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We analyse fiscal policy responses in oil rich countries by developing a Bayesian regime-switching panel country analysis. We use parameter restrictions to identify procyclical and countercyclical fiscal policy regimes over the sample in 23 OECD and non-OECD oil producing countries. We find that fiscal policy is switching between pro- and countercyclial regimes multiple times. Furthermore, for all countries, fiscal policy is more volatile in the countercyclical regime than in the procyclical regime. In the procyclical regime, however, fiscal policy is systematically more volatile and excessive in the non-OECD (including OPEC) countries than in the OECD countries. This suggests OECD countries are able to smooth spending and save more than the non-OECD countries. Our results emphasize that it is both possible and important to separate a procyclical regime from a countercyclical regime when analysing fiscal policy. Doing so, we have encountered new facts about fiscal policy in oil rich countries.

JEL-codes: C13, C14, C51, C53, E62, Q43

Keywords: Dynamic Panel Model, Mixed-Frequency, Markov Switching, Bayesian Inference, Fiscal Policy, Resource Rich Countries, Oil Prices

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1 Introduction

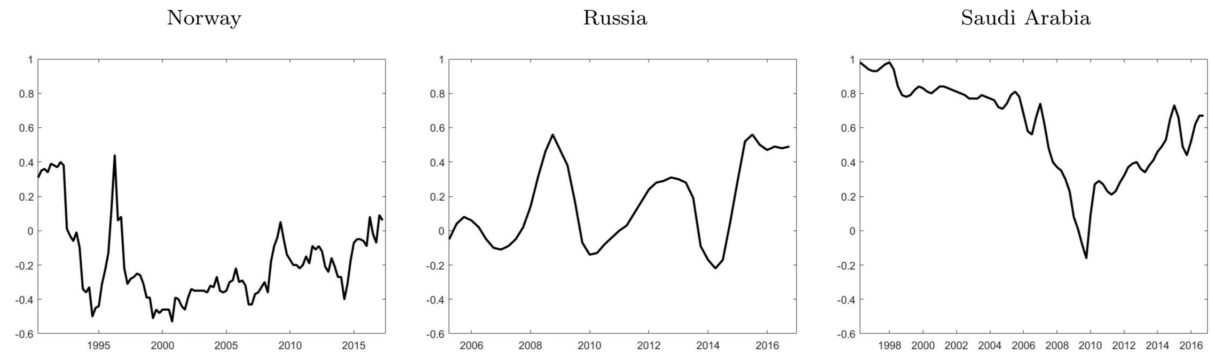
In a standard neoclassical model, fiscal policy should be countercyclical and smoothed over the business cycles (see Barro, 1979). Yet, in many countries fiscal policy is procyclical, so that public spending increases in the boom. This exacerbates the business cycle, leaving the countries more vulnerable in the subsequent recession. The problem seems to be especially worrisome for oil-rich countries. As government oil revenue constitutes a large component of total government revenues, changes in revenues will have a direct impact on public spending. Many resource-rich countries are therefore advised to save parts of their income for rainy days. This would entail government spending to be operated countercyclically, thereby sheltering the economy from fluctuations in revenues and preventing over-spending on the part of the government.

Several papers have investigated the conduct of fiscal policy in oil producing countries, finding evidence of procyclical behaviour. For instance, Lopez-Murphy and Villafuerte (2010) analyse the average fiscal policy responses of oil producing countries to the recent oil price cycle. They find that the non-oil primary balances worsened substantially during the 2003-2008 boom as primary spending increased. Related findings are reported in Bova, Medas, and Poghosyan (2016), suggesting fiscal policy in resource-rich countries have been procyclical during the last decades. Moreover, their findings indicate that the adoption of fiscal rules does not have, on its own, a significant impact on reducing procyclicality, unless supported by strong political institutions. At the other end, Céspedes and Velasco (2014) find results that suggest fiscal policy has been less procyclical over time. Using a panel data analysis, they estimate the response in government expenditures and revenues to commodity prices in a large panel of commodity exporting countries over two different cycles. Doing so they find fiscal spending to be less procyclical in the recent commodity price boom (2000-2009). They argue that the changes have materialised as many countries have improved their institutional quality, i.e., they have adopted fiscal policy rules. This has allowed fiscal policy to be less expansionary when commodity prices increase and more expansionary when commodity prices decrease, i.e., countercyclical behaviour.

