Investigating the Interaction between Oil and Macroeconomic Indicators in the US, UK, and Beyond

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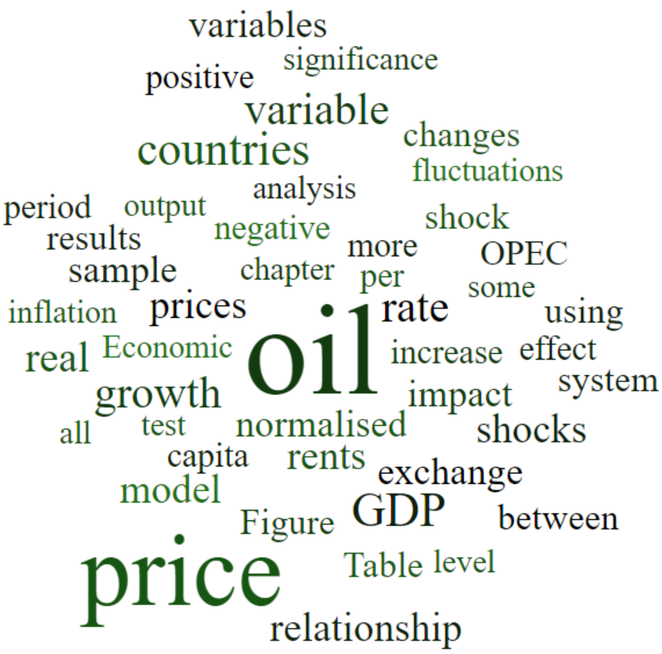
Abstract

This thesis makes contributions towards understanding the relationships between energy, economic growth, and macroeconomics by focussing on the linkages between oil prices and output growth as well as oil sector profits and the real exchange rate. Following an introductory chapter, Chapters 2 and 3 investigate how the oil price–macroeconomy relationship in the United States and the United Kingdom has evolved over time and draw comparisons between the two countries. As a part of this, I estimate time-varying vector autoregression models using a rolling-window approach. I then used impulse response functions to estimate the size of an oil price shock of a standard magnitude. The findings in these chapters identify differences and similarities between the two countries in question, and suggest that the oil price–macroeconomy relationship is sensitive to variable choice, model specification, and sample period. Chapter 4 studies the existence of resource curse and the Dutch disease on a global scale in oil-exporting countries. Using a unique, large-N, large-T dataset, I find evidence of a long-run relationship between rents in the oil sector and the real exchange rate of oil exporters as well as short-run adjustment towards an equilibrium. Although non-OPEC members exhibit behaviour in line with theory, the impact on OPEC countries' real exchange rates is the largest.



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Declarations

This dissertation is submitted in accordance with the requirements for a Doctorate of Philosophy by the School of Social Sciences at Heriot-Watt University. I declare that I have written this thesis under the guidance of my supervisor. All work was my own with the exception of the following:

Chapter 4: The data for this chapter were collected, processed, and stored in collaboration with Anna Brocklebank. Parts of the analysis provided in the chapter are also collaborative. The Chapter presented in this thesis is approximately 75% my contribution with the rest being my co-author's.

The problem now is that uncertainty hangs over the economy like a black cloud, emitting a steady, dampening drizzle. Oil prices remain high even though world oil production has returned to pre-crisis levels. Interest rates are slow to fall. Businesses are postponing investment decisions. And consumer confidence is plunging. Until all the uncertainty ends, an economic recovery is highly unlikely.

Wall Street Journal, 3 December 1990

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List of Abbreviations

ADF	Augmented Dickey-Fuller
B-S effect	Balassa-Samuelson effect
DOLS	Dynamic ordinary least squares
ECM	Error correction model
FE	Fixed effects
GARCH	Generalised autoregressive conditional heteroskedasticity
GDP	Gross domestic product
GEM	Global Economic Model (Wood Mackenzie)
GLS	Generalised least squares
IB rate	Interbank rate
IRF	Impulse response function
MG	Mean group
MTOE	Million tonnes of oil equivalent
NOPI	Net oil price increase
OECD	The Organisation for Economic Co-operation and Development
OLS	Ordinary least squares
OPEC	Organisation of Petroleum Exporting Countries
PMG	Pooled mean group
PPI	Producer price index
RAC	Refiners' acquisition cost
RE	Random effects
RMSE	Root-mean-square error
SOPD	Scaled oil price decrease
SOPI	Scaled oil price increase
SUR	Seemingly unrelated regressions
TB rate	Treasury Bill rate
UK	United Kingdom
UKCS	UK continental shelf
US	United States
VAR	Vector autoregression
WM	Wood Mackenzie

1 General Introduction

1.1 Energy and Economic Growth

An economy's long-run growth and development critically depend on its resilience and susceptibility to shocks (Balassa, 1986; Martin, 2012; Romer & Romer, 2004). Energy shocks have been placed in the centre of this observation, since growth-inducing activities are highly dependent on access to energy. It has widely been observed that inexpensive access to energy could relate to economic growth. Given that oil has been the single most important source of energy in the global fuel mix since World War II, it has enjoyed the limelight for decades. The striking link between oil prices and US business cycles did not escape economists: almost every recession was preceded by a rise in energy prices (see Figure 2.1). Following oil crises of the 1970s, economists have sought to understand the implications of oil price shocks on the macroeconomy and confirm this casual observation. Among these are Hamilton (1983, 1996b, 2003, 2005), Hamilton & Herrera (2004), Rotemberg & Woodford (1996), and Kilian (2008). Although oil has lost market share to other fuels recently, it maintains its significance as the fuel with the largest share. As Figure 1.1 shows, oil accounted for a third of global primary energy consumption in 2016 (BP, 2017). Nordhaus (1980) and Nordhaus, Houthakker, & Sachs (1980) made early contributions to this theme by discussing channels through which oil prices may hinder economic activity and growth. Among others, Kümmel, Henn, & Lindenberger (2002), Ayres & Warr (2005), Allan (2009), and Stern & Kander (2012) have investigated the role energy plays in inducing or preventing growth. In basic terms, a rise in the price of oil raises the cost of energy which, with a price-inelastic demand, increases expenditure on energy. Oil products enter households' consumption functions as well. Jointly, the impact is often reduced production and consumption of goods and services, which reduces GDP. In oil-importing countries, this also hurts the balance of payments and puts an upward pressure on prices.

Using post-World War II data through the early 1980s, Hamilton (1983) found a statistically significant relationship between oil price increases and recessions in the US. Since then, researchers have observed shifts in the relationship—in terms of its statistical significance, the magnitude of the impact, and the characteristics of shocks. One major avenue of further investigation has been what makes economies more capable of absorbing shocks and returning to the original growth path. Along this vein, there is some evidence that economic development itself enables countries to adjust to new economic conditions and bounce back more quickly. For example, Blanchard & Galí (2007) have argued that declining reliance on energy in production processes, more flexible labour markets, and better monetary policies can help ameliorate the detrimental effects of oil price hikes. In this line of work, Dhawan & Kesje (2006) found that developed economies have become more resilient to oil shocks since 1986, and Kilian (2009) argued that the nature of shocks matters. Chapters 2 and 3 of this thesis add to this literature by introducing an alternative approach. Based on the findings, I argue that the observed relationship has links to underlying oil price volatility, and that modelling this explicitly helps understand the true nature of the oil price-macroeconomy relationship.

The rich literature on the topic, inspired by Hamilton (1983), consistently identified negative impacts of oil price hikes on GDP in industrialised, industrialising, oil importing, and oil exporting economies (Ferderer, 1997; Jiménez-Rodríguez & Sanchez, 2005; Lee, Ni, & Ratti, 1995; Mork, 1989, 1994; Papapetrou, 2001). Numerous studies found that the impact of oil prices on GDP declined over time. As an example, Hamilton (1983, 1996b) estimated a larger impact coefficient for pre-1973 than post-1973. Similarly, Baumeister & Peersman (2013a, 2013b), Blanchard & Galí (2007), and Kilian (2008) found a smaller and declining effect in the early 1980s. More recently, oil price dynamics appear to be getting more complex: Hamilton (2009) and Kilian & Murphy (2013) concluded that price speculation played a role in the 2007-08 oil price fluctuations. For the US economy, most studies found a negative impact on GDP growth of an oil price increase too large to explain given the share of oil expenditures in GDP. Economic theory has struggled to describe this empirical finding (Atkeson & Kehoe, 1999; Rotemberg & Woodford, 1996). In an effort to disentangle the underlying mechanisms, Kilian (2008) broke down the transmission mechanisms into roughly two categories. The first category is concerned with energy as an input into economic activity. Operating costs of durables that rely on oil as an input rises due to an oil price hike, which restricts their use. In addition, because demand for energy is expected to be price inelastic, rising costs decrease overall disposable income and reduce the consumption of other goods. On this basis, Finn (2000) argued that energy price shocks could act like technology shocks and hypothetically cause GDP fluctuations more than twice the magnitude that would be expected given the share of energy in GDP. The second category relates to behaviour and expectations. Capturing these effects in traditional economic models is complicated and an asymmetric response of GDP to energy price variation is likely, as these effects tend to be stronger when energy prices rise than when they fall. An uncertainty effect underlies this. Changing energy prices often create uncertainty about the future path of energy prices and cause consumers and producers to delay irreversible investments (Bernanke, 1983; Pindyck, 1990). Additionally, rises in energy prices could induce precautionary savings for consumption smoothing, whereas a fall in prices would not provide as strong an incentive to spend existing savings. Evidence of an asymmetric response of GDP to oil prices as documented by Hamilton (1996b, 2003), Lee et al. (1995), Mork (1989, 1994), and Mory (1993) suggests that this mechanism may play a substantial role in determining the GDP response to an oil price shock. This is another focal point of Chapters 2 and 3, where I provide a detailed overview of the relevant literature and discuss empirical findings based on the implemented methodology.

Brief Remarks on the Global Oil Market and Prices

There have been major changes in the global oil market over the sample period considered. The establishment of OPEC in 1960 and the 1970s price shocks signalled a fundamental change in the way the global oil market operated. Although there is an ongoing debate about the true underlying nature of these shocks, researchers agree that the events marked the emergence of a new regime in the market for crude oil. The balance of power had shifted from the Seven Sisters (multinational oil companies of the Consortium for Iran oligopoly, which dominated the global petroleum industry from 1940s to 1970s) to OPEC, and OPEC were not afraid to use their influence. Price controls used during this period in response to the sharp rise in oil prices exacerbated the impact and disrupted the day-to-day running of the economy. Figure 1.2 plots global crude oil production by region in an effort to demonstrate the overall increasing trend in production—hence the size of the global oil market—and the role Middle Eastern producers play relative to the rest of the world. The dip in Middle Eastern production in 1974-75 corresponds to the OPEC oil embargo, and the shrinking contribution by the region's producers observed in mid-1980s was short-lived given the trend that followed. These are examples of large dynamics in the global oil market that could have profound economic impact across the globe. This is partly the motivation for the emphasis on sample period in Chapters 2 and 3.

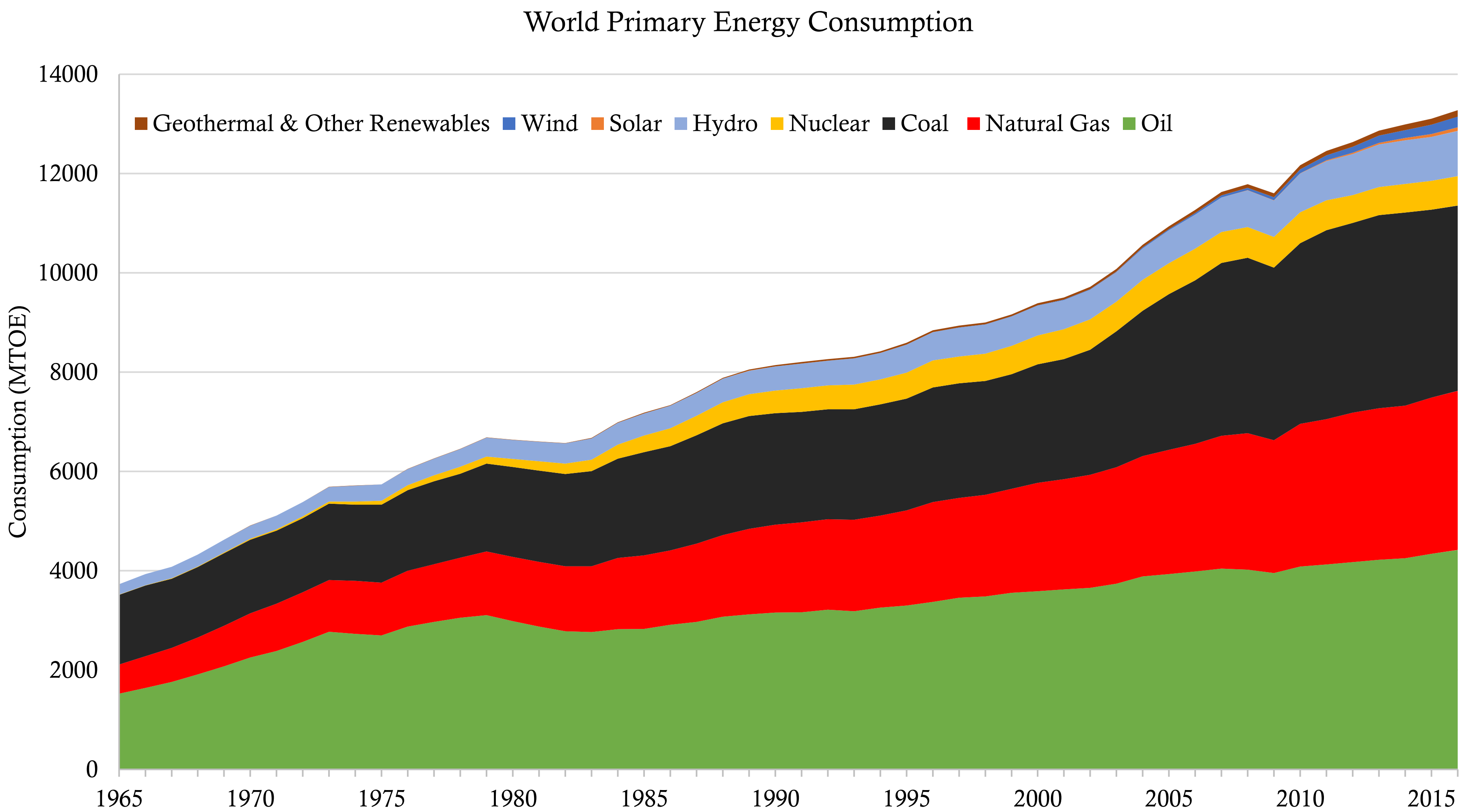

Figure 1.1. World primary energy consumption in million tonnes of oil equivalent (MTOE) by fuel. Source: BP Statistical Review of World Energy 2017.

Although informative, Figure 1.2 masks some OPEC versus non-OPEC dynamics, which are shown explicitly in Figure 1.3 along with an oil price series. The figure shows that the OPEC contribution was at its maximum in 1973 with 52% of global oil production. As noted previously, this corresponds to one of the fundamental shifts in the oil market not only in terms of price dynamics but also global perception of the commodity. Arguably, the events of 1970s have influenced perception so much that the economic impact of oil price changes is no longer only due to the fluctuations themselves but expectations around each shock as well. Thus, perhaps oil price changes should not be considered or modelled in isolation but within the context they occur. This is yet another motivation for Chapters 2 and 3, where oil price volatility before a price shock is captured. Observing OPEC countries' contributions to global oil production in Figure 1.3 and slow economic growth figures for these countries prompted my interest in the resource curse and Dutch disease themes, which are the focal points of Chapter 4.

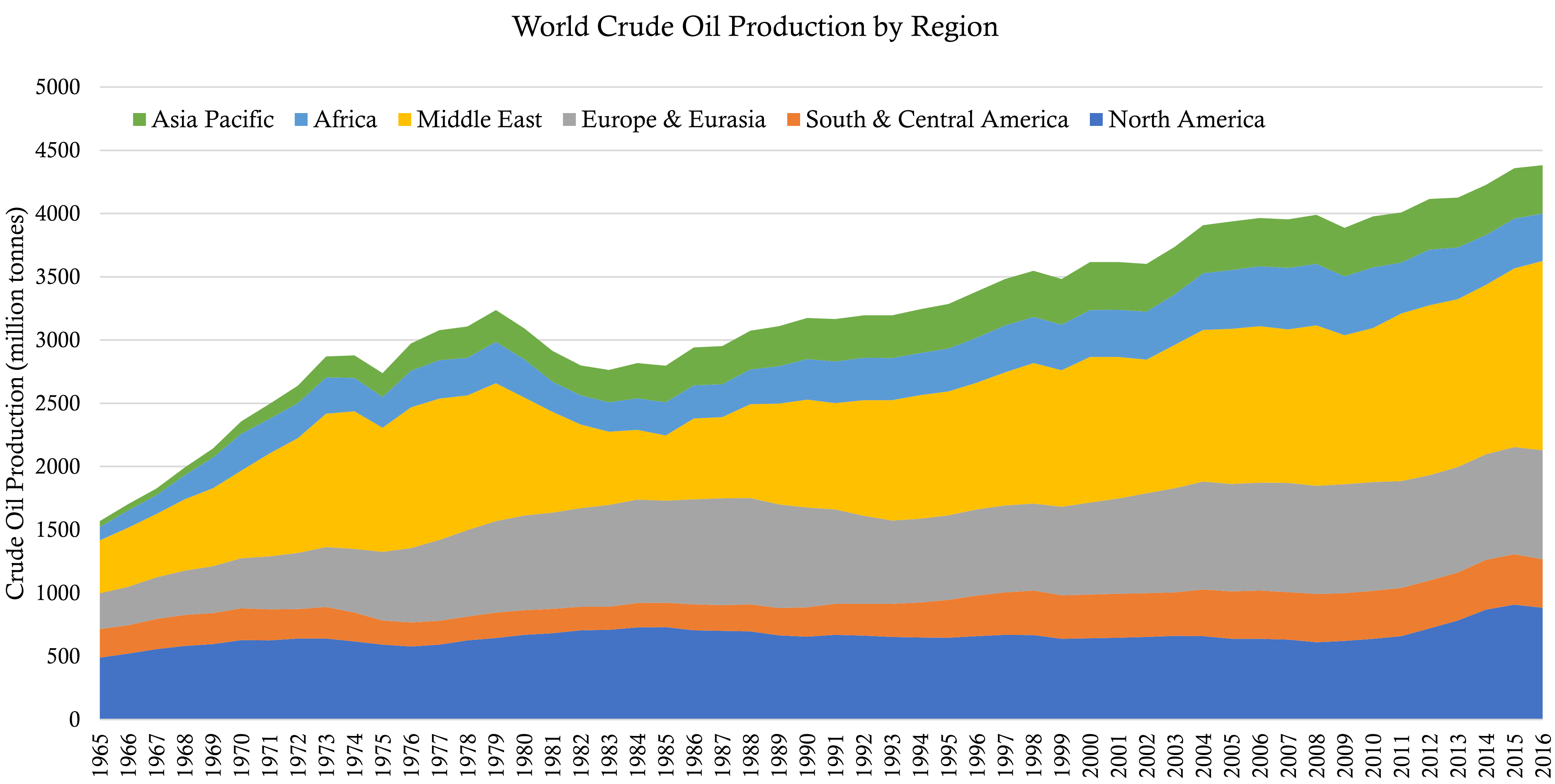

Figure 1.2. Global crude oil production by region in million tonnes (MT). Source: BP Statistical Review of World Energy 2017.

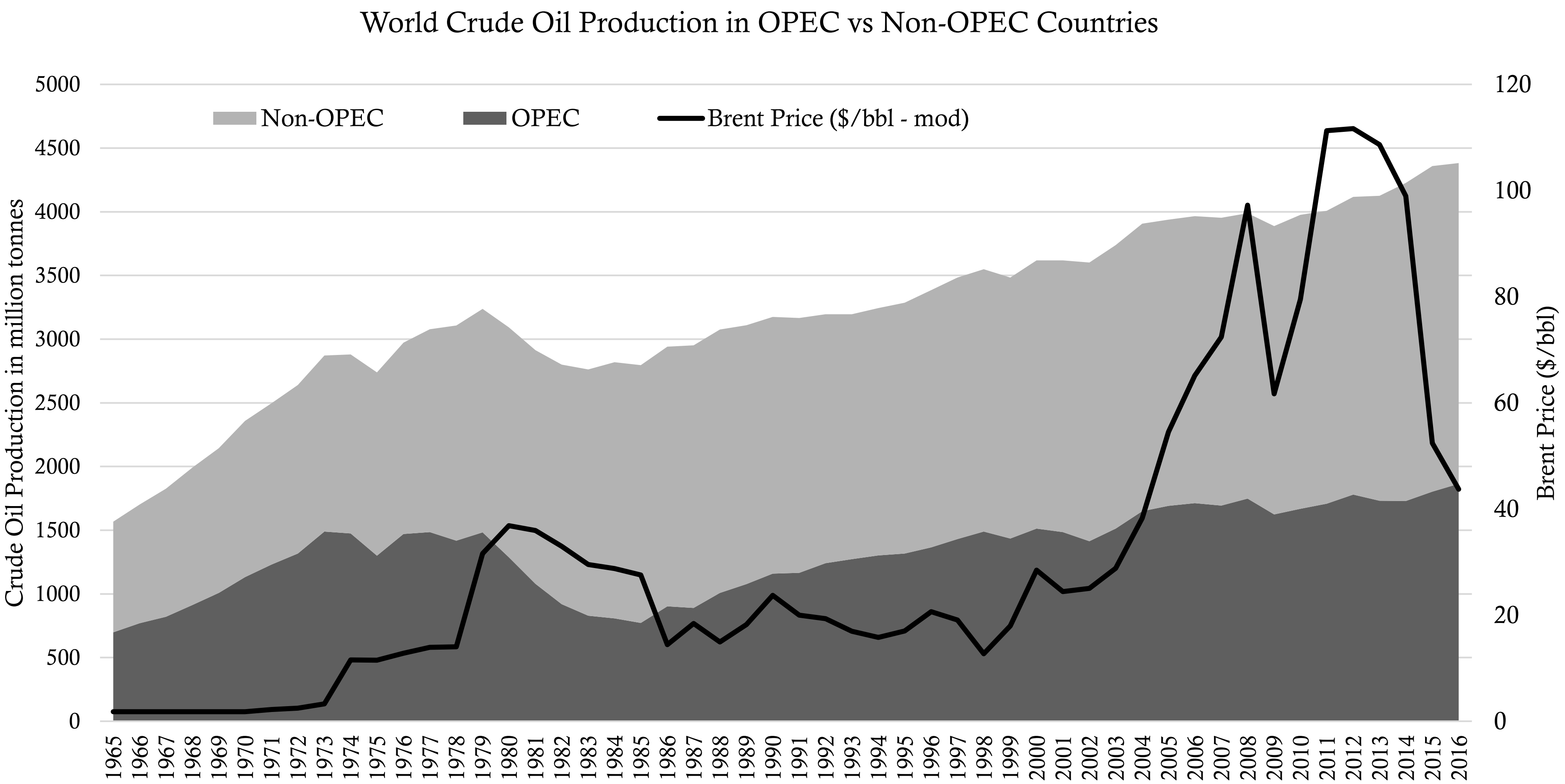

Figure 1.3. OPEC and non-OPEC crude oil production in million tonnes. Oil price series is expressed in nominal (money of the day) terms with Arabian Light posted at Ras Tanura for 1965-1983 and dated Brent for 1984-2016. Source: BP Statistical Review of World Energy 2017.

1.2 Resource Curse, Dutch Disease, and the Balassa-Samuelson Effect

The relationship between oil price changes and economic growth is certainly not the only critical link in the wider energy-economic growth context. Another observation that has received ample attention is resource curse, where abundance of natural resources becomes an obstacle to development. Inexpensive access to abundant natural resources should, in theory, encourage growth and not hinder it. Therefore, observing the opposite effect in practice worldwide has become a paradox that is widely thought to have deep causes related to macroeconomic fundamentals. The resource curse, or the paradox of plenty, has a wide-reaching definition and is often used as an umbrella term for underlying fundamental mechanisms. It was originally coined by Auty (1993) and includes effects relating to exchange rate fluctuations, worse institutions in countries with abundant natural resources, less democracy, and so on. Together, these effects have made transforming subsurface assets, such as hydrocarbons, into surface assets, such as capital that generates employment and economic growth, challenging (Venables, 2016). With the exception of a few cases, such as Norway and Australia, most resource-rich countries have experienced lacklustre growth. Examples include Bolivia, Nigeria, Venezuela. Crucially, Ross (2012) noted about growth performance of resource-rich economies that "[…] the real problem is not that growth […] has been slow when it should have been normal, but that it has been normal when it should have been faster than normal."

The overview of the multi-stage process for economic implications of natural resource exploitation could be summarised as follows. Once resources are discovered, up-front investment is often required to develop them. The resulting revenues are then shared between the government, investors, and other parties. Each participant tends to have different incentives for seeking the resources, and revenues are used accordingly. To encourage growth, spending needs to be directed towards growth-inducing activities and those with particularly high social return. Unfortunately, these can be difficult to identify and in developing nations, there are considerable incentives to increase current spending instead of making investments for future social pay-off. Poor resource management could undermine economic growth, if investments are not made in sectors that can sustain jobs and stimulate the economy (Venables, 2016).

However, effective use of resource earnings does not eliminate all potential harm to growth. The Dutch disease effect suggests that even with job-creating investments, increased resource exports can appreciate the exchange rate and hurt other tradable sectors. If not addressed, this appreciation could crowd out other sectors, leaving the nation exposed to global fluctuations in a single sector. In this context, capability of governments as well as their far-sightedness and intentions play a pivotal role. However, most resource-abundant nations have poor institutional quality and often succumb to political corruption exacerbated by the nature of resource wealth. A mechanism closely related to Dutch disease, the Balassa-Samuelson (B-S) effect, also affects what implications natural resource abundance may have on economic performance. In the context of Dutch disease, capital inflows may appreciate a currency through a demand effect and the exchange rate appreciation leads to a loss of competitiveness in the tradable sector. Although there have been no changes in productivities in these sectors, they are less competitive on the global market. The B-S effect is concerned with an aspect of this: positive wealth shocks due to high productivity in the tradable natural resource sector, such as oil production, result in higher demand for non-traded goods and services and create excess demand for them. This raises their prices, which includes input costs and wages, and squeezes profit margins in traded activities whose end products are influenced by the law of one price on the global market. In turn, these changes can have an economy-wide impact and slow down the growth process.

Venables (2016) summarises observations about resource-rich economies and their potential growth-impeding characteristics in four patterns. First, many resource-rich countries are heavily dependent on these natural resources for income and fiscal revenues, and "fiscal dependency is particularly acute for oil producers" (Venables, 2016). Second, savings have been low in resource-rich low-income countries. Third, resource-rich economies have had limited economic growth except just a few countries, which itself received plenty of attention. For example, Sachs & Warner's (1995, 1997) seminal work found GDP per capita growth to be negatively affected by natural resource dependence. The authors estimated that if natural resource exports as a percentage of GDP increased by 10 percentage points, annual GDP growth would be expected to fall by 0.77-1.1 percentage points. Fourth, revenues from natural resources—particularly from oil—are highly volatile. Most fluctuations are unpredictable and due to commodity price volatility. In this context, Venables (2016) noted that resource rents, measured by the World Bank as gross revenues from oil, natural gas, coal, minerals, and forests minus their estimated extraction costs, have fluctuated between 1.5% and 7% of world GDP in the past two decades. Further, coefficients of variation of export revenues in resource-rich nations often exceed those in others by 100% for oil-rich countries—and to a lesser extent for mineral-rich countries (Venables, 2016).

The complex and multi-channel nature of the link between natural resource production and consumption on the economy has made it challenging to identify why exploitation of these valuable resources has been so difficult to transform into wealth and development. Although there are some success stories, others have been cursed in an idiosyncratic way that is difficult to generalise. Despite this, conclusions can be drawn from a comparison of resource-rich nations that have achieved sustained growth and those that have not. In particular, as more and better data become available, determining the existence of Dutch disease and B-S-type effects has become feasible and robust. The section below provides an overview of each chapter's structure, overview, and contributions.

1.3 Chapter Structure, Overview, and Contributions

Chapter 2 investigates the impact of oil price fluctuations on US GDP growth using a series of VAR models and quarterly data from 1950 through 2015. Impulse response analysis provides estimates of the size of the impact. Parameter estimates are analysed across model specification and sample period. As a part of the former, I focus not only on variable choice in each system but also on proxy choice for oil prices. Oil prices are modelled with and without asymmetry to assess empirical implications of each alternative. Further, oil price volatility is modelled using a GARCH (1,1) specification, which provides deeper insights into the characteristics of the oil price-GDP growth relationship. The importance of sample period for parameter estimates is investigated using both a static and a time-varying approach. The rolling-window time-varying parameter methodology provides richer insights and sheds light on some puzzles in the literature. In Chapter 2, I find evidence that oil price rises constrain US GDP growth. I also find strong evidence for asymmetry: increases in the price of oil affect GDP to a larger extent than price falls. The magnitude and statistical significance of the impact are time-dependent: although there is slightly weaker evidence for Granger-causality between oil price changes and

GDP growth in more recent years, the estimated impact is greater. I also discuss whether the seemingly-weaker relationship is due to a weaker underlying economic relationship or a weaker statistical relationship and worse model fit.

Chapter 3 follows a similar structure to the previous one. The time-varying VAR and IRF techniques are implemented to analyse the oil price-macroeconomy relationship in the UK based on quarterly data from 1955 through 2015. This chapter highlights the differences and similarities between the US and UK, which leads to an interesting discussion around the two countries' oil dependence, historical imports and exports, and how oil prices affect macroeconomic fundamentals besides GDP. Asymmetry of oil prices and modelling of price volatility are implemented here as a first for the UK and provide insightful conclusions about the economy. As a part of this, I investigate additional dynamics that apply to the UK as a small open economy, such as the role real exchange rates play and how this can be captured in model specifications through . Overall, I find a weakening link between oil prices and UK economy across time. Particularly after the UK became a net exporter of oil in the early 1980s, the nature of the relationship seems to have changed. The rolling-window implementation of IRFs provides details of this shift and its implications for econometric modelling.

Chapter 4 turns to rents from the oil sector and what implications they may have on the real exchange rate. In this chapter, I make contributions to the Balassa-Samuelson literature by introducing a new and unique measure of oil rents into the analysis. This variable is based on upstream costs from Wood Mackenzie's Global Economic Model and captures profits from the oil sector in a large number of countries. Two competing measures of oil rents were used in the analysis as a robustness check and to discern whether oil rents are expected to have a greater impact on the real exchange rate in countries where the oil sector constitutes a larger share of GDP. There is some evidence towards this, but both measures indicated an ambiguous relationship in OPEC countries with some coefficient estimates having an unexpected sign. Upon investigation, the unexpected results pointed towards failure of some B-S assumptions, including those stemming from labour market dynamics in OPEC countries. I exploit the large-N, large-T panel structure of the dataset and implement mean group and pooled mean group estimators as well as dynamic OLS. I find that the B-S mechanism holds in some oil-exporting countries but not all. For most countries, the relationship is non-negligible in size and statistically significant.

Surprisingly, non-OPEC members showed a particularly significant link between their real exchange rates and oil rents. The largest observed effect was for OPEC countries. Oil prices were identified as another covariate with coefficients of a similar size and sign to oil rents.

2 Estimating the Oil Price – Macroeconomy Relationship: The Role of Model Specification and Sample Period

Abstract

This chapter analyses the oil price-macroeconomy relationship using vector autoregression models on quarterly US data from 1950 to 2015. As a part of the analysis, model performance is investigated across two broad aspects: model specification and sample period. First, I examine model performance with and without control variables and determine the role of price volatility at the time of oil price shocks. Then, I evaluate the impact of proxy choice for oil prices and the effect on parameter estimates of allowing for asymmetry in a VAR system. I also implement a time-varying approach using a rolling window in VARs and rolling IRFs. I find no clear evidence of the oil price-macroeconomy relationship weakening over time in a Granger causality sense, and the coefficient estimates do not fall substantially in post-1986 data. Parameter estimates are sensitive to model specification and choice of proxy. Controlling for asymmetry is shown to be a favourable trait for VAR models in this context, as I find strong evidence for an asymmetric effect of oil prices on output growth across specifications, proxy, and sample period. Through impulse response analysis, a one-time, 10 percent rise in oil prices is estimated to cause a 0.14-0.16 percent decline in output growth rate over 5 years in my pre-1986 sample, and a 0.30-0.34 percent over 5 years in post-1986 data.

2.1 Introduction

For the past few decades, heavy global dependence on non-renewable energy sources has been considered a significant threat to sustainable economic growth. Hamilton (1983) observed in post-World War II data that about 90% of U.S. recessions were preceded by drastic increases in oil prices. As a result, the oil price-macroeconomy relationship became a central focus of research throughout the 1980s and 1990s, and it continues to remain that way. As has historically been the case, recent political turmoil in the Middle East has increased attention to the topic. Recently, the desire to control carbon emissions and to incorporate more renewables into the energy mix have raised interest in the subject.

For net importers of oil, the nature of the relationship between oil prices and macroeconomic activity seems obvious: an oil price hike should, *ceteris paribus*, slow down economic growth through more expensive imports and other channels. However, despite numerous theoretical predictions and empirical studies, debates continue, and many researchers believe that the negative correlation between oil price rises and output growth dissipated after the 1980s. This chapter uses vector autoregression models to determine the impact of oil price changes on US output. The sample period in question starts from the first quarter of 1950 and runs through to the second quarter of 2015. Not all variables are available for the whole sample period and these are outlined in Section 2.4.

The next section provides an overview of theoretical approaches, the literature, transmission mechanisms through which oil prices propagate, and observed characteristics of the oil price-macroeconomy relationship. Section 2.3 outlines the models used for empirical analysis in the paper, and Section 2.5 presents the results obtained from their implementation. As a part of the analysis, model performance is investigated across three dimensions in Section 2.5.3. Empirical analysis is finalised with a discussion of impulse response functions in Section 2.6, and Section 2.7 concludes the analysis.

2.2 Theoretical Analysis and Literature Review

2.2.1 Oil Price-Macroeconomy Relationship

Cyclical behaviour of macroeconomic variables, the cause of such fluctuations, and their implications for welfare has attracted much interest and research among economists. In this context, two main strands of scholarly work have emerged within econometrics: predicting the paths of real macroeconomic variables in the presence of random shocks and forecasting when a recession is likely. Achieving the latter objective hinges crucially on identifying the underlying cause of recessions. In turn, this would facilitate timely policy interventions aimed at limiting the detrimental effects of exogenous shocks on economic activity.

The link between oil price fluctuations and macroeconomic fundamentals—particularly economic growth—became a central focus for research because post-World War II data tell an interesting story as demonstrated in Figure 2.1: almost all US recessions were preceded by drastic oil price increases.

Visually inspecting the data certainly seems to point in an obvious direction: increases in the price of oil lead to a fall in GDP growth. One of the objectives of the literature as well as this chapter has been to investigate whether this is merely a case of *post hoc ergo propter hoc*. If true, a rise in oil price would, *ceteris paribus*, be expected to cause a decline in real GDP growth. Although the *a priori* expectation is a negative correlation between oil price increases and GDP growth, some researchers have found that empirical results do not match what may theoretically be expected and what the data appear to reveal. Therefore, the rich literature has arguments for both sides.

Hamilton (2005) pointed out that an OLS regression of GDP growth on its lags and the lags of logarithmic changes in nominal oil prices would be a simple but effective approach to determine the correlation, if any, between oil price fluctuations and GDP growth. This is shown in equation 2.1 below.

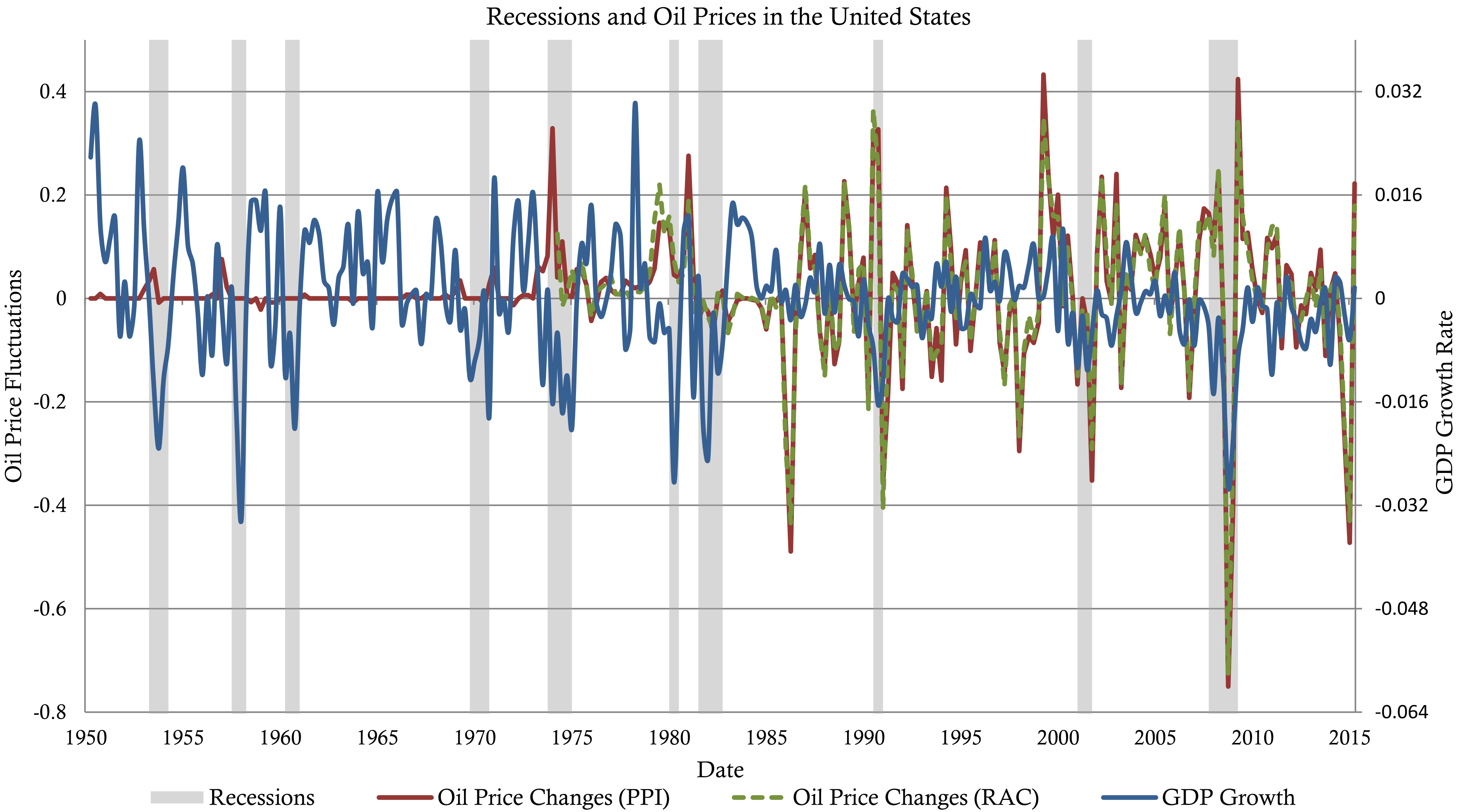

Figure 2.1 Recessions and oil prices in the United States

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \beta_3 y_{t-3} + \beta_4 y_{t-4} + \beta_5 o_{t-1} + \beta_6 o_{t-2} + \beta_7 o_{t-3} + \beta_8 o_{t-4} + \varepsilon_t \quad (2.1)$$

where, y_t denotes changes in real GDP in period t, o_t changes in nominal oil prices in period t, and ε_t is the error term such that $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$.

Hamilton's (2005) analysis found a statistically significant negative relationship between real GDP growth rate and lagged logarithmic changes in nominal oil prices using a dataset spanning 1949:2[1] through 1980:4. An F-test on the joint significance of the coefficients on oil prices confirmed the rejection of the null hypothesis that all coefficients on the lags of oil price changes are zero. Having observed this, Hamilton (2005) discussed two further findings: the impact of period considered and the transmission mechanism of oil price shocks. For the former, the model in equation 2.1 was re-estimated using data through 2005. This led to a fall in not only the size of the coefficients of interest but also the statistical significance. As for the latter, through an output elasticity analysis, Hamilton (2005) deduced that "if these oil shocks did contribute to economic downturns, it would have to be attributed to the movements they induced in other factors of production rather than the value of the lost energy per se." This chapter investigates both points, among others, by implementing a time-varying approach to observe the evolution of the relationship over time. Doing so within a VAR system allows controlling for indirect effects as well.

Acknowledging the above observation, many researchers have opted for VAR and structural VAR models capable of capturing more complex relationships than OLS to reach a more robust conclusion (Abeysinghe, 2001; Dalsgaard, Andre, & Richardson, 2002; Hamilton, 1983, 1996, 2003, 2005; Hooker, 1996a, 1996b; Jiménez-Rodríguez & Sanchez, 2005). Further analyses extended to macroeconomic variables other than GDP growth and concluded that oil prices have a statistically significant impact on the macroeconomy in general (Carruth, Hooker, & Oswald, 1998; Hamilton, 1983, 1996, 2003, 2005; Raymond & Rich, 1997). In their estimations, many researchers use nominal

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[1] Dates are denoted as Year:Quarter.

prices and argue that real prices can bias empirical results: by definition, real prices incorporate inflation, which is endogenous to the economy at any given time.

A number of researchers further argue that the transmission mechanism between oil prices and macroeconomic variables is indirect and that the observed relationship between, for instance, GDP growth and oil price fluctuations is mostly due to the two variables' correlation with a third one (Barsky & Kilian, 2001, 2004; Hooker, 1996b, 1999). Implemented and popularised by Hamilton (1983), one approach to ruling this possibility out is to confirm that oil price fluctuations cannot be predicted by other variables in the model and their lags.

Another key point of debate is the exogeneity of oil price shocks. Within this discussion, I differentiate between two types of exogeneity: macroeconomic and econometric. In a macroeconomic modelling sense, it would be difficult to argue for the strict exogeneity of oil price fluctuations since oil is an input to many production processes and has been the dominant source of energy for decades. However, this does not automatically imply econometric endogeneity of oil price fluctuations in a GDP growth equation of a VAR system. In fact, most oil price changes in history have been driven by exogenous factors, such as military conflicts, which provides evidence for the price shocks being exogenous (Hamilton, 1983, 2005). Further, the period considered in this chapter does not cover the increased oil production in the US through the so-called shale revolution. This is done intentionally to minimise endogeneity and avoid the risk of US production directly affecting the global oil price and, therefore, becoming endogenous. For much of 1950 through 2015, US production and consumption were small enough relative to their global counterparts that exogeneity assumptions are plausible. Nevertheless, Hamilton's exogeneity claims have been criticised in the literature. For instance, Hooker (1999) argued that oil price shocks acted through unemployment and that much of the impact of price hikes on output is indirect. More specifically, the author concluded that oil price increases lead to a heightened natural level of unemployment and impede output growth as a by-product. Another perspective was offered by Barsky and Kilian (2001, 2004), who argued that monetary policy—sometimes in response to oil price changes themselves—is the cause of some large drops in GDP growth. Since tests have corroborated both claims under certain circumstances, such as model specification and sample period, I have included several control variables in my analysis. These include unemployment, 3-month TB rate, real wage inflation, and import price inflation, and they help isolate the true impact of oil prices.

Another theoretical view with its origin dating back to late 1980s is the asymmetric impact of oil price shocks on output: an oil price increase may have a greater absolute effect on output than a fall in price. Several researchers found strong evidence for this. See Lee, Ni, & Ratti (1995), and Mork (1989) for early examples. This issue is discussed theoretically in Section 2.2.3, formally introduced in Section 2.3.2, and tested empirically in Sections 2.5.2 and 2.5.3.

2.2.2 The Transmission Mechanisms

The main channels through which changes in oil prices affect macroeconomic variables are largely agreed upon: supply side, demand side, and terms of trade. Even though the contribution of each channel can be case-specific, all three matter in most cases. To see how an oil price shock may propagate through the economy, suppose there is a rise in the price of oil. The immediate supply-side impact is increased production costs. Although firms can adopt streamlined and energy-efficient processes in the long run, frictions prevent these efficiency gains in the short run. This translates into a negative impact on supply in the short term, and the long-run impact is expected to be less pronounced. Even so, implementing changes in production processes comes at a cost. Firms need to pay fixed costs for training and infrastructure (Schneider, 2004). Given these additional costs, which may be affected by oil prices themselves, firms need to solve a new profit maximisation problem: is it optimal to continue an energy-intensive production process in the new price environment or is investment to improve energy efficiency warranted? Depending on which side of the threshold firms find themselves, this decision may lead to a bias in what we observe. If most firms opt to continue production as is, the effect of an oil price increase on GDP growth may appear negligible.

On the demand side, the impact of the price increase is two-fold. First, since consumers demand oil products directly, the shock feeds into inflation and drives the general price level up. Considering US transport sector has accounted for over two-thirds of oil demand in the past few decades, the price increase also affects individual goods. This decreases real disposable incomes across the economy and reduces aggregate demand (Schneider, 2004). Second, falling real wages put pressure on downward rigid nominal wages, lower the level of employment[2], and lead to a fall in output.

Since oil is a globally traded commodity, fluctuations in its price can affect nations through channels outside of their domestic economies. For an oil importing country, a rise in price are equivalent to an increase in import prices. This deteriorates terms of trade and, in many cases, welfare in importers' domestic markets. Unsurprisingly, the magnitude of this impact depends on what fraction of import value oil accounts for: the greater the share of oil in total expenditure, the larger the impact of the shock (Rasmussen & Roitman, 2011).

In addition to the supply, demand, and trade channels, oil price shocks can have a substantial impact on the financial sector and, by extension, on macroeconomic fundamentals. One main message from this rich and developing part of the literature is that investor and consumer confidence play a key role in their respective behaviours in the economy and the stock market. If such loss of confidence due to fluctuations in oil prices is reflected in stock markets, the overall impact could be amplified (Schneider, 2004).

Besides these transmission channels in the context of a *laissez faire* economy, researchers unanimously acknowledge that policy responses to oil price fluctuations can influence the final impact of the shock. For instance, in response to an oil price increase, an oil-importing country's central bank could attempt to mitigate the negative implications by manipulating the policy tools available. The extent to which policy affects the outcome can vary and is a point of debate. On one extreme, Bernanke, Gertler, & Watson (1997) argued that most of the impact of price shocks were caused by tighter monetary policy responses as opposed to the price fluctuations themselves. On the other end of the

[2] I assume wages are rigid downwards and that the level of employment is determined by labour demand.

spectrum, Hamilton & Herrera (2004) claimed that restrictive monetary policy could not explain all of the impact of the shocks and that the direct effects were greater than those caused by policy responses. Since there are often many moving parts, it is difficult to disentangle the impact into its components. For instance, the monetary authority faces a trade-off between inflation dampening and output stabilisation and objectives can vary across countries. Similarly, each shock occurs under different circumstances and policy may be implemented differently for what appears to be the same type of shock. Although policy-making is beyond the scope of this chapter, the results can inform policy-makers and facilitate effective interventions.

Oil price volatility is key as well. Frequent large oil price fluctuations increase uncertainty in the general economic environment and can affect consumer behaviour. Durable goods purchases, including real estate and cars, subside and can have economy-wide trickle-down implications (Hamilton, 2005). Stock markets respond to volatility the same way. Periods of volatile oil prices are generally associated with lower investor confidence, which can lead to cautious trading. This effect has been demonstrated through a number of country-specific studies on the link between oil price volatility and stock market returns (e.g. Arekar & Jain, 2017; Sathyanarayana, Harish, & Gargesha, 2018). From an modelling perspective, this chapter incorporates volatility into the analysis through the use of a GARCH model as outlined in Section 2.2.3, while Section 2.2.4 provides an overview of the related literature. GARCH models are effective in this context, as they allow explicit modelling of unexpected shocks that surprise economic agents whose expectations are determined by historical trends. More generally, increased uncertainty often leads to precautionary savings, slowing down economic activity and, if sustained over a longer period, dampen economic growth. Pindyck (2004b) pointed out that persistent volatility has wide-reaching implications. Within the oil and gas sector, it can expose producers and industrial consumers to risk and influence their investment decisions. In turn, these have an impact on oil inventories and production and transportation facilities (Pindyck, 2004b). Outwith the oil and gas industry, volatility has an impact on commodity-based contingent claims and, therefore, derivative valuation and hedging decisions. Furthermore, firm may revise their investment decisions in physical capital linked to production and consumption of oil and natural gas (Pindyck, 2004b). According to Pindyck (2004a), there are even wider implications. The author argued that volatility can affect the total marginal cost of production, which is reflected in firms' operating options and the opportunity cost of current production. Generally, the higher the oil price volatility, the more uncertainty it creates and the more likely economic instability becomes in both oil-exporting and oil-importing countries. If the volatility is linked to increasing oil prices, rising inflation following threatening a recession in oil-dependent countries.

2.2.3 The Asymmetric Effect of Oil Prices

Section 2.2.1 touched on the idea that the negative impact on GDP growth of a positive price shock may not have the same absolute size as the positive impact an equivalent negative price shock would have. Given the theoretical potential for this, a number of empirical studies have investigated and found evidence for a non-linear relationship between oil price fluctuations and output growth (Gronwald, 2012; Hamilton, 1996; Lee et al., 1995; Mork, 1989; Mory, 1993). The leading explanation for this phenomenon is the dispersion hypothesis, which states that frictions in reallocating factors of production across sectors exacerbate the detrimental effect of price fluctuations. In the context of oil price analysis, consumer behaviour in fuel-inefficient automobile industry is a good example of this. One of the immediate effects of an oil price hike is a fall in demand for fuel-inefficient vehicles. Since labour and capital are immobile in the short-run, factors of production cannot move freely from fuel-inefficient automobile industry to other sectors (Hamilton, 2005). This may lead to extended idle periods for labour and capital in this part of the economy following the sudden fall in demand, causing a potentially sizeable fall in output.

Following a decrease in oil prices of the same size, however, demand for fuel-inefficient cars does not increase substantially. According to Atkeson & Kehoe's (1999) and Hamilton's (1988) theoretical models, technological costs of adjusting capital and labour to be adopted by other sectors could magnify the effects of oil price fluctuations on macroeconomic variables. In some cases, oil price decreases could reduce output growth in the short-run as capital and labour are reallocated to other industries (Hamilton, 2005). Further, these models found that demand side output responses to oil price shocks are not log-linear. Returning to the example above, consumers may postpone purchasing (fuel-inefficient) vehicles when oil prices increase but do not buy a second car when they decrease (Hamilton, 2005).

Downward nominal wage rigidities also play a role in this asymmetric relationship between GDP growth and changes in the oil price. An increase in price reduces workers' purchasing power and puts an upward pressure on wages as workers press for higher pay. Increased wages can, in turn, have implications for the level of employment, inflation, and more generally, aggregate demand and supply. On the contrary, nominal wages are largely unaffected (i.e., not adjusted downwards) if the oil price shock is a negative one and real wages rise.

Empirically, the nature of the hypothesised effect of oil price fluctuations on macroeconomic variables appears to depend on a number of factors. For instance, sample period has been a key point of discussion in this context. Lee et al. (1995) found that statistical significance of the asymmetry hypothesis depends on sample period. Through pairwise equality tests of oil price increases and decreases, the authors concluded that the null hypothesis of equal positive and negative effects could not be rejected for the sample from 1949:1 through 1986:1. However, the same hypothesis was rejected for 1949:1-1988:2 and 1949:1-1992:3 samples, leading to the final conclusion that output growth appears to respond asymmetrically to oil price disturbances in recent samples and not in earlier ones. In their original analysis, Kilian & Vigfusson (2011a) used a Monte Carlo integration method to argue that GDP, consumption, and unemployment respond symmetrically to positive and negative oil price innovations. However, with a dataset updated to the fourth quarter of 2009, the authors rejected the null hypothesis of symmetry in response to a 2-standard deviation price shock (Kilian & Vigfusson, 2011b). Recently, Karaki (2017) repeated Kilian & Vigfusson's (2011a) analysis with data through 2016 and found that asymmetry could not be rejected for a 2-standard deviation innovations and could only be rejected for small price shocks. This provided further motivation for the analysis in this chapter as normalised oil price shocks introduced in Section 2.3.3 can help shed light on the definition of a "large" price shock.

On a sectoral and firm level, the extent to which an oil price shock affects industry and firm output depends critically on the production processes: firms with capital intensive production processes, those with a high capital to labour ratio, and those that produce durable goods are affected most due to their energy requirements and hence susceptibility to price fluctuations in the energy sector (Davis & Haltiwanger, 2001).

2.2.4 Literature Review

Building on the previous subsections, this one aims to provide a general overview of the oil price–macroeconomy literature with a focus on how methodology, econometric models, and variable choice have evolved over time by discussing competing hypotheses.

Theoretical and empirical papers examining the macroeconomic consequences of oil price shocks date back to early 1980s. A number of seminal papers have come out of this literature, which mainly focussed on the US economy. An early example of this is Hamilton's (1983) paper that spurred interest in the topic and made the observation that "all but one of the U.S. recessions since World War II have been preceded […] by a dramatic increase in the price of crude petroleum." Estimating the relationship in question appeared an ordinary one at first: OLS was used to estimate the coefficient of interest. However, researchers noted that this type of analysis was missing a critical component: system dynamics. VAR models, popularised by Sims (1980), were adopted to account for this and remain the most widely used empirical approach to model the oil price – macroeconomy relationship.

As with most empirical work, model specification and variable choice have been key points of discussion for the estimation of the theoretical relationship at hand. An issue that received particular attention is the choice of oil price variable. Bernanke et al. (1997) noted that "it is surprisingly difficult to find an indicator of oil price shocks that produces the expected responses of macroeconomic and policy variables in a VAR setting." Various attempts have been made to capture the true nature of oil price shocks using different oil price measures and introduction of non-linear oil price specifications. Along this vein, Hamilton (2003) provided evidence for the non-linear nature of the oil price-macro relationship, Hooker (1996b) investigated the stability of the relationship, and

Kilian (2009) argued that the underlying causes of oil price shocks change over time and that this matters for the relationship in question.

Further, other scholarly work, including but not limited to Blanchard & Galí (2007), observed that the relationship between oil price shocks and macroeconomic fundamentals has evolved over the years. This observation provides part of the motivation for this chapter because it aims to observe, analyse, and ultimately address the econometric difficulties experienced by the literature through the use of time-varying parameters in a rolling-window impulse response approach. This is akin to Blanchard & Galí's (2007) bivariate rolling VARs but with larger VAR systems and, therefore, more complicated system dynamics. Large number of observations in my dataset has allowed a rolling impulse response analysis using high-dimensional VARs. Besides providing better system dynamics, this approach eliminates the need to conduct sophisticated structural break testing. The rest of this section provides an overview of how the literature has developed over the years and different specifications implemented to address obstacles along the way.

Model Specification and Choice of Oil Price

Using Sims' (1980) 6-variable quarterly VAR model for GDP equation as a basis, Hamilton (1983) found a strong causal relationship between oil price fluctuations and output growth based on U.S. data from 1948 to 1980. Mork (1989) repeated the analysis with data through the second quarter of 1988 and observed only a marginally significant relationship between oil price changes and real GDP growth. Hooker (1996b) further extended the dataset and claimed that the relationship between oil price changes and output growth was no longer statistically significant by the early 1990s.

In his work mentioned above, Mork (1989) illustrated that oil price fluctuations only marginally improve the goodness of fit of Sims' GDP equation when the sample period is extended into the 1980s. The author suggested that the findings differed from those made by Hamilton (1983) due to three main reasons: how oil prices are modelled, what oil price measure is used, and how monetary policy is controlled for. These three factors had an influence on the direction of the literature as econometricians attempted to model these accurately.

The VAR implementations became larger as longer time series became available. As a part of this, Mork (1989) proposed extending the 7-variable system into an 8-variable one in order to allow for an asymmetric oil price impact. He did this by splitting oil price fluctuations into their positive and negative counterparts. In addition, Mork proposed two further fundamental changes to Hamilton's (1983) approach. First, he argued that refiner's acquisition cost of crude oil is a better proxy for oil price than the traditionally-used producer price index in crude petroleum. The biggest justification for this was the bias in what PPI measured in the 1970s, as it reflected only the controlled prices of domestically produced oil (Mork, 1989). Second, he suggested replacing M1 with 3-month TB rate to capture the behaviour of monetary policy makers. Through these changes, Mork improved the accuracy of the test and observed an asymmetric relationship between oil price fluctuations and GDP growth. Like Mork, I opted for 3-month TB rate as the measure of monetary policy. This variable is key to the analysis, since policy implementations in response to an oil price shock could distort the observed impact on macroeconomic performance. As an example, looser monetary policy in response to an oil price rise could potentially outweigh the effects of the original shock. Given the established relationship between interest rates and GDP growth, the *a priori* expectation is a negative coefficient on the 3-month TB rate. I find some evidence towards the importance of modelling interest rates appropriately in later sections, although the effect appears to be time- and specification-dependent. The motivation for choosing TB rate instead of an alternative measure, such as the federal funds rate, is twofold. First, what matters for agents' decisions most is the interest rate and yield available to households and firms through the bill rates as opposed to the official rate set by the Fed. Second, 3-month bills are shortest-term assets and are likely to reflect the changes in the federal funds rate and adjust more rapidly. In this sense, it would be less justifiable to use TB rates with much longer maturities, as factors other than the underlying rate set by the central bank are more likely to bring in noise into the observed series.

Lee et al. (1995) proposed building upon Mork's (1989) analysis by modelling the volatility of oil prices. The authors argued that, *ceteris paribus*, unexpected oil shocks have a larger impact on GDP growth than expected ones. Further, the authors observed that surprise shocks tend to have a higher statistical significance. To observe this, the authors re-estimated Mork's (1989) 7-variable VAR model. The variables involved were real GDP growth, GDP deflator inflation, 3-month TB rate, unemployment rate, wage inflation measured as the average hourly earnings for production workers in manufacturing, import price inflation, and oil price changes. The extended model added a new oil price variable that captured the "unanticipated component of real oil price movement and the time-varying conditional variance of oil price change forecasts" (Lee et al., 1995). This variable evaluates how different the current shock is from the prior distribution of oil prices in an attempt to capture the effect of unexpected price shocks. Although the sets of results from the two studies could not be compared directly due to data source and format differences,[3] Lee et al. (1995) found this variable to be highly correlated with GDP growth in various sample periods. Section 2.5.3 investigates whether this is still the case with an updated dataset.

Lee et al. (1995) has been a stepping stone for introducing normalised oil price shock variables into VAR systems to account for the surprise element of a shock. This has been a critical step forward in understanding the impact of unexpected shocks on macroeconomic fundamentals as well as how, if at all, they differ from their expected counterparts. Unsurprisingly, this approach requires us to categorise oil price fluctuations and define which ones are unexpected. In practice, this could be modelled in various forms. A robust and relatively uncomplicated approach implemented by Lee et al. (1995) used a univariate generalised autoregressive conditional heteroskedasticity error process to compute the unexpected part and conditional variance of the oil price shock. In this chapter, I adopt this process and give further details of the GARCH model implementation in Section 2.2.3.

[3] Lee et al. (1995) used quarterly data from a different source, whereas Mork (1989) had monthly series.

Lee et al. (1995) found empirical evidence that an unexpected oil price shock has a greater effect on output than an anticipated one. Given the implementation of unanticipated oil price shocks, this translates into a shock having greater impact on GDP growth if it immediately follows a long period of stable prices. Similarly, an oil price fluctuation of the same magnitude is expected to have a smaller impact on output growth if it is preceded by a period of volatile prices. The authors observed that although parts of the literature found oil price shocks to have lost their statistical significance in recent decades, the normalised price shocks remained important. The conclusion was, therefore, that oil price fluctuations remain relevant in explaining macroeconomic activity when price variability is captured.

In contrast, others have argued that the robust relationship between oil prices and macroeconomic variables broke down after the highly volatile oil price movements of the 1980s. From the middle of 1990s onwards, a number of analyses emerged empirically testing this claim. As an example, Hooker (1996b, 1999, 2002) observed that mainstream model specifications led to considerably different outcomes when differing sample periods were considered. The author argued, therefore, that oil price fluctuations affect macroeconomic fundamentals indirectly; they propagate through interest rates, unemployment, and inflation such that an oil price shock may induce a departure from Okun's law. Building on the existing literature, this chapter revisits and reassesses the relationship between oil price and macroeconomic activity. As a part of this, I compare model performance across specifications and sample periods as well as investigate the effects of variable choice. Sections 2.3.2 and 2.3.3 outline the implementation of these models, and their output is presented in Sections 2.5.2 and 2.5.3.

2.2.5 Structural Interpretation of the Model

The VAR models adopted as part of the analysis here have an implicit structural assumption via variable ordering. As is the norm with VARs, explanatory variables have been used in order of exogeneity. However, sensitivity analysis using different variable ordering has shown that the main results are not sensitive to this choice. In an effort to identify different transmission mechanisms and differentiate between the US (discussed in this chapter) and the UK (discussed in the next chapter), I adopt a simple macroeconomic model. This model is in line with Blanchard & Galí's (2007) work and has a similar focus: explaining the different response of the economy to oil price shocks across time.

Like Blanchard & Galí (2007), I start with a standard new-Keynesian model. Oil is then introduced as an input to firms' production function as well as direct consumption. For an oil importer whose demand is not large enough to influence the global oil price, fluctuations in the price of oil are exogenous. This is a key difference between this chapter and the next, as the UK has had a more complex history with oil trade. This aspect of the underlying model forms the basis of the different interpretation and results observed in the two chapters. This is discussed further in the next chapter. Lastly, in the labour market, wages are rigid downwards. This section provides a brief overview of the log-linearised model implemented in this chapter as adopted from Blanchard & Galí (2007).

