Changes in the Global Oil Market

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Abstract

Changes in the parameters of a recursively identified oil market model are examined through an iterative algorithm that tests for possible breaks in coefficients and variances. The analysis detects breaks in the coefficients of the oil production and price equations, together with volatility shifts in all three equations of the model. Coefficient changes imply an enhanced response of production to aggregate demand shocks after 1980; and that the price response to supply shocks is more persistent from the mid-1990s. All variables evidence changes in the relative contributions of individual shocks to their forecast error variances, with coefficient and volatility breaks in the first half of the 1990s being particularly important in this respect. The results show that analysts of this market should eschew constant parameter models estimated over an extended period.

JEL classification: E42, Q43.

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1 Introduction

A growing literature has underlined the importance of distinguishing between demand and supply shocks in the global oil market. In particular, the seminal paper of Kilian (2009) argues that traditional vector autoregressive (VAR) modeling methodologies do not separate these shocks and hence an increase in the price of oil following an expansion in the level of global economic activity could be wrongly attributed as an oil price shock. To avoid this problem, Kilian (2009) proposes ordering restrictions to define a structural VAR (SVAR) model that captures the essential features of the world oil market and, consequently, disentangles demand and supply shocks.

Nevertheless, the nature of the oil market has changed over the four decades following the oil price shocks of the mid-1970s. The transition from the 'official price' regime of the earlier period, when the oil price was set by long-term contracts, to the current market-based system of direct trading in spot and futures markets, has seen the power balance shift away from the Organization of the Petroleum Exporting Countries (OPEC); see Mabro (2006) for a detailed account of the changes in pricing regimes. Moreover, OPEC itself experienced internal structural instability, leading to its near-collapse in 1986, while the new millennium saw an oil price boom and an important role played by emerging economies (Hamilton, 2014, Kilian and Hicks, 2013, Kilian and Lee, 2014), but a very recent price collapse. These considerations suggest change may apply in the parameters of oil market SVAR models since the 1970s. The present paper examines this question through a model adopting the identifying restrictions proposed by Kilian (2009) to which recently developed structural break tests are applied.

The analysis of Kilian (2009), together with many subsequent studies (including Kilian and Murphy, 2014, Kilian and Park, 2009), assumes the model parameters are constant over time. However, if the parameters change then false conclusions may be drawn about both the past and, more importantly, the contemporary consequences of oil shocks. That is, analysis through the conventional SVAR tools of impulse response analysis and forecast error variance decompositions can be seriously misleading if constant parameters are assumed when, in fact, the parameters have changed over the period used for estimation.

Despite the predominant assumption of constant parameters, some authors have recognised the potential importance of change in oil market models. For example, both Sadorsky (1999) and Peersman and Van Robays (2012) assume change occurs at the end of 1985, whereas Baumeister and Peersman (2013b) employ a time-varying parameter SVAR (TVP-SVAR) specification that implies continuous evolution in all parameters. Lütkepohl and Netšunajev (2014), on the other hand, apply a Markov switching model for the volatility of oil market shocks in a specification with other parameters constant. Our formal structural breaks analysis provides complementary information to these studies, allowing for discrete breaks of unknown number and, in particular, permitting the null hypothesis of no change to be explicitly considered. A discrete break test of the type that we use is known to have power against other alternatives, such as one in which the coefficients follow a random walk (see Stock and Watson, 1998 and Boivin and Giannoni, 2006). While the continuous change implied by the random walk assumption (used by Baumeister and

Peersman, 2013b) is flexible in modelling terms, it results in a loss of estimation accuracy if employed in a period of constant coefficients.

To the best of our knowledge, the present paper is the first to apply formal statistical tests to examine the existence and nature of change in both the structural coefficients and the shock volatilities of an oil market model. In other words, rather than assuming either constant parameters or change at specific dates, we 'let the data speak'. Further, since parameters are constant in our model within regimes, we are able to construct conventional confidence intervals for impulse response functions and forecast error variance decompositions, whereas these tools have limited applicability in a model with continuous change. For these reasons, we prefer to test for parameter change (or structural breaks), rather than impose either continuous change or to (perhaps arbitrarily and potentially incorrectly) pre-specify the date or dates at which change may occur.

An important implication of the analysis of Baumeister and Peersman (2013b) is that changes in coefficients and the volatilities of shocks in this market may apply at different dates, and we allow for this through the testing approach of Bataa, Osborn, Sensier and van Dijk (2013). However, the latter applies to a conventional VAR model, so the methodology is here extended to the recursively ordered SVAR context. In particular, by considering each equation separately, our methodology not only permits coefficients and volatilities to change at different dates, but dates of change may also differ over equations. Prior to estimation, the respective null hypotheses of no change are explicitly examined for coefficients and volatility in each equation. Although our focus is the world oil market, the structural break testing methodology developed here can be used within any recursively ordered SVAR model.

Our results confirm that both the SVAR coefficients and the volatilities of shocks have changed over the four decades to early 2014, so that constant parameter modelling is not appropriate. Further, these changes have important implications for understanding the world oil market. More specifically, coefficient changes are found in the oil production equation at the end of 1980, with supply shocks having a transient effect on production before that date but permanent effects subsequently. On the other hand, breaks are found in the oil price equation in 1988 and 1994, with the post-1994 period showing distinct responses compared with earlier subperiods. Indeed, only this latest period (1994 to 2014) shows positive price responses to negative supply shocks at all horizons and it also exhibits substantially faster price responses to oil-specific demand shocks. Therefore, predictions based on a model not allowing for change would substantially underestimate the responsiveness of the oil price to both supply and demand shocks. Interestingly, the global financial crisis (GFC) and other events of the new millennium do not appear to have altered the coefficients of these relationships.

Further, volatility changes are uncovered in all three equations, but the only volatility break apparently associated with the onset of the GFC occurs in the economic activity equation. Volatility as well as coefficient changes over the period are shown to have important effects on the forecast error variance decompositions, with oil supply shocks contributing less and oil specific demand shocks more for all variables over the second half of our sample period. In particular, whereas supply shocks were the most important contributor to oil price inflation volatility two or more years ahead in the period to the mid-1980s, the dominant role has been played by oil-specific demand shocks since 1994. The increased importance of these shocks is compatible with emerging economies, including China and India, becoming important contributors to world oil demand over the last two decades.

The structure of the paper is as follows. Section 2 presents the methodology employed for structural break testing in a SVAR model, while the data series and their properties are discussed in Section 3. Substantive results are provided in Section 4, covering structural break test results, together with impulse response and forecast error variance decomposition analyses over the regimes identified by the detected breaks. Conclusions can be found in a final section.

2 Structural VAR Methodology

In an SVAR framework, Kilian (2009) proposes contemporaneous ordering restrictions to identify oil supply shocks, demand shocks that drive all industrial commodities, and oil market specific demand shocks. His approach leads to very clear conclusions: the main drivers of oil price changes since the 1970s have come from demand, not oil supply, and hence oil prices must be treated as endogenous in modeling the world or US economy.

An important strand of recent literature on the oil market, including Peersman and Van Robays (2009, 2012), Baumeister, Peersman and Van Robays (2010), Baumeister and Peersman (2013a, 2013b), aims to identify analogous shocks to those of Kilian (2009) using sign restrictions. For our purposes, however, sign restriction methodologies are less amenable to the application of formal structural break inference than the exclusion restrictions imposed by Kilian (2009). Further, the framework of Kilian (2009) remains the main benchmark against which other approaches to modelling the world oil market are compared.

This section first describes the oil market model we employ, with subsection 2.2 then outlining the iterative method based on Bataa, Osborn, Sensier and van Dijk (2013) we use to disentangle structural breaks in the SVAR. Finally, the methodology employed for computing confidence intervals for impulse response functions and forecast error decomposition standard errors is discussed in subsection 2.3.

2.1 The oil market model

Our model is estimated using monthly data for $\Delta_1 \mathbf{z}_t = (\Delta_1 prod_t, \Delta_1 rea_t, \Delta_1 rpo_t)$, where $prod_t$ is the logarithm of global crude oil production, rea_t refers global real economic activity and rpo_t denotes the real price of oil in logarithms. As discussed in the next section, and indicated by the notation, all three variables are differenced in our analysis. With no intercepts or seasonal dummy variables required (see Section 3), the SVAR can be written as

$$\mathbf{A}_0\Delta_1\mathbf{z}_t = \sum_{i=1}^{24} \mathbf{A}_i\Delta_1\mathbf{z}_{t-i} + \boldsymbol{\varepsilon_t} \tag{1}$$

where $\boldsymbol{\varepsilon}_t = (\varepsilon_{oils,t}, \varepsilon_{aggd,t}, \varepsilon_{oild,t})'$ denotes a vector of structural shocks with variances of oil supply, aggregate demand and oil specific demand shocks σ^2_{oils}, σ^2_{aggd}, σ^2_{oild}, respectively. The shock vector $\boldsymbol{\varepsilon}_t$ is both serially and mutually uncorrelated and hence $E(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t') = \boldsymbol{\Sigma}$ is diagonal.

Kilian (2009) identifies separate shocks for oil supply, aggregate demand and oil-specific demand shocks through contemporaneous ordering restrictions in $\mathbf{A}_0$ of (1). More specifically, he assumes supply is unaffected by any within-month demand shocks, while aggregate global demand is contemporaneously unaffected by oil specific demand shocks. Oil specific demand shocks then capture all contemporaneous influences on oil prices that are not reflected in oil supply and aggregate demand shocks, and include effects arising from fluctuations in the precautionary demand for oil. As in Kilian (2009), a lag length of 24 is employed in (1), which allows for relatively long lagged responses to shocks; see also Hamilton and Herrara (2004) and Kilian (2008). However, testing for structural changes in a large number of coefficients is infeasible, especially when economic arguments suggest potential changes relatively early in the sample. In order to counter the curse of dimensionality while retaining lags to a maximum of two years, we adopt the heterogeneous autoregression (HAR) approach of Corsi (2009). This convenient coefficient reduction technique is widely used in the finance literature to capture long lagged effects (or so-called long memory); see Bandi, Russell and Yang (2013) and Wang, Bauwens and Hsiao (2013), among others.

Our specific structural heterogeneous VAR (SHVAR) is given by

$$\mathbf{A}_0\Delta_1\mathbf{z}_t = \boldsymbol{\Psi}_1\Delta_1\mathbf{z}_{t-1} + \boldsymbol{\Psi}_2\Delta_3\mathbf{z}_{t-1} + \boldsymbol{\Psi}_3\Delta_6\mathbf{z}_{t-1} + \boldsymbol{\Psi}_4\Delta_{12}\mathbf{z}_{t-1} + \boldsymbol{\Psi}_5\Delta_{24}\mathbf{z}_{t-1} + \boldsymbol{\varepsilon_t} \tag{2}$$

where the k-lag difference operator is $\Delta_k = (1 - L^k)$ and L is the conventional lag operator. Thus, our SHVAR specification (2) allows the current monthly change $\Delta_1\mathbf{z}_t$ to depend on short term, medium term and longer term dynamics, represented here by change over the previous month, quarter, six months, one year and two years. Although the choice of these periods is relatively arbitrary, it allows reasonable flexibility within a specification with relatively smooth effects over lags. We are also mindful that conventional order selection criteria point to the use of a low lag order in (1), with Lütkepohl and Netšunajev (2014), for example, using three lags for monthly data as selected by AIC over their sample period. Our specification of (2) is quite flexible at low lags, allowing the very short-run one month responses to differ from those at two or three months, which in turn differ from the longer lagged responses.

Note that our SHVAR is a restricted SVAR model in which the responses over 24 lags for each of the three variables are captured through a total of only 15 coefficients. Since $\Delta_k\mathbf{z}_t = \mathbf{z}_t - \mathbf{z}_{t-k} = \sum_{j=0}^{k-1}\Delta_1\mathbf{z}_{t-j}$, the restricted SVAR coefficients of (1) can be recovered from those of

(2) as

$$\begin{aligned}
\mathbf{A}_1 &= \sum_{j=1}^{5} \mathbf{\Psi}_j,\ \mathbf{A}_2 = \mathbf{A}_3 = \sum_{j=2}^{5} \mathbf{\Psi}_j,\ \mathbf{A}_4 = \mathbf{A}_5 = \mathbf{A}_6 = \sum_{j=3}^{5} \mathbf{\Psi}_j, \\
\mathbf{A}_7 &= \mathbf{A}_8 = \ldots = \mathbf{A}_{12} = \sum_{j=4}^{5} \mathbf{\Psi}_j,\ \mathbf{A}_{13} = \mathbf{A}_{14} = \ldots = \mathbf{A}_{24} = \mathbf{\Psi}_5. \qquad (3)
\end{aligned}$$

These relationships imply 57 coefficient restrictions in each SHVAR equation and these are tested against the general form SVAR, as explained in the following subsection. After imposing these restrictions (when valid), estimates from the SHVAR can be used to conduct conventional SVAR analyses, such as the examination of impulse responses.

2.2 Testing for multiple structural breaks

As noted above, we employ an iterative methodology based on the procedure of Bataa, Osborn, Sensier and van Dijk (2013, 2014) to examine structural breaks in the coefficients and shock variances of the global oil market model. The simulation studies of these authors show that the iterative procedure generally works well in detecting true breaks, with the coefficient and volatility (or covariance) tests also having satisfactory empirical sizes.

Using the recursive ordering in the structural model of (1), the individual equations can be written as:

$$\Delta_1 prod_t = \sum_{i=1}^{24} \mathbf{a}_{i,(1)} \Delta_1 \mathbf{z}_{t-i} + \varepsilon_{oils,t} \qquad (4)$$

$$\Delta_1 rea_t = a_{21}\Delta_1 prod_t + \sum_{i=1}^{24} \mathbf{a}_{i,(2)} \Delta_1 \mathbf{z}_{t-i} + \varepsilon_{aggd,t} \qquad (5)$$

$$\Delta_1 rpo_t = a_{31}\Delta_1 prod_t + a_{32}\Delta_1 rea_t + \sum_{i=1}^{24} \mathbf{a}_{i,(3)} \Delta_1 \mathbf{z}_{t-i} + \varepsilon_{oild,t} \qquad (6)$$

where $\mathbf{a}_{i,(j)}, j = 1, 2, 3$ are the j^{th} rows of $\mathbf{A}_i$, and a_{ij} are elements of $\mathbf{A}_0$ in (1). The restrictions of (3) are imposed when these are compatible with the data, so that equations (4) to (6) then constitute a SHVAR model.

As in the structural break testing strategy of Bataa Osborn, Sensier and van Dijk (2013), our procedure employs the multiple structural break tests of Qu and Perron (2007), but iterates between coefficient and variance breaks. Although heteroskedasticity consistent inference is used in the initialization of the procedure to detect possible coefficient breaks, subsequent iterations employ appropriate generalized least squares (GLS) transformed data, based on residual variance estimates that incorporate breaks. The procedure allows coefficient and variance breaks to be estimated and dated separately.