One caveat of the above-mentioned studies is that the results will be dependent on the sample under study and the variables examined. As there may be different shocks hitting the economy in different periods, this can affect the results. Countries also adopt fiscal rules in response to changing economic conditions. Fiscal policy design is therefore often particularly complex insofar as countries combine the objectives of sustainability with the need for flexibility in response to shocks. Hence, the conduct of fiscal policy may be changing.

Figure 1 illustrates this well. The figure graphs the correlation between the cyclical component of oil revenues and some fiscal variables in three different oil producing coun-

Figure 1. Five-year rolling correlations between cyclical components of oil revenues and selected fiscal variables in Norway, Russia and Saudi Arabia



(a) Correlations between total government expenditure and government oil revenues

(b) Correlations between the share of public employment (relative to total employment) and government oil revenues

Notes: The cyclical components have been estimated using the Hodrick-Prescott Filter with a smoothing parameter equal to 1,600 on the logarithm of the variables. The sample for Norway is 1990:Q1-2017:Q2, for Russia is 2005:Q1-2016:Q4 and for Saudi Arabia is 1996:Q1-2016:Q4.

tries: Norway, Russia and Saudi Arabia.[1] In particular, Figure 1 (a) exhibits the five-year rolling correlations between government oil revenues and total government expenditure while Figure 1 (b) exhibits the five-year rolling correlations between government oil revenues and the share of public employment (in total employment). The graphs suggest there are large fluctuations in the cyclical pattern for fiscal policy, with the correlation coefficient switching from positive to negative several times over the sample. These aspects call for models with time-varying properties, allowing the cyclical pattern for fiscal policy to change over the sample. Comparing the conduct of fiscal policy on exogenously given sub-periods may therefore yield biased results. This has also been pointed out in Bjørnland and Thorsrud (2019) that analyse fiscal policy in Norway, by controlling for various shocks and allowing for time varying responses.

[1] In Section 2, we present the full list of countries of our empirical analysis.

In this paper we take a different approach. To account for the changing nature of economic conditions and fiscal rules, rather than assuming fiscal policy is constant, we will allow it to switch between regimes of procyclical and countercyclical behaviour over the sample. The switches has a natural interpretation of fiscal policy shocks. Moreover, rather than splitting the sample more or less arbitrarily, and then analysing whether fiscal policy has changed after the split, we infer *when* fiscal policy has been procyclical or countercyclical. For this purpose, we propose a Bayesian Markov switching panel model where parameters change between the procyclical and countercyclical fiscal policy regimes over time according to a Markov process. Then we use parameter restrictions to identify procyclical and countercyclical fiscal policy regimes, and evaluate fiscal policy's response in the different regimes.

To identify the different regimes, we will place restrictions on the mean responses of variables, keeping volatility unrestricted. We let a procyclical fiscal policy regime be defined as the period when growth in government oil revenues (relative to GDP) and growth in government expenditures (relative to GDP) both increase, or decrease, i.e., a spend as you go fiscal regime. Hence, if oil revenues increase, so does expenditures, and vice versa. A countercyclical fiscal regime, on the other hand, is defined as the period when growth in government oil revenues (relative to GDP) and growth in expenditures (relative to GDP) move in opposite directions. Hence, a countercyclical regime is a period with declining oil revenues is met by increasing government expenditures to smooth the cycle, or vice versa. Based on such minimum identifying restrictions, we can separate a procyclical regime from a countercyclical regime when analysing fiscal policy. We believe this is the first time that fiscal policy has been evaluated in this way.

