence from EU-15 countries*	Empirical findings suggest a unique long-term equilibrium relationship between natural gas prices, industrial production and stock prices in Austria, Denmark, Finland, Germany and Luxembourg. However, no relationship is found between these variables in the other ten EU-15 countries. Although a significant long-run relationship between stock prices and natural gas prices is detected, Granger causality test results imply an indirect Granger causal relationship between these two variables. Increase in natural gas prices seem to impact industrial production growth at the first.
Kilian & Hicks (2013) *Did unexpectedly strong economic growth cause the oil price shock of 2003–2008?*	The main contributors to the strong increase are positive demand shocks from emerging countries and their rapid economic growth.
Benhmad (2013) *Dynamic cyclical movements between oil prices and US GDP. A wavelet perspective*	Before 1984Q1, oil prices leading US GDP cycle, granger cause GDP After 1984Q1: reverse causality run from GDP to oil price

Baumeister & Peersman (2013) *Time-varying effects of oil sypply shocks on the US economy*	No sample split. Allow for time-varying heteroscedasticity in the VAR innovations that accounts for changes in the magnitude of structural shocks and their immediate impact. Identify oil supply shocks based on sign restrictions that oil supply shocks move oil prices and production in opposite directions.
Arora & Lieskovsky (2014) *Natural gas and US economic activity*	Both seasonality and trend removed. Supply is the primary means through which US natural gas market impacts domestic economic activity. Shale gas revolution changed the relationship between natural gas supply and US economic activity.
Herrera & Karaki (2015) *The effects of oil price shocks on job reallocation*	No evidence of asymmetry in the response of job flows to positive and negative oil price innovations.
Liu et al. (2016) *Distangling the determinants of real oil prices*	Oil demand from the US and China, particularly the latter, plays a crucial role in oil price changes after 2000.
Baumeister & Kilian (2016) *Lower oil prices and the US economy: is this time different*	0.9% stimulus is offset by large reduction in real investment in oil sector after oil price decline. Net stimulus since June 2014 is close to zero.
Karacaer–Ulusoy & Kapusuzoglu (2017) *The dynamics of financial and macroeconomic determinants in natural gas and crude oil markets*	For most of the OECD, GCC and OPEC countries; there were no long-term relationships between energy prices and industrial production. The general findings of the Granger causality tests showed that in most of the OECD, GCC and OPEC countries there was a unidirectional causality running from oil prices to industrial production. The results are in line with the studies of Burbidge and Harrison(1984) and Cuñado and de Gracia (2003).
Shi, Hurn & Phillips (2018) *Causal change detection in possibly integrated systems*	Simulation experiments suggest that the recursive evolving window algorithm provides the most reliable results, followed by the rolling window method. The forward expanding window procedure is shown to have the worst performance. Both the rolling window and recursive evolving approaches show evidence of Granger causality running from money to income during the Volcker period in the 1980s. The forward algorithm does not produce any evidence of causality over the entire sample period.
Gong & Lin (2018) *Time-varying effects of oil supply and demand shocks on China's macro-economy*	The effects of oil supply, oil aggregate demand, and oil specific demand shocks on China's output and inflation are time-varying, and even change the direction of the effects over the period from 1995 to 2015.
Raza et al. (2018) *Testing for wavelet based time-frequency relationship between oil prices and US economic activity*	Significant long run relationship between oil price and economic activity in US. Feedback exits. 1979–2013.

Troster, Shahbaz & Uddin (2018) *Renewable energy,oil prices and economic activity: A Granger-causality in quantiles analysis*	Evidence of bidirectional causality between changes in renewable energy consumption and economic growth, unidirectional causality from fluctuations in oil prices to economic growth, dependence from changes in oil prices to changes in renewable energy consumption.