As discussed in Hansen (2000), structural changes in the marginal distribution of regressors can lead to size distortions when inference is applied to the stability of regression coefficients. This, combined with the application of asymptotic tests in our finite sample context, leads us to subject rejections indicated by the use of asymptotic critical values based on stable marginal distributions to further test through a finite sample bootstrap procedure that takes account of breaks and the recursive nature of the three equations, as discussed below. For computational feasibility, this bootstrap procedure treats break dates estimated through the asymptotic procedure as if they are known dates of potential change.

Due to the contemporaneous causality assumption embodied in (4)-(6), together with the diagonal covariance matrix of a SVAR (or SHVAR) model, each equation can be validly estimated by ordinary least squares (OLS). Therefore, we directly test for structural breaks in these individual equations, thus reducing the burden of testing for multiple breaks compared with a system approach, while adding flexibility in allowing different break dates across equations. Such an equation-wise testing strategy is relatively old and used in, for example, Bernanke and Mihov (1998) and Bagliano and Favero (1998).

The algorithm for the first equation, namely (4), is:

1. (a) Test the overall null hypothesis of no coefficient breaks using the heteroskedasticity robust 'double maximum' *WDmax* test statistic against the possibility of $l \leq M_c$ breaks, where the maximum number of breaks M_c is pre-specified. The statistic allows both the number of breaks (l) and their dates to be unknown, with asymptotic critical values applied. If the asymptotic *WDmax* test does not reject the null hypothesis of no coefficient breaks, estimate the coefficients by conventional OLS and proceed to step 2; otherwise go to step 1(b).

   (b) Apply sequential F-type tests (with their asymptotic critical values) to estimate the number of coefficient breaks and their locations, as recommended by Bai and Perron (1998). If l breaks are detected at dates $\hat{T}_1^{(c)}, \ldots, \hat{T}_l^{(c)}$ regime-specific observations $t = \hat{T}_{k-1}^{(c)} + 1, \ldots, \hat{T}_k^{(c)}$ are used to obtain $\hat{\mathbf{a}}_{i,(1)}^{(k)} (i = 1, ..., 24)$ and the corresponding residuals $\hat{\varepsilon}_{oils,t}$ for each regime $k = 1, \ldots, l+1$.

   (c) Verify the significance of each detected coefficient break $k = 1, \ldots, l$ through a heteroskedasticity robust $Wald$-statistic test of the null hypothesis $\mathbf{a}_{i,(1)}^{(k)} = \mathbf{a}_{i,(1)}^{(k+1)}$, with inference conducted conditional on all other $l-1$ estimated breaks. The computed statistic is compared to the empirical distribution obtained from a bootstrap data generating process (DGP) that employs estimated coefficients restricted through $\mathbf{a}_{i,(1)}^{(k)} = \mathbf{a}_{i,(1)}^{(k+1)}$ and a wild bootstrap process for $\varepsilon_{oils,t}$ in equation (4)[1].

   (d) If not all coefficient breaks $k = 1, \ldots, l$ are individually significant, reduce the number of coefficient breaks to $l-1$ and estimate new break dates, together with corresponding coefficients and residuals, and return to step 1(b). Repeat until all coefficient breaks

[1]Based on the Monte Carlo studies of the wild bootstrap (Godfrey and Orme, 2004, Davidson and Flachaire, 2008), we set $\varepsilon^*_{oils,t} = \omega_t \hat{\varepsilon}_{oils,t}$, $t = 1, \ldots, T$, in which the scalar random variable ω_t has the Rademacher distribution, taking the two possible values $+1$, -1 with probabilities of 0.5.

are individually significant. If no breaks are significant, estimate the coefficients by OLS using the whole sample.

2. (a) Based on the residuals $\hat{\varepsilon}_{oils,t}$ obtained in step 1 (or 3 below), apply the asymptotic 'double maximum' likelihood ratio-type test statistic to test the null $H_0 : \sigma^2_{oils,1} = \ldots = \sigma^2_{oils,m+1}$ for an unknown number of volatility regimes with $m \leq M_v$ and M_v pre-specified. If the null hypothesis is not rejected, no volatility breaks are detected and proceed to step 3.

   (b) If the null hypothesis is rejected, the number of breaks is estimated using a sequential test procedure, now based on likelihood ratio-type tests and asymptotic critical values (see Bataa Osborn, Sensier and van Dijk, 2013). If m volatility breaks are detected at dates $\hat{T}_1^{(v)}, \ldots, \hat{T}_m^{(v)}$, $\widehat{\sigma}^2_{oils,j}$ for each regime $j = 1, \ldots, m+1$ is estimated using observations $t = \hat{T}_{j-1}^{(v)} + 1, \ldots, \hat{T}_j^{(v)}$.

   (c) For each identified volatility break $j = 1, \ldots, m$, and conditioning on all other $m-1$ breaks, compute the usual quasi-likelihood ratio test statistic, LR, for the null hypothesis $\sigma^2_{oils,j} = \sigma^2_{oils,j+1}$. For inference on break j, the shock vector $\hat{\varepsilon}_{oils,t}$ for $t = \hat{T}_{j-1}^{(v)} + 1, \ldots, \hat{T}_j^{(v)}, \ldots \hat{T}_{j+1}^{(v)}$ is randomly *i.i.d.* re-sampled, with a wild bootstrap employed in other regimes to create the bootstrapped shocks $\hat{\varepsilon}^*_{oils,t}$[2]. Then $\hat{\varepsilon}^*_{oils,t}$, together with the $(l+1)$ sets of coefficient estimates found in step 1 (or 3), form the bootstrap DGP that is used to obtain the empirical null distribution, and hence the empirical p-value, for LR[3].

   (d) If not all variance breaks are individually significant, reset m to the previous value minus one; then estimate new variance break dates and regime-specific variances. Return to step 2(c) until all m variance breaks are individually significant.

3. Re-estimate the number and dates of coefficient breaks using a feasible GLS approach, achieved by dividing all observations entering (4) for $t = \hat{T}_{j-1}^{(v)} + 1, \ldots, \hat{T}_j^{(v)}$ by $\widehat{\sigma}_{oils,j}$, $j = 1, \ldots, m+1$. Re-apply the coefficient test procedure as in step 1, but now apply the homoskedastic version of the multiple breaks test procedure to the coefficient vector $\mathbf{a}_{i,(1)}^{(k)}$ in the GLS-transformed equation.

4. Iterate between steps 2 and 3 until the numbers and dates of coefficient and variance breaks do not change[4]. Note that step 2 is always applied to the residuals calculated using the original observed (not GLS-transformed) values.

Analogous procedures are applied to detect breaks in the economic activity and price equations, (5) and (6), with the relevant contemporaneous coefficients included in the coefficient

[2] The *i.i.d.* bootstrap within the regimes under test enforces the null hypothesis of unchanged variance, whereas the wild bootstrap for the remaining observations allows variances to differ across the other regimes.

[3] The coefficients and shocks are re-estimated for the bootstrap DGP, but the coefficient break dates are assumed known at $\hat{T}_1^{(c)}, \ldots, \hat{T}_l^{(c)}$.

[4] Although it is possible the procedure may converge to a cycle of dates, rather then a single date, this did not occur in the oil market model application.

break tests. There is, however, an important difference in the bootstrap break testing procedure applied for these latter equations. For the first equation of the system, bootstrap production data are generated recursively from (4), with observed values of the other two series used in the bootstrap replications[5]. For the activity equation (5), however, bootstrap values for production are employed, based on the breaks detected in the coefficients of (4), and these are used when recursively generating bootstrapped values for economic activity. Similarly, when the procedure is applied to the price equation, the bootstrapped values of oil production and economic activity are generated, conditional on the estimated breaks in each of their respective equations, and these values are employed in (6) when recursively generating bootstrapped price data.

In addition to break date estimates, the methodology of Qu and Perron (2007) is used to obtain associated confidence intervals. Nevertheless, due to the iterative procedure employed, these should be taken as merely indicative.

The coefficient restrictions of (3) imposed in the SHVAR model are also tested. More explicitly, to take account of any detected volatility breaks in the shocks of (4)-(6), the restrictions are tested equation by equation using GLS transformed data, with tests applied both over the whole sample and each of the potential regimes defined by the coefficient breaks. The test is a conventional F-test of the coefficient restrictions compared to (1), with a finite sample *i.i.d.* bootstrap employed for this purpose[6]. The bootstrap employed when testing structural breaks and restrictions uses 10,000 replications.

2.3 Impulse response and forecast error variance analyses

It is now conventional to analyse the implications of an SVAR model through the use of impulse response functions and forecast error variance decompositions (FEVDs). As noted in the Introduction, our analysis also employs these tools. However, in the presence of structural breaks, these apply within each regime identified by the relevant structural breaks. It also should be noted that the impulse response and FEVD computations assume the regime does not change within the horizon considered.

SVAR coefficients show how shocks are transmitted through a system, and hence the impulse response functions are unaffected by volatility changes. Although our analysis does not restrict breaks to occur at the same dates in each of the three equations of the oil market model, nevertheless, due to their system nature, impulse responses are affected by the occurrence of a coefficient break in any equation. Therefore the number of distinct regimes for impulse response computation is determined by the total number of distinct coefficient break dates detected across all equations of the system.

One and two standard deviation confidence bands (approximate 66% and 95% confidence intervals) are obtained for the impulse response functions using a recursive-design wild boot-

[5]Hansen (2000) shows that a fixed bootstrap procedure works well for structural break testing in a single equation from a VAR system.

[6]An *i.i.d.* bootstrap is employed as the GLS transformation removes detected heteroskedasticity. The asymptotic 5% critical value under homoskedasticity from $F(60, \infty)$ is 1.32.

strap procedure, as in Kilian (2009). In our case, artificial bootstrap data are generated and the SHVAR coefficients re-estimated within each replication over the sub-periods given by the (equation-specific) coefficient break dates, which are treated as known. Use of the wild bootstrap takes account of any volatility changes, which would otherwise affect the confidence intervals. Computation of the impulse responses resulting from these estimated models over 2000 replications leads to the distributions summarized through the confidence bands.

Volatility shifts, in addition to coefficient breaks, contribute to the FEVDs and the number of regimes for these is determined by the total number of distinct coefficient and volatility breaks in the system. A bootstrap procedure with 2000 replications is again adopted in order to compute FEVD standard errors, with parameters re-estimated within each detected coefficient or volatility regime, as appropriate. The bootstrap takes account of volatility breaks through the use of separate *i.i.d.* re-sampling within each volatility regime.

3 Data and Preliminary Analysis

Following Kilian (2009), the three oil market variables consist of monthly global crude oil production, the real price of oil and global economic activity. Prior to analysis, logarithms are taken for real oil prices and production, while the global activity measure is expressed as percentage deviations from trend[7]; the variables are plotted in this form in the left-hand panel of Figure 1 over our sample period, from December 1972 to February 2014[8]. As in Kilian (2009) and Baumeister and Peersman (2013a, 2013b), the oil price variable is US refiners' cost of oil imports[9], deflated by US seasonally adjusted CPI to derive the real price of oil.

Our sample extends over four decades and hence covers a variety of periods, including the oil price rises of the 1970s, the partial breakdown of OPEC and price collapse in 1986, the period of the so-called Great Moderation, the 2003-2008 oil price boom and the GFC. We are particularly interested in whether recent events are reflected in changes in the oil market model and the nature of its shocks. Since we test for structural breaks, the data is allowed to determine whether the relationships over recent years do, indeed, differ from earlier periods. The changing features over our extended sample appear particularly evident in the graphs in the right-hand panel of Figure 1, which shows month to month changes (after logarithmic transformations for oil production and real oil prices).

As a preliminary to our SVAR analysis, the remainder of this section examines, firstly, the unit root properties of our series using tests robust to breaks in the trend and, secondly, applies univariate structural break tests. Unit root tests are undertaken as a guide to the differencing

[7]The last is constructed by Kilian (2009) and based on detrended real bulk dry cargo freight rates. More specifically, the original series in US dollars is deflated by the US CPI and detrended. The underlying cargo rates are not readily available, and we employ the data provided by Kilian after these transformations.

[8]Our data sources are the US Department of Energy for the oil variables (except that global oil production for December 1972 is from the data of Baumeister and Peersman (2013a)), with global activity from Kilian's website. In addition, CPI is obtained from the FRED database of the Federal Reserve Bank of St. Louis.

[9]Although the data are available only from 1974, we follow and Kilian (2009) and backdate this series using the US producer price index for oil.

applicable for each variable in the SVAR, while the univariate analysis of the oil market data series aids understanding of their characteristics.

3.1 Unit root tests

Perron (1989) draws attention to the importance of trend breaks for the conduct of unit root tests, with recent developments allowing for possible trend breaks under both the unit root null hypothesis and the trend stationary alternative. We apply the procedure of Kejriwal and Perron (2010) that employs sequential hypothesis tests to estimate the number of trend breaks using procedures that are robust to the unit root properties of the data, with unit root tests then applied to the appropriately detrended data. This procedure is well described in Kejriwal and Lopez (2013). In brief, stability of the trend function is initially tested against one break in slope and level using the test of Perron and Yabu (2009). If this is rejected, the unit root test allows possible multiple trend breaks under both the null and alternative hypotheses using the procedure of Carrion-i-Silvestre, Kim and Perron (2009). Unit root tests are then based on so-called M-tests analysed by Ng and Perron (2001) with quasi-generalized least squares (GLS) detrending and lag specification as proposed by Qu and Perron (2007).

Estimation of trend breaks using the Kejriwal and Perron (2010) procedure requires a priori specification of the maximum number of breaks, which we specify as five. Since their method is a sequential procedure based on sample splitting, we allow the 'trimming' parameter required in the structural break procedure to increase as the effective sample size decreases. In particular, we set this to 10% (that is, 10% of the total sample is required to be in each regime) when only one break is considered for over the whole sample, increase it to 15% when testing for single breaks in each of two sub-samples and increase it further to 25% for additional sub-division of the original sample. All tests are conducted at an asymptotic 5 percent level. We use AIC with the maximum lag length $p_{max} = integer[12 \times (T/100)^{1/12}]$ to select the appropriate AR order. Note that break dates are re-estimated after each sequential identification of an additional break.