Our model is applied to 23 oil producing and exporting resource rich countries across the globe, including OECD, non-OECD and OPEC countries. Production from these countries corresponds to 84% of the world oil production. For each country, we collect data on relevant fiscal variables, including government expenditures, government oil revenues, non-oil fiscal balance and public employment. We also include the real oil price, the real exchange rate and real Gross Domestic Product, which are important variables for capturing the economic situation in resource rich economies. The time series are collected from both international and national data sources, and provide us with a novel data set of relevant fiscal variables for oil rich countries.

We emphasize, however, that while our focus is on analysing fiscal policy in oil-rich countries, the framework suggested may be used for many different policy applications, also for non-oil countries. Indeed, we believe that our MS modelling approach for the analysis of oil fiscal policy presents several advantages over standard linear models. Firstly, fiscal regimes can be easily identified by imposing prior restrictions on the regime-specific intercepts of the variables of interest as we described above. Secondly, the Markov-switching dynamics provides identification schemes for the VAR model based on further restrictions on the switching parameters (see, for example, Rubio-Ramirez, Waggoner, and Zha, 2006; Lanne, Lütkepohl, and Maciejowska, 2010; Netsunajev, 2013), thus avoiding the largely criticized indirect identification methods, such as a recursive identification scheme. In so doing, we extend the idea in Baumeister and Hamilton (2015), Baumeister and Hamilton (2018) and Baumeister and Hamilton (2019) of using Bayesian inference and prior distribution to achieve identification in the inference process. Furthermore, the flexibility of our model makes it possible to compare fiscal policy in a relatively large set of countries and on many variables, that would not be possible adopting a standard VAR model.

We have three main findings. First, we find that there are multiple periods over the sample when fiscal policy is in a procyclical regime. Hence, studies that try to analyse fiscal policy using a split sample framework will misrepresent the changing pattern of how fiscal policy alternates between procyclical and countercyclical regimes. Second, for all countries, government oil revenues and expenditures are always more volatile in the countercyclical regime than in the procyclical regime. This seems plausible, as the decline in oil revenues is often associated with recessionary periods, which are abrupt in nature. Third, in the procyclical regime, fiscal policy is always more volatile and excessive in the non-OECD countries (including OPEC countries) than in the OECD countries. Hence, during the booming periods, when government oil revenues increase, the OECD countries are able to smooth spending and save more than the non-OECD/OPEC countries. A notable exception is the recovery following the oil price decline in 2014/2015, where fiscal policy in OECD and non-OECD countries become more expansionary as oil revenues pick up again. Our results emphasize that it is both possible and important to separate a procyclical regime from a countercyclical regime. Doing so, we have been able to encounter new facts about fiscal policy in oil rich countries.

The remainder of the paper is structured as follows. Section 2 introduces the dataset. Section 3 describes the model and the estimation procedure. Section 4 discusses the results, while Section 5 concludes.

2 Data

We consider the following twenty-three major world oil producing and exporting countries: Algeria, Angola, Australia, Azerbaijan, Canada, Colombia, Ecuador, Gabon, Iran, Iraq, Kazakhstan, Kuwait, Libya, Mexico, Nigeria, Norway, Qatar, Russia, Saudi Arabia, UAE, UK, US and Venezuela. These countries are chosen because they represent the majority of

