Centre for Energy Economics Research and Policy

The Crude Oil Market and US Economic Activity:

Revisiting the Empirical Evidence

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March 2020

Abstract

This paper empirically analyses the relationship between oil prices and real economic activity in the US. We seek to contribute to the literature by reconsidering the measurement of oil prices. We do so by accounting for whether oil price shocks follow periods of quiescence or volatility, since the former oil price changes could be more shocking. This study also accounts for asymmetry of shocks, since both theory and our empirical findings indicate that positive shocks to oil prices have a greater impact on economic activity than negative ones. We implement a rolling window approach in VARs and IRFs to investigate the time-varying nature of the relationship. Based on these, we find no clear evidence of the oil price-macroeconomy relationship weakening over time. There is strong evidence for asymmetry across specifications, proxies, and sample periods. Impulse response analysis suggests that a rise in oil prices is expected to lead to a decline in output growth rate and that this effect is larger in the second half of the dataset.

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1 Introduction

An economy's long-run growth and development critically depend on its resilience and susceptibility to shocks (Balassa, 1986; Romer & Romer, 2004; Martin, 2012). Energy shocks have been placed at the centre of this observation, since growth-inducing activities are highly dependent on access to energy. 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 US recessions were preceded by drastic increases in oil prices, which made the oil price-macroeconomy relationship a central focus of research for decades. Recent political turmoil in the Middle East as well as the desire to control carbon emissions and to incorporate more renewables into the energy mix have increased attention to the topic once again.

For net importers of oil, the nature of the relationship between oil prices and macroeconomic activity seems obvious: an oil price rise should, *ceteris paribus*, reduce economic growth through higher costs for individuals and firms (Hamilton, 2005). However, despite numerous theoretical predictions and empirical studies, debates continue, and there is mixed empirical evidence of a link between oil prices and macroeconomic activity.

This study argues that this debate is partly fuelled by the way in which empirical modelling is done. A central argument in this study is that robust results can be obtained using a relatively uncomplicated vector autoregressive (VAR) models and without relying on proxies or explicitly identifying the nature of oil price shocks. More broadly, this paper is motivated by three controversial questions within the oil price-macroeconomy theme, as discussed in Herrera et al. (2019) and seeks to make the following contributions to the literature. First, we extend the literature on oil price modelling by normalising oil price fluctuations. Second, we analyse the stability of the relationship over time. Third, we test for asymmetry explicitly. Finally, we argue that normalising oil price shocks by their volatility aids empirical modelling without the need to model the nature of shocks, as in Kilian (2009), which has attracted criticism.

A key focus and contribution in this study is the combination of the implementation of normalised (volatility-adjusted) oil price series and a time-varying parameter approach using a rolling-window technique. The rolling-window implementation is akin to that adopted by Blanchard & Galí (2007) but without being restricted to bivariate rolling VARs. This study is also distinct from Baumeister & Peersman (2013b), whose approach allows for time-varying parameters, and Hooker (1996b), who uses disjointed subsamples, but resembles Gronwald's (2012) estimation strategy. As noted in Gronwald (2012), the innovative rolling-window implementation of a commonly-favoured VAR technique is robust and lends itself to easy interpretation and comparison of results.

The key contributions of this paper are as follows. First, oil price changes are normalised (volatility-adjusted), which captures the effect of oil price volatility preceding an oil price shock. Second, a rolling window approach is adopted, which highlights how the relationship has evolved over time.

The results in this study indicate that the impact of oil price rises on GDP growth is larger in the 1970s than early 1980s, but that this reverses after 1986. Further, we observe no loss of statistical significance of oil price hikes in the GDP growth equation in recent samples, which disagrees with some earlier findings in the literature. We argue that this is due to the use of volatility-adjusted oil price series. We also find evidence that refiners' acquisition cost (RAC) is, in some cases, a more robust measure of oil prices than producer price index (PPI) in crude petroleum. We find strong evidence for asymmetry in the way GDP growth reacts to changes in oil prices: a price increase is likely to have an impact on US output growth, but a price fall is not.

2 Literature Review

The choice of oil price variable has received particular attention in the literature. 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." Although West Texas Intermediate (WTI) and Brent prices seem like obvious choices, they are not necessarily well suited for econometric analysis given their sensitivity to logistical

disruptions. For example, although WTI is expected to cost more than Brent due to its more desirable petrochemical properties, logistical bottlenecks have translated into the opposite relationship between the two benchmark crude prices over the last decade. Various attempts have been made to capture the true nature of oil price shocks, including the use of different oil price measures (for example, producer price indices and refiners' acquisition cost) and introduction of non-linear oil price specifications (for example, Hamilton, 2003; Hooker, 1996b; Kilian, 2009).

More recently, the topic has received considerable attention with researchers implementing larger VAR specifications (for example, 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, 2011). Both Mory (1993) and Lee et al. (1995) found evidence for an asymmetric effect of oil price hikes on the US economy, and the latter further concluded that volatility of oil prices – and not just changes in the levels of the variable – matters for the relationship. Following Blanchard & Galí's (2007) observation that the nature of the relationship evolved over time and Gronwald's (2008, 2012) findings that oil price shocks need to be sufficiently large to have a significant impact on macroeconomic variables, this paper offers a novel hybrid approach. We argue that an oil price shock of the same absolute magnitude has a different effect on macroeconomic fundamentals depending on oil price volatility in the time periods leading up to it.

There are several key reasons oil price volatility matters for the oil price – macroeconomic activity relationship. First, although supply and demand underlie oil price fluctuations, the way these are manifested in agents' behaviour is what determines the aggregate impact. In this context, expectations matter and volatility-adjustment of oil price fluctuations is critical. Pindyck (2004b) highlighted the importance of volatility by stating that persistent changes in volatility can expose producers and consumers to risk and affect investment decisions, including those in production facilities and transportation. Further, the author determined that volatility has implications for derivative valuation, hedging decisions, and investment

decisions in physical capital tied to production and consumption of oil. Volatility has implications for total marginal cost of production and influences firms' operating options and opportunity cost of production (Pindyck, 2004a). Given that oil price volatility has increased over time, capturing oil price volatility in this study has provided further identifying variation unexploited in traditional models.

Understanding the role of oil price volatility is a key objective in this study. The literature in this area spans a wide range of themes: 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 products, and natural gas prices; and B.-N. Huang et al. (2005) and Narayan & Narayan (2007) examined the asymmetry of oil price shocks' impact on economic activity. Modelling oil prices using high-frequency data, Wei et al. (2010) found that nonlinear GARCH-class models exhibit greater forecasting accuracy than the linear ones.

In the last few decades, part of the debate within the oil price – macroeconomy literature morphed into a practical discussion of the exogeneity of oil prices and how to model them. In this context, oil price rises are thought to have different underlying causes with researchers on both sides of the argument. 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.

Researchers have attempted to identify proxies to categorise oil shocks, 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 (2008) 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 […]."

This paper proposes a normalisation process and asymmetric split of price changes as an alternative approach. 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.