Summary results are reported in Table 1, with panel a showing that the sequential procedure indicates one break for global activity[10] and the maximum of five for both oil production and real oil price. The test results in panel a are clear in all cases in relation to the critical values, including the rejection of no break against the alternative of one break. Nevertheless, as many as five trend breaks may be considered implausible in our data spanning four decades; hence panel b provides unit root test statistics for all numbers of breaks from zero to five. Overall, the conclusion that oil production is $I(1)$ is robust, unless one considers the maximum of five breaks. Real oil prices are also supported as $I(1)$ unless three or four breaks are employed, but neither number is indicated in panel a. Indeed Blanchard and Riggi (2013) note that real price of oil shows a near random walk response. However, conclusions relating to unit root in the

[10] Although the activity data provided by Kilian are detrended, this does not rule out the possibility that broken trends are concealed in the available series. Hence trend breaks are considered for this series on the same basis as oil production and prices.

activity measure are fairly marginal in respect to the unit root test statistics in relation to their asymptotic critical values.

Our subsequent analysis employs first difference of all three variables. Although, as just noted, the tests for economic activity suggest deliver marginal rejection of the unit root null hypothesis at 5%, we are mindful that the variable is persistent[11] and structural break tests do not perform well for such data (see Diebold and Chen, 1996, and Prodan, 2008, among others). Therefore, on balance, we prefer to analyse the structural stability of the SVAR estimated after differencing all three variables. This is in line with a number of recent studies such as Apergis and Miller (2009), Kilian and Lewis (2011), Jo (2014), Baumeister and Peersman (2013a, 2013b), Ratti and Vespignani (2015).

3.2 Univariate analysis

Having decided to difference all three variables, Table 2 provides the results of a univariate structural breaks analysis using the methodology of Bataa, Osborn, Sensier and van Dijk (2014), where observed changes in an oil market variable $\Delta_1 Y_t$ are decomposed into components capturing the level (L_t), deterministic seasonality (S_t), outliers (O_t) and dynamics (y_t) using

$$\Delta_1 Y_t = L_t + S_t + O_t + y_t \tag{7}$$

and structural breaks are permitted in all components, except O_t. Since our series are expressed as differences, L_t consists of a mean (which is allowed to change over regimes), while S_t is defined so that seasonality sums to zero over the calendar year. Dynamics are captured through an AR model without an intercept, with breaks permitted in the AR coefficients and disturbance variance for y_t. All breaks (level, seasonality, dynamics and variance) can occur at distinct points of time, and hence regimes are specific to these individual components, while outliers are detected allowing for any mean and seasonality shifts. The procedure is based on significance tests, which are conducted at a 5% significance level, with 15% trimming employed for L_t and dynamics in y_t, but 20% for S_t since month-specific seasonal effects are observed only once per year.

Seasonality is included in (7) since oil market variables may exhibit seasonal effects due to both demand and supply factors; see, for example, International Energy Agency (1996). In particular, demand for heating oil surges during winter months and petroleum consumption rises during northern hemisphere holiday periods (Moosa, 1995). Seasonality is weaker on the supply side, but there are periods during which annual maintenance is undertaken for refineries and climatic influences (such as the hurricane season in the Gulf of Mexico) can affect supply. Perhaps as a result of these factors, world oil prices tend to be strongest in the autumn and weakest in the spring[12]. Further, the global economic activity measure of Kilian (2009) is based on shipping

[11] This persistence is evident in the impulse response functions provided by Kilian (2009), particularly the economic activity and oil price responses to aggregate demand and oil-specific demand shocks, respectively.

[12] See Oil Market Basics, an online publication of US Energy Information Administration (EIA), at http://www.eia.gov/energyexplained/index.cfm?page=oil_prices

freight rates, which (according to Stopford, 2009) follow seasonal demand patterns. In an SVAR model similar to the one we employ, albeit with the inclusion of crude oil inventories, Kilian and Murphy (2014) take account through the inclusion of seasonal dummy variables, whereas we allow the possibility of change in these effects. As seen from Table 2, heteroscedasticity and autocorrelation robust (HAC) F-tests show the seasonal dummy variables to be highly statistically significant for all detected seasonal regimes for production and economic activity, although not always for the real oil price. It may also be noted that, unit root tests (not reported) rule out the presence of nonstationary stochastic seasonality[13].

Baumeister and Peersman (2013b) emphasize changes in the volatility of oil market variables, and our results in Table 2 confirm the presence of volatility changes in all three variables. Production growth is most volatile in the turbulent oil market period to 1990, with the lowest volatility in the most recent period, from late 2004. On the other hand, changes in activity show greatest volatility from the beginning of the GFC, with subdued volatility over the period from 1980 to October 2008; see also Figure 1. Real oil price inflation, on the other hand, shows highest volatility between 1986 and 2009. Although the estimated volatility break dates differ across series, they all point to changes in the first decade of the twenty first century, providing an indication of changes in the nature of shocks to the global oil market over this period. Confidence intervals for volatility break dates are fairly tight, although these should be taken as only indicative in the context of our iterative methodology.

Detected seasonality in the real oil price inflation changes at January 1986 and November 1998, whereas no breaks are detected in either the level (mean) of the series analysed or in their dynamics. Other characteristics of interest shown in the table are the generally low persistence and short dynamics, the latter indicated by the AR orders selected by the Hannan-Quinn criterion. Indeed, no dynamics at all are selected for oil production while real oil price inflation is moderately persistent. The analysis also detects three outliers in oil production growth in the latter part of the 1970s and these outlier observations are replaced by the median of the neighbouring six observations. Note, however, that we apply a relatively loose criterion for defining outliers at seven times the interquartile range, in order to avoid losing observations containing valuable economic information, including that relating to the recent global recession.

In addition to correcting for outliers, the results of Table 2 are used to remove seasonality and means from the data, with means constant over the sample and seasonality changing only for oil price inflation. The removal of seasonality and the mean from each series eliminates intercepts and seasonal dummies from our SVAR equations, allowing us to focus on our key interest of possible changes in cross-variable interactions and volatility.

[13]Results of seasonl unit root tests are available from the authors on request. It is also noteworthy that Gallo, Mason, Shapiro and Fabritius (2010) also find little support for seasonal unit roots in oil market data, including oil price and supply.

4 Results

This section presents our main results, with subsection 4.1 examining possible time variation in the structural VAR parameters through the application of the procedure outlined in subsection 2.2, while subsections 4.2 and 4.3 examine the implications of the detected breaks through impulse responses and forecast error variance decompositions, respectively. As discussed in Section 3, the analysis is based on the three oil market variables after (first) differencing, with means and deterministic seasonality removed, together with three outliers in the production series. To facilitate comparisons, all results are expressed in percentage terms. Also note that the sample period for estimation starts in January 1975, due to the lags embedded in the model.

4.1 Breaks in structural parameters

As implied by the discussion of Section 2, the analysis requires specification of the maximum number of breaks permitted and the minimum proportion of the overall sample in each regime. Essentially this involves a trade-off between allowing a sufficient maximum number of breaks to capture adequately changes that may have occurred over the sample and leaving sufficient observations in each regime for reliable parameter estimation. With this in mind, a maximum of five breaks is permitted in the coefficients of each SHVAR equation ($M_c = 5$), with a minimum of 15% of the sample required in each regime. With at least 15% of the sample in each regime, the earliest and the latest dates at which breaks can be detected are November 1980 and April 2008, respectively. In particular, this latest date is close to the onset of the GFC and hence allows some conclusions to be drawn as to whether this major event led to changes in the SHVAR coefficients. With only one variance parameter associated with each equation, the maximum number of breaks is set at eight ($M_v = 8$), with a minimum of 10% of the total sample in each volatility regime. Thus each volatility regime has a duration of at least 3 years and 11 months.

The results of the structural break tests are reported in Table 3, together with asymptotic critical values for a 5% level of significance in parentheses[14]. It may be noted that the iterative procedure converges quickly, after 3 iterations for the production equation, 2 for economic activity and 4 for the real price, as can be seen from panel III of Table 3. Also note that 2 iterations implies that convergence takes place immediately, after the initialization and one subsequent iteration, as the procedure finds no coefficient break.

A feature of the results across all SHVAR equations is that the overall $WDmax$ test statistics, which test the null hypothesis of no variation in coefficients or volatility (as appropriate), soundly reject the constancy hypothesis according to the asymptotic critical values; see the top lines of panels I(A) and II(A) in Table 3 for the coefficients and shock variances, respectively. For

[14]Qu and Perron's (2007) test statistics have the same limit distributions as those in Bai and Perron (1998), who tabulate critical values up to 10 parameters. Although Bai and Perron (2003) provide response surfaces for estimating critical values, Hall and Sakkas (2013) show these surfaces can lead to misleading inferences with a large number of parameters. Therefore we simulate critical values for the number of parameters considered here; details are available from the authors on request.

example, the statistic for the oil production equation, at 255.42, easily rejects the null hypothesis of constant coefficients in relation to the asymptotic 5% critical value of 38.82. These first results indicate that constant parameter modelling should not be undertaken over the sample period and hence provides support for analyses, including Baumeister and Peersman (2013b), that allow time variation in both coefficients and oil market shock volatilities.

Further examination of the oil production equation results shows that the asymptotic sequential test does not reject the null of one break (against two), and hence no further coefficient breaks are sought. The bootstrap procedure confirms the existence of this single break (p-value 0.1%), dated at December 1980, with a tight 90% confidence interval, of October 1980 to February 1981. This break occurs early in a period of surplus capacity and competitive price cuts by OPEC members, during which (as evident in Figure 1) production declined. The corresponding procedure for volatility (panel II(A)) finds two breaks, in 1990 and 2004, which are essentially those identified in the univariate analysis of subsection 3.2. These both mark declines in the volatility of oil production shocks; this pattern is in line with the findings of Baumeister and Peersman (2013b), whose sample ends in 2010.

The role of our finite sample bootstrap procedure to confirm asymptotically detected breaks is seen in the results for economic activity in panel I(A) of Table 3. In this case the overall asymptotic test rejects constancy and, as for the production equation, the sequential test does not find more than one break. However, the bootstrap test for the activity equation delivers a p-value of nearly 25% at the estimated break date, and hence does not confirm the existence of this break[15]. Based on the Monte Carlo experiments of Bataa, Osborn, Sensier and van Dijk (2013) that finds bootstrap inference to be more reliable in finite samples, we conclude there is no break in the coefficients of (5). The contemporaneous coefficient a_{21} of Panel I(B) indicates that activity has a negative contemporaneous estimated point response to increases in oil production throughout the period. The volatility breaks asymptotically detected for activity in 1979 and 2008, shown in panel II(A), are robust to the bootstrap test[16]. The first of these marks the end of the turbulence of the 1970s, resulting in a volatility reduction, and the latter the onset of the GFC[17]. Although Lütkepohl and Netšunajev (2014) also find that economic activity experiences a general volatility reduction over their sample period to 2007, the Markov switching volatility model they employ applies to the system and the switch is estimated to occur later (in 1987) than we detect. The flexibility of our procedure in allowing volatility changes to occur at different dates over equations is evident in the results of Table 3.

In contrast to the stability of the coefficients of the oil production and economic activity

[15]The deleted coefficient break is dated at April 2008. If this break is included, the first volatility break remains unchanged, while the second is dated four months earlier.

[16]Note however that the lower end of the 90% confidence interval of the former is slightly outside the effective sample size.

[17]The aggregate demand volatility reduction dated at September 1979 could also be associated with the construction of the index used to proxy global economic activity. In particular, Kilian (2009, notes to Figure 1) states that two tariffs are used in constructing the index prior to 1980, after which this increases to 15 series. Unless the underlying series are perfectly correlated, a standard portfolio theory argument (Markowitz, 1952) indicates the index will become less volatile as more tariffs are used in its construction.

equations (the former from 1980), oil price inflation responses exhibit breaks in May 1988 and October 1994. Notice from panel I (A) that the use of asymptotic critical values indicates four breaks, but the bootstrap procedure finds one of these to have a p-value of 85%, and deletion of this finds a further break that is not significant (p-value of 83%). In addition, three breaks are uncovered in the volatility of shocks[18]. In line with Baumeister and Peersman (2013b), the coefficient and volatility breaks detected in (6) point to important changes taking place in the determination of oil prices over the last two decades of the twentieth century. Competition amid declining prices, not only among OPEC member countries such Iraq and Iran but also non-OPEC countries, led to precautionary demand shocks of relatively small magnitude until the near-collapse of OPEC in 1986, with volatility being particularly small in the first half of that decade in relation to subsequent periods. Indeed, we find both coefficient and volatility breaks occur between 1986 and 1988, and also in the mid- to late-1990s.

Although a number of recent studies examine the role of emerging economies (for example Kilian and Hicks, 2013, Aastveit, Bjørnland and Thorsrud, 2015) or oil inventories (Kilian and Murphy, 2014, Kilian and Lee, 2014), with the latter especially focusing particularly on explaining the sustained oil price increases over 2003 to 2008, our results do not indicate any change in the coefficients of the oil demand equation associated with omission of these effects from the model. Nevertheless, it may be noted that oil price shock volatility is estimated to substantially increase in 1998, and the wide confidence interval seen for this break date in panel II(A) implies that the break may apply early in the new century.

As anticipated for a model capturing demand and supply, positive oil production shocks immediately lead to lower prices (the estimated value of a_{31} is negative) while prices increase in response to an aggregate demand shock (positive a_{32}); see the contemporaneous coefficients of panel I (B). However, under the pricing regime in the early part of our sample period, effectively no contemporaneous price response to a production shock is found until the latter part of the 1980s. The extent of the price response to a production change is tempered from the mid-1990s, with the estimated contemporaneous response declining from -1.81 to -0.42. On the other hand, the contemporaneous oil price response to an aggregate demand shock is reduced over the middle coefficient regime (the end of the 1980s to the mid-1990s), but is then essentially restored to its value in the early part of the sample period. Therefore, at least as seen in the contemporaneous coefficients, oil prices were largely unresponsive to demand changes in the early 1990s, with the restoration of the link possibly associated with the rise of China and other large emerging economies. These are, however, only point estimates of the contemporaneous responses, with a fuller discussion of dynamic effects in the following subsection.

Finally, panel IV of Table 3 provides evidence that the structural coefficient restrictions of (3) in the SHVAR form, examined equation by equation, are compatible with the data. This is the case whether the tests are applied to the whole sample of data, assuming no breaks in coefficients, or within the identified coefficient regimes. Note, however, that the test statistic

[18] Including the four asymptotic coefficient breaks would lead to omission of the 1981 volatility break, illustrating the role of iteration between coefficient and volatility breaks.

cannot be calculated in some regimes, due to the large number of coefficients in the unrestricted equation compared with the number of observations in the relevant sub-sample.

4.2 Impulse responses

Impulse response functions, computed using appropriate sub-sample estimates, provide a quantitative comparison of time-variation in the coefficients of the model[19]. In our case, four regimes are given by the coefficient breaks identified in panel I of Table 3, namely January 1975 to December 1980, January 1981 to May 1988, June 1988 to October 1994, and November 1994 to February 2014. Cases of particular interest are the oil production response to shocks before and after the coefficient break in December 1980, and changes over the sub-periods identified in the real oil price inflation response equation (until May 1988, June 1988 to October 1994, and the period since then). Coefficients are estimated separately for each equation over the relevant subsamples, so that the first break applies only in the production equation and the remaining two breaks in the oil price equation; the coefficients of the activity equation are constant throughout.