Table 1. Major world oil producing and exporting countries

Average Share of Total Production, 1965-2019		Average Share of Oil Exports, 1971-2017	
Country	%	Country	%
US	15.15	Saudi Arabia	18.38
Russia	12.35	Russia	10.00
Saudi Arabia	11.80	Iran	7.63
Iran	5.65	Nigeria	5.36
Venezuela	4.36	United Arab Emirates	5.07
Canada	3.61	Venezuela	5.05
Kuwait	3.47	Iraq	4.70
Mexico	3.40	Kuwait	4.05
Iraq	3.09	Norway	3.83
UAE	3.05	Mexico	3.78
Nigeria	2.61	Libya	3.62
Libya	2.50	Canada	3.54
Norway	2.39	UK	3.20
UK	2.15	Algeria	2.21
Algeria	1.98	Kazakhstan	2.05
Kazakhstan	1.34	Angola	1.85
Qatar	1.11	Qatar	1.59
Angola	0.91	Azerbaijan	0.82
Australia	0.69	Ecuador	0.66
Colombia	0.65	Colombia	0.64
Azerbaijan	0.63	Gabon	0.62
Ecuador	0.43	Australia	0.42
Gabon	0.31	US	0.41
Total	83.63	Total	89.49

Sources: BP Statistical Review of World Energy 2020 and International Energy Agency Oil Information.

world oil producers and exporters. As one can see from Table 1, for the period 1965-2019, the total oil production from these countries corresponds to 84% of world oil production on average over the sample. Table 1 also shows the average share of oil exports for the same set of countries during the period 1971-2017. In total, they add to 89% of world oil exports as an average over the sample. Focusing on individual countries, we observe that Russia and Saudi Arabia are among top three world oil producers and the top two world oil exporters. Norway is the top oil exporter among OECD countries. For this reason, in Section 4, while spelling out the results for all countries, we will also focus in detail on these three countries.

As described in Kaminsky, Reinhart, and Vegh (2004), many indicators can be used to assess the degree of procyclical or countercyclical fiscal policy. In order to allow for more robust conclusions for all the countries in our analysis we consider a set of relevant fiscal variables: total government expenditure relative to GDP ($y_{i1,t}$); government oil revenues relative to GDP ($y_{i2,t}$); non-oil fiscal balance relative to GDP ($y_{i3,t}$) and public employment relative to total employment ($y_{i4,t}$). We also include the real oil price ($y_{i5,t}$) and the real exchange rate ($y_{i6,t}$), which are important variables for capturing the economic situation in resource rich economies.

In total we have 138 variables in our model. The data series are collected from both international and national data sources. The data sample varies according to the data availability of each country.[2] The data is expressed in terms of quarterly growth.[3] For those countries for which data are available only at yearly frequency, we used the Denton method (see Di Fonzo and Marini, 2012) to disaggregate data into quarterly frequency. Appendix B reports a detailed explanation on how we constructed all the variables of our empirical analysis.

3 Model

We jointly model all fiscal variables, including the share of public employment on total employment, the real oil price and the real exchange rate of the oil producing countries following a VAR framework, see Canova and Ciccarelli (2009) for a multi-country VAR. Country-specific hidden Markov chain processes are specified in order to extract fiscal regimes and their duration, see Krolzig (1997). We follow a Bayesian approach with hierarchical prior distributions to deal with overfitting issues in high dimensional models. This class of prior allows for exchange of information across units and thus is well suited for unbalanced panel data. Moreover, the prior distributions allow for heterogeneity across panel units and for the inclusion of prior identifying restrictions.

For each country of the panel and across all them, our parameter restrictions identify procyclical and countercyclical regimes. The resulting panel Markov switching VAR (PMS-VAR) model, see Billio, Casarin, Ravazzolo, and Van Dijk (2016); Casarin, Foroni, Marcellino, and Ravazzolo (2019), is applied to make inference on the cyclical fiscal policy of the countries listed in the previous section.

[2] In the online Appendix, we show the number of countries that changes over time in our sample.

[3] Tables B.1-B.4 in Appendix B show the sources, the samples and the frequencies for each variable.