3 Methodology and Data

Several model specifications with increasing complexity and coverage are implemented to facilitate an analysis of the four key questions mentioned above. Starting with a base model similar to that used by Hamilton (1983), the study incorporates ideas put forth by Mork (1989) and Lee et al. (1995), including non-linear modelling of oil prices and normalisation of oil price series. Further, 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 its evolution over time.

The base model is a 5-variable VAR system and consists of GDP growth, oil price changes, GDP implicit deflator inflation, real wage inflation, and unemployment. 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). This involves splitting oil price changes into two parts to model oil price increases and decreases separately. Denoting oil price changes as o_t, the new variables are:

$$o_t^+ = \begin{cases} o_t, & o_t > 0 \\ 0, & o_t \leq 0 \end{cases}$$

$$o_t^- = \begin{cases} 0, & o_t \geq 0 \\ o_t, & o_t < 0 \end{cases}$$

(1)

Having done this, we implement a further extension to capture the nature of oil price fluctuations more accurately. This involves using a univariate generalised autoregressive conditional heteroscedasticity, GARCH (1,1), process to calculate the conditional variance of oil price changes and normalise unanticipated real oil price fluctuations. These normalised oil price changes capture the idea that small price increases within volatile periods are predicted to have little effect on economic agents' behaviour, if they do not generate enough uncertainty to delay irreversible investments (Hooker, 1999).

The idea underpinning this approach is that the mean of real oil price changes may rise over time without agents being surprised as long as the distribution of oil price fluctuations remains unchanged. In other words, oil prices may increase or decrease over time (in levels) without any impact on economic activity in the absence of unanticipated shocks. Normalised variables are constructed as follows:

$$z_t = \alpha_0 + \sum_{i=1}^{4} \alpha_i z_{t-i} + \varepsilon_t \tag{2}$$

$$h_t = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \gamma_2 h_{t-1} \tag{3}$$

where, $\varepsilon_t | I_{t-1} \sim N(0, h_t)$, and z_t are oil prices measured as the change in refiners' acquisition cost (RAC) or producer price index in crude petroleum (PPI). The unexpected part of the oil price shock is the residual term of equation 2, $\hat{\varepsilon}_t = z_t - \hat{z}_t$. Normalised oil price shocks are then calculated as,

$$\varepsilon_t^* = Normalised\ Oil\ Price\ Shock = \frac{\hat{\varepsilon}_t}{\sqrt{h_t}} \tag{4}$$

Finally, the resulting variable is split into two parts as,

$$Normalised\ Positive\ Oil\ Price\ Shock\ (\varepsilon_t^{*+}) = \max(0, \varepsilon_t^*) \tag{5}$$

$$\text{Normalised Negative Oil Price Shock } (\varepsilon_t^{*-}) = \min(0, \varepsilon_t^*) \qquad (6)$$

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 link to real GDP than either z_t or $\hat{\varepsilon}_t$ (Lee et al., 1995). As in Lee et al. (1995), our *a priori* expectation is that unexpected oil price shocks have a greater effect on output than anticipated ones. That is, a shock should have a greater impact on GDP growth if it immediately follows a long period of stable prices. Similarly, an oil price change of the same magnitude is expected to have a smaller impact on output growth, if it is preceded by a period of volatile prices.

Although not a main focus of this study, VAR systems using Hamilton's (1996) net oil price increases (NOPI) are estimated as a robustness check. With quarterly data, 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,

$$NOPI_t = \max(0, 100 \times \{\ln(o_t) - \ln[\max(o_{t-1}, o_{t-2}, o_{t-3}, o_{t-4})]\}) \qquad (7)$$

Throughout the analysis, oil price changes are captured using two proxies: PPI in crude petroleum and RAC. Using the former has been criticised with RAC being proposed as a robust alternative, so this study lays the groundwork for a direct comparison in the context of VAR systems. Lastly, some researchers, including Hamilton (1996b), have deflated their measure of output using PPI in all commodities. We 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.

Orthogonalised impulse responses are calculated following Cholesky decomposition to visualise the VAR results. The impulse response functions cover a 20-quarter period and are reported with standard error bands, which are used to comment on their statistical significance. Table A1 in the Appendix provides a summary of all model specifications implemented as part of the analysis.

All data are in quarterly frequency. Most series are available from 1950:1 through 2015:2. The exceptions are RAC, import price index, and 3-month Treasury Bill (TB) rate, which are available from 1974:1, 1982:3, and 1972:1, respectively. All series are expressed in first-differenced natural logarithm except for real wage growth, which is only first-differenced. The sample period stops in mid-2015 to avoid potential biases from the rapid increase in oil production in the shale revolution and, more recently, the ongoing distortions due to COVID-19 pandemic.

Figure 1 demonstrates the impact of normalising RAC-based oil price fluctuations 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 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.
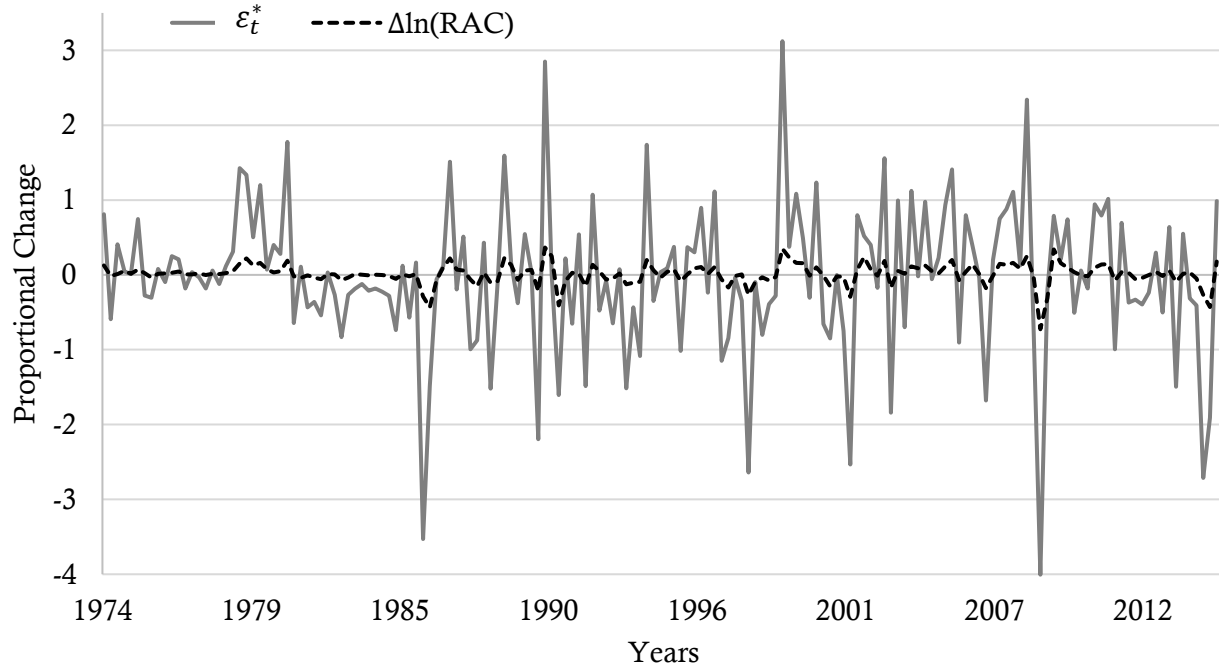
Figure 1. Oil price changes and normalised oil price fluctuations.
Notes: In this figure, ε_t^* denotes the oil price variable normalised using the approach outlined in equation 4. RAC is refiners' acquisition cost.