Oil as an input to consumption and production

Oil features in the model in two ways: as in input for firms' production and as a direct input into consumption. Production and consumption are given by the following two equations.

$$q_t = a_t + \alpha_n n_t + \alpha_m m_t \tag{2.2}$$

$$c_t = (1-\chi)c_{q,t} + \chi c_{m,t} \tag{2.3}$$

where

q_t	Domestic output
a_t	Exogenous technology parameter
n_t	Labour
m_t	Imported oil used in production
c_t	Consumption
$c_{q,t}$	Consumption of domestic production
$c_{(m,t)}$	Consumption of imported oil

There are two points of note here. First, $\alpha_n + \alpha_m \leq 1$. Second, there are two prices at play – the price of domestic production ($p_{q,t}$) and the price of consumption ($p_{c,t}$). If $p_{m,t}$ is the price of oil and the real price of oil is given by $s_t = p_{m,t} - p_{q,t}$, the consumption equation implies $p_{c,t} = p_{q,t} + \chi s_t$ such that an increase in the real price of oil raises the consumption price relative to the price of domestic output.

Households

Two equations determine the behaviour of households:

$$c_t = E_t\{c_{t+1}\} - (i_t - E\{\pi_{c,(t+1)}\}) \tag{2.4}$$

$$w_t - p_{(c,t)} = c_t + \phi n_t \tag{2.5}$$

where

i_t	Nominal interest rate
$\pi_{c,t} \equiv p_{c,t} - p_{(c,(t-1))}$	Inflation
w_t	Nominal wage
n_t	Employment
ϕ	Frisch elasticity of labour supply

Equation 2.5 implies that wages equal the marginal rate of substitution between consumption and leisure. To introduce real wage rigidities, equation 2.5 can be modified to include a parameter, $\gamma \in [0, 1]$, that aims to capture the idea that real wages may not respond to labour market conditions as implied by a model with perfectly competitive markets. This modified version is given in equation 2.6.

$$w_t - p_{(c,t)} = (1 - \gamma)(c_t + \phi n_t) \tag{2.6}$$

Firms

Firms' cost minimisation problem, together with the production function, implies that their demand for oil is $m_t = -\mu_t^p - s_t + q_t$, where μ_t^p denotes the price mark-up. Substituting for m_t in equation 2.2 yields the following reduced-form production function:

$$q_t = \frac{1}{1-\alpha_m}(a_t + \alpha_n n_t - \alpha_m s_t - \alpha_m \mu_t^p) \qquad (2.7)$$

Hence, output is inversely related to the real price of oil, s_t, for a given level of employment and technology. Further, for a given level of productivity, a rise in the real oil price could have one or more of the following effects: (1) lower wages, (2) lower employment, and (3) lower mark-up.[4] In a world with perfectly competitive labour markets and flexible prices and wages, a rise in the price of oil would be reflected entirely on wages. However, as noted and demonstrated by Blanchard & Galí (2007), sticky prices mean that wages respond less and that mark-ups vary as a result. This is a critical dynamic for the asymmetric impact of oil price changes on macroeconomic fundamentals. For instance, this structural setup implies an increase in the price of oil may lead to lower wages, higher unemployment, or lower mark-up. A decrease, however, does not necessarily lead to the opposite outcome in each of these. More specifically, a fall in oil price may not lead to higher wages or lower unemployment. Because mark-ups are flexible, lower cost of production may – at least in the short run – lead to a higher mark-up with little change in wages and unemployment level.

The Effect of Oil Prices on Inflation

At the equilibrium, the relationship between inflation and the real oil price can be shown to be

$$\pi_{q,t} = \beta E_t\{\pi_{q,t+1}\} + \lambda_p \Gamma_n n_t + \lambda_p \Gamma_s s_t - \lambda_p \Gamma_a a_t \qquad (2.8)$$

where

$$\Gamma_n \equiv \frac{(1-\alpha_n-\alpha_m)\gamma + (1-\alpha_m)(1-\gamma)(1+\phi)}{\big(1-(1-\gamma)(\alpha_m-(1-\alpha_m)\eta)\big)} \geq 0$$

$$\Gamma_a \equiv \frac{\gamma}{\big(1-(1-\gamma)(\alpha_m-(1-\alpha_m)\eta)\big)} \geq 0$$

$$\Gamma_s \equiv \frac{\gamma(\alpha_m + (1-\alpha_m)\chi)}{\big(1-(1-\gamma)(\alpha_m-(1-\alpha_m)\eta)\big)} \geq 0$$

[4] Further details of the model as well as the derivation of the relationships are given in Blanchard & Galí (2007).

$$\eta \equiv \frac{\alpha_m}{\mathrm{M^p} - \alpha_m}$$ such that $\mathrm{M^p}$ denotes the levels of steady state gross mark-up

Therefore, in simple terms, an increase in the real price of oil is expected to raise domestic inflation directly through equation 2.8.

2.3 Models and Methodology

My analysis of model performance and the estimation procedure begins with a base model similar to that used by Hamilton (1983). This model is then progressively extended to incorporate the ideas put forth by Mork (1989) and Lee et al. (1995). At that stage, time-varying parameters are estimated using a rolling-window technique to provide further insights as to the nature of the oil price – macroeconomy relationship and how it may have evolved over time. Variables used in the estimation are listed in Section 2.4 and have been selected based on the debate and criticisms in the relevant literature. As in most recent studies, GDP is used as the measure of output as opposed to GNP, although Sims' original VAR model used the latter. All estimations presented in Section 2.5 using GDP have been repeated with GNP, but the results did not change substantially.[5] In addition, whether nominal or real GDP should be used in the system has been a point of controversy. Hamilton used nominal log differences in output growth because the implicit deflator itself is included in the model and this gives identical results to using real log differences (Mork, 1989). Lastly, some researchers, including Hamilton (1996b), have deflated their measure of output using PPI in all commodities. I find this to be problematic, because it introduces an artificial correlation between oil prices and deflated GDP, since some commodities that enter the PPI measure are oil-related products. As a result, my analysis uses PPI in finished goods to deflate GDP.[6] Lastly, it is important to note that oil price changes are captured using two proxies: PPI in crude petroleum and RAC. Hamilton has been criticised for using PPI as a measure of oil

[5] The difference between GDP and GNP is not substantial for the US, but if the analysis were to be repeated for a country like Mexico, GDP should be preferred, since income earned by Mexican residents abroad constitutes a considerable fraction of the country's GDP.
[6] The estimation was repeated using GDP deflated using PPI in finished goods and CPI with a base year, but the sign and significance of the resulting parameter estimates remained unchanged.

prices, and the use of RAC has been proposed as a robust alternative. In my analysis, the entire estimation procedure is repeated using each of these variables in order to evaluate relative performance and the robustness of the VAR systems.

2.3.1 The Base Model

The base model is an extension of Sims' (1980) VAR specification. The 6-variable VAR system proposed by Sims is expanded to include an oil price variable. This 7-variable system consists of GDP growth, oil price changes, GDP implicit deflator inflation, 3-month TB rate, real wage inflation, unemployment, and import price inflation.[7] Estimation results and empirical analysis using this model are given in Section 2.5.1.

2.3.2 Asymmetric Effects Model

The first extension to the base model incorporates the asymmetric response idea popularised by Mork (1989) and later adopted by Lee et al. (1995) and Hamilton (1996). To evaluate the effects of oil price increases and decreases separately, oil price changes are split into two distinct parts. The resulting variables are added to the VAR resulting in an 8-variable system. Denoting oil price changes as o_t, the new variables are generated as follows:

$$o^+ = \begin{cases} x, & x > 0 \\ 0, & x \leq 0 \end{cases}$$
$$o^- = \begin{cases} 0, & x \geq 0 \\ x, & x < 0 \end{cases} \tag{2.9}$$

The regression results using this specification are analysed in depth in Section 2.5.2. It is worth noting here that although this chapter has opted for this method to capture asymmetry, other methods, such as threshold autoregressive (TAR) models, could also be implemented. The reason was this choice two-fold. First, this asymmetry implementation is an intermediate step in the build-up to a normalised oil price variable. Second, the threshold approach limits the distribution of the least squares estimator and,

[7] Due to data availability, the estimated base model specification is limited for some sample periods. Please see the section 2.4 for details.

despite being consistent under some regularity assumptions, has some shortcomings. Three key issues raised in the TAR literature relate to 1) the unverifiable nature of strong assumptions, 2) the testing for linearity and, therefore, the validity of using TAR as an alternative, and 3) the difficulty in the inference of the threshold parameter. Tong (2011) discussed the latter two points and, as noted in Hansen (2011), highlighted that the threshold parameter is required to construct confidence intervals. Although Hansen (2000) proposed a nuisance parameter-free asymptotic approximation, some modelling difficulties remain.

2.3.3 Normalised and Net Oil Price Model

Lee et al. (1995) proposed a further extension to capture the nature of oil price fluctuations more accurately. Using a univariate GARCH (1,1) process, the authors calculated the conditional variance of oil price changes and used it to normalise unanticipated real oil price fluctuations (Lee et al., 1995). These normalised oil price changes aim to capture the idea that small price increases within volatile periods are predicted to have little effect on economic agents' behaviour "if they do not push agents across time-varying S,s bands or generate enough uncertainty to delay irreversible investments" (Hooker, 1999). Lee et al. (1995) proposed using positive and negative normalised price shocks in addition to non-normalised ones in order to introduce an additional degree of asymmetry into the model. In the literature, these variables are referred to as scaled oil price increases (SOPI) and scaled oil price decreases (SOPD). By construction, SOPI incorporate the surprise factor through changes in variance and not in the level of oil price. That is, the mean of real oil price changes may rise over time without agents being surprised as long as the new distribution of oil price changes remains the same. These variables are constructed as follows:

$$z_t = \alpha_0 + \sum_{i=1}^{4} \alpha_i z_{t-i} + \varepsilon_t \tag{2.10}$$

$$h_t = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \gamma_2 h_{t-1} \tag{2.11}$$

Here, $\varepsilon_t | I_{t-1} \sim N(0, h_t)$, and z_t are oil prices measured as the change in RAC. The unexpected part of the oil price shock is simply the residual term of equation 2.10, $\hat{\varepsilon}_t = z_t - \widehat{z_t}$. Normalised oil price shocks are then calculated as,

$$\varepsilon_t^* = Normalised\ Oil\ Price\ Shock = \frac{\hat{\varepsilon}_t}{\sqrt{h_t}} \tag{2.12}$$

This variable is then split into two parts as,

$$SOPI_t = Normalised\ Positive\ Oil\ Price\ Shock\ (\varepsilon_t^{*+}) = \max(0, \varepsilon_t^*) \tag{2.13}$$

$$SOPD_t = Normalised\ Negative\ Oil\ Price\ Shock\ (\varepsilon_t^{*-}) = \min(0, \varepsilon_t^*) \tag{2.14}$$

Assuming unexpected variation in real oil prices has an impact on how the price shocks affect real output, the normalised variable, ε_t^*, is predicted to have a "more systematic causal relation to real GDP than either z_t or $\hat{\varepsilon}_t$" (Lee et al., 1995).

Hamilton (1996) proposed an alternative to scaled oil price changes: net oil price increases (NOPI). This variable is defined as the amount by which log oil prices in quarter t exceed the maximum value over the past four quarters. If log oil price in the current quarter does not surpass any of the previous 4 values, NOPI takes on the value of 0. Therefore,

$$NOPI_t = \max(0, 100 \times \{\ln(o_t) - \ln[\max(o_{t-1}, o_{t-2}, o_{t-3}, o_{t-4})]\}) \tag{2.15}$$

Here, o_t denotes the same oil price series used by Mork (1989), but in quarterly frequency. Having observed asymmetric effects in their empirical models, some researchers, including Hamilton (1996), have used only oil price increases (NOPI or SOPI) in their estimations. This introduces an extreme level of asymmetry into the model by entirely ignoring the effect of oil price decreases. Such changes in price can, of course, be captured using SOPD. This chapter focuses on overall model performance and robustness and, therefore, uses all three variables in the analysis. This is discussed further in the Empirical Results section (2.5) below. Finally, a summary of model specifications used in the analysis is given in Table 2.1 below.

Model Specification	GDP Growth	Oil Price Change	Oil Price Increase	Oil Price Decrease	Normalised Oil Shock	Normalised Positive Oil Shock	Normalised Negative Oil Shock	Net Oil Price Increase	GDP Deflator Inflation	3m TB rate	Unemp. Rate	Real Wage Inflation	Import Price Inflation
Base Model	✓	✓							✓		✓	✓	
Asym. Eff. Model	✓		✓	✓					✓	✓	✓	✓	✓
6-variable System 1	✓	✓			✓				✓		✓	✓	
6-variable System 2	✓					✓	✓		✓		✓	✓	
6-variable System 3	✓				✓				✓	✓	✓	✓	
7-variable System 1	✓	✓			✓				✓	✓	✓	✓	
7-variable System 2	✓					✓	✓		✓	✓	✓	✓	
7-variable System 3	✓					✓	✓		✓	✓	✓	✓	
8-variable System 1	✓	✓			✓				✓	✓	✓	✓	✓
8-variable System 2	✓					✓	✓		✓	✓	✓	✓	✓
8-variable System 3	✓	✓				✓	✓		✓	✓	✓	✓	
NOPI System 1	✓							✓	✓		✓	✓	
NOPI System 2	✓							✓	✓	✓	✓	✓	
NOPI System 3	✓							✓	✓	✓	✓	✓	✓

Table 2.1. Model specifications.

2.3.4 Impulse Response Analysis

Impulse response analysis used in this chapter and the next is a standard approach. This section provides an overview of the implementation, interpretation, and details of the technique. Since the impulse response functions (IRFs) are implemented following a VAR model, I started with a pth order VAR with exogenous variables given by

$$y_t = v + A_1 y_{t-1} + \cdots + A_p y_{t-p} + B x_t + u_t \tag{2.16}$$

where y_t is a $K \times 1$ vector, A_i are $K \times K$ matrices of parameters, x_t is an $L \times 1$ vector of exogenous variables, B is a $K \times L$ matrix of coefficients, and u_t is a white noise error term with $E(u_t) = 0$, $E(u_t u_t') = \Sigma$, and $E(u_t u_s') = 0$ for $t \neq s$.

The VAR has a moving-average representation if it is stable (Lütkepohl, 2005). Therefore, assuming the variables are covariance-stationary and there is no high-order autocorrelation, it can be rewritten as

$$y_t = \mu + \sum_{i=0}^{\infty} \Phi_i u_{t-i} \tag{2.17}$$

where μ is the $K \times 1$ mean of y_t.

IRFs describe how the innovations to one variable affect another one after a certain number of periods. In this notation, Φ_i are IRFs and the j, k element of Φ_i represents the impact of a one-time unit increase in the kth element of u_t on the jth element of y_t after i periods. Φ_i have the following representation

$$\Phi_i = \begin{cases} I_K & \text{if } i = 0 \\ \sum_{j=1}^{i} \Phi_{i-j} A_j & \text{if } i = 1, 2, \dots \end{cases} \tag{2.18}$$

In a time-series context, u_t are contemporaneously correlated, however, which implies equation 2.17 cannot provide a causal inference. In other words, a shock to one variable in the system would imply shocks to others making it impossible to hold everything other than the intended shock constant. A workaround to this is the Cholesky decomposition, which helps rewrite equation 2.17 in terms of mutually uncorrelated innovations. This leads to the so-called orthogonalised IRFs that do allow a causal interpretation.

2.4 Data and Descriptive Statistics

The data are from various sources but were downloaded from Thomson Reuters Datastream in quarterly frequency. All variables in the VAR system, with the exception of real wage inflation, are expressed in natural logarithm. Since the variables exhibit non-stationarity and are determined to be integrated of order 1, their first differences are used. Time trend is also removed from the variables where appropriate. In this analysis, de-trending was applied to GDP deflator, import price inflation, unemployment rate, and 3-month TB rate. Table 2.2 summarises the variables, data treatment, period of availability, and sources.

Variable	Description	Period	Data Treatment	Source
GDP	Gross Domestic Product ($\$_{2009}$)	1950:1 - 2015:2	Natural log, first difference, deflated using PPI in finished goods	Bureau of Economic Analysis
GDP deflator	Chain-type price index of GDP	1950:1 - 2015:2	Natural log, de-trend, first difference	Bureau of Economic Analysis
PPI in crude petroleum	Index, 2009=100	1950:1 - 2015:2	Natural log, first difference	Bureau of Labor Statistics
Refiners' acquisition cost	Refiners' acquisition cost of domestic & imported crude oil	1974:1 - 2015:2	Natural log, first difference	Department of Energy
Import price index	Import Prices, All commodities, Index, 2000=100	1982:3 - 2015:2	Natural log, de-trend, first difference	Bureau of Labor Statistics
Real wage growth	Real hourly compensation, manufacturing, % change	1950:1 - 2015:2	First difference	Bureau of Labor Statistics
3-month TB rate	3-month Treasury Bill rate	1972:1 - 2015:2	Natural log, de-trend, first difference	Federal Reserve
Unemployment rate	Total unemployment rate	1950:1 - 2015:2	Natural log, de-trend, first difference	Bureau of Labor Statistics

Table 2.2. Variable descriptions, availability, and sources.

GDP is used as a measure of output and the variable enters the VAR system as $\ln(y_t/y_{t-1})$, where y_t denotes GDP deflated using PPI in finished goods. Two proxies for oil price are used: PPI in crude petroleum and refiners' acquisition cost

(RAC). As described above, these variables also undergo a logged differencing transformation. Therefore, changes in the resulting variables can be interpreted as percentage point fluctuations. Since not all variables were available from 1950:1, some of the analysis was conducted with a shorter time series. These are shown in Table 2.3 and also noted in the results section where appropriate.

Variable	**Statistic**	**1950:1 - 1986:1**	**1974:1 - 2015:2**	**1986:1 - 2015:2**	**1950:1 - 2015:2**
Δln(GDP)	Mean	-0.0002	-0.0016	0.0009	0.0003
	Std dev	0.0179	0.0151	0.0118	0.0155
Δln(PPI in crude petroleum)	Mean	0.0123	0.0108	0.0074	0.0101
	Std dev	0.0509	0.1511	0.1738	0.1221
Δln(RAC)	Mean	0.0185	0.0118	0.0090	0.0118
	Std dev	0.0764	0.1412	0.1607	0.1412
Δln(GDP deflator)	Mean	0.0010	-0.0008	-0.0037	-0.0011
	Std dev	0.0070	0.0061	0.0024	0.0059
ΔReal wage growth	Mean	-0.0597	-0.0121	-0.0410	-0.0513
	Std dev	3.8090	7.0859	8.1793	6.1505
Δln(Unemployment rate)	Mean	-0.0009	-0.0012	-0.0037	-0.0022
	Std dev	0.0824	0.0513	0.0447	0.0680
Δln(3-month TB rate)	Mean	0.0358	-0.0147	-0.0297	-0.0085
	Std dev	0.1635	0.3428	0.3922	0.3365
Δln(Import price)	Mean	-0.0093	-0.0010	0.0000	-0.0010
	Std dev	0.0164	0.0260	0.0267	0.0260

Table 2.3 Descriptive statistics.

Some model specifications discussed in Section 2.5 require data to be processed and transformed further. To this end, oil price fluctuations are split into positive and negative changes. Further, normalised oil price shocks are estimated through a series of GARCH models. Under larger model specifications, normalised shocks are also broken down into their positive and negative counterparts to capture any asymmetrical patterns. Figure 2.2 demonstrates the impact of normalising oil price fluctuations using RAC from 1974:1 through 2015:2. As illustrated by the diagram, normalisation process rescales the oil price fluctuations based on price behaviour in the preceding four quarters. More specifically, if a price increase is preceded by a period of relatively stable prices, it is exaggerated. Similarly, a price change following a particularly volatile period is scaled down. An example of the former is observed in the fourth quarter of 2008 where the -74% fall in price is represented as a much larger decline in estar (ε_t^*). The end of 2008 saw a rapid decline in oil prices, although the previous four quarters had been relatively stable. After normalisation, therefore, the fourth quarter's price fall is scaled up substantially. Having observed a volatile quarter at the end of 2008, however, the further decline in prices in the first quarter of 2009 is scaled down and the normalised oil price shock is less, in absolute value, than the true price change.

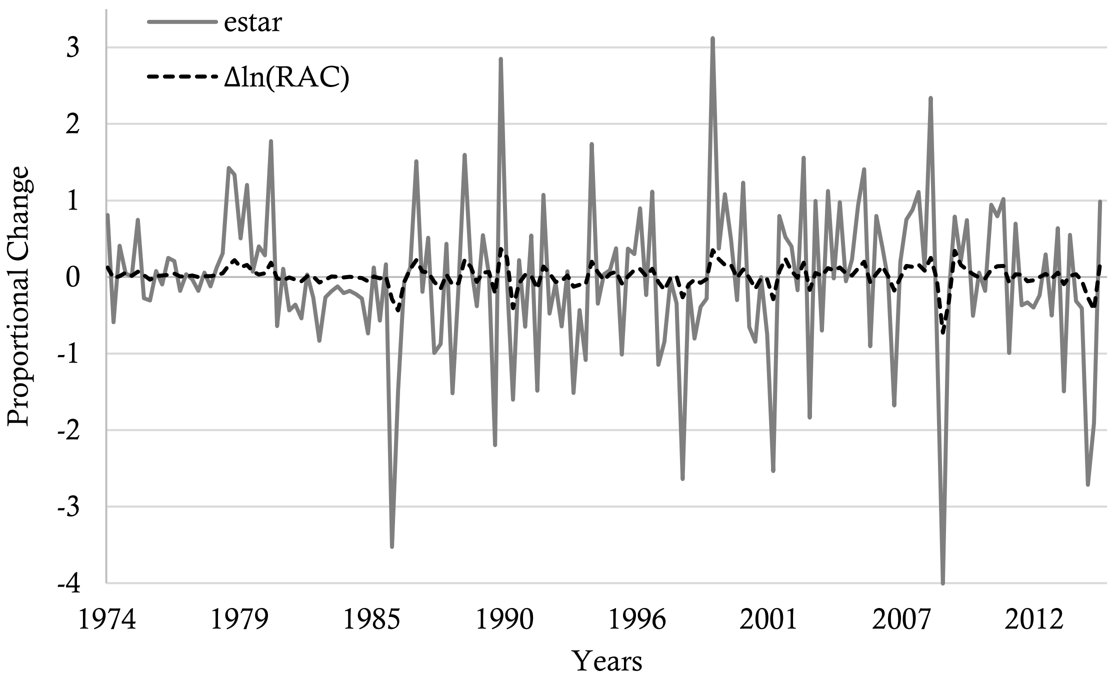

Figure 2.2 Oil price changes and normalised oil price fluctuations.

2.5 Empirical Results

This chapter examines the oil price–macroeconomy relationship using four models each of which is implemented with different specifications and over different subsample periods to evaluate relative performance as well as sensitivity of each model to additional control variables. Estimations over a few subsamples also allow an analysis of whether the relationship is losing significance over time. Results from each of the models are discussed in detail below. In these results, statistical significance refers to Granger causality with a null hypothesis that has a binary outcome. Throughout the discussion in this section, the rejection of the null hypothesis suggests the coefficient estimates in question are statistically significantly different from zero and, thus, provide evidence for Granger causality. Similarly, if the null hypothesis is not rejected, there is no evidence for Granger causality. In other words, the null hypothesis is equivalent to no Granger causality, whereas the alternative suggests Granger causality.

2.5.1 The Base Model

The analysis begins with a base model over different subsamples. The sample periods analysed separately are 1950:1 through 1986:1, 1974:1 through 2015:2, 1986:1 through 2015:2, and finally the entire sample period. The first sample period is used to compare the results with those obtained by Lee et al. (1995). RAC series is available from 1974:1 onwards so the second sample period begins then and allows for a direct comparison between RAC and PPI in crude petroleum as proxies for oil price. Furthermore, this subsample avoids the bias introduced by Nixon price controls that ended in April 1974. Lastly, this sample period avoids, and allows the testing of, the criticism that oil price–macroeconomy relationship vanished after 1973 but appears significant in recent sample periods only because pre-1973 observations drive the relationship. The third period is used largely because data on import price index are available beginning 1986:1, and finally, the entire sample period is included for comparison.

Table 2.4 shows a summary of exclusion tests, which are joint F-tests for the significance of all four lags of the oil price change variable in the GDP growth equation of the corresponding model. The null hypothesis is that none of the four coefficients are statistically different from zero. Therefore, these tests can also be considered Granger causality tests.

Base Model	Variable	1950:1-1985:4 †	1974:1-2015:2 ††	1986:1-2015:2 †††	1950:1-2015:2 †
PPI	Oil Price Change	27.959*** (0.000)	18.326*** (0.001)	9.598** (0.048)	21.632*** (0.000)
RAC	Oil Price Change	—	22.807*** (0.000)	11.190** (0.025)	—

Table 2.4. Exclusion tests for the base model. The values in parentheses are p-values. Statistical significance is shown at the 10% level (*), 5% level (**) and 1% level (***).

Note that the model specification used in each of the subsamples is different due to data availability, and the most comprehensive specification is used over the period 1986:1-2015:2.[8] The 7-variable VAR system consists of real GDP growth, oil price

[8] Table 2.4 shows results for different model specifications corresponding to each sample period: 5-variable VAR (base model, denoted as †), 6-variable VAR (base model + 3-month TB rate, denoted as ††) and 7-variable VAR (base model + 3-month TB rate + import price inflation, denoted as †††)

changes, implicit GDP deflator inflation, real wage inflation, unemployment rate, 3-month TB rate and import price inflation. Because import price index series are only available from the third quarter of 1982, the specification used in the 1974:1 through 2015:2 subsample omits this variable and instead uses a 6-variable system. Finally, the remaining two sample periods are analysed using a 5-variable VAR where the 3-month TB rate is omitted due to limitations on data availability. Based on the resulting test statistics, I reject the null hypothesis in all model specifications across all subsamples at the 5% level and conclude that oil price changes do Granger-cause fluctuations in real GDP growth in every specification. Note, however, that these specifications do not allow for any degree of asymmetry as oil price increases and decreases are pooled into one variable.

For comparison with the 7-variable system shown in Table 2.4, the 5-variable system was estimated over the sample period 1986:1-2015:2. The F-statistic for the joint test of coefficients on all four lags of oil price changes was 18.296 with a p-value of 0.001 when PPI in crude oil was used as the proxy for oil prices, and 20.891 with a p-value of 0 when RAC was used. After a preliminary analysis of the difference in test statistics across model specification and information criteria, 3-month TB rate and import price inflation appear to be valuable control variables: they increase the explanatory power of the model and in their absence, oil price variables have higher statistical significance pointing to a potential omitted variable bias. Although oil price fluctuations are of particular interest here, I conduct a formal test of the joint significance of all four lags of the two control variables using exclusion tests as discussed above. The results are surprising: using RAC as the proxy over 1986:1-2015:2 sample period yielded an F-statistic for the joint significance of four lags of 3.90 for TB rate and 0.64 for import price inflation. The corresponding p-values were 0.420 and 0.959, respectively, suggesting that the null hypothesis could not be rejected for either variable. It is worth mentioning, however, that this sample period consists of 118 observations and a small sample bias might be affecting the results when using a 7-variable VAR system with four lags, despite a small sample correction.

To summarise, the results obtained from the 5-variable base model are unreliable due to two main problems. First, omission of 3-month TB rate and import price inflation is likely to bias parameter estimates. Second, the model does not allow for the asymmetric effect of oil price shocks on GDP growth, which is found to be statistically significant in later sections.

2.5.2 Asymmetric Effects Model

Building on Hamilton's (1983) work, Mork (1989) was first to point out the asymmetric effect of oil price fluctuations on GDP growth rate. Table 2.5 summarises the F-statistics of exclusion tests obtained by separating oil price changes into their positive and negative counterparts.[9] The test results indicate that oil price increases Granger-cause changes in GDP growth. In subsamples 1974:1 through 2015:2 and 1986:1 through 2015:2, RAC-based oil price increases have a higher statistical significance than the PPI-based ones. This is due to the degree to which PPI for crude petroleum and RAC are correlated with the included control variables. For example, since oil imports constitute a considerable portion of all US imports, oil and import prices are expected to be correlated. Further investigation indicates that PPI for crude petroleum is significantly more correlated with import price inflation than RAC. Therefore, including import price inflation in the system renders PPI-measured oil price increases less statistically significant, while it only diminishes the significance of RAC-based oil price increases leaving the variable statistically significant at the 1% or 5% levels. Part of this investigation revealed that the root-mean-square error (RMSE) did not change substantially across models and sample periods, suggesting that the observed variation in results is not due to worse model fit in general.

[9] Table 2.5 shows results for different model specifications corresponding to each sample period: 5-variable VAR (base model, denoted as †), 6-variable VAR (base model + 3-month TB rate, denoted as ††) and 7-variable VAR (base model + 3-month TB rate + import price inflation, denoted as †††)

Proxy	Variable	1950:1-1985:4 †	1974:1-2015:2 ††	1986:1-2015:2 †††	1950:1-2015:2 †
PPI	Oil Price Increase	32.186*** (0.000)	19.140*** (0.001)	10.211** (0.037)	25.313*** (0.000)
	Oil Price Decrease	1.583 (0.812)	12.629** (0.013)	8.425* (0.077)	8.632* (0.071)
	Inflation, GDP Deflator	2.676 (0.613)	8.131* (0.087)	3.349 (0.501)	16.023*** (0.003)
	3-month TB Rate	—	1.952 (0.745)	5.616 (0.230)	—
	Unemployment Rate	9.932* (0.080)	14.392*** (0.006)	12.374** (0.015)	13.917*** (0.008)
	Real Wage Inflation	7.779 (0.100)	2.356 (0.671)	2.269 (0.686)	5.519 (0.238)
	Import Price Inflation	—	—	1.049 (0.902)	—
RAC	Oil Price Increase	—	26.356*** (0.000)	15.754*** (0.003)	—
	Oil Price Decrease	—	8.758* (0.067)	8.116* (0.087)	—
	Inflation, GDP Deflator	—	6.941 (0.139)	3.134 (0.536)	—
	3-month TB Rate	—	2.301 (0.681)	6.494 (0.165)	—
	Unemployment Rate	—	11.835** (0.019)	11.471** (0.022)	—
	Real Wage Inflation	—	2.111 (0.715)	2.123 (0.713)	—
	Import Price Inflation	—	—	0.759 (0.944)	—

Table 2.5. Exclusion tests of asymmetric effects model with GDP growth as the dependent variable. The values in parentheses are p-values. Statistical significance is shown at the 10% level (*), 5% level (**) and 1% level (***).

In order to isolate the effect of including import price inflation in the VAR system, a 7-variable model (which excludes import price inflation) with PPI for crude petroleum was estimated in the sample period 1986:1 through 2015:2. The test statistics for positive and negative oil price changes were 14.69 (0.005) and 10.88 (0.028), respectively, where the values in parentheses are p-values. Further, a 6-variable model (which excludes 3-month TB rate and import price inflation) was estimated for the same sample period. The results suggest that, unsurprisingly, control variables play a role in the diminished significance of oil price increases in this subsample. Hence, significance of positive oil price changes themselves do not decrease in this period and the fall in test statistics is mostly due to the additional variables included in the system. [10] This provides some evidence against the validity of Hooker's (1996a, 1996b) claim that the statistical significance of oil prices in explaining output fluctuations has declined in recent datasets. Throughout this analysis, RAC was more isolated from import price inflation than PPI for crude petroleum and should be favoured in estimation procedures, as it increases the robustness of the model and parameter estimates. Most exclusion tests on oil price decreases returned a p-value greater than 0.05. Thus, the results confirmed that the asymmetric impact of oil price shocks on output growth continues to hold in most recent data. This asymmetry effect is robust to the specification of the model, since larger specifications displayed the same pattern.

2.5.3 Normalised and Net Oil Price Models

Table 2.3 above shows the summary statistics for oil price variables being used in estimation for all sample periods. From the table, oil prices appear more volatile in more recent samples. Hence, oil price volatility could provide further identifying variation unexploited in traditional models, and implementing a volatility-scaled measure for price fluctuations could lead to more accurate results. Table 2.6 lists the estimated coefficients from the GARCH (1,1) model expressed by equations 2.3 and 2.4 above.

[10] This pattern was not observed universally. For example, the subsample 1986:1-2011:1 shows a fall in the significance of oil price increases even when the control variables are omitted. This suggests a weaker link between oil price changes and GDP growth in more recent years. Time-varying parameter estimation discussed later in this chapter sheds more light on this.

Proxy	Parameter	1950:1-1985:4	1974:1-2015:2	1986:1-2015:2	1950:1-2015:2
PPI	α_0	0.011**	0.017	0.013	0.003
		(0.028)	(0.222)	(0.379)	(0.377)
	α_1	0.770***	0.258	0.264**	0.394**
		(0.000)	(0.121)	(0.014)	(0.026)
	α_2	0.007	-0.300**	-0.336**	-0.393**
		(0.959)	(0.017)	(0.011)	(0.010)
	α_3	0.064	0.110	0.141*	0.250
		(0.244)	(0.419)	(0.097)	(0.274)
	α_4	0.035	-0.067	-0.161*	-0.056
		(0.378)	(0.505)	(0.064)	(0.792)
	γ_0	0.000	0.004	0.012***	0.000
		(0.333)	(0.617)	(0.008)	(0.325)
	γ_1	5.951**	0.433	0.217	1.220*
		(0.017)	(0.154)	(0.222)	(0.055)
	γ_2	0.014	0.497	0.328	0.493***
		(0.483)	(0.110)	(0.135)	(0.000)
RAC	α_0	—	0.016	0.015	—
			(0.117)	(0.310)	
	α_1	—	0.411***	0.309**	—
			(0.003)	(0.013)	
	α_2	—	-0.371***	-0.318***	—
			(0.004)	(0.005)	
	α_3	—	0.230**	0.318	—
			(0.023)	(0.213)	
	α_4	—	0.085	0.375***	—
			(0.145)	(0.009)	
	γ_0	—	0.004	0.009***	—
			(0.332)	(0.003)	
	γ_1	—	0.384*	0.008**	—
			(0.054)	(0.020)	
	γ_2	—	0.421	0.311**	—
			(0.128)	(0.039)	

Table 2.6. Parameter estimates for GARCH (1,1). The values in parentheses are p-values. Statistical significance is shown at the 10% level (*), 5% level (**) and 1% level (***).

From these results, GARCH (1,1) representation of oil prices to compute conditional variance of oil price shocks appears to be appropriate. The main observation is that ARCH and GARCH terms, γ_1 and γ_2, are statistically significant in several sample periods. Most notably, recent time periods exhibit GARCH behaviour in errors. Estimated parameters are qualitatively identical to those obtained by Lee et al. (1995) and have the expected signs. As a side observation, in early sample periods, α_i have loosely alternating signs such that α_1 is positive, α_2 is negative, α_3 is positive, and α_4 is negative. This is shown in columns four and six of Table 2.5. The marginally-significant GARCH coefficient in Lee et al. (1995) is not statistically significant in my dataset—see column three of Table 2.5.

An analysis of autocorrelation in residuals of the GARCH model in each sample period showed that there is no unexploited information in residuals for sample periods 1974:1 and later. Although there is some autocorrelation in residuals for earlier samples, increasing the number of AR lags or ARCH and GARCH terms did not improve the behaviour of the residuals. For the 1974:1-2015:2 subsample, PPI and RAC GARCH (1,1) residuals resulted in a Ljung-Box Q statistic of 19.23 (p=0.739) and 12.92 (p=0.968), respectively. Furthermore, Bollerslev, Chou, & Kroner (1992) argue that low-order GARCH models outperform alternative methods the authors investigate. In light of these, GARCH (1,1) specification is adopted as a parsimonious representation of the conditional variance of ε_t in equation 2.17 above. Therefore, this specification is used to calculate ε_t^*.

Analysis of different sample periods showed that the characteristics of the conditional variance process of ε_t changed over time. More specifically, in earlier sample periods, the sum of $\hat{\gamma}_1$ and $\hat{\gamma}_2$ is greater than one suggesting that the conditional variance process is highly persistent. In Engle & Bollerslev's (1986) terminology, this corresponds to an integrated GARCH model with integration order higher than one. In samples from 1974 onwards, however, this sum is much lower and less than one. This provides further evidence that the GARCH (1,1) specification is appropriate for recent subsamples, as persistence in the conditional variance process could be indicative of the variance equation being misspecified. An example of this is Lamoureux & Lastrapes (1990), who provide empirical evidence that persistence in stock return variance is sensitive to model specification and decreases when control variables are included. To ensure consistency and comparability in this analysis, the same GARCH specification is adopted for all sample periods. Lastly, the model employed in this analysis was assumed to exhibit the asymptotic properties of GARCH processes outlined in Bougerol & Picard (1992), Lumsdaine (1991, 1996), and Nelson (1990).

Table 2.7 provides exclusion test results for each specification and sample period having introduced normalised oil price shocks into each system. From this output, there is little evidence that the normalised oil price shocks are more highly correlated with changes in real GDP than oil price changes. Test statistics for normalised price shock variables are not statistically significant except in early sample periods (see columns four and seven of the table). Interestingly, although normalised price shocks are not statistically significant individually, when considered with oil price changes, they are jointly significant. This is likely caused by the strong correlation between oil price changes and normalised oil price shocks; including normalised oil price shocks in the VAR system seems to decrease the individual impact of oil prices substantially but conserve the joint significance of the two variables taken together. Note here that early parts of the sample period where normalised oil price shocks are highly statistically significant match the periods in which Lee et al. (1995) found a statistically significant relationship between normalised oil price shocks and real GDP fluctuations. Their result is reflected here but appears to dissipate in later sections of my sample.

Specification	Proxy	Variable	1950:1-1985:4	1974:1-2015:2	1986:1-2015:2	1950:1-2015:2
6-variable System 1	PPI	Oil Price Change	5.353 (0.253)	7.932* (0.094)	11.293** (0.023)	12.568** (0.014)
		Normalised Oil Price Shock (ε*)	25.408*** (0.000)	4.159 (0.385)	5.388 (0.250)	28.266*** (0.000)
	RAC	Oil Price Change	—	5.220 (0.265)	2.939 (0.568)	—
		Normalised Oil Price Shock (ε*)	—	1.612 (0.807)	3.780 (0.437)	—
7-variable System 1	PPI	Oil Price Change	—	8.713* (0.069)	11.648** (0.020)	—
		Normalised Oil Price Shock (ε*)	—	4.533 (0.339)	5.723 (0.221)	—
	RAC	Oil Price Change	—	6.004 (0.199)	3.065 (0.547)	—
		Normalised Oil Price Shock (ε*)	—	2.085 (0.720)	4.567 (0.335)	—
8-variable System 1	PPI	Oil Price Change	—	—	11.934** (0.018)	—
		Normalised Oil Price Shock (ε*)	—	—	7.295 (0.121)	—
	RAC	Oil Price Change	—	—	3.283 (0.512)	—
		Normalised Oil Price Shock (ε*)	—	—	4.634 (0.327)	—

Table 2.7. Exclusion tests for normalised oil price shocks. The values in parentheses are p-values. Statistical significance is shown at the 10% level (*), 5% level (**) and 1% level (***).

In addition, 3-month TB rate is highly correlated with output growth. When included in the system, this variable weakens the observed relationship between oil prices and GDP growth. Therefore, monetary policy plays an important role in determining the path of output growth rate, and fluctuations in interest rate can potentially have large effects on the macroeconomy. This introduces the challenge of disentangling two distinct effects on GDP growth when the monetary authority reacts to an oil price shock with an interest rate adjustment. From an econometric perspective, 3-month TB rate is a key control variable in the VAR systems, as in its absence, oil price fluctuations are wrongly credited with having had a large impact on GDP growth.

As discussed earlier, a key aim is to test for the existence of an asymmetric relationship between oil price fluctuations and changes in GDP under normalised price shocks as well. To do so, extensions to each specification from Section 2.5.2 are required such that positive and negative price changes are modelled separately. The objective here is to investigate whether positive normalised oil price changes have a statistically significant impact on GDP growth (Granger-cause changes in GDP growth) while negative changes do not. The results are striking, especially in comparison to those shown in Table 2.7 above: positive normalised oil price shocks are statistically significant across all sample periods and model specifications whereas negative ones are not. This outcome is in sharp contrast with the earlier evidence that normalised oil price shocks are not strongly linked to output growth rate. One underlying implication of this is that when price changes are taken as a whole, their statistical significance weakens due to an averaging out effect of positive and negative price shocks. When modelled explicitly, normalised positive oil price shocks are highly statistically significant even in larger specifications with key control variables identified in earlier sections. The results in this table facilitate deeper analysis of the oil price – GDP growth relationship across four key dimensions. First, the exclusion tests show each specification's performance across different sample periods. Second, robustness checks for each specification and proxy pair can be conducted by adding control variables to the system. Third, the sensitivity of each specification to proxy choice for oil prices can be observed, and lastly, the impact of allowing for asymmetry in the specifications on model performance can be investigated in this new context.

Specification	Proxy	Variable	1950:1-1985:4	1974:1-2015:2	1986:1-2015:2	1950:1-2015:2
6-variable System 2	PPI	Normalised Positive Oil Price Shock (ε*+)	62.376***	11.238**	13.112**	67.683***
			(0.000)	(0.024)	(0.011)	(0.000)
		Normalised Negative Oil Price Shock (ε*-)	0.816	2.614	3.648	1.859
			(0.936)	(0.624)	(0.456)	(0.762)
	RAC	Normalised Positive Oil Price Shock (ε*+)	—	18.513***	19.877***	—
				(0.001)	(0.001)	
		Normalised Negative Oil Price Shock (ε*-)	—	0.539	4.222	—
				(0.970)	(0.377)	
7-variable System 2	PPI	Normalised Positive Oil Price Shock (ε*+)	—	11.487**	14.855***	—
				(0.022)	(0.005)	
		Normalised Negative Oil Price Shock (ε*-)	—	2.898	6.042	—
				(0.575)	(0.196)	
	RAC	Normalised Positive Oil Price Shock (ε*+)	—	18.896***	21.980***	—
				(0.001)	(0.000)	
		Normalised Negative Oil Price Shock (ε*-)	—	0.725	6.158	—
				(0.948)	(0.188)	
8-variable System 2	PPI	Normalised Positive Oil Price Shock (ε*+)	—	—	9.421*	—
					(0.051)	
		Normalised Negative Oil Price Shock (ε*-)	—	—	6.604	—
					(0.158)	
	RAC	Normalised Positive Oil Price Shock (ε*+)	—	—	16.900***	—
					(0.002)	
		Normalised Negative Oil Price Shock (ε*-)	—	—	6.110	—
					(0.191)	
NOPI System 1	PPI	Net Oil Price Increase	31.141***	5.881	3.549	14.062***
			(0.000)	(0.208)	(0.470)	(0.007)
	RAC	Net Oil Price Increase	—	14.457***	8.861*	—
				(0.006)	(0.065)	
NOPI System 2	PPI	Net Oil Price Increase	—	5.951	4.286	—
				(0.203)	(0.369)	
	RAC	Net Oil Price Increase	—	14.896***	9.627**	—
				(0.005)	(0.047)	
NOPI System 3	PPI	Net Oil Price Increase	—	—	1.010	—
					(0.908)	
	RAC	Net Oil Price Increase	—	—	4.767	—
					(0.312)	

Table 2.8. Exclusion tests for specifications with normalised and net oil price changes with asymmetry. The values in parentheses are p-values. Statistical significance is shown at the 10% level (*), 5% level (**) and 1% level (***).

The Effect of Proxies for Oil Price

Table 2.7 corroborates the claim that choice of oil price proxy has an impact on the statistical significance of the shocks in the output growth equation as well as the robustness of the whole VAR system. Although the statistical significance of normalised positive oil price shocks appears reasonably stable across specifications and sample periods, the variable loses statistical significance in some cases when PPI is used as the proxy. When RAC is used as the proxy instead, the relationship appears more robust. This is particularly clear in the test results for 8-variable system 2 and NOPI systems 1 and 2. With RAC as the proxy, normalised positive oil price shocks are highly statistically significant in all sample periods, whereas the PPI-based variable is significant only at a 10% level. In the context of NOPI specifications, a more prominent pattern emerged: observing only PPI-based results, one would argue that the impact of oil price increases on output growth has vanished in more recent years—specifically, from 1974 onwards. This was indeed what many researchers observed around that time. Turning to RAC results show, however, that the underlying relationship remains significant. NOPI systems 1 and 2 show statistically significant oil price increase variables in large specifications with unemployment rate, 3-month TB rate, and real wage inflation as control variables.

A pattern of note here is that the statistical significance of the relationship, even with RAC as the oil price proxy, displays a downward trend. This is further evidenced by NOPI system 3 where neither oil price increase variable is statistically significant. As touched on previously, the weakening relationship observed here could be due to a weaker underlying economic link between oil prices and GDP growth or a deterioration in model performance across time. Most previous research reached conclusions about the underlying economic relationship without explicitly addressing the possibility of a break-down from an empirical modelling perspective. In an effort to address this, I analysed how the RMSE behaved based on specification, proxy choice, and sample period. Upon further investigation of the weakening relationship, two root causes for this pattern emerged: first, when large model specifications are used in the most recent sample period, small sample bias is a concern. NOPI system 3 comprises 8 variables with 4 lags each with a sample size of 118. Second, and more importantly, net imports of crude oil in the US started an increasing trend from February 1985. This increased the share of crude oil in the country's imports and how much crude oil imports contributed to overall import price inflation. This is reflected in the dataset as an increase in the correlation coefficients between RAC[11] (and PPI in crude petroleum) and import price inflation from 1986 onwards. As a result, including import price inflation as a control variable for this period reduces the statistical significance of net oil price increases as they share much of the identifying variation. Unsurprisingly, the reverse of this is true as well: removing 3-month TB rate and import price inflation from the VAR system inflates the test statistics for oil price variables. 8-variable system 2, particularly when RAC is used as the oil price proxy, is robust to this. Positive normalised oil price shocks in this large VAR system remain highly statistically significant in the most recent sample period. RAC-based oil price changes are, therefore, more robust to model specification and sample period.

Returning to the observation that RAC is preferable to PPI in crude petroleum as the oil price measure, 8-variable system 2 indicated that the lack of strong evidence for Granger causality between PPI-based oil price changes and GDP growth in the most recent sample is not due higher RMSE. 8-variable system 2 with PPI and RAC as proxies yielded virtually identical RMSE values. Furthermore, the same holds for same model specifications across time. For example, 7-variable system 2 using RAC showed that RMSE did not change substantially when the model was estimated in the 1974:1-2015:2 sample period versus 1986:1-2015:2. Jointly, these suggest that when a weaker relationship is observed, it tends to be due to changing parameter estimates as opposed to the point estimates being less precisely estimated. Having established this, later sections focus on the magnitude of the impact as opposed to the statistical significance of parameter estimates.

The Oil Price-GDP Relationship Across Time

A heavily-debated claim in the oil price-macroeconomy literature is whether oil price fluctuations are still as relevant today as they used to be. Some researchers argue that the relationship has been weakening over time and that this is reflected in empirical results (Hooker, 1996b, 1996a). However, results in Table 2.8 show little evidence

[11] Recall that the RAC variable is constructed using the prices of both domestically-produced and imported crude.

that oil price shocks no longer Granger-cause changes in output growth in recent sample periods. In fact, statistical significance of positive oil price shocks increases under most model specifications when a later sample used. An example of this is 7-variable system 2 with PPI as the oil price proxy. Under this specification, positive normalised oil price variable is statistically significant at the 5% level in the 1974:1-2015:2 sample period and at the 1% level with the later sample beginning in 1986:1. This occurs with other specifications in Table 2.8 regardless of proxy choice.

The exceptions to this observation are NOPI models 1 and 2. When normalised oil price shocks are substituted by net oil price increases, statistical significance decreases in recent samples. As an example, the exclusion test for RAC-based NOPI returns a p-value of 0.005 in the 1974:1-2015:2 column and a p-value of 0.047 in the 1986:1-2015:2 column. Having observed these contradictory results, it is difficult to make definitive statements. It appears, however, that robust oil price measures, such as the normalised variables, retain their statistical significance in recent samples whereas those currently more prevalent in the literature do not. Note that these statements are strictly in a Granger causality sense and *not* about the size of the effect. Later sections find that coefficient estimates on oil price shocks and overall impact on output growth estimated through impulse response analysis increase in recent samples. This will be discussed in greater detail in those sections.

To address this issue more rigorously, this chapter implements a time-varying parameter approach using a rolling window. More specifically, a rolling window of 132 quarters is estimated sequentially from 1974:1 onwards. Exclusion tests are conducted after each iteration to observe changes in statistical significance of oil price shocks over time. [12] The resulting p-values on normalised positive PPI-based oil price shocks in 7-variable system 2 are shown in Figure 2.3 below. [13]

[12] Note that although this section focuses on a discussion of statistical significance, other sections put an emphasis on interval estimates and how wide they are. The purpose of focussing on point estimates and p-values here is to address the ongoing debate in the literature.
[13] P-values shown in the figures are not identical to those presented in Table 2.8, since the former use a 132-quarter rolling window sample period whereas the latter uses as much of the sample period as available.

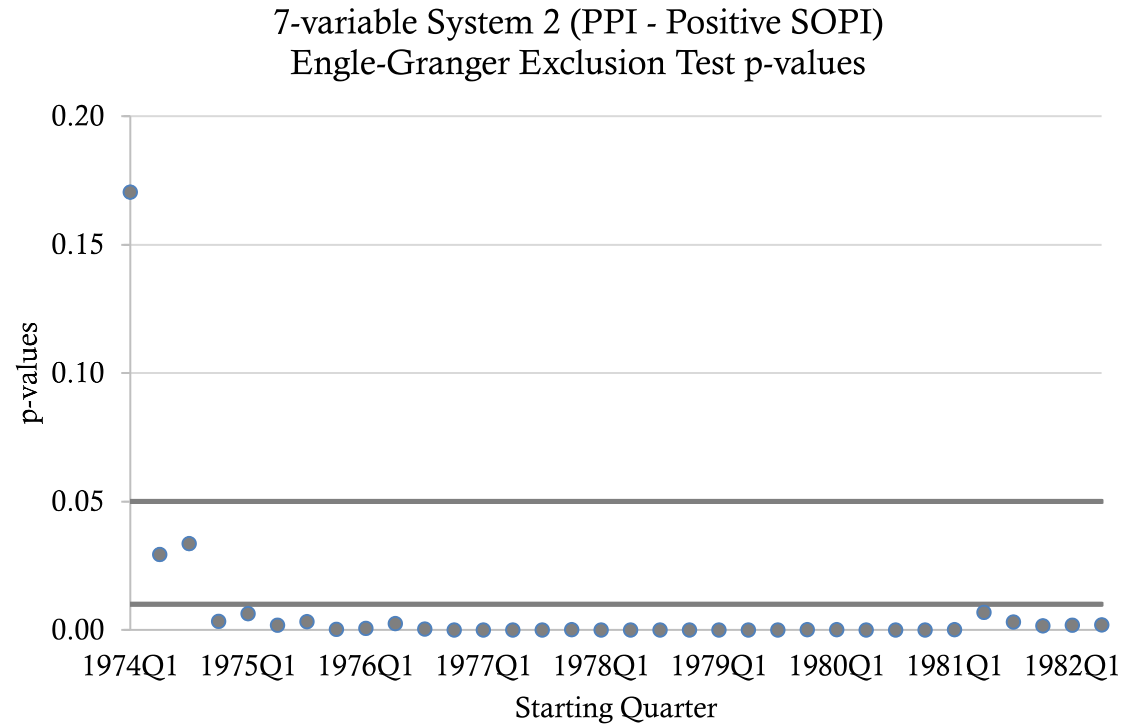

Figure 2.3. Exclusion test p-values for PPI-based normalised positive oil price shocks in 7-variable system 2 using a rolling window against starting quarter.

Only the first three p-values—those where estimations start in 1974:1 through 1974:3—are greater than 0.01. A clear conclusion is that the normalised positive shocks used in his system remain statistically significant in recent periods. P-values calculated for RAC-based normalised positive price shocks follow a virtually identical pattern (see Figure 2.4).

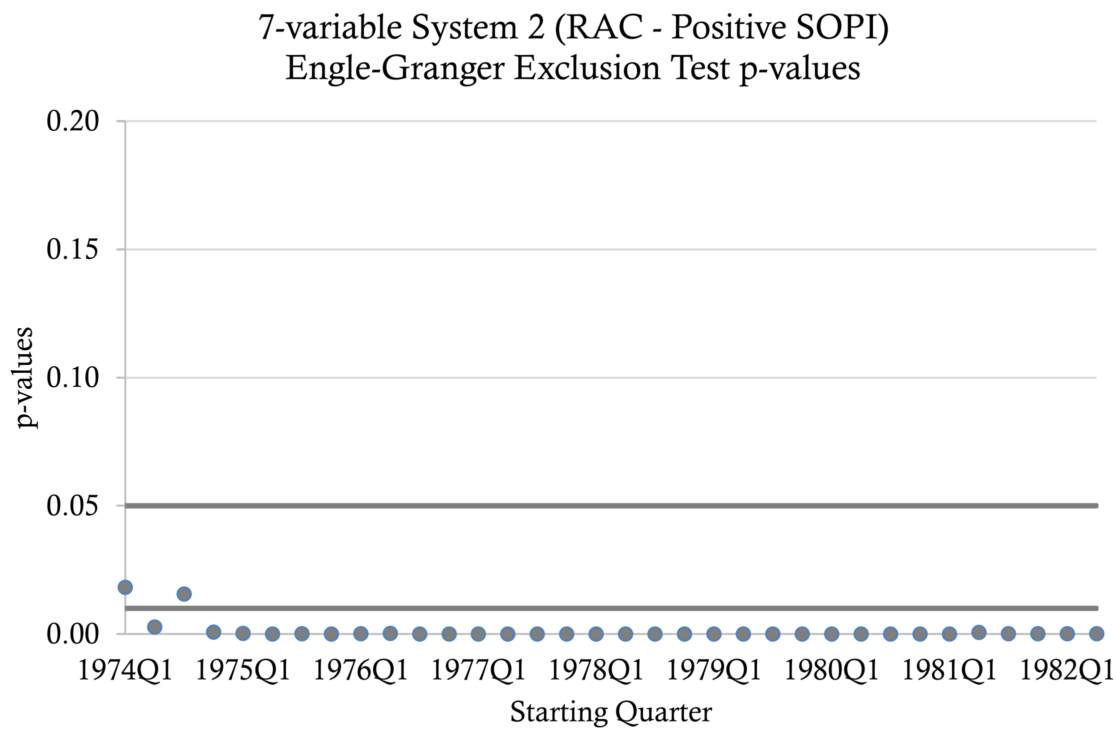

Figure 2.4. Exclusion test p-values for RAC-based normalised positive oil price shocks in 7-variable system 2 using a rolling window against starting quarter.

With RAC as the proxy, only the first and third starting quarters result in a p-value greater than 0.01. Unlike the PPI case in Figure 2.3, all p-values are below 0.05 in this case. These observations on the statistical significance of normalised positive oil price shock variables are in sharp contrast with their negative counterparts. Figure 2.5 and Figure 2.6 summarise the p-values observed for PPI- and RAC-based, normalised negative oil price shocks.

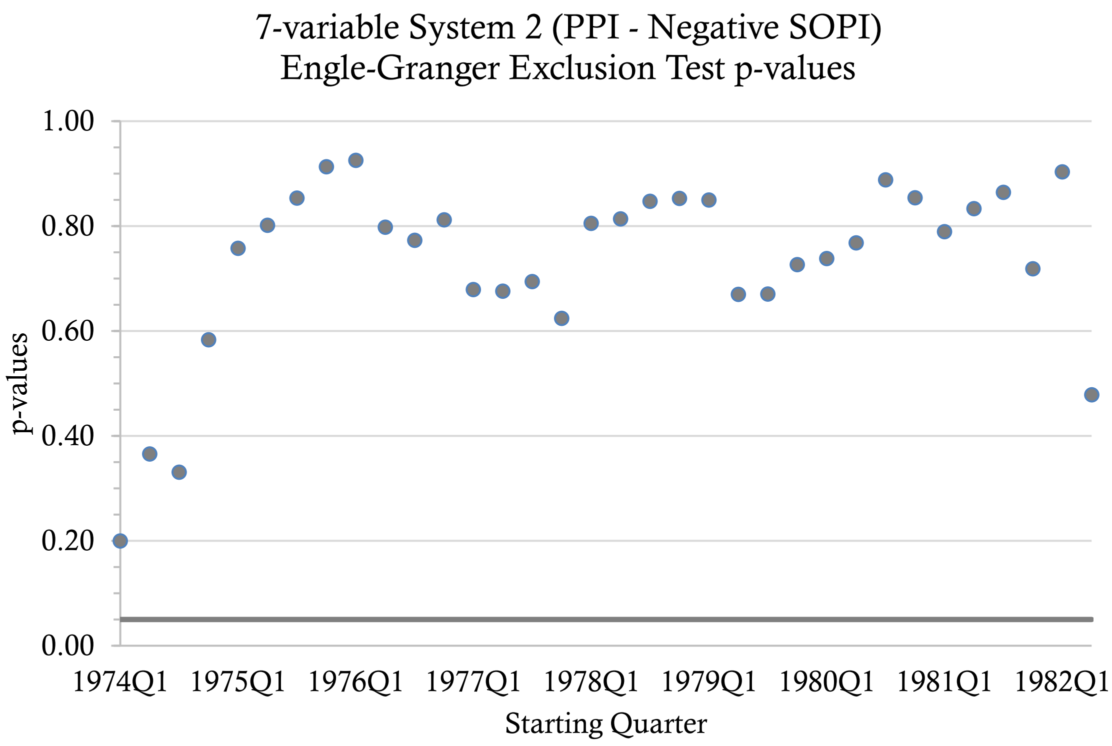

Figure 2.5. Exclusion test p-values for PPI-based normalised negative oil price shocks in 7-variable system 2 using a rolling window against starting quarter.

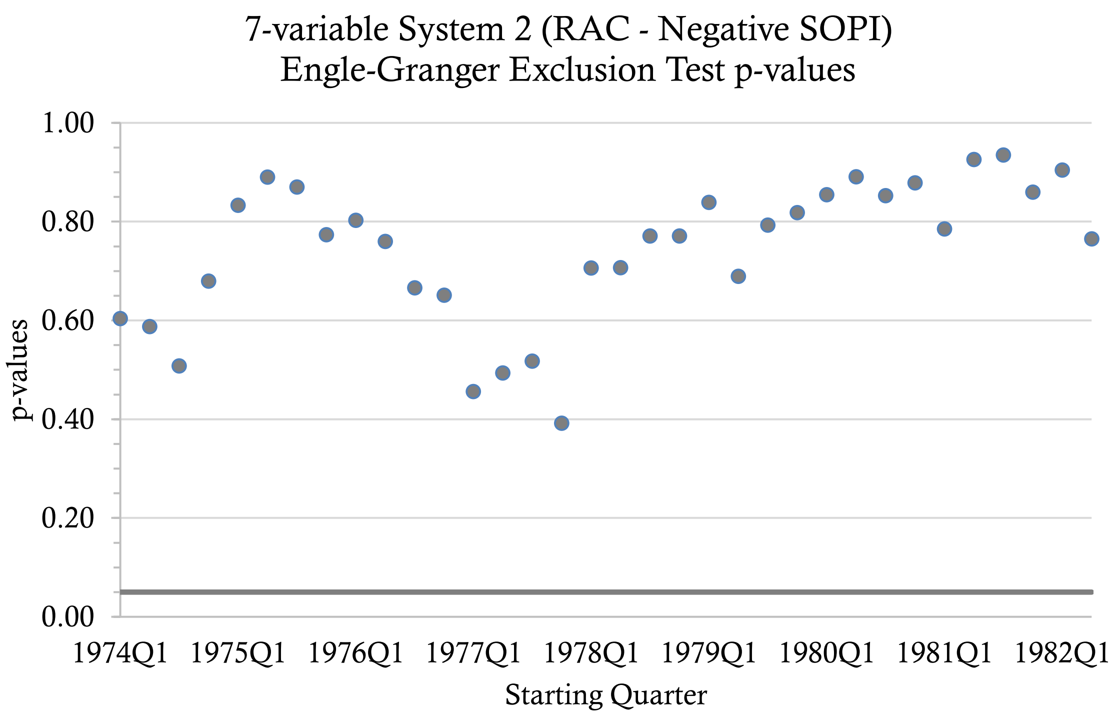

Figure 2.6. Exclusion test p-values for RAC-based normalised negative oil price shocks in 7-variable system 2 using a rolling window against starting quarter.

These two figures corroborate the earlier observation of an asymmetric relationship between oil price fluctuations and output growth: within this dataset, across time periods, oil price increases have a statistically significant impact on GDP growth whereas oil price drops do not. The next sub-section elaborates on how this observation holds across different model specifications and focusses on the asymmetry discussion observed earlier but revisits it in the normalised oil price context. Before moving on to a discussion concerning asymmetry and model specification, however, I return to ordinary (non-normalised) shocks in a rolling-window context to finalise the temporal investigation. Similar to earlier observations, this exercise revealed a weaker relationship between oil price changes and GDP growth than only positive price changes. This is due to an averaging out effect of positive and negative price shocks, where statistically significant positive shocks appear to matter much less due to negative shocks being included in the same variable. In Figure 2.7, p-values from exclusion tests on PPI-based oil price changes in 7-variable system 1 are greater than 0.05 from 1974:1 through 1976:2 inclusive. P-values fall sharply when the sample period starts after 1976:2 providing evidence against a weakening relationship between oil price fluctuations and output growth in the US from a statistical significance perspective. This pattern repeats for RAC-based oil price fluctuations as shown in Figure 2.8. These findings relate to the next sub-section and are a good segue to that discussion where asymmetry is discussed in the presence of normalised price shocks.