The unbroken lines in Figures 2 to 4 show estimated impulse responses associated with each of the four coefficient regimes, together with (as dashed or dotted/dashed lines) corresponding one and two standard deviation bands; computation of the latter is discussed in subsection 2.3. The shaded areas in each graph provide corresponding information for the impulse responses implied by the SHVAR model estimated over the full sample with constant coefficients. When making comparisons, however, it should be noted that different vertical scales are often employed across sub-samples. As in Kilian (2009), the sign of each shock is normalized such that it would be anticipated to lead to an increase in the oil price. To aid comparisons, shocks of the same magnitude are applied across regimes, with these equal to one standard deviation of the corresponding shock as estimated using the whole sample with no breaks (see panel II(B) of Table 3). Although our SHVAR is estimated in differences, the cumulated impulse responses are shown; the responses presented are therefore comparable to those of Kilian (2009, Figure 3).

Indeed, the patterns of responses for the constant parameter model, seen in the background of Figures 2 to 4, are qualitatively very similar to those reported by Kilian (2009), indicating that our differencing of the economic activity measure and log real oil prices and the longer sample period has relatively little effect on these responses. Perhaps the most marked difference is that real activity responds positively to an oil-specific demand shock for only six months after the shock and is significant (compared to the one standard deviation band marked with a darker shade) for only three months in our extended sample.

Interesting differences apply across the identified sub-periods in Figure 2, which tracks the impact of a supply shock. In particular, the responses in the first regime (to 1980) indicate that the initial production loss is almost wiped out after 2 years, implying that the shock is not permanent and production eventually returns to its trend level. After 1980, the shock leads to a

[19]Note that the impulse responses, and also the forecast error variance decompositions of the next subsection, are computed under the assumption that there is no break over the horizon considered.

permanent production loss, albeit estimated to be less severe than the magnitude of the initial shock. Oil supply shocks have relatively little effect on real activity, with these never significant according to the two standard error confidence bands.

Negative supply shocks[20] lead to short-run increases in real oil prices, but sometimes after a delay of two or three months. Nevertheless, the negative very short-run price responses in the sub-periods to 1988 may indicate that oil supply shocks are not well identified in this early period. The pattern of price increases in response to the shock is clear in the regime extending from June 1988 to October 1994, the period after the near-collapse of OPEC in 1986. Here the price response is fast, with prices significantly increasing in the month of the shock. However, even in this regime, the real price of oil subsequently falls and is depressed after a delay of around six months. Although the shock represents bad news, excess capacity was then at a record high level. Thus, a production disruption causes prices to increase immediately, but a relatively quick recovery in production is also possible. The current regime, from 1994, shows a distinctive price response to the supply shock compared with earlier sub-periods. In particular, the effect of the shock is persistent (although not always statistically significant), with all estimated responses positive at all horizons examined. A pattern of positive price responses is also obtained from the whole sample estimates, but this is not typical of the entire period when breaks are taken into account.

The model implies that the transmission mechanism for the effects of aggregate demand shocks has also changed; see Figure 3. In particular, aggregate demand shocks have more immediate and longer lasting effects on the real price of oil after 1994 than previously, with these being statistically significant and leading to persistent effects in the final regime. As in Figure 2 (and also Figure 4), the period between 1988 and 1994 contrasts with other sub-periods for the effects of shocks on oil prices. In particular, after a delay of a few months, positive demand shocks are found to lead to significant (and perverse) real price declines. The negative response of oil production to this shock in the earliest sub-period also appears perverse, perhaps indicating that production was largely set in the light of political rather than market considerations during the 1970s[21]. This pattern of negative production responses at longer lags carries over to the full sample estimates without breaks (and also in Kilian, 2009), illustrating the danger of not recognizing changes in the market over these four decades. Allowing for breaks, however, Figure 3 shows that aggregate demand shocks result in positive and significant production responses, as anticipated, from 1981 onwards.

Finally, Figure 4 presents the responses over sub-samples to an oil-specific demand shock for each variable in the system. After a short-lived positive effect, the oil-specific demand shock depresses oil production before 1980; otherwise, the production responses are generally not significant according to the two standard error bands, which applies also for the full sample estimates.

[20]Note that a different scale is used when plotting the price responses for the last two sub-samples as compared to other periods.

[21]Although it falls outside our estimation period, this is illustrated by the Organisation of Arab Petroleum Exporting Countries imposing an embargo on exports to the US and other countries in response to their supplying Israel with arms during the Yom Kippur War.

The response of aggregate activity to an oil-specific demand shock response varies relatively little over time (except for the 1988-1994 sub-period), with a short-run positive response followed by decline. The final regime, from 1994, however, sees a different response of the price of oil to this shock than earlier periods. Whereas the price effect is persistent in the sub-periods to 1988, and to a lesser extent between 1988 and 1994, the post-1994 regime sees the effect of the shock effectively disappear after two years.

4.3 Forecast error variance decompositions

To shed further light on the nature of changes in the oil market over the four decades of our sample, Table 4 provides forecast error variance decompositions (FEVDs) for each variable, taking account of the breaks identified in Table 3. Since both coefficient and volatility shifts are relevant for FEVDs, multiple regimes are shown in Table 4, some of which are of short duration. Note again, however, that re-estimation is undertaken separately for each equation and only as indicated by the specific coefficient or volatility breaks. In particular, since no coefficient breaks are detected after 1994, subsequent regimes are due entirely to changes in the volatilities of oil market shocks. The final values shown in square brackets within each panel are based on estimation of a constant parameter model over the entire period (January 1975 to February 2014). Standard errors are provided for all FEVD values, as discussed in subsection 2.3.

The decompositions apply to the differenced variables as employed in the SVAR, and hence examine the effects of the different oil market shocks on forecast errors for future changes in the respective variables. The table employs four forecast horizons: 1 month, 6 months, two years and five years. The last of these is included in order to illustrate the long run implications of each regime were it to continue over an extended period, but it is emphasized that the estimated regimes typically do not extend over a period of this length.

Our SHVAR model allowing for structural breaks implies that a substantial change occurs over time in the FEVD for oil production; see the upper horizontal panel of Table 4. Although supply shocks always explain at least 80% of the oil production forecast error variance at all horizons, nevertheless demand shocks play a substantial role after the supply shock volatility decreases associated with the breaks of October 1990 and especially September 2004 (documented in panel II(B) of Table 3). In particular, the contribution of demand shocks (aggregate plus oil-specific) to the two-year ahead forecast error variance for oil production growth increases from 0.2% over the 1980s to almost 20% in the recent sub-periods of the oil price boom (2004-2008) and the GFC. Of this latter figure, oil-specific shocks make the larger contribution, with the aggregate demand shock's role reaching its peak in the post-GFC period when it contributes around 8% at the two year horizon. These changes are, of course, missed by the constant parameter model (figures in square brackets), which imply that oil supply shocks account for 98% of the forecast error variance at this horizon.

According to our model, oil supply shocks play a large role in the FEVD for changes in economic activity until 1990, accounting for 24-44% of its forecast error variance at a six month horizon and even more at two years. We find a large drop in supply shock volatility from November 1990, perhaps due to the Gulf War marking the end of an era[22]. After 1990, supply shocks play relatively little role and most of the forecast error variance for activity is due to its own shocks, albeit with some contribution from oil-specific demand shocks. Another supply volatility reduction applies after the September 2004 break and is associated with a further dampening of its role for real activity. In this otherwise tranquil period leading up to the GFC (2004-2008), an increase in the volatility of oil-specific demand shocks causes their contribution to real activity forecast error variances to rise to around 8% at the two year horizon, and to 10% if projected to a five year horizon. Nevertheless, as pointed out by Baumeister and Peersman (2013b), in this model with no other forward-looking variables, such shocks are not necessarily associated with the oil market alone, but can be driven by revisions to expectations about aggregate activity; see also Kilian and Hicks (2013). In contrast to these changed roles, the constant parameter model indicates that oil supply shocks contribute only about 2% and oil-specific demand shocks 3% to the economic activity FEVD, with own shocks being the dominant contributor.

Perhaps the most interesting changes over time in Table 4 concern the contributions of the shocks to real oil price inflation volatility. In the earlier part of the sample period, until March 1981, more than half of the forecast error variance for real oil price inflation at a two-year horizon is explained by oil supply shocks and about 40% by the oil specific demand shocks. Oil-specific demand shock volatility then becomes much more muted (see panel II(B) of Table 3) and its role in the oil price FEVD for the first half of the 1980s is effectively absorbed by the oil supply shock, whose contribution at a six month forecast horizon and beyond exceeds 70%. During this sub-sample, the aggregate demand shock's contribution at a one-month forecast horizon reaches 24%, although this very substantially reduces at longer horizons.

A change of policy by Saudi Arabia, then the world's largest oil producer, from defence of prices to defence of market share (Mabro, 1986, Fattouh, 2006) and the near collapse of OPEC, events captured in our model through the large increase in oil-specific demand shock volatility from March 1986, pushes its role in price volatility above 80% at horizons of six months to five years. Amid weak global demand and large spare capacity of oil, the contribution of the oil supply shock to the price volatility (as measured by forecast error variance) falls below 20% at these horizons[23]. This brief regime ends when the coefficients of the real oil price inflation equation experience a structural break in May 1988, which may reflect the wide acceptance gained for the 'market related' or formula pricing regime in that year; see Mabro (2006). The role of the supply shock is restored and the aggregate demand shock plays a more important role than previously, as might be anticipated. This sub-period, from June 1988 to October 1990, includes the Iraqi invasion of Kuwait and witnessed the oil supply shock contributing more than 60% of the real oil price inflation volatility at almost all forecast horizons from one month to two years.

[22]The Gulf War occurred between 2 August 1990 and 28 February 1991, and the upper end of 90% confidence interval for the October 1990 break date is January 1991 in panel II(A) of Table 3. Baumeister and Peersman (2013b) also find this break. Note that the estimated shock variance reduces from 2.79 to 0.74 at this break

[23]Note that Kilian (2009) interprets oil specific demand shock as precautionary demand shock arising from the uncertainty about shortfalls of expected supply relative to expected demand.

However, October 1990 not only ends the era of high supply shock volatility and its contribution towards real economic volatility, but also its contribution toward oil price volatility. The contribution of supply shocks to the price FEVD at a two year horizon falls sharply to only 5%, which is statistically insignificant (at a 5% significance level) using the bootstrap standard deviation. At this time, demand shocks' contributions are amplified; aggregate demand shocks now account for 32% and oil specific demand shock for 63% of two year ahead oil price inflation volatility.

The second (and last) coefficient break in the oil price inflation equation in October 1994 decreases the role of aggregate demand shocks in the real oil price inflation FEVD and increases that of the oil specific demand shock, with the contribution of the latter exceeding 90% at the six month or two year horizon. This coefficient break is relatively more important for the oil price inflation FEVD than the subsequent volatility breaks, which include the doubling of the oil specific demand shock variance in October 1998 and the nearly tenfold increase in that for aggregate demand in October 2008[24]. It is also noteworthy that the real oil price inflation FEVD for a model with constant parameters largely represents the shock contributions over this period from late 1994, rather than those over earlier sub-periods.

Lütkepohl and Netšunajev (2014) provide a FEVD analysis of the real price of oil obtained from their Markov-switching volatility model, for which their state 1 is essentially the period from around 1986 to the end of their sample in 2007 while state 2 is the predominant regime over 1975 to 1986. The implication from Table 4 that oil specific demand shocks explain almost all of the forecast error variance for real price of oil inflation from late 1994 onwards largely agrees with their findings. However, we find a substantially smaller role for these shocks overall, and a greater role for oil supply shocks, in oil price inflation volatility in the earlier period than do Lütkepohl and Netšunajev (2014).

5 Conclusions

With oil a key resource for any economy , clear understanding of its market dynamics is important for economists and policymakers. For such analyses, the model of Kilian (2009) has become the standard framework. For example, Güntner (2014), Kang and Ratti (2013) and Kilian and Park (2009), among others, adopt versions of this model when examining the effect of oil market shocks on stock markets. Our interest, however, is on the logically prior question of whether the parameters of the Kilian (2009) model have remained constant over the four decades often used for analysis.

[24]We run two further experiments, the results of which are in Table A.2 of the Appendix. In the first experiment we set the sizes of shock volatilities equal to their whole sample estimates and recognize only the coefficient breaks of Table 3. The 1994 break then pulls down the extremely high share of the supply shock in real oil price inflation volatility to a level much closer those featured in earlier periods. More importantly, this break restores the importance of the oil specific demand shock. In the second experiment we allow for breaks in the shock volatilities only. Then the share of the oil specific demand shock in the oil price inflation volatility reaches above 90% as early as 1986 and the 1998 break increases it only marginally. Finally, the importance of the aggregate demand shock does not also alter much after its volatility break in 2008.

Employing an extended form of the structural break testing methodology of Bataa, Osborn, Sensier and van Dijk (2013), which allows the possibility of distinct changes in coefficients and volatilities of recursively identified structural equations, we find strong statistical evidence that both the transmission mechanism and the volatilities of shocks have changed. Although some of our results are broadly in line with the implications of studies, such as Baumeister and Peersman (2013b), which employ time-varying specifications, our study is (to our knowledge) the first to employ formal structural break tests. This allows us a more explicit focus on the timing and nature of any such changes that may have occurred.. In particular, while the coefficients of the oil supply and oil-specific demand equations exhibit changes over the two decades to 1994, no subsequent coefficient breaks are found . Moreover, the coefficients of the equation modelling global economic activity are found to be stable during this period, which highlights the importance of testing for time variation, rather than imposing it.

In line with both Baumeister and Peersman (2013b) and Lütkepohl and Netšunajev (2013), we find breaks in the volatilities of shocks to be a feature of the oil market, not least in recent years. In particular, we find an increase in the volatility of oil-specific demand shocks that may be associated with growth in emerging economies (Kilian and Hicks, 2013, Aastveit, Bjørnland and Thorsrud, 2015) and/or speculative trading and inventories (Kilian and Murphy, 2014, Kilian and Lee, 2014). We also find that the volatility of oil production shocks has been at an historic low since 2004, so making supply more predictable, whereas the volatility of aggregate demand shocks increases at the time of the GFC.