4 Empirical Results

The primary aim of this study is twofold. First, it investigates what effect, if any, oil price volatility preceding an oil price shock has on the oil price-macroeconomy relationship. Second, it focuses on how the relationship has evolved over time using a rolling window approach.

The results are presented starting with the base model and ending with larger specifications. Estimations over a few discrete subsamples allow a preview of the relationship over time before the rolling-window implementation covering a continuum of subsamples. The sample periods analysed separately are 1950:1 through 1986:1, 1974:1 through 2015:2, 1986:1 through 2015:2, and the entire sample period. The sample periods have been chosen partly to compare the results with those in the existing literature more easily and partly due to data availability. A key consideration in selecting the second and third subsamples was to avoid the bias introduced by Nixon price controls that ended in April 1974. This is to test for and address the criticism that the oil price-macroeconomy relationship vanished after 1973 but

appears significant in recent sample periods only because pre-1973 observations drive the relationship. The whole sample period is included for reference.

To formally test the link between standardised oil prices and economic activity, we use Granger causality tests. In these results, statistical significance refers to Granger causality: rejection of the null hypothesis provides evidence for Granger causality, and a failure to reject the null hypothesis provides no evidence for Granger causality. More specifically, in each equation the VAR system, the null hypothesis is that (lagged) explanatory variables have no statistically significant relationship with the dependent variable. Hence, a rejection of the null points to evidence that (lagged) explanatory variables are related to the dependent variable and that they Granger cause the latter. If the null is not rejected, explanatory variables do not Granger cause the dependent variable. Overall, the null hypothesis is equivalent to no Granger causality, and the alternative suggests Granger causality.

4.1 Base Model

Table 2 shows a summary of exclusion tests for Granger causality. These 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.

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. Exclusion tests for the base model. P-values are given in parentheses. Statistical significance is shown at the 10% level (*), 5% level (**) and 1% level (***). This table 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 †††).

The table shows different model specifications in each of the subsamples. The most comprehensive 7-variable specification is used over the most recent period, 1986:1-2015:2. A smaller specification without import price inflation is estimated over the 1974:1 through 2015:2 subsample due to the availability of this series. The remaining two sample periods are

analysed using a 5-variable VAR where 3-month TB rate is also omitted. Based on the resulting test statistics, we 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 and sample period.

For direct comparison with the 7-variable system shown in Table 2, we estimated the 5-variable system over 1986:1-2015:2. The test statistic for the joint significance of coefficients on all four lags of oil price changes is 18.296 with a p-value of 0.001 when PPI in crude oil is used as the proxy for oil prices, and 20.891 with a p-value of 0 when RAC is 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. A general observation in line with the literature is that statistical significance becomes weaker in more recent subsamples even with identical specifications. Having observed this, we turn to models that allow for asymmetry to investigate whether that has implications for the stability and robustness of the causal relationship.

4.2 Asymmetric Effects Model

Table 3 summarises the F-statistics of exclusion tests obtained by separating oil price changes into their positive and negative counterparts. Test results indicate that oil price increases Granger-cause changes in GDP growth, whereas the relationship is less clear for oil price decreases. 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. 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. The next section introduces normalised oil

prices to further extend the estimated systems and focus on the effect of normalisation on the observed relationship.

Proxy	Variable	(I) 1950:1-1985:4 †	(II) 1974:1-2015:2 ††	(III) 1986:1-2015:2 †††	(IV) 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 3. Exclusion tests of asymmetric effects model with GDP growth as the dependent variable. P-values are given in parentheses. Statistical significance is shown at the 10% level (*), 5% level (**) and 1% level (***). This table 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 †††).

4.3 Normalised and Net Oil Price Models

Before incorporating normalised oil price variables into the VAR systems, we run preliminary tests to examine the suitability of a GARCH (1,1) process in this context. Table 4 lists the estimated coefficients from the GARCH model expressed by equations 2 and 3 above.

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

Table 4. Parameter estimates for GARCH (1,1). P-values are given in parentheses. 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. The marginally-significant GARCH coefficient in Lee et al. (1995) is not statistically significant in our dataset—see column (I) of Table 4.

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 above. Therefore, this specification is used to calculate ε_t^*.

Characteristics of the conditional variance process of ε_t appear to have 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, We adopt the same GARCH specification for all sample periods. Lastly, the model employed in this analysis is assumed to exhibit the

asymptotic properties of GARCH processes outlined in Bougerol & Picard (1992), Lumsdaine (1991, 1996), and Nelson (1990).

Table 5 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 (I) and (IV) 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 caused by the strong correlation between oil price changes and normalised oil price shocks. Note 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 the sample.

Specification	Proxy	Variable	(I) 1950:1-1985:4	(II) 1974:1-2015:2	(III) 1986:1-2015:2	(IV) 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 5. Exclusion tests for normalised oil price shocks. P-values are given in parentheses. 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, which suggests that monetary policy plays an important role in determining the path of output growth rate. 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, and highlights the key role policy plays in the ultimate outcome of an oil price shock. From an econometric modelling perspective, this makes 3-month TB rate 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.

We now shift focus to test for the existence of an asymmetric relationship between oil price fluctuations and changes in GDP. To do so, the normalised oil price series are modelled in a

non-linear fashion as shown in equation 1. The aim is to determine whether positive normalised oil price changes Granger-cause GDP growth while negative changes do not. The results in Table 6 are striking, especially in comparison to those in Table 5 above: positive normalised oil price shocks Granger-cause GDP growth across all sample periods and model specifications, whereas negative ones do not. This outcome is in sharp contrast with the earlier evidence that normalised oil price shocks are not strongly linked to output growth rate. The 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, RAC is a better proxy for oil prices than the PPI-based measure. This is particularly clear in NOPI systems 1 and 2: using PPI, the null hypothesis of no Granger causality would not have been rejected based on columns (II) and (III) of the table, which would have suggested a weakening relationship between oil prices and GDP growth in those sample periods. This applies to 8-variable system 2 as well and explains why researchers observed a weakening relationship when recent data became available. Using RAC as the proxy shows, however, that the relationship remains important even in large systems. Second, there is no evidence of a weaker relationship in more recent sample periods when normalised price variables are used, unlike in Table 5, where a weakening relationship was observed across time. Third, there is strong evidence of asymmetry: positive price shocks have explanatory power that negative shocks do not. This holds in all specifications and sample periods. Fourth, capturing volatility effectively is central to these results, as normalised positive oil price fluctuations retain their explanatory power in the GDP growth equation when the NOPI system 3—the largest NOPI system, which is analogous to 8-variable system 2—does not.

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

Table 6. Exclusion tests for specifications with normalised and net oil price changes with asymmetry. P-values are given in parentheses. Statistical significance is shown at the 10% level (*), 5% level (**) and 1% level (***).