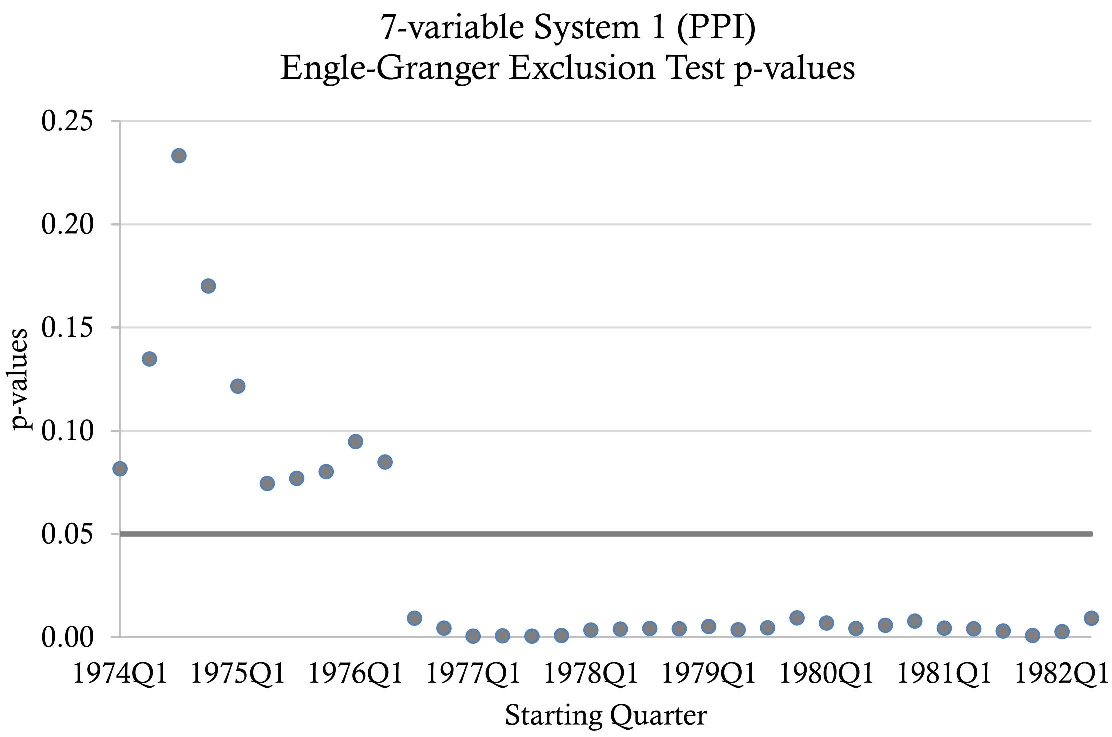

Figure 2.7. Exclusion test p-values for PPI-based oil price shocks in 7-variable system 1 using a rolling window against starting quarter.

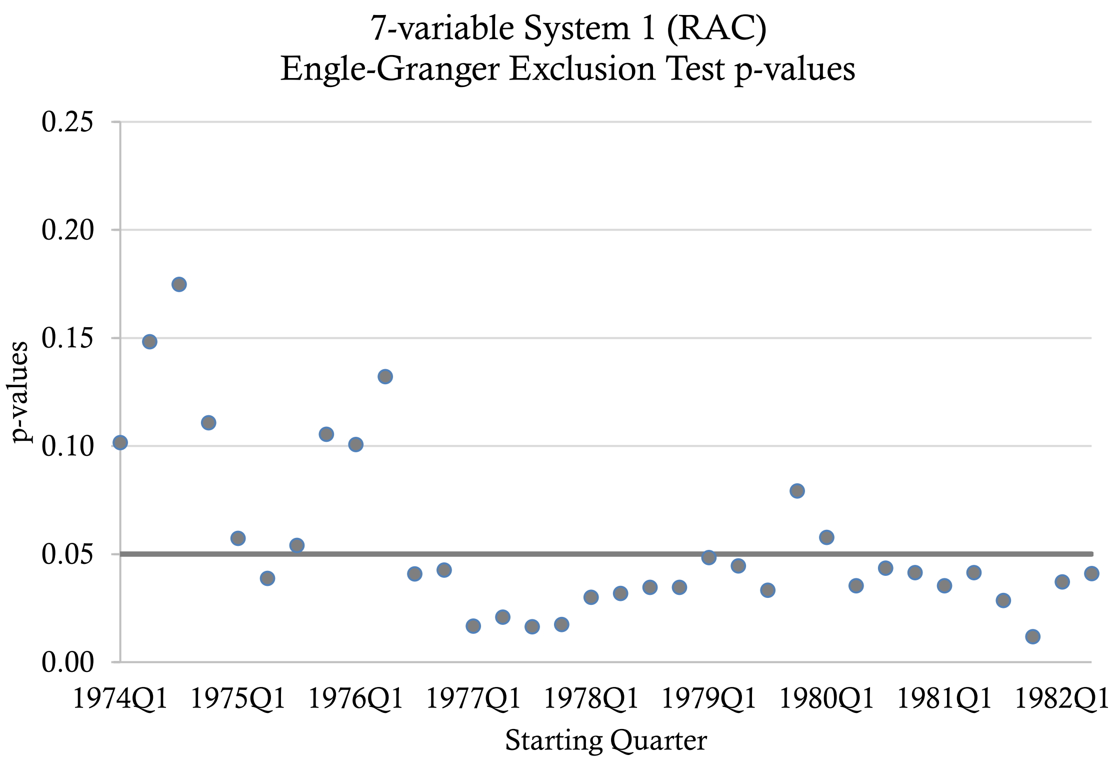

Figure 2.8. Exclusion test p-values for RAC-based oil price shocks in 7-variable system 1 using a rolling window against starting quarter.

A key interpretation of these time-varying estimations is that an analysis focussing on the sample period 1980:1 onwards (due to data availability at the time of writing, for instance) would have concluded that oil price changes do not have a statistically significant impact on GDP growth. This is what has been observed in the literature for part of this sample period which, in light of the findings from this section, is an incomplete analysis and misrepresents the true nature of the oil price-macroeconomy relationship. In a Granger-causality sense, there is little evidence here that the link between oil prices and output growth has vanished over the past few decades. Later sections investigate whether the size of the impact has changed considerably over the years.

Model Performance across Specifications

This sub-section is split into two main parts: testing for asymmetry in the presence of normalised price shocks and conducting robustness checks using larger model specifications with more control variables. The latter part focuses on the inclusion of import price inflation in particular. For the former discussion, especially to draw final conclusions on asymmetry effectively in the presence of normalised price shocks, 6-variable system 3 and 7-variable system 3 have been set up. These specifications differ only in how much asymmetry they allow for. Namely, the 6-variable system uses normalised oil shocks whereas the 7-variable specification splits it into its positive and negative components. Looking at Figures 2.9 and 2.10, a pattern emerges. A handful of tests return p-values greater than 0.05 and several greater than 0.01 when 6-variable system 3 is used. Only a few p-values are greater than 0.01 when positive shocks are tested under 7-variable system 3.

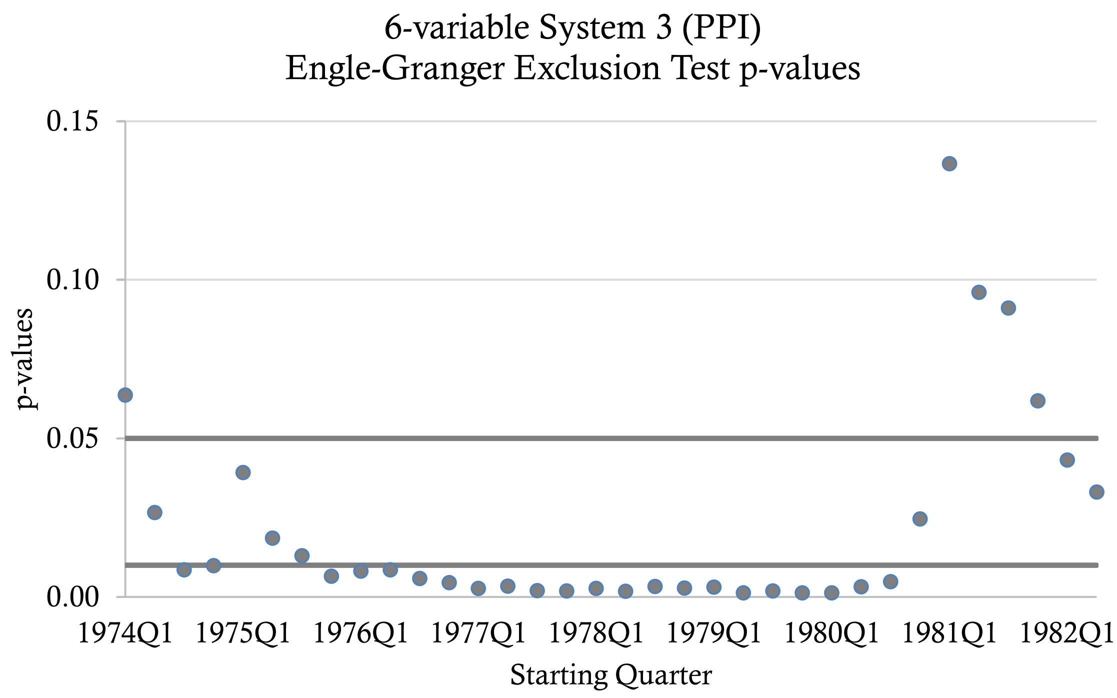

Figure 2.9. Exclusion test p-values for PPI-based normalised oil price shocks in 6-variable system 3 using a rolling window against starting quarter.

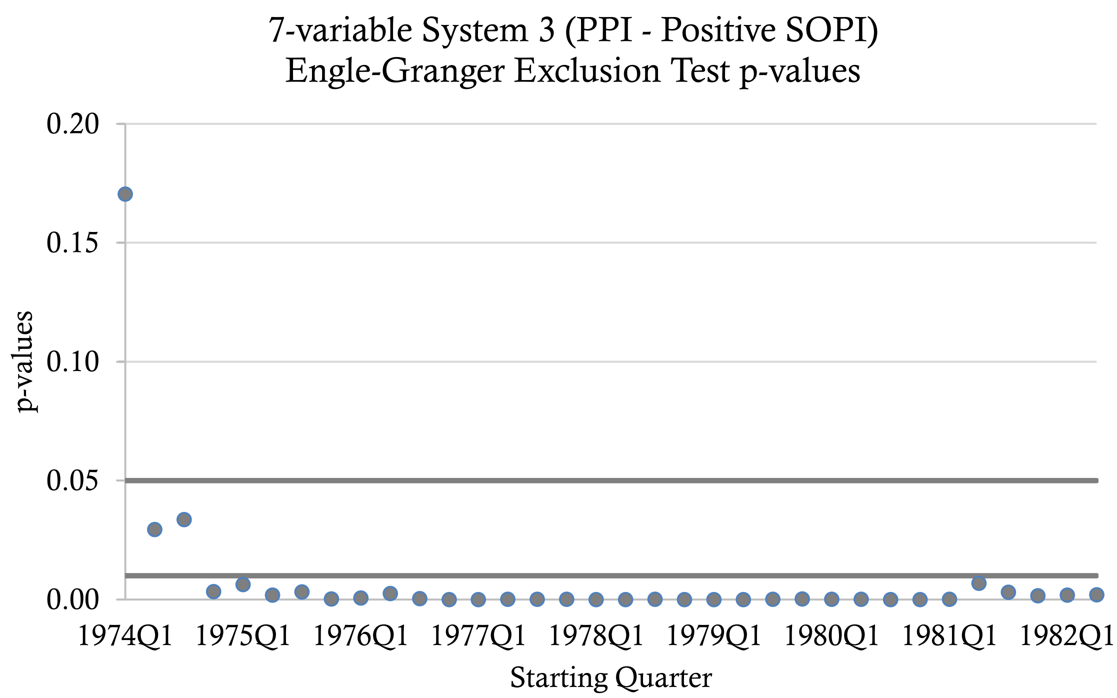

Figure 2.10. Exclusion test p-values for PPI-based normalised positive oil price shocks in 7-variable system 3 using a rolling window against starting quarter.

In contrast, Figure 2.11 shows p-values on negative price shocks using the same system. Since the normalised oil price shock in the 6-variable system is simply a combination of positive and negative price shocks in the 7-variable one, separating positive and negative fluctuations amounts to stripping the original component of variation unrelated to GDP growth leaving just the part that matters.

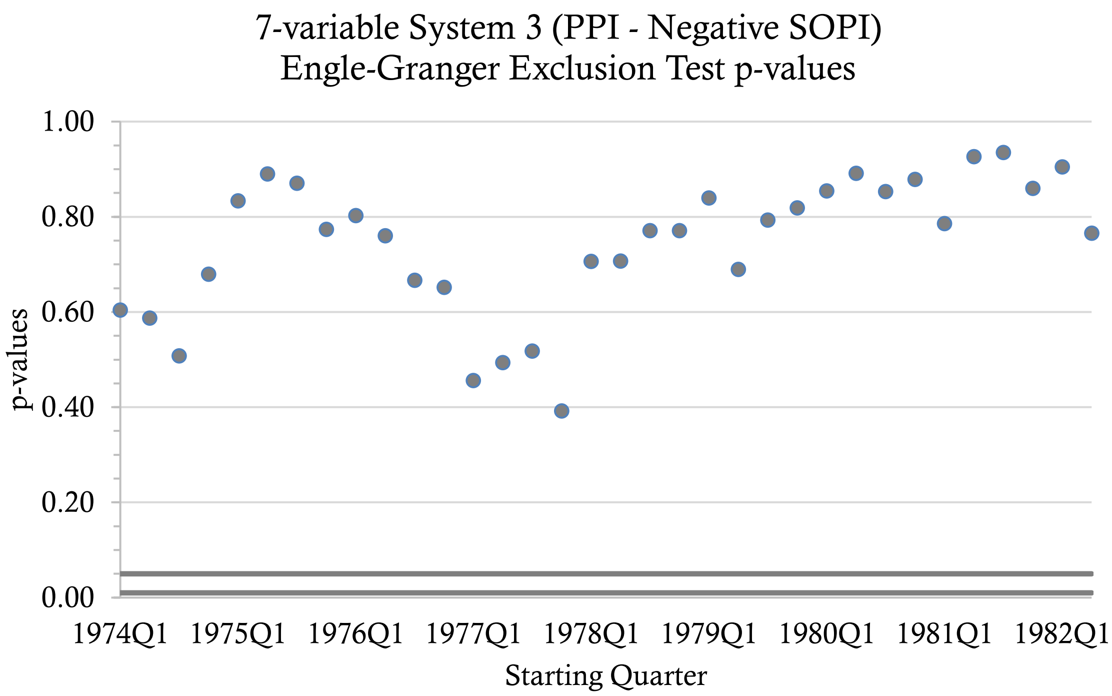

Figure 2.11. Exclusion test p-values for PPI-based normalised negative oil price shocks in 7-variable system 3 using a rolling window against starting quarter.

Findings beginning from Section 2.5.2 and continuing throughout 2.5.3 provide evidence for an asymmetric relationship between oil price changes and real GDP growth. Independently of proxy choice for oil price, sample period, and model specification, oil price increases have a statistically significant impact on output growth and oil price decreases do not. This section has investigated this hypothesis in the context of normalised oil price shocks and reached the same conclusion. Therefore, there is strong empirical evidence for an asymmetric relationship predicted by economic theory in Section 2.2.3.

Model specification offers an avenue for interesting discussion here. Table 2.8 has a structure to facilitate this: 6-variable system 2 plus 3-month TB is 7-variable system 2, and 7-variable system 2 plus import price inflation is 8-variable system 2. The same incremental structure holds for NOPI models presented in the table. This allows direct interpretation of adding control variables. Focussing on the first pair, there is little impact on the statistical significance positive oil price shocks of including 3-month TB rate as a control. The coefficient estimate and the confidence interval show little change as well. Statistical significance of 3-month TB rate in the real GDP equation greatly depends on sample period. Having controlled for other variables, this variable has limited contribution on its own. This, coupled with its limited correlation with oil price shocks in this sample, translate into minimal impact on coefficients of interest.[14]

Both specifications discussed in this section so far ignore import price inflation. Adding this additional control variable uncovers an interesting dynamic. Although import price inflation itself is not statistically significant in the real GDP growth equation, it has implications for the estimated coefficient on positive oil price changes. More specifically, when controlling for import price inflation, coefficients on lags of oil price rises decrease in absolute value while their standard errors remain roughly unchanged. This leads to the smaller test statistics observed in the 8-variable system 2 row of Table 2.8. This is not an entirely surprising result, as import price inflation was previously observed to be correlated with producer price index in crude petroleum and refiners' acquisition cost. It would, therefore, be expected that when import price inflation is omitted, the coefficient on a variable highly correlated with import price inflation (oil price fluctuations in this case) would capture its effect. Further investigation led to an important discovery, however: even though fluctuations in RAC are more highly correlated with import price inflation than those in PPI, RAC-based normalised positive oil price shocks are marginally less correlated than PPI-based ones. This is also reflected in Table 2.8. The test statistic on ε^{*+} drops from 14.855 to 9.421 when PPI is used but from 21.98 to 16.9 with RAC. Arguably, therefore, RAC is a more robust proxy than PPI as previously discussed in earlier parts of this section. There is further evidence for this in the NOPI system results in the same table, since RAC-based NOPI variables retain their statistical significance in recent samples and PPI-based ones do not. A previously-observed outcome from NOPI models relate to systems 2 and 3. Statistical significance of oil price increases falls when the specification is extended to include import price inflation. The fact that NOPI lose statistical significance with a narrow confidence interval around zero signals some level of multicollinearity. Hence, there is reason to believe the variables

[14] A surprising outcome of this analysis was the increase in the test statistic on positive oil price shocks when switching from 6-variable system 2 to its 7-variable counterpart in the 1986:1-2015:2 sample period. Further investigation showed that there is no clear underlying fundamental reason for this change.

in the system are sufficient and that import price inflation does not contribute further identifying variation not already provided by existing variables. Much of the analysis in the rest of this chapter proceeds on this basis and focuses predominantly on 6- and 7-variable systems with references to 8-variable systems where appropriate.

A final dimension of model specification explored here was whether normalised oil price variables perform better than non-normalised ones both in terms of statistical significance and in the context of impulse response analysis. The latter is explored further in Section 2.6 below. An investigation into the former revealed a weaker relationship between non-normalised price variables and GDP growth than normalised ones. Revisiting tables and figures from previous sections can shed light onto this. Tables 2.7 and 2.8 have output from specifications that allow this, and Figures 2.3, 2.4, 2.7, 2.8, 2.9, and 2.10 put the results into a time-varying parameter context. Figure 2.12 below is a summary of exclusion test p-values (z-axis) across model specification (y-axis) with varying starting quarter (x-axis). The right-most specification, 6-variable system 1, has the least stable exclusion test p-values among those considered here. Particularly in the early parts of the sample, exclusion test p-values on RAC-based oil price changes are considerably higher than those in other specifications. Even though PPI- and RAC-based oil price changes in 7-variable system 1 are much smaller, the specifications with normalised price fluctuations have much flatter p-value profiles within the $[0, 0.05]$ range. The three-dimensional representation below also allows a snapshot across specifications at a given starting quarter. As an example, considering a slice across specifications on 1976:1 indicates p-values less than 0.05 for the first three specifications and greater than 0.05 for the rest.

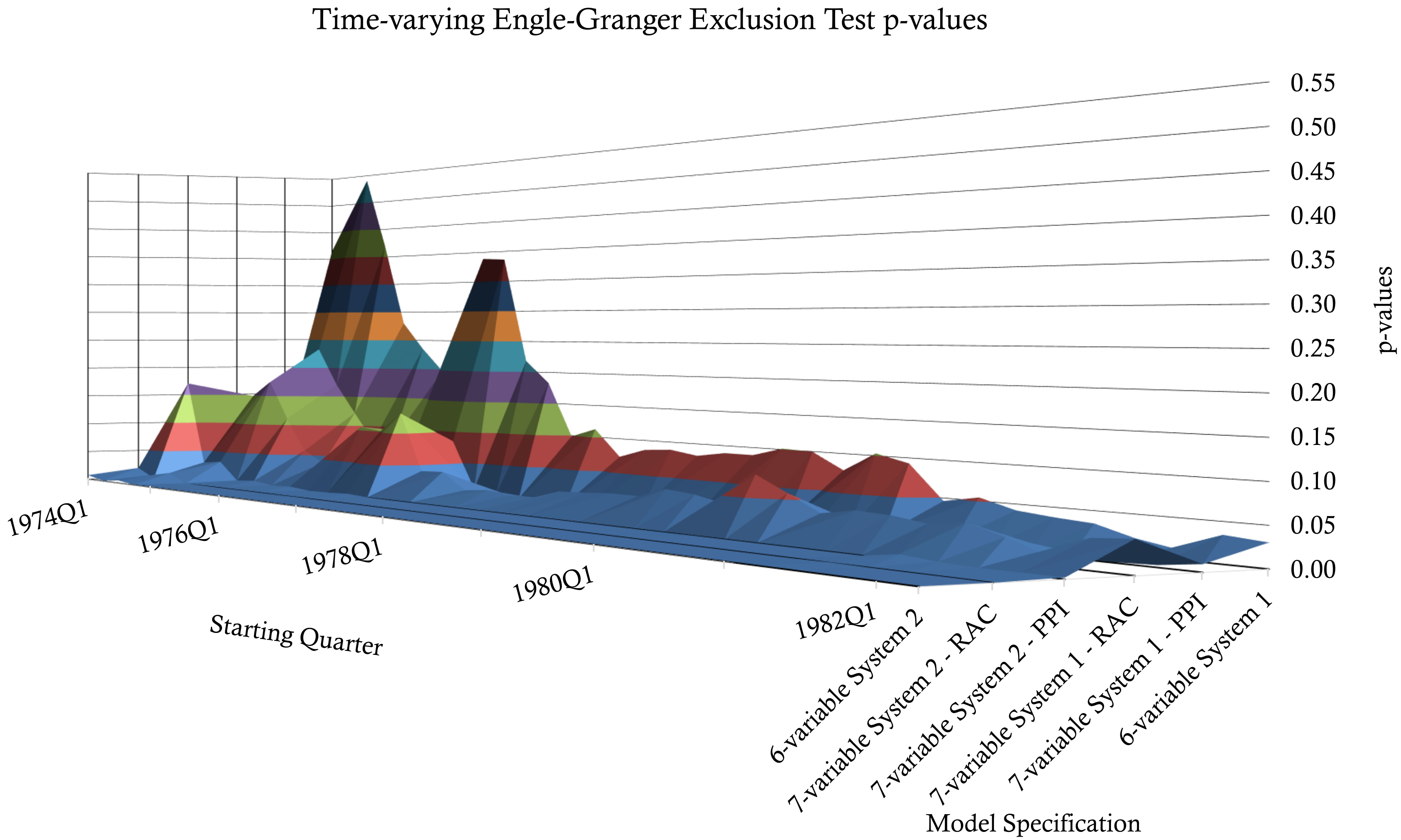

Figure 2.12. Exclusion test p-values (z-axis) across model specification (y-axis) with varying starting quarter (x-axis). Excluded variables as follows. 6-variable system 1: RAC-based oil price changes; 6-variable system 2: normalised positive oil price changes; 7-variable system 1: PPI- and RAC-based oil price changes; 7-variable system 2: PPI- and RAC-based normalised positive oil price changes. Each colour contour on the z-axis represents an increment of 0.05.

2.5.4 Exogeneity of Oil Price Shocks

Since the early years of the literature, the oil price-macroeconomy discussions have made references to exogeneity of oil price shocks. As the literature matured, this interest morphed into two opposing views and debates followed. At the heart of this discussion, researchers have asked whether oil price shocks could be considered exogenous even though the price hikes may have different underlying causes. As a result, numerous studies, starting with Kilian (2009) and Hamilton (2009), have tried to model oil prices differently based on their root cause. As a part of this, Hamilton (2009) has argued that oil price rises have traditionally been viewed as exogenous shocks caused by supply disruptions but that there is increasing consensus that the price hike of 2007-2008 was due to a combination of strong demand for oil and stagnating world oil production. Other studies since then have found contradicting results pointing out that other factors, such as sample period and reliance on oil versus other fuels, matter more than the nature of oil price fluctuations. No matter the true nature of the relationship, the original reason researchers turned to splitting oil price shocks into their structural components was to retain their statistical significance in the real GDP equation—a well-founded and desirable outcome based on theoretical models. In this respect, this chapter proposes the normalisation and asymmetric split of price changes as an alternative approach. As discussed above, normalised positive oil price shocks retain their explanatory power across all sample periods as well as in the rolling-window context. One advantage of this approach is that it does not require unreliable proxies. The normalisation process is self-contained within the model, whereas identifying different types of shocks requires local and global oil demand series as well as an indicator of global economic activity. Researchers have attempted to identify proxies for these, including global shipping traffic under the Baltic Dry Index as an indication of global economic activity, but this is hardly a reliable measure as there are many logistical reasons unrelated to global economic performance this variable can change behaviour. Blanchard & Galí (2007) mention that identifying a more exogenous proxy for oil prices is an option but that it is unnecessary. The authors state, in response to Kilian's (2008a) attempt to use global oil production as a proxy, that "what matters, however, to any given country is not the level of global oil production, but the price at which firms and households can purchase oil […]." Furthermore, popular models often adopt a two-country approach with the country in question and rest of the world. This approach is rather simplistic and groups together a very heterogeneous group of countries as a single entity all in an effort to identify whether an observed price shock is demand- or supply-side. In addition, splitting an oil price series into three or more components inflates VAR systems to be estimated, causing degrees of freedom obstacles. In the context of this chapter's rolling-window approach, longer windows would be required to estimate each system reducing the overall observational window due to fewer number of estimations. Finally, as the price shock variable is split into more components, the identifying variation in each gets progressively smaller. This is a concern, especially in small samples with limited information. These have jointly motivated the search for a better, more robust, and more straight-forward approach to modelling oil price innovations.

A distinction often ignored within the exogeneity discussion of oil price fluctuations is whether we can differentiate between econometric exogeneity and macroeconomic exogeneity. Focussing on the latter first, it is reasonable to argue that, albeit being large and influential, the US is still "small" within the global oil market. As such, it is unclear whether trends in the US alone would have global implications within the oil market. Studies have found and argued that endogeneity of oil prices is not stable over time. There is some basis for this, since the share of US oil consumption in global consumption has declined from 37.5% in 1965 to 20.3% in 2016 according to the BP Statistical Review of World Energy 2017. Over the years, this has also contributed to analyses focussing on structural breaks as the nature of the relationship appeared to change across time. From an empirical modelling perspective, and given the scope of this analysis, econometric exogeneity carries more importance than exogeneity in a macroeconomic modelling sense.[15] The exclusion tests discussed throughout this chapter can shed light on this. Table 2.9 lists Granger causality exclusion test results in the corresponding oil price equation for real GDP growth. Based on the results, real output fluctuations do not appear to Granger-cause oil price changes in these specifications across most sample periods. Separating positive and negative shocks resulted in high test statistics for oil price increases in the most recent subsample shown in Table 2.9.

[15] Requirements within a dynamic stochastic general equilibrium (DSGE) model may differ depending on the modelling objective.

Proxy	Variable	1950:1-1985:4 †	1974:1-2015:2 ††	1986:1-2015:2 †††	1950:1-2015:2 †
PPI	Oil Price Change	23.244***	3.121	4.768	2.200
		(0.000)	(0.538)	(0.312)	(0.699)
RAC	Oil Price Change	—	3.899	3.781	—
			(0.420)	(0.436)	
PPI	Oil Price Increase	20.631***	5.294	12.398**	7.757
		(0.000)	(0.258)	(0.015)	(0.101)
	Oil Price Decrease	11.397**	2.697	1.373	11.233**
		(0.022)	(0.610)	(0.849)	(0.024)
RAC	Oil Price Increase	—	7.281	10.396**	—
			(0.122)	(0.034)	
	Oil Price Decrease	—	3.094	1.046	—
			(0.542)	(0.903)	

Table 2.9. Exclusion tests for real GDP growth in each corresponding oil price equation. The values in parentheses are p-values. Statistical significance is shown at the 10% level (*), 5% level (**) and 1% level (***). Recall that different model specifications are used in each sample period: 5-variable VAR (base model, denoted as †), 6-variable VAR (base model + 3-month TB rate, denoted as ††) and 7-variable VAR (base model + 3-month TB rate + import price inflation, denoted as †††)

However, a further investigation of this using a rolling window showed that the endogeneity does not persist more than one quarter. An exception to this is the early sample period covering 1950-60. There is some evidence in more recent years that demand-side influences originating from the US may have played a role in some price rises in line with Hamilton's (2009) discussion of 2007-2008 price shock. In the VAR implementation here, oil prices are endogenous within the system, and the relevant equations are estimated with the rest of the variables on the right-hand side.

2.5.5 Interim Conclusion

A key finding of this section is that normalised positive oil price changes are consistently more highly correlated with output fluctuations than any other oil price variable. In addition to being statistically significant across model specifications and sample period, normalised positive shocks have a narrow confidence band. In contrast, normalised negative oil price fluctuations do not Granger-cause GDP fluctuations (i.e. coefficients are not statistically significant), and their relationship with real GDP growth is less well-defined. Once again, this holds regardless of specification and sample period providing strong evidence of an asymmetric response in output growth to oil price changes. Choice of oil price proxy matters as well. RAC is more robust than PPI in crude petroleum and although sample period alone does not have a clear impact on oil prices Granger-causing output growth rate, some traditional measures of oil prices lose their explanatory power in more recent samples. Model specification can also influence estimation results. In particular, omitting relevant variables, such as 3-month TB rate, can inflate test statistics on other variables and result in misleading estimates. In this dataset, this is especially true when PPI is used as the oil price proxy. Overall, there is little evidence that the oil price-macroeconomy relationship has entirely disappeared in recent decades. In fact, when appropriately captured, oil price increases retain their importance in the GDP equation even in large specifications with several control variables. The next section turns to impulse response analysis as it steps away from statistical significance and emphasises size of the impact.

2.6 VAR Results and Impulse Response Analysis

Previous sections focussed on a discussion of statistical significance in line with the current literature. This section focuses on parameter estimates, their interpretation, and impulse responses. Orthogonalised impulse response functions were implemented to interpret VAR results, as these parameter estimates are not easily interpretable on their own. IRFs in this chapter have undergone the appropriate Cholesky decomposition and consider a twenty-quarter time horizon. Throughout this section, independently of model specification and sample period, the estimated coefficients on positive oil shocks were negative, while those on negative oil shocks had alternating signs. In all estimated impulse response functions, only some quarters showed a statistically significant impact. With oil price increases as the impulse, this tended to be in the first and third quarters. Although there are some instances where other quarters had a 95% confidence interval that excluded zero, the interpretation is that the US economy adjusts to oil price increases quickly, making an impulse transient. The results that follow are interpreted with this understanding, although the main focus is on the overall trend and total impact as opposed to individual point estimates.

IRF analysis starts with the 7-variable system 2 using both price proxies over the 1974:1-2015:2 subsample. The response of output growth rate to a 10% shock to PPI-based normalised oil price increase and decrease are shown in Figures 2.13 and 2.14, respectively.

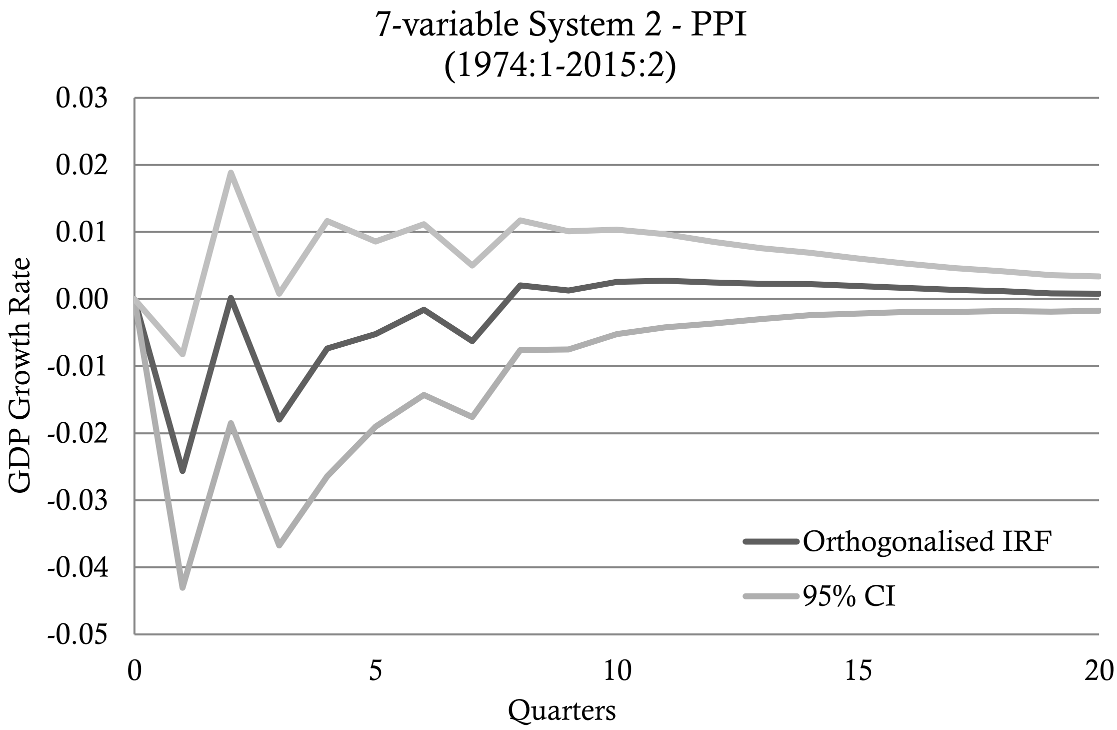

Figure 2.13. IRF with a 10% PPI-based normalised positive oil price shock.

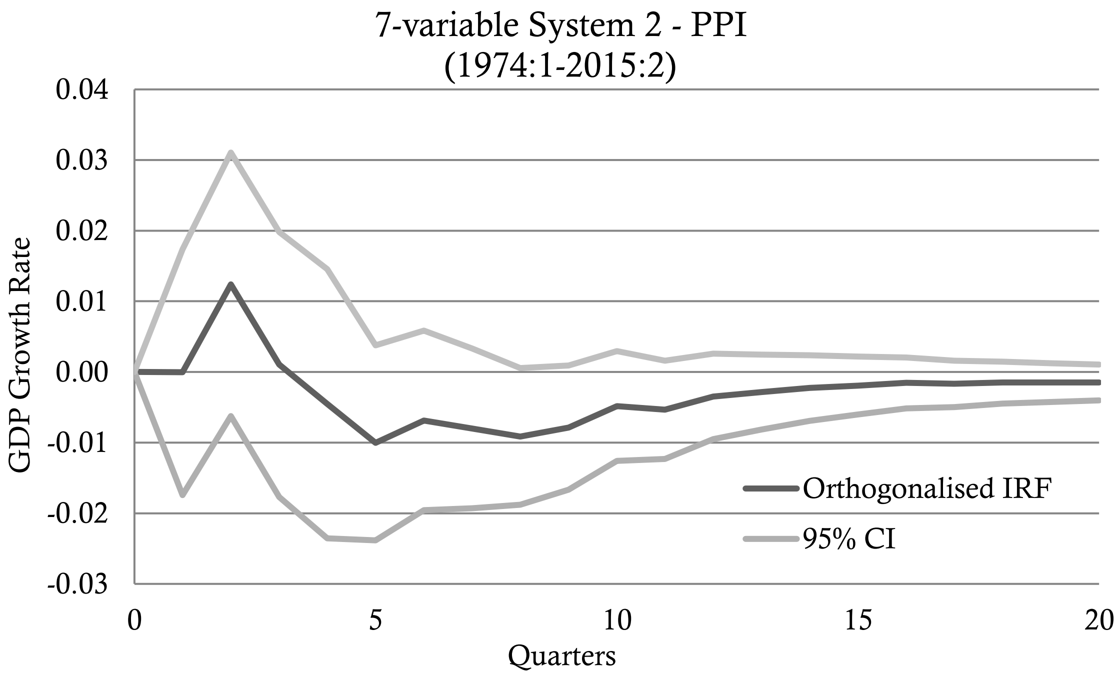

Figure 2.14. IRF with a 10% PPI-based normalised negative oil price shock.

The confidence bands indicate that the impulse responses are statistically significant in the first and third quarters in the top figure, and the estimated response becomes weaker over time. Point estimates from the eighth quarter onwards are positive indicating a slight overshooting as the economy adjusts to the new oil price environment about two years after the initial shock. The total estimated impact of a 10% increase in the price of oil on annualised real output growth over 20 quarters is -0.2% in this specification, proxy, and sample period combination. This figure implies that a 10% increase in oil price is expected to reduce real GDP growth by 0.2% over a five-year horizon. RAC-based oil price impulse yielded a similar result shown in Figure 2.15. Referring to Section 2.2.5, the transmission mechanism for this effect is through inflation, unemployment, wages, and firms' mark-ups. The increase in oil price has an immediate impact on inflation through equation 2.8. It also has an impact on firms' behaviour based on equation 2.7, leading to one or more of the main transmission channels, which are higher unemployment, lower wages, and a lower mark-up.

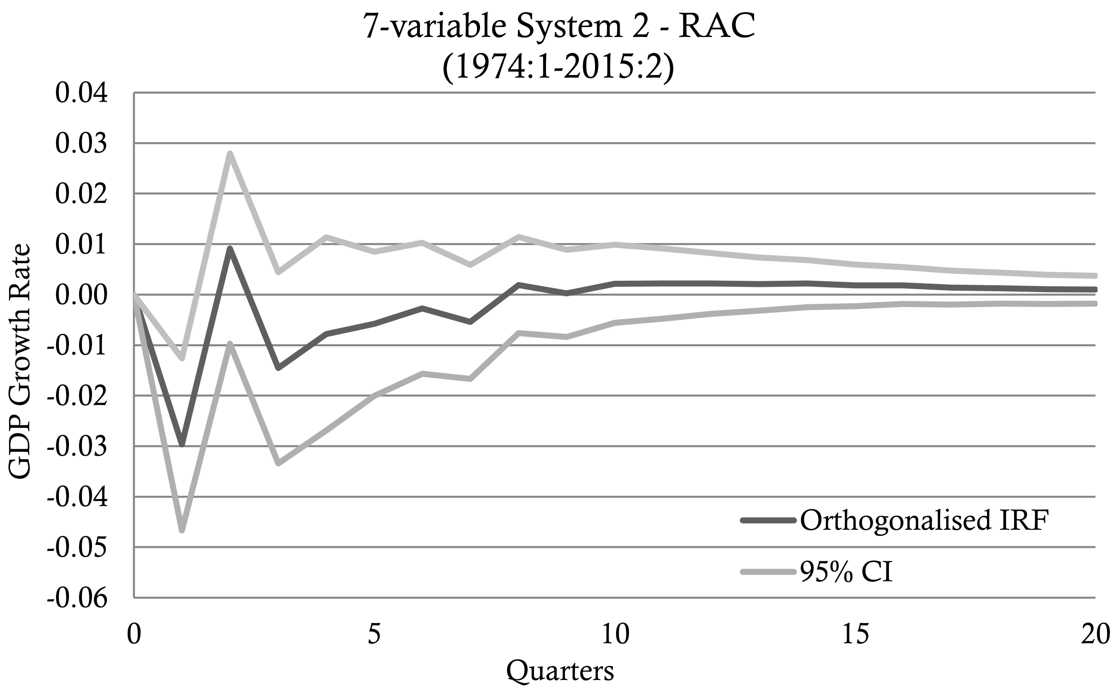

Figure 2.15. IRF with a 10% RAC-based normalised positive oil price shock.

Interestingly, a fall in the price is estimated to have a negative impact on output growth rate as shown in Figure 2.14. The first-quarter impact is positive but negative ones follow immediately after leading to an overall decline. Potential underlying reasons for such behaviour were touched on in Section 2.2. In all these three figures, the graph shows that the estimated OIRF converges to zero, which indicates that an orthogonalised innovation to the corresponding oil price variable does not have a permanent effect on real GDP growth rate in the US. The overall annualised impact estimated here is on par with those calculated by Lee et al. (1995) and Blanchard & Galí (2007). Further, much like Blanchard & Galí's (2007) findings, I observe a larger impact earlier in the sample than later.

This is more apparent in Figure 2.16 and Figure 2.17 below, which were constructed using rolling IRFs and give a more detailed view of the results. Regardless of sample period and proxy, the first quarter following an oil price increase showed a negative GDP growth rate followed by an overshooting effect in the second quarter. Another common feature across the two figures is the dying out effect of the original shock roughly from the eighth quarter onwards—represented by the flattening out of the surfaces in the two figures. Further, as the starting quarter moves from mid- to late-1970s, both the initial negative impact and the overshooting effect that follows it become more pronounced with the largest observed impact corresponding to 1977.

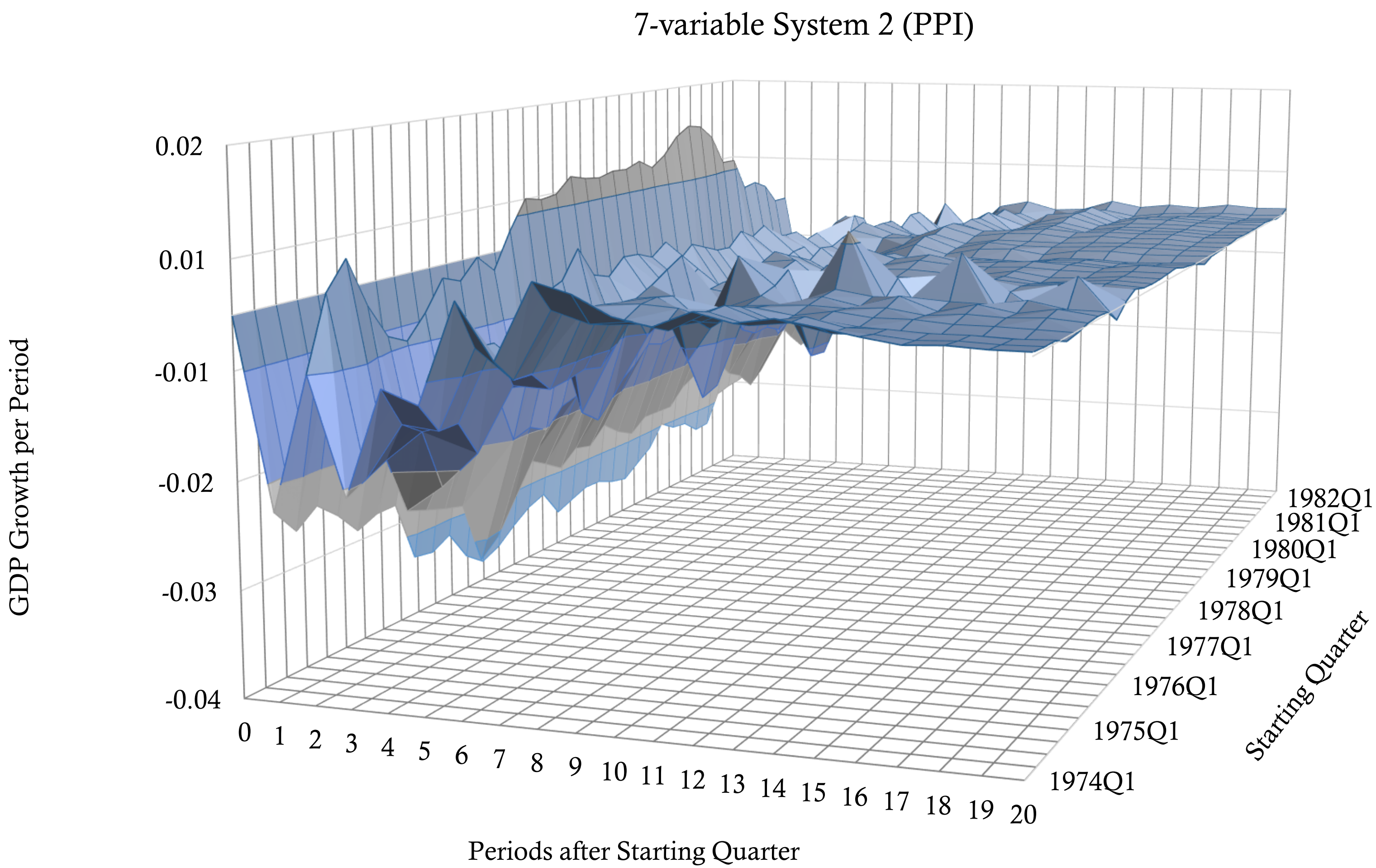

Figure 2.16. Rolling IRFs with a 10% PPI-based normalised positive oil price shock.

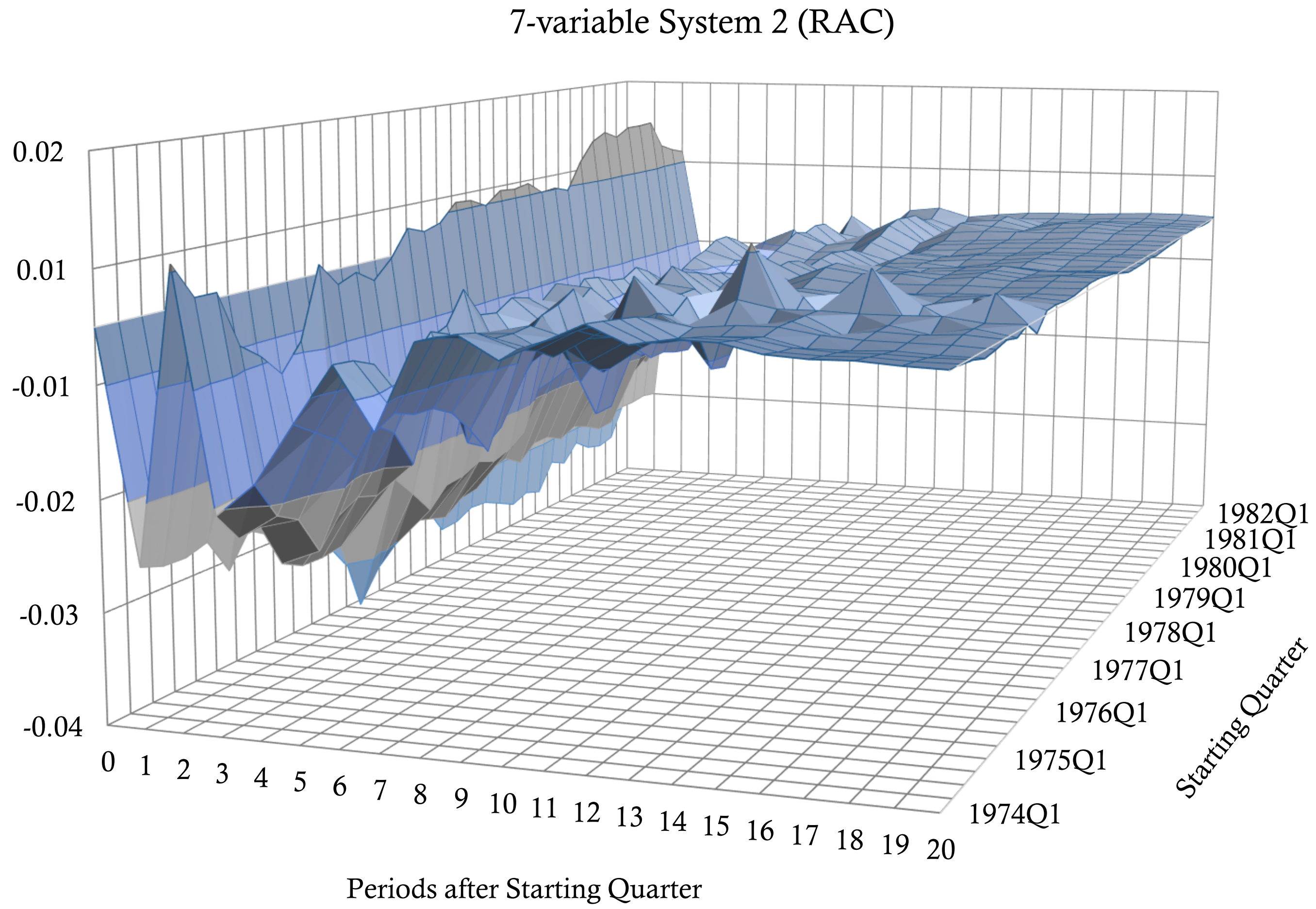

Figure 2.17. Rolling IRFs with a 10% RAC-based normalised positive oil price shock.

The authors write "in the [1970s], output is estimated to decline as much as 1 percent two years after the 10 percent change in the price of oil" (Blanchard & Galí, 2007). IRFs based on 7-variable system 2 yielded a similar total annualised figure as mentioned above but smaller quarterly effects. Similarly, Lee et al. (1995) estimated the response after 24 quarters to be -0.65—larger than the one observed here. Having said that, estimated IRFs behave similarly and demonstrate the same sign characteristics: an immediate negative impact on GDP growth followed by a period of overshooting and convergence towards the x-axis such that much of the effect dissipates eight quarters after the impulse.

8-variable system 2 was also used to generate IRFs for sense- and robustness-checking purposes. Although this specification uses a more recent and shorter sample period, estimated IRFs behave similarly to the 7-variable system. Annualised impact on real GDP growth of a 10% increase in oil price is estimated as -0.3 over a 20-quarter horizon independently of proxy used. This figure is quite close to the sum of estimated responses from the 7-variable system within the same sample period and translates to an average of 0.06% fall in GDP growth rate per year for 5 years. Figure 2.18 and Figure 2.19 show the functions where RAC is used.

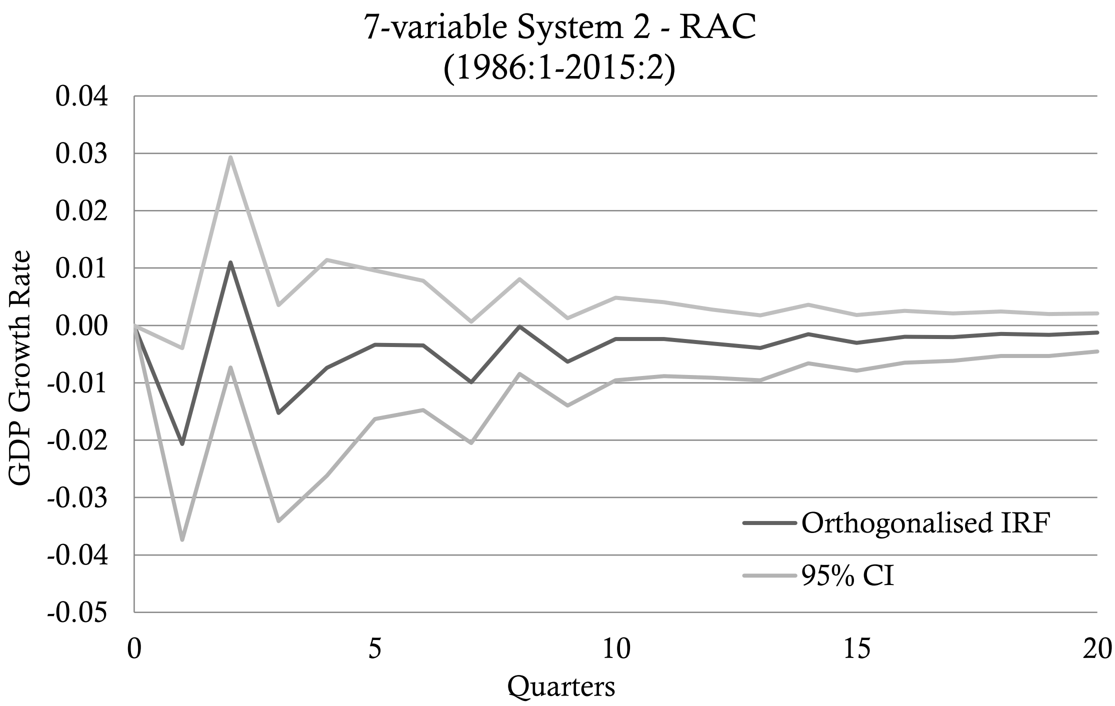

Figure 2.18. IRF with a 10% RAC-based normalised positive oil price shock.

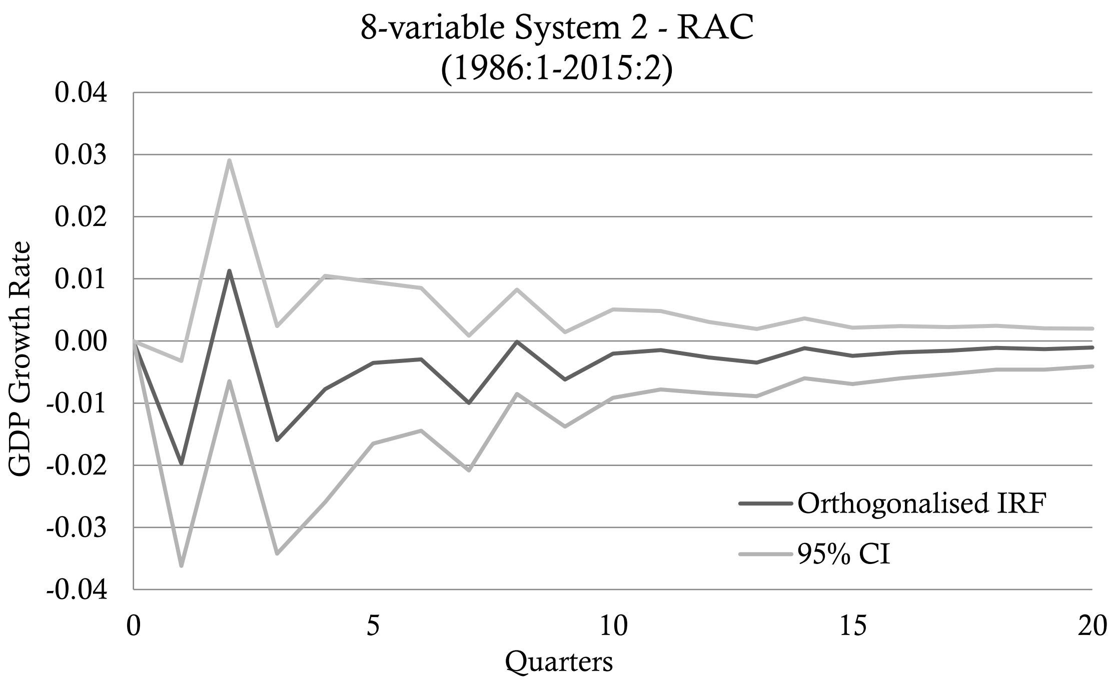

Figure 2.19. IRF with a 10% RAC-based normalised positive oil price shock.

The increase in overall impact in the most recent sample suggests that normalised positive oil price changes not only retain their statistical significance (Section 2.5.3) but also the magnitude of impact. This is a new finding in the oil price-macroeconomy literature, as most studies have found evidence of a weakening relationship. This could be investigated further using the rolling IRF implementation on the 8-variable system in the recent sample, but it is, regrettably, infeasible to do so given the small number of observations remaining in the dataset. This would be worth revisiting in the future to observe how the models behave with the latest data available. For completeness, IRF impact estimates for both specifications and subsamples are given in Table 2.10.

Specification	Proxy	1974:1-2015:2	1986:1-2015:2
7-variable System 2	PPI	-0.16 (-0.03)	-0.34 (-0.07)
	RAC	-0.14 (-0.03)	-0.32 (-0.06)
8-variable System 2	PPI	—	-0.32 (-0.06)
	RAC	—	-0.30 (-0.06)

Table 2.10. IRF results: Annualised percent changes in output growth rate as a response to a 10 percent increase in oil prices over a 20-quarter horizon. Values in parentheses are average per year responses of output growth rate to the impulse.

These estimates lie within the range of other studies in the literature. In addition to those mentioned above, Schneider (2004) outlines that estimated per-year response of US output growth ranges from -0.02 percent as estimated by Abeysinghe (2001) using an SVAR and -0.06 percent as estimated by Jiménez-Rodríguez & Sanchez (2005) using a VAR. More recently, Rasmussen & Roitman (2011) reported that a 25% increase in oil prices is expected to cause a 1% decrease in GDP for countries whose oil imports account for 4% of total expenditure in a panel study. My findings suggest that a 10% increase in the price of oil is expected to cause an average of 0.03% per year fall in GDP growth for five years in the early sample and 0.06% per year fall in the later sample.

2.7 Conclusion

This chapter has investigated the oil price and macroeconomy relationship across a number of dimensions with the goal of determining the most robust specification and the magnitude of the effect of an oil price change on output. Based on the results and analysis, RAC was found to be a more robust measure of oil price level than PPI for crude oil. The study found limited evidence that the oil price shocks do not Granger-cause fluctuations in output growth rate in recent samples and concluded that the impact of the shocks increased in post-1986 data. Model specification and not controlling for all relevant variables in the VAR system influence parameter estimates greatly and can result in misleading outcomes. Conditioning variables, such as 3-month TB rate and import price inflation, were found to be important in avoiding this bias in estimates, although the latter appeared redundant in some specifications. Furthermore, the statistical significance of control variables, including but not limited to 3-month TB rate, highlight the complexity of oil price-macroeconomy relationship and that many variables and monetary policy play an important role in determining the ultimate impact of oil price shocks on economic activity.

Section 2.5.2 found strong evidence for an asymmetric effect of oil prices on output across model specification and sample period. Moreover, normalised positive oil price shocks are more highly correlated with output growth rate than any other oil price variable considered. This provides evidence for the claim that volatility of oil prices before a shock occurs matters. Hence, unexpected positive oil price shocks are predicted to have a much larger impact on macroeconomic activity than anticipated ones. These findings contradict some researchers' views and findings (e.g., Hooker,

1999) that oil price changes do not Granger-cause fluctuations in output in most recent subsamples. There is some evidence that the magnitude of the effect was larger in 1970s than 1980s, but that this reversed in post-1986 samples. Analysis throughout Sections 2.5.2 and 2.5.3 found that models that allow for asymmetry generally perform better. Without separating oil price variables into their positive and negative counterparts, the statistical significance of the former is reduced by the latter. Therefore, it is preferable to distinguish between positive and negative shocks in a VAR system.

Section 2.6 introduced orthogonalised impulse response functions to determine the impact of oil price changes on the growth rate of output. Positive oil price shocks were found to have a significant negative impact on output growth rate, whereas the impact of oil price falls was not statistically significant. Post-1974 data indicate that the effect on annual output growth rate of a 10% increase in oil prices ranges between -0.014 and -0.034% over a horizon of 20 quarters, although most of the impact dissipates about eight quarters after the shock.

Obtaining parameter estimates and impulse responses across sample periods and model specifications has allowed a unique perspective on a relationship with a long macroeconomic and econometric history. I observed results that match popular work in the literature, such as Blanchard & Galí's (2007) observation that the impact of oil price rises on GDP growth is larger in the 1970s than early 1980s. I also encountered output that contradicts other researchers' findings, such as observing no loss of statistical significance in recent samples. I argue that these contradicting results are the outcome of the new way in which I modelled oil prices.

As part of future research on the topic and as more data become available, implementing a rolling IRF using larger specifications to investigate changing trends is key. An interesting extension would be to add a measure of investor and consumer confidence in the VAR system, since these are often reflected in economic agents' decisions, including stock market behaviour, which has become an important determinant of output growth path.

In addition to econometric research potential, the topic offers opportunities for macroeconomics-oriented research as well. Since monetary authorities could, and sometimes do, intervene in the face of an oil price shock, an optimal response could theoretically be identified based on this new way of modelling oil prices. Keeping in mind the strong linkages between 3-month TB rate and money supply and output growth rate, a reaction by the monetary policy authority could have a larger impact on growth than the oil price change would. Despite the amount of research devoted to the topic, there is no consensus on how central banks should respond to exogenously and endogenously rising oil prices. Identifying such policies can help prevent recessions and steep declines in output growth rates following oil price hikes.

3 Evaluating the Relationship between the UK Economy and Oil Prices: The Differences and Similarities between the US and the UK

Abstract

This chapter implements VAR models on quarterly UK data to analyse the oil price–macroeconomy relationship in the country. Data coverage is from 1955 through 2015. A primary objective is to determine how the oil price-macroeconomy relationship has evolved over time with an emphasis on the importance of oil price volatility. The analysis extends beyond GDP and includes other key macroeconomic variables, including inflation and unemployment. I found some evidence of Granger-causality between oil price fluctuations and GDP growth, and concluded that this relationship is stronger with normalised oil price changes. This suggests that oil price volatility leading up to a price shock contributes to its macroeconomic implications: unanticipated price shocks—those occurring after a period of stable prices—tend to have a larger impact on the economy. There was some, albeit muted, evidence for an asymmetric impact of oil price shocks on output growth rate. A rolling-window time-varying parameter approach concluded that after 1980, oil price implications have dwindled in terms of magnitude despite retaining statistical significance in VAR specifications. This time-dependency of parameters carried onto IRF estimates. Although not all point estimates were statistically significant, the responses pointed to a time-dependent relationship. More specifically, 1974:2-2015:2 subsample suggested a 0.24% decrease in GDP growth as a result of a 10% increase in normalised oil prices, whereas the same model estimated over 1986:1-2015:2 led to a 0.11% increase in GDP growth in response to the same shock. In spite of significant differences between the US and UK economies, this chapter highlights some fundamental similarities. For instance, unemployment rate is expected to follow a similar pattern following an oil price disturbance, since both countries have oil production activities and extensive direct and indirect employment within the sector.

3.1 Introduction

This chapter shares much of its methodology with Chapter 2 but has just as strong a motivation, as the global oil market and its historical fluctuations have had implications for the UK as well as the US. More indirectly, as world economies become more closely linked through trade and financial markets, the same oil price shocks can have exaggerated effects on multiple economies simultaneously. With growing focus on renewable energy sources and a shift away from fossil fuels, dependence on non-renewable energy sources have been viewed as a global challenge. At the extreme, these traditional sources of energy have been described as an obstacle for sustainable global development and economic growth. The reasoning is twofold: first, if economic growth is closely linked to non-renewable sources, there will eventually be a scarcity of energy. Second, while these fuels continue to be important, fluctuations in their markets and prices can have significant impact on nations' performance before reserves are exhausted.

Numerous studies have examined the relationship between oil prices and GDP growth in the United States, but there has not been as much focus on determining the relationship between the price of oil and economic growth in the United Kingdom. As a net importer of oil, the nature of the relationship between oil prices and US GDP seems obvious: an oil price hike should, *ceteris paribus*, slow down economic growth. An in-depth analysis of this and empirical results are discussed in chapter 2. Because the UK had been a net exporter of oil until recently, the oil price hikes have traditionally been viewed from a different perspective. For many years, price rises have been thought to contribute to output growth in the UK and not hinder it. However, since the UK became a net importer of oil within the last decade, there has been growing concern that oil price hikes might affect growth in the UK the same way it does in the US. Although the market share of oil consumption has fallen for almost twelve years in a row, it still occupies a large part of the market accounting for 39 percent of total primary energy consumption in the country (BP, 2017). Figure 3.1 shows crude oil imports and exports of the UK from 1970 onwards. These series from the Digest of UK Energy Statistics show that the UK became a net exporter of oil in 1981 and remained a net exporter until 2005. *A priori*, therefore, from 1980s onwards, we may observe a positive relationship between oil price increases and GDP growth in the country.