Impulse response functions are a key tool for the analysis of the SVAR model. These show how shocks permeate through the system. A key finding of our study concerns the response of oil production to an aggregate demand shock. In particular, a constant parameter specification that ignores the possibility of parameter change implies that oil production is unresponsive to an aggregate demand shock for up to a year, followed by a (perverse) medium term decline. Taking account of breaks (and, for this case, particularly in the coefficients of the oil supply equation) overturns this conclusion, with responses positive and significant from 1981 onwards. Partly because production has become more predictable due to declines in its volatility, oil supply shocks contribute little to the forecast error variance for economic activity and the real price of oil from 1990, but they play an important role prior to that date. Indeed, in the turbulent period of the 1970s and early 1980s, our forecast error variance decomposition implies that most of the volatility in oil prices at horizons of two or more years can be attributed to oil supply shocks. Shocks during that period contribute to around one third of the variation in aggregate demand volatility. However, the 1980s and 1990s see important changes in the characteristics of the world oil market.

Perhaps driven by emerging economies, impulse responses show that the real price of oil responds to aggregate demand shocks more strongly (and with greater statistical significance) from the mid-1990s onwards, at the same time becoming less persistent than previously in response to oil specific demand shocks. In terms of forecast error variance, however, oil price volatility is thereafter dominated by oil-specific demand shocks from this period, in contrast to the earlier dominance of supply shocks at the two year or longer horizon.

Our results imply that analysts interested in the movements of oil price inflation or the effects of oil price shocks need to recognise that the nature of the world oil market has changed over the last four decades. Studies employing the SVAR methodology of Kilian (2009) implicitly discount the possibility of parameter change even over long periods. For example, in their analyses of effects on stock markets, Kang and Ratti (2013) employ data over 1985 to 2011, while the sample of Güntner (2014) starts in 1974. The results presented here call into question the validity of these and many other analyses which assume that the model parameters have remained constant over extended periods.

6 References

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7 Appendix

In this appendix we test for structural breaks in an unrestricted SVAR(24) rather than in SHVAR(1,3,6,12,24) as in the main text[25]. We also provide FEVD analyses additional to those of Table 4, by employing only coefficient or volatility breaks.

The asymptotic and bootstrap break results for the SVAR(24) are provided in Table A.1. The null hypothesis of constant coefficients is rejected very strongly against an alternative of an unknown number of breaks up to 2 in all three equations, using the asymptotic critical values. There are two mean breaks in economic activity and real oil price equations and one mean break in the production equation[26].

Given that there are 72, 73 and 74 coefficients in the three equations, respectively, and consequently the trimming is set at 30% for the coefficient break test (for volatility break test it is 10%) there has to be at least 11 years and 9 months (for volatility breaks 3 years and 11 months) between any two breaks, including at the beginning and the end of the sample. Thus, by construction, the test cannot pick up any coefficient breaks associated with the GFC, if such breaks occur. The estimated break dates, when found significant, are either strictly binding or very close to their permitted boundaries. For example the October 1986 break is on the upper boundary of a regime that starts at the beginning of the sample. The distance between the two asymptotically detected coefficient breaks in the activity equation is also exactly 11 years and 9 months.

The bootstrap procedure concludes that there is no coefficient break in any of the equations, however it is worth pointing out that the power of the test will be very low with so many parameters. Moreover, if the procedure is forced to choose a break date that satisfies the minimum length requirement, the Chow test used in the bootstrap will be invalid if this differs from the actual break date.

Interestingly, asymptotic and bootstrap inferences agree there is one volatility break in the oil supply shock, in line with the results in the main analysis. Both inferences of Table A.1 also find the September 2008 break as for the aggregate demand shock volatility (real activity equation) of Table 3. However the presence or otherwise of coefficient breaks has important implications for the remaining aggregate demand volatility breaks in Table A.1, thus highlighting the importance of our iteration between mean and volatility breaks. For the oil specific demand shock volatility, both asymptotic and bootstrap inferences in the SVAR framework detect one or two breaks fewer than those of the SHVAR framework (Table 3).

These results suggest that the use of an unrestricted SVAR may miss important coefficient

[25]Data are log differenced, with seasonality, means and outliers removed, as in the main text. We also applied the testing procedure to the data and specification of Kilian (2009), which yields structural break results and problems similar to those discussed in this Appendix. These results are available upon request.

[26]The break test for each of the former two converges to a two-cycle. Of these, the set not selected by the information criteria is May 1987 and December 2001 for the economic activity and February 1987 and December 1998 for the real price equation. The volatility breaks in these cases also change. The second break in the aggregate demand shock volatility is then dated in February 2002 and there is an additional volatility break for the oil-specific demand shock in February 1999.

breaks because their timing does not satisfy the minimum length requirement needed to justify the formal statistical tests. It may also be the case that bootstrap rejects breaks detected by the use of asymptotic critical values due to power issues and because the actual breaks dates differ from estimated ones which satisfy the minimum length requirement. Our main paper therefore proposes a more parsimonious specification in order to mitigate the number of coefficients employed.

Table 1. Unit root test results with structural breaks

	Oil Production		Economic Activity		Real Oil Price	
Panel a: Tests for structural breaks in trend						
	Statistic	5% Crit.val.	Statistic	5% Crit.val.	Statistic	5% Crit.val.
0 v 1 break	11.58*	3.16	8.92*	3.16	8.18*	3.16
1 v 2 break	10.17*	3.66	2.79	3.66	16.87*	3.66
2 v 3 breaks	7.32*	3.71			10.50*	3.71
3 v 4 breaks	7.82*	3.96			26.57*	3.96
4 v 5 breaks	245.93*	4.13			26.57*	4.13
Panel b: GLS-detrended unit root tests allowing trend breaks						
	Statistic	5% Crit.val.	Statistic	5% Crit.val.	Statistic	5% Crit.val.
No break	5.77	5.54	4.77*	5.54	15.56	5.54
1 break	9.26	6.39	**4.56***	**4.87**	18.04	7.40
2 breaks	10.45	6.49	6.84*	6.90	21.80	7.12
3 breaks	8.55	7.61	9.16	7.14	5.03*	7.11
4 breaks	12.13	8.77	9.18	8.29	7.50*	8.40
5 breaks	**7.12***	**9.51**	8.78	8.51	**11.93**	**8.49**

Notes: The test in the first row of panel a is the exponential Wald statistic discussed by Perron and Yabu (2009) for one break in both slope and level, valid for both I(0) and I(1) error components, while those in the remaining rows are the suprema of that statistic when applied to the subsamples defined under the corresponding null, the critical values for such sequentially applied statistics being provided in Kejriwal and Perron (2010). Statistics in panel b are GLS-detrended M unit root test statistics, analysed by Ng and Perron (2001) for no trend breaks and extended by Carrion-i-Silvestre et al. (2009) to multiple breaks; bold statistics correspond to the number of breaks selected through the Kejriwal and Perron (2010) procedure. *Indicates the rejection of the relevant null hypothesis (namely, the lower number of indicated breaks in panel a and presence of a unit root in panel b) at the 5% level. Rejection in panel a (panel b) applies when the statistic is greater (less) than the critical value. All critical values are asymptotic and from the indicated studies.

Table 2. Univariate iterative decomposition

	Oil Production	Economic Activity	Real Oil Price
Level component			
Number of breaks	0	0	0
Seasonality			
Number of breaks	0	0	2
Break dates			**1985.11** (83.06-88.04)
			1998.09 (97.05-00.01)
F-test for no seasonality (p-value)	36.13 (0.02)	62.71 (0.00)	13.73 (24.82); 33.08 (0.05); 30.69 (0.12)
[Ignoring breaks]	[36.13 (0.02)]	[62.71 (0.00)]	[19.64 (5.05)]
Outliers			
Dates	1970.12, 1977.01, 1978.01	None	None
Dynamics			
AR order	0	2	1
Number of breaks	0	0	0
Persistence	0.05	0.17	0.46
Volatility			
Number of breaks	2	2	3
Break dates	**1990.09** (88.03-90.12)	**1980.04** (74.06-80.11)	**1977.02** (74.01-77.10)
	2004.08 (00.10-05.10)	**2008.08** (08.07-11.04)	**1985.12** (85.11-88.08)
			2009.10 (04.12-11.05)
Standard deviations			
Across regimes	1.87, 0.90, 0.60	6.33, 3.94, 12.12	4.33, 2.17, 7.07, 4.85
[Ignoring breaks]	[1.36]	[6.10]	[5.85]
Number of iterations for convergence			
Main loop	2	2	5
Dynamics sub-loop	2	2	2

Notes: Decomposition as in (7) using the iterative method of Bataa *et al.* (2014), with breaks detected using the Qu and Perron (2007) test using a 5% significance level (trimming 15% and maximum of 5 breaks, except for the seasonal component with 20% trimming and maximum of 2 breaks). F test of insignificance of seasonal dummies along with its $p-$value (using HAC inference and expressed as a percentage) is reported for each seasonal regime and also ignoring the break(s). Outliers are defined as being 7 times the interquartile range from the median after removal of level and seasonality breaks. The AR order of the dynamic component is selected according to the Hannan-Quinn (HQ) information criterion, and used at entry to the dynamic/volatility sub-loop; an AR(1) is employed if 0 lags are selected by HQ. Persistence is computed as the sum of the estimated AR coefficients within the relevant dynamic regime, with the standard deviation of disturbances also shown within volatility regimes. When breaks are detected, the estimated breaks dates are shown **in bold** together with their asymptotic 90% confidence intervals in parentheses. Finally, the numbers required to achieve convergence of the loops of the algorithm are shown.

Table 3. Coefficient and variance break test results for the oil market SHVAR

	Oil Production	Economic Activity	Real Oil Price	
	I (A). Coefficients breaks			
Overall test	255.42* (38.82)	206.82* (40.86)	243.78* (42.61)	
Seq(2/1)	33.26 (37.63)	36.71 (39.37)	51.29* (41.22)	
Seq(3/2)			57.51* (42.59)	
Seq(4/3)			57.51* (43.89)	
bootstrap p-value for each break	0.1	24.47	85.42	
			83.34	
			1.08	
			1.42	
Break 1	**1980.12**		**1988.05**	
	(80.10-81.02)		(88.02-88.08)	
Break 2			**1994.10**	
			(94.07-95.01)	
	I (B). Contemporaneous coefficients			
	n.a.	a_{21}	a_{31}	a_{32}
Across regimes	-	-0.17	0.06, -1.81, -0.42	0.17, 0.03, 0.20
[Ignoring breaks]	-	[-0.17]	[-0.28]	[0.16]
	II (A). Variance breaks			
Overall test	137.75*	171.81*	126.69*	
Seq(2/1)	17.11*	24.06*	21.79*	
Seq(3/2)	9.89	5.34	21.63*	
Seq(4/3)			12.14	
bootstrap p-value for each break	0.0	0.04	0.40	
	0.31	0.0	0.0	
			0.15	
Break 1	**1990.10**	**1979.09**	**1981.03**	
	(88.02-91.01)	(73.04-80.02)	(79.06-81.11)	
Break 2	**2004.09**	**2008.09**	**1986.02**	
	(99.08-06.04)	(08.08-11.06)	(86.01-86.12)	
Break 3			**1998.09**	
			(98.01-09.11)	
	II (B). Shock standard deviations			
	σ_{oils}	σ_{aggd}	σ_{oild}	
Across regimes	1.67, 0.86, 0.60	6.21, 3.94, 11.88	2.65, 1.60, 4.64, 6.72	
[Ignoring breaks]	[1.31]	[5.98]	[5.61]	
	III. Number of iterations required to converge			
	3	2	4	
	IV. F statistic (bootstrap p-value) for SHVAR restrictions			
Regime I	n.c.	1.28 (15.2)	1.08 (24.6)	
Regime II	0.92 (70.9)	-	n.c.	
Regime III	-	-	1.56 (12.8)	
All sample	0.94 (72.3)	1.28 (36.3)	1.42 (30.47)	

Notes: Values reported in panels I (A) and II (A) are at convergence of the iterative procedure of Bataa, Osborn, Sensier and van Dijk (2013). The overall test examines the null hypothesis of no break against an unknown number of breaks, to a maximum of 5 breaks for each SHVAR equation and 8 for the variance. If the overall statistic is significant at 5%, sequential tests are applied starting with the null hypothesis of one break and continuing until the relevant statistic is not significant. Asymptotic critical values for the 5% significance level are reported next to respective test statistics in parenthesis in panel II (A) since the number of parameters are different in the SVAR equations. The critical values for shock volatilities applicable to II (B) are 10.67, 10.97, 11.88 and 12.49 for the Overall test, Seq(2/1), Seq(3/2), and Seq(4/3), respectively. * indicates the statistic is significant at 5%. The estimated break dates and their 90% confidence intervals (in parenthesis) are also reported. Bootstrap p-values corresponding to the null hypothesis that an asymptotically detected break does not exist are also reported. Panels I (B) and II (B) show estimated contemporaneous coefficients and shock standard deviations respectively across sub-samples defined by the break dates. Also shown in square brackets are those quantities that ignore the breaks. Panel III reports the number of iterations required to converge in coefficient and volatility break dates. The last panel reports on the validity of the SHVAR restrictions by F tests over the sub-samples defined by the mean break dates and over the whole sample. The asymptotic 5% critical value from $F(60, \infty)$ is 1.32. n.c. indicates it was impossible to compute the F statistic over the sub-sample due to non-invertability issue (too many parameters with not long enough sub-sample).