3.1 Panel Markov-switching VAR specification

The PMS-VAR model is given by:

$$\mathbf{y}_{it} = \mathbf{a}_i(s_{i\,t}) + \sum_{p=1}^{P} A_{ip}\mathbf{y}_{it-p} + \boldsymbol{\varepsilon}_{it}, \quad \boldsymbol{\varepsilon}_{it} \sim \mathcal{N}_M(\mathbf{0}, \Sigma_i(s_{i\,t})) \tag{1}$$

where $\mathbf{y}_{it}$ is a sequence of $t = \tau_i, \dots, T_i$ time observations on an M-dimensional vector of variables for $i = 1, \dots, N$ countries. Moreover, $\mathbf{a}_i(s_{i\,t})$ and $\Sigma_i(s_{i\,t})$ denote the parameters depending on Markov chains whereas A_{ip} is kept constant. The residuals are denoted by ε_{it}. Finally, $\{s_{i\,t}\}$ indicate the unit-specific and independent K-states Markov-chain processes with values in $\{1, \dots, K\}$ and transition probabilities $\mathbb{P}(s_{it} = k | s_{i\,t-1} = l) = \pi_{i,kl}$ with $k, l \in \{1, \dots, K\}$.

We introduce the indicator variable $\xi_{ikt} = \mathbb{I}(s_{i\,t} = k)$, which takes value 1 if $s_{i\,t} = k$ and 0 otherwise for $k = 1, \dots, K$, $i = 1, \dots, N$, and $t = \tau_i, \dots, T_i$. The vector of indicators $\boldsymbol{\xi}_{it} = (\xi_{i1t}, \dots, \xi_{iKt})'$ collects information about the realizations of the i-th unit-specific Markov chain over the sample period. Using these indicator variables, parameter shifts can be written as:

$$\mathbf{a}_i(s_{i\,t}) = \sum_{k=1}^{K} \mathbf{a}_{i,k}\xi_{ikt}, \quad \Sigma_i(s_{i\,t}) = \sum_{k=1}^{K} \Sigma_{ik}\xi_{ikt}.$$

where $\mathbf{a}_{i,k} = (a_{i1,k}, \dots, a_{iM,k})' \in \mathbb{R}^M$ are M dimensional column vectors representing the country- and regime-specific VAR intercepts and $\Sigma_{ik} \in \mathbb{R}^M \times \mathbb{R}^M$ are M-dimensional unit- and regime-specific covariance matrices. Following Frühwirth-Schnatter (2006), in order to simplify the exposition, we consider a re-parameterisation based on a partitioning of the set of regressors $(1, \mathbf{y}'_{it-1}, \cdots, \mathbf{y}'_{it-P})$ into $K+1$ subsets $\bar{\mathbf{x}}_{i0t} = (\mathbf{y}'_{it-1}, \dots, \mathbf{y}'_{it-P})'$ and $\bar{\mathbf{x}}_{ikt} = 1$, $k = 1, \dots, K$. The PMS-VAR in Eq. 1 writes as:

$$\mathbf{y}_{it} = (I_M \otimes \bar{\mathbf{x}}'_{i0t})\boldsymbol{\gamma}_{i0} + \xi_{i1t}\boldsymbol{\gamma}_{i1} + \ldots + \xi_{iKt}\boldsymbol{\gamma}_{iK} + \boldsymbol{\varepsilon}_{it}, \quad \boldsymbol{\varepsilon}_{it} \sim \mathcal{N}_M(\mathbf{0}, \Sigma_i(\boldsymbol{\xi}_{it})) \tag{2}$$

where $\boldsymbol{\gamma}_{i0} \in \mathbb{R}^{MM_0}$, $\boldsymbol{\gamma}_{ik} \in \mathbb{R}^M$, $k = 1, \dots, K$, $i = 1, \dots, N$, and $\Sigma_i(\boldsymbol{\xi}_{it}) = \Sigma_i(\boldsymbol{\xi}_{it} \otimes I_M)$ and $\Sigma_i = (\Sigma_{i1}, \cdots, \Sigma_{iK})$. The relationship between the new parameterisation and the previous one is: $\boldsymbol{\gamma}_{i0} = \mathrm{vec}((A_{i1}, \cdots, A_{iP})')'$, and $\boldsymbol{\gamma}_{ik} = \mathbf{a}_{i,k}$.