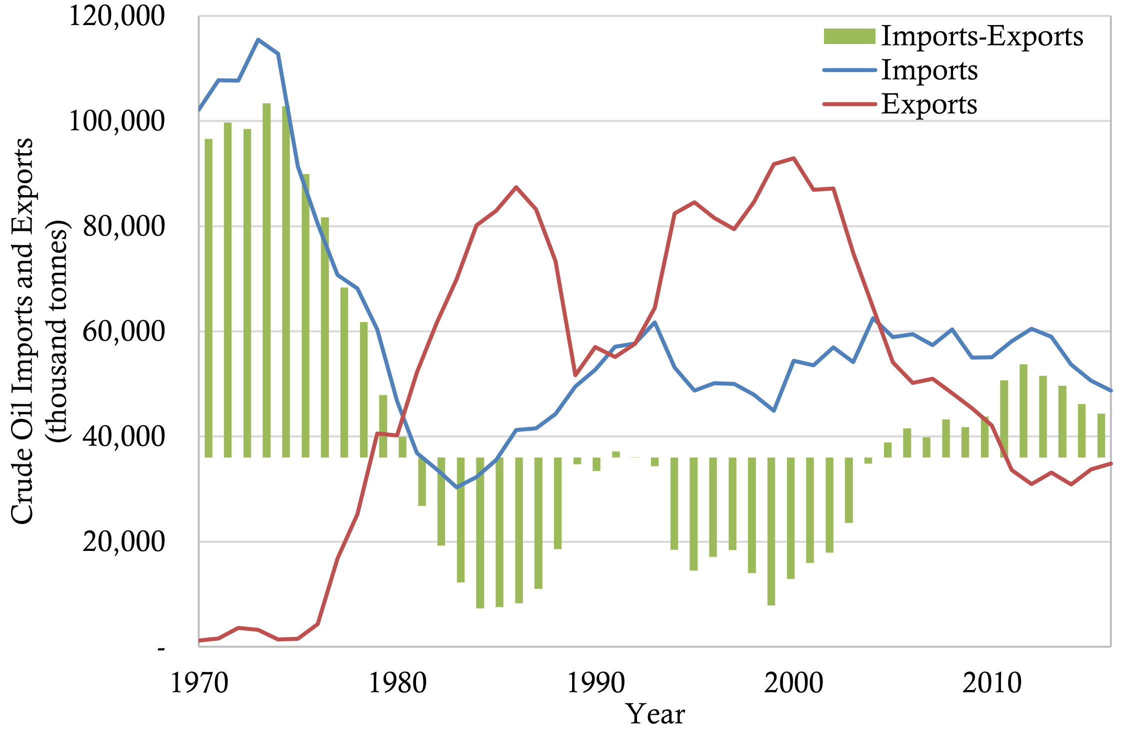

Figure 3.1. Crude oil imports and exports in the UK. Source: DUKES.

Du, Yanan, & Wei (2010) implemented an approach similar to the one in this chapter to scrutinise the linkages between oil price fluctuations and the Chinese macroeconomy. Jiménez-Rodríguez & Sanchez (2005) used a panel of OECD countries to investigate the same relationship, and Park & Ratti (2008) studied the US and 13 European countries' stock market performance following oil price shocks. Although different sets of countries have been studied along this vein, the UK has not received due attention on its own. When included in a study, the UK tended to be grouped with other European countries despite important macroeconomic differences, including the Bank of England's independent monetary policy tool. This chapter aims to fill this gap and provide insights as to the nature of the relationship, its sensitivity to sample period and model specification. It also introduces a volatility component and implements time-varying parameter VARs in an impulse response context, none of which have been done for the UK.

The sample period consists of the first quarter of 1955 through the second quarter of 2015. Some variables have a shorter time series due to limitations on data availability. These are outlined in later sections.

The next section is devoted to the description of the theoretical approach, literature review, transmission mechanisms through which oil prices propagate, and observed properties of the oil price–macroeconomy relationship. Section 3.3 outlines the models used for empirical analysis, and Section 3.4 presents the results obtained from these models. As a part of the analysis, VAR models are used to investigate empirical results across different dimensions, including sample period and model specification. This analysis is finalised with a discussion of impulse response functions in Section 3.5, and Section 3.6 discusses similarities and differences observed between the US and the UK, followed by a conclusion in Section 3.7.

3.2 Theoretical Analysis and Literature Review

3.2.1 Oil Price-Macroeconomy Relationship

Once the apparent relationship between the cyclical behaviour of macroeconomic variables and oil price movements was observed in US data, the relationship between these variables received considerable attention in the literature. Undoubtedly, one of the most important research aims within this framework has been forecasting when a recession is likely following an oil price shock. Accurately anticipating this would allow for various policy interventions ahead of time and diminish the detrimental effects of these shocks on economic activity.

Similarly to the pattern observed in US data, post-World War II data indicate that majority of UK recessions were preceded by drastic increases in oil prices (Figure 3.2). However, effects of changes in oil prices on real macroeconomic variables in the UK are likely to be more complex than those in nations that have historically been net importers. In the case of net importing and exporting countries alike, not all theoretical predictions have been corroborated by empirical estimations and impulse response analyses. *A priori*, unlike the case of US, I did not expect to find a negative correlation between oil price increases and GDP growth in the UK. On the contrary, during the period the UK was a net exporter of oil, we may expect an oil price hike to lead to faster growth. However, since findings in Chapter 2 suggested that oil price rises could cause a fall in GDP growth in the US, there could be indirect detrimental effects on the UK and global economy despite localised positive effects. As a result, *ceteris paribus*, the effect of a higher oil price level on the UK economy remains ambiguous from a theoretical perspective.

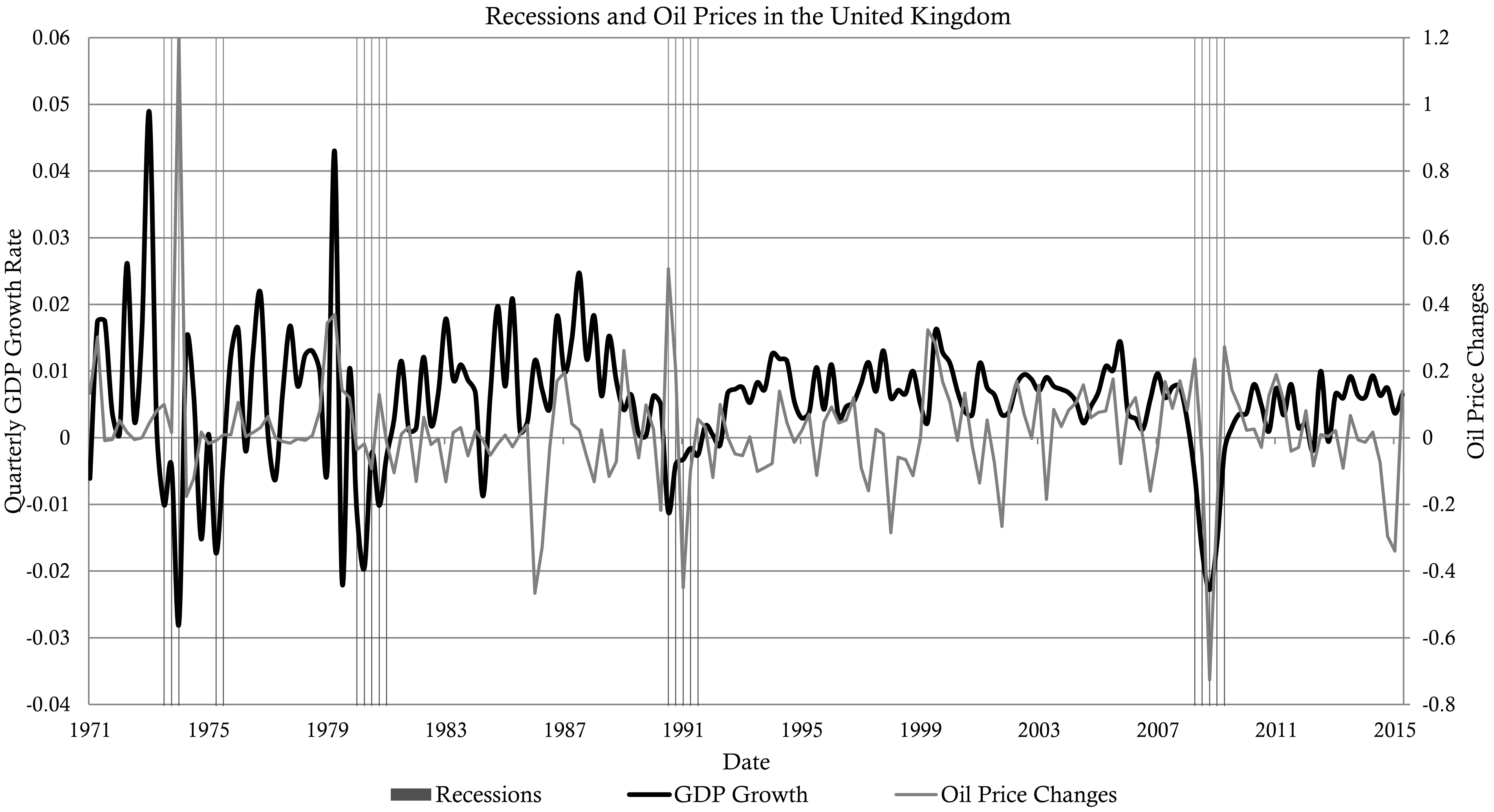

Figure 3.2. Recessions and oil prices in the United Kingdom.

Hamilton's (2005) simple OLS regression of GDP growth rates on its lagged values and the lags of logarithmic changes in nominal oil prices, shown in equation 2.1, found a statistically significant relationship between GDP and the lags of oil prices in the US from 1949:2 to 1980:4. As noted earlier, however, the simple OLS approach has been criticised and is not thought to provide reliable evidence of the relationship. Therefore, many researchers have resorted to more robust VAR and SVAR systems or general equilibrium models to reach a conclusion (Abeysinghe, 2001; Dalsgaard et al., 2002; Hamilton, 1983, 1996, 2003, 2005; Hooker, 1999; Jiménez-Rodríguez & Sanchez, 2005; Millard & Shakir, 2012). Most studies concluded that oil prices do have a statistically significant effect on the US economy (Carruth et al., 1998; Hamilton, 1983, 1996, 2003, 2005; Raymond & Rich, 1997; Rotemberg & Woodford, 1996), whereas Millard & Shakir's (2012) study of the UK economy found that the nature of the shock as well as the sample period affect the overall impact.

Several researchers have also argued that the statistically significant impact of oil prices on macroeconomic variables is indirect and acts mostly through the two variables' correlation with a third one (Barsky & Kilian, 2001, 2004, Hooker, 1996b, 1999). Hamilton ruled out this possibility in pre-1980 US data by confirming that oil price changes cannot be predicted by lagged values of other macroeconomic variables in his dataset. In addition, he claimed that exogenous factors, such as military conflicts, have mostly driven oil price hikes in history, which provides evidence for the shocks being exogenous. However, the former claim has been widely criticised. Barsky & Kilian (2001, 2004) argued that monetary policy is a likely cause of some large drops in output growth, whereas Hooker (1999) stated that most of the effect of price hikes on output is through their impact on unemployment. More specifically, he argued that oil price increases lead to a heightened natural level of unemployment and impede output growth as a by-product (Hooker 1999). In the following analysis, I have included conditioning variables, such as unemployment, 3-month interbank rate, and import price inflation in an effort to isolate the real impact of increases in oil prices. Another idea that emerged in the literature in the late 1980s, and one that was extensively discussed in the previous chapter, is that of an asymmetric effect of oil price shocks on output. Several researchers found strong evidence that an oil price increase has a greater negative impact on output in absolute value than the positive effect of an oil price decrease (Lee et al., 1995; Mork, 1989). This issue is discussed theoretically in Section 3.2.3 and empirically in Sections 3.3.3 and 3.3.4.

3.2.2 The Transmission Mechanisms

The channels through which changes in oil prices affect macroeconomic variables in the UK are, to a large extent, the same as those discussed in the context of the US in Chapter 2. Please refer to the discussion in Section 2.2.2 for details. This subsection provides further insights applicable to the UK and are relevant here. I begin by recognising that important differences between the two countries may mean additional channels prove to be important for the UK. By way of example, as a net exporter for part of the sample period, the UK's export revenues are expected to rise as the price of oil increases. This additional income could translate into increased economic activity, investment, and eventually GDP growth. On the contrary, these additional sales could appreciate the exchange rate and decelerate exports of other goods and services slowing down export-led growth in the country. This resource curse and Dutch disease idea is investigated at length on a global scale in the next chapter.

To demonstrate how the effect of an oil price change propagates through each of the three transmission mechanisms discussed by Schneider (2004)—supply side, demand side, and terms of trade—suppose there is a rise in the price of oil. The immediate effect of the shock is increased production costs and thus a negative impact on aggregate supply. In the long-run, firms can opt for more energy-efficient production processes, but this switch is not feasible in the short run due to frictions. Reallocating the means of production is also costly, and firms are forced to pay fixed costs to implement a more energy-efficient production procedure (Schneider, 2004). Therefore, firms must decide whether the cost of continuing production using an oil-intensive production process is indeed higher than increasing the energy efficiency of their production processes. These supply-side effects are shared with the US, although there are additional forces at play in the case of the UK. The price shock could cause to a global economic slow-down which could affect non-oil UK exports negatively and decrease slow down overall growth. Similarly, as noted above, an increase in oil sector profits due to an increase in price could have implications for the exchange rate. An appreciation due to an oil price increase could crowd out other exports with detrimental effects on growth.

On the demand side, inflation is expected to rise as a result of the price hike because oil is a raw input in the domestic market. Although the rise in inflation would reduce aggregate demand through lower real disposable income (Schneider, 2004), rising exports could offset this effect once again resulting in an ambiguous overall impact of the oil price innovation. The labour market is also affected. Decreasing real wages increase the pressure on downward rigid nominal wages, lead to lower demand for employment, and result in a decreased level of output. In the special case of the UK, the rising prices could lead to a booming oil sector and drive wages up across industries. These spillover effects could contribute to higher nominal wages stabilising real wages and preventing a fall in demand for employment. Investors' and consumers' confidence also play an important role in the relationship through their behaviour in the stock market. Because fluctuating oil prices can lead to a loss of confidence and the financial sector continues to have a substantial impact on macroeconomic fundamentals, the effect of the oil price shock can be amplified if the loss of confidence is passed on to the stock market (Schneider, 2004). This part of the literature has received abundant attention with numerous studies of the stock markets and oil price behaviour in various countries, including the UK. Some examples are Sadorsky (1999) for US and Canada, Park & Ratti (2008) for the US and 13 European countries, (Cong, Wei, Jiao, & Fan, 2008) for China, (Kilian & Park, 2009) for the US, and Fayyad & Daly (2011) for Gulf Coast countries, the UK, and the US. These studies have generally found that an oil price increase has a positive impact on stock market returns in oil-exporting countries and a negative one in oil-importing ones.

Lastly, monetary policy responses to a change in the price of oil are likely to have significant effects on the economy as well. Researchers unanimously acknowledge that the effect of an innovation in the price of oil on a *laissez faire* economy is different from the case with intervention by the central bank. However, the magnitude of this impact is a point of debate. Bernanke et al. (1997) paper on the US argued through VAR simulations that the real effects of oil price shocks are mostly caused by the tightening of monetary policy as a response to the price shock and not by oil price shocks themselves. On the other hand, Hamilton & Herrera (2004) claimed that there are greater direct effects from the shock than those brought about by restrictive monetary policy. Since the monetary authority faces a trade-off between output stabilisation and inflation dampening and that central banks' goals vary greatly across countries, the effect of monetary policy response critically depends on the country in question.

3.2.3 The Asymmetric Effect of Oil Prices

As mentioned earlier and investigated thoroughly in the previous chapter, the impact of oil prices on US output growth was found to be asymmetric. Numerous other empirical studies have found strong evidence of asymmetric effects (Hamilton, 1996; Lee et al., 1995; Mork, 1989; Mory, 1993). More recently, Herrera, Karaki, & Rangaraju (2017) and Baumeister & Kilian (2016) found that the oil price fall of 2014-15 had a negligible net stimulating effect on unemployment and real GDP in the US. However, in UK-centric studies, oil prices have not been explicitly modelled asymmetrically. This raises questions as to the validity of the asymmetry claim and how much it can be generalised beyond the US. To address these questions, two types of asymmetric oil prices are modelled here over sample periods in which the UK was a net oil exporter as well as a net importer.

The question of asymmetry is just as interesting for the UK as it is for the US, since the dispersion hypothesis applies here as well and arguably to a greater extent. This hypothesis deals with reallocation of factors of production across sectors and underpins the idea that a rise in the price of oil may translate into higher inflation and lower output in the short run. As an example, an oil price rise may cause a fall in demand for fuel-inefficient goods. Despite the imbalance this causes in the demand for fuel-efficient and inefficient goods, labour and capital market frictions prevent free movement across sectors and limit production of highly demanded fuel-efficient goods in the short run. On the contrary, a decrease in oil prices may not have the opposite and equally-sized impact. Chapter 2 demonstrated this phenomenon for the US and this chapter investigates it for the UK. An added complication here is the most recent fall in oil prices. Since this fall in price had implications for the already-declining crude oil production in the UK continental shelf and led to early decommissioning of some productive assets, the impact of a negative oil price change may be amplified. The impact on output is exacerbated by the lack of free movement of labour and capital across sectors as unemployment may rise temporarily as agents require additional training to change industries. In empirical results, this would be reflected by a larger effect, in absolute value, on output growth of a fall in the price of oil in the UK than the US. Hamilton (1988) and Atkeson & Kehoe (1999) have confirmed that demand side output responses to oil prices are not log-linear implying that consumers may delay purchasing a car when oil prices increase but do not buy a second one when they decrease (Hamilton, 2005). More generally, a fall in the price of oil can add to uncertainty surrounding prices and lead to losses in output as factors of production are being reallocated (Hamilton, 2005).

Another transmission mechanism underpinning asymmetric responses is downward nominal wage rigidities. Workers' reaction to a drop in purchasing power due to an increase in oil prices is to press for higher wages. However, an increase in workers' real wages as a result of a fall in oil prices does not lead to lower wages. As above, frequent oil price fluctuations introduce uncertainty to the economic environment, and consumers tend to slow down their purchases of durable goods, such as cars, real estate, and insulation, which can be perceived as the beginning of an economy-wide chain reaction (Hamilton, 2005). In this sense, volatility of oil prices could have implications for the oil price-macroeconomy relationship. This is one motivation for modelling oil price volatility in this context. Details are given in Section 3.3.4 with empirical results in Section 3.4.3.

For the US, there is some evidence that the significance of the asymmetry observation depends on sample period. Pair-wise equality tests in some studies for increases and decreases in oil price concluded that the null hypothesis of equal positive and negative effects was not rejected for the sample period 1949:1 to 1986:1 but was rejected for 1949:1-1988:2 and 1949:1-1992:3. Besides asymmetry, researchers have observed that the impact of an oil price shock greatly depends on the industry and the production process of the firm. In particular, Davis & Haltiwanger (2001) demonstrated that firms with a high capital to labour ratio, which have capital intensive production processes, produce durable goods, and have strong needs for energy are most affected by price shocks.

3.2.4 Modelling Literature Review

The next section introduces each model specification in separate subsections. These specifications are increasingly complex and attempt to capture a different dynamic within the oil price-macroeconomy relationship. These are extensions of VAR models that appeared in the literature after the 1980s following Sims' original implementation. Hamilton (1983) based his analysis on Sims' (1980) 6-variable quarterly VAR model to demonstrate a strong causal relationship between oil price fluctuations and output growth using US data from 1948 through 1980. Mork (1989) extended the dataset to the second quarter of 1988 and concluded that the correlation between oil price changes and real GDP growth had weakened and was only marginally significant. Hooker (1996b) revisited the topic and claimed that the relationship between oil price changes and output growth was no longer statistically significant in its original form. More recently, the topic has received considerable attention with researchers implementing larger VAR specifications (e.g., Hamilton, 2005; Jiménez-Rodríguez & Sanchez, 2005; Kilian, 2009), allowing for different types of oil price shocks (for example, Kilian, 2009), using groups of countries for their study (for example, Gómez-Loscos, Gadea, & Montañés, 2012), and explicitly testing for the asymmetric impact discussed above (for example, Kilian & Vigfusson, 2011a). Most of these studies have focussed on the US with little attention to the UK even in studies involving the UK as one of the countries in the dataset. An exception is Millard & Shakir (2012) study of the relationship in the UK using an SVAR. The authors opted for a Kilian-like oil price modelling and concluded that nature of the shock as well as the sample period affect the overall impact of a price change on UK GDP. This literature is discussed further in Section 2.2 where details of how the debate has progressed over time are also available.

As a part of oil price modelling, understanding oil price volatility has been a key objective in the literature. In essence, if oil price changes can help us anticipate a recession and determine the correct policy intervention, understanding the price behaviour and its implications would be key. As a part of this, researchers within economics and finance have implemented a suite of techniques mainly focussing on oil price volatility. Sadorsky (2006) attempted to forecast volatility; Lee et al. (1995), Ferderer (1997), Yang, Hwang, & Huang (2002), and Chen & Chen (2007) investigated the relationship between oil price volatility and the economy; Huang, Masulis, & Stoll (1996), and Sadorsky (1999, 2003) examined the linkages between oil price volatility and stock price performance; Plourde & Watkins (1998), Pindyck (1999), and Regnier (2007) studied the relative volatility of crude oil, refined petroleum product, and natural gas prices; and B.-N. Huang, Hwang, & Peng (2005) and Narayan & Narayan (2007) examined the asymmetry of oil price shocks' impact on economic activity. The latter focussed particularly on understanding the asymmetry and persistence of shocks and implemented an exponential GARCH specification. The authors found that positive and negative oil price shocks have different implications for volatility. Along these lines, Pindyck (2004b) argued that understanding oil price volatility is critical, since persistent changes in volatility can expose producers and consumers to risk and affect investment decisions, including those in production facilities and transportation. Modelling oil prices using high-frequency data, Wei, Wang, & Huang (2010) found that "nonlinear GARCH-class models, which are capable of capturing long-memory and/or asymmetric volatility, exhibit greater forecasting accuracy than the linear ones." The motivation behind these studies has been, at least partially, based on some of Pindyck's observations. This study also stated that volatility has implications for derivative valuation, hedging decisions, and investment decisions in physical capital tied to production and consumption of oil. Lastly, Pindyck (2004a) argued that volatility has implications for total marginal cost of production and influences firms' operating options and opportunity cost of production. As outlined in the next section, this chapter implements a unique approach by allowing explicitly for asymmetry and introducing oil price volatility into the VAR model through a GARCH model in line with the literature.

3.2.5 Structural Differences between the US and the UK

Among fundamental differences in the US and the UK economies, in the context of this chapter, the critical difference between the two is the role oil and gas sectors have played in the economy over the past several decades. As established in the introductory section, the UK has been both an importer and exporter of oil over the sample period considered. This has implications for empirical results as well as the transmission mechanisms at play. Based on the model introduced in Chapter 2, a key difference for the UK (while it was a net exporter of oil) is that m_t in equation 2.2 is carries much less weight. Furthermore, the impact of oil price fluctuations on wages, employment, and firms' mark-ups is ambiguous and depends on the relative significance of the oil sector in the economy as a whole. Given that the UK is a small open economy with too little production or consumption of oil to influence the global oil price, domestic inflation and households' behaviour are still affected by the oil price fluctuations in a similar fashion to the US.

An additional transmission mechanism not raised in Chapter 2 but may be relevant for the UK is the real exchange rates. In theory, significant changes in oil price could influence the trade composition and influence relative prices—further discussion of this in a global context in Chapter 4. Since oil exports have accounted for a modest percentage of GDP in the UK, the most pronounced transmission mechanism from real exchange rates to macroeconomic fundamentals is the price level. To capture this and avoid introducing noise through the inclusion of nominal exchange rate series, I have opted to use inflation and import price inflation as proxy variables. These two variables bring in the identifying variation that would be expected in a real exchange rate series without the noise from the financial sector.

3.3 Data, Models, and Methodology

Models and methodology implemented here are similar to those discussed in the previous chapter. For completeness, this section provides an overview of each model in a UK context with references to the previous chapter, where appropriate. The analysis begins with a base model, which is sequentially extended to incorporate asymmetric oil price effects and oil price volatility. In later sections, a time-varying parameter approach using a rolling-window technique helps shed light on the nature of the relationship in the UK over time. Variables used in the estimation are listed in Section 3.3.1 and have been selected based on the debate and criticisms in the relevant literature. Although early studies preferred GNP, recent research has focussed on GDP, which is the case here. The choice between nominal and real GDP has been a point of debate. In VAR systems with an inflation measure, this concern is circumvented, since the inclusion of an implicit deflator in the model gives identical results to using real log differences (Mork, 1989). Lastly, some researchers, including Hamilton (1996), have deflated their measure of output using PPI in all commodities. To avoid introducing correlation between oil price and deflated GDP artificially, I have opted for PPI in manufactured goods, which excludes raw commodities like oil. Lastly, oil prices are captured using the Brent price as the most applicable measure for the UK. Refiners' acquisition cost is not available for the UK and is arguably less useful than in the US due to limited refining activity in the former.

3.3.1 Data and Descriptive Statistics

Data are available through Thomson Reuters Datastream in quarterly frequency and originate from various sources. All variables in the VAR system are expressed in natural logarithm and are first-differenced to ensure their order of integration is zero.

Augmented Dickey-Fuller tests have been used to verify this across the board. Following natural logarithm and first difference transformations, removing time trends was not necessary in any variable. Table 3.1 below summarises the variables, data treatment, period of availability, and sources:

Variable	Description	Period	Data Treatment	Source
GDP	Gross Domestic Product ($\$_{2010}$)	1955:1 - 2015:2	Natural log, first difference, deflated using PPI in manufactured goods	Office for National Statistics
GDP deflator	Implicit price deflator	1955:1 - 2015:2	Natural log, first difference	Office for National Statistics
Brent oil price	Spot UK price	1957:1 - 2015:2	Natural log, first difference	International Financial Statistics, IMF
Import price index	Import prices, Goods, Index, 2012=100	1970:1 - 2015:2	Natural log, first difference	Office for National Statistics
Real wage growth	Weekly earnings, Index, 2005=100	1963:1 - 2015:2	Natural log, first difference	Main Economic Indicators, OECD
3-month IB rate	3-month Interbank rate	1960:1 - 2015:2	Natural log, first difference	Eurostat
Unemployment rate	Unemployment rate based on claimant count	1971:1 - 2015:2	Natural log, first difference	Office for National Statistics

Table 3.1. Variable descriptions, availability, and sources.

GDP is used as a measure of output and the variable enters the VAR system as $\ln(y_t/y_{t-1})$, where y_t denotes GDP deflated using PPI in manufactured goods. Since all variables undergo a logged differencing transformation, fluctuations in the resulting variables can be interpreted as percentage changes. Not all variables date back to the same starting point, so parts of the analysis were conducted with a shorter time series. Descriptive statistics for each sample period are shown in Table 3.2.

Variable	Statistic	1955:1 - 1986:1	1974:1 - 2015:2	1986:1 - 2015:2	1955:1 - 2015:2
Δln(GDP)	Mean	-0.0143	-0.0067	-0.0001	-0.0063
	Std dev	0.0242	0.0180	0.0097	0.0190
Δln(Brent)	Mean	0.0185	0.0084	0.0107	0.0146
	Std dev	0.1403	0.1463	0.1566	0.1484
Δln(GDP deflator)	Mean	0.0182	0.0137	0.0076	0.0130
	Std dev	0.0165	0.0146	0.0072	0.0139
Δln(Real wage growth)	Mean	0.0271	0.0174	0.0111	0.0182
	Std dev	0.0162	0.0153	0.0077	0.0145
Δln(Unemployment rate)	Mean	0.0268	0.0015	-0.0130	0.0005
	Std dev	0.0698	0.0585	0.0529	0.0619
Δln(3-month IB rate)	Mean	0.0096	-0.0192	-0.0274	-0.0100
	Std dev	0.1319	0.1317	0.1300	0.1319
Δln(Import price)	Mean	0.0265	0.0093	0.0038	0.0118
	Std dev	0.0315	0.0221	0.0183	0.0261

Table 3.2. Descriptive statistics.

As a part of empirical modelling, oil prices are split into the variable's positive and negative counterparts to explicitly allow for asymmetry in the VAR model. In addition, oil price changes are modelled using GARCH specifications to normalise or scale them based on previous quarters' price behaviour. Details of this approach are given in Section 3.3.4 in this chapter and in Section 2.3.3 in the previous one. Figure 3.3 demonstrates the outcome of normalising oil price fluctuations from 1974:1 through 2015:2. The result of the normalisation process is a rescaled oil price change variable, where each quarter's value is adjusted to incorporate oil price behaviour in the preceding two quarters.[16] An oil price change preceded by a period of relatively stable prices is scaled upwards in absolute value to emphasise the unexpected nature of that particular shock. The opposite applies when an oil price change follows a period of highly variable oil prices. A particularly striking example of this is price behaviour in the first and second quarters of 1986. First quarter of this year saw a 46% decline in the Brent price. This was preceded by particularly small fluctuations in 1985. Therefore, this fall in price is represented by a much larger magnitude in the rescaled series, ε^*. Further, the second quarter of 1986 experienced a further 32% decline in the oil price. However, because it was preceded by the large

[16] Unlike the previous chapter, where four quarters were used in GARCH modelling, two quarters are used here.

46% fall in the previous quarter, normalisation process scales this change down to the equivalent of approximately a 20% decrease in price.

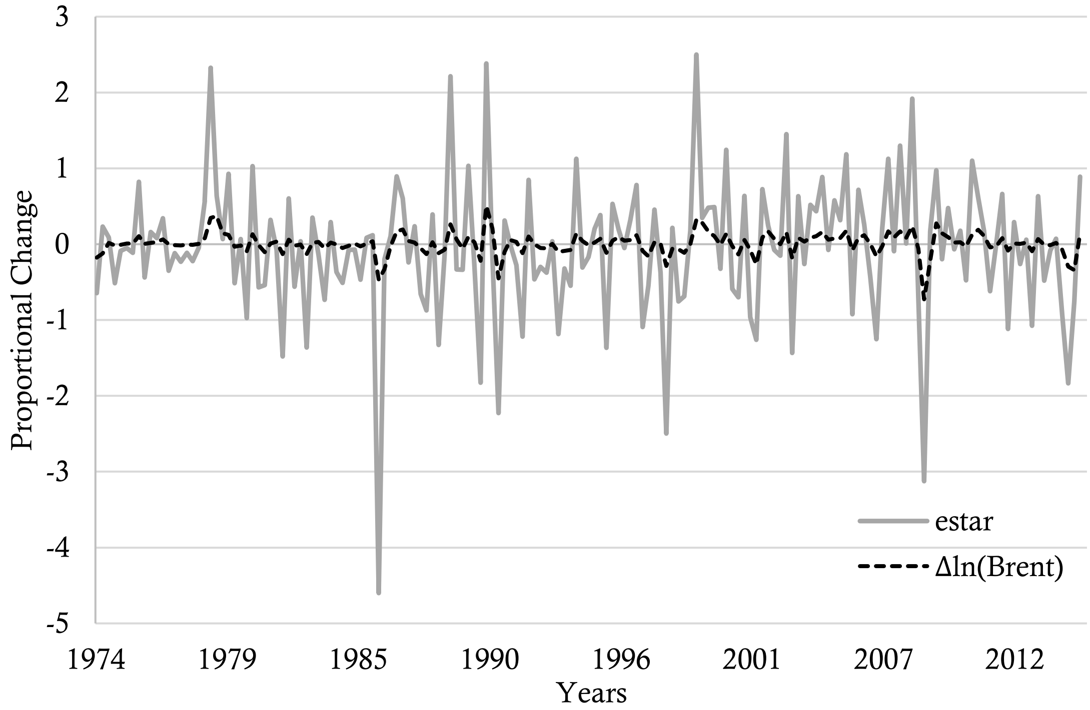

Figure 3.3. Oil price changes and normalised oil price fluctuations.

3.3.2 The Base Model

As in the previous chapter, the model introduced here serves as a starting point for the empirical investigation of the oil price-GDP growth relationship in the UK. Although simple, this model is informative since it has not been applied to the UK. This 7-variable system is based on Sims' (1980) VAR specification and includes oil prices as an extension. Thus, the VAR system consists of GDP growth, oil price changes, GDP implicit deflator inflation, 3-month IB rate, real wage inflation, unemployment, and import price inflation. Formally, the GDP growth equation has the following form:

$$y_t = \beta_0 + \sum_{i=1}^{4} \beta_i y_{t-i} + \sum_{i=1}^{4} \gamma_i o_{t-i} + \sum_{i=1}^{4} \sum_{j=1}^{k} \delta_{ij} x_{t-i,j} + \varepsilon_t \tag{3.1}$$

where, y_t denotes changes in real GDP in period t, o_t changes in nominal oil prices in period t, x_t changes in other explanatory variables at time t, and ε_t is the error term. Estimation results of this equation are shown in Section 3.4.1.

3.3.3 Asymmetric Effects Model

This section introduces an extension to the base model, in which oil prices are modelled using their positive and negative components. Oil price increases and decreases enter the VAR system as separate variables to allow explicit evaluation of each variable's contribution to the specification. As described in the previous chapter, the new variables are formulated as shown in equation 3.2 and extend the 7-variable base model to an 8-variable one. Denoting oil price changes as o_t, the new variables, o^+ and o^-, are defined as follows:

$$
\begin{aligned}
o^+ &= \begin{cases} x, & x > 0 \\ 0, & x \leq 0 \end{cases} \\
o^- &= \begin{cases} 0, & x \geq 0 \\ x, & x < 0 \end{cases}
\end{aligned}
\tag{3.2}
$$

Regression results using this model are given in Section 3.4.2.

3.3.4 Normalised Oil Price Model

For the reasons discussed in this chapter and the previous one, modelling oil prices has received plenty of attention. If oil price changes can help us anticipate a recession and determine the correct policy intervention, understanding the price behaviour would be key. As a part of this, researchers within economics and finance have implemented a suite of techniques mainly focussing on oil price volatility. In this part of the literature, Narayan & Narayan (2007) motivated their study by explaining that highly volatile oil prices could introduce uncertainty and have a knock-on effect on the economy as a whole. In their study, the authors implemented an exponential GARCH model and found that positive and negative oil price shocks have different implications for volatility. Along these lines, Pindyck (2004b) argued that understanding oil price volatility is critical, since persistent changes in volatility can expose producers and consumers to risk and affect investment decisions. Modelling oil prices using high-frequency data, Wei et al. (2010) found that "nonlinear GARCH-class models, which are capable of capturing long-memory and/or asymmetric volatility, exhibit greater forecasting accuracy than linear ones." This chapter uses a GARCH (1,1) process to model positive and negative oil price innovations. In this implementation, oil price fluctuations are scaled (or normalised) using conditional variance of oil price changes estimated through the GARCH process. These normalised oil price changes aim to capture the idea that small price increases within volatile periods are expected to have little effect on economic agents' behaviour, since small changes in a highly uncertain price environment are not surprising and do not incentivise irreversible investment decisions. These variables are often referred to as scaled oil price increases (SOPI) and scaled oil price decreases (SOPD). By construction, these variables contain identifying variation from changes in variance and not the level of oil prices. That is, the mean of real oil price changes may rise over time without agents being surprised as long as the new distribution of oil price changes remains the same. As in Chapter 2, these variables are constructed as follows:

$$z_t = \alpha_0 + \sum_{i=1}^{4} \alpha_i z_{t-i} + \varepsilon_t \tag{3.3}$$

$$h_t = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \gamma_2 h_{t-1} \tag{3.4}$$

Here, $\varepsilon_t | I_{t-1} \sim N(0, h_t)$, and z_t are oil prices measured as RAC. The unexpected part of the oil price shock is simply the residual term of equation 3.3, $\hat{\varepsilon}_t = z_t - \widehat{z_t}$. Normalised oil price shocks are then calculated as,

$$\varepsilon_t^* = Normalised\ Oil\ Price\ Shock = \frac{\hat{\varepsilon}_t}{\sqrt{h_t}} \tag{3.5}$$

This variable is then split into two parts as,

$$SOPI_t = Normalised\ Positive\ Oil\ Price\ Shock\ (\varepsilon_t^{*+}) = \max(0, \varepsilon_t^*) \tag{3.6}$$

$$SOPD_t = Normalised\ Negative\ Oil\ Price\ Shock\ (\varepsilon_t^{*-}) = \min(0, \varepsilon_t^*) \tag{3.7}$$

Assuming unexpected variation in real oil prices indeed has an impact on how the price shocks affect real output, the normalised variable, ε_t^*, is predicted to have a "more systematic causal relation to real GDP than either z_t or $\hat{\varepsilon}_t$" (Lee et al., 1995). These variables are used in a number of model specifications. A summary of specifications is given in Table 3.3 below. Following VAR analysis with these specifications, impulse response functions are used to evaluate the size of the impact across model specification and sample period. Details of this implementation are given in Section 2.3.4.

Model Specification	GDP Growth	Oil Price Change	Oil Price Increase	Oil Price Decrease	Normalised Oil Shock	Normalised Positive Oil Shock	Normalised Negative Oil Shock	Net Oil Price Increase	GDP Deflator Inflation	3m IB rate	Unemp. Rate	Real Wage Inflation	Import Price Inflation
Base Model	✓	✓							✓		✓	✓	
Asym. Eff. Model	✓		✓	✓					✓	✓	✓	✓	✓
6-variable System 1	✓	✓			✓				✓		✓	✓	
6-variable System 2	✓					✓	✓		✓		✓	✓	
6-variable System 3	✓				✓				✓	✓	✓	✓	
7-variable System 1	✓	✓			✓				✓	✓	✓	✓	
7-variable System 2	✓					✓	✓		✓	✓	✓	✓	
7-variable System 3	✓					✓	✓		✓	✓	✓	✓	
8-variable System 1	✓	✓			✓				✓	✓	✓	✓	✓
8-variable System 2	✓					✓	✓		✓	✓	✓	✓	✓
8-variable System 3	✓	✓				✓	✓		✓	✓	✓	✓	

Table 3.3. Model specifications.

3.4 Empirical Results

As in the previous chapter, empirical results and hypothesis testing in this section refer to Granger causality with a null hypothesis that has a binary outcome. Throughout the discussion in this section, the rejection of the null hypothesis suggests the coefficient estimates in question are statistically significantly different from zero and, thus, provide evidence for Granger causality. Similarly, if the null hypothesis is not rejected, there is no evidence for Granger causality. In other words, the null hypothesis is equivalent to no Granger causality, whereas the alternative suggests Granger causality.

3.4.1 The Base Model

This section provides an outline of the empirical results obtained through the implementation of the model described in Section 3.3.2 across different sample periods. The periods in question are 1963:1 through 1986:1, 1974:1 through 2015:2, 1986:1 through 2015:2, and finally the entire sample period. These have been selected for ease of comparison with results from Chapter 2, which is a key objective for this chapter. As in the previous chapter, these sample periods allow a formal investigation of the oil price-macroeconomy relationship over time and pave the way for a rolling-window implementation in later sections.

Table 3.4 is a summary of test statistics and p-values from joint F-tests of the overall significance of four lags of oil price changes in the GDP growth equation. Often referred to as exclusion tests, these tests are a formal way of investigating whether oil price fluctuations Granger-cause changes in GDP growth controlling for other variables in the system. The null hypothesis is that none of the four coefficients are statistically different from zero, which translates into no Granger causality between oil price changes and GDP growth.

Variable	1963:1-1985:4 †	1974:1-2015:2 ††	1986:1-2015:2 †††	1963:1-2015:2 †
Oil Price Change	2.131 (0.712)	3.022 (0.554)	12.064** (0.017)	2.120 (0.714)

Table 3.4. Exclusion tests for the base model. The values in parentheses are p-values. Statistical significance is shown at the 10% level (*), 5% level (**) and 1% level (***).

Interestingly, the results indicate that oil price fluctuations Granger-cause changes in GDP growth only in the most recent sample. Formally, I failed to reject the null hypothesis of no Granger-causality for all sample periods and model specifications except in the 1986:1-2015:2 subsample, where the null hypothesis is rejected at the 5% level. This is in line with the *a priori* expectation established based on Figure 3.1 but is not considered conclusive evidence of a robust relationship due to two main reasons. First, oil prices in this model specification do not allow for asymmetry. Modelling this explicitly could change the outcome. Second, model specifications shown in the table above vary across sample periods due to data availability and for purposes of comparison. The most comprehensive specification, indicated with †††, is estimated over the period 1986:1-2015:2.[17] The 7-variable VAR system consists of real GDP growth, oil price changes, implicit GDP deflator inflation, real wage inflation, unemployment rate, 3-month TB rate, and import price inflation. Estimating the 7-variable system using the 1974:1-2015:2 subsample yielded the same outcome as the 6-variable system shown in Table 3.4, suggesting that import price inflation is not the underlying cause for the significance of the oil price variable in the more recent sample period. This is in sharp contrast with the US results in Table 2.4 and is an early indication of the differences between the two countries in question.

5- and 6-variable specifications estimated over the 1986:1-2015:2 sample period yielded similar results to the 7-variable model: exclusion tests on oil price changes resulted in the rejection of the null hypothesis across all specifications in this sample period. Similarly, using the 5-variable base specification over 1974:1-2015:2 instead of the 6-variable system resulted in qualitatively similar results. Control variables appear to play an important role as well. The GDP deflator and real wage inflation both showed statistical significance in the GDP equation across sample period and model specification. In the same equation, there was less evidence of Granger causality for unemployment, 3-month interbank rate, and import price inflation. However, the first two showed statistical significance in the GDP deflator equation indicating that unemployment and 3-month interbank rate are closely linked to the deflator. Further, both GDP deflator and import price inflation had p-values less than 0.05 in the 3-month interbank rate equation. These observations provide evidence for an indirect transmission mechanism from oil price fluctuations to GDP growth

[17] Table 3.4 shows results for different model specifications corresponding to each sample period: 5-variable VAR (base model, denoted as †), 6-variable VAR (base model + 3-month TB rate, denoted as ††) and 7-variable VAR (base model + 3-month TB rate + import price inflation, denoted as †††)

patterns. As an example, based on the 7-variable VAR system estimated over 1986:1-2015:2, an oil price increase is expected to induce an increase in the GDP deflator and/or import prices. These changes then translate into an increase in the 3-month interbank rate, unemployment rate, and real wages. Jointly, these have a negative impact on GDP growth. As discussed in Section 3.2.5, the significance of import price inflation is linked to real exchange rate dynamics as well. In an oil exporting country like the UK over much of this sample period, exchange rate dynamics and balance of payments can have a pronounced impact on macroeconomic fundamentals. Empirical findings in this section support the notion that import price inflation, and by extension real exchange rate dynamics, have a direct impact on GDP growth as well as an indirect impact through interbank rate, unemployment rate, and real wages. There is an opposite direct effect as well. Increasing oil prices mean greater revenue from that sector, more government income, and higher sectoral wages and employment. Hence, the overall impact is ambiguous and further investigation is required. I return to this idea in the context of impulse responses.

The results in this section serve as a good starting point: the VAR implementation has pointed to the importance of control variables and indirect transmission mechanisms. Moreover, sample period appears to be key: oil price changes have a significant impact on output growth only in the most recent sample period. Having established appropriate control variables for the VAR system, the next section turns to modelling asymmetry in oil prices explicitly.

3.4.2 Asymmetric Effects Model

Having observed a potential link between oil price fluctuations and GDP growth in the most recent subsample, this section aims to differentiate between the impact of oil price increases and decreases through the implementation outlined in section 3.2.3. Table 3.5 below contains exclusion test results for all variables in the output growth equation.

Variable	1963:1-1985:4 †	1974:1-2015:2 ††	1986:1-2015:2 †††	1963:1-2015:2 †
Oil Price Increase	2.372 (0.668)	6.860 (0.143)	2.395 (0.664)	4.835 (0.305)
Oil Price Decrease	1.965 (0.742)	0.288 (0.991)	4.004 (0.405)	0.964 (0.915)
Inflation, GDP Deflator	4.437 (0.350)	10.931** (0.027)	8.976* (0.062)	4.828 (0.305)
3-month IB Rate	—	12.946** (0.012)	5.061 (0.281)	—
Unemployment Rate	6.795* (0.095)	9.115* (0.058)	2.290 (0.683)	11.198** (0.024)
Real Wage Inflation	6.709 (0.152)	10.574** (0.032)	5.651 (0.227)	18.869*** (0.001)
Import Price Inflation	—	—	11.482** (0.022)	—

Table 3.5. Exclusion tests of asymmetric effects model with GDP growth as the dependent variable. The values in parentheses are p-values. Statistical significance is shown at the 10% level (*), 5% level (**) and 1% level (***).

The results demonstrate the sensitivity of the observed oil price-GDP growth relationship to model specification. When the oil price series is split into its positive and negative components, neither of the variables appear to significantly affect growth throughout the whole sample period. However, inflation, 3-month IB rate, unemployment rate, real wage inflation, and import price inflation all play an important role in the GDP growth equation. Estimated coefficients on these control variables had the expected signs. Although not shown in the table, estimating the 8-variable system over 1974:1-2015:2 yielded similar results such that both real wage and import price inflation Granger-cause output growth. On this basis, this set of control variables were considered robust and relevant within the VAR framework.

Interestingly, both increases and decreases in oil price appear to have an impact on other variables included in the system. As shown in Table 3.6, oil price rises were linked to an increase in inflation across all sample periods and model specifications. Similarly, oil price decreases were related to a fall in inflation except in the earlier subsample. 3-month IB rate appears to react to decreases in the price of oil more than increases. Specifically, oil price falls tended to relate to looser monetary policy with high statistical significance in Granger-causality tests, whereas price rises had an ambiguous effect on the interest rate. This suggests that in the relevant sample period, decreases in oil price may have triggered an increase in the 3-month IB rate due to either direct or indirect reaction by the Bank of England. Given the observation that oil price fluctuations may not affect GDP growth directly (Table 3.5), the corresponding change in interest rates is likely to be a reaction to other macroeconomic fundamentals. In this context, inflation is of particular importance but so are unemployment rate, real wage inflation, and import price inflation. Using 1974:1-2015:2 sample period as an example, results in Table 3.6 suggest that a decrease in the price of oil could lead to a fall in GDP deflator inflation, unemployment rate, real wage inflation, and import price inflation.[18] Jointly, these changes could strengthen growth and allow more flexible monetary policy, suggesting that the Bank of England has not reacted to oil price fluctuations but rather their consequences.

There are also signs of an asymmetric relationship between oil price changes and the macroeconomic variables in question. By way of example, increases in the oil price appear to have a more pronounced and stable relationship with rising real wages than decreases in oil price do with falling wages. Hence, oil price increases are expected to have a larger impact on output growth through this transmission channel than decreases in price. Furthermore, 7- and 8-variable systems estimated over the 1974:1-2015:2 sample period suggested a fall in the unemployment rate regardless of the direction of oil price movements. This is in contrast to the apparent relationship in the US and introduces a new dynamic into the system: the negative effect on GDP growth of oil price increases observed for the US may be ameliorated in the UK through the positive impact on employment. In a deeper sense, the meaning of "asymmetry" appears to shift in the UK vis-à-vis the US. I return to this theme in later sections in the context of impulse response analysis to observe the dynamics in question across time and model specification.

[18] Although the equation for import price inflation is not shown in Table 3.6 for consistency with Table 3.5, the results are as described in the text.

Equation	Variable	1963:1-1985:4 †	Coefficient Sign	1974:1-2015:2 ††	Coefficient Sign	1986:1-2015:2 †††	Coefficient Sign	1963:1-2015:2 †	Coefficient Sign
Inflation, GDP Deflator	Oil Price Increase	14.119*** (0.007)	+	18.651*** (0.001)	+	13.311*** (0.010)	+	14.005*** (0.007)	+
	Oil Price Decrease	8.187* (0.085)	+	9.199* (0.056)	-	15.843*** (0.003)	-	9.530** (0.049)	-
3-month IB Rate	Oil Price Increase	—	—	4.912 (0.296)	+/-	8.669* (0.070)	+/-	—	—
	Oil Price Decrease	—	—	38.597*** (0.000)	+	39.606*** (0.000)	+	—	—
Unemployment Rate	Oil Price Increase	37.581*** (0.000)	+/-	21.144*** (0.000)	-	4.211 (0.378)	+	21.652*** (0.000)	+/-
	Oil Price Decrease	15.554*** (0.004)	-	15.336*** (0.004)	-	16.081*** (0.003)	-	12.661** (0.013)	-
Real Wage Inflation	Oil Price Increase	20.096*** (0.000)	+	24.238*** (0.000)	+	5.223 (0.265)	+	26.758*** (0.000)	+
	Oil Price Decrease	11.873** (0.018)	-	7.821* (0.098)	-	5.102 (0.277)	-	4.869 (0.301)	-
Import Price Inflation	Oil Price Increase	—	—	—	—	6.836 (0.145)	+	—	—
	Oil Price Decrease	—	—	—	—	6.570 (0.160)	-	—	—

Table 3.6. Exclusion tests in control variables' equations. Coefficient signs are based on the cumulative sum of estimated coefficients. The values in parentheses are p-values. Statistical significance is shown at the 10% level (*), 5% level (**) and 1% level (***).

3.4.3 Normalised Oil Price Model

Based on the discussion in Sections 3.2 and 3.3, there is theoretical reason to believe that the impact of an oil price shock has a different impact on macroeconomic variables depending on oil price behaviour in preceding time periods. Having observed slightly increasing standard deviations in oil prices over time, this section focusses on the estimation of equations 3.3 and 3.4 as well as the implementation of equations 3.5 through 3.7 within a VAR system. Table 3.7 summarises the estimated coefficients from the GARCH (1,1) model.

Parameter	1963:1-1985:4	1974:2-2015:2	1986:1-2015:2	1963:1-2015:2
α_0	-0.002	0.013	0.026	0.020*
	(0.742)	(0.288)	(0.162)	(0.062)
α_1	0.770***	0.409**	0.458**	0.302*
	(0.000)	(0.014)	(0.036)	(0.056)
α_2	0.255	-0.313***	-0.366***	-0.235**
	(0.242)	(0.004)	(0.001)	(0.042)
α_3	0.281	0.184**	0.172*	0.119
	(0.333)	(0.021)	(0.055)	(0.151)
α_4	-0.095*	-0.095	-0.103	-0.074
	(0.099)	(0.224)	(0.267)	(0.130)
γ_0	0.001	0.010***	0.011***	0.017*
	(0.309)	(0.001)	(0.000)	(0.068)
γ_1	5.494	0.333	0.556	0.107
	(0.190)	(0.314)	(0.280)	(0.568)
γ_2	—	0.166	0.106	0.171
		(0.272)	(0.591)	(0.149)

Table 3.7. Parameter estimates for GARCH (1,1). The numbers in parentheses are p-values. Statistical significance is shown at the 10% level (*), 5% level (**) and 1% level (***).

Note that the second sample period starts from 1974:2 as opposed to 1974:1 due to lack of convergence in the GARCH specification using the latter as the starting point. The reason for lack of convergence is that 1974:1 coincides with the OPEC embargo of the period and is an outlier in the series. Overall, the GARCH (1,1) representation appears more accurate for refiners' acquisition cost and PPI in crude petroleum in the US case than for the Brent series in the UK case. Although there is still evidence of AR(4) behaviour in more recent samples, ARCH and GARCH terms are not as central in capturing fluctuations in Brent price. Further, there is evidence of a moving average (MA) component in the series. I investigate this in detail in Section 3.6.1 and discuss its implications. For the remainder of this section, I proceed with the GARCH specifications, as the output presented in Table 3.7 are point estimates in each sample period and the main objective here is to implement a time-varying approach and recalculate the parameters in question over many different sample periods.

An analysis of autocorrelation in residuals of the GARCH model showed that there is no unexploited information in residuals in any sample period. Although there is some autocorrelation in residuals for the most recent sample period, increasing the number of AR lags or ARCH and GARCH terms did not improve the behaviour of the residuals. For the 1963:1-2015:2 subsample, GARCH (1,1) residuals resulted in a Ljung-Box Q statistic of 17.25 (p=0.838). Furthermore, Bollerslev, Chou, & Kroner (1992) argue that low-order GARCH models outperform alternative methods. Hence, the GARCH (1,1) specification is adopted as a parsimonious representation of the conditional variance of ε_t and this specification is used to calculate ε_t^*.

As an intermediate step towards using normalised price changes as the main oil price variable in the VAR models, three transitional specifications are estimated. Table 3.8 provides exclusion test results for 6-, 7-, and 8-variable systems over each sample period. There is little evidence here that the normalised oil price shocks are more highly correlated with changes in real GDP than oil price changes. Test statistics for normalised price shock variables do not provide evidence for Granger causality between them and GDP growth except in the earliest sample period. As discussed in the previous chapter, the correlation between oil price changes and their normalised counterparts is masking the true underlying link between normalised price changes and output growth. When normalised and non-normalised price variables are tested together, they are jointly significant, which suggests that when considered together, oil prices fluctuations Granger-cause changes in GDP growth (i.e. the null hypothesis of no Granger causality is rejected). More importantly, however, these specifications lack asymmetry in oil prices. It is, therefore, possible that positive or negative changes have a statistically significant effect on GDP, but that effect is simply not observed when the two series are merged. It is worth noting that the control variables retain their importance in these specifications, as they appear to Granger-cause fluctuations in GDP as well as being linked to oil price changes. This corroborates the claim that a monetary policy response to an oil price shock could have a much larger impact on the macroeconomy than the original shock. It is interesting to note that the change in statistical significance of normalised oil price shocks from 1963:1-1985:4 to later sample periods were not due to worse model fit, as measured by RMSE, since all specifications had comparable RMSE across sample periods.

Specification	Variable	1963:1-1985:4	1974:2-2015:2	1986:1-2015:2	1963:1-2015:2
6-variable System 1	Oil Price Change	3.200 (0.525)	2.141 (0.710)	3.614 (0.461)	6.679 (0.154)
	Normalised Oil Price Shock (ε*)	10.922** (0.027)	2.692 (0.611)	1.313 (0.859)	6.691 (0.153)
7-variable System 1	Oil Price Change	—	1.128 (0.890)	4.051 (0.399)	—
	Normalised Oil Price Shock (ε*)	—	1.521 (0.823)	1.791 (0.774)	—
8-variable System 1	Oil Price Change	—	—	6.878 (0.142)	—
	Normalised Oil Price Shock (ε*)	—	—	2.826 (0.587)	—

Table 3.8. Exclusion tests for normalised oil price shocks. The numbers in parentheses are p-values. Statistical significance is shown at the 10% level (*), 5% level (**) and 1% level (***).

Given that testing for asymmetry is a key objective, these specifications are extended to include positive and negative price changes explicitly. The results, shown in Table 3.9, indicate that normalised positive oil price shocks have a highly significant impact on GDP growth in the two earlier sample periods. Negative price shocks do not have a statistically significant impact in any sample period, as I fail to reject the null hypothesis of no Granger causality between normalised negative oil price fluctuations and output growth. Therefore, as speculated above, using positive and negative oil price shocks together appears to weaken their joint statistical significance. Furthermore, there is a strong indication that the oil price-GDP growth link has weakened over time, particularly just after the UK became a net exporter of oil. In line with previous discussion, this could have two different underlying causes. The underlying economic relationship may have fundamentally changed over time or the model specification is not appropriate in all sample periods. Information on the latter can be deduced from RMSE for each estimation. The RMSE values suggested that the models perform equally well across sample periods, which suggests that the point estimates are responsible for the observed pattern and not how precisely they are estimated by the models. Based on these observations, the remainder of this section discusses the implications of modelling choices on findings in detail.

Specification	Variable	1963:1-1985:4	1974:2-2015:2	1986:1-2015:2	1963:1-2015:2
6-variable System 2	Normalised Positive Oil Price Shock (ε*+)	11.720**	17.390***	4.479	3.043
		(0.020)	(0.002)	(0.345)	(0.551)
	Normalised Negative Oil Price Shock (ε*-)	0.841	2.541	0.994	0.445
		(0.933)	(0.637)	(0.911)	(0.979)
7-variable System 2	Normalised Positive Oil Price Shock (ε*+)	—	19.407***	4.625	—
			(0.001)	(0.328)	
	Normalised Negative Oil Price Shock (ε*-)	—	5.486	2.467	—
			(0.241)	(0.651)	
8-variable System 2	Normalised Positive Oil Price Shock (ε*+)	—	—	4.699	—
				(0.320)	
	Normalised Negative Oil Price Shock (ε*-)	—	—	3.872	—
				(0.424)	

Table 3.9. Exclusion tests for specifications using normalised oil prices with asymmetry. The values in parentheses are p-values. Statistical significance is shown at the 10% level (*), 5% level (**) and 1% level (***).

The Oil Price-GDP Relationship Across Time

Table 3.9 suggests that although increases in oil prices Granger-caused changes in UK GDP growth in the past, this apparent relationship no longer has as much evidence. 6- and 7-variable models estimated in several sample periods corroborated this. Formally, I find that normalised positive oil price shocks Granger-caused a fall in UK GDP growth until 1986 but not in more recent decades. This was mainly driven by changes in parameter estimates and not higher RMSE across sample periods. To refrain from putting too much weight on a single set of point estimates, a rolling-window time-varying parameter approach is adopted here. A rolling window of 132 quarters is estimated sequentially from 1974:2 onwards. Exclusion tests are conducted after each iteration to observe changes in statistical significance of oil price shocks over time.[19]

[19] Note that although this section focuses on a discussion of statistical significance of point estimates, other sections put an emphasis on interval estimates and how wide they are. The purpose of focussing on point estimates and p-values here is to address the ongoing debate in the literature.

The resulting p-values on normalised positive oil price shocks in 7-variable system 2 are shown in Figure 3.4 below.[20] With the exception of a few quarters, there is a clear pattern: normalised oil price rises had a significant impact on GDP growth in the UK until the second quarter of 1979. From 1980 onwards, the exclusion test p-values are considerably larger, and the oil price-GDP link appears to have disappeared. Unlike positive oil price shocks, negative ones do not appear to have a strong link as shown in Figure 3.5. Since focussing solely on one model specification to draw conclusions would be unwise, the next subsection investigates how model specification may affect these findings. One objective is to extend the VAR systems with additional control variables, such as import price inflation, as a robustness check.

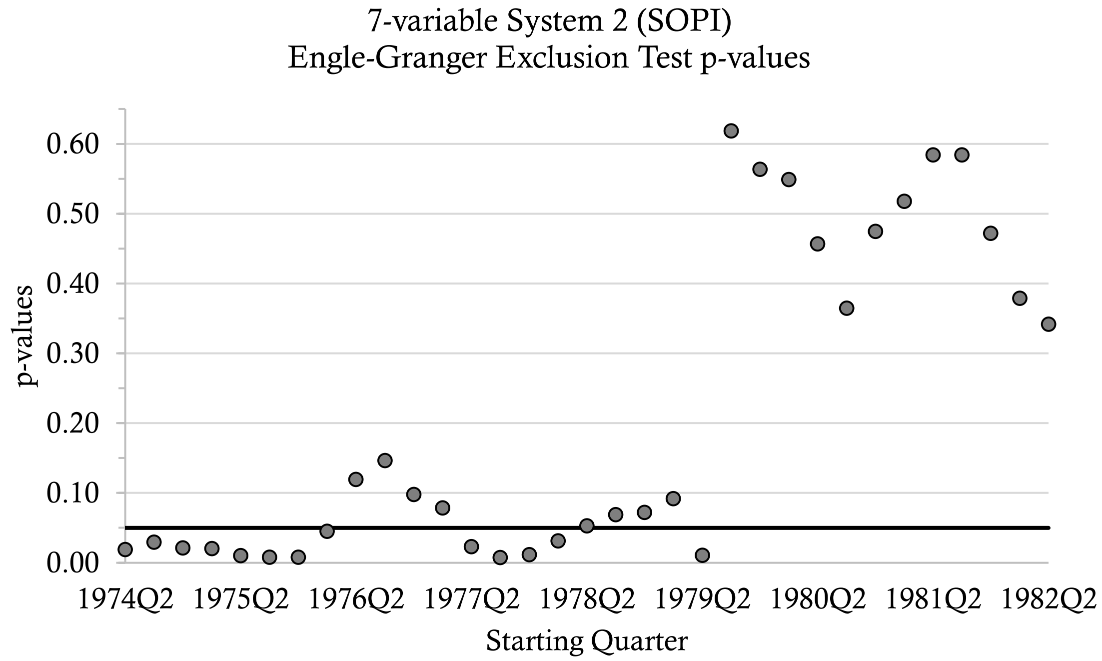

Figure 3.4. Exclusion test p-values for normalised positive oil price shocks in 7-variable system 2 using a rolling window against starting quarter.

[20] P-values shown in the figures are not identical to those presented in Table 3.9, since the former use a 132-quarter rolling window sample period whereas the latter uses as much of the sample period as available.

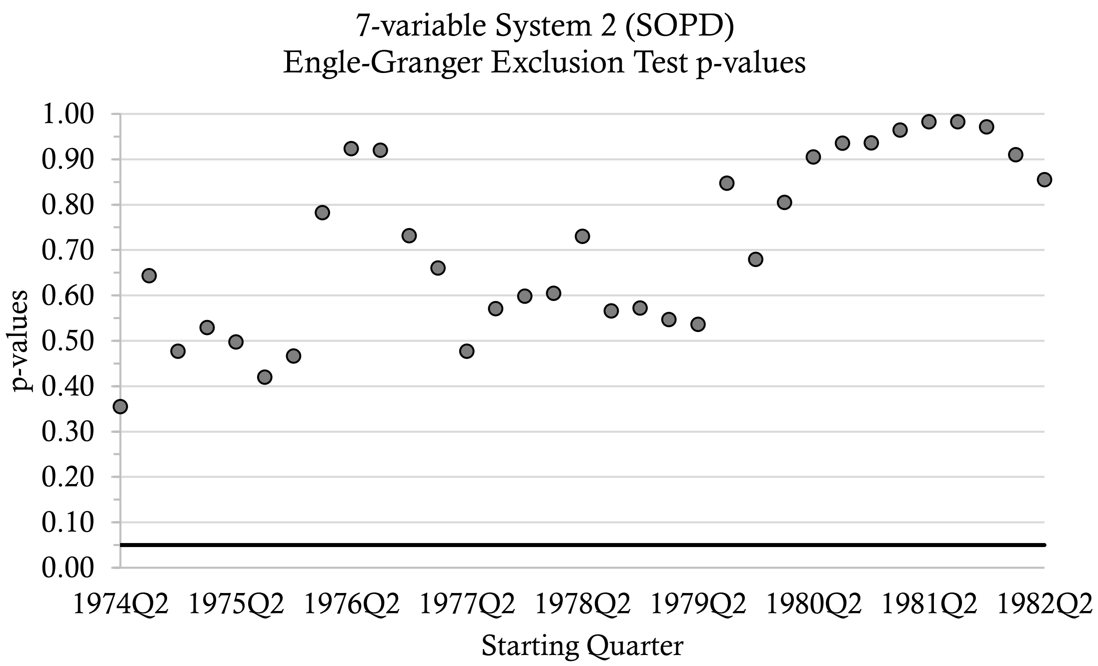

Figure 3.5. Exclusion test p-values for normalised negative oil price shocks in 7-variable system 2 using a rolling window against starting quarter.