Table 4. Forecast error variance decomposition

Series	Regimes	Oil supply shock (ε_{oils})				Aggregate demand shock (ε_{aggd})				Oil specific demand shock (ε_{oild})			
		$h=1$	$h=6$	$h=24$	$h=60$	$h=1$	$h=6$	$h=24$	$h=60$	$h=1$	$h=6$	$h=24$	$h=60$
Oil production	75.01-79.09	100.0 (0.0)	99.6 (0.5)	98.7 (1.0)	98.1 (1.6)	0.0 (0.0)	0.1 (0.2)	0.5 (0.4)	0.9 (0.6)	0.0 (0.0)	0.3 (0.5)	0.9 (0.9)	1.0 (1.3)
	79.10-80.12	100.0 (0.0)	99.4 (0.7)	97.9 (1.4)	96.8 (2.3)	0.0 (0.0)	0.3 (0.5)	1.2 (1.0)	2.2 (1.6)	0.0 (0.0)	0.3 (0.5)	0.9 (0.9)	1.0 (1.2)
	81.01-81.03	100.0 (0.0)	100.0 (0.0)	99.9 (0.1)	99.9 (0.1)	0.0 (0.0)	0.0 (0.0)	0.1 (0.1)	0.1 (0.1)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
	81.04-86.02	100.0 (0.0)	100.0 (0.0)	99.9 (0.1)	99.9 (0.1)	0.0 (0.0)	0.0 (0.0)	0.1 (0.1)	0.1 (0.1)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
	86.03-88.05	100.0 (0.0)	99.9 (0.1)	99.8 (0.1)	99.8 (0.2)	0.0 (0.0)	0.0 (0.0)	0.1 (0.1)	0.1 (0.1)	0.0 (0.0)	0.1 (0.1)	0.1 (0.1)	0.1 (0.2)
	88.06-90.10	100.0 (0.0)	99.9 (0.1)	99.8 (0.3)	99.8 (0.6)	0.0 (0.0)	0.0 (0.0)	0.1 (0.2)	0.1 (0.3)	0.0 (0.0)	0.1 (0.1)	0.1 (0.2)	0.1 (0.3)
	90.11-94.10	100.0 (0.0)	96.9 (2.4)	94.4 (5.5)	93.5 (9.0)	0.0 (0.0)	1.2 (1.1)	2.5 (2.9)	3.0 (5.0)	0.0 (0.0)	1.9 (2.0)	3.0 (3.5)	3.6 (5.5)
	94.11-98.09	100.0 (0.0)	97.4 (2.0)	95.9 (2.4)	95.5 (2.6)	0.0 (0.0)	1.0 (0.9)	1.8 (1.2)	1.9 (1.3)	0.0 (0.0)	1.6 (1.8)	2.3 (2.0)	2.6 (2.1)
	98.10-04.09	100.0 (0.0)	96.3 (2.9)	94.3 (3.3)	93.8 (3.5)	0.0 (0.0)	1.0 (0.9)	1.8 (1.2)	1.8 (1.2)	0.0 (0.0)	2.6 (2.8)	3.9 (3.1)	4.3 (3.2)
	04.10-08.09	100.0 (0.0)	89.6 (7.0)	84.4 (7.1)	83.2 (7.4)	0.0 (0.0)	2.9 (2.3)	4.9 (2.9)	5.0 (2.9)	0.0 (0.0)	7.5 (6.9)	10.6 (7.0)	11.8 (7.2)
	08.10-14.02	100.0 (0.0)	87.8 (7.0)	81.6 (7.2)	80.4 (7.5)	0.0 (0.0)	4.8 (3.4)	8.1 (4.1)	8.2 (4.1)	0.0 (0.0)	7.4 (6.7)	10.3 (6.8)	11.4 (7.0)
	[Ignoring breaks]	[100.0 (0.0)]	[99.2 (0.9)]	[97.7 (1.4)]	[97.3 (1.6)]	[0.0 (0.0)]	[0.2 (0.5)]	[1.6 (1.1)]	[1.8 (1.3)]	[0.0 (0.0)]	[0.7 (0.8)]	[0.7 (0.9)]	[0.8 (0.9)]
Real activity	75.01-79.09	5.3 (7.1)	43.8 (13.0)	47.9 (12.6)	48.5 (12.7)	94.7 (7.1)	55.7 (12.9)	50.7 (12.5)	49.7 (12.6)	0.0 (0.0)	0.6 (0.8)	1.4 (1.7)	1.7 (2.4)
	79.10-80.12	2.1 (3.0)	23.5 (9.1)	26.9 (9.7)	27.4 (10.4)	97.9 (3.0)	76.2 (9.1)	72.3 (9.8)	71.6 (10.6)	0.0 (0.0)	0.3 (0.4)	0.8 (0.9)	1.0 (1.4)
	81.01-81.03	2.1 (2.7)	29.5 (10.2)	35.1 (10.6)	35.2 (10.5)	97.9 (2.7)	70.1 (10.1)	64.3 (10.5)	64.1 (10.4)	0.0 (0.0)	0.4 (0.3)	0.6 (0.5)	0.7 (0.6)
	81.04-86.02	2.1 (2.9)	29.6 (10.1)	35.3 (10.5)	35.4 (10.4)	97.9 (2.9)	70.3 (10.1)	64.6 (10.5)	64.4 (10.3)	0.0 (0.0)	0.1 (0.1)	0.2 (0.1)	0.2 (0.2)
	86.03-88.05	2.1 (2.8)	28.9 (10.0)	34.0 (10.5)	34.1 (10.3)	97.9 (2.8)	68.6 (9.8)	62.3 (10.0)	62.0 (9.9)	0.0 (0.0)	2.4 (1.9)	3.7 (2.6)	3.9 (3.6)
	88.06-90.10	2.1 (3.0)	24.4 (9.9)	26.4 (11.4)	29.4 (13.0)	97.9 (3.0)	71.8 (9.6)	65.0 (11.3)	59.0 (13.1)	0.0 (0.0)	3.7 (2.5)	8.6 (4.9)	11.6 (7.6)
	90.11-94.10	0.1 (0.1)	1.1 (0.7)	1.2 (1.1)	1.4 (1.7)	99.9 (0.1)	94.0 (3.1)	87.2 (7.0)	82.4 (11.1)	0.0 (0.0)	4.9 (3.1)	11.5 (6.8)	16.2 (10.8)
	94.11-98.09	0.1 (0.1)	1.3 (0.8)	1.7 (1.0)	1.7 (1.2)	99.9 (0.1)	95.3 (2.5)	93.3 (3.0)	92.0 (3.9)	0.0 (0.0)	3.4 (2.3)	5.0 (2.8)	6.3 (3.6)
	98.10-04.09	0.1 (0.1)	1.3 (0.8)	1.6 (1.0)	1.7 (1.0)	99.9 (0.1)	93.1 (3.8)	90.2 (4.4)	88.1 (5.5)	0.0 (0.0)	5.6 (3.7)	8.2 (4.2)	10.3 (5.3)
	04.10-08.09	0.0 (0.0)	0.4 (0.3)	0.5 (0.4)	0.5 (0.4)	100.0 (0.0)	93.9 (3.7)	91.1 (4.3)	89.0 (5.5)	0.0 (0.0)	5.7 (3.6)	8.3 (4.3)	10.4 (5.5)
	08.10-14.02	0.0 (0.0)	0.3 (0.2)	0.3 (0.3)	0.3 (0.3)	100.0 (0.0)	96.3 (2.8)	94.6 (3.5)	93.3 (4.4)	0.0 (0.0)	3.4 (2.8)	5.1 (3.4)	6.4 (4.4)
	[Ignoring breaks]	[0.1 (0.7)]	[2.0 (1.6)]	[2.4 (1.8)]	[2.4 (1.8)]	[99.9 (0.7)]	[96.3 (2.3)]	[94.8 (2.7)]	[94.4 (2.9)]	[0.0 (0.0)]	[1.7 (1.5)]	[2.7 (2.0)]	[3.1 (2.1)]
Real oil price	75.01-79.09	0.2 (4.9)	39.0 (11.3)	57.3 (11.3)	58.0 (11.9)	3.3 (0.5)	1.9 (1.0)	2.4 (2.2)	3.5 (2.7)	96.5 (5.0)	59.1 (11.2)	40.4 (10.9)	38.6 (11.5)
	79.10-80.12	0.2 (5.1)	37.8 (10.9)	55.2 (11.0)	55.0 (11.4)	8.1 (1.3)	4.8 (2.5)	5.8 (5.0)	8.4 (5.9)	91.7 (5.2)	57.4 (10.8)	38.9 (10.0)	36.6 (10.6)
	81.01-81.03	0.2 (5.2)	44.7 (11.7)	56.1 (10.4)	56.7 (10.8)	8.1 (1.2)	4.3 (2.1)	4.1 (3.8)	4.0 (4.4)	91.7 (5.4)	51.0 (11.4)	39.8 (9.3)	39.3 (9.6)
	81.04-86.02	0.5 (12.7)	71.0 (9.6)	78.8 (7.6)	79.3 (8.3)	24.2 (3.5)	6.8 (3.4)	5.8 (5.0)	5.6 (5.7)	75.3 (12.8)	22.3 (8.3)	15.4 (4.8)	15.1 (5.0)
	86.03-88.05	0.0 (0.9)	12.3 (5.3)	18.3 (6.6)	18.7 (7.1)	1.4 (0.2)	1.2 (0.6)	1.4 (1.2)	1.3 (1.5)	98.6 (1.0)	86.5 (5.3)	80.3 (6.6)	80.0 (7.3)
	88.06-90.10	61.4 (11.1)	68.3 (16.1)	61.0 (16.4)	58.3 (16.6)	0.0 (1.9)	6.8 (7.9)	13.2 (10.8)	14.8 (11.4)	38.6 (11.1)	24.9 (13.6)	25.8 (11.9)	26.9 (11.8)
	90.11-94.10	5.2 (0.7)	6.9 (1.9)	5.1 (3.1)	4.6 (3.6)	0.0 (2.1)	19.9 (9.8)	32.2 (14.2)	33.9 (15.3)	94.8 (2.2)	73.3 (9.7)	62.7 (13.6)	61.6 (14.7)
	94.11-98.09	0.2 (0.7)	0.6 (1.8)	1.5 (2.7)	1.6 (2.9)	2.0 (0.4)	5.9 (2.3)	6.2 (2.6)	6.6 (3.0)	97.8 (0.8)	93.5 (2.9)	92.3 (3.7)	91.8 (4.2)
	98.10-04.09	0.1 (0.4)	0.4 (1.0)	0.9 (1.6)	1.0 (1.8)	1.2 (0.2)	3.6 (1.3)	3.8 (1.5)	4.0 (1.8)	98.7 (0.5)	96.1 (1.6)	95.3 (2.2)	95.0 (2.6)
	04.10-08.09	0.0 (0.1)	0.1 (0.4)	0.3 (0.6)	0.3 (0.7)	1.2 (0.2)	3.6 (1.3)	3.8 (1.5)	4.0 (1.8)	98.8 (0.2)	96.3 (1.4)	95.9 (1.7)	95.7 (2.0)
	08.10-14.02	0.0 (0.2)	0.1 (0.4)	0.3 (0.6)	0.3 (0.7)	2.0 (0.3)	6.0 (2.0)	6.3 (2.3)	6.6 (2.8)	98.0 (0.4)	93.9 (2.1)	93.4 (2.4)	93.0 (2.9)
	[Ignoring breaks]	[0.4 (1.9)]	[0.7 (1.7)]	[1.3 (1.9)]	[1.3 (1.9)]	[3.0 (2.6)]	[6.3 (3.8)]	[6.7 (3.9)]	[7.1 (4.0)]	[96.6 (3.3)]	[93.0 (4.1)]	[92.0 (4.3)]	[91.6 (4.3)]

Notes: FEVD table for four forecast horizons: h =1,6,12,60 months. The ij^{th} entry of the matrix gives the percent of forecast error variance of series i due to shock j. They are allowed to be different over the sub-samples defined by the statistically significant structural breaks. Bootstrap standard deviation is also provided in parenthesis. The quantities estimated over the whole sample, ignoring the structural breaks are in square brackets.

Table A.1. Coefficient and variance break test results for the oil market SVAR

	Asymptotic inference				Bootstrap inference			
	Oil Production	Economic Activity	Real Oil Price		Oil Production	Economic Activity	Real Oil Price	
	I (A). Coefficients breaks							
Overall test	238.29* [113.36]	187.48* [114.89]	208.56* [116.35]		245.81* [113.36]	176.96* [114.89]	226.63* [116.35]	
Seq(2/1)	97.41 [113.90]	115.81* [114.20]	150.74* [116.59]		99.17 [113.90]	114.50* [114.20]	131.71* [116.59]	
bootstrap p-value	n.a.	n.a.	n.a.		15.65	99.03	19.59	
for each break	n.a.	n.a.	n.a.			67.92	28.83	
Break 1	**1986.10**	**1987.02**	**1987.10**					
	[86.09-86.11]	[86.11-87.05]	[87.08-87.12]					
Break 2		**1998.11**	**2001.07**					
		[98.08-99.02]	[01.05-01.09]					
	I (B). Contemporaneous coefficients							
	n.a.	a_{21}	a_{31}	a_{32}	n.a.	a_{21}	a_{31}	a_{32}
Across regimes	-	-0.124, -0.449, 0.460	0.003, -0.921, -0.808	0.214, 0.131, 0.217	-	-0.104	-0.246	0.202
[Ignoring breaks]	-	[-0.104]	[-0.267]	[0.202]	-	[-0.104]	[-0.267]	[0.202]
	II (A). Variance breaks							
Overall test	80.54* [10.67]	140.52* [10.67]	94.47* [10.67]		120.65* [10.67]	141.96 [10.67]	85.17* [10.67]	
Seq(2/1)	7.63 [10.97]	23.36* [10.97]	8.63 [10.97]		9.19 [10.97]	17.47* [10.97]	17.00* [10.97]	
Seq(3/2)		20.96* [11.88]	6.13 [11.88]			3.88 [11.88]	7.42 [11.88]	
Seq(4/3)		9.81 [12.49]						
bootstrap p-value	n.a.	n.a.	n.a.		0.0	0.02	0.31	
for each break	n.a.	n.a.	n.a.			0.0	0.0	
Break 1	**1990.10**	**1986.03**	**1986.02**		**1990.10**	**1980.05**	**1981.03**	
	[87.07-91.03]	[82.02-87.03]	[86.01-89.06]		[88.08-91.01]	73.04-80.12	[78.08-81.10]	
Break 2		**1998.12**				**2008.09**	**1985.12**	
		[98.07-01.02]				[08.08-11.02]	[85.11-87.03]	
Break 3		**2008.09**						
		[08.06-12.05]						
	II (B). Shock standard deviations							
	σ^2_{oils}	σ^2_{aggd}	σ^2_{oild}		σ^2_{oils}	σ^2_{aggd}	σ^2_{oild}	
Across regimes	1.590, 0.487	12.73, 5.90, 19.65, 77.15	3.88, 19.63		2.744, 0.640	31.27, 17.71, 110.84	9.88, 3.79, 34.19	
[Ignoring breaks]	[1.48]	[30.30]	[26.69]		[1.48]	[30.30]	[26.69]	
	III. Number of iterations required to converge							
	3	19	19		2	2	2	