Further investigation into these observations revealed that they are not simply due to higher RMSE. For example, 8-variable system 2 with PPI and RAC as proxies yielded virtually identical RMSE values. The same holds for same model specifications across time, such that

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 point estimates.

4.3.1 The Oil Price-GDP Relationship Across Time

This section elaborates on the findings outlined above to address the heavily debated claim in the oil price-macroeconomy literature that oil price fluctuations may not be 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 6 show little evidence that oil price shocks no longer Granger-cause changes in output growth in recent sample periods, especially when normalised oil prices are used. This observation comes with the caveat that it relates strictly to Granger causality and *not* the size of the effect. Impulse response analysis in the next section examines this aspect in greater detail.

In this section, we implement a time-varying parameter approach using a rolling window of 132 quarters estimated sequentially from 1974:1 onwards. Exclusion tests are conducted after each iteration to observe changes in the statistical significance of oil price shocks over time.[1] The resulting p-values on normalised positive PPI- and RAC-based oil price shocks in 7-variable system 2 are shown in the left and right panels of Figure 2 below, respectively.[2] In the left panel, 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 this system remain statistically significant in recent periods. P-values calculated for RAC-

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[1] 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.

[2] P-values shown in the figures are not identical to those presented in Table 6, since the former use a 132-quarter rolling window sample period whereas the latter uses as much of the sample period as available.

based normalised positive price shocks follow a virtually identical pattern (see right panel of Figure 2). These observations on the statistical significance of normalised positive oil price shock variables are in sharp contrast with their negative counterparts shown in Figure 3.
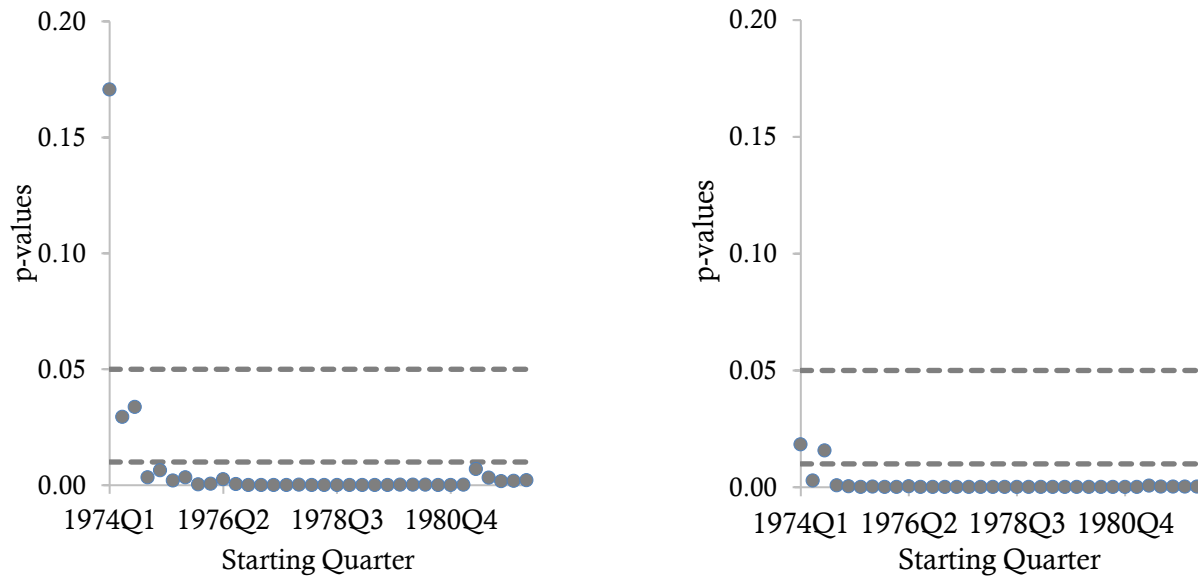

Figure 2. Exclusion test p-values for PPI- (left) and RAC-based (right) normalised positive oil price shocks in 7-variable system 2 using a rolling window against starting quarter.
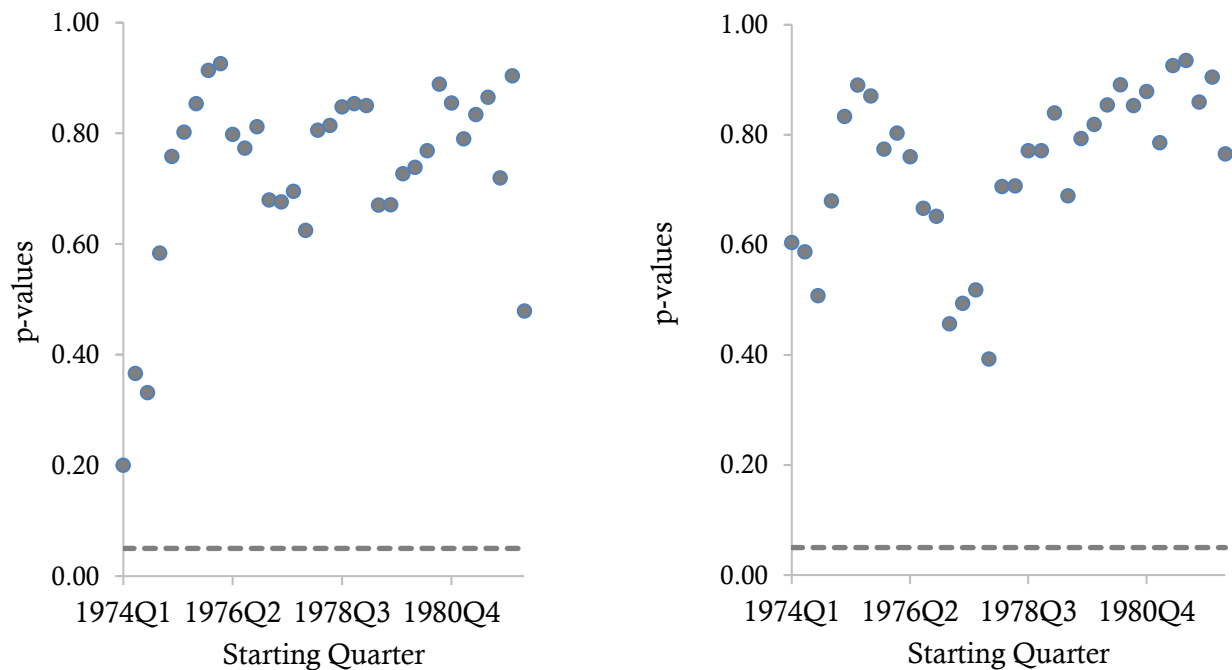

Figure 3. Exclusion test p-values for PPI- (left) and RAC-based (right) normalised negative oil price shocks in 7-variable system 2 using a rolling window against starting quarter.

Figure 3 corroborates the earlier asymmetry observation: within this dataset, independently of sample period, oil price increases have an impact on GDP growth and oil price falls do not.