The Effect of Allowing for Asymmetry

Figure 3.4 and Figure 3.5 show that SOPI Granger-cause fluctuations in GDP growth for much of history whereas SOPD do not. This subsection revisits this asymmetry discussion in a time-varying parameter context across different model specifications. Figure 3.6 and Figure 3.7 below summarise the estimated p-values in 8-variable system 2 and 6-variable system 2 using normalised negative oil price shocks, respectively. Both figures provide evidence for asymmetry, highlighting that SOPD have historically not had a strong link with real GDP growth.

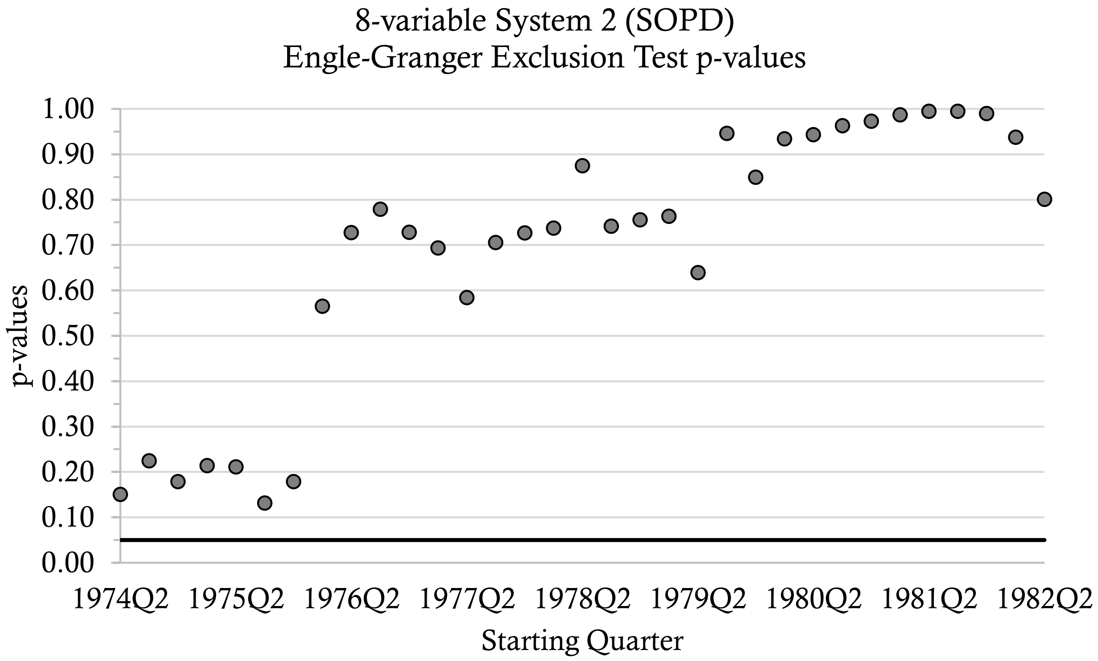

Figure 3.6. Exclusion test p-values for normalised negative oil price shocks in 8-variable system 2 using a rolling window against starting quarter.

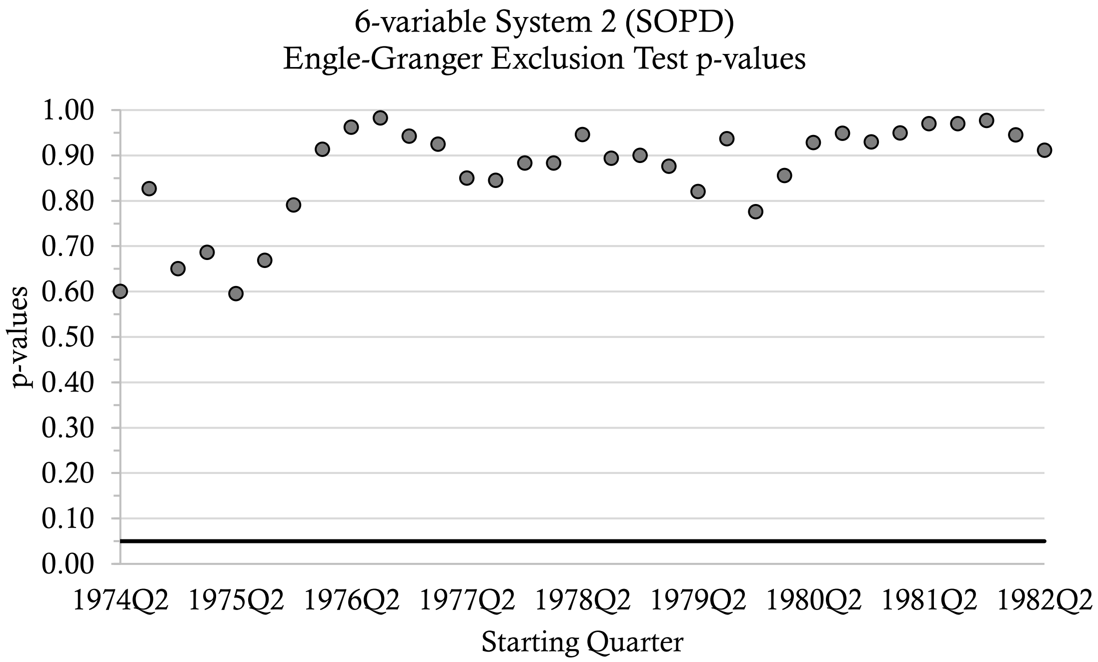

Figure 3.7. Exclusion test p-values for normalised negative oil price shocks in 6-variable system 2 using a rolling window against starting quarter.

Model Performance Across Specifications

To investigate model performance across model specifications, the models are set up with a nested structure. For example, as shown in Table 3.3, 6-variable system 2 is nested within 7-variable system 2, which is in turn nested within 8-variable system 2.

These specifications are estimated separately, and their results are interpreted to identify the optimal model. In this context, the optimal model is not only based on performance parameters and information criteria but also a series of observations. In this chapter, I have put weight on parameter stability across sample periods and across choice of oil price proxy, stability of impulse responses each model generated, and overall model size. To elaborate on the final objective, a key aim was to strike a balance between the size of each model and avoiding omitted variables. Throughout the analysis, these two aspects of modelling were in competition because smaller models were tempting to maximise degrees of freedom but risked the omission of critical identifying variation. Based on the underlying structural model, I chose optimal models that captured key variables but were not too large to prohibit the rolling-window implementation adopted here, while maintaining the other objectives listed above. Looking ahead, the optimal model could depend on sample period considered, but 7- and 8-variable system 2 (one of the largest specifications) have performed well and capture the richest dynamics. The latter model includes import price inflation, which is used as a proxy for real exchange rate dynamics. As a result, much of the following analysis focuses on these two model specifications with three-dimensional surface plots in the Chapter Appendix based on the latter.

Returning to Table 3.9 and re-estimating 8-variable system 2 over the 1974:2-2015:2 sample period yields an intriguing result. The exclusion test statistics on positive and negative normalised oil price shocks were 4.30 ($p=0.367$) and 4.34 ($p=0.361$), respectively. Regardless of sample period, import price inflation plays a key role in the GDP growth equation. This finding begs an obvious question: is the significant relationship between rises in oil prices and output growth observed in Table 3.9 and Figure 3.4 simply due to an omitted variable? To investigate this and to ensure an isolated case does not dictate the overall conclusion, I estimated the 8-variable specification in question over a rolling window as above. Turning to Figure 3.8 below, I observed a similar pattern to that in Figure 3.4. Namely, SOPI remain statistically significant until 1979:3. This suggests that the oil price-GDP growth Granger-causality tests are robust to additional variables, and that sample period is a more fundamental determinant of the underlying relationship.

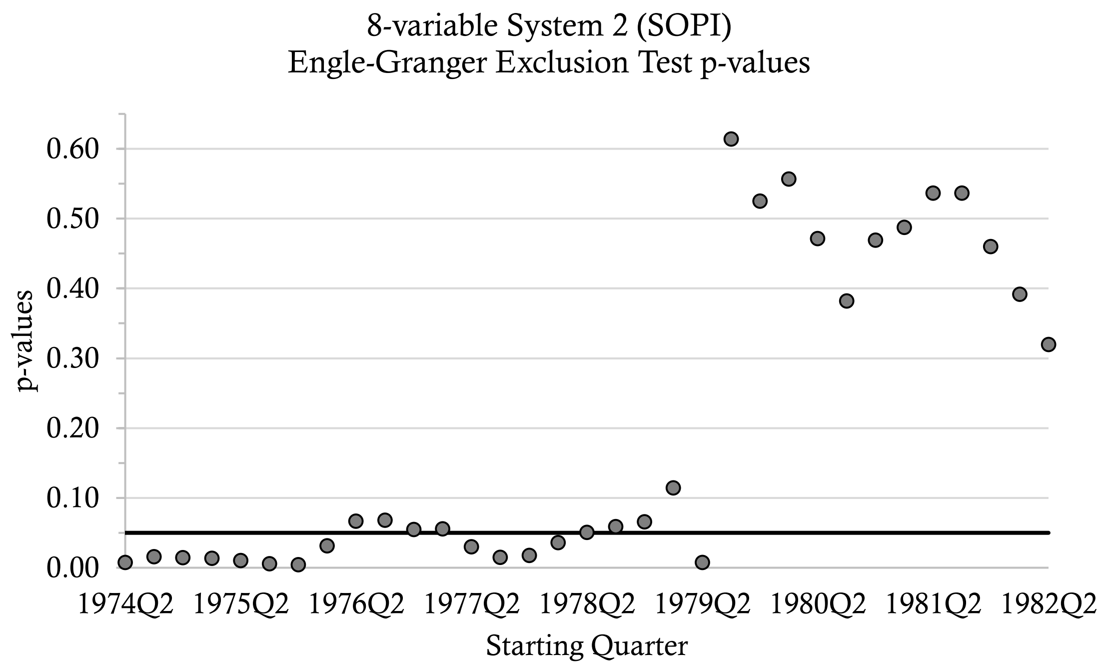

Figure 3.8. Exclusion test p-values for normalised positive oil price shocks in 8-variable system 2 using a rolling window against starting quarter.

A similar observation holds for extending 6-variable system 2 to 7-variable system 2 by including 3-month IB rate in the model specification. Figure 3.9 shows exclusion test p-values based on 6-variable system 2, which are qualitatively identical to those in Figure 3.4 (7-variable system 2) and Figure 3.8 (8-variable system 2).

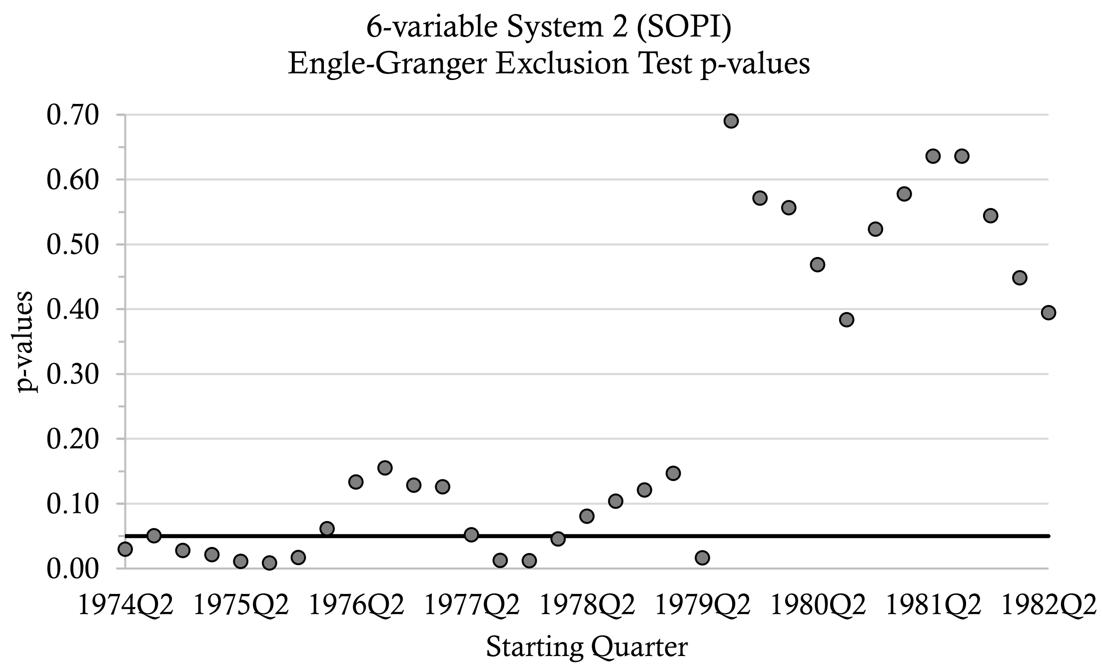

Figure 3.9. Exclusion test p-values for normalised positive oil price shocks in 6-variable system 2 using a rolling window against starting quarter.

One final objective within the model specification discussion was to determine whether normalised oil price variables Granger-cause fluctuations in GDP growth more often and in a more stable manner than non-normalised measures. This question is revisited in an impulse response context in the next section. From a statistical significance perspective, revisiting tables and figures above can help shed some light. Table 3.8 and Table 3.9 have pointed to normalised variables having a more robust and sustained link to GDP growth, and Figure 3.4, Figure 3.8, and Figure 3.9 provide further evidence in a rolling-window time-varying context. Figure 3.10 below provides a more elaborate overview of exclusion test p-values (z-axis) across model specification (y-axis) against starting quarter (x-axis). The two left-most specifications, 6- and 7-variable system 1, demonstrate that with a non-normalised oil price series, the empirical model would indicate no Granger-causality between oil prices and real output growth. This is indeed what many researchers have observed. 6- and 7-variable system 2 yield a much different p-value profile, however. As observed earlier in this section, normalised oil price rises Granger-cause GDP growth in the UK until 1980. The three-dimensional representation below also allows a snapshot across specifications at a given starting quarter. As an example, considering a slice across specifications on 1975:1 indicates p-values greater than 0.05 for the first two specifications and less than 0.05 for the rest.

Ultimately, the way oil prices are captured and how they enter a VAR appears to greatly influence the observed oil price-macroeconomy relationship. In addition to this, two further key points have emerged from this discussion: 1) sample period appears to matter with recent years showing a weakening relationship between oil price fluctuations and GDP growth in a Granger-causality sense, and 2) modelling asymmetry in oil prices is critical, as only rises in oil price appear to matter.

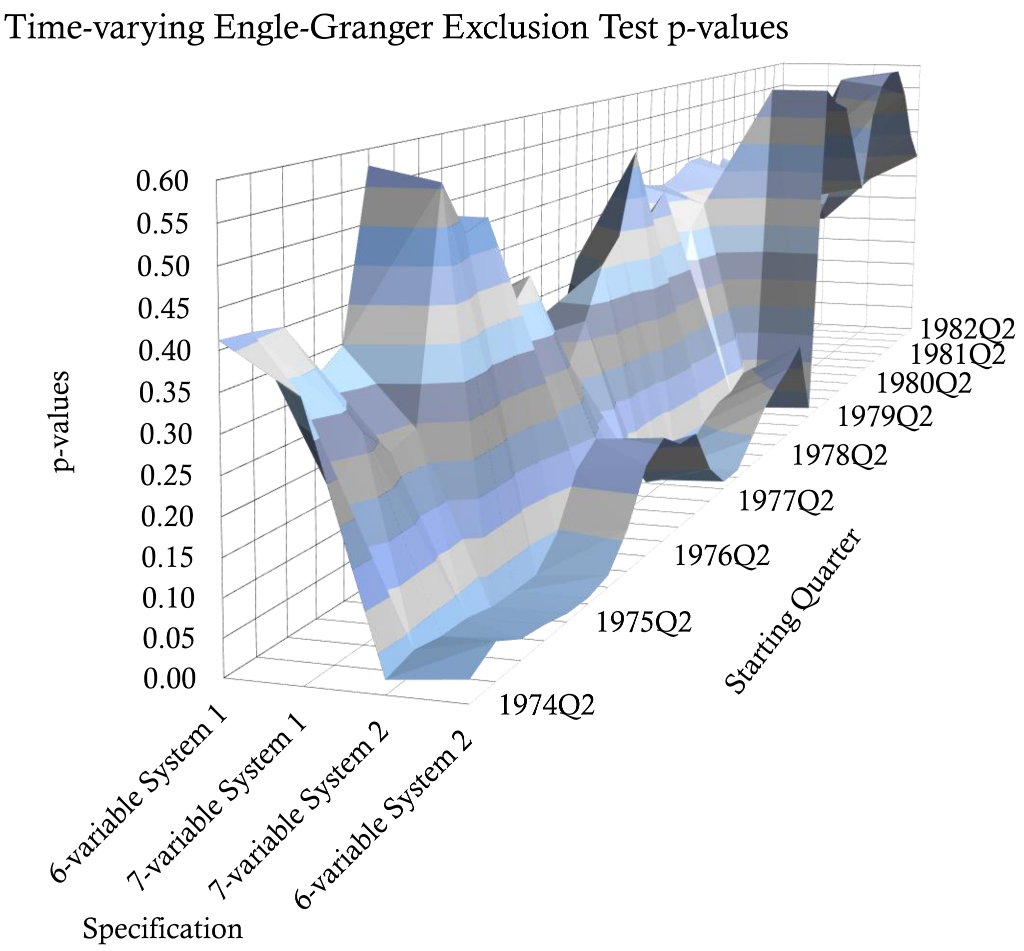

Figure 3.10. Exclusion test p-values (z-axis) across model specification (y-axis) with varying starting quarter (x-axis). Excluded variables as follows. 6-variable system 1: oil price changes; 6-variable system 2: normalised positive oil price changes; 7-variable system 1: oil price changes; 7-variable system 2: normalised positive oil price changes. Each colour contour on the z-axis represents an increment of 0.05.

3.5 VAR Results and Impulse Response Analysis

Having discussed statistical significance in previous sections, this part turns its focus to estimating the magnitude of the impact oil price fluctuations have on macroeconomic variables. Cholesky-decomposed orthogonalised impulse response functions (IRFs) were used for this purpose, which captured a twenty-quarter time horizon. Static IRFs based on 7-variable system 2 estimated over the 1974:2-2015:2 subsample suggested a negative cumulative impact on GDP growth of a positive normalised oil price shock. A negative price innovation of the same size using the same specification over the same sample period yielded a positive cumulative effect. Figure 3.11 and Figure 3.12 show an overview of the estimated impact on GDP growth in each case with a 10% normalised oil price shock.

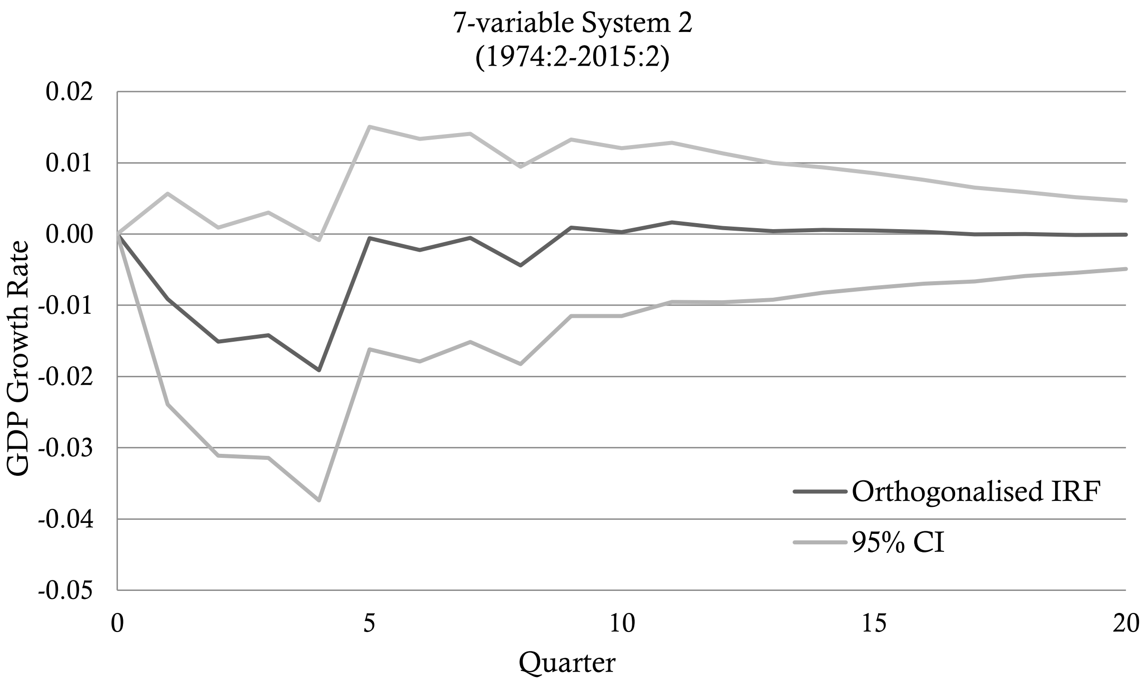

Figure 3.11. IRF showing GDP growth response to a 10% normalised positive oil price shock.

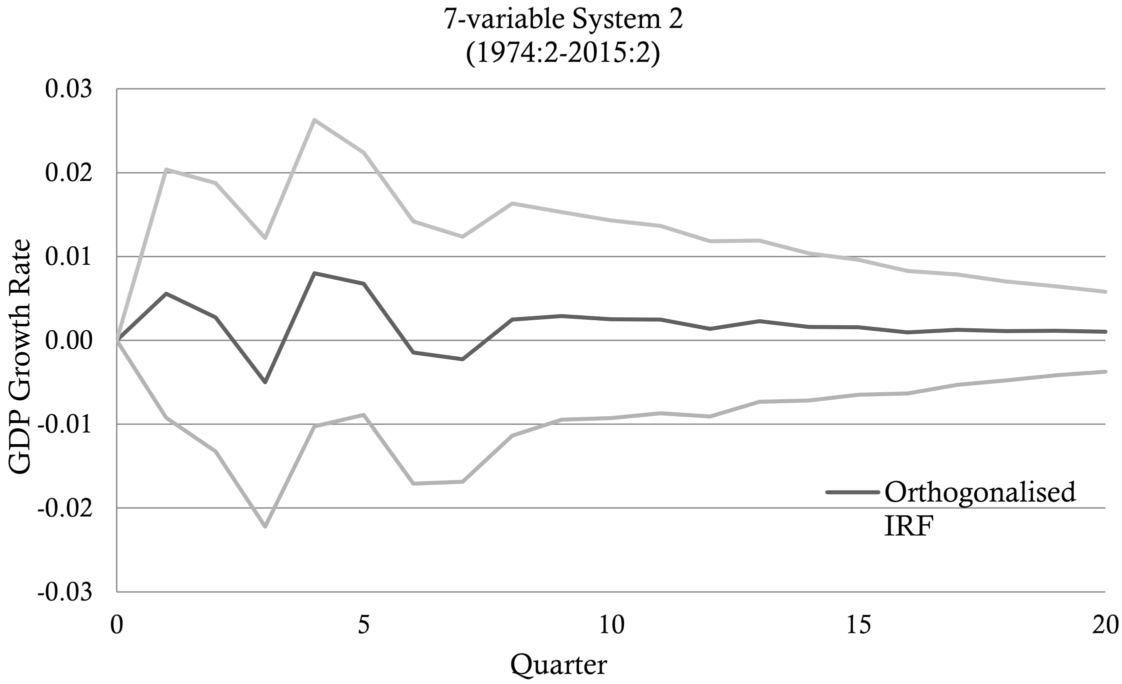

Figure 3.12. IRF showing GDP growth response to a 10% normalised negative oil price shock.

Starting with Figure 3.11, I observed that only the fourth quarter's confidence bands exclude zero and that the GDP response becomes weaker over time. Unlike in the case of the US, there is minimal overshooting in this case such that negative point estimates continue until the ninth quarter and positive estimates are small. Keeping in mind the confidence intervals include zero, I interpret the cumulative effect cautiously. The estimated annualised effect on GDP growth of a 10% increase in normalised oil price was -0.24 after 20 quarters in this model specification and sample period combination. This suggests that a 10% increase in price is expected to reduce real GDP growth by 0.24% over a five-year horizon. 8-variable system 2 over the same sample period resulted in a virtually identical outcome. Figure 3.15 in the chapter appendix shows the estimated IRF for this specification over the most recent sample period, 1986:1-2015:2. This figure shows more of an overshooting behaviour in GDP growth following an oil price increase, which is further discussed in a time-varying parameter context below. In all these figures, the estimated OIRF converges to zero, which suggests that an orthogonalised innovation to the corresponding oil price variable does not have a permanent effect on real GDP growth rate in the UK.

A fall in oil price has a more ambiguous but positive effect on GDP growth based on the results shown in Figure 3.12. Much like positive shocks, negative ones also do not appear to have a long-run impact on GDP growth. Although the confidence interval includes zero throughout the 20-quarter horizon, the estimated impact in the first five quarters, except the third quarter, is positive. The estimated cumulative annualised effect on GDP growth of a 10% decrease in normalised oil price was 0.15%. This effect was halved in the later sample period, however: IRF estimated based on 7-variable system over 1986:1-2015:2 resulted in an overall impact of just 0.07%. This provides further evidence for the previously observed pattern of a weakening relationship over time.

To investigate changes in the magnitude of the impact over time, I implemented rolling-IRFs using a rolling-window approach akin to the approach introduced above in a VAR context. Figure 3.13 shows the estimated GDP growth effect from a positive shock, while Figure 3.14 summarises the results of a negative shock. Starting with the latter, I confirm the observation above, as the estimated impact on output growth rate of a negative price shock decreases along the y-axis. The former figure implies a similar characteristic as well. The largest impact, in absolute value, on GDP growth of an oil price rise is estimated in the sample window starting in the third quarter of 1977 with previous quarters of that year close behind. In sample periods starting after 1980, the overall effect is greatly diminished. In the early 1980s, there is a short-lived positive overshooting effect observed as two distinct domes in the three-dimensional surface. It is no coincidence, of course, that this was a period of increasing oil production in the UK and a turning point for the country, since it became a net exporter of oil in 1981. This is reflected with the opposite effect in Figure 3.14, where the early 1980s did not see a rise in GDP growth because of a fall in oil prices even though earlier periods had done so. These results were not sensitive to model specification, as 8-variable system 2 resulted in the same conclusions (see Figure 3.16 and Figure 3.17 in Chapter Appendix). In fact, the negative GDP growth implications of an oil price rise are so diminished in recent decades that the overall estimated effect becomes positive over a 5-year horizon. Table 3.10 highlights this observation using two static sample periods.

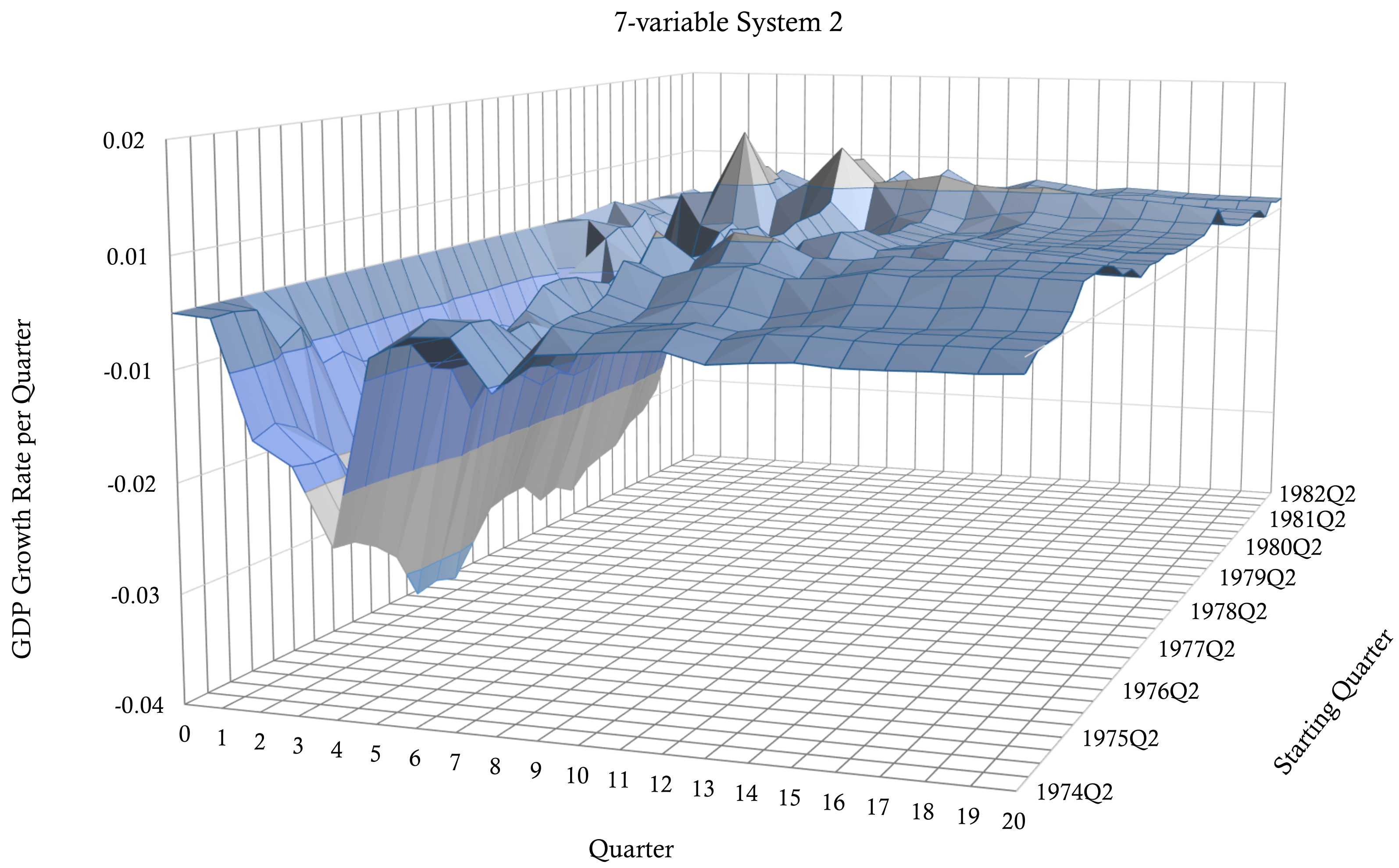

Figure 3.13. Rolling IRFs showing the impact on GDP growth rate of a 10% normalised positive oil price shock.

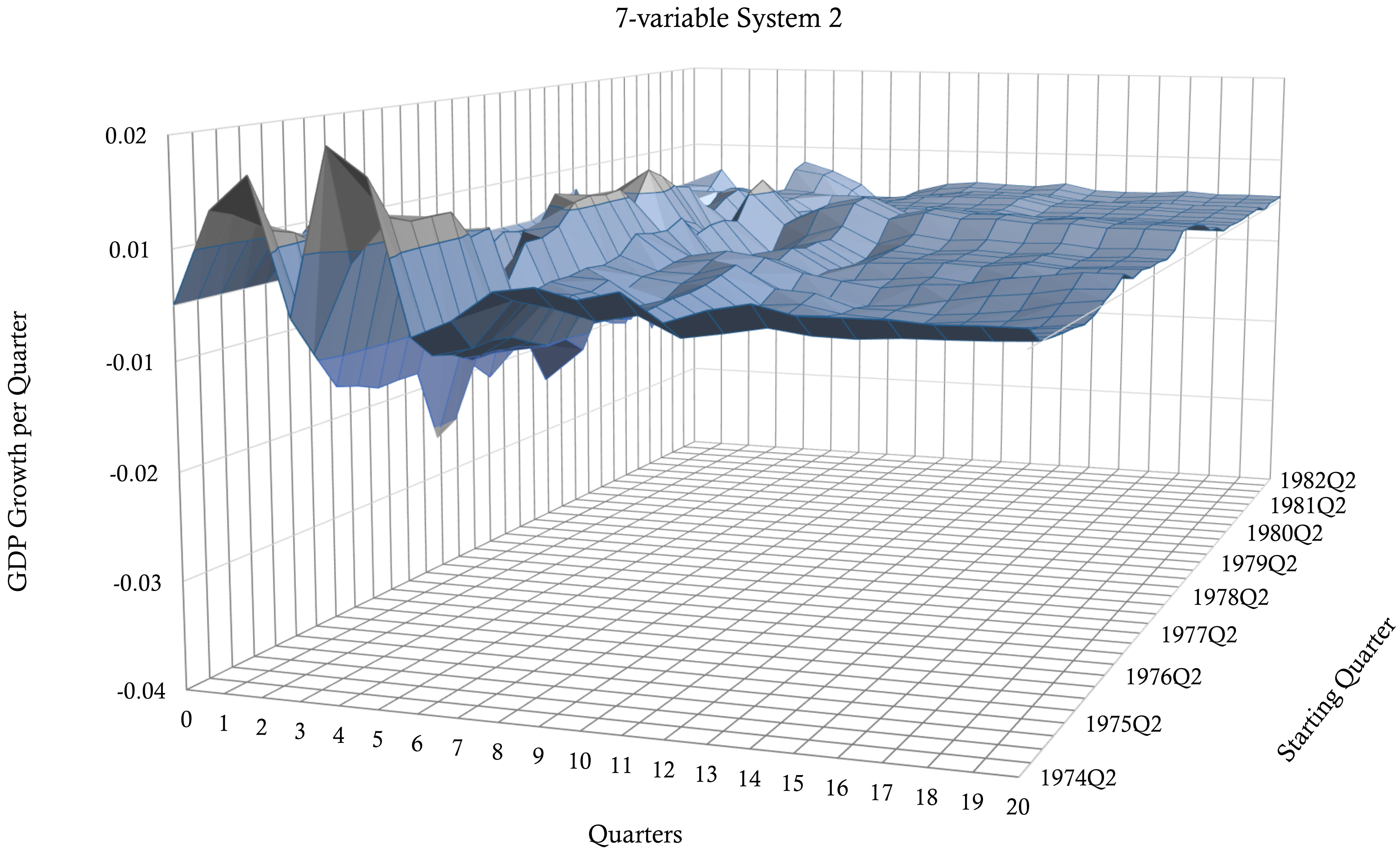

Figure 3.14. Rolling IRFs showing the impact on GDP growth rate of a 10% normalised negative oil price shock.

Specification	Proxy	1974:2-2015:2	1986:1-2015:2
7-variable System 2	Oil Price Increase	-0.24 (-0.05)	0.11 (0.02)
	Oil Price Decrease	0.15 (0.03)	0.07 (0.01)
8-variable System 2	Oil Price Increase	—	0.07 (0.01)
	Oil Price Decrease	—	0.10 (0.02)

Table 3.10. IRF results: Annualised percent changes in output growth rate as a response to a 10 percent change in oil prices over a 20-quarter horizon. Values in parentheses are average per year responses of output growth rate to the impulse.

The results in this table confirm numerically that the nature of the oil price-GDP growth relationship has evolved over time in the UK. This can partially explain why coefficient estimates on oil prices were not statistically significant for some sample periods, which in turn emphasises the importance of rolling-window modelling. There is also evidence for asymmetry in the earlier sample since the estimated cumulative impacts have different signs. The remaining discussion in this section focuses on the impact of oil price fluctuations on other macroeconomic variables.

Inflation has obvious links to oil prices as the commodity is not only consumed by households directly but also by firms in their production processes. Figure 3.18 in chapter appendix demonstrates how inflation adjusts in response to an oil price rise. The striking characteristic of the surface plot is that, much like GDP growth, post 1980s showed a much smaller effect feeding from the oil price increases to inflation. IRFs often indicated alternating signs on inflation as a result of the shock such that the first quarter two quarters saw a small decline in inflation followed by a larger increase and another small fall. The impact tended to die out by the sixth quarter, especially in more recent years. Response of unemployment is another key transmission mechanism of oil price pass-through. This dynamic is particularly interesting in the UK due to large employment potential in the oil industry. Based on Figure 3.19, a 10% oil price rise is expected to cause an increase in unemployment. Although this effect is small in the first few quarters, by quarter four, it is substantial. Despite the isolated dip in the surface corresponding to 9-13th quarters of mid 1970s, the overall impact is overwhelmingly positive such that an increase in price causes an increase in unemployment. The response to a fall in oil price is less clear. Figure 3.20 suggests that an initial large fall in unemployment rate in response to the fall in price is matched by a rise in unemployment of roughly the same size a few quarters later. The effect subsides from approximately the 9th quarter onwards, but the cumulative impact on unemployment is estimated to be negative in all cases. This contradicts theoretical predictions for an oil exporting country and the UK exhibits characteristics of an oil importer in this context. The primary reason for this is that, although relatively large, UK's oil industry has not accounted for a large share of its GDP throughout history. Having said that, underlying the apparent outcome lies a more complex dynamic: following a fall in oil price, unemployment falls initially (as in an oil importer) but eventually rises (as in an oil exporter) as the industry responds to the new price environment. The latter effect has more of a lag than the former due to investment inertia in the oil sector as well as inflexibility of upstream exploration and production activities.[21] The dynamics remain prominent throughout the entire sample period, but the estimated cumulative impact is more muted in recent years, adding to previous evidence that oil price fluctuations may indeed be losing relevance in the UK macroeconomic context.

3.6 Differences and Similarities between the US and the UK

This study is in a unique position to compare the oil price-macroeconomy relationship in two of the most important economies of the world. Having implemented the modelling approach in both countries, I now turn to a comparison of findings.

3.6.1 Measures of Oil Price and Suitability of GARCH

Chapter 2 normalised oil prices based on a GARCH (1,1) specification with an AR(4) structure. This setup worked effectively for both oil price measures (refiners' acquisition cost and producer price index in crude petroleum). This approach proved appropriate for the UK as well, but further investigation of modelling Brent price series led to some side findings that are worth mentioning. There is a rich literature on modelling and forecasting global oil prices. Among these are He, Yu, & Lai

[21] For example, it is unusual for an upstream exploration and production company to change activities immediately following an oil price change. Among other reasons, such as investment commitments made to shareholders and formal applications to the Oil and Gas Authority, this is driven by the nature of conventional oil production. Reservoir pressure and characteristics need to be maintained throughout the production process. If production is stopped and started repeatedly, operators risk formation damage and a lower recovery factor.

(2012), Jammazi & Aloui (2012), Morana (2001), Narayan & Narayan (2007), Sadorsky (1999), Xie, Yu, Xu, & Wang (2006), and Yu, Wang, & Lai (2008). Fields outside of economics and econometrics have made contributions to this effort as well. Examples include Wang, Yu, & Lai (2005) and Xie et al. (2006). Each approach has its advantages and has seen some success, but Bollerslev et al. (1992) insisted on low-order GARCH models—GARCH (1,1) in particular—as they tend to perform well within economic modelling and often outperform alternative methods based on standard testing. In this case, I find that there is some merit to capturing oil price dynamics using a GARCH (1,0) with an AR(3) structure. For part of the sample, this approach appeared to fit the series better than the original approach. There is also some evidence of a moving average structure in the oil price series, as an ARMA (4,2) also performed well. These findings did not apply to the US and I opted for the GARCH (1,1) specification for consistency in the analysis and because modelling conditional variance of oil prices was an intermediate step to investigating a more general relationship. Certain model specifications could be better suited for parts of the sample but implementing a different model for each window introduces confounding factors into the analysis and makes it impossible to disentangle whether the observed effects are influenced by changes in the underlying model.

3.6.2 Exogeneity of Oil Prices

How oil prices behave in empirical models has also been a focus of scrutiny. Researchers, including Kilian (2009) and Hamilton (2009) have tried to understand the root cause of oil price shocks and capture this information in modelling oil prices. A detailed overview of this literature can be found in Section 2.5.4. Blanchard & Galí (2007) summarised their approach by suggesting that a more exogenous proxy for oil shocks could be used, which is the approach adopted by Kilian (2009) through the construction of a proxy for unexpected movements in global oil production. In addition to validity concerns of this measure and other attempts at constructing proxies, Blanchard & Galí (2007) argued that the price households and firms pay, and not the level of global oil production, is what matters. From this perspective, higher Chinese demand leading to a rise in the price of oil is just as exogenous to other countries as an OPEC-induced supply shock. In practice, there is some evidence of endogeneity of oil prices. This was observed for the US in Section 2.5.4. An important difference between the US and the UK oil industries is, of course, their sizes. It is conceivable that US production, especially since the US shale revolution, influences the global oil price. The UK is smaller by comparison and this potential is more limited. For empirical investigation, Table 3.11 summarises Granger-causality tests for real GDP growth in the oil price equation in the VAR system. Based on the results, real output fluctuations appear to Granger-cause oil price changes in most sample periods. Separating positive and negative shocks resulted in a lower test statistic for oil price increases in the most recent subsample.

Equation	1963:1-1985:4 †	1974:1-2015:2 ††	1986:1-2015:2 †††	1963:1-2015:2 †
Oil Price Change	17.913***	24.093***	13.798***	17.556***
	(0.001)	(0.000)	(0.008)	(0.002)
Oil Price Increase	11.743**	27.483***	6.864	21.114***
	(0.019)	(0.000)	(0.143)	(0.000)
Oil Price Decrease	6.338	9.600**	17.106***	5.876
	(0.175)	(0.048)	(0.002)	(0.209)

Table 3.11. Exclusion tests for real GDP growth in each corresponding oil price equation. The values in parentheses are p-values. Statistical significance is shown at the 10% level (*), 5% level (**) and 1% level (***). Recall that different model specifications are used in each sample period: 5-variable VAR (base model, denoted as †), 6-variable VAR (base model + 3-month TB rate, denoted as ††) and 7-variable VAR (base model + 3-month TB rate + import price inflation, denoted as †††)

Given these observations, it is empirically more accurate to include oil prices in the VAR system as an endogenous variable such that its equation is estimated jointly with all other macroeconomic variables, which was also the case for the US.

3.6.3 Impulse Responses and Asymmetry

The US and the UK appear to share a complex form of asymmetry in the response of some macroeconomic variables to changes in oil price. An example is the two countries' unemployment rates. Since both countries have substantial oil production activities and employment within the industry, they exhibit characteristics that would be expected in oil importers and oil producers. As discussed in Section 3.5, an oil price rise is expected to cause an overall increase in UK unemployment rate, and this largely holds in the US as well (see Figure 3.21). Further, the impact of a decline in oil price appears to follow a similar pattern in the two countries. A difference emerges, however, when the total estimated impact of an oil price fall on unemployment rate is calculated: although such a change leads to an overall decline in unemployment in both countries, the magnitude of the effect is lessening in the UK but increasing in the US. Moreover, the response of US unemployment seems to be more exaggerated than the UK unemployment rate. As Figure 3.22 shows, US unemployment declines very rapidly immediately following the fall in oil prices, which is in line with characteristics of a country where oil production activities have far-reaching employment implications. Five quarters after the original shock, unemployment starts increasing as the rest of the economy adjusts to the new price environment.

3.7 Conclusion

This chapter has focussed on identifying the implications of oil price fluctuations on the UK economy. With an emphasis on GDP growth, I have investigated the nature of the oil price-macroeconomy relationship in the UK over time, across model specifications, and in the presence of asymmetric oil prices. I found some evidence of Granger-causality between oil price fluctuations and GDP growth, and concluded that this relationship is stronger with normalised oil price changes. This suggests that oil price volatility leading up to a price shock contributes to its macroeconomic implications. More specifically, unanticipated price shocks—those occurring after a period of stable prices—tend to have a larger impact. I also found evidence that changes in price have linkages with other macroeconomic variables, such as inflation and unemployment rate, pointing to indirect transmission mechanisms for oil price passthrough to output growth. Section 3.4.2 provided evidence of an asymmetric impact of price shocks but this was not as pronounced as in the US. Further, there was some evidence that significance of oil for the economy may have weakened in recent decades. A rolling-window time-varying parameter approach concluded that after 1980, oil price implications have dwindled in terms of magnitude despite retaining statistical significance in VAR specifications.

To estimate the magnitude of the impact, I implemented orthogonalised impulse response functions. Although not all point estimates were statistically significant, the estimated responses pointed to a time-dependent relationship. More specifically, 7-variable system 2 estimated over the 1974:2-2015:2 subsample suggested a 0.24% decrease in GDP growth as a result of a 10% increase in normalised oil prices, whereas the same model estimated over 1986:1-2015:2 led to a 0.11% increase in GDP growth in response to the same shock. This observation was corroborated by rolling IRFs, which showed that the characteristics of the relationship have shifted as the UK's domestic oil production increased. Lastly, Section 3.6 focussed on the comparison between the US and the UK. Despite significant differences between the two economies, results from this chapter and the previous one highlighted some fundamental similarities. For example, since both countries have oil production activities, unemployment rate appears to react to oil price fluctuations in a similar fashion.

As a part of future work on this theme, different (G)ARCH specifications could be used to model the Brent series. As more frequent data and a longer time series become available, implementing rolling models with larger specifications are becoming feasible. Modelling oil price volatility has recently regained importance in the finance literature in the context of stock market behaviour. The error variance modelling approach implemented here has applications in that literature and could be an extension to the work presented here.

From a macroeconomic modelling and policy perspective, monetary policy response is often a key determinant of economic performance. As a next step, optimal monetary policy could be investigated in response to an oil price shock. Based on the findings in this chapter, the monetary authority should not respond to every shock the same way because price volatility in preceding periods is shown to matter. If identified correctly, an optimal policy implementation could, in theory, ameliorate the detrimental effects of the shocks in question.

3.8 Chapter Appendix

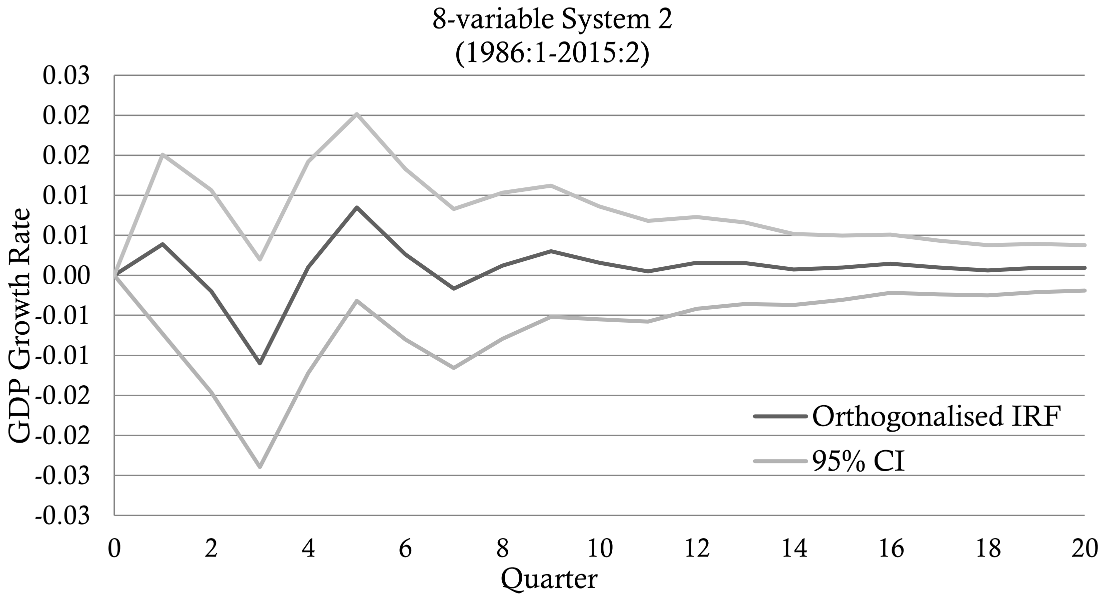

Figure 3.15. IRF showing GDP growth response to a 10% normalised positive oil price shock.

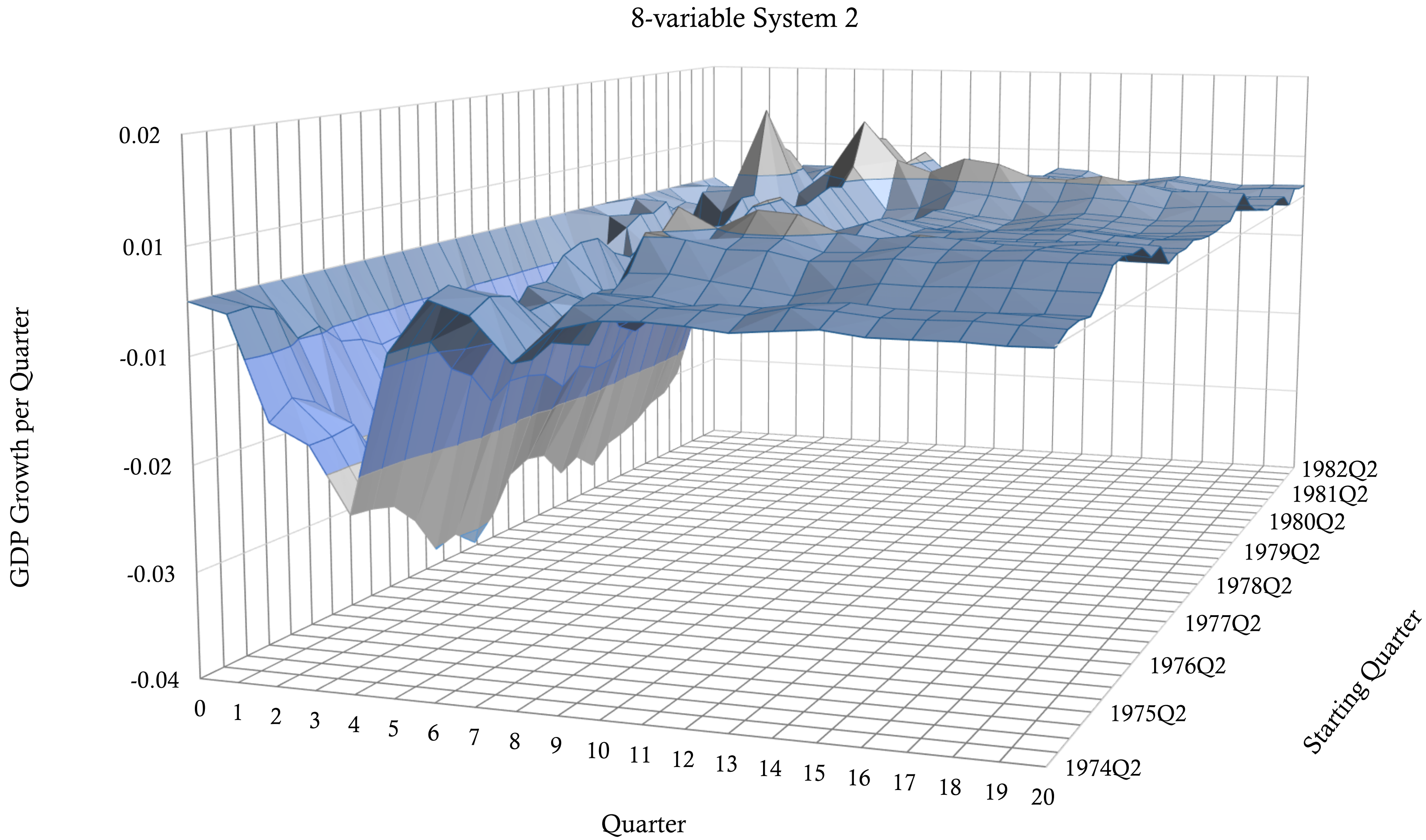

Figure 3.16. Rolling IRFs showing the impact on GDP growth rate of a 10% normalised positive oil price shock.

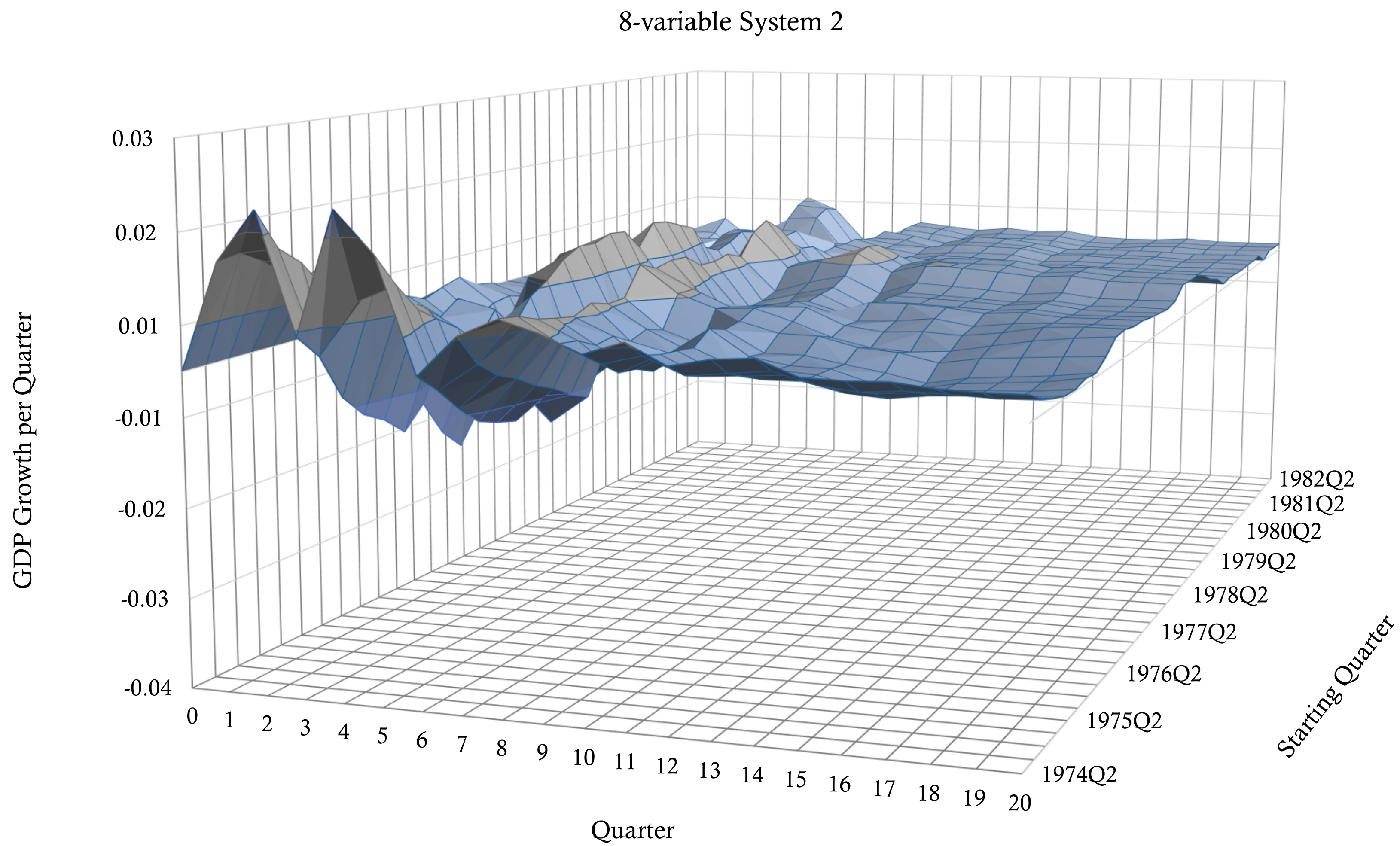

Figure 3.17. Rolling IRFs showing the impact on GDP growth rate of a 10% normalised negative oil price shock.

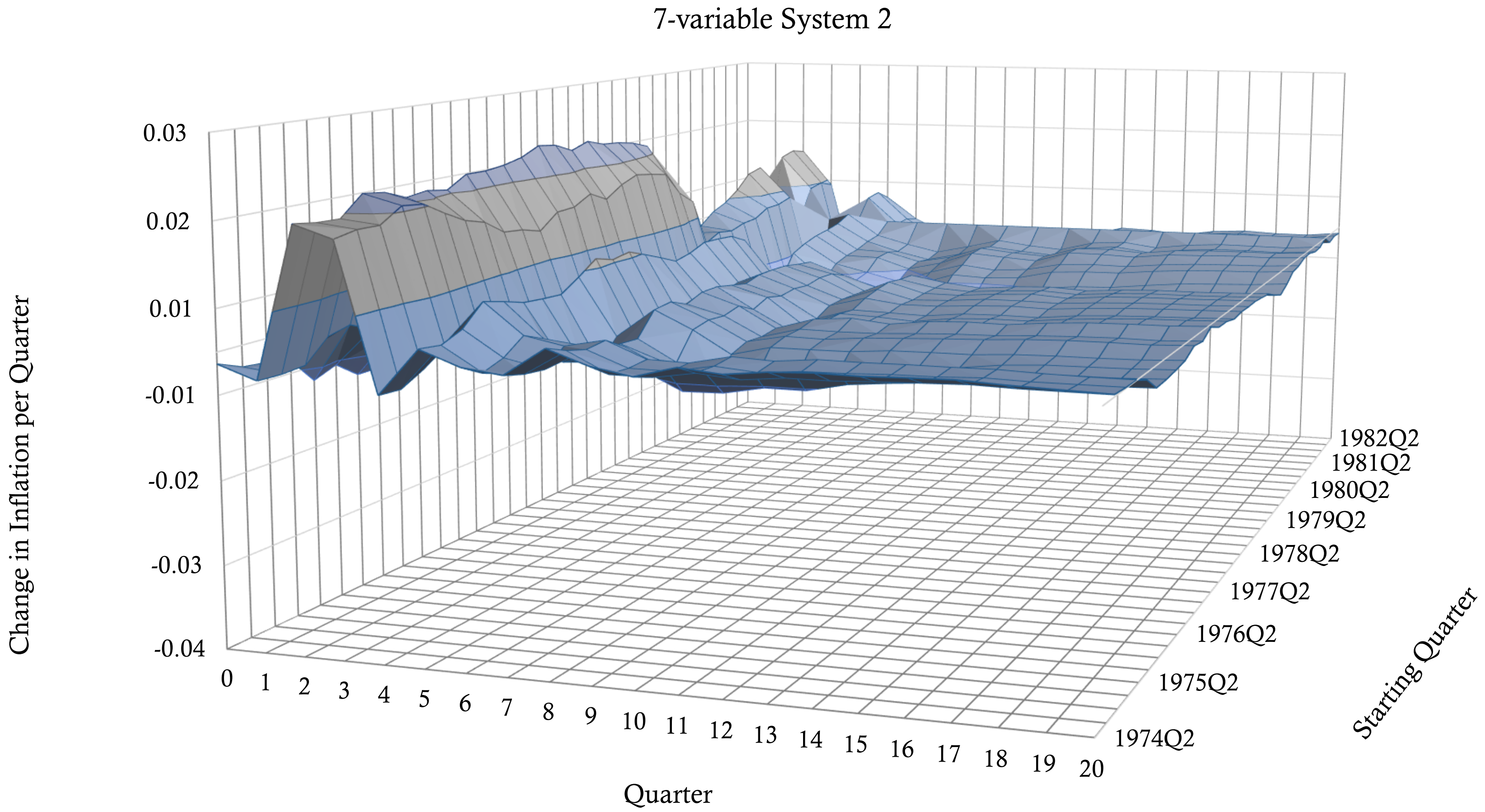

Figure 3.18. Rolling IRFs showing the impact on GDP deflator inflation of a 10% normalised positive oil price shock.

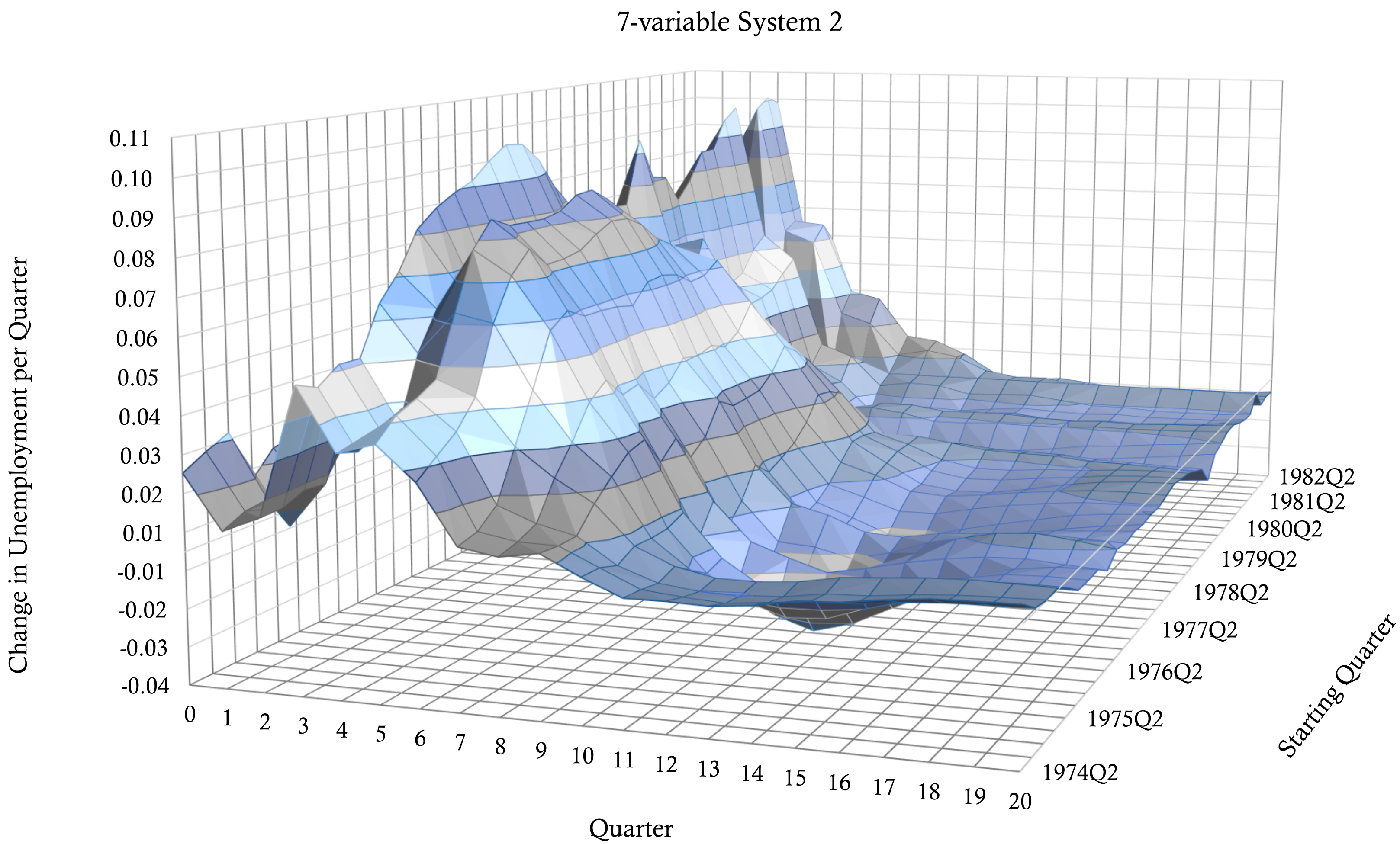

Figure 3.19. Rolling IRFs showing the impact on unemployment of a 10% normalised positive oil price shock.