We assume a mixture prior, which allows us to model heterogeneity between panel units, including different sample sizes, in combination with a hierarchical specification strategy, which allows us to avoid overfitting issues. In our analysis, we divide OECD versus non-OECD countries. The hierarchical prior value is unique for both groups, but prior believes are updated separately for the two groups. Our decision stems from the fact that we expect *a priori* less uncertain fiscal rules for OECD countries than non-OECD. Moreover, on average, data sample is longer for OECD countries.

For regime identification, we impose identification constraints on the parameters. This practice is followed to a large extent in macroeconomics and it is related to the natural interpretation of the different regimes as different phases (e.g. recession and expansion) of the business cycle. We generalize the idea to fiscal policy identification and discuss constraints in Section 3.2. Prior and full posterior distributions are provided in Appendix A. We provide a summary in the next section, before moving to the regime identification in Section 3.2.

3.2 Regimes identification

As emphasized above, the fiscal regimes will be identified by imposing prior restrictions on the regime-specific intercepts of the variables of interest. Regime changes have the interpretation of fiscal policy shocks, thus the prior restrictions on the intercepts can be used to identify procyclical and countercyclical fiscal policy, and the economic identification constrains will be naturally incorporated in the parameter estimates through the prior-posterior updating. This avoids the largely criticized indirect identification methods, such as the recursive (zero) identification scheme. In so doing, we extend the idea in Baumeister and Hamilton (2015), Baumeister and Hamilton (2018) and Baumeister and Hamilton (2019) of using Bayesian inference and prior distribution to achieve identification in the inference process.

Table 2. Regime identification scheme common to all countries $i = 1, \ldots, 23$, based on the intercepts a_{ijk} of the variables $j = 1, \ldots, 6$ and regime $k = 1, 2$.

Variables			Fiscal Regimes Identification	
Label	Description	Intercept	Procyclical ($k = 1$)	Countercyclical ($k = 2$)
y_{i1t}	Total Gov. Exp. / GDP	a_{i1k}	+	+
y_{i2t}	Gov. Oil Rev. / GDP	a_{i2k}	+	-
y_{i3t}	Non-Oil Fiscal Bal. / GDP	a_{i3k}	NA	NA
y_{i4t}	Public Emp. / Total Emp.	a_{i4k}	NA	NA
y_{i5t}	Real Oil Price	a_{i5k}	NA	NA
y_{i6t}	Real Exchange Rate	a_{i6k}	NA	NA

We let the number of regimes be fixed to two, $K = 2$, so that we can identify one regime characterised with procyclical fiscal policy and one regime that is characterised with countercyclical fiscal policy. The restrictions are placed on the intercept parameters $a_i(s_{it})$, whereas autoregressive components are left unrestricted. We interpret the intercept of variable i as the regime conditional expected mean, whereas autoregressive components capture short-term dynamics. Therefore, our restrictions refer to the average patterns in a given regime, even if dynamics can partially vary at each quarter. Furthermore, volatility parameters are left unrestricted (i.e., weak identification) so that we can investigate whether fiscal policy minimizes uncertainty.

Table 2 shows the chosen restrictions to identify the two regimes. In the procyclical regime, intercepts for total government expenditures over GDP and government oil revenues over GDP are both positive. Hence, when growth in government oil revenues relative to GDP increases (decreases), growth in government expenditure relative to GDP increases (decreases). This can be interpreted as a "spend as you go" fiscal regime. In the countercyclical regime, the intercept for total government expenditures over GDP is positive, while the intercept for government oil revenues over GDP is negative.