We now briefly return to ordinary (non-normalised and linear) shocks in a rolling-window context to finalise the temporal investigation. Similar to my earlier findings, 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. Figure 4 highlights once again why researchers focussing on sample periods starting in 1970s found a weakening relationship between oil price changes and GDP growth. Exclusion tests fail to reject the null hypothesis of no Granger causality in sample periods starting from 1974:1 through 1976:2 inclusive. Therefore, based on the right panel of Figure 4, 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. In light of the findings from this section, however, this is an incomplete analysis and misrepresents the true nature of the oil price-macroeconomy relationship. Following this period, there is evidence against a weakening relationship between oil price fluctuations and output growth in the US. Generally, in a Granger-causality sense, there is little evidence that the link between oil prices and output growth has vanished over the past few decades, although these results do not reveal any information about the size of the effect, which is investigated in the next section.
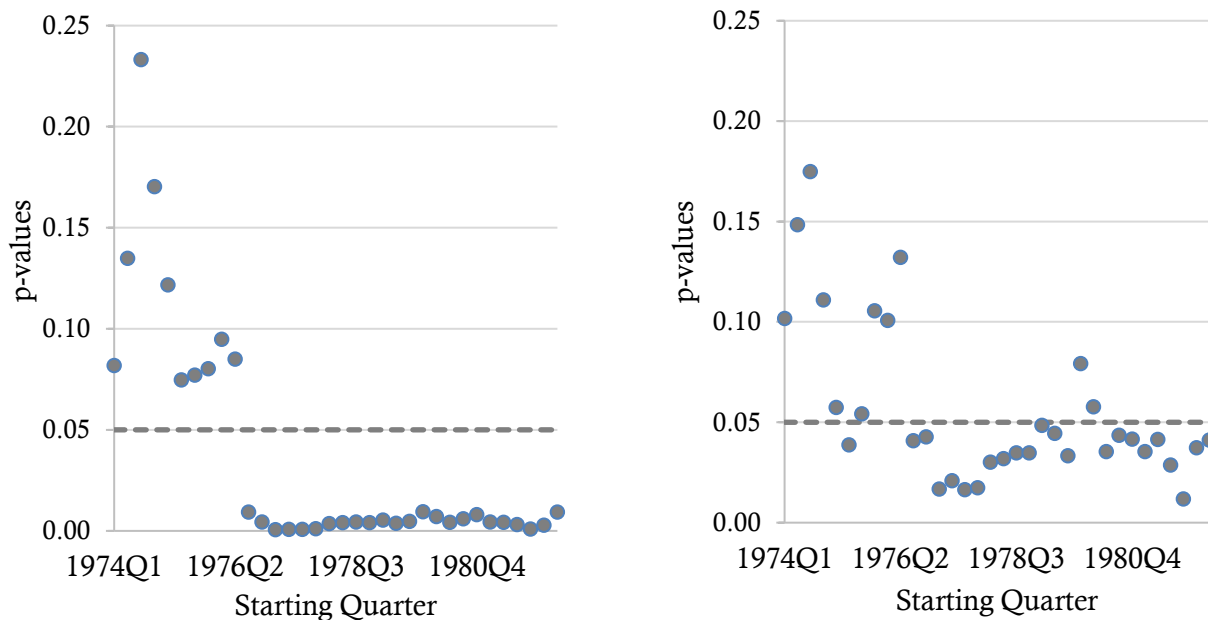
Figure 4. Exclusion test p-values for PPI- (left) and RAC-based (right) non-normalised oil price shocks in 7-variable system 1 using a rolling window against starting quarter.

The remaining question is whether normalised oil price variables have more explanatory power in key estimated equations than non-normalised ones. In this study, we find evidence of a weaker relationship between non-normalised price variables and macroeconomic fundamentals than normalised ones (see, for example, p-values shown in Figure 2 versus Figure 4). Revisiting tables and figures from previous sections can shed light on this. Tables 5 and 6 have output from specifications that allow this, and Figures 2, 3, and 4 put the results into a time-varying parameter context.

For a richer visualisation, Figure 5 below provides a three-dimensional representation 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. The specifications with normalised price fluctuations have much flatter p-value profiles within the $[0, 0.05]$ range than those with non-normalised series. This three-dimensional representation also allows a snapshot across specifications at a given starting quarter. As an example, considering a slice across specifications on 1976:1 indicates

low p-values for the first three specifications (those with normalised oil price variables) and high ones for the rest (those with non-normalised oil price variables). As a result, we conclude that normalised variables have more systematic relationship with output growth than their non-normalised counterparts.
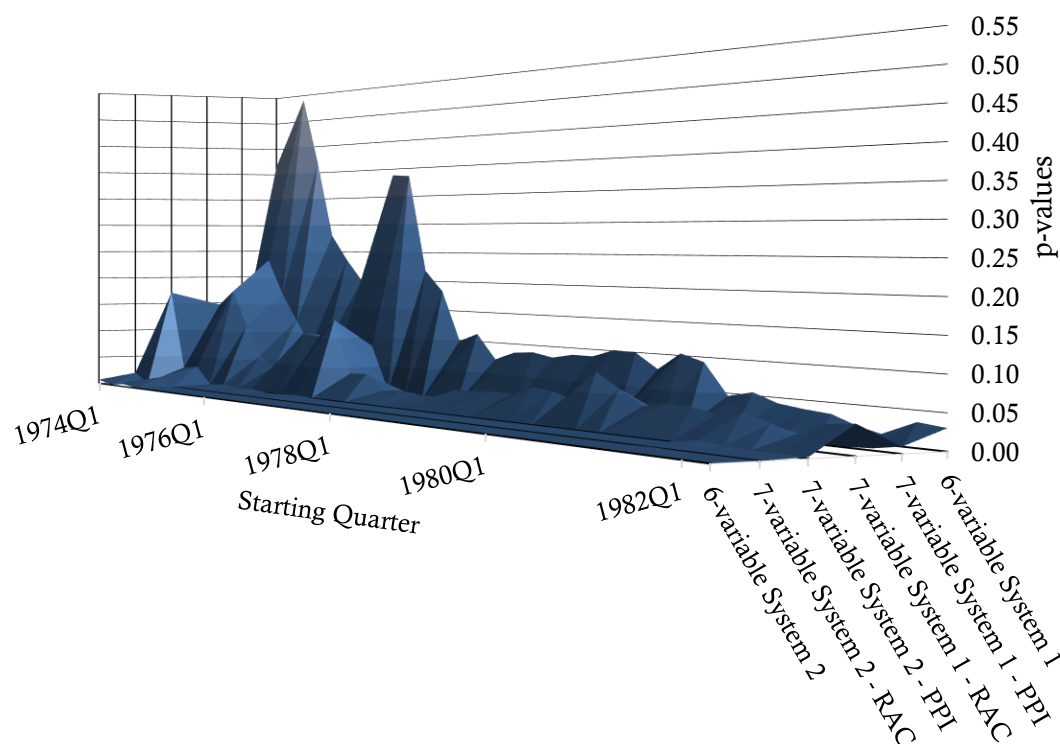

Figure 5. Exclusion test p-values (z-axis) across model specification (y-axis) with varying starting quarter (x-axis). Excluded variables as follows. 6-variable system 1: RAC-based oil price changes; 6-variable system 2: normalised positive oil price changes; 7-variable system 1: PPI- and RAC-based oil 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.