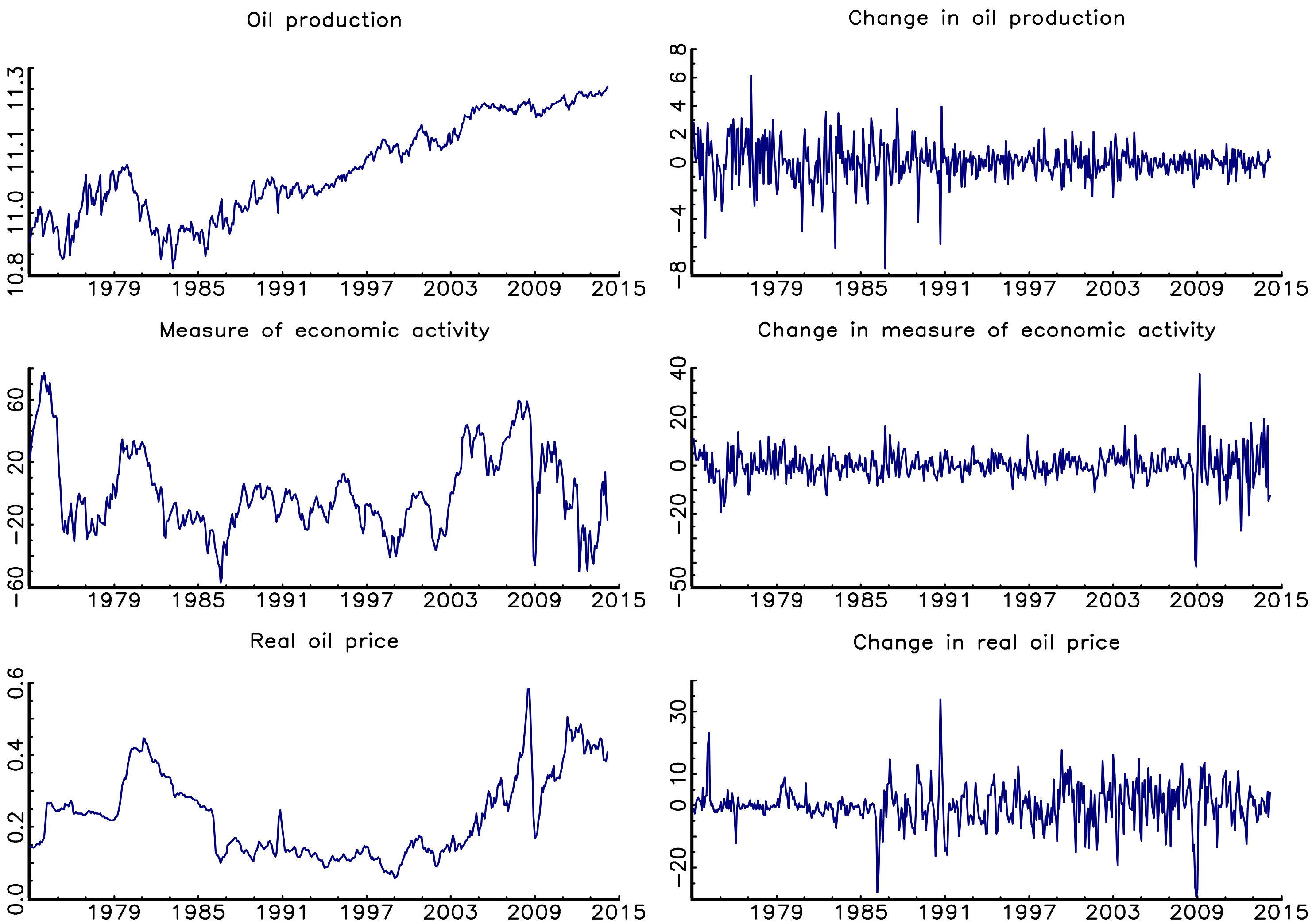
Notes: See Notes to Table 3 in the main text. n.c. means the date was some months outside the sample period, thus not calculated. n.a. means not applicatble.

Table A.2. Forecast error variance decompositions for coefficient/volatility breaks only

Series	Regimes	Oil supply shock (ε_{oils})				Aggregate demand shock (ε_{aggd})				Oil specific demand shock (ε_{oild})			
		$h=1$	$h=6$	$h=24$	$h=60$	$h=1$	$h=6$	$h=24$	$h=60$	$h=1$	$h=6$	$h=24$	$h=60$
A. Coefficient breaks only (no conditional volatility breaks)													
Oil production	75.01-80.12	100.0 (0.0)	94.3 (2.7)	84.3 (4.7)	80.5 (6.1)	0.0 (0.0)	0.6 (0.8)	2.4 (1.4)	4.4 (2.4)	0.0 (0.0)	5.1 (2.6)	13.2 (4.4)	15.1 (5.5)
	81.01-88.05	100.0 (0.0)	99.8 (0.3)	99.5 (0.4)	99.5 (0.4)	0.0 (0.0)	0.1 (0.1)	0.1 (0.1)	0.2 (0.2)	0.0 (0.0)	0.2 (0.2)	0.3 (0.3)	0.3 (0.4)
	88.06-94.10	100.0 (0.0)	99.7 (0.3)	99.5 (0.7)	99.4 (1.3)	0.0 (0.0)	0.1 (0.1)	0.2 (0.3)	0.3 (0.5)	0.0 (0.0)	0.2 (0.3)	0.3 (0.5)	0.4 (0.9)
	94.11-14.02	100.0 (0.0)	99.8 (0.3)	99.6 (0.3)	99.6 (0.4)	0.0 (0.0)	0.1 (0.1)	0.2 (0.1)	0.2 (0.1)	0.0 (0.0)	0.2 (0.3)	0.2 (0.3)	0.3 (0.3)
		[[100.0 (0.0)]	[99.2 (0.9)]	[97.7 (1.4)]	[97.3 (1.6)]	[0.0 (0.0)]	[0.2 (0.5)]	[1.6 (1.1)]	[1.8 (1.3)]	[0.0 (0.0)]	[0.7 (0.8)]	[0.7 (0.9)]	[0.8 (0.9)]
Real activity	75.01-80.12	0.9 (1.9)	11.3 (6.4)	12.7 (6.8)	12.8 (7.0)	99.1 (1.9)	86.1 (6.6)	80.6 (7.8)	79.0 (9.2)	0.0 (0.0)	2.6 (2.3)	6.8 (4.2)	8.1 (6.0)
	81.01-88.05	0.9 (2.1)	14.6 (7.5)	17.7 (8.3)	17.8 (8.2)	99.1 (2.1)	81.8 (7.5)	76.7 (8.2)	76.4 (8.1)	0.0 (0.0)	3.6 (2.2)	5.6 (2.8)	5.9 (3.3)
	88.06-94.10	0.9 (2.0)	11.9 (7.0)	12.9 (8.8)	14.5 (10.5)	99.1 (2.0)	82.8 (7.1)	75.0 (9.7)	68.9 (12.5)	0.0 (0.0)	5.3 (2.8)	12.1 (5.8)	16.5 (8.8)
	94.11-14.02	0.9 (1.8)	14.0 (7.1)	17.1 (7.8)	17.6 (7.6)	99.1 (1.8)	82.4 (7.2)	77.8 (7.7)	76.0 (7.8)	0.0 (0.0)	3.6 (2.3)	5.1 (2.5)	6.4 (3.0)
		[[0.1 (0.7)]	[2.0 (1.6)]	[2.4 (1.8)]	[2.4 (1.8)]	[99.9 (0.7)]	[96.3 (2.3)]	[94.8 (2.7)]	[94.4 (2.9)]	[0.0 (0.0)]	[1.7 (1.5)]	[2.7 (2.0)]	[3.1 (2.1)]
Real oil price	75.01-80.12	0.0 (1.7)	3.5 (4.0)	7.2 (5.5)	7.6 (6.3)	1.2 (0.4)	1.1 (1.0)	1.8 (2.4)	2.7 (3.4)	98.8 (1.8)	95.4 (4.1)	90.9 (6.0)	89.7 (7.8)
	81.01-88.05	0.0 (1.7)	4.6 (4.7)	7.2 (5.6)	7.4 (6.0)	1.2 (0.4)	1.0 (1.0)	1.3 (1.9)	1.2 (2.2)	98.8 (1.7)	94.3 (4.8)	91.5 (5.8)	91.3 (6.2)
	88.06-94.10	35.6 (5.9)	43.7 (11.5)	36.6 (14.3)	34.1 (15.0)	0.0 (1.0)	10.2 (5.9)	18.8 (9.1)	20.4 (9.7)	64.4 (6.0)	46.0 (10.8)	44.6 (11.8)	45.4 (12.2)
	94.11-14.02	2.4 (1.7)	5.7 (5.0)	13.7 (7.5)	14.6 (7.9)	1.6 (0.2)	4.7 (1.5)	4.5 (1.5)	4.7 (1.7)	96.1 (1.7)	89.6 (5.0)	81.8 (7.4)	80.7 (7.7)
		[[0.4 (1.9)]	[0.7 (1.7)]	[1.3 (1.9)]	[1.3 (1.9)]	[3.0 (2.6)]	[6.3 (3.8)]	[6.7 (4.0)]	[7.1 (4.0)]	[96.6 (3.3)]	[93.0 (4.1)]	[92.0 (4.3)]	[91.6 (4.4)]
B. Conditional volatility breaks only (no coefficient breaks)													
Oil production	75.01-79.09	100.0 (0.0)	99.9 (0.1)	99.7 (0.2)	99.6 (0.3)	0.0 (0.0)	0.0 (0.1)	0.3 (0.2)	0.3 (0.2)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.1)
	79.10-81.03	100.0 (0.0)	99.9 (0.2)	99.3 (0.5)	99.2 (0.6)	0.0 (0.0)	0.1 (0.2)	0.7 (0.5)	0.8 (0.6)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.1)
	81.04-86.02	100.0 (0.0)	99.9 (0.2)	99.3 (0.5)	99.2 (0.6)	0.0 (0.0)	0.1 (0.2)	0.7 (0.5)	0.8 (0.6)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
	86.03-90.10	100.0 (0.0)	99.7 (0.4)	99.0 (0.6)	98.9 (0.8)	0.0 (0.0)	0.1 (0.2)	0.7 (0.5)	0.8 (0.6)	0.0 (0.0)	0.3 (0.3)	0.3 (0.3)	0.4 (0.4)
	90.11-98.09	100.0 (0.0)	98.3 (1.7)	95.3 (2.7)	94.6 (3.2)	0.0 (0.0)	0.3 (1.1)	3.3 (2.2)	3.7 (2.5)	0.0 (0.0)	1.4 (1.3)	1.4 (1.5)	1.7 (1.6)
	98.10-04.09	100.0 (0.0)	97.2 (2.4)	94.2 (3.2)	93.3 (3.7)	0.0 (0.0)	0.3 (1.0)	3.2 (2.2)	3.6 (2.4)	0.0 (0.0)	2.5 (2.2)	2.6 (2.4)	3.0 (2.5)
	04.10-08.09	100.0 (0.0)	92.7 (5.6)	85.4 (6.5)	83.5 (7.0)	0.0 (0.0)	0.8 (2.4)	8.2 (4.5)	9.0 (4.8)	0.0 (0.0)	6.5 (5.3)	6.5 (5.3)	7.5 (5.4)
	08.10-14.02	100.0 (0.0)	92.2 (5.6)	80.8 (7.0)	78.5 (7.8)	0.0 (0.0)	1.4 (3.4)	13.1 (6.1)	14.4 (6.5)	0.0 (0.0)	6.5 (4.9)	6.1 (4.8)	7.1 (4.9)
		[[100.0 (0.0)]	[99.2 (0.9)]	[97.7 (1.4)]	[97.3 (1.6)]	[0.0 (0.0)]	[0.2 (0.5)]	[1.6 (1.1)]	[1.8 (1.2)]	[0.0 (0.0)]	[0.7 (0.8)]	[0.7 (0.9)]	[0.8 (0.9)]
Real activity	75.01-79.09	0.8 (1.4)	11.5 (6.3)	13.5 (6.9)	13.7 (6.9)	99.2 (1.4)	88.0 (6.3)	85.7 (6.9)	85.4 (6.9)	0.0 (0.0)	0.5 (0.5)	0.8 (0.8)	1.0 (0.8)
	79.10-81.03	0.3 (0.5)	4.9 (2.6)	5.8 (3.0)	5.9 (3.1)	99.7 (0.5)	94.9 (2.6)	93.8 (3.0)	93.7 (3.1)	0.0 (0.0)	0.2 (0.2)	0.4 (0.3)	0.4 (0.3)
	81.04-86.02	0.3 (0.5)	4.9 (2.7)	5.8 (3.1)	5.9 (3.1)	99.7 (0.5)	95.1 (2.7)	94.1 (3.1)	94.0 (3.1)	0.0 (0.0)	0.1 (0.1)	0.1 (0.1)	0.1 (0.1)
	86.03-90.10	0.3 (0.5)	4.8 (2.6)	5.7 (2.9)	5.7 (2.9)	99.7 (0.5)	93.5 (2.9)	91.6 (3.4)	91.2 (3.5)	0.0 (0.0)	1.7 (1.4)	2.7 (2.0)	3.1 (2.2)
	90.11-98.09	0.1 (0.1)	1.0 (0.6)	1.2 (0.7)	1.2 (0.7)	99.9 (0.1)	97.2 (1.6)	96.0 (2.2)	95.6 (2.5)	0.0 (0.0)	1.8 (1.5)	2.8 (2.1)	3.2 (2.4)
	98.10-04.09	0.1 (0.1)	1.0 (0.6)	1.2 (0.7)	1.2 (0.7)	99.9 (0.1)	95.8 (2.6)	93.8 (3.5)	93.1 (3.7)	0.0 (0.0)	3.2 (2.5)	5.1 (3.4)	5.7 (3.7)
	04.10-08.09	0.0 (0.0)	0.4 (0.2)	0.4 (0.3)	0.4 (0.3)	100.0 (0.0)	96.4 (2.5)	94.5 (3.4)	93.8 (3.7)	0.0 (0.0)	3.2 (2.5)	5.1 (3.4)	5.8 (3.7)
	08.10-14.02	0.0 (0.0)	0.2 (0.2)	0.3 (0.2)	0.3 (0.2)	100.0 (0.0)	97.9 (1.8)	96.7 (2.6)	96.2 (2.9)	0.0 (0.0)	1.9 (1.8)	3.1 (2.6)	3.5 (2.8)
		[[0.1 (0.7)]	[2.0 (1.6)]	[2.4 (1.8)]	[2.4 (1.8)]	[99.9 (0.7)]	[96.3 (2.3)]	[94.8 (2.7)]	[94.4 (2.9)]	[0.0 (0.0)]	[1.7 (1.5)]	[2.7 (1.9)]	[3.1 (2.1)]
Real oil price	75.01-79.09	6.7 (3.3)	10.6 (8.8)	17.1 (10.3)	17.6 (10.4)	7.8 (1.1)	14.9 (4.0)	14.8 (4.3)	15.3 (4.4)	85.5 (3.5)	74.4 (9.0)	68.1 (10.0)	67.0 (10.1)
	79.10-81.03	6.0 (3.3)	8.6 (8.4)	14.0 (9.8)	14.3 (9.8)	17.6 (2.7)	30.9 (8.7)	30.6 (9.0)	31.6 (9.0)	76.4 (4.2)	60.5 (10.3)	55.4 (10.2)	54.2 (10.3)
	81.04-86.02	13.1 (7.9)	15.1 (13.5)	23.0 (13.3)	23.1 (13.1)	38.4 (7.6)	54.1 (14.0)	50.4 (12.8)	51.2 (12.6)	48.5 (10.3)	30.9 (12.0)	26.6 (8.6)	25.7 (8.3)
	86.03-90.10	1.0 (0.5)	1.7 (1.8)	3.0 (2.7)	3.1 (2.9)	2.9 (0.4)	6.1 (1.9)	6.5 (2.4)	6.8 (2.5)	96.1 (0.6)	92.2 (2.7)	90.5 (3.7)	90.1 (4.0)
	90.11-98.09	0.2 (0.1)	0.3 (0.4)	0.6 (0.7)	0.6 (0.7)	2.9 (0.4)	6.2 (2.1)	6.7 (2.7)	7.0 (2.8)	96.9 (0.4)	93.4 (2.1)	92.7 (2.8)	92.4 (3.0)
	98.10-04.09	0.1 (0.1)	0.2 (0.2)	0.3 (0.3)	0.4 (0.4)	1.6 (0.2)	3.5 (1.1)	3.8 (1.4)	4.0 (1.4)	98.3 (0.2)	96.3 (1.1)	95.9 (1.4)	95.7 (1.5)
	04.10-08.09	0.0 (0.0)	0.1 (0.1)	0.1 (0.1)	0.1 (0.1)	1.6 (0.2)	3.5 (1.1)	3.8 (1.3)	4.0 (1.4)	98.3 (0.2)	96.4 (1.1)	96.1 (1.4)	95.9 (1.4)
	08.10-14.02	0.0 (0.0)	0.1 (0.1)	0.1 (0.1)	0.1 (0.1)	2.7 (0.4)	5.8 (1.6)	6.2 (2.1)	6.6 (2.2)	97.2 (0.4)	94.1 (1.6)	93.6 (2.1)	93.3 (2.3)
		[[0.4 (1.9)]	[0.7 (1.7)]	[1.3 (1.9)]	[1.3 (1.9)]	[3.0 (2.6)]	[6.3 (3.8)]	[6.7 (4.0)]	[7.1 (4.0)]	[96.6 (3.3)]	[93.0 (4.1)]	[92.0 (4.3)]	[91.6 (4.4)]