Hence, when growth in government oil revenues relative to GDP decreases (increases), growth in government expenditure relative to GDP increases (decreases). This can be interpreted as a fiscal regime of saving for a rainy day (i.e., spend more in the recessions).[4] For the other variables, the parameters are left unrestricted.

3.3 Posterior Approximation

A Gibbs sampler is used for posterior approximation, see Krolzig (1997), Frühwirth-Schnatter (2006), Canova and Ciccarelli (2009), Billio, Casarin, Ravazzolo, and Van Dijk (2016), Agudze, Billio, Casarin, and Ravazzolo (2018), Casarin, Foroni, Marcellino, and Ravazzolo (2019). The sampler iterates over different blocks of unit-specific parameters in equation (2).

Let $\mathbf{y}_i = \text{vec}\left((\mathbf{y}_{i1}, \ldots, \mathbf{y}_{iT_i})\right)$ be the MT_i-dimensional vector of observations collected over time for the i-th unit of the panel, $\mathbf{y} = \text{vec}\left((\mathbf{y}_1, \ldots, \mathbf{y}_N)'\right)$ the $(\sum_i^N MT_i)$-dimensional vector of observations collected over time and panel units and $\boldsymbol{\xi} = \text{vec}\left((\Xi_1, \ldots, \Xi_N)\right)$ the $(\sum_i^N KT_i)$-dimensional vector of allocation variables, with $\Xi_i = (\boldsymbol{\xi}_{i1}, \ldots, \boldsymbol{\xi}_{iT})$. We define the vector of regression coefficients, $\boldsymbol{\gamma} = \text{vec}\left((\boldsymbol{\gamma}_1, \ldots, \boldsymbol{\gamma}_N)\right)$ where $\boldsymbol{\gamma}_i = \text{vec}\left((\boldsymbol{\gamma}_{i0}, \boldsymbol{\gamma}_{i1}, \ldots, \boldsymbol{\gamma}_{iK})\right)$, the set of covariance matrices, $\Sigma = (\Sigma_1, \ldots, \Sigma_N)$, and the transition probability vector, $\boldsymbol{\pi} = \text{vec}\left((\boldsymbol{\pi}_1, \ldots, \boldsymbol{\pi}_N)\right)$ where $\boldsymbol{\pi}_i$ is a K-dimensional transition matrix.

Under the conditional independence assumption, the complete data likelihood function, associated to the PMS-VAR model, writes as:

$$p(\mathbf{y}, \boldsymbol{\xi} | \boldsymbol{\gamma}, \Sigma, \boldsymbol{\pi}) = \prod_{i=1}^{N} p(\mathbf{y}_i, \boldsymbol{\xi} | \boldsymbol{\gamma}_i, \Sigma_i, \boldsymbol{\pi}_i) \tag{3}$$

[4] Note that the intercepts for the ratios have opposite sign. Still we assume that government oil revenues and GDP move in the same direction. Hence, if the government oil revenues over GDP increase, total government expenditure must decrease (or vice versa) in the countercyclical regime.

where:

$$p(\mathbf{y}_i, \boldsymbol{\xi}|\boldsymbol{\gamma}_i, \Sigma_i, \boldsymbol{\pi}_i) = (2\pi)^{-\frac{T_i M}{2}} \prod_{t=\tau_i}^{T_i} |\Sigma_i(s_{it})|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}\mathbf{u}_{it}' \Sigma_i(s_{it})^{-1}\mathbf{u}_{it}\right\} \prod_{k,l=1}^{K} \pi_{i,kl}^{\xi_{ikt}\xi_{ilt-1}} \quad (4)$$

with $\mathbf{u}_{it} = \mathbf{y}_{it} - ((1, \boldsymbol{\xi}_{it}') \otimes I_M) X_{it} \boldsymbol{\gamma}_i$ and $X_{it} = (\boldsymbol{\iota}_K \otimes (I_M \otimes \bar{\mathbf{x}}_{i0t}'), I_{KM})$. The joint posterior distribution associated to the likelihood function and the