4.4 Impulse Response Analysis

Previous sections focussed on a discussion of statistical significance in line with much of the literature. This section focuses on parameter estimates, their interpretation, and impulse responses. Orthogonalised impulse response functions, which have undergone the appropriate Cholesky decomposition and consider a twenty-quarter time horizon, were implemented to interpret VAR results. Throughout this section, independently of model specification and sample period, the estimated coefficients on positive oil shocks in the output growth equation were negative, while those on negative oil shocks had alternating signs. In

all estimated impulse response functions, only some quarters showed an impact outside of the 95% confidence interval. 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 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. Starting with the 7-variable system 2 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 Figure 6.
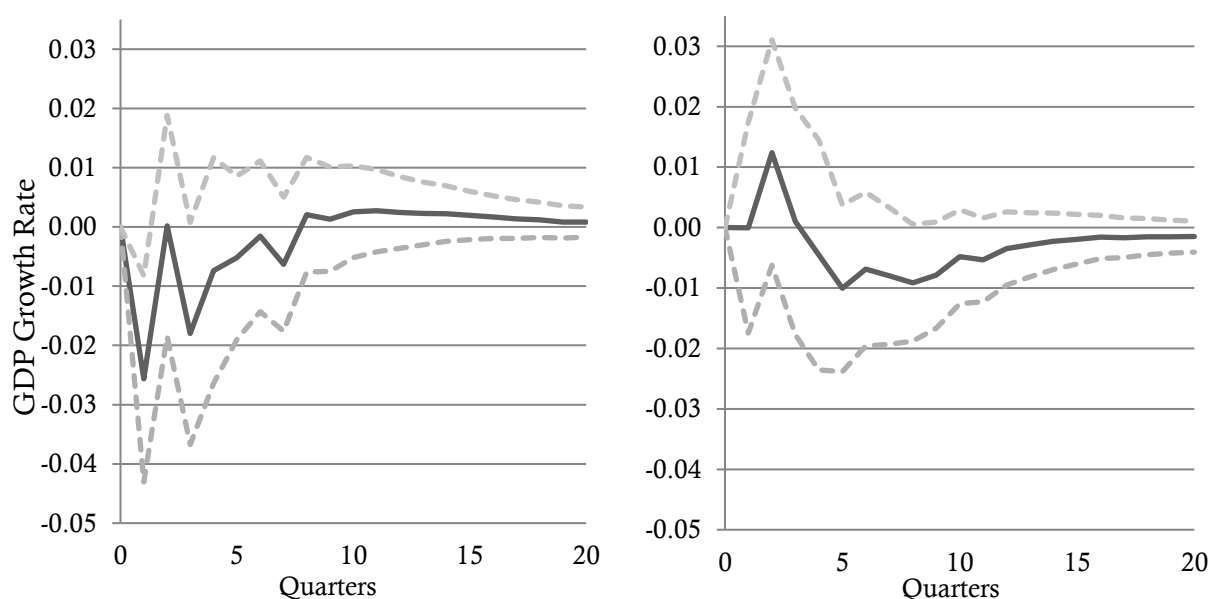

Figure 6. Response of real GDP growth to a 10% PPI-based normalised positive (left) and negative (right) oil price shock. IRF estimated based on 7-variable system 2 in 1974:1-2015:2 sample period. 95% confidence interval shown with dashed lines.

In the left panel, the confidence bands indicate that only the first and third quarters' responses are different from zero and that 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%[3] in this specification, proxy, and sample period combination. This 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 shocks yielded similar results as shown in Figure 7.
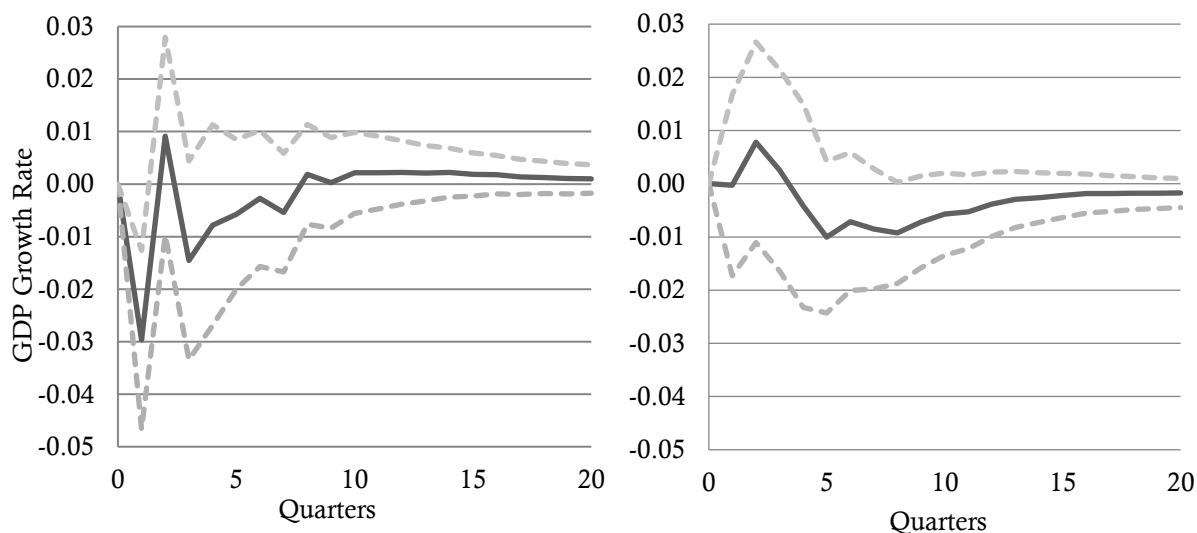

Figure 7. Response of real GDP growth to a 10% RAC-based normalised positive (left) and negative (right) oil price shock. IRF estimated based on 7-variable system 2 in 1974:1-2015:2 sample period. 95% confidence interval shown with dashed lines.

Interestingly, a fall in the price is estimated to have a negative impact on output growth rate as shown in the right panels of Figures 6 and 7. The initial flat effect in the first quarter is followed by a positive one in the second quarter, but negative ones follow immediately after, leading to an overall decline in the response variable. In these two figures, 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, We observe a larger impact in the middle of the sample period than later.

This is more apparent in Figure 8 below and Figure A1 in Appendix A, 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

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[3] These results are expressed in percentage points but shown as a percentages for simplicity.