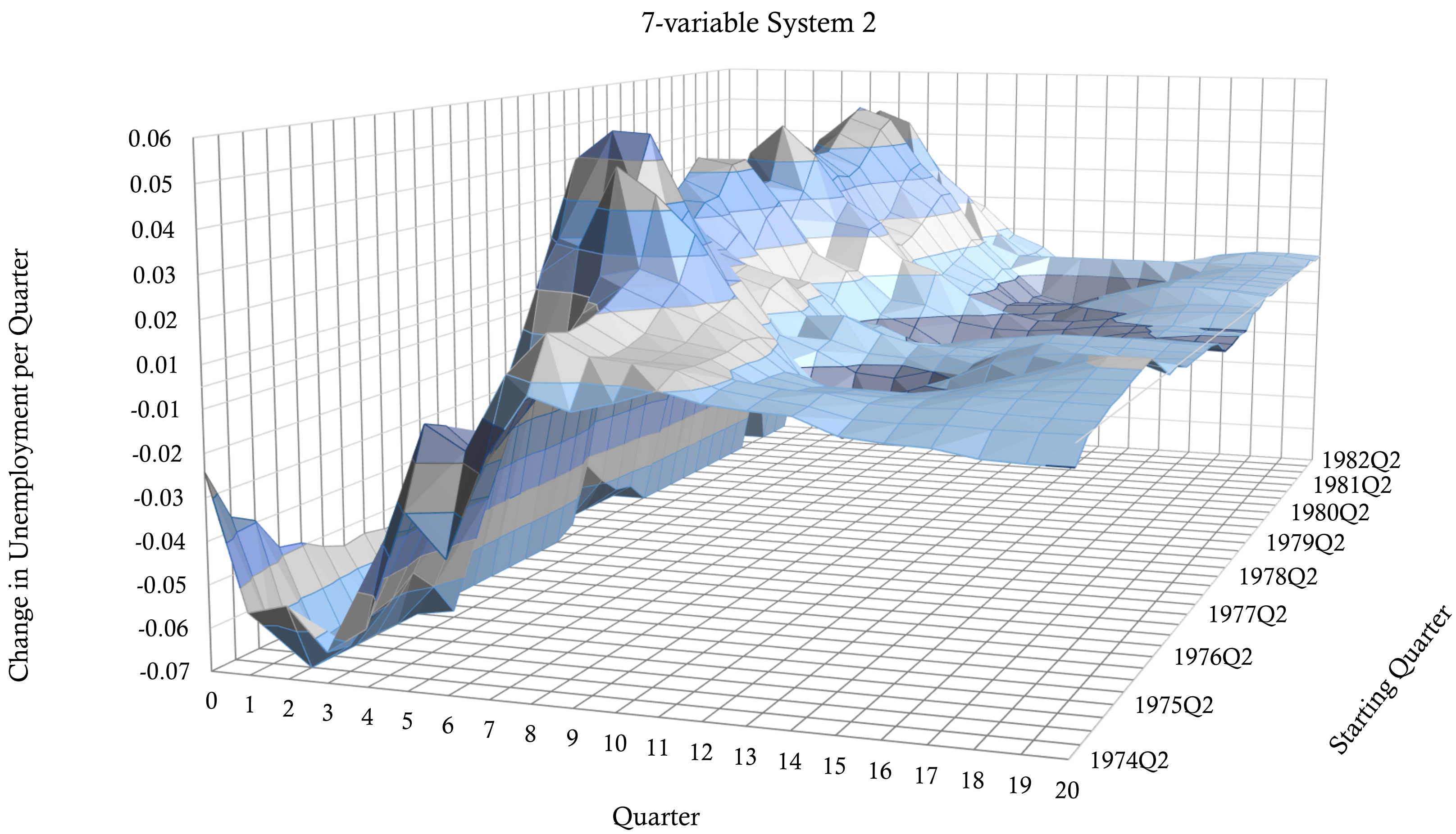

Figure 3.20. Rolling IRFs showing the impact on unemployment of a 10% normalised negative oil price shock.

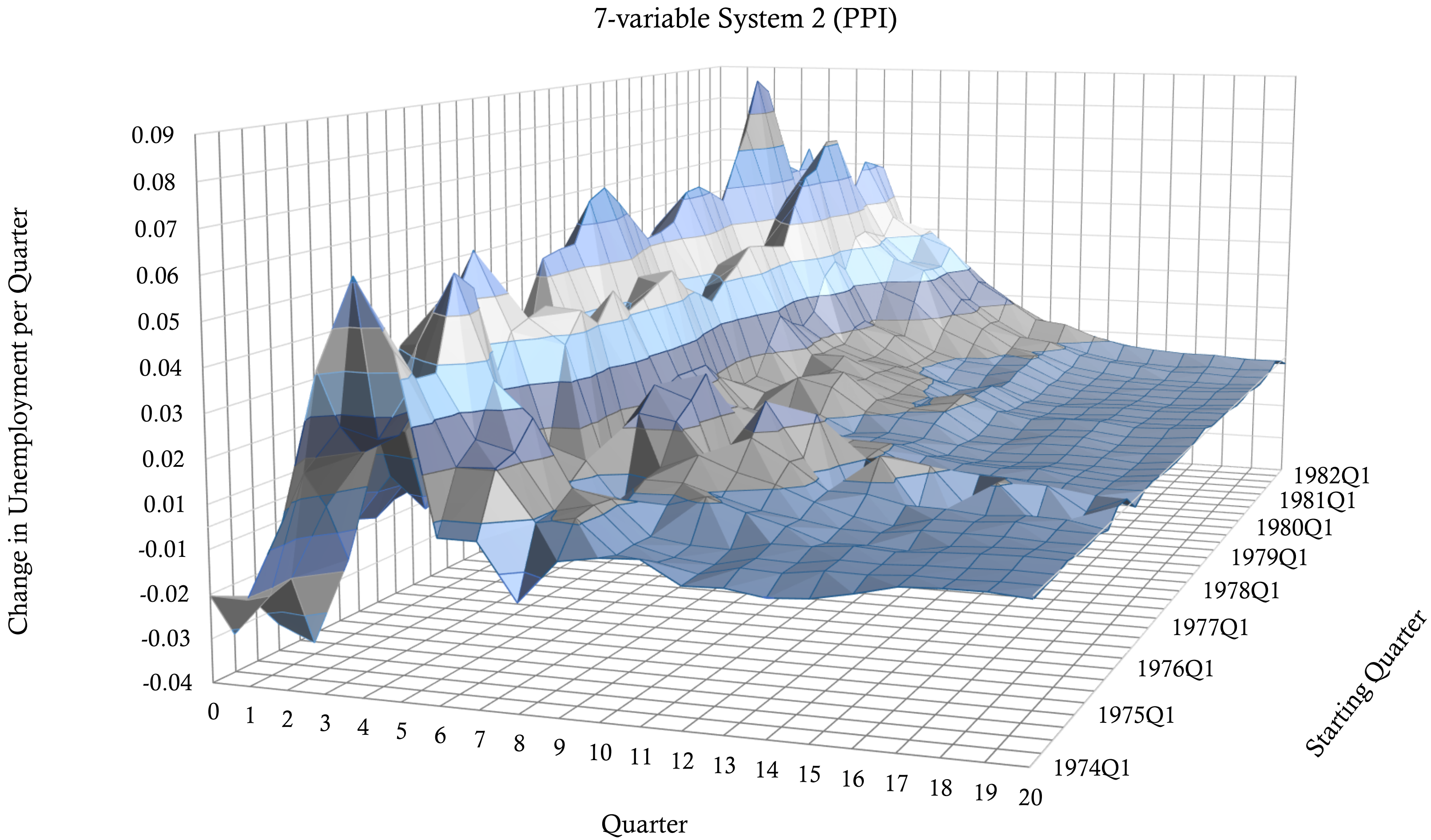

Figure 3.21. Rolling IRFs showing the impact on unemployment of a 10% normalised positive oil price shock for the US.

7-variable System 2 (PPI)

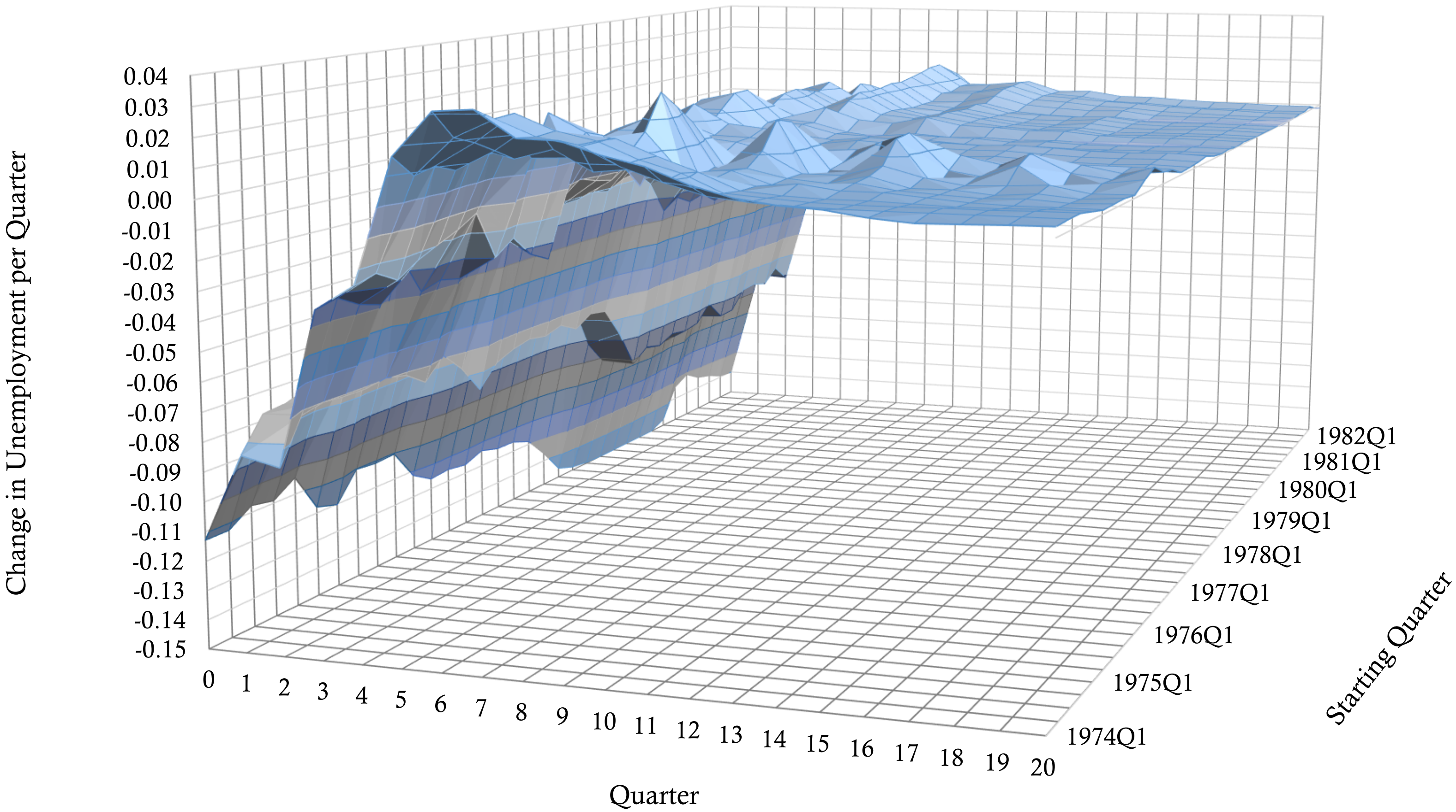

Figure 3.22. Rolling IRFs showing the impact on unemployment of a 10% normalised negative oil price shock for the US.

4 Oil Rents and the Real Exchange Rate[22]

Abstract

This chapter investigates whether a relationship exists between oil rents and the real exchange rate in oil-exporting countries. When a relationship exists, it is analysed from a Balassa-Samuelson perspective. Empirical modelling is based on two new measures of profits in countries' oil sectors in a large-N, large-T panel dataset. Exploiting this dataset structure, I find that the B-S mechanism holds in some oil-exporting countries but not all. For most countries, the relationship is non-negligible in size and precisely estimated. I also find some evidence that oil rents have a more pronounced effect on the real exchange rate in countries where the oil sector accounts for a larger share of the country's GDP. However, surprising findings include an ambiguous relationship in OPEC countries. Potential underpinnings for this are discussed in the chapter alongside empirical testing of hypothesised explanations, such as differing currency regimes and validity of assumptions. Throughout the analysis, oil prices were identified as an important covariate with coefficients of a similar size and sign to oil rents variables.

[22] In collaboration with Anna Brocklebank as described in the Declarations section.

4.1 Introduction

It seems counter-intuitive for abundant valuable natural resources to lead to sluggish economic growth and development. Observing this in practice begs a question about its underlying causes and transmission mechanisms. A popular explanation has been the Dutch disease, where an increase in resource wealth leads to a real appreciation of the exchange rate that crowds out other exports. This topic has been widely studied in an effort to verify or refute the existence of this pattern and explain the poor growth performance of some resource-rich countries. In addition to making the casual observation that most resource-rich countries have relatively low levels of GDP, Sachs & Warner (2001) have empirically illustrated that high resource intensity is correlated with slow growth. Other post-war growth studies have corroborated this finding (see Sachs & Warner, 1995, 1997, for example). As discussed in Sala-i-Martin & Subramanian (2003), the case of Nigeria is particularly interesting because per capita oil revenues rose from $33 in 1965 to $325 in 2000 with very little rise in real GDP per capita. Counter-examples, such as Norway and Australia, have led to a debate about the existence and significance of resource curse leading to the conclusion that other factors, such as corruption, account for most of the problems associated with slow economic development. In order to shed light on this debate, Sachs & Warner (1997) have implemented empirical models that included up to nine control variables, including corruption, and found that natural resource abundance still plays a key role in determining growth rates. In light of this finding, it has been postulated that exchange rates affect growth through hindrance of export-led growth. However, the existence of the resource curse is still controversial: some authors (Atkinson & Hamilton, 2003; Sachs & Warner, 1999) argue that it exists and is important, while others disagree (Brunnschweiler & Bulte, 2008; Mehlum, Moene, & Torvik, 2006). For a review of evidence in favour of the resource curse in oil, see Ross (2012).

The resource curse literature is relevant in a study of the relationship between resource rents and the real exchange rate because one of the mechanisms by which resources are meant to curse a country is via the real exchange rate. The idea is that a resource bonanza could cause a real appreciation which would, in turn, make other exports, such as manufactured exports, uncompetitive. Origins of this phenomenon date back to The Netherlands in 1959 following the discovery of large gas fields in the country. If the exports and economic activity being crowded out by the appreciation were in industries with large positive externalities, such as agglomeration economies, economies of scale, and knowledge spillovers, crowding them out could reduce a country's long-run growth rate, even though it is following its comparative advantage in the short run. And while the presence or absence of a real appreciation in response to an increase in resource rents would not conclusively prove or disprove the existence of the resource curse, concluding one versus the other could strengthen or weaken the case. If an exchange rate transmission channel does not exist, resource curse must be operating through other means, such as corruption of the political system.

This chapter focuses on a particular mechanism behind the real exchange rate appreciation, which is closely linked to the Dutch disease—the Balassa-Samuelson or the Harrod-Balassa-Samuelson hypothesis. This hypothesis explains the exchange rate appreciation phenomenon through relative productivity changes of tradable and non-tradable sectors in resource-rich economies. The chapter contributes to the general literature on the Balassa-Samuelson effect but specifically focuses on the oil-producing countries. There are three distinctive features of the chapter: a new dataset has been constructed based on revenues and costs of oil exporters from Wood Mackenzie's (WM) Global Economic Model (GEM), which has not been used in this context before; a diverse set of oil-exporting countries is analysed; and Pesaran & Smith's (1995) pool mean group estimator is implemented. This approach restricts the long-run coefficients for all panels to be the same but allows the short-run coefficients to vary. This is a desirable property given the heterogeneous nature of the countries in the dataset, since there is reason to believe that short-run dynamics may differ across countries but converge towards a common long-run equilibrium. These new data and techniques have allowed me to quantify the long-run relationship between movements in real exchange rates that could be attributed to the changes in the oil rents per capita and oil rents as a percentage of GDP. Two findings are worth noting: I found evidence in favour of the Balassa-Samuelson hypothesis for most countries in the sample but evidence for OPEC countries is ambiguous.

The chapter is organised as follows: Section 4.2 reviews the Balassa-Samuelson (B-S) hypothesis and its transition mechanism, Section 4.3 provides a literature review, Section 4.4 describes the dataset in detail, Section 4.5 focuses on the determining stationarity properties of the variables, Section 4.6 describes the econometric methods implemented and provides the results of the estimations, and Section 4.7 concludes.

4.2 The Balassa-Samuelson Effect and the Transmission Mechanisms

One popular explanation for the resource curse has a crowding-out logic. If activity X drives growth and the extraction of natural resources crowds-out this activity, natural resources harm growth through the elimination of activity X. This activity could be in a manufacturing industry with positive externalities that would lead to improved efficiency and international competitiveness. Since natural resource exports dominate, however, other industries cannot compete in the global market and productivity-boosting spillovers are minimal. Therefore, if production and exports of natural resources lead to the appreciation of the domestic currency, domestic economic growth would be hurt. In addition, positive wealth shocks from the natural resource sector result in higher demand for non-traded goods and create excess demand for non-traded products driving up their prices. This rise in prices includes input costs and wages which squeezes profits in traded activities, including manufacturing, that use the non-traded products as inputs but sell on the international market at relatively fixed prices. The decline in manufacturing then has ramifications that slow down the growth process.

Balassa (1964), Harrod (1933), and Samuelson (1964) all independently pointed at precisely this phenomenon. They noted that countries with more productive labour in the tradable sector should have relatively higher prices in their non-tradable sector. This would then lead to a higher overall price level in countries with productive tradable sectors and indirectly to the appreciation of the currency. For instance, consider oil-exporting countries A and B. The former is similar to the United Arab Emirates and has a highly productive oil sector in which capital and labour input costs are low. The latter is similar to Kazakhstan where productivity in the oil sector is considerably lower and input costs are much higher. Exports of oil from both countries represent a high fraction of total exports and a large portion of their GDP. Assuming capital is perfectly mobile across sectors within and between countries, but labour is mobile only within the country and not internationally, I would expect a higher overall price level in country A than in B. The external mechanism through which this occurs can be explained as follows:

$P_T = XRAT \times P_T^*$	Law of one price holds for tradable goods only
$RER = \frac{XRAT}{P}$	Rodrik (2008) and Macdonald & Vieira (2010)
$W_T = P_T \times MPL_T \rightarrow P_T = \frac{W_T}{MPL_T}$ $W_N = P_N \times MPL_N \rightarrow P_N = \frac{W_N}{MPL_N}$	Workers are paid their marginal product
$W_N = W_T$	Workers can move freely between sectors
$P = P_T^{\alpha} \times P_N^{1-\alpha}$	Overall price level composition
$\frac{P_N}{P_T} = \frac{1}{P_T} \times \frac{W_N}{MPL_N} = \frac{1}{P_T} \times \frac{W_T}{MPL_N} = \frac{P_T}{P_T} \times \frac{MPL_T}{MPL_N} = \frac{MPL_T}{MPL_N}$	
$MPL_T \uparrow \Longrightarrow P_N \uparrow \Longrightarrow P \uparrow \Longrightarrow RER \downarrow$	Appreciation of the currency

Table 4.1. The B-S effect transmission mechanism.

In Table 4.1, P_T denotes the price of tradables, P_N the price of non-tradables, P_T^* the price of tradables abroad, XRAT the nominal exchange rate, which is defined as the number of units of the domestic currency that buy one US dollar, P the overall domestic price level, α the share of tradables in the overall domestic price level, W_T the wages in tradable sector, W_N the wages in non-tradable sector, MPL_T the marginal product of labour in tradable sector, MPL_N the marginal product of labour in non-tradable sector, and RER the real exchange rate. Using the definition of the exchange rate introduced here, increases in the exchange rates are equivalent to depreciation of the domestic currency.

Since the marginal product of labour in country A is higher than that in country B, $MPL_T^A > MPL_T^B$, the price level of non-tradables will be higher leading to a higher overall price level in the country. This, in turn, drives the appreciation of the real exchange rate. In fact, Balassa made the observation that "the greater are the productivity differentials in the production of tradable goods between countries, the larger will be the differences in wages and in the prices of services and correspondingly the greater will be the gap between purchasing power parity and the equilibrium exchange rate" (Balassa, 1964).

Although the B-S has been observed globally, the magnitude of the effect can be influenced by country-specific characteristics. For example, if oil rents account for a relatively small proportion of GDP, increases in oil rents or revenues may not have a notable impact on the domestic price level and the real exchange rate. To isolate this effect, this chapter focuses on subsets of countries with certain characteristics—further details of this are given in Section 4.4. Furthermore, the transmission mechanisms may be weaker if assumptions of the B-S effect fail to hold. As explained earlier in this section, an efficient labour market is key to B-S effect's transmission to real exchange rates. If workers are paid their marginal product, can move freely between sectors, and the labour market is competitive such that all workers doing the same job are paid the same wage, increased productivity in the tradable sector (rising oil rents in this context) should lead to an appreciation of the local currency. However, labour markets in some countries in my dataset do not exhibit these characteristics. In such cases, the observed effect can be distorted. This phenomenon is discussed in detail in Section 4.6.4.

4.3 Literature Review

After Balassa (1964) popularised the aforementioned notion, it was adopted not only in the exchange rate and resource curse literature but also created a new niche of its own. Atkinson & Hamilton (2003), Brunnschweiler & Bulte (2008), Mehlum et al. (2006), Sachs & Warner (1995, 1997, 1999, 2001), and Sala-i-Martin & Subramanian (2003) are some of the significant contributions to the resource curse literature. Within the B-S literature, time series and panel analyses largely support the B-S hypothesis, whereas initial cross-sectional analyses have led to mixed results.

Balassa (1964) was first to attempt to verify the B-S hypothesis empirically by regressing PPP as a percentage of exchange rates on per capita GNP. The author analysed 12 OECD countries in 1960 and found a significant relationship, which was interpreted as a confirmation for his proposition. This study gave rise to a large cross-sectional literature, which includes Clague (1986, 1988), De Vries (1968), Officer (1976), and others. Most studies used the real exchange rate or PPP as the dependent variable with various measures of productivity as the explanatory variables of interest. These include GDP per capita, ratios of total factor productivity, and real income. Control variables, such as openness to trade, trade balance, money supply growth, sometimes feature in the analysis as well. This part of the literature has not provided conclusive results, as different specifications yielded different outcomes.

In the 1980s and 1990s, researchers took a different approach as more and better data became available. This part of the literature on the productivity bias hypothesis focused on country-level time-series analysis which took country-specific circumstances into account that could not have been captured in cross-sectional studies. These studies include Bahmani-Oskooee & Rhee (1996), Hsieh (1982), Rogoff (1992), and others. Different time series approaches were implemented, including Johansen approach, Engle-Granger analysis, Dickey-Fuller tests, and ARDL modelling. Bahmani-Oskooee & Nasir (2005) provide a comprehensive review of this literature, in which most studies supported the B-S hypothesis.

More recently, starting from the late 1990s and early 2000s, studies of the B-S mechanism have predominantly been based on panel econometric methods. The then-new non-stationary panel methods were adopted into the B-S literature in an effort to exploit cross-country relationships. Studies before this stage had tested individual countries for cointegration and proceeded with conventional panel methods, such as seemingly unrelated regressions (SUR) or fixed effects (FE) estimations. Asea & Mendoza (1994) and De Gregorio, Giovannini, & Wolf (1994) were among the first influential studies. Both papers included demand side variables in accordance with Rogoff (1992), and the latter showed that the ratio of sectoral productivity per capita should be used in the context of the B-S hypothesis instead of levels productivity per capita. However, the literature consequently continued to use levels as a proxy.

Many studies have since questioned the assumptions of the empirical models and their validity as a whole versus the validity of parts of the model. For instance, Égert et al. (2003) implemented a panel cointegration analysis to study nine Central and Eastern European countries using quarterly average labour productivity data over the period from 1995 to 2000. Although their conclusion suggested strong evidence in favour of the B-S effect, the authors noted that only part of the phenomenon is being captured. They argued that the increase in the price level could also be explained by increasing quality of goods, which was not captured by CPI. Faria & León-Ledesma (2003) tested for evidence of a long-run B-S effect using relative real output per capita as a proxy for relative labour productivity among four countries—Germany, Japan, the UK, and the US—for the period 1960 to 1996. The authors implemented models using levels and first-differences, but neither pointed to a significant long-run relationship between price level and output ratios. However, they suggested that their rejection of the B-S effect did not necessarily mean the PPP hypothesis holds: their investigation of the first-differenced output ratios suggested that causality exists, but that it goes from price ratios to output ratios, which violates the assumptions of PPP. On the contrary, Choudhri & Khan's (2005) analysis of 16 developing countries with different income levels over the period from 1976 to 1994 illustrated the existence of a long-run relationship between the countries' productivity differentials and their real exchange rates. According to the findings, the strength of the relationship is sensitive to variation in income levels and the authors argue that terms of trade also have an influence on the real exchange rate.

García-Solanes, Sancho-Portero, & Torrejón-Flores (2008) extended the Égert et al. (2003) study and, similarly to Asea & Mendoza (1994), found that the internal transmission mechanism—an increase in the overall price level in response to an increase in productivity in the tradable sector—holds in their sample, but that the appreciation of the real exchange rate cannot be fully attributed to productivity differentials. Their work involved six new EU countries (Czech Republic, Estonia, Latvia, Lithuania, Poland, and Slovak Republic) and six other countries from EU-15 (Finland, France, Italy, Netherlands, Spain, and Sweden) using data from 1995 through 2004. They suggested that the external transition mechanism is not fulfilled because PPP does not hold in the tradable sector. However, García-Solanes et al. (2008) showed that both internal and external mechanisms exist in their analysis of 16 Latin American countries. This is in contrast with 16 OECD countries, where only internal mechanisms were confirmed. Drine & Rault's (2002) analysis of six Asian countries using panel cointegration techniques questioned the assumptions of the B-S hypothesis and provided evidence that two assumptions of the model—PPP for tradable goods and the relationship between prices of non-tradables and the real exchange rate—can sometimes be violated, which would explain the rejection of the B-S hypothesis in empirical work.

Chong, Jordà, & Taylor (2012) evaluated the adjustment of the real exchange rate to its long-run equilibrium for 21 OECD countries and confirmed that the B-S effect is not just an essential component of the equilibrium, but the size of the B-S effect varies by country and influences the speed of adjustment of the real exchange rate to the equilibrium after a shock. Chinn (2000) estimated a panel error correction model and found some evidence in support of the productivity bias hypothesis in five East Asian countries. He also investigated effects of government spending and real oil prices on the real exchange rates and found that, contrary to Chinn's (1997) study of 14 OECD countries, government spending did not exhibit a significant effect, and the oil price was significant for only three countries in his sample—one oil exporter and two oil importers. These three countries had the predicted sign: an increase in price led to an appreciation of the currency for the oil exporter (Indonesia) and depreciation for the other two (Japan and South Korea).

Despite extensive coverage of the B-S hypothesis in the literature, there has been limited focus on oil-producing and developing countries. Most research concerns OECD countries, even though the B-S effect is more likely to be present in poorer countries. In the last decade, transition economies have gained attention, including oil exporters such as Russia and Kazakhstan. However, manifestation of the productivity bias hypothesis through the oil-producing sector has yet to be explored. This is a good avenue for research, since oil producer countries tend to rely on primary exports for revenue and growth, and exports of crude oil form a large portion of these exports. Korhonen & Juurikkala (2009) investigated this relationship with a primary interest in the effects of oil prices on the real exchange rates of OPEC countries. Using GDP per capita as a measure of productivity, they rejected the B-S hypothesis for their sample but found a strong and significant relationship between the oil price and the real exchange rates of these countries. The authors emphasise that it would be useful to analyse all oil-exporting countries—including non-OPEC—in one panel framework, as similar results were found for non-OPEC countries, such as Russia (Oomes & Kalcheva, 2007) and OPEC countries, such as Venezuela (Zalduendo, 2006).

Égert (2005) included Russia and South Eastern European countries, such as Ukraine and Turkey, in his analysis of exchange rate behaviour in transition economies with undervalued currencies—those with nominal exchange rates below the PPP exchange rate. The author concluded that the B-S effect is not strong and noted that the B-S assumption that an increase in productivity causes relative price increases does not seem to hold. A particularly interesting result was that oil revenues do not prove to be important for exchange rate fluctuations in Russia. On the contrary, Égert, Halpern, & Macdonald (2006) provided an extensive overview of the exchange rate behaviour in 14 transition economies and despite stating that the movements in the exchange rate should not be attributed to the B-S mechanism, the authors noted that Russia and Kazakhstan—both of which feature in the analysis in this chapter—are negatively affected by the Dutch disease, and that the oil price has a significant effect on real exchange rate movements. In contrast, however, Egert & Leonard (2008) examined the Kazakh economy for the presence of Dutch disease and tested for the B-S effect during the years 1996 through 2005 when oil prices had been rising. The authors concluded that the non-oil tradable sector was unaffected by the increase in oil revenues and that the appreciation of the currency was mostly due to the change in the nominal rate instead of an increase in the price level. In more recent work, Amin & El-Sakka (2016) found a long-run relationship between oil prices, GDP, and real exchange rates of dollar-pegged GCC countries and noted that there is causality going from oil prices to the exchange rate but that the adjustment of the exchange rate to the equilibrium is very slow.

Due to limitations in publicly available data, most studies that analyse oil-exporting countries focus on the effects of changes in the oil price rather than on country-level changes in productivity. For example, Habib & Kalamova (2007) found no relationship between oil prices and real exchange rates in Norway and Saudi Arabia but established a positive relationship in Russia. Aziz & Bakar (2009), however, found no long-run relationship for net oil exporters—Canada, Denmark, and Malaysia—but net oil importers in their sample appeared to have a negative relationship between the oil price and their currency values. Further discussion on the relationship between the oil price and the real exchange rates in oil-rich countries can be found in Rickne (2009) and Frankel (2017).

Although the literature on the B-S hypothesis is extensive and spans several decades and econometric approaches, I hope to fill three main gaps: 1) analysing the effect with data on country-level productivity rather than revenue; 2) using a more diverse set of oil-exporting countries; and 3) implementing panel estimation methods that require large-N and large-T data structure. Previous work suggests the second point as a possible extension of current work, and the first and third points are feasible only with a dataset like the one used here.

4.4 Data and Descriptive Statistics

4.4.1 Sources and Format

The main sources of data are Penn World Table version 7.1, Wood Mackenzie's Global Economic Model, and BP's Statistical Review of World Energy. Table 4.2 below lists all the key variables and their sources.

Variable	Abbreviation	Description	Source
Real exchange rate	*rer*	Real exchange rate (local currency units per I$)	PWT 7.1
Oil rents per capita	*oilrents_pc*	Total oil rents (constant million 2005 US$) divided by population	Wood Mackenzie & BP
Real GDP per capita	*rgdpch*	PPP converted GDP per capita chain series (2005 I$)	PWT 7.1
Brent price	*brent*	Brent oil price (2005 US$)	Thomson Reuters Datastream
Openness to trade	*openc*	Openness at current prices (%)[23]	PWT 7.1

Table 4.2. Key variables and their sources.

The dataset has a panel format and covers 42 countries over 45 years: 1965 through 2009. The panel is unbalanced with partial gaps in most countries' time series. Table 4.4 outlines the number of years available for each country. The shortest time series available are for Romania, Azerbaijan, and India with 6, 9, and 11 years of data, respectively. On average, the dataset has 28 years of data for each of the 42 countries for a total of 1114 observations of oil rents. Table 4.3 provides summary statistics for key variables and their natural logarithms, where appropriate.

[23] Defined as the sum of exports and imports as a fraction of GDP

Variable	N	Mean	Standard Deviation	Minimum	Maximum
Oil rents per capita	1114	1632	3545	1.90	40979
ln(oil rents per capita)	1114	5.81	1.95	0.64	10.62
Oil rents as % of GDP	1114	1.16	0.18	1.00	2.15
ln(oil rents as % of GDP)	1114	0.14	0.14	0.00	0.76
Real exchange rate	1114	1.72	0.96	0.21	15.00
ln(real exchange rate)	1114	0.42	0.48	-1.54	2.71
Real GDP per capita	1114	14428	16684	612	118771
ln(real GDP per capita)	1114	8.98	1.12	6.42	11.68
Brent	45	39.55	19.82	15.07	91.12
ln(brent)	45	3.56	0.47	2.71	4.51
Openness to trade	1114	74.87	40.14	14.68	354.11
ln(openness to trade)	1114	4.19	0.50	2.69	5.87

Table 4.3. Coverage by variable (N + T dimension).

Country	Country code	Number of years	OPEC	D10[24]
Algeria	DZA	45	✓	✓
Angola	AGO	24	✓	✓
Argentina	ARG	18	-	-
Australia	AUS	37	-	-
Azerbaijan	AZE	9	-	✓
Brazil	BRA	17	-	-
Brunei	BRN	36	-	✓
Canada	CAN	25	-	-
China	CHN	13	-	-
Colombia	COL	24	-	-
Congo, Republic of	COG	34	-	✓
Denmark	DNK	32	-	-
Ecuador	ECU	13	✓	✓
Egypt	EGY	37	-	✓
Equatorial Guinea	GNQ	17	-	✓
Gabon	GAB	37	-	✓
India	IND	11	-	-
Indonesia	IDN	42	-	-
Iraq	IRQ	40	✓	✓
Italy	ITA	36	-	-
Kazakhstan	KAZ	13	-	✓
Libya	LBY	24	✓	✓
Malaysia	MYS	37	-	✓
Mexico	MEX	16	-	-
Nigeria	NGA	36	✓	✓
Norway	NOR	32	-	✓
Oman	OMN	36	-	✓

[24] Countries, in which oil rents exceed 10% of GDP in 2008.

Peru	PER	30	-	-
Qatar	QAT	24	✓	✓
Romania	ROM	6	-	-
Russia	RUS	20	-	✓
Saudi Arabia	SAU	24	✓	✓
Sudan	SDN	10	-	✓
Syria	SYR	36	-	✓
Thailand	THA	25	-	-
Trinidad & Tobago	TTO	35	-	✓
Tunisia	TUN	43	-	-
United Arab Emirates	ARE	24	✓	✓
United Kingdom	GBR	34	-	-
Venezuela	VEN	21	✓	✓
Vietnam	VNM	20	-	✓
Yemen	YEM	21	-	✓

Table 4.4. Coverage by country (time dimension) and subsample composition.

4.4.2 Construction of Oil Rents per Capita and its Natural Log

As an intermediate step to calculating total oil rents, I calculate a cost ratio. This interim variable is the ratio of total costs and gross revenue from Wood Mackenzie's GEM. The former consists of capital and operating costs that are summed to get total costs. Due to the nature and coverage of GEM data (further explained in Section 4.4.3 below), revenues from Wood Mackenzie are not used directly in my estimations. Instead, I calculate oil revenues using BP production figures and Brent price series obtained from Datastream. These steps are summarised in Table 4.5:

$$Depreciated\ Capex_t\ (WM) = 0.2 \times \sum_{t=-4}^{0} Capex_t$$

$$Total\ costs = Depreciated\ Capex_t\ (WM) + Opex_t\ (WM)$$

$$Cost\ ratio = \frac{Total\ costs\ (WM)}{Gross\ revenue\ (WM)}$$

$$Oil\ revenue \coloneqq Oil\ production\ (BP) \times Brent\ price$$

$$Oil\ rents = Oil\ revenue \times (1 - Cost\ ratio)$$

Table 4.5. Construction of oil rents.

4.4.3 Data Treatment and Limitations

All key variables with the exception of *openc*, which is expressed as a percentage, are used in natural logarithm form.[25] One important limitation of GEM data was its coverage. The database was structured based on concessions and exploration license areas. To get an idea of the whole country's petroleum industry, I aggregated the granular data points. In some cases, however, Wood Mackenzie's coverage of the country's production was limited to certain areas only. This posed a problem for the oil rents variable, since the underlying assumption of the calculation shown in Section 4.4.2 is that the cost ratio is applicable to the whole country. This may not hold if the GEM database's coverage of the country is quite limited. To resolve this, I impose a restriction that an oil rents observation is used only if WM's field-by-field cost estimations cover at least 10% of the country's production as captured by BP's Statistical Review of World Energy. This procedure discards observations where the WM data is less likely to be representative of the country as a whole. Figure 4.1 and Figure 4.2 facilitate visualisation of the resulting series for all the countries in the dataset in two selected years—2000 and 2009, respectively.

[25] In a small number of year and country combinations, per capita oil rents were observed to be negative. These tend to occur in countries with relatively small economies and in years just after a discovery when substantial upstream investment is taking place within the petroleum industry such that total costs exceed gross revenue. Examples of this include Australia in 1970-71 and Brunei in 1970-1973). The negative numbers posed a data treatment issue while transforming the variable with the natural log function. To avoid this obstacle, a small number of observations were dropped. However, I repeated the analysis with other transformations, such as Winsorising, and adding a constant to the series to eliminate negatives. The choice of method does not appear to affect any of the main qualitative findings.

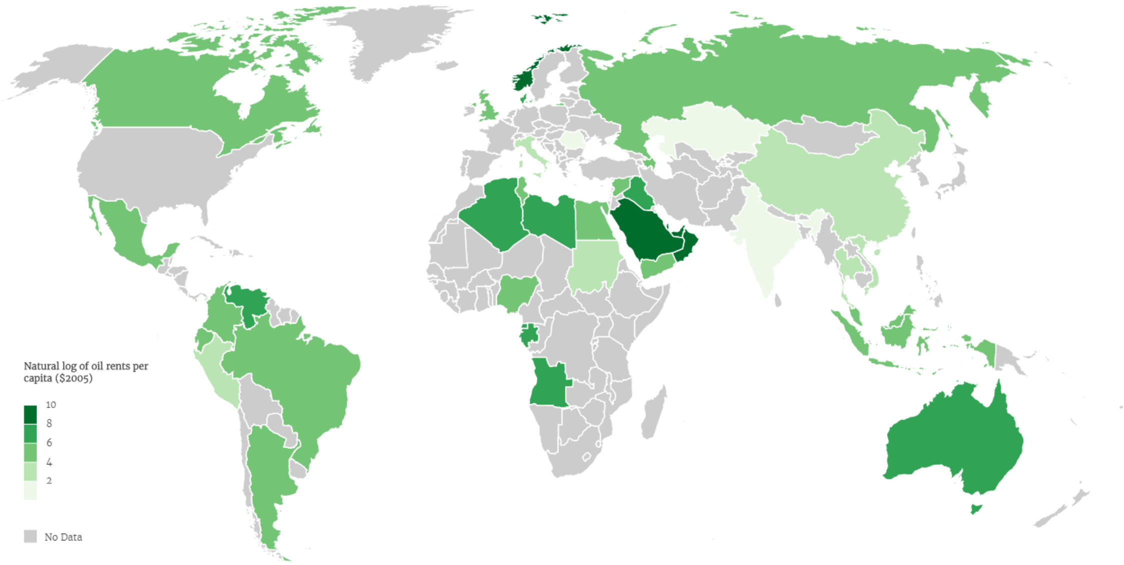

Figure 4.1. Natural logarithm of oil rents per capita in 2000.

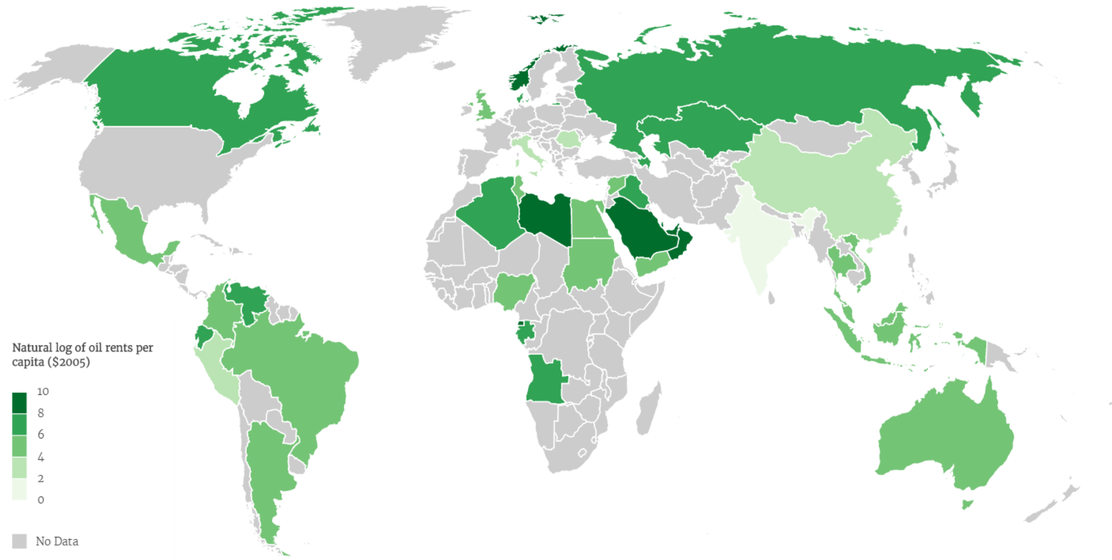

Figure 4.2. Natural logarithm of oil rents per capita in 2009.

4.4.4 Country Coverage and Subsamples

Since I expect to observe stronger evidence for the hypothesis in oil-dependent countries, I focus on two subsamples of countries: OPEC countries and those in which oil rents exceed 10% of GDP in 2008—referred to as "D10" countries. Unsurprisingly, these categories are not mutually exclusive. Table 4.4 shows which countries OPEC and D10 categories consist of and Table 4.6 summarises the key variables for each subsample.

Oil rents per capita in OPEC and D10 countries are considerably higher than in the rest of the world. Mean oil rents, in 2005 US$, per capita for OPEC and D10 countries are about $2800 and $2200 per capita, respectively, whereas that for the rest of the countries is $150 per capita. Note here that OPEC is a subset of D10 countries and that not all OPEC countries are covered by the dataset. Note, also, that Indonesia was not included in OPEC countries because it was often a marginal member due to relatively low exports. Indonesia originally joined OPEC in 1962 but left in 2009 after being a net importer for some years. The country then re-joined in 2016 only to suspend its membership by the end of the year.

Variable	OPEC			
	Mean	Standard Deviation	Minimum	Maximum
Oil rents per capita	2980.38	4766.74	6.98	40978.83
ln(oil rents per capita)	7.03	1.48	1.94	10.62
Oil rents as % of GDP	1.28	0.21	1.00	2.15
ln(oil rents as % of GDP)	0.23	0.15	0.00	0.76
Real exchange rate	1.67	1.11	0.21	7.76
ln(real exchange rate)	0.35	0.61	-1.54	2.05
Real GDP per capita	16161.26	21983.25	975.75	118770.50
ln(real GDP per capita)	8.90	1.24	6.88	11.68
Openness to trade	85.59	48.72	23.61	354.11
N / n	10 / 275			
	D10			
	Mean	Standard Deviation	Minimum	Maximum
Oil rents per capita	2471.91	4232.11	2.14	40978.83
ln(oil rents per capita)	6.65	1.71	0.76	10.62
Oil rents as % of GDP	1.23	0.19	1.00	2.15
ln(oil rents as % of GDP)	0.20	0.14	0.00	0.76
Real exchange rate	1.78	1.09	0.21	15.00
ln(real exchange rate)	0.45	0.52	-1.54	2.71
Real GDP per capita	14682.95	19046.53	612.40	118770.50
ln(real GDP per capita)	8.89	1.19	6.42	11.68
Openness to trade	87.80	42.06	23.61	354.11
N / n	26 / 705			
	World (excl. D10)			
	Mean	Standard Deviation	Minimum	Maximum
Oil rents per capita	184.31	250.97	1.90	1777.12
ln(oil rents per capita)	4.37	1.44	0.64	7.48
Oil rents as % of GDP	1.03	0.04	1.00	1.29
ln(oil rents as % of GDP)	0.03	0.03	0.00	0.26
Real exchange rate	1.60	0.67	0.64	4.88
ln(real exchange rate)	0.39	0.40	-0.45	1.58
Real GDP per capita	13988.43	11535.15	711.97	40820.35
ln(real GDP per capita)	9.12	0.99	6.57	10.62
Openness to trade	52.60	23.59	14.68	151.71
N / n	16 / 409			
	World			
	Mean	Standard Deviation	Minimum	Maximum
Oil rents per capita	1632.03	3545.29	1.90	40978.83
ln(oil rents per capita)	5.81	1.95	0.64	10.62
Oil rents as % of GDP	1.16	0.18	1.00	2.15
ln(oil rents as % of GDP)	0.14	0.14	0.00	0.76
Real exchange rate	1.72	0.96	0.21	15.00
ln(real exchange rate)	0.42	0.48	-1.54	2.71
Real GDP per capita	14427.96	16683.82	612.40	118770.50
ln(real GDP per capita)	8.98	1.12	6.42	11.68
Openness to trade	74.87	40.14	14.68	354.11
N / n	42 / 1114			

Table 4.6. Descriptive statistics by subsample.

Figure 4.3 and Figure 4.4 show the distribution and evolution over time of the real exchange rate in OPEC countries and the rest of the world. With the exception of the early years in the dataset, OPEC countries' real exchange rates behave similarly to the rest of the world. More specifically, from 1990 onwards, log real exchange rate has a similar median in OPEC and non-OPEC countries, although the minima and first quartiles are slightly larger in OPEC countries.

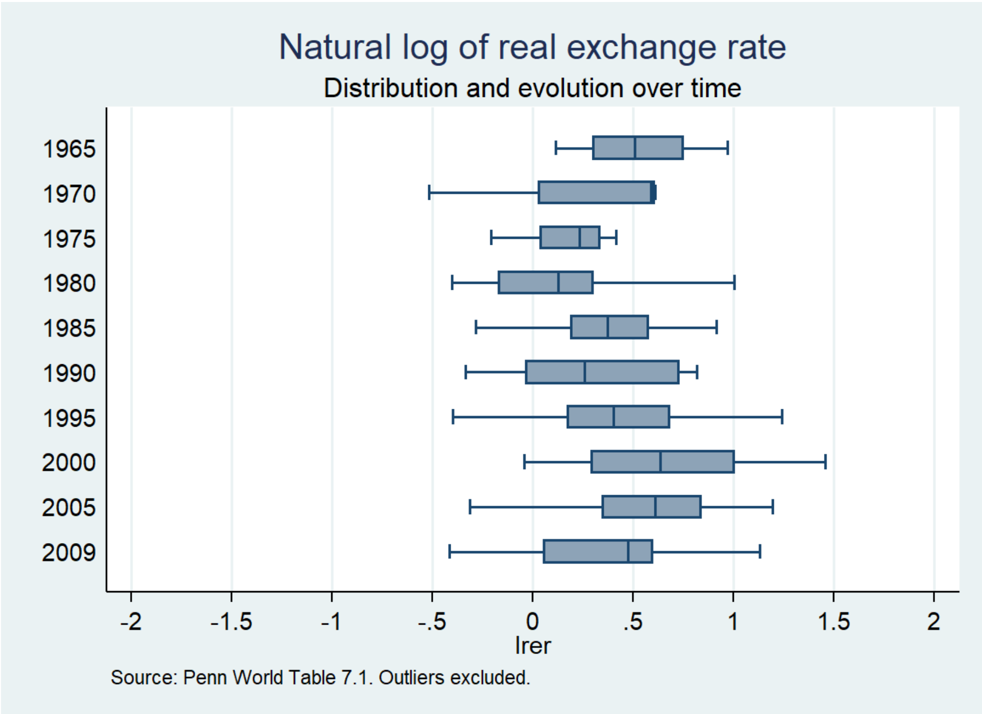

Figure 4.3. Natural log of real exchange rate across time.

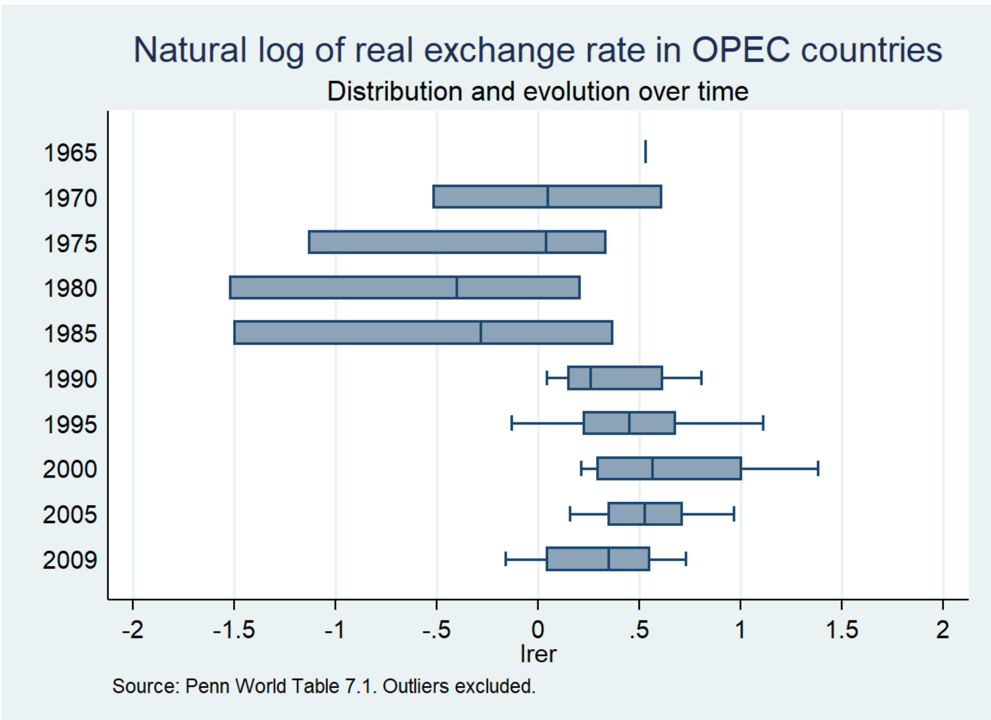

Figure 4.4. Natural log of real exchange rate across time in OPEC countries.

In Figure 4.5 and Figure 4.6, I turn to one of the main explanatory variables, oil rents per capita. Unsurprisingly and as previously observed, OPEC countries have higher per capita oil rents than the rest of the world. This holds across time as shown by larger median values in OPEC countries as well as a tighter distribution around these.

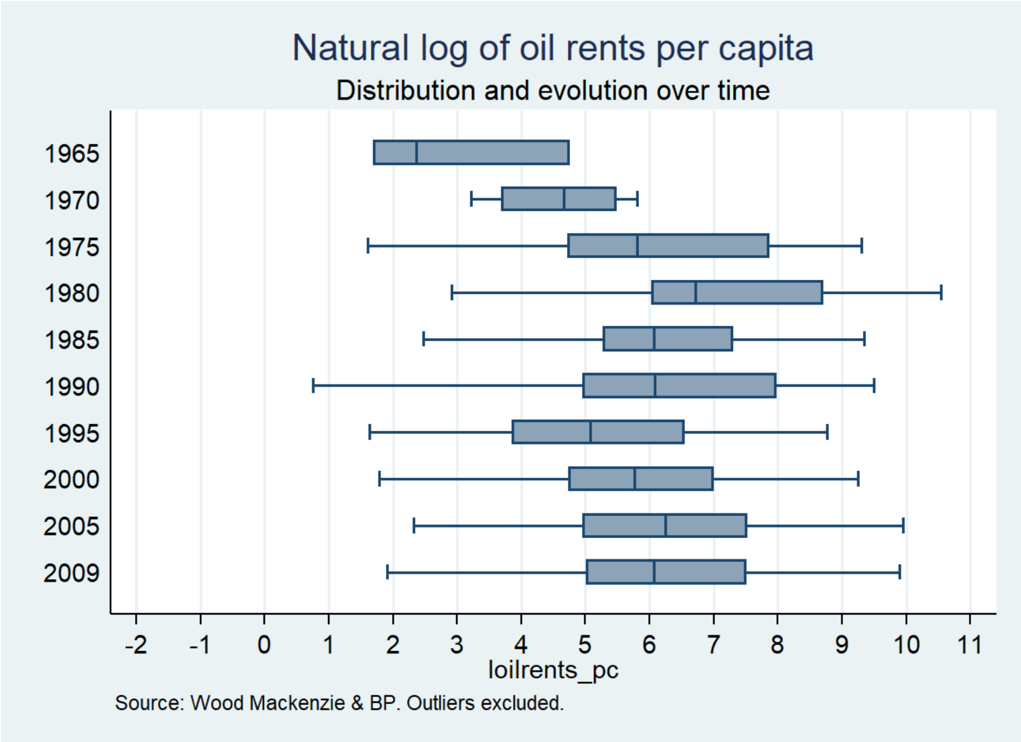

Figure 4.5. Natural log of oil rents per capita.

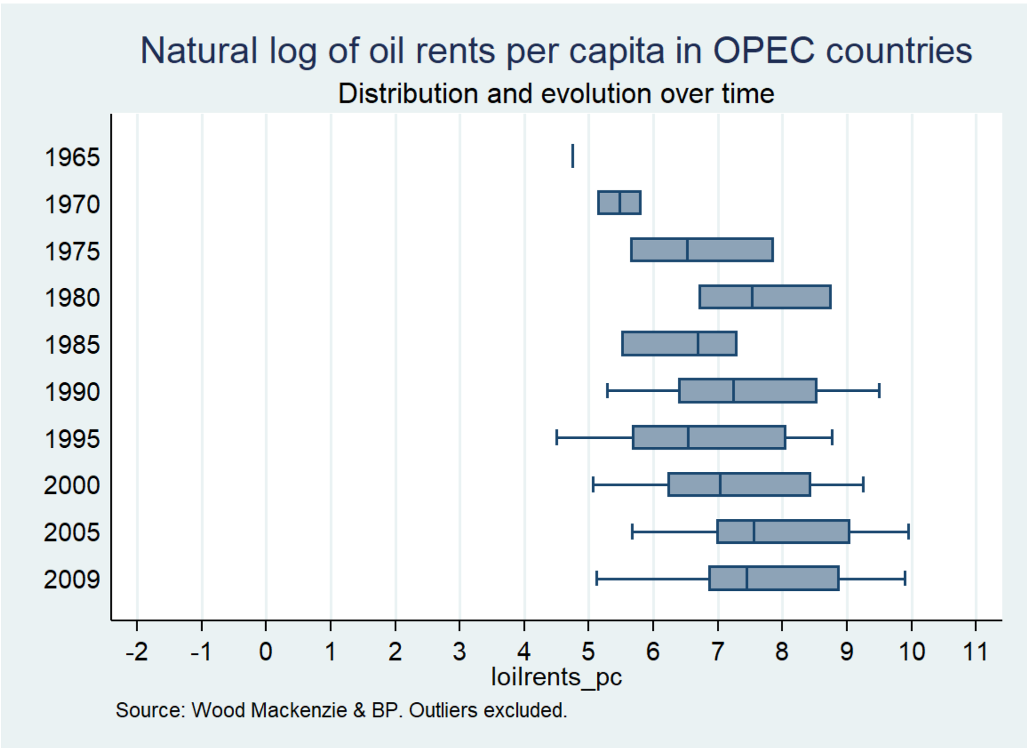

Figure 4.6. Natural log of oil rents per capita in OPEC countries.

A second measure adopted in this chapter is oil rents as a percentage of GDP to emphasise how important oil rents are relative to the size of the economy. Box plots of this variable are shown in Figure 4.7 and Figure 4.8.

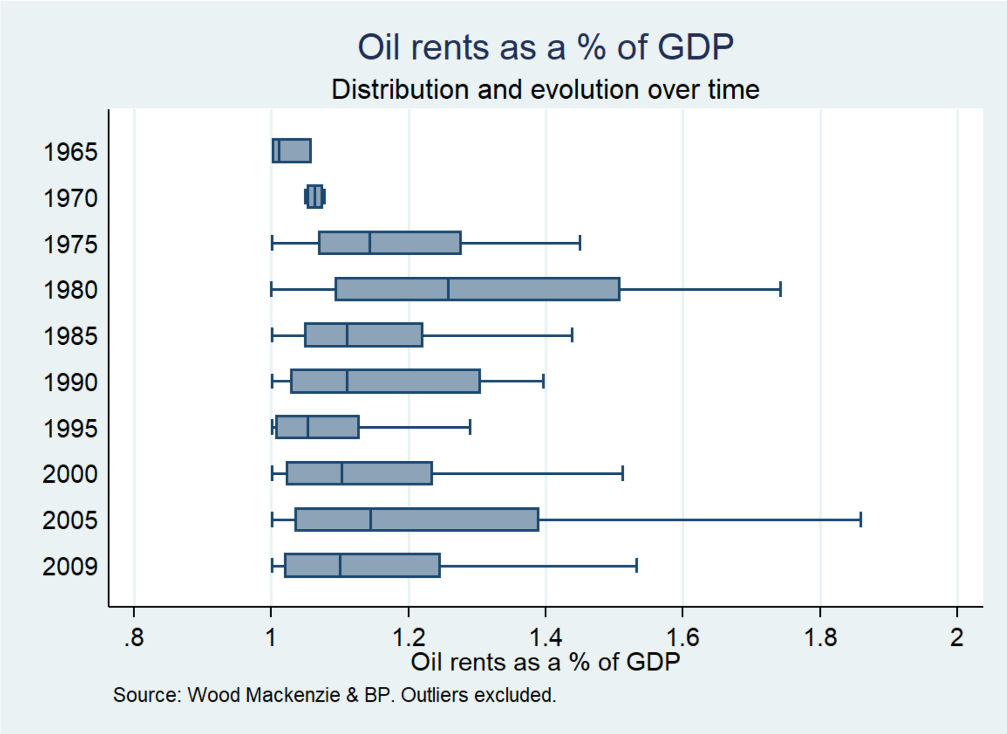

Figure 4.7. Oil rents as a percentage of GDP.

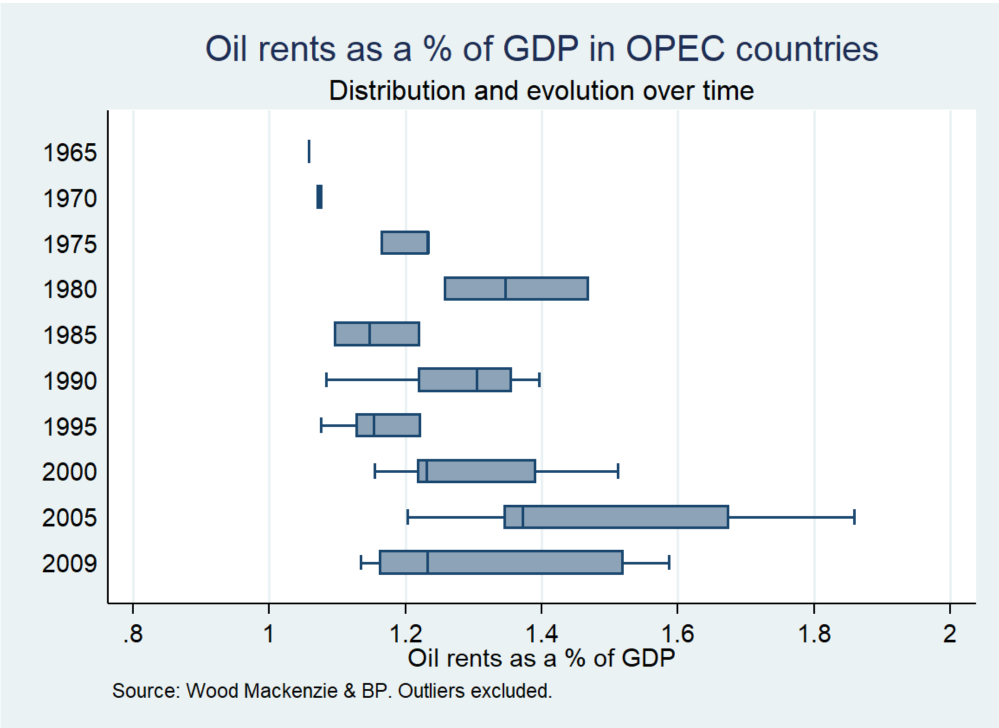

Figure 4.8. Oil rents as a percentage of GDP in OPEC countries.

This measure reveals a similar pattern to oil rents per capita, since oil rents constitute a larger share of OPEC countries' GDP than the rest of the world, especially from

1985 onwards. Unlike the rest of the world, no OPEC country has oil rents accounting for 0% of GDP. Further, non-OPEC countries have a wider distribution around a smaller median value throughout the sample period. Figure 4.9 and Figure 4.10 below show that although mean GDP for OPEC countries is very similar to the global average (as shown in Table 4.6), the series has behaved differently over time. For instance, global GDP appears to have a positive time trend, whereas this is much less pronounced in OPEC countries, especially in the earlier years of the dataset. As Ross (2012) observed, this is part of the resource-curse puzzle. Resource-rich economies do not seem to experience higher growth rates in practice. In fact, generally, OPEC countries' median GDP per capita appears slightly lower than the rest of the world. Although this is not indicative of a causal link between high oil rents as a percentage of GDP and lower GDP per capita, it signals a potential explanation. This GDP per capita behaviour in OPEC countries over time is partially due to the fluctuations in oil prices and production in some years, since oil rents constitute a relatively large portion of these countries' GDPs.