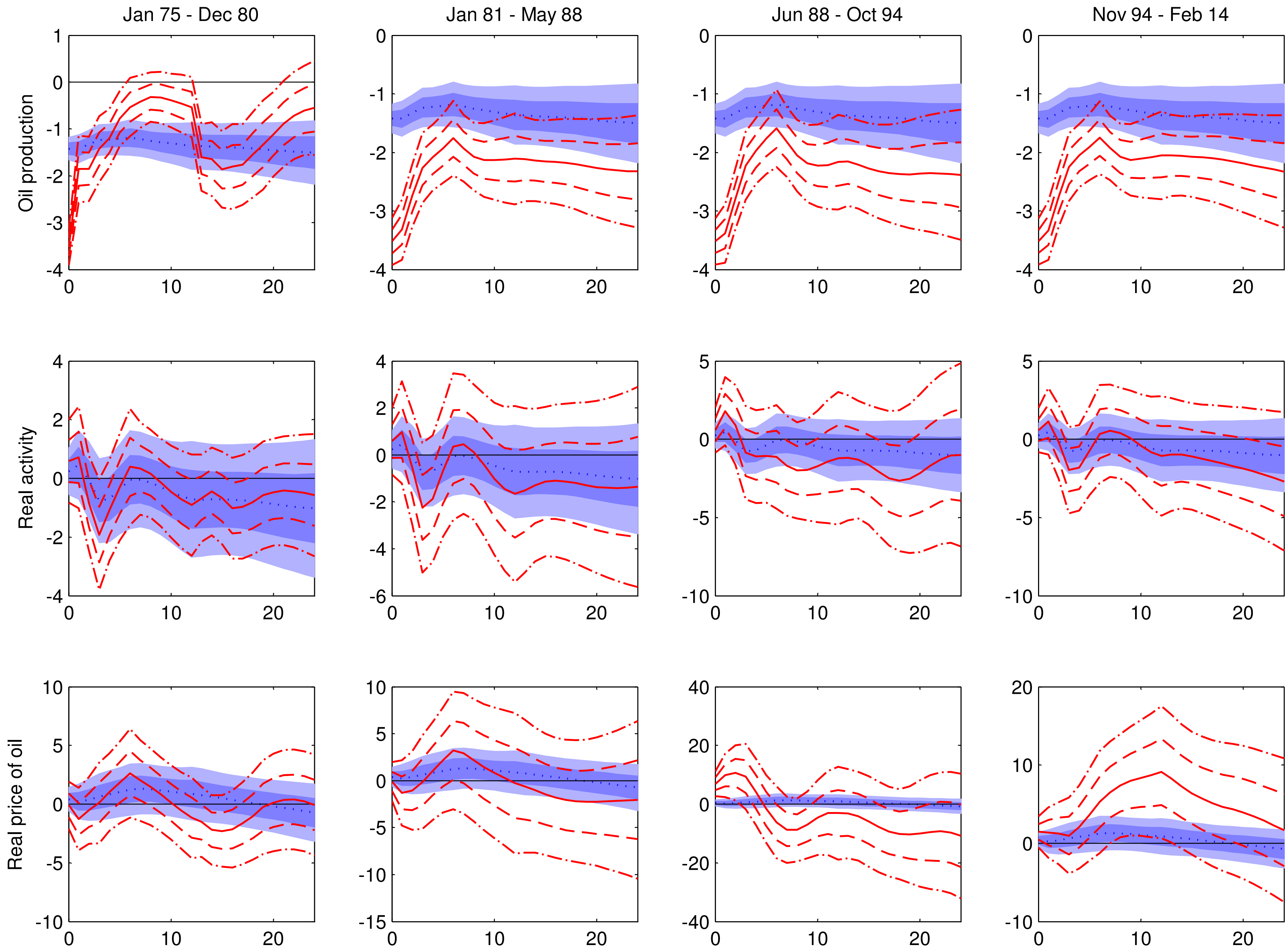
Notes: As for Table 4, except that Panel A employs only the coefficient break dates and Panel B the variance break dates given in Table 3.

Figure 1. Data



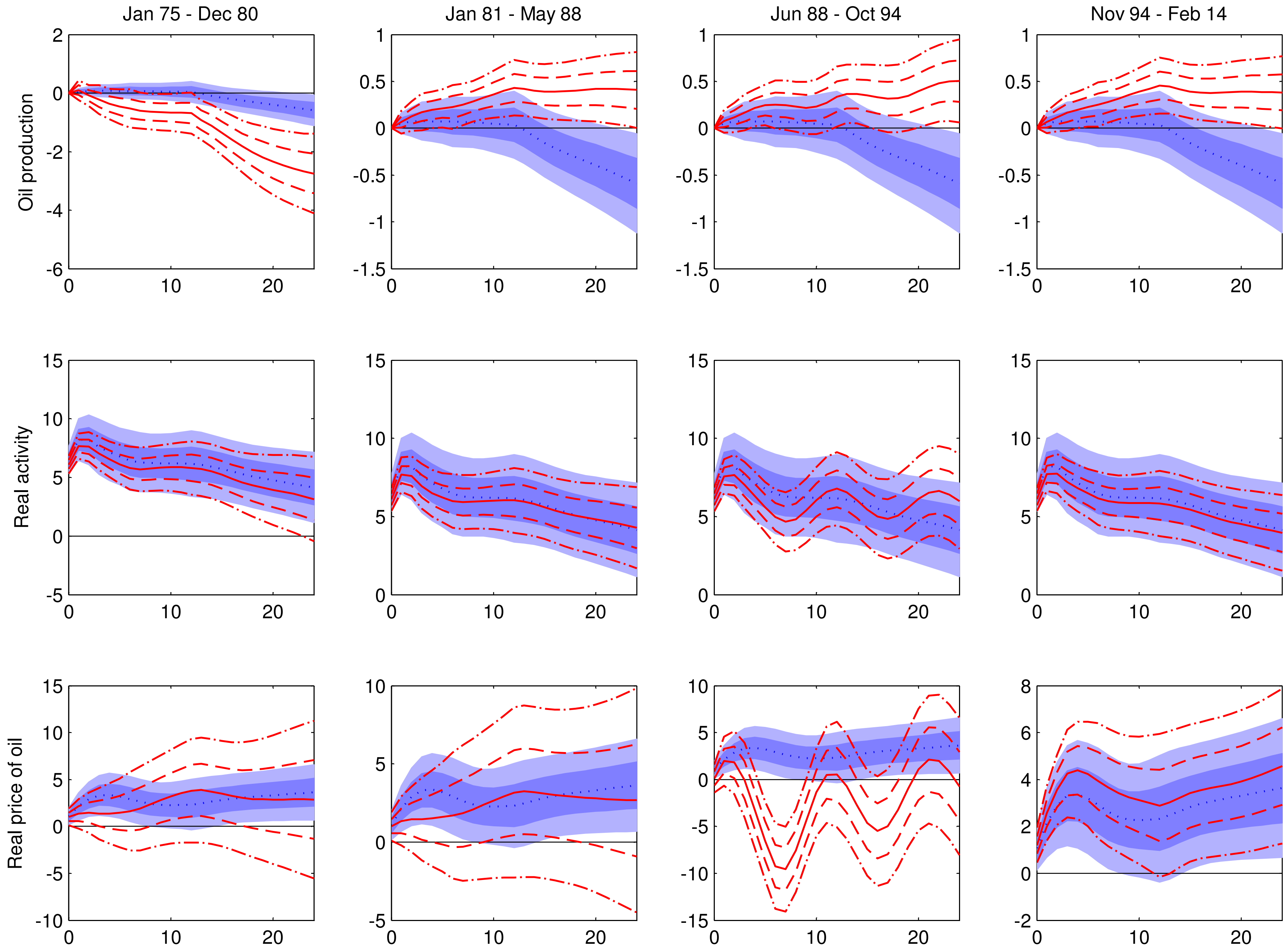
Notes: In the first column, oil production is the logarithm of the number of barrels produced per day, the measure of economic activity is the detrended series of Kilian (2009), downloaded from http://www-personal.umich.edu/ lkilian/, the real oil price is the logarithm of the price measured in US dollars and deflated by the US CPI. The data in panel b are differenced (oil production and real oil price are also multiplied by 100), with deterministic seasonality and outliers removed; see Section 3 of the text.

Figure 2. Response to a supply shock



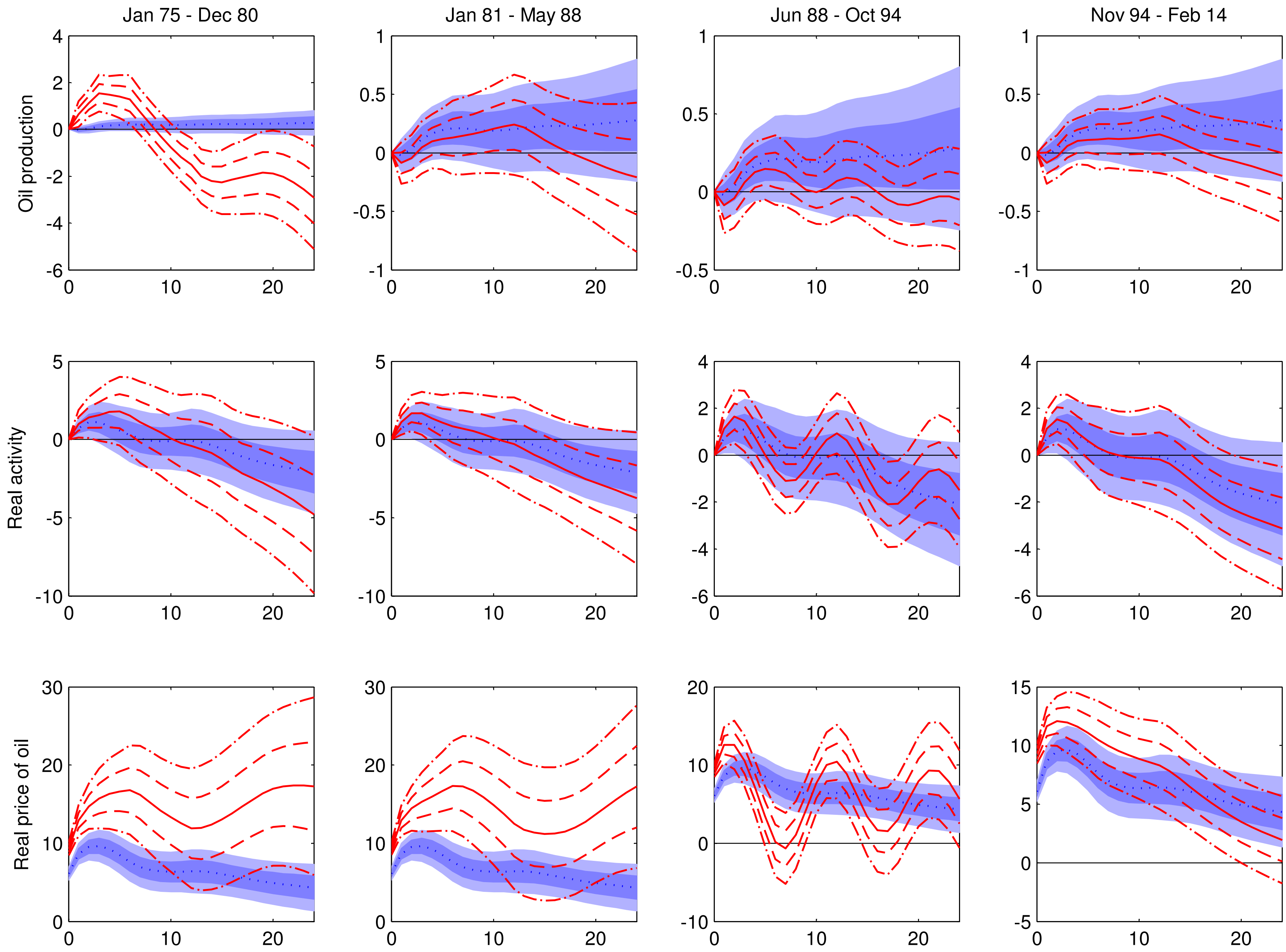
Notes: Each graph shows the cumulated impulse responses to a shock of a common magnitude, equal to one standard deviation estimated over the whole sample with no breaks. Each of the four columns represents a sub-sample as defined by the coefficient break dates of Table 3. Each plot includes one (blue dashed line) and two (green dashed-dotted line) standard deviation confidence bands (see text). The background shaded areas provide corresponding confidence intervals around the responses (dotted line) for a constant parameter model estimated over the whole sample period.

Figure 3. Response to an aggregate demand shock



Notes: See Figure 2.

Figure 4. Response to an oil specific demand shock



Notes: See Figure 2.