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 become more pronounced with the largest observed impact corresponding to 1977.
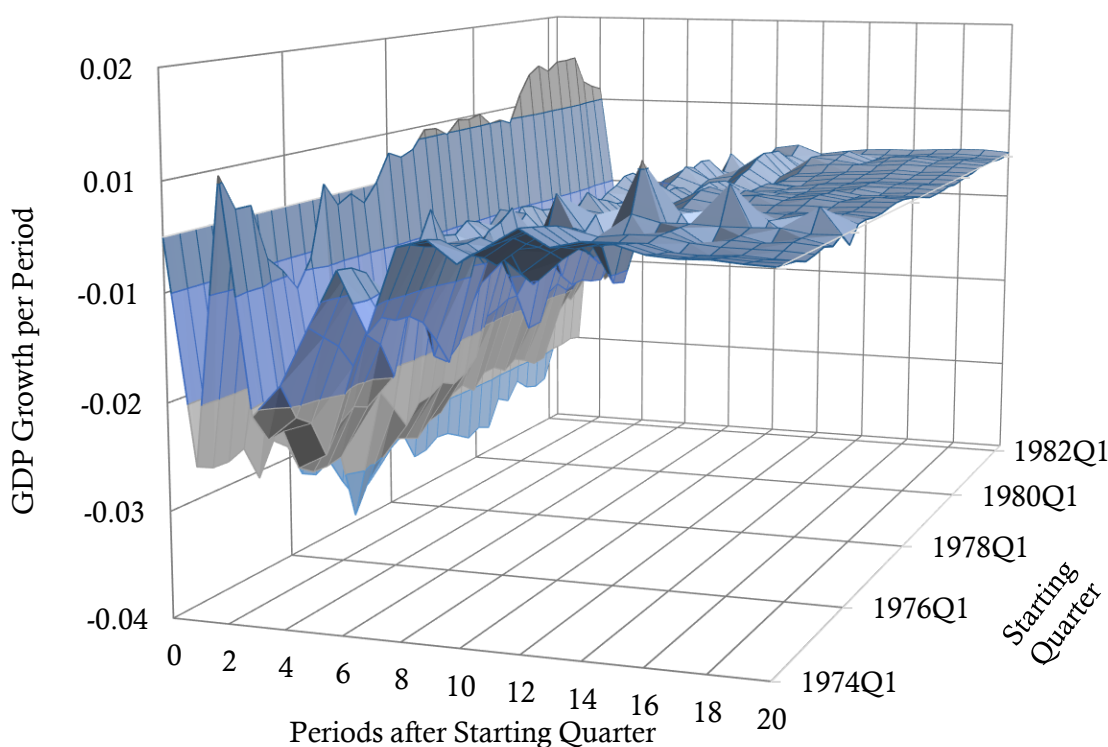

Figure 8. Rolling IRFs with a 10% RAC-based normalised positive oil price shock using 7-variable system 2.

Blanchard & Galí (2007) 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." IRFs based on 7-variable system 2 yielded a similar total annualised figure 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—but 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.

IRFs based on 8-variable system 2 were also generated 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 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. Figures A2 and A3 in Appendix A show the functions where RAC is used. The increase in overall impact in the most recent sample suggests that normalised positive oil price changes not only retain their explanatory power 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 in recent sample periods, and is due to the way in which oil prices are modelled. IRF impact estimates for both specifications and subsamples are given in Table 7.

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 7. 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.

5   Conclusions and Policy Implications

This paper has investigated the oil price and macroeconomy relationship across several dimensions with the goal of answering four pending questions in the literature. These relate to the results observed in empirical studies depending on the (i) choice of oil price measure, (ii) sample period considered, (iii) level asymmetry built into the model, and (iv) role of volatility.

Addressing each of these questions one by one: (i) based on the results and analysis, RAC was found to be a more robust measure of oil price level than PPI for crude oil; (ii) there is limited evidence that the oil price shocks do not Granger-cause fluctuations in output growth rate in recent samples. Further, the findings suggest that the impact of the shocks increased in post-1986 data, and model specification and choice of sample period influence parameter estimates greatly, resulting in misleading outcomes; (iii) there is strong evidence for an asymmetric effect of oil prices on output across model specification and sample period; and lastly, (iv) 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 (for example, 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. Throughout the analysis, models that allow for asymmetry generally performed better—without separating oil price variables into their positive and negative counterparts, the statistical significance of the former is diluted by the latter, making the non-linear transformation adopted here a necessary step in this type of analysis. The approach outlined here does not rely on strong assumptions about underlying

causes of individual oil price shocks or indices that help categorise the shocks into a pre-determined structure.

Impulse response analysis found that positive oil price shocks have a significant negative impact on output growth rate in the US, whereas the impact of oil price falls matter much less. 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 and rich perspective on a relationship with a long macroeconomic and econometric history. Modelling implications and recommendations are summarised below.

Modelling implications	Recommendation based on this study
Choice of oil price measure can change estimation results	Use RAC to measure oil prices
Oil price shocks no longer Granger-cause fluctuations in GDP growth in the US	When modelled correctly (normalisation and non-linear transformation), oil price increases Granger-cause changes in US output growth
Oil price shocks have a negligible effect on US economic growth	Analysis of post-1986 data indicates that oil price hikes have a larger impact on real GDP growth than early 1980s
Oil price shocks must be modelled based on their underlying cause	Relying on structural assumptions or indices is not necessary. Normalisation and non-linear transformation of oil prices are sufficient in a VAR context

Table 8. Modelling implications and recommendations based on this study.

These findings have policy implications in several dimensions. First, policy variables, such as 3-month TB rate, still play a key role in determining the path of real output growth. Second,

using RAC as the oil price proxy has modelling advantages. Third, oil price-macroeconomy relationship has evolved over time, so parameter estimates and model calibration are sensitive to sample period. Fourth, the relationship in question can be modelled accurately without resorting to structural assumptions or unreliable proxies to describe oil price behaviour, because adjusting for volatility suffices. The rolling-window implementation in this study corroborates these conclusions and ensures they are not sensitive to sample period.

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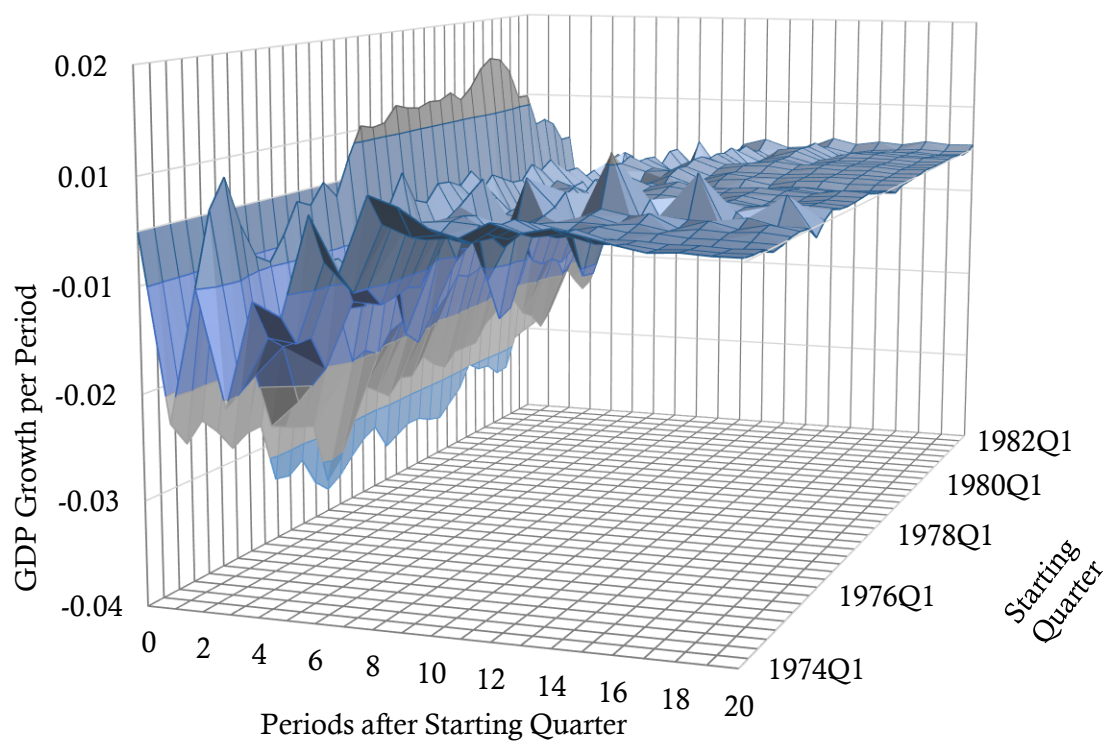# 7 Appendix A: Supplementary Tables and Figures