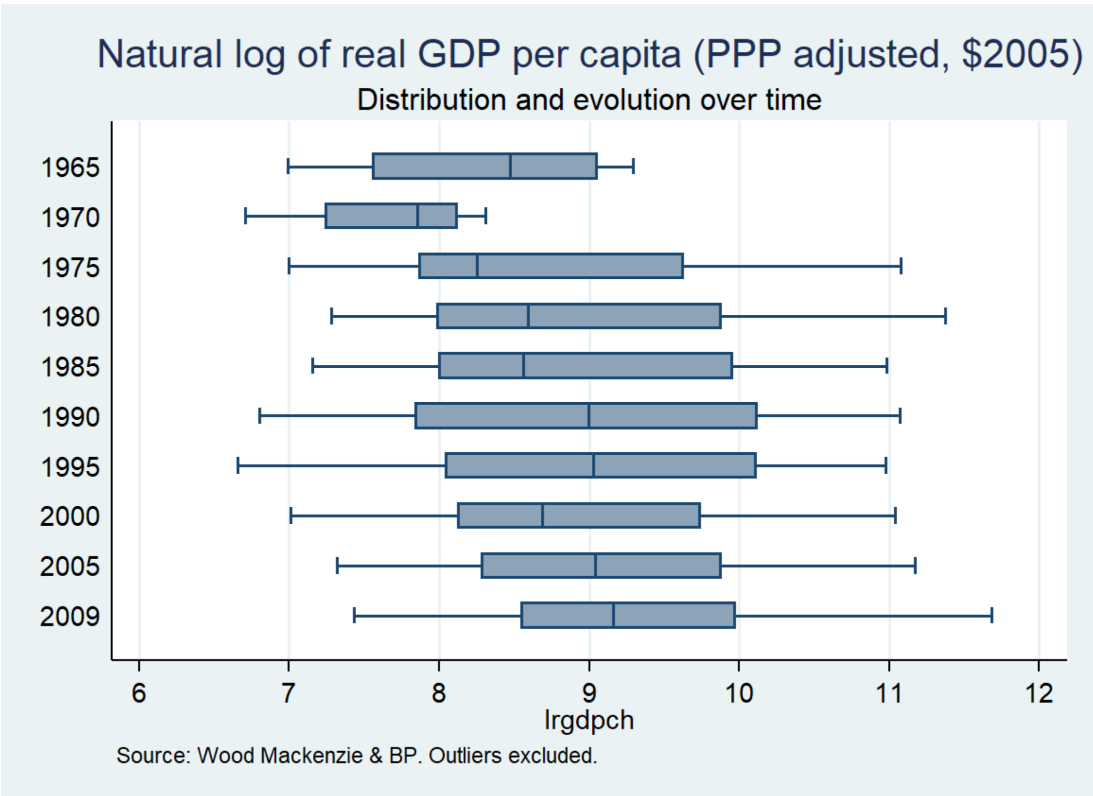

Figure 4.9. Natural log of real GDP per capita.

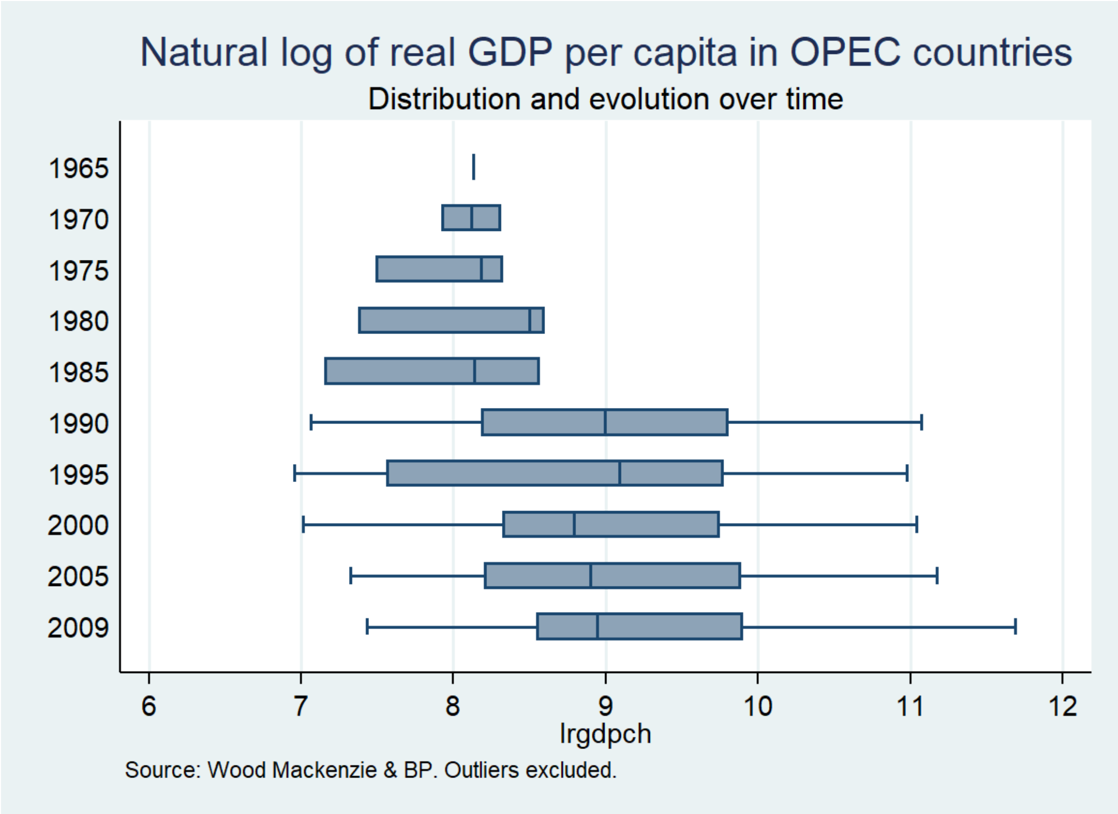

Figure 4.10. Natural log of real GDP per capita in OPEC countries

Finally, Figure 4.11 and Figure 4.12 combine the first set of key variables in question. Casual inspection reveals a negative relationship between real exchange rates and oil rents per capita. To see this, a simple linear line fitted into the top-right quadrant of these two figures would be sloping downward, suggesting that lower *lrer* is more likely (appreciation) at higher oil rents per capita. This is along the lines of what theory predicts and will be discussed in detail in the rest of the chapter. Interestingly, the OPEC subsample has a clearer and more negative relationship. This provides preliminary evidence for the B-S hypothesis and is investigated further in later sections. Before formal testing, I observe that this is in sharp contrast with the pattern that emerges using oil rents as a percentage of GDP. As Figure 4.13 and Figure 4.14 demonstrate, the relationship between real exchange rates and rents is much less clear when the latter is measured as a percentage of output. Furthermore, the relationship changes sign in OPEC countries, which is a surprising result that not only contradicts the findings with per capita oil rents but also the existence of a B-S-type dynamic. This finding motivated me to explore the impact of variable specification on the estimated relationship. The results of this investigation are presented where appropriate and the analysis proceeds with both explanatory variables in mind.

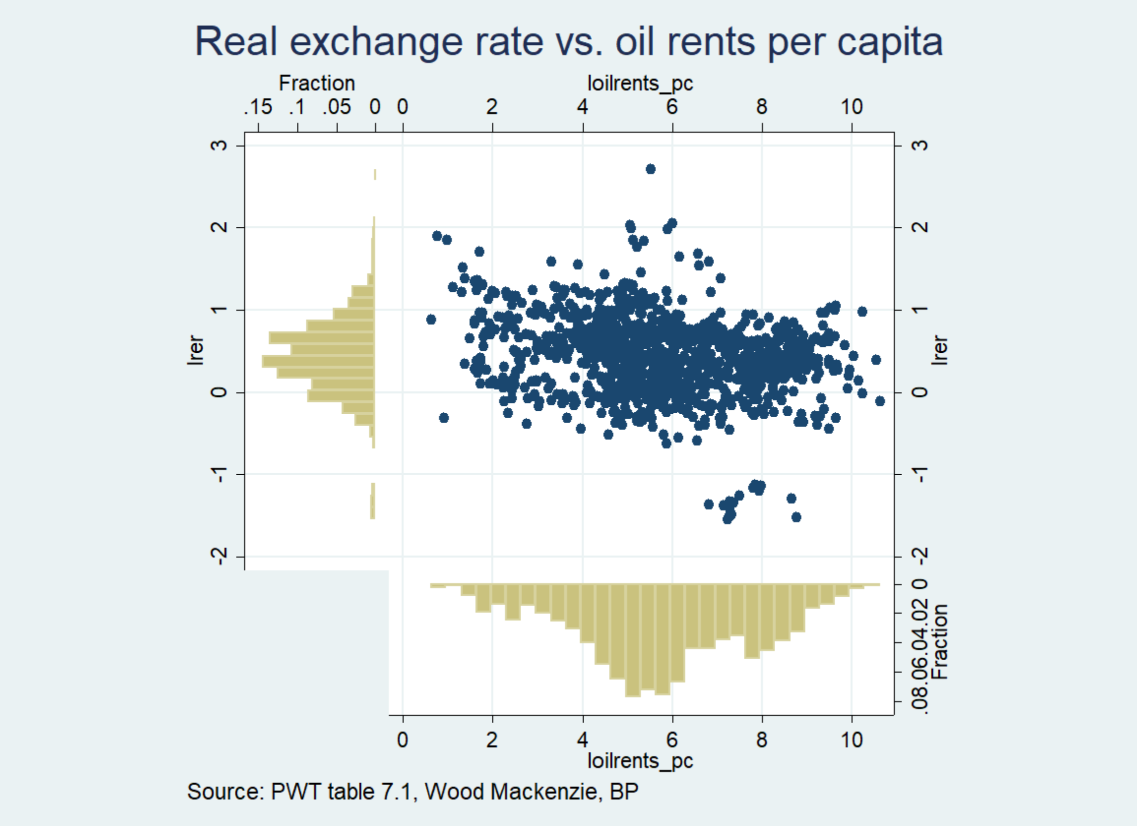

Figure 4.11. Real exchange rate versus oil rents per capita.

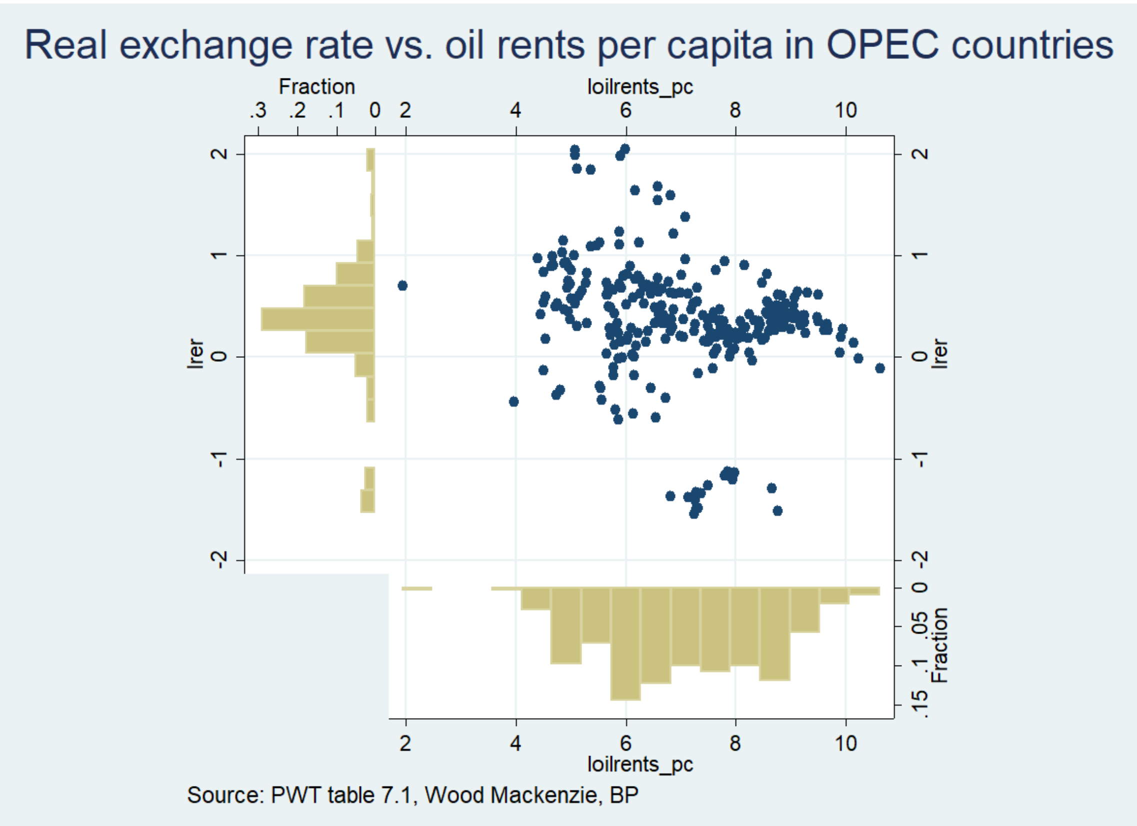

Figure 4.12. Real exchange rate versus oil rents per capita in OPEC countries.

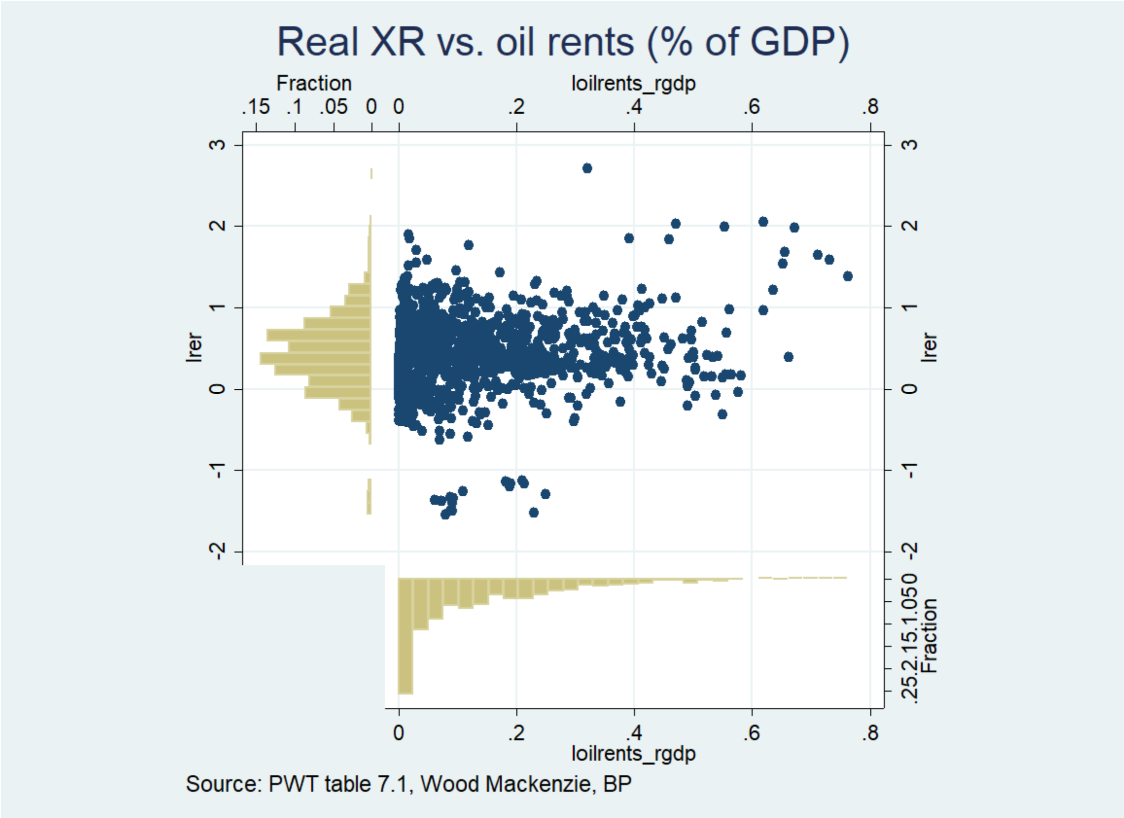

Figure 4.13. Real exchange rate versus oil rents as a percentage of GDP.

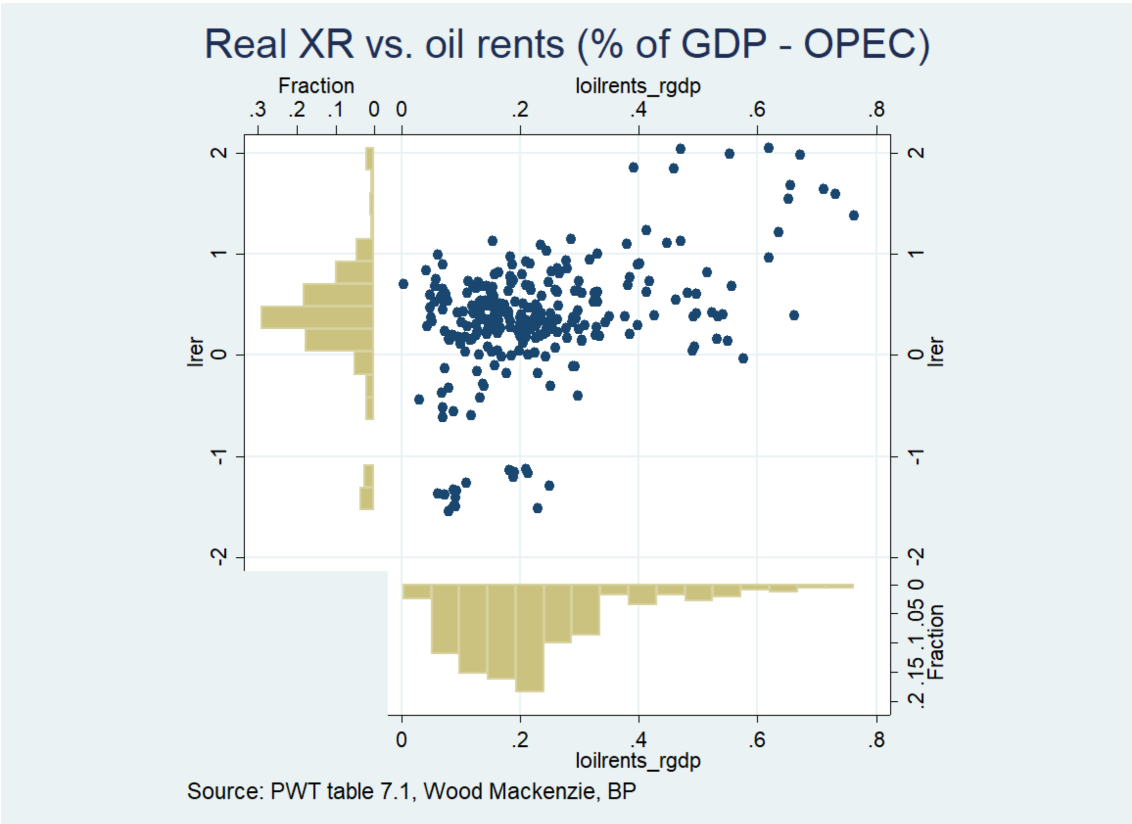

Figure 4.14. Real exchange rate versus oil rents as a percentage of GDP in OPEC countries.

4.4.5 Individual Country Statistics and Plots

This section aims to provide further clarity on individual countries in the dataset by summarising and graphing key variables. Generally, I observe a negative relationship between the logarithm of real exchange rates, *lrer*, and the main explanatory variable, the logarithm of per capita oil rents, *loilrents_pc*. The simple correlation coefficient between the two variables using the whole dataset is -0.26.[26] This coefficient is -0.33 when the sample is restricted to D10 countries. It is, therefore, not surprising that I observe an inverse relationship between the two series in most countries in the dataset. Angola and Norway are shown below as examples.

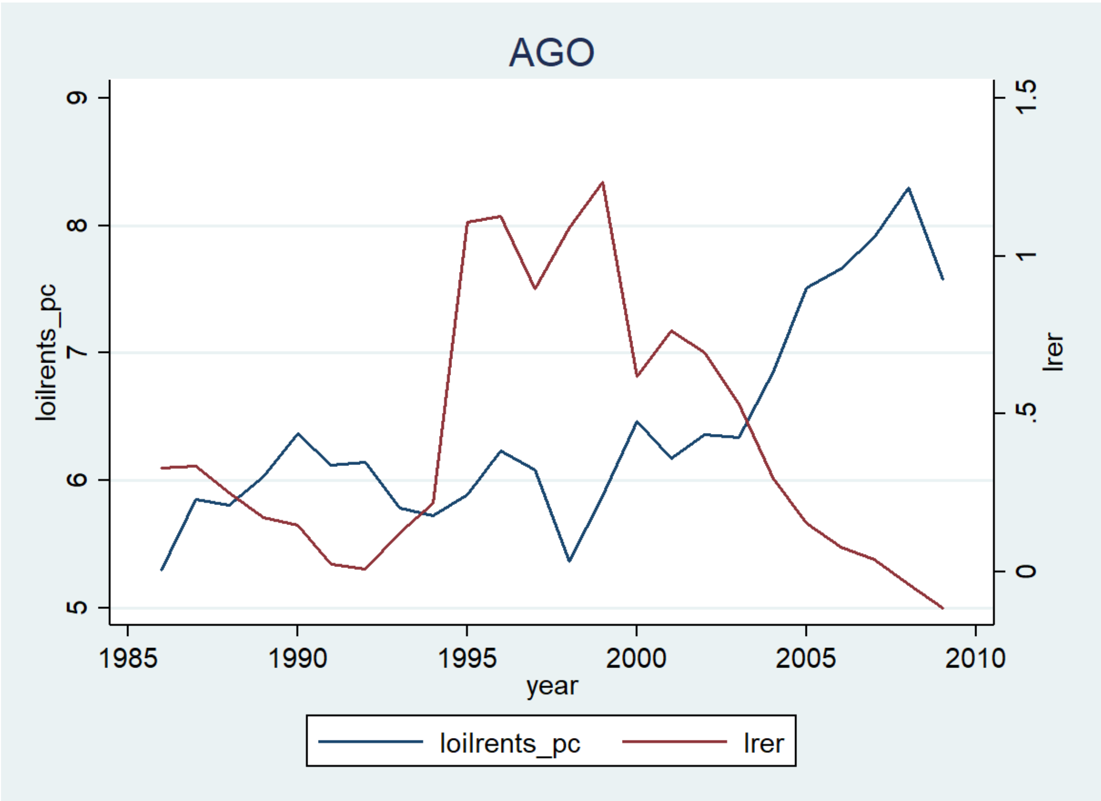

Figure 4.15. Real exchange rates and oil rents per capita in Angola.

[26] Recall that the exchange rate is defined as national currency per US dollar, so that an increase in the variable represents a depreciation. Thus, a correlation coefficient of -0.26 implies that a rise in oil rents is associated with an appreciation (i.e. a decrease in *lrer*).

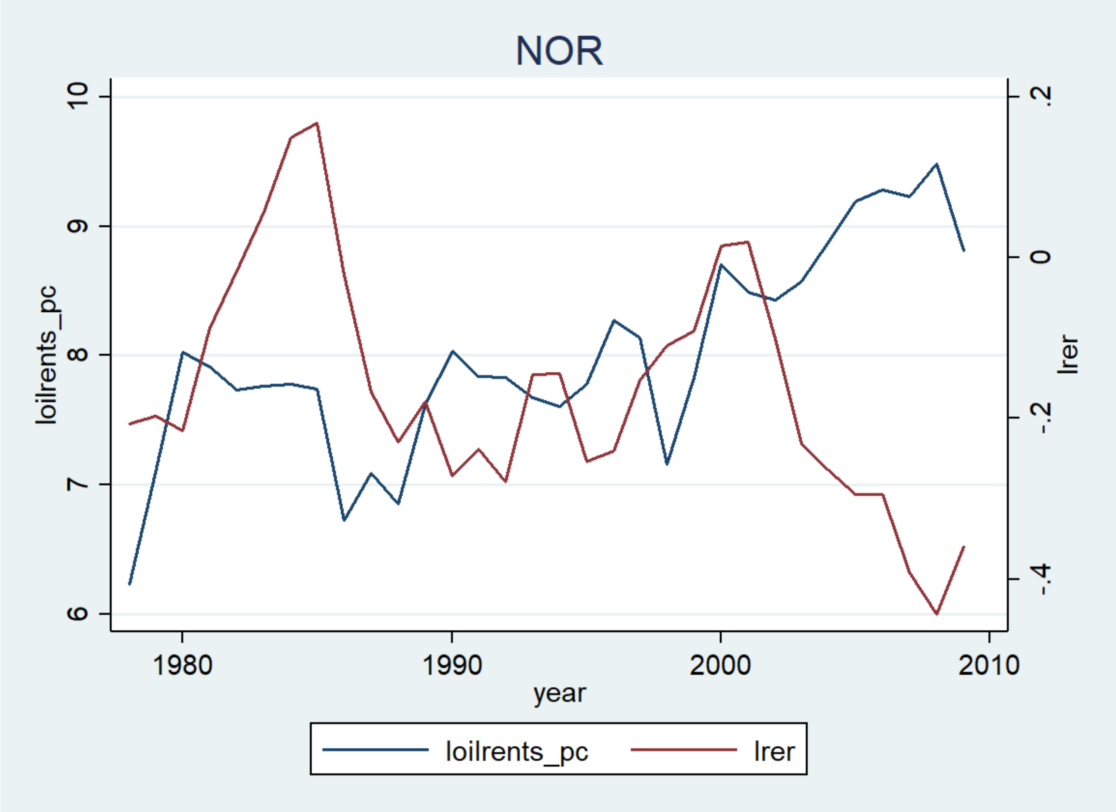

Figure 4.16. Real exchange rates and oil rents per capita in Norway.

In Figure 4.15 and Figure 4.16, increases in oil rents tend to be associated with a fall in the exchange rate measure suggesting an appreciation of the currency. This pattern is common throughout the dataset but, unsurprisingly, not all countries follow it. A counter example is Australia, where the real exchange rate fluctuates independently of per capita oil rents in parts of the series. The underlying reason for this is the little contribution of oil rents in Australian GDP: mean oil rents in Australia are 1.3% of GDP and they have never exceeded 4% of GDP. Despite this, I observe periods with a clear link between the real exchange rate and oil rents, but overall there are larger drivers of the Australian real exchange rate than rents from oil production.

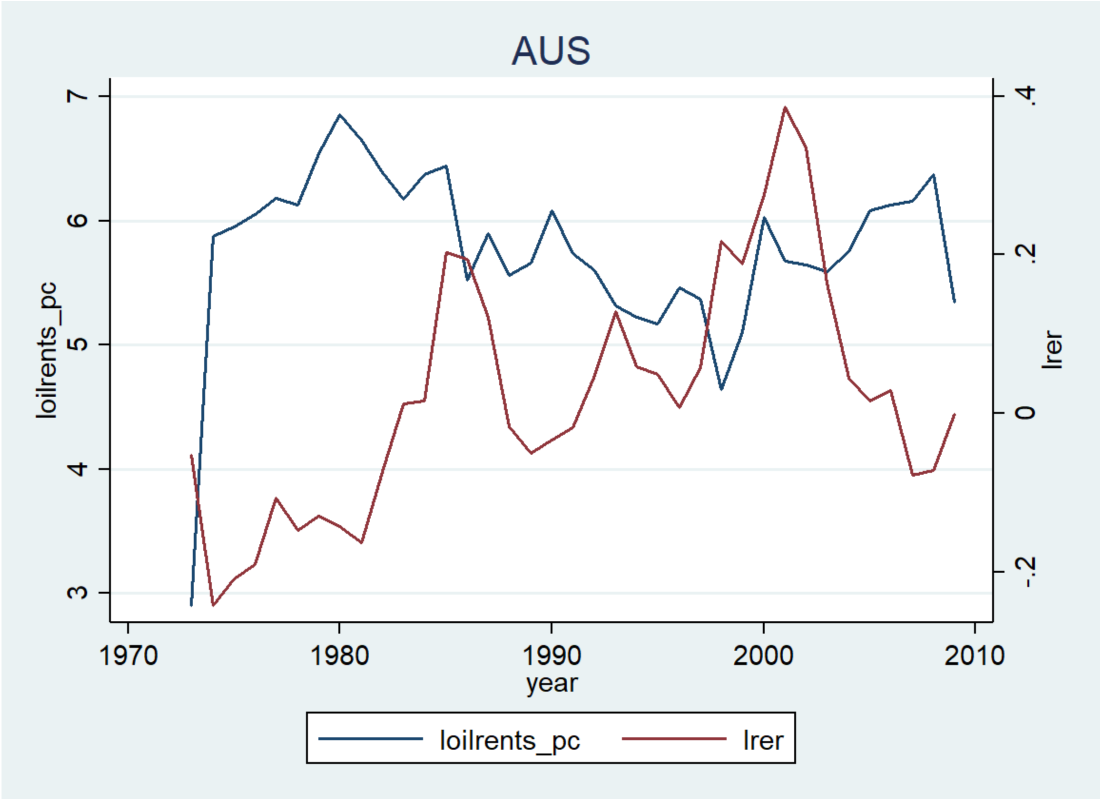

Figure 4.17. Real exchange rates versus oil rents per capita in Australia.

This motivated further investigation of the alternative oil rents measure using rents as a share of GDP. Returning to the same countries discussed above, I observe a less stable relationship between exchange rates and rents as a percentage of GDP. All three countries—Angola, Australia, and Norway—show signs of both a positive and negative link between the two series at different time periods. Since visual analysis is inconclusive in this context, formalised results are reported in later sections.

4.5 Unit Root Tests

I start the analysis by testing for stationarity of the variables. This has implications for the estimation techniques to be adopted and often involves multiple tests in a panel context. A popular early panel unit root tests is the Levin and Lin test, originally introduced in 1992. In recent literature, the most commonly used tests in applied research are LLC (Levin, Lin, & Chu, 2002), IPS (Im, Pesaran, & Shin, 2003), Hadri (2000), and Fisher-type tests (Fisher, 1925). Preference is generally given to tests that can be applied to unbalanced panels that do not assume a common unit root process (a requirement for LLC and Hadri tests) or require the same number of observations in all panels (a requirement for IPS test). To overcome these obstacles, I use a Fisher-type test proposed by Maddala & Wu (1999), which carries out individual independent unit root tests for each panel and combines resulting p-values. The test does not restrict panels to have the same number of observations or the same number of lags. Another useful property of the test is that it can combine significance levels from different individual unit root tests. These are desirable in my case given the heterogenous nature of countries in the dataset. Restricting the sample, such as dropping observations to reduce it to a balanced panel, is an option to potentially improve size and power properties and perform the more restrictive panel unit root tests. However, Maddala & Wu (1999) showed that the Fisher test outperforms LLC and IPS in Monte-Carlo studies. Given the trade-off between loss of observations and the ability to run additional tests, the Fisher-type test is the best choice here. Besides, Pesaran (2012) noted that there is no theoretical basis for a homogeneous autoregressive structure in the context of testing the PPP hypothesis, which makes the LLC and Hadri tests even less appropriate for this analysis. Further, Davidson & MacKinnon (2004) compared augmented the Dickey-Fuller (ADF) test to others and found that the former exhibits better power properties in finite samples.

These tests assume, in principle, that number of panels, N, is fixed and number of time periods, T, tends to infinity. This is reasonable for some panels within the dataset, but the number of panels exceeds the average observations per country in the unbalanced panel structure. Table 4.7 reports the results of the Fisher-type test with individual ADF regressions. The number of lags varies from zero to two, and all tests are performed with and without a trend. The null hypothesis states that all the panels contain unit roots and the default significance level is chosen to be 5%.

Variable	Trend	Number of lags	Test statistic	p-value	Result
lrer	No	0	79.51	0.62	All panels are non-stationary
	No	1	133.63	0.00	At least some panels are stationary
	No	2	119.80	0.01	At least some panels are stationary
	Yes	0	61.22	0.97	All panels are non-stationary
	Yes	1	233.87	0.00	At least some panels are stationary
	Yes	2	105.43	0.06	All panels are non-stationary
loilrents_pc	No	0	191.43	0.00	At least some panels are stationary
	No	1	118.05	0.01	At least some panels are stationary
	No	2	73.39	0.79	All panels are non-stationary
	Yes	0	183.86	0.00	At least some panels are stationary
	Yes	1	119.61	0.01	At least some panels are stationary
	Yes	2	45.25	1.00	All panels are non-stationary
loilrents_rgdp	No	0	119.61	0.01	At least some panels are stationary
	No	1	95.80	0.18	All panels are non-stationary
	No	2	72.31	0.81	All panels are non-stationary
	Yes	0	83.90	0.48	All panels are non-stationary
	Yes	1	72.08	0.82	All panels are non-stationary
	Yes	2	67.49	0.91	All panels are non-stationary
lrgdpch	No	0	61.20	0.97	All panels are non-stationary
	No	1	94.25	0.21	All panels are non-stationary
	No	2	87.70	0.37	All panels are non-stationary
	Yes	0	94.86	0.20	All panels are non-stationary
	Yes	1	113.75	0.02	At least some panels are stationary
	Yes	2	63.30	0.96	All panels are non-stationary
lopenc	No	0	180.92	0.00	At least some panels are stationary
	No	1	172.19	0.00	At least some panels are stationary
	No	2	97.74	0.15	All panels are non-stationary
	Yes	0	198.49	0.00	At least some panels are stationary
	Yes	1	136.09	0.00	At least some panels are stationary
	Yes	2	58.55	0.98	All panels are non-stationary

Table 4.7. Panel unit root tests.

Based on these results, $lrer$ appears to be non-stationary with no lags in the DF regression, but the null hypothesis is rejected when one or more lags are included. $loilrents\_pc$ and $lopenc$ exhibit the opposite behaviour: I fail to reject H_0 of non-stationarity of all panels when two lags are included. The test results strongly suggest that the GDP-based measures, $loilrents\_rgdp$ and $lrgdpch$, are non-stationary. The null hypothesis is rejected only in one specification for $lrgdpch$.

Although powerful in some respects, Fisher-type tests have a major drawback: the null hypothesis is formulated such that it implies non-stationarity of all panels against the alternative hypothesis that some are stationary. Given that the test has low power properties in small samples, it may be informative and practical to run individual unit root tests for each panel. This approach can become impractical in datasets with large N but offers the most flexibility: each panel can be tested on its own for different orders of integration. The results from individual ADF tests are presented in Table 4.22 through Table 4.26 of the Chapter Appendix. A summary of these tables is presented in Table 4.8.

Variable	Trend	No of lags	Number of countries (out of 42) for which the null hypothesis is rejected	Fraction of countries for which the null hypothesis is not rejected
loilrents_pc	No	0	7	83%
	No	1	3	93%
	No	2	2	95%
	Yes	0	6	86%
	Yes	1	6	86%
	Yes	2	1	98%
loilrents_rgdp	No	0	4	90%
	No	1	1	98%
	No	2	2	95%
	Yes	0	2	95%
	Yes	1	3	93%
	Yes	2	2	95%
lrer	No	0	2	95%
	No	1	6	86%
	No	2	6	86%
	Yes	0	2	95%
	Yes	1	6	86%
	Yes	2	3	93%
lrgdpch	No	0	2	95%
	No	1	3	93%
	No	2	4	90%
	Yes	0	2	95%
	Yes	1	5	88%
	Yes	2	2	95%
lopenc	No	0	4	90%
	No	1	6	86%
	No	2	2	95%
	Yes	0	5	88%
	Yes	1	6	86%
	Yes	2	2	95%

Table 4.8. Summary of country-by-country ADF tests. 5% significance level is used. H_0 is that a unit root is present in the series.

These results paint a different picture in that most of the series appear non-stationary and some of the results observed through the Fisher-type panel unit root test may have been driven by a minority of panels. *lbrent* was tested separately using Elliot, Rothenberg, & Stock's (1996) DF-GLS test, a more powerful modification of the ADF test. The lag length is chosen according to the modified Akaike information criterion (Ng & Perron, 2001) and set to one. The null hypothesis is not rejected at the 10% significance level for up to 9 lags, which confirms that the Brent price series is non-stationary. All 45 observations are used for this test as opposed to restricting the series to some panels' time series. The test results are shown in Table 4.9.

Variable	Trend	Number of lags	Test statistic	Result
lbrent	No	1	-1.65	Series is non-stationary
lbrent	Yes	1	-1.97	Series is non-stationary

Table 4.9. Unit root test for *lbrent*. Maximum lag length determined by Schwert criterion, and the optimal lag length by modified Akaike information criterion. Critical values are non-standard.

In these tests, maximum lag length was determined by the Schwert criterion[27] and the optimal lag length by the modified Akaike information criterion. Given these findings, I proceed with the analysis on the basis that all variables are non-stationary.

4.6 Methodology and Estimations

4.6.1 Testing for Cointegration

Having established the non-stationarity properties of the variables in Section 4.5, the analysis continues with an investigation of a cointegrating relationship between $lrer$ and $oilrents\_pc$ or $oilrents\_rgdp$. Other potential determinants of the real exchange rate are also included in this analysis. If the variables prove to have a long-run relationship, then the dynamic ordinary least squares estimator (DOLS) introduced by Stock & Watson (1993), the mean-group estimator (MG) of Pesaran & Smith (1995) and the pooled mean-group estimator (PMG) of Pesaran, Shin, & Smith (1999) will be used to evaluate the magnitude of the coefficients in the long-run equation. The short-run dynamics will also be discussed. The DOLS estimator has been frequently used in the literature in the context of the B-S hypothesis (e.g., Chong et al., 2012, and MacDonald & Ricci, 2007), but the MG and PMG estimators are not yet prevalent, despite some analyses along these lines, such as Camarero (2008).

[27] As discussed in Schwert (1989).

OLS estimation of the cointegrated non-stationary variables also produces consistent estimates, but they generally do not follow a Gaussian distribution, so the conventional test statistics are meaningless. Stock & Watson's (1993) DOLS was suggested as a solution to this problem. The estimator is asymptotically efficient and normally distributed. This is achieved by the inclusion of the leads and lags of the differenced explanatory variables, which orthogonalises the error term with respect to the innovations in the regressors. This has the added advantage of eliminating potential endogeneity between the error term and the stationary component of the non-stationary variables. Asymptotically valid standard errors can be computed using a heteroskedasticity and autocorrelation consistent estimator. In this case, Newey-West standard errors will be used. According to Kao & Chiang (2001), DOLS outperforms panel OLS and fully modified least squares estimator (FMOLS) because of smaller bias and smaller finite sample size distortions. The DOLS equation has the following form:

$$lrer_{it} = X_{it}\,\beta + \alpha_i + \sum_{k=-a}^{b} \Delta X_{it+k}\theta + \varepsilon_{it} \tag{4.1}$$

Where $lrer_{it}$ is the real exchange rate of country i at time t measured in natural logarithm, X_{it} is the vector of explanatory variables, β is the vector of the long-run DOLS coefficients, α_i are the country fixed effects, θ is a vector of the coefficients on the lags and leads of the first-differenced explanatory variables, and ε_{it} denotes the error term. Maximum lag and lead lengths are shown by a and b, respectively.

To test for the presence of cointegration in the context of panel data, Pedroni (1999, 2004) suggested seven test-statistics in the Engle-Granger tradition. The null hypothesis of the tests is no cointegration. Four statistics are panel and three are group statistics. The former assume homogeneity of the panels and pool the data across the within dimension, constraining the coefficients to be the same. Group statistics allow for heterogeneity of the panels and calculate averages for the statistics from individual time-series estimations. The latter are more relevant for the estimation, as it would be reasonable to expect coefficients to vary across countries. The residuals for the Pedroni test are obtained from the long-run DOLS equation that has the following form:

$$lrer_{it} = loilrents\_pc_{it}\,\beta + \alpha_i + \sum_{k=-1}^{1} \Delta\, loilrents\_pc_{it+k}\theta + \varepsilon_{it} \tag{4.2}$$

The results for the Pedroni tests are presented in Table 4.10. In all specifications for this test and for the subsequent DOLS estimation, one lead and one lag are used in order to avoid constraining the number of observations, particularly in the case of countries with a short time series. The main findings are robust to an increased number of leads and lags in constrained datasets with these countries dropped. The table indicates that two out of seven tests reject the null of no cointegration at the 10% significance level for the whole sample as shown in column (1) of the table. D10 countries show stronger evidence of cointegration with four rejections of the null hypothesis. Interestingly, however, there seems to be no cointegrating relationship between per capita oil rents and real exchange rate in OPEC countries. This is an unexpected result, as it suggests that the productivity bias hypothesis does not explain movements in the real exchange rate through the productivity of the oil sector in these countries, even though the oil sector accounts for a large fraction of exports.

The results are qualitatively the same when oil rents are captured using $loilrents\_rgdp$ for the whole sample and D10 countries. They differ substantially for OPEC countries. For comparison, the test statistics calculated using oil rents as a percentage of GDP are given in column (4) of Table 4.10. Six out of seven tests reject the null hypothesis of no cointegration in this subsample, which is the strongest evidence of cointegration I have identified in the sample. This provides further evidence that the way oil rents are measured matters. More specifically, and as theory would suggest, there is a stronger link between oil rents and real exchange rate in countries where rents account for a large part of GDP.

Test statistic		(1)	(2)	(3)	(4)
Panel	v-statistic	2.639***	1.906*	1.046	1.738*
	rho-statistic	-1.838*	-2.109**	-1.201	-2.509**
	t-statistic	-1.547	-2.203**	-1.208	-2.937***
	ADF-statistic	-0.977	-1.508	-1.571	-2.203**
Group	rho-statistic	0.3997	-0.8219	0.3235	-0.7922
	t-statistic	-1.287	-3.18***	-0.6863	-2.89***
	ADF-statistic	-1.47	-0.5297	-2.216**	-2.503**
Oil rents variable		*loilrents_pc*	*loilrents_pc*	*loilrents_pc*	*loilrents_rgdp*
Subsample		World	D10	OPEC	OPEC
N		42	26	10	10
Lags		1	1	1	1

Table 4.10. Pedroni (1999, 2004) cointegration test results using oil rents per capita and oil rents as a percentage of GDP. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Test statistics have a standard normal distribution under the null hypothesis of no cointegration.

To further investigate the existence of a key cointegrating relationship, I conduct Westerlund (2007) cointegration tests. Unlike Pedroni tests, these tests are robust to cross-sectional dependence and are based on estimating an ECM-type equation, as shown in equation 4.3, and testing whether the panels are error-correcting. The original test has four test statistics, which share a common null hypothesis but have different alternative hypotheses. The tests are: Gt, Ga, Pt, and Pa. Gt and Ga test the null hypothesis of no cointegration, $\phi_i = 0$ for all i, against the alternative that at least one panel contains a cointegrating relationship, $\phi_i < 0$ for at least one i. Pt and Pa share the same null hypothesis, but the alternative is formulated such that all panels exhibit cointegration, $\phi_i < 0$ for all i. I focus on Pt and Pa because some panels have small numbers of observations and Gt and Ga are more likely to suffer from low power, which is exacerbated by lags and leads in the ECM used to estimate the residuals reducing the degrees of freedom available for the test even further. The lag length is once again set to one, although if the sample is restricted to countries with larger number of observations and the optimal leg length is selected according to the Akaike information criterion, the results remain unchanged.

$$\Delta lrer_{it} = \varphi_i(lrer_{it-1} - \beta_i loilrents\_pc_{it-1}) + \alpha_i + \sum_{k=1}^{p} \Delta\, lrer_{it-p}\delta_i + \sum_{k=0}^{p} \Delta\, loilrents\_pc_{it-k}\theta_i + v_{it} \tag{4.3}$$

where φ_i is a speed of adjustment coefficient, δ_i is a $p \times 1$ vector of coefficients on the lagged first-differenced dependent variable, θ_i is a $((p+1) \times 1)$ vector of coefficients on the lagged first-differenced regressor, and v_{it} denotes the error term.

Westerlund cointegration test results are shown in Table 4.11 and Table 4.12. The former uses oil rents per capita and the latter uses oil rents as a percentage of GDP. The two sets of results follow roughly the same pattern. Columns (1) and (2) of the tables suggest a cointegrating relationship, since both Pt and Pa statistics reject the null in almost all cases. Lack of cointegration in OPEC countries shown in column (3) of Table 4.11 is in agreement with Pedroni tests discussed previously. This finding is in line with test statistics reported in columns (4) and (5), since the cointegrating relationship appears to strengthen from a statistical significance perspective when OPEC countries are omitted from the sample. It is noteworthy that all test statistics in these columns reject the null hypothesis at the 1% significance level. Column (3) in Table 4.12 contradicts Pedroni test results, however. Even though the Pedroni test suggested cointegration between the real exchange rate and oil rents as a percentage of GDP, results of the Westerlund test disagree. Both test statistics fail to reject the null hypothesis of no cointegration for OPEC countries. This result is further corroborated by columns (4) and (5) where I observe evidence for a cointegrating relationship in the rest of the world. I investigate this further in the sections that follow.

	(1)	(2)	(3)	(4)	(5)
Pt	2.85***	2.33**	0.48	4.62***	3.87***
	(0.002)	(0.010)	(0.316)	(0.000)	(0.000)
Pa	1.32*	0.84	0.60	4.57***	3.61***
	(0.094)	(0.200)	(0.727)	(0.000)	(0.000)
Subsample	World	D10	OPEC	World-OPEC	D10-OPEC
N	40	25	10	30	15
Lags & leads	1	1	1	1	1

Table 4.11. Westerlund (2007) panel cointegration tests using oil rents per capita. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. H_0: No cointegration in any panel ($\phi_i = 0\ \forall i$; H_a: Cointegration in the panel as a whole ($\phi_i < 0\ \forall i$). Two countries, Romania and Sudan, were dropped for these tests due to their short time series.

	(1)	(2)	(3)	(4)	(5)
Pt	2.95***	2.06**	0.60	3.46***	2.37***
	(0.002)	(0.020)	(0.273)	(0.000)	(0.009)
Pa	2.95***	1.90**	0.31	3.89***	2.56***
	(0.002)	(0.029)	(0.378)	(0.000)	(0.005)
Subsample	World	D10	OPEC	World-OPEC	D10-OPEC
N	40	25	10	30	15
Lags & leads	1	1	1	1	1

Table 4.12. Westerlund (2007) panel cointegration tests using oil rents as a percentage of GDP. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. H_0: No cointegration in any panel ($\phi_i = 0\ \forall i$); H_a: Cointegration in the panel as a whole ($\phi_i < 0\ \forall i$). Two countries, Romania and Sudan, were dropped for these tests due to their short time series.

As a part of this analysis, cointegration tests were performed using other explanatory variables (oil price and real per capita GDP) as well. Albeit less clear than oil rents, these variables appear to have a cointegrating relationship with the real exchange rate in countries outside of OPEC. As observed earlier, no cointegration is identified in OPEC countries. The results are presented in Table 4.27 and in the Chapter Appendix. Although surprising at first glance, the no-cointegration result in OPEC countries is not entirely unexpected. As raised in Section 4.2, labour market assumptions of B-S effect are likely to fail in these countries, obscuring the link between oil rents and the real exchange rate.

To summarise, the cointegration tests discussed here strongly suggest that there is a long-run relationship between the real exchange rate and productivity of the oil sector in most oil-exporting countries in the sample. This relationship is less clear in OPEC countries due to contradicting test results. OPEC countries are kept in the sample for further analysis and because they are a particularly interesting group in this context. I interpret the results relating to OPEC countries accordingly and further discuss the potential failure of the B-S hypothesis in OPEC countries in Section 4.6.4.

4.6.2 Dynamic OLS Results

As noted earlier, DOLS estimations are used as a robust alternative to Panel OLS. The number of observations for some panel units are limited and pooling data can improve the power of the results. My main interest lies in the long-run relationship between the real exchange rate and the main explanatory variables, oil rents per capita and oil rents as a percentage of GDP. A panel cointegration model using DOLS is implemented to treat the non-stationarity of the variables appropriately. This approach has been used extensively within the B-S literature. Following Stock & Watson's (1993) work introducing the approach, Kao & Chiang (2001) showed that DOLS estimates have a smaller bias in finite samples than POLS and fully modified OLS. Similarly to Section 4.6.1, one lag and one lead are used such that $a = b = 1$ in equation 4.4. The main findings are robust to an increased number of leads and lags. Time fixed effects are excluded in the model, as these were observed to have little effect on the results. Furthermore, unlike in Gubler & Sax (2011), where time fixed effects were critical, my dependent variable is calculated relative to the US dollar.

Having established the existence of panel cointegration in the previous section, I interpret β in equation 4.1 as the long-run coefficient. In addition to estimating this long-run relationship, I include an error correction specification to capture the short-run dynamic adjustment of the real exchange rate towards equilibrium. The error correction model (ECM) has the following form:

$$\Delta lrer_{it} = \gamma + \varphi gap_{it-1} + \sum_{j=1} \Delta lrer_{it-j}\phi_j + \sum_{j=0}^{1} \Delta X_{it-j}\omega_j + \nu_{it} \tag{4.4}$$

where

$$gap_{it} = lrer_{it} - X_{it}\,\beta - \alpha_i - \sum_{k=-1}^{1} \Delta X_{it+k}\theta \tag{4.5}$$

and gap_{it} is estimated as the residuals of equation 4.1.

The empirical results are shown in Table 4.13 below. In almost all specifications and subsamples, I find a negative coefficient that is significantly different from zero at the 5% level on the per capita oil rents variable. A larger coefficient, in absolute value, is observed in the case of OPEC countries. This result corroborates the B-S hypothesis in the sample and suggests that the impact of oil rents per capita on real exchange rate is greater in OPEC countries than the rest of the world. Since these long-run coefficients have an elasticity interpretation, a 10% increase in oil rents per capita in D10 countries leads to a 1.2% appreciation of the currency based on column (8). In the case of OPEC countries, column (12) implies that a 10% increase in per capita oil rents implies approximately 11.5% appreciation of the currency. However, results for OPEC countries could be spurious as I failed to establish cointegration in the earlier section.

Having observed a stable cointegrating relationship between the real exchange rate and oil rents as a percentage of GDP, all model specifications were re-estimated using $loilrents\_rgdp$ instead of $loilrents\_pc$. The results, shown in Table 4.14, are puzzling in some respects but unsurprising in others. The speed of adjustment coefficient is estimated to be negative and statistically significant at the 1% level across the board. This suggests a cointegrating relationship in all specifications and subsamples. Although qualitatively identical with $loilrents\_pc$ results, these results generally indicate a slower adjustment—a longer half lifetime. With regard to long-run coefficients, oil rents appear to play a much more muted role in non-D10 and non-OPEC countries as indicated by columns (1) through (4) of the table. However, long-run coefficients on oil rents become highly statistically significant when I focus on D10 and OPEC countries. This is demonstrated by columns (6) through (12). To refrain from placing too much weight on point estimates, the confidence interval of the coefficient estimate for $loilrents\_rgdp$ was [0.13, 1.25] in column (6), [0.12, 1.15] in column (8), and [4.09, 4.95] in column (12). These suggest that the coefficients are precisely estimated with reasonable standard errors and hypothesis testing is meaningful.

Perhaps the most puzzling outcome of this exercise was the change in sign of the estimated long-run coefficient on oil rents when switching from oil rents per capita to oil rents as a percentage of GDP. Moreover, the estimated positive coefficients have a much larger magnitude suggesting that the real exchange rate is highly sensitive to movements in rents as a share of GDP. Based on column (8) of Table 4.14, a 1% increase in oil rents' share in GDP of D10 countries is expected to lead to a 0.6% increase in the real exchange rate. This impact is amplified in OPEC countries and as shown in column (12) of the same table, a 1% increase in $loilrents\_rgdp$ is expected to cause a 4.5% depreciation of the currency. This movement is in the opposite direction of theoretical predictions as well as empirical findings, including those in this chapter. Interestingly, however, the sign change on oil rents is accompanied—and to some extent compensated for—by a sign change on oil price and GDP per capita variables. The negative coefficient on $lbrent$ highlights the linkages between the global oil price and currencies of countries that rely on their oil exports. This long-run relationship appears important for all countries in the sample and not only those in D10 and OPEC. By way of example, column (8) suggests that a 10% increase in the price of oil is expected to cause a 3% appreciation of the current in D10 countries. This pattern is not observed for real GDP per capita. In non-OPEC countries, an increase in $lrgdpch$ is expected to have a positive impact on the real exchange rate—a depreciation. This is reversed in OPEC countries such that an increase in real per capita GDP leads to an appreciation of the currency. Lastly, the short-run adjustment terms show a clear decreasing pattern with increasing specification size in OPEC countries—see columns (9) through (12) of Table 4.14. This signals that the equilibrium adjustment of the real exchange rate may have transmissions mechanisms through variables in addition to oil rents. This is hardly surprising given the complexity of real exchange rate dynamics and strong linkages within an economy but differs from what I observed in Table 4.13 when per capita oil rents were used.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
loilrents_pc	-0.055***	-0.020	-0.067**	-0.066**	-0.068***	-0.007	-0.142***	-0.121***	-0.407***	-0.956***	-1.190***	-1.157***
	(0.001)	(0.454)	(0.013)	(0.012)	(0.007)	(0.868)	(0.001)	(0.008)	(0.000)	(0.000)	(0.000)	(0.000)
lbrent	—	-0.089**	-0.053	-0.071**	—	-0.177***	-0.048	-0.071	—	0.930***	1.051***	1.014***
		(0.022)	(0.151)	(0.049)		(0.004)	(0.424)	(0.235)		(0.000)	(0.000)	(0.000)
lrgdpch	—	—	0.272***	0.126**	—	—	0.380***	0.248***	—	—	0.506	0.582
			(0.000)	(0.015)			(0.000)	(0.001)			(0.173)	(0.106)
lopenc	—	—	—	0.005***	—	—	—	0.004***	—	—	—	-0.002
				(0.000)				(0.000)				(0.265)
Speed of adjustment	-0.238***	-0.236***	-0.249***	-0.242***	-0.254***	-0.267***	-0.281***	-0.272***	-0.111**	-0.132**	-0.108**	-0.108**
Half Lifetime (years)	2.55	2.58	2.42	2.50	2.37	2.23	2.10	2.18	5.87	4.91	6.07	6.05
Subsample	World excl. OPEC				D10 excl. OPEC				OPEC			
N	32				16				10			
Number of observations	819				415				245			

Table 4.13. Dynamic OLS results using oil rents per capita. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Columns (1) through (4) use the whole sample excluding OPEC countries, whereas columns (5) through (8) restrict it to D10 countries excluding OPEC, and (9) through (12) to OPEC countries only. In each of these cases, the model specification becomes increasingly more general such that columns (1), (5), and (9) are based a DOLS regression of real exchange rate on oil rents per capita. In turn, columns (2), (6), and (10) come from regressions with oil rents per capita and oil price as explanatory variables.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
loilrents_rgdp	-0.205	0.338	0.279	0.441**	-0.128	0.691**	0.566**	0.634**	3.297***	4.701***	4.561***	4.524***
	(0.228)	(0.122)	(0.193)	(0.033)	(0.470)	(0.016)	(0.045)	(0.016)	(0.000)	(0.000)	(0.000)	(0.000)
lbrent	—	-0.168***	-0.187***	-0.210***	—	-0.296***	-0.314***	-0.309***	—	-0.923***	-0.789***	-0.794***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
lrgdpch	—	—	0.163***	0.032	—	—	0.201***	0.098*	—	—	-0.472**	-0.359**
			(0.000)	(0.477)			(0.000)	(0.096)			(0.014)	(0.025)
lopenc	—	—	—	0.005***	—	—	—	0.005***	—	—	—	-0.002**
				(0.000)				(0.000)				(0.012)
Speed of adjustment	-0.211***	-0.207***	-0.209***	-0.203***	-0.220***	-0.226***	-0.234***	-0.225***	-0.107***	-0.263***	-0.227***	-0.239***
Half Lifetime (years)	2.92	2.99	2.95	3.06	2.80	2.70	2.60	2.72	6.11	2.27	2.70	2.54
Subsample	World excl. OPEC				D10 excl. OPEC				OPEC			
N	32				16				10			
Number of observations	819				415				245			

Table 4.14. Dynamic OLS results using oil rents as a percentage of GDP. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Columns (1) through (4) use the whole sample excluding OPEC countries, whereas columns (5) through (8) restrict it to D10 countries excluding OPEC, and (9) through (12) to OPEC countries only. In each of these cases, the model specification becomes increasingly more general such that columns (1), (5), and (9) are based a DOLS regression of real exchange rate on oil rents per capita. In turn, columns (2), (6), and (10) come from regressions with oil rents per capita and oil price as explanatory variables.

4.6.3 Mean Group and Pooled Mean Group Results

In addition to the DOLS approach, I re-estimated the ECM using Mean Group and Pooled Mean Group estimators. Although not very common within the B-S literature, these estimators exploit the large-N, large-T panel structure effectively. The general model has the following form:

$$lrer_{it} = \sum_{j=1}^{p} \lambda_{ij} lrer_{i,t-j} + \sum_{j=0}^{q} \eta'_{ij} x_{i,t-j} + \mu_i + \varepsilon_{it} \tag{4.6}$$

where x_{it} is a $k \times 1$ vector of explanatory variables for group i, μ_i represent country fixed effects, λ_{ij} are scalar coefficients, η_{ij} is a $k \times 1$ vector of coefficients to be estimated, and ε_{it} denote the error term. If the variables are $I(1)$ and cointegrated, they respond to deviation from the long-run equilibrium. Therefore, it is helpful to reparametrise this general model into the ECM form as follows:

$$\Delta lrer_{it} = \varphi_i (lrer_{i,t-1} - \beta_i' X_{it}) + \sum_{j=1}^{p-1} \lambda_{ij}^{*} \Delta lrer_{i,t-j} + \sum_{j=0}^{q-1} \eta_{ij}'^{*} \Delta X_{i,t-j} + \mu_i + \varepsilon_{it} \tag{4.7}$$

where $\varphi_i = -(1 - \sum_{j=1}^{p} \lambda_{ij})$, $\beta_i = \sum_{j=0}^{q} \eta_{ij} / (1 - \sum_k \lambda_{ik})$, $\lambda_{ij}^{*} = -\sum_{m=j+1}^{p} \lambda_{im}$ with $j = 1, 2, \dots, p-1$, and $\eta_{ij}^{*} = -\sum_{m=j+1}^{q} \eta_{im}$, with $j = 1, 2, \dots, q-1$.

In most cases, including mine, the parameter of interest is φ_i, which represents the speed of adjustment of the real exchange rate towards the long-run equilibrium. As in all ECM parameterisations, if a long-run relationship exists among the variables, the speed of adjustment is expected to be negative and significant. The parameter vector β_i' contains the long-run coefficients and has an important interpretation in this context.

As noted by Frank & Blackburne (2007), when N and T are large, equation 4.7 can be estimated by a few methods; the spectrum of estimators runs from fixed effects estimation to Pesaran & Smith's (1995) Mean Group estimator. If the former is implemented, the intercepts are allowed to vary across panel units, but not the slope coefficients. FE is consistent only if the slope parameters are homogeneous. If they are not, the MG estimator, which is on the other end of the spectrum, should be used. MG estimates a separate set of coefficients for each panel unit and calculates the arithmetic average. This allows all parameters, including error variances, to vary across countries. In this context, this approach has an *a priori* advantage, since the countries in the dataset have some heterogeneous characteristics. A hybrid approach between these two estimators is Pesaran et al.'s (1999) Pooled Mean Group estimator, which pools the long-run coefficients across panels, while averaging intercepts, short-run coefficients and error variances. In order to select the appropriate approach between MG and PMG estimator, I use a traditional Hausman test. If the null hypothesis that the two sets of coefficients are not systematically different is not rejected, PMG is preferred as a more efficient estimator. Otherwise, MG is more appropriate.

Before turning to empirical results, it is helpful to form *ex ante* expectations about the choice of estimator. As hinted at earlier, a heterogenous group of countries would warrant the use of the MG estimator. However, we can observe efficiency gains by using the PMG estimator when dealing with countries with common long-run coefficients. Given the wide country coverage in my global dataset, it would be appropriate to expect different long-run coefficients. However, it is conceivable that smaller subsamples, such as OPEC countries, share a common long-run relationship, even if their short-run dynamics differ. The same could be said for D10 countries, since the oil sector forms a non-negligible part of their economies. In general, the link between oil rents and real exchange rates is my focus, so a different long-run relationship between per capita GDP and the real exchange rate in a given group of countries is of little interest. To investigate this formally, I opted for a standard Hausman test approach with the expectation that subsamples used in the estimation are likely to share a common long-run coefficient. Table 4.15 shows the results from the models that have been selected by the test.[28]

Focussing on columns (1) through (4), I observe negative and statistically significant speed of adjustment coefficients across all specifications and estimation techniques. These coefficients as well as others in the table are estimated precisely with narrow confidence intervals. For example, the confidence interval around the speed of adjustment terms in columns (5) and (6) were [-0.35, -0.14] and [-0.33, -0.14]

[28] Note that Azerbaijan, Romania, and Sudan were dropped from the sample for this analysis due to their short time series.

respectively. These findings point to the existence of a cointegrating relationship in each specification and provide a robustness check to the cointegration tests discussed in Section 4.6.1. Columns (1) and (2) show PMG results, since relevant Hausman tests failed to reject the null hypothesis that MG and PMG results are not systematically different. The estimated long-run coefficients on oil rents per capita and oil price variables are also significantly different from zero in these columns. Using column (1) as an example, I find that a 10% increase in oil rents per capita leads to a two percent appreciation of the currency in the long run. This provides evidence for the B-S hypothesis, but the effect is not very pronounced. Turning to column (2) changes this interpretation. When the per barrel oil price was also considered, the long-run coefficient on per capita oil rents became positive. This suggests that a 10% increase in oil rents per capita is expected to cause a 2% depreciation in the real exchange rate, which would be compensated for by the negative long-run coefficient estimated on the price of oil. Given the coefficients, the estimated effect of a 10% oil price rise would be a 4% appreciation of the currency.

Dependent variable: *Δlrer*												
Specifications	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Hausman (MG vs PMG)	PMG	PMG	DOLS	DOLS	PMG	PMG	DOLS	DOLS	PMG	PMG	DOLS	DOLS
Speed of adjustment	-0.220***	-0.245***	-0.238***	-0.236***	-0.246***	-0.237***	-0.254***	-0.267***	-0.168***	-0.225***	-0.111**	-0.132**
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.047)	(0.023)
Long-run Coefficients												
loilrents_pc	-0.162***	0.204***	-0.055***	-0.020	-0.158***	-0.147***	-0.068***	-0.007	-0.205***	0.113	-0.407***	-0.956***
	(0.000)	(0.000)	(0.001)	(0.454)	(0.000)	(0.000)	(0.007)	(0.868)	(0.000)	(0.217)	(0.000)	(0.000)
lbrent	—	-0.407***	—	-0.089**	—	-0.020	—	-0.177***	—	-0.481**	—	0.930***
		(0.000)		(0.022)		(0.748)		(0.004)		(0.002)		(0.000)
Half Lifetime (years)	2.8	2.5	2.55	2.58	2.5	2.6	2.37	2.23	3.8	2.7	5.87	4.91
Subsample	World excl. OPEC				D10 excl. OPEC				OPEC			
N	29				14				10			
N x T	775		819		392		415		265		245	
Log likelihood	725.3	758.6	437.5	439.1	331.5	341.9	431.4	431.7	196.4	204.0	415.8	427.7

Table 4.15. Error correction model estimation results using oil rents per capita. P-values in parentheses. Hausman test was used to determine whether mean group or pooled mean group results should be reported. Half lifetime was calculated as $\ln(0.5) / \ln(1 + \varphi)$. DOLS results reproduced from Table 4.13 for ease of comparison here. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Half-life, calculated as $\ln(0.5) / \ln(1 + \varphi)$, was approximately 2.5 years. This implies that we may expect the real exchange rate to close half of the gap between its current level and the long-run equilibrium in a 2.5-year period. DOLS results reproduced here are a subset of those presented in Table 4.13 and are shown for ease of comparison. Relative to PMG results, DOLS estimates of the long-run parameters are smaller in absolute value. However, the speed of adjustment as well as half-life figures are similar in magnitude. This pattern holds for the smaller D10 subsample, whose results are shown in columns (5) through (8). PMG estimates for D10 countries excluding OPEC members generally showed a slightly quicker speed of adjustment: half-lives were calculated as 2.8 and 2.5 years in columns (1) and (5), respectively. This is in agreement with DOLS results, where I observed the same pattern in columns (3) and (7) as well as (4) and (8).

Columns (3) and (4) and, to a lesser extent, columns (1) and (2) viewed as pairs signal that, for non-OPEC countries, the inclusion of oil price in the specification has implications for the sign, size, and statistical significance of the coefficient estimate on oil rents per capita. More specifically, including the Brent price appears to increase the standard error and therefore reduce significance of oil rents. This is demonstrated by the confidence intervals corresponding to the point estimates in question. The confidence interval for the coefficient on *loilrents_pc* in column (3) was [-0.09, -0.02], whereas that in column (4) was [-0.07, 0.03]. This pattern is less clear in D10 and OPEC countries where oil rents retain their importance in larger model specifications. Even so, column (10) suggests that only the oil price is cointegrated with the real exchange rate, since the long-run coefficient on oil rents per capita is not significant and that on Brent is. This is further evidenced by columns (4) and (8), since oil rents lose their statistical significance when Brent is added to the model. Recall from columns (9) through (12) of Table 4.13, however, that in OPEC countries, oil rents per capita appeared to matter independently of model specification. Having observed this, investigating the behaviour in non-OPEC and non-D10 countries could shed light on the underlying mechanism of this pattern. Table 4.16 shows DOLS estimation results of the ECM using oil rents per capita. The evidence here, especially in columns (14) and (15), points to the absence of a long-run relationship between oil rents or oil price and the real exchange rate. Real GDP per capita and openness to trade appear to matter more in this set of countries, since there is no strong link between these countries' economies and the oil sector. In practice, this is represented by a cointegrating relationship between the real exchange rate and real GDP per capita or openness to trade as opposed to oil rents or Brent.

Variables	(13)	(14)	(15)	(16)
loilrents_pc	-0.040* (0.062)	-0.029 (0.348)	-0.026 (0.387)	-0.058* (0.064)
lbrent	—	-0.006 (0.890)	-0.018 (0.680)	-0.046 (0.250)
lrgdpch	—	—	0.220*** (0.001)	-0.044 (0.568)
openc	—	—	—	0.008* (0.060)
Speed of adjustment	-0.213***	-0.211***	-0.203***	-0.183***
Half Lifetime (years)	2.90	2.92	3.06	3.43
Subsample	World excl. D10			
N	16			
Number of observations	404			

Table 4.16. Dynamic OLS error correction results using oil rents per capita. P-values in parentheses. Half lifetime was calculated as $\ln(0.5) / \ln(1 + \varphi)$. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Lastly, I move on to OPEC output shown in columns (9) through (12) of Table 4.15. I interpret these coefficients cautiously, keeping in mind the discussion of OPEC countries in Section 4.6.1 on cointegration testing. Firstly, I note that the highly significant speed of adjustment coefficients contradicts some of the earlier findings using Pedroni and Westerlund panel cointegration tests: both PMG and DOLS ECM estimations point to the existence of a cointegrating relationship. The speed of adjustment coefficients are smaller, in absolute value, than in the rest of the sample and imply a half-life of about five to six years when using DOLS and three to four years when using PMG. Secondly, despite a smaller—in absolute value—speed of adjustment coefficient, I observe a larger—again in absolute value—long-run coefficient on per capita oil rents. DOLS results in column (12) imply a nearly unit-elastic long-run coefficients, such that a 10% increase in oil rents per capita leads to approximately 10% appreciation of the currency. In addition to being much smaller than DOLS long-run coefficient estimates, PMG estimates are more sensitive to model specification. Even so, the significant coefficient in column (9) implies a 2% appreciation of the currency as a result of a 10% increase in oil rents per capita. As a final comment, a likely cause for the sensitivity to model specification observed here is data availability and the fact that the number of panels is small for both OPEC and

D10 excluding OPEC subsamples. Given the asymptotic properties of the PMG estimator and the requirement for both N and $T \rightarrow \infty$, I acknowledge the unreliability of these estimates and put more weight on DOLS results. In this sense, I include PMG results as a robustness check as opposed to a conclusive estimate.

In the output Table 4.15 above, I have opted for smaller model specifications consisting of per capita oil rents and oil price. This was to focus on the main message, since including real GDP per capita and openness to trade did not lead to a previously-unobserved outcome. To see this, I turn to Table 4.17 below, which summarises the PMG results estimated using the largest subsample. Note that, as above, the Hausman test was used to determine whether MG or PMG is more appropriate.

Dependent variable: *Δlrer*

Specifications	(1)	(2)	(3)	(4)
Hausman (MG vs PMG)	PMG	PMG	PMG	PMG
Speed of adjustment	-0.220***	-0.245***	-0.213***	-0.167***
	(0.000)	(0.001)	(0.000)	(0.000)
Long-run Coefficients				
loilrents_pc	-0.162***	0.204***	-0.089***	0.122***
	(0.000)	(0.000)	(0.000)	(0.001)
lbrent	—	-0.407***	-0.075**	-0.172***
		(0.000)	(0.048)	(0.000)
lrgdpch	—	—	-0.188**	-0.595***
			(0.023)	(0.000)
lopenc	—	—	—	1.252***
				(0.000)
Half Lifetime (years)	2.8	2.5	2.9	3.8
Subsample	World excl. OPEC			
N	29			
N x T	775			
Log likelihood	725.345	758.594	835.311	1004.21

Table 4.17. Pooled Mean Group error correction results using oil rents per capita. P-values in parentheses. Half lifetime was calculated as $\ln(0.5) / \ln(1 + \varphi)$. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Although I observe negative and statistically significant speed of adjustment coefficients across all specifications, long-run coefficients behave unexpectedly in columns (2) and (4). More specifically, *loilrents_pc* has a positive coefficient that cannot simply be explained by model specification. Interestingly, the coefficient in question becomes negative when real GDP per capita is added as an additional explanatory variable but reverts to positive when openness to trade is introduced. To investigate this further, I analysed output from other subsamples and a pattern emerged. There is some evidence that the coefficients on real GDP per capita and openness to trade are heterogeneous across countries unlike oil rents per capita and oil price, particularly in D10 and OPEC countries. Estimating a simple specification with GDP per capita as the only explanatory variable confirmed this observation. The inverted sign on oil rents can, at least partially, be explained by the link between $loilrents\_pc$ and $lrgdpch$, especially in D10 and OPEC countries. Based on Balassa's (1964) original work and the findings elsewhere in this chapter, I would expect a negative and significant coefficient. Given that the speed of adjustment coefficient is negative and significantly different from zero, this behaviour could be attributed to the correlation between the three explanatory variables in specification (3) in Table Table 4.17. Calculating a simple correlation matrix shows that the correlation between $loilrents\_pc$ and $lrgdpch$ is approximately 0.5, which appears to be sufficiently high to cause misleading results. Due to these observations, I have opted for smaller model specifications.

Having concluded the analysis using one potential measure for oil rents, oil rents per capita, I now turn to the alternative measure, oil rents as a percentage of GDP. Table 4.18 was produced as an analogue to Table 4.15 and provides a summary of the ECM results using $loilrents\_rgdp$. As observed earlier, the short-run adjustment coefficient is negative and significantly different from zero across all subsamples and model specifications. Estimated half lifetime durations are also similar to those calculated for per capita oil rents, although the adjustment appears slower here. Sign-switching of the oil rents variable observed earlier applies here too: columns (1) and (2), columns (5) and (6), and columns (9) and (10) demonstrate this. Unlike the results so far, PMG estimates are more robust to increasing model specification here than DOLS in non-OPEC countries. As an example, in the largest subsample with all countries excluding OPEC, PMG coefficient estimates on oil rents as a percentage of GDP remain significantly different from zero—columns (1) and (2)—whereas those indicated by DOLS do not—columns (3) and (4). Turning now to columns (9) through (12), the two estimation techniques point to the same relationship between rents and real exchange rates in OPEC countries. There is a short-run adjustment in the real exchange rate when oil rents' share of GDP changes. As in Section 4.6.2, the long-run coefficient on oil rents is not negative as expected. Based on this outcome, I find evidence of a long-run link between real exchange rates and oil rents but in the opposite direction of the theoretical prediction. I investigate this further in this section and the next. To ensure the findings in this section did not suffer from empirical modelling inaccuracies, I reviewed not only the point estimates but also confidence intervals and other estimation characteristics. The changing parameter estimates and statistical significance are due to different coefficients and not a side effect of model choice.

Dependent variable: *Δlrer*												
Specifications	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Hausman (MG vs PMG)	PMG	PMG	DOLS	DOLS	PMG	PMG	DOLS	DOLS	PMG	PMG	DOLS	DOLS
Speed of adjustment	-0.157***	-0.148***	-0.211***	-0.207***	-0.181***	-0.143***	-0.220***	-0.226***	-0.133***	-0.237***	-0.107***	-0.263***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.007)	(0.000)	(0.000)	(0.000)	(0.002)	(0.007)	(0.000)
Long-run Coefficients												
loilrents_rgdp	-0.449**	8.136***	-0.205	0.338	-0.506***	1.441***	-0.128	0.691**	-1.883***	4.099***	3.297***	4.701***
	(0.020)	(0.000)	(0.228)	(0.122)	(0.010)	(0.000)	(0.470)	(0.016)	(0.002)	(0.000)	(0.000)	(0.000)
lbrent	—	-0.244***	—	-0.168***	—	-0.365***	—	-0.296***	—	-0.822***	—	-0.923***
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Half Lifetime (years)	4.1	4.3	2.92	2.99	3.5	4.5	2.80	2.70	4.9	2.6	6.11	2.27
Subsample	World excl. OPEC				D10 excl. OPEC				OPEC			
N	29				14				10			
N x T	775		819		392		415		265		245	
Log likelihood	725.3	758.6	437.5	439.1	331.5	341.9	431.4	431.7	196.4	204.0	415.8	427.7

Table 4.18. Error correction model estimation results using oil rents as a percentage of GDP. P-values in parentheses. Hausman test was used to determine whether mean group or pooled mean group results should be reported. Half lifetime was calculated as $\ln(0.5) / \ln(1 + \varphi)$. DOLS results reproduced from Table 4.13 for ease of comparison here. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

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In an effort to disentangle the observation I have made here, I refocus attention to other subsamples. Further investigation of D10 countries excluding OPEC revealed that there is reason to believe real exchange rates react differently to changes in oil rents and other explanatory variables across countries. Table 4.19 corroborates this claim, since the Hausman test suggested systematic differences in coefficient estimates of MG and PMG for larger specifications shown in columns (3) and (4).

Dependent variable: *Δlrer*

Specifications	(1)	(2)	(3)	(4)
Hausman (MG vs PMG)	PMG	PMG	MG	MG
Speed of adjustment	-0.181***	-0.143***	-0.483***	-0.515***
	(0.000)	(0.007)	(0.000)	(0.000)
Long-run Coefficients				
loilrents_rgdp	-0.506***	1.441***	3.095***	2.345***
	(0.010)	(0.000)	(0.000)	(0.005)
lbrent	—	-0.365***	-0.465***	-0.485***
		(0.000)	(0.000)	(0.000)
lrgdpch	—	—	0.286	0.667
			(0.326)	(0.176)
lopenc	—	—	—	0.296
				(0.297)
Half Lifetime (years)	3.5	4.5	1.1	1.0
Subsample	D10 excl. OPEC			
N	14			
N x T	392			
Log likelihood	347.418	418.967	519.004	582.323

Table 4.19. Mean Group and Pooled Mean Group error correction results using oil rents as a percentage of GDP. Half lifetime was calculated as $\ln(0.5) / \ln(1 + \varphi)$. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

The unexpected sign on oil rents in these countries could have a few explanations in line with the B-S hypothesis. First, although oil rents are important in D10 countries, they may not be the main driver of economic activity at least temporarily.[29] Second, the share of rents may fall not because the productivity of the oil sector has declined but because other sectors have grown. If this secondary growth is not in a tradable sector, the importance of oil rents and exports could be masked by an increase in GDP in general. Although unlikely to be the case for all OPEC countries, recent years

[29] Recall that D10 countries are those in which oil rents accounted for at least 10% of the country's GDP in 2008.

have seen growth in sectors outside of oil in some of these countries. This highlights the difference between the two measures of oil rents used in this analysis. Oil rents per capita are not as sensitive to changes in the composition of the economy as oil rents as a percentage of GDP. It may, therefore, be the preferred measure if there is evidence for strong growth in non-oil activities in a group of countries. Based on columns (9) through (12) in Table Table 4.15 and Table Table 4.18, there is empirical evidence of this phenomenon in OPEC countries. This implies that parameter estimates based on $loilrents\_rgdp$ measure more than the B-S effect. The next section focuses on OPEC countries to investigate the failure of B-S assumptions.

4.6.4 Further Investigation of OPEC Countries

The discussion in this section emphasises per capita oil rents, since Pedroni tests involving this variable did not find a cointegrating relationship between rents and real exchange rate. Westerlund tests of both oil rents variable found no cointegrating relationship as well, so reference is also made to oil rents as a percentage of GDP. To investigate the potential lack of a long-run relationship, I opted for country-by-country cointegration tests based on the traditional Engle & Granger (1987) approach. As a part of this approach, I applied ADF tests on the residuals from static regressions of the real exchange rate on oil rents. Critical values for this test differ from the standard ADF test and are provided by MacKinnon (2010). Although the results are robust to lag length selection, optimal lag length was chosen according to Ng & Perron (1995). As shown in Table 4.20, cointegration was identified for only three countries at the 5% level and four countries at the 10% level.[30] Further investigation revealed that real exchange rate and the oil price are not cointegrated either. Moreover, if oil price, oil rents, and the real exchange rate were used in the same long-run equation, there was no strong evidence for cointegration in these countries.

[30] Ecuador was dropped from the sample due to its short time series.

Country Code	Optimal Lag Length	Maximum Lag Length	Test statistic	1% cr.value	5% cr.value	10% cr.value	No of obs
AGO	0	8	-1.60	-3.77	-3.517	-3.091	15
ARE	5	8	-3.75**	-3.77	-2.96	-2.489	15
DZA	0	9	-1.81	-3.77	-3.273	-2.96	35
IRQ	5	9	-3.52**	-3.77	-2.988	-2.683	30
LBY	0	8	-2.40	-3.77	-3.517	-3.091	15
NGA	0	9	-2.56	-3.77	-3.373	-3.039	26
QAT	6	8	-2.91*	-3.77	-3.024	-2.482	15
SAU	0	8	-2.83	-3.77	-3.517	-3.091	15
VEN	3	8	-3.44**	-3.77	-3.079	-2.574	12

Table 4.20. Country-by-country cointegration tests for OPEC countries using oil rents per capita. Optimal lag length determined according to Ng and Perron (1995), and maximum lag length determined by Schwert criterion. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

One potential explanation for the difference in the exchange rate behaviour of OPEC countries from the other oil exporters in the sample could be linked to the countries' currency regimes. Appreciation of the real exchange rate could be due to an appreciation of the nominal exchange rate or an increase in the price level. The latter change, when caused by an increase in productivity of tradable goods and services, is the mechanism behind the B-S hypothesis. Devereux (2014) noted that the nominal exchange rate fluctuations introduce noise into the estimation of the B-S effect as they tend to change more rapidly compared to the price level. In practice, for much of history, most OPEC countries did not have free floating currency regimes. Saudi Arabia, Qatar, and the United Arab Emirates all peg their currencies to the US dollar and have done so throughout the estimation period. Similarly, Venezuela pegged their currency to the US dollar in 2003, and Ecuador adopted the US dollar as an official currency in 2000 after almost two decades of a crawling peg. Iraq's currency regime is a managed float, but the official rate has been pegged to the US dollar at various times. Lastly, Libya's currency is pegged to a composite exchange rate anchor.[31] In theory, for a pegged currency, it should be easier to separate changes in the real exchange rate attributable to adjustments in the price level versus the nominal exchange rate, since the numerator of the real exchange rate is fixed. It is possible that the long-run relationship found in D10 minus OPEC countries is driven by the nominal exchange rate rather than the price level adjustments, and the absence of the

[31] The discussion here has benefited from Reinhart & Rogoff's (2004) exchange rate classification.

B-S mechanism is just more prominent in OPEC countries. This is exacerbated by the fact that the nominal exchange rate in some non-OPEC countries—Russia, for example—is likely to be highly responsive to oil price fluctuations. This phenomenon would be most evident in countries where oil represents a large fraction of exports. As an example, despite its short time series, Sudan was identified to have a cointegrating relationship between its real exchange rate and oil rents. Considering 85% of Sudan's 2009 exports consisted of crude oil and refined petroleum products,[32] it is possible that the relationship detected earlier is not driven by the B-S mechanism but by the nominal appreciation of the currency. This is more likely to occur for oil than other tradable commodities, since oil has a price inelastic demand in the short- to medium-run.

To test the proposition above, Westerlund cointegration tests have been conducted using log of nominal exchange rate, $lxrat$, and log of PPP price level, $lppp$, as dependent variables and oil rents per capita or oil rents as a percentage of GDP as an independent variable. However, the results presented in Table 4.21 do not support this proposition. There is strong evidence of cointegration between both the nominal exchange rate and the price level and oil sector productivity—measured by both oil rents variables—in non-OPEC countries. Neither of the two dependent variables are cointegrated with either of the oil rents measures in OPEC countries.

[32] According to The Atlas of Economic Complexity, http://atlas.cid.harvard.edu/

Dependent variable	Independent variable		(1)	(2)	(3)
lxrat	*loilrents_pc*	Pt	-16.64***	-30.30***	1.17
			(0.000)	(0.000)	(0.122)
		Pa	-6.00***	-10.28***	1.14
			(0.000)	(0.000)	(0.873)
	loilrents_rgdp	Pt	-18.59***	6.54***	2.97
			(0.000)	(0.000)	(0.999)
		Pa	-7.14***	1.79**	2.07
			(0.000)	(0.037)	(0.981)
lppp	*loilrents_pc*	Pt	-19.10***	-44.88***	0.19
			(0.000)	(0.000)	(0.426)
		Pa	-7.82***	-18.32***	1.28
			(0.000)	(0.000)	(0.900)
	loilrents_rgdp	Pt	-24.88***	-14.80***	3.94
			(0.000)	(0.000)	(1.000)
		Pa	-10.72***	-5.37***	2.64
			(0.000)	(0.000)	(0.996)
Subsample			World-OPEC	D10-OPEC	OPEC
N			30	15	10
Lags & leads			1	1	1

Table 4.21. Westerlund (2007) cointegration tests for nominal exchange rate, $lxrat$, and price level, $lppp$. P-values in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. H_0: No cointegration in any panel ($\phi_i = 0\ \forall i$; H_a: Cointegration in the panel as a whole ($\phi_i < 0\ \forall i$). Two countries, Romania and Sudan, were dropped for these tests due to their short time series.

Another potential explanation for this observation is that some assumptions of the B-S hypothesis may not hold in practice in the context of OPEC countries. More specifically, the price level in these countries may not be adjusting as expected when productivity in a tradable sector rises. In fact, most OPEC countries appear to have a lower price level than non-OPEC countries with similar per capita income levels. Figure 4.18 provides evidence for this. Of particular interest are Qatar, Saudi Arabia, UAE, and Libya, which have lower-than-expected price levels. These countries also share migration policies that allow large numbers of temporary low-wage workers (De Bel-Air, 2014c, 2014b, 2014a).[33] Given the migration policies in these countries

[33] For Libya, we are referring to the pre-civil war. "Migrant workers make up the majority of the population in Bahrain, Oman, Qatar, and the United Arab Emirates (and more than 80 per cent of the population in Qatar and the United Arab Emirates); while in construction and domestic work in Gulf States, migrant workers make up over 95 per cent of the work force." (Labour Migration (Arab

and how actively local and migrant workers are differentiated, these migrants often receive much lower wages and depress the overall wage level in the country. In many ways, migrant and local workers' wages do not affect each other. These workers could lower productivity in the non-tradable sector relative to a non-OPEC country like Norway as well. This dynamic could effectively undermine the B-S assumption that workers can freely move between tradable and non-tradable sector. In such a case, wages in the non-tradable sector would not adjust, or adjust only partially, to wage fluctuations in the tradable sector and keep the overall price level low.

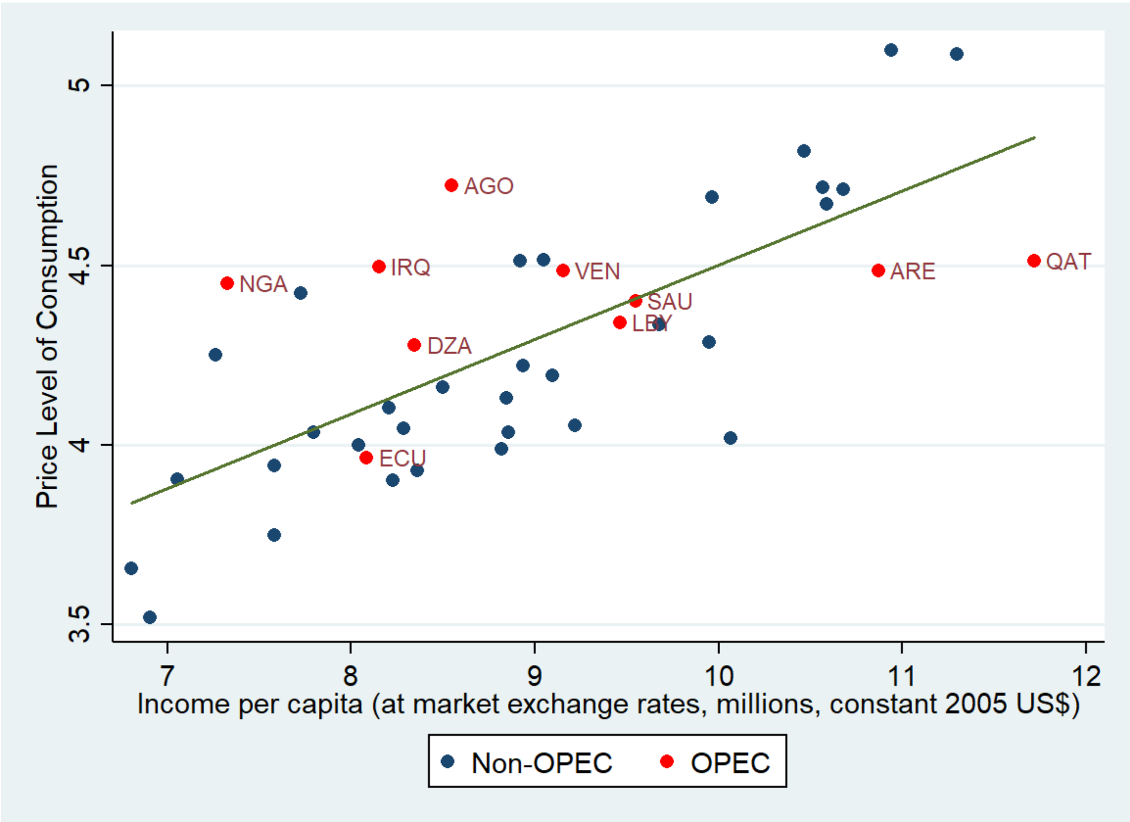

Figure 4.18. Natural log of price level of consumption against per capita income in OPEC and non-OPEC countries in 2008.

This observation in conjunction with the shortcomings of the dataset and power limitations of individual cointegration tests meant that, in principle, it is difficult to reject the null of no cointegration for an individual country even when behaviour does follow the B-S hypothesis. When taken as a panel, cointegration could still be

States), International Labor Organization, Accessed 08/04/2017, http://www.ilo.org/beirut/areasofwork/labour-migration/lang--en/index.htm)).

rejected when countries exhibit different behaviour, which appears to be the case for OPEC.

4.7 Conclusion

In this chapter, I attempted to identify whether changes in oil sector productivity can explain fluctuations of the real exchange rate in oil-exporting countries. This could, in turn, explain whether the countries in my dataset are affected by the Dutch disease and shed light on the wider resource curse theme. The analysis was based on a unique dataset that allowed me to calculate profits made in the oil sector in a large number of countries over a relatively long period. This enabled me to target increases in the productivity of the oil sector without having to use noisier traditional measures, such as GDP, as a proxy for productivity. Identifying such an impact carries importance for policy-making, especially in developed and developing countries as noted by Chen & Rogoff (2002).

I found that the B-S mechanism holds in some oil-exporting countries but not all. For most countries, the relationship is non-negligible in size and statistically significant. Surprisingly, countries that are not OPEC members showed a particularly significant link between their real exchange rates and oil rents. Even so, the largest observed effect was for OPEC countries: nearly 12% appreciation in the real exchange rate in response to a 10% increase in oil sector productivity measured as oil rents per capita. Oil prices were identified as another covariate with coefficients of a similar size and sign.

Two measures of oil rents were captured throughout the analysis and discussion as a robustness check and to discern whether oil rents are expected to have a greater impact on the real exchange rate in countries where the oil sector constitutes a larger share of GDP. There was some evidence towards this, especially since oil rents as a percentage of GDP were cointegrated with the real exchange rate in OPEC countries, whereas oil rents per capita were not. Both measures indicated an ambiguous relationship in OPEC countries with some coefficient estimates having an unexpected sign. In general, oil rents as a percentage of GDP is preferable to oil rents per capita, since the latter does not consider the size of the oil sector within the economy. By way of example, I would expect a one-dollar increase in oil rents to have a larger impact in Kuwait than in Australia. Further analysis on OPEC countries revealed no link between oil rents and the nominal exchange rate or the price level. Sections 4.6.2 through 4.6.4 have discussed potential explanations for this unexpected result. I found some evidence, as in Korhonen & Juurikkala (2009), that the real oil price has an impact on the real exchange rate. In practice, at least one assumption of the B-S hypothesis appears to fail in some OPEC countries due to the lack of free movement of labour between tradable and non-tradable sectors.

Overall, I find evidence for the B-S hypothesis in most oil-exporting countries. Further, the larger the share of GDP oil sector accounts for, the larger the impact of oil rents on the real exchange rate is expected to be. I also identified patterns that contradict this, which suggests other potential explanations of resource curse should be considered. In this sense, my results are consistent with Van der Ploeg (2011), who found that although the B-S mechanism is responsible for the resource curse to a certain extent, the main contributors are corruption, low quality of institutions, and underdeveloped financial systems that fail to mitigate the high volatility of commodity prices. Future work in this context would benefit from a larger dataset, especially in the time dimension.

4.8 Chapter Appendix

ISO-code	0 lags		1 lags		2 lags		0 lags		1 lags		2 lags	
	without trend						with trend					
	p-value	n	p-value	n	p-value	n	p-value	n	p-value	n	p-value	n
AGO	0.715	23	0.845	22	0.923	21	0.671	23	0.683	22	0.895	21
ARE	0.263	23	0.245	22	0.402	21	0.509	23	0.415	22	0.722	21
ARG	0.585	17	0.528	16	0.818	15	0.083	17	0.007	16	0.431	15
AUS	0.000	36	0.175	35	0.325	34	0.000	36	0.252	35	0.402	34
AZE	0.683	7	0.984	5	1.000	3	0.077	7	0.943	5	1.000	3
BRA	0.484	16	0.384	15	0.463	14	0.335	16	0.012	15	0.310	14
BRN	0.543	35	0.524	34	0.550	33	0.832	35	0.779	34	0.854	33
CAN	0.179	20	0.991	16	0.842	12	0.304	20	0.996	16	0.980	12
CHN	0.644	12	0.183	11	0.624	10	0.082	12	0.245	11	0.781	10
COG	0.006	32	0.056	31	0.329	30	0.052	32	0.212	31	0.661	30
COL	0.233	23	0.577	22	0.770	21	0.254	23	0.394	22	0.835	21
DNK	0.406	30	0.009	29	0.491	28	0.017	30	0.000	29	0.125	28
DZA	0.293	44	0.345	43	0.313	42	0.628	44	0.677	43	0.633	42
ECU	0.416	12	0.026	11	0.863	10	0.001	12	0.003	11	0.599	10
EGY	0.027	35	0.131	34	0.232	33	0.063	35	0.221	34	0.346	33
GAB	0.148	35	0.137	34	0.254	33	0.337	35	0.271	34	0.484	33
GBR	0.000	33	0.207	32	0.146	31	0.000	33	0.426	32	0.359	31
GNQ	0.911	15	0.958	13	0.951	11	0.907	15	1.000	13	1.000	11
IDN	0.207	41	0.189	40	0.235	39	0.451	41	0.368	40	0.363	39
IND	0.163	10	0.676	9	0.642	8	0.729	10	0.980	9	0.987	8
IRQ	0.276	39	0.339	38	0.284	37	0.528	39	0.596	38	0.447	37
ITA	0.183	35	0.282	34	0.416	33	0.288	35	0.396	34	0.563	33
KAZ	0.191	11	0.880	9	0.000	8	0.084	11	0.884	9	0.990	8
LBY	0.572	23	0.521	22	0.792	21	0.634	23	0.522	22	0.892	21
MEX	0.597	15	0.590	14	0.870	13	0.462	15	0.338	14	0.484	13
MYS	0.000	36	0.077	35	0.037	34	0.011	36	0.306	35	0.193	34
NGA	0.262	35	0.336	34	0.459	33	0.590	35	0.593	34	0.839	33
NOR	0.117	31	0.302	30	0.785	29	0.067	31	0.058	30	0.324	29
OMN	0.085	35	0.165	34	0.409	33	0.280	35	0.456	34	0.782	33
PER	0.166	29	0.170	28	0.183	27	0.641	29	0.739	28	0.893	27
QAT	0.659	23	0.752	22	0.941	21	0.553	23	0.616	22	0.934	21
ROM	0.006	5	0.000	4	1.000	3	0.908	5	1.000	4	1.000	3
RUS	0.737	19	0.650	18	0.884	17	0.548	19	0.537	18	0.689	17
SAU	0.592	23	0.474	22	0.790	21	0.599	23	0.493	22	0.872	21
SDN	0.797	9	0.314	8	0.684	7	0.733	9	0.959	8	0.978	7
SYR	0.040	35	0.073	34	0.173	33	0.177	35	0.252	34	0.458	33
THA	0.833	24	0.813	23	0.926	22	0.047	24	0.759	23	0.756	22
TTO	0.418	34	0.447	33	0.656	32	0.758	34	0.801	33	0.970	32
TUN	0.288	42	0.249	41	0.531	40	0.509	42	0.439	41	0.741	40
VEN	0.472	20	0.467	19	0.852	18	0.468	20	0.194	19	0.740	18
VNM	0.561	19	0.578	18	0.778	17	0.223	19	0.047	18	0.860	17
YEM	0.488	20	0.540	19	0.643	18	0.319	20	0.034	19	0.034	18

Table 4.22. Country-by-country ADF test results for *loilrents_pc*.

ISO-code	0 lags		1 lags		2 lags		0 lags		1 lags		2 lags	
	without trend						with trend					
	p-value	n	p-value	n	p-value	n	p-value	n	p-value	n	p-value	n
AGO	0.096	23	0.246	22	0.398	21	0.027	23	0.026	22	0.094	21
ARE	0.181	23	0.121	22	0.139	21	0.508	23	0.376	22	0.424	21
ARG	0.674	17	0.708	16	0.564	15	0.893	17	0.954	16	0.933	15
AUS	0.126	36	0.463	35	0.610	34	0.013	36	0.214	35	0.335	34
AZE	0.448	7	0.890	5	1.000	3	0.213	7	0.912	5	1.000	3
BRA	0.689	16	0.760	15	0.628	14	0.778	16	0.912	15	0.841	14
BRN	0.434	35	0.599	34	0.509	33	0.804	35	0.924	34	0.888	33
CAN	0.214	20	0.743	16	0.764	12	0.385	20	0.790	16	0.920	12
CHN	0.290	12	0.088	11	0.273	10	0.582	12	0.661	11	0.829	10
COG	0.174	32	0.099	31	0.241	30	0.493	32	0.321	31	0.521	30
COL	0.164	23	0.463	22	0.508	21	0.345	23	0.592	22	0.741	21
DNK	0.608	30	0.697	29	0.774	28	0.367	30	0.513	29	0.594	28
DZA	0.241	44	0.211	43	0.224	42	0.546	44	0.503	43	0.526	42
ECU	0.550	12	0.403	11	0.722	10	0.395	12	0.498	11	0.740	10
EGY	0.359	35	0.067	34	0.353	33	0.388	35	0.043	34	0.261	33
GAB	0.180	35	0.072	34	0.069	33	0.437	35	0.170	34	0.122	33
GBR	0.486	33	0.447	32	0.333	31	0.317	33	0.342	32	0.149	31
GNQ	0.700	15	0.644	13	0.697	11	0.749	15	0.878	13	0.930	11
IDN	0.387	41	0.365	40	0.576	39	0.390	41	0.301	40	0.455	39
IND	0.010	10	0.459	9	0.766	8	0.259	10	0.982	9	0.985	8
IRQ	0.673	39	0.744	38	0.707	37	0.880	39	0.945	38	0.931	37
ITA	0.179	35	0.254	34	0.261	33	0.481	35	0.582	34	0.587	33
KAZ	0.513	11	0.850	9	0.622	8	0.536	11	0.625	9	0.888	8
LBY	0.875	23	0.842	22	0.707	21	0.825	23	0.663	22	0.733	21
MEX	0.478	15	0.507	14	0.750	13	0.692	15	0.414	14	0.455	13
MYS	0.129	36	0.182	35	0.251	34	0.297	36	0.350	35	0.380	34
NGA	0.069	35	0.007	34	0.035	33	0.231	35	0.050	34	0.151	33
NOR	0.095	31	0.116	30	0.502	29	0.196	31	0.178	30	0.502	29
OMN	0.251	35	0.282	34	0.386	33	0.411	35	0.427	34	0.602	33
PER	0.005	29	0.067	28	0.108	27	0.167	29	0.536	28	0.685	27
QAT	0.157	23	0.291	22	0.504	21	0.392	23	0.505	22	0.808	21
ROM	0.044	5	0.908	4	1.000	3	0.392	5	1.000	4	1.000	3
RUS	0.009	19	0.058	18	0.017	17	0.059	19	0.236	18	0.000	17
SAU	0.563	23	0.842	22	0.820	21	0.535	23	0.834	22	0.862	21
SDN	0.623	9	0.787	8	0.943	7	0.168	9	0.178	8	0.003	7
SYR	0.114	35	0.263	34	0.469	33	0.266	35	0.416	34	0.633	33
THA	0.790	24	0.951	23	0.909	22	0.354	24	0.858	23	0.864	22
TTO	0.596	34	0.407	33	0.568	32	0.501	34	0.244	33	0.693	32
TUN	0.522	42	0.322	41	0.443	40	0.641	42	0.387	41	0.524	40
VEN	0.377	20	0.236	19	0.370	18	0.707	20	0.320	19	0.662	18
VNM	0.616	19	0.535	18	0.735	17	0.798	19	0.561	18	0.661	17
YEM	0.592	20	0.557	19	0.595	18	0.968	20	0.939	19	0.994	18

Table 4.23. Country-by-country ADF test results for *loilrents_rgdp*.

ISO-code	0 lags		1 lags		2 lags		0 lags		1 lags		2 lags	
	without trend						with trend					
	p-value	n	p-value	n	p-value	n	p-value	n	p-value	n	p-value	n
AGO	0.676	23	0.658	22	0.709	21	0.921	23	0.923	22	0.952	21
ARE	0.902	23	0.826	22	0.873	21	0.595	23	0.314	22	0.417	21
ARG	0.603	17	0.663	16	0.680	15	0.632	17	0.669	16	0.676	15
AUS	0.415	36	0.076	35	0.152	34	0.674	36	0.287	35	0.321	34
AZE	0.994	7	0.014	5	1.000	3	0.200	7	0.000	5	1.000	3
BRA	0.655	16	0.347	15	0.032	14	0.911	16	0.755	15	0.276	14
BRN	0.108	35	0.061	34	0.027	33	0.283	35	0.167	34	0.107	33
CAN	0.509	20	0.167	16	0.005	12	0.891	20	0.543	16	0.105	12
CHN	0.994	12	0.932	11	0.948	10	0.968	12	0.997	11	1.000	10
COG	0.335	32	0.116	31	0.052	30	0.811	32	0.545	31	0.422	30
COL	0.684	23	0.076	22	0.075	21	0.863	23	0.206	22	0.194	21
DNK	0.455	30	0.096	29	0.311	28	0.352	30	0.054	29	0.365	28
DZA	0.470	44	0.477	43	0.498	42	0.688	44	0.729	43	0.663	42
ECU	0.635	12	0.350	11	0.773	10	0.375	12	0.000	11	0.057	10
EGY	0.552	35	0.230	34	0.363	33	0.627	35	0.092	34	0.203	33
GAB	0.228	35	0.324	34	0.420	33	0.575	35	0.787	34	0.892	33
GBR	0.141	33	0.002	32	0.012	31	0.449	33	0.003	32	0.005	31
GNQ	0.880	15	0.605	13	0.031	11	0.967	15	0.939	13	0.071	11
IDN	0.425	41	0.463	40	0.567	39	0.566	41	0.624	40	0.692	39
IND	0.851	10	0.706	9	0.844	8	0.517	10	0.299	9	0.633	8
IRQ	0.727	39	0.715	38	0.612	37	0.827	39	0.797	38	0.604	37
ITA	0.527	35	0.307	34	0.270	33	0.497	35	0.148	34	0.241	33
KAZ	0.932	11	0.680	9	0.294	8	0.963	11	0.940	9	0.940	8
LBY	0.763	23	0.687	22	0.579	21	0.566	23	0.396	22	0.093	21
MEX	0.542	15	0.032	14	0.356	13	0.073	15	0.983	14	0.994	13
MYS	0.715	36	0.624	35	0.743	34	0.522	36	0.089	35	0.356	34
NGA	0.338	35	0.163	34	0.074	33	0.497	35	0.220	34	0.055	33
NOR	0.608	31	0.152	30	0.236	29	0.589	31	0.122	30	0.113	29
OMN	0.000	35	0.003	34	0.021	33	0.004	35	0.005	34	0.012	33
PER	0.338	29	0.550	28	0.466	27	0.475	29	0.714	28	0.606	27
QAT	0.792	23	0.956	22	0.292	21	0.734	23	0.977	22	0.794	21
ROM	0.294	5	0.749	4	1.000	3	0.995	5	1.000	4	1.000	3
RUS	0.051	19	0.030	18	0.140	17	0.028	19	0.000	18	0.366	17
SAU	0.857	23	0.769	22	0.958	21	0.593	23	0.232	22	0.599	21
SDN	0.467	9	0.576	8	0.703	7	0.978	9	0.133	8	0.833	7
SYR	0.525	35	0.395	34	0.593	33	0.367	35	0.088	34	0.217	33
THA	0.661	24	0.267	23	0.450	22	0.915	24	0.576	23	0.749	22
TTO	0.410	34	0.186	33	0.225	32	0.675	34	0.486	33	0.507	32
TUN	0.186	42	0.146	41	0.066	40	0.314	42	0.231	41	0.069	40
VEN	0.948	20	0.906	19	0.879	18	0.882	20	0.813	19	0.569	18
VNM	0.046	19	0.003	18	0.075	17	0.546	19	0.003	18	0.022	17
YEM	0.659	20	0.288	19	0.330	18	0.942	20	0.506	19	0.787	18

Table 4.24. Country-by-country ADF test results for *lrer*.

ISO-code	0 lags		1 lags		2 lags		0 lags		1 lags		2 lags	
	without trend						with trend					
	p-value	n	p-value	n	p-value	n	p-value	n	p-value	n	p-value	n
AGO	0.990	23	0.994	22	0.990	21	0.935	23	0.960	22	0.896	21
ARE	0.123	23	0.064	22	0.319	21	0.063	23	0.004	22	0.352	21
ARG	0.958	17	0.808	16	0.868	15	0.959	17	0.622	16	0.642	15
AUS	0.992	36	0.935	35	0.954	34	0.000	36	0.542	35	0.467	34
AZE	0.990	7	0.888	5	1.000	3	0.622	7	0.975	5	1.000	3
BRA	0.872	16	0.931	15	0.986	14	0.817	16	0.718	15	0.843	14
BRN	0.818	35	0.643	34	0.661	33	0.603	35	0.331	34	0.752	33
CAN	0.939	20	0.175	16	0.453	12	0.802	20	0.842	16	1.000	12
CHN	0.999	12	0.964	11	0.998	10	0.791	12	0.458	11	0.983	10
COG	0.016	32	0.004	31	0.008	30	0.096	32	0.012	31	0.012	30
COL	0.967	23	0.928	22	0.905	21	0.942	23	0.705	22	0.421	21
DNK	0.562	30	0.300	29	0.162	28	0.985	30	0.882	29	0.867	28
DZA	0.549	44	0.224	43	0.346	42	0.488	44	0.378	43	0.513	42
ECU	0.953	12	0.952	11	0.860	10	0.215	12	0.000	11	0.272	10
EGY	0.690	35	0.255	34	0.004	33	0.926	35	0.848	34	0.801	33
GAB	0.385	35	0.145	34	0.008	33	0.218	35	0.045	34	0.023	33
GBR	0.718	33	0.412	32	0.735	31	0.977	33	0.505	32	0.750	31
GNQ	0.965	15	0.924	13	0.135	11	1.000	15	1.000	13	0.997	11
IDN	0.090	41	0.310	40	0.320	39	0.479	41	0.281	40	0.367	39
IND	0.996	10	0.990	9	0.596	8	0.243	10	0.437	9	0.625	8
IRQ	0.161	39	0.164	38	0.246	37	0.431	39	0.435	38	0.547	37
ITA	0.222	35	0.007	34	0.345	33	0.997	35	0.994	34	1.000	33
KAZ	0.912	11	0.082	9	0.268	8	0.329	11	0.997	9	0.997	8
LBY	0.247	23	0.055	22	0.035	21	0.353	23	0.247	22	0.167	21
MEX	0.706	15	0.027	14	0.304	13	0.372	15	0.785	14	0.853	13
MYS	0.604	36	0.716	35	0.429	34	0.872	36	0.775	35	0.692	34
NGA	0.589	35	0.454	34	0.406	33	0.948	35	0.894	34	0.976	33
NOR	0.459	31	0.624	30	0.702	29	0.977	31	0.516	30	0.861	29
OMN	0.019	35	0.515	34	0.422	33	0.000	35	0.071	34	0.069	33
PER	0.947	29	0.575	28	0.825	27	0.938	29	0.515	28	0.791	27
QAT	0.998	23	0.995	22	0.992	21	0.948	23	0.961	22	0.910	21
ROM	0.546	5	0.694	4	1.000	3	0.953	5	1.000	4	1.000	3
RUS	0.939	19	0.401	18	0.642	17	0.107	19	0.014	18	0.179	17
SAU	0.695	23	0.298	22	0.404	21	0.488	23	0.447	22	0.231	21
SDN	0.989	9	0.975	8	0.959	7	0.526	9	0.183	8	0.256	7
SYR	0.369	35	0.739	34	0.862	33	0.273	35	0.573	34	0.673	33
THA	0.126	24	0.129	23	0.141	22	0.848	24	0.346	23	0.219	22
TTO	0.990	34	0.954	33	0.884	32	0.995	34	0.988	33	0.974	32
TUN	0.275	42	0.251	41	0.241	40	0.264	42	0.368	41	0.176	40
VEN	0.265	20	0.064	19	0.343	18	0.591	20	0.228	19	0.668	18
VNM	0.944	19	0.894	18	0.971	17	0.677	19	0.081	18	0.469	17
YEM	0.484	20	0.769	19	0.269	18	0.859	20	0.834	19	0.816	18

Table 4.25. Country-by-country ADF test results for *lrgdpch*.

ISO-code	0 lags		1 lags		2 lags		0 lags		1 lags		2 lags	
	without trend						with trend					
	p-value	n	p-value	n	p-value	n	p-value	n	p-value	n	p-value	n
AGO	0.180	23	0.264	22	0.233	21	0.752	23	0.919	22	0.840	21
ARE	0.331	23	0.229	22	0.194	21	0.713	23	0.556	22	0.513	21
ARG	0.524	17	0.597	16	0.635	15	0.708	17	0.839	16	0.584	15
AUS	0.484	36	0.760	35	0.567	34	0.046	36	0.121	35	0.148	34
AZE	0.108	7	0.907	5	1.000	3	0.981	7	0.136	5	1.000	3
BRA	0.755	16	0.658	15	0.176	14	0.953	16	0.962	15	0.806	14
BRN	0.041	35	0.029	34	0.200	33	0.173	35	0.135	34	0.510	33
CAN	0.492	20	0.124	16	0.015	12	0.983	20	0.978	16	0.857	12
CHN	0.638	12	0.238	11	0.450	10	1.000	12	0.997	11	1.000	10
COG	0.561	32	0.474	31	0.651	30	0.527	32	0.521	31	0.681	30
COL	0.681	23	0.638	22	0.518	21	0.244	23	0.679	22	0.820	21
DNK	0.676	30	0.615	29	0.846	28	0.673	30	0.358	29	0.511	28
DZA	0.429	44	0.081	43	0.337	42	0.703	44	0.213	43	0.654	42
ECU	0.333	12	0.135	11	0.424	10	0.513	12	0.274	11	0.342	10
EGY	0.018	35	0.128	34	0.150	33	0.093	35	0.375	34	0.418	33
GAB	0.063	35	0.095	34	0.318	33	0.182	35	0.219	34	0.494	33
GBR	0.246	33	0.160	32	0.226	31	0.271	33	0.092	32	0.138	31
GNQ	0.196	15	0.004	13	0.267	11	0.538	15	0.020	13	0.638	11
IDN	0.103	41	0.069	40	0.125	39	0.125	41	0.257	40	0.442	39
IND	0.689	10	0.909	9	0.657	8	0.289	10	0.879	9	0.908	8
IRQ	0.304	39	0.101	38	0.055	37	0.635	39	0.315	38	0.202	37
ITA	0.512	35	0.413	34	0.603	33	0.592	35	0.638	34	0.684	33
KAZ	0.220	11	0.986	9	0.992	8	0.818	11	0.765	9	0.701	8
LBY	0.846	23	0.776	22	0.671	21	0.846	23	0.802	22	0.758	21
MEX	0.000	15	0.324	14	0.420	13	0.000	15	0.600	14	0.748	13
MYS	0.301	36	0.722	35	0.452	34	0.980	36	0.975	35	0.980	34
NGA	0.249	35	0.531	34	0.320	33	0.200	35	0.541	34	0.232	33
NOR	0.134	31	0.012	30	0.220	29	0.180	31	0.009	30	0.355	29
OMN	0.244	35	0.078	34	0.850	33	0.425	35	0.029	34	0.766	33
PER	0.352	29	0.386	28	0.396	27	0.528	29	0.607	28	0.574	27
QAT	0.278	23	0.289	22	0.073	21	0.371	23	0.205	22	0.323	21
ROM	0.893	5	0.949	4	1.000	3	0.000	5	1.000	4	1.000	3
RUS	0.001	19	0.000	18	0.270	17	0.008	19	0.000	18	0.641	17
SAU	0.871	23	0.792	22	0.885	21	0.915	23	0.816	22	0.945	21
SDN	0.551	9	0.465	8	0.495	7	0.792	9	0.995	8	0.991	7
SYR	0.481	35	0.699	34	0.573	33	0.404	35	0.674	34	0.570	33
THA	0.224	24	0.061	23	0.200	22	0.790	24	0.526	23	0.675	22
TTO	0.121	34	0.265	33	0.210	32	0.270	34	0.348	33	0.303	32
TUN	0.145	42	0.006	41	0.008	40	0.370	42	0.013	41	0.025	40
VEN	0.552	20	0.440	19	0.384	18	0.752	20	0.698	19	0.618	18
VNM	0.578	19	0.721	18	0.891	17	0.009	19	0.027	18	0.048	17
YEM	0.296	20	0.025	19	0.286	18	0.910	20	0.891	19	0.965	18

Table 4.26. Country-by-country ADF test results for *lopenc*.

	(1)	(2)	(3)	(4)	(5)
Pt	2.07**	1.84**	0.55	5.78***	5.73***
	(0.019)	(0.033)	(0.710)	(0.000)	(0.000)
Pa	0.39	0.15	1.22	5.12***	4.66***
	(0.348)	(0.440)	(0.888)	(0.000)	(0.000)
Subsample	World	D10	OPEC	World-OPEC	D10-OPEC
n	40	25	10	30	15
Lags & leads	1	1	1	1	1

Table 4.27. Westerlund (2007) panel cointegration tests using oil price (*lbrent*). Dependent variable is real exchange rate, *lrer*. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. H_0: No cointegration in any panel ($\phi_i = 0\ \forall i$; H_a: Cointegration in the panel as a whole ($\phi_i < 0\ \forall i$). Two countries, Romania and Sudan, were dropped for these tests due to their short time series.

	(1)	(2)	(3)	(4)	(5)
Pt	3.11***	2.54***	0.45	6.33***	5.93***
	(0.001)	(0.006)	(0.327)	(0.000)	(0.000)
Pa	0.29	0.10	1.07	5.46***	5.51***
	(0.387)	(0.462)	(0.857)	(0.000)	(0.000)
Subsample	World	D10	OPEC	World-OPEC	D10-OPEC
n	40	25	10	30	15
Lags & leads	1	1	1	1	1

Table 4.28. Westerlund (2007) panel cointegration tests using real GDP per capita (*lrgdpch*). Dependent variable is real exchange rate, *lrer*. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. H_0: No cointegration in any panel ($\phi_i = 0\ \forall i$; H_a: Cointegration in the panel as a whole ($\phi_i < 0\ \forall i$). Two countries, Romania and Sudan, were dropped for these tests due to their short time series.

5 Conclusion

5.1 Summary and Implications of Findings

This thesis has focussed on the energy elements of economies' susceptibility to shocks and how, if at all, disturbances in the energy sector—oil prices or productivity of the oil sector, for example—may affect sustained economic growth. By following a review of existing literature and providing a theoretical framework for key transmission mechanisms, each chapter provided insights into the complex linkages in question through empirical modelling. Literature review sections identified gaps in the literature that each chapter attempted to fill. This involved revisiting previously-introduced approaches to compare against alternative techniques introduced here, including but not limited to alternative measures of key variables, modelling richer price dynamics, and conducting time-varying analyses.

Chapter 2 investigated the oil price and macroeconomy relationship to determine whether oil price fluctuations Granger-cause changes in output growth rate in the US using VAR models. Although the chapter has an empirical focus, I describe a structural model that demonstrates the transmission mechanisms from oil price fluctuations to macroeconomic fundamentals. Findings showed that the chosen oil price measure, model specification, and sample period all have an effect on the nature of the relationship being tested. Although traditional approaches suggested a weakening relationship between oil price changes and GDP growth in the US, I found limited evidence for this observation using the approaches described. As a part of this, asymmetric modelling of oil prices as well as capturing oil price volatility proved important. Among possible oil price measures, RAC was the most robust mainly due to its smaller correlation with control variables. Control variables themselves were shown to play a key role in determining the effect of an oil price shock on macroeconomic fundamentals. Returning to the importance of modelling, Chapter 2 found evidence for asymmetry: oil price hikes affected US GDP growth to a larger extent than price falls. Further, oil price shocks normalised by preceding periods' volatility were more highly correlated with output growth than their non-normalised versions. This suggests that a shock of the same size could have different implications depending on when it occurs. To estimate the magnitude of the impact, IRFs were used with a 20-quarter horizon. A rolling-window IRF approach provided evidence of changing characteristics of the relationship over time. VARs and IRFs estimated using post-1974 data indicated that GDP growth could be between -0.014 and -0.034 less over a 5-year horizon due to a 10% increase in the price of oil.

Chapter 3 shifted the attention to the UK. The primary objective was to determine how the oil price-macroeconomy relationship has evolved over time with an emphasis on the importance of oil price volatility modelling using methodology akin to that in the previous chapter. This primary objective extended to drawing comparisons between the US and the UK. At this stage, the analysis went beyond GDP growth and turned to other key variables identified in the analysis, such as inflation and unemployment rates in the two countries. In this chapter, I found some evidence of Granger-causality between oil price fluctuations and GDP growth, and concluded that this relationship is stronger with normalised oil price changes. As in the US, this suggests that oil price volatility leading up to a price shock contributes to its macroeconomic implications: unanticipated price shocks—those occurring after a period of stable prices—tend to have a larger impact on the economy. Inflation and unemployment rate, along with others, were also shown to have a strong link with oil price fluctuations. There was some, albeit muted, evidence for an asymmetric impact of oil price shocks on output growth rate. A rolling-window time-varying parameter approach concluded that after 1980, oil price implications have dwindled in terms of magnitude despite retaining statistical significance in VAR specifications. This time-dependency of parameters carried onto IRF estimates. Although not all points estimates were statistically significant, the responses pointed to a time-dependent relationship. More specifically, 1974:2-2015:2 subsample suggested a 0.24% decrease in GDP growth as a result of a 10% increase in normalised oil prices, whereas the same model estimated over 1986:1-2015:2 led to a 0.11% increase in GDP growth in response to the same shock. This observation was corroborated by rolling IRFs, which showed that the characteristics of the relationship have shifted as the UK's domestic oil production increased. A key difference between the two countries was the role real exchange rates played in the UK as a small open economy. This dynamic was captured by import price inflation and domestic inflation, which were tested through nested model specifications. In spite of significant differences between the US and UK economies, results from Chapters 2 and 3 highlighted some fundamental similarities—particularly because, in some sample periods, the UK exhibited the behaviour of an oil importer and exporter. For instance, unemployment rate is expected to follow a similar pattern following an oil price disturbance, since both countries have oil production activities and extensive direct and indirect employment within the sector.

Chapter 4 took a more global approach and concentrated on the B-S hypothesis. Using a private dataset, I constructed a measure of profits in the oil sectors of a large number of countries to investigate the incidence of Dutch disease. My objective was to determine whether there is a long-run relationship between productivity in the oil sector and the real exchange rate as well as short-run adjustment towards the equilibrium. While working towards this goal, my variable allowed me to avoid the noisier traditional measures of productivity, such as GDP. I found that the B-S mechanism holds in some oil-exporting countries but not all. For most countries, the relationship is non-negligible in size and statistically significant. Surprisingly, countries outside of OPEC showed a particularly significant link between their real exchange rates and oil rents. However, the largest observed effect was for OPEC countries: nearly 12% appreciation in the real exchange rate in response to a 10% increase in oil sector productivity as measured by our oil rents per capita. Oil prices were identified as another covariate with coefficients of a similar size and sign. In addition to per capita oil rents, oil rents as a percentage of GDP was introduced as an alternative. The chapter presented some theoretical and empirical evidence that the latter variable is a better option, especially since oil rents as a percentage of GDP were cointegrated with the real exchange rate in OPEC countries and oil rents per capita were not. Furthermore, the oil rents per capita variable does not capture the size and significance of the oil sector relative to the rest of the economy. In this context, I would expect a one-dollar increase in oil rents to have a larger impact in Kuwait than in Australia. Nevertheless, both measures indicated an ambiguous relationship between oil rents and real exchange rate in OPEC countries. Investigating this further revealed an interesting dynamic about the two oil rents variables. Of note is the fact that oil rents measured as a percentage of GDP may appear to be shrinking if a country's economy grows without a matching growth in the oil sector. Furthermore, no link was observed between oil rents and the nominal exchange rate or the price level in OPEC countries. In line with other researchers, I found some evidence that the real oil price has an impact on the real exchange rate. In practice, at least one assumption of the B-S hypothesis appears to fail in some OPEC countries due to the lack of free movement of labour between tradable and non-tradable sectors. On a global scale, I found evidence for the B-S hypothesis in most oil-exporting countries. Moreover, the estimated impact was larger in countries whose oil sector accounts for a larger share of GDP. I also found some contradictory results which suggested that although B-S mechanism is responsible for resource curse to some extent, other factors, such as corruption and underdeveloped financial systems, also matter.

Implications for policymakers and other stakeholders

The findings in all three chapters have policy implications. Understanding the strengths and weaknesses of an economy as well as how a market economy would react to a shock are invaluable to policy-makers, especially since there is reason to believe that policy responses to energy shocks could mitigate or exacerbate the final impact. Chapters 2 and 3 identified a critical dynamic: the effect of an oil price shock is dependent on the volatility of oil prices in periods preceding its occurrence. This suggests, therefore, that optimal policy response may differ across shocks that are otherwise identical. More specifically, a 10% rise on oil price may require a different policy response for the same desired outcome depending on whether it occurs following a highly volatile period or a calm one. Furthermore, IRF analysis often showed an overshooting effect in the response of macroeconomic variables to an oil price innovation. Hence, policy tools that take time to take effect may worsen the original shock it attempted to counteract. By way of example, Chapter 2 demonstrated that an oil price increase has a negative GDP growth effect in the second quarter followed by a positive effect in the third. Thus, without loss of generality, if an interest rate adjustment takes a quarter to take full effect, the initial impact of the shock may no longer be relevant. In this sense, it is not simply the size and sign of the shock's effects we want to understand but rather the nature of the macroeconomic response as well as its timing. The fact that there is no consensus on how central banks should respond to exogenously and endogenously rising oil prices could be simply because it is not just the shock that matters but also when it occurs and how the economy reacts. Chapters 2 and 3 shed light on this notion providing evidence that oil price volatility preceding the shock plays a key role and should, therefore, be considered by policymakers. This comment applies to Chapters 3 and 4 as well. Although the latter takes a global view of the oil rents and real exchange rate relationship, understanding what encourages and impedes economic growth has been a key objective for policymakers. In this context, Chapter 4 fits into the literature that provides the groundwork for ameliorating the curse of natural resources as we look to improve our understanding of how these valuable subsurface assets can be transformed into wealth and development as well as the appropriate policy response when faced with volatile commodity prices. Beyond policymakers, findings presented in the thesis may interest other stakeholders. The link between oil rents, real exchange rates, and economic growth is relevant for national oil companies. Having observed and quantified a relationship in Chapter 4, ministries and oil companies can get a better understanding of the implications productivity in the oil sector has on the wider economy. This can, in turn, influence investment and policy decisions to counteract detrimental effects and capitalise on growth-inducing ones.

5.2 Further Work and Concluding Remarks

Economists have long observed fundamental shifts in the structure of economies over time. There is no denying that we are currently undergoing a significant transformation and that energy is at the heart of it all. Over the past few decades, we changed how we view energy sources (shifts from hydrocarbon-oriented growth towards renewable energy sources), what we use energy for (shifts from transport and heating to so much more), and how efficient we are at using it (notable improvements in energy efficiency across the board). Inevitably, these major shifts have had implications for the macroeconomic dynamics that interest us. As such, theoretical and empirical modelling should adjust accordingly to capture these effects. This thesis addresses this by offering alternative approaches both in variable choice and modelling techniques.

There is still a lot of potential for further research. For example, non-linear VARs have received attention in the time-series literature but have not been fully adopted into the oil price context. Extending current models could provide insights into a new dimension of analysis such that we understand not only how volatility affects the implications of a shock but also its size. In addition, as more data become available, larger specifications become feasible. Large-dimensional VARs that were previously impossible to estimate are now within reach. Within this, the Bayesian framework and composite likelihood functions can offer an avenue for research. Since Chapters 2 and 3 found that modelling oil price volatility is key, understanding which model specifications capture the underlying dynamics best can inform modelling decisions. For example, oil price series could be modelled using a different (G)ARCH specification and using monthly instead of quarterly series could help identify the appropriate specification. If asymmetry is to be modelled differently, threshold autoregressive models are a good option. Under some regularity assumptions, these models are root-n consistent and asymptotically normally distributed. A related by distinct approach could be to focus more explicitly on agents' expectations and behavioural implications of oil price dynamics. There is evidence in Chapters 2 and 3 that oil price volatility plays a key role, so modelling behaviour formally could provide further insights. Lastly, Chapter 4 and econometric methods within it benefit from long time series. Unfortunately, the dataset imposed limitations on which methods I could use and what analysis I could conduct. In addition to allowing more detailed analysis, a larger dataset—especially in the time dimension—would enhance the asymptotic properties of estimates and may provide more accurate results. Building on the surprising results presented in this chapter, especially those pertaining to OPEC countries, a strand of research could focus on failure of B-S assumptions in these countries, the role the labour market plays in this, and how this could be modelled more explicitly. This has far-reaching economic development implications, as developing economies' compositions evolve over time, and understanding what this means for economic growth and prosperity can help maximise welfare.

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