Figure A1. Rolling IRFs with a 10% PPI-based normalised positive oil price shock using 7-variable system 2.
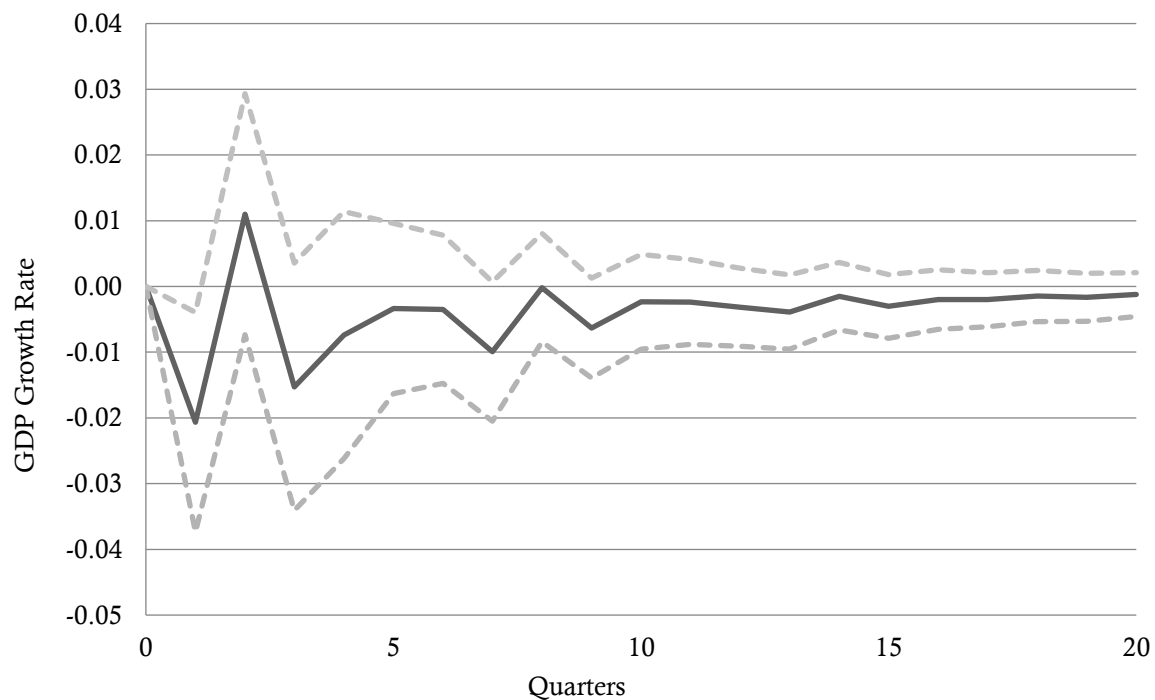
Figure A2. Response of real GDP growth to a 10% RAC-based normalised positive oil price shock. IRF estimated based on 7-variable system 2 in 1986:1-2015:2 sample period. 95% confidence interval shown with dashed lines.
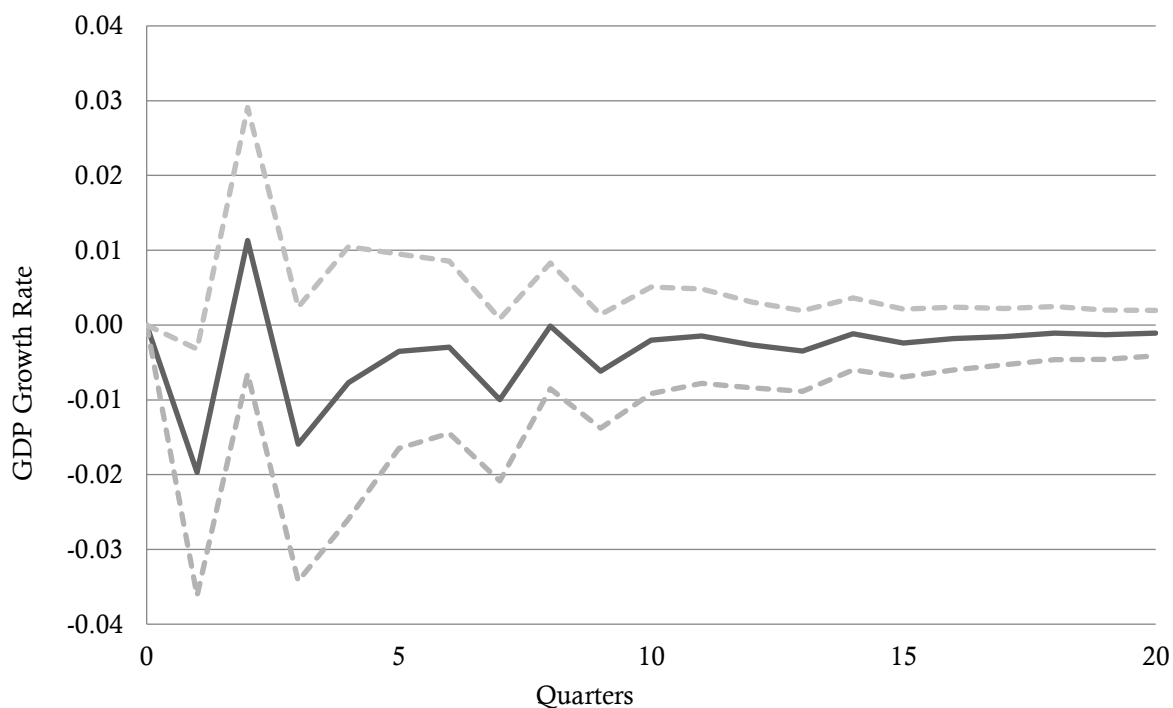

Figure A3. Response of real GDP growth to a 10% RAC-based normalised positive oil price shock. IRF estimated based on 8-variable system 2 in 1986:1-2015:2 sample period. 95% confidence interval shown with dashed lines.

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 A1. Model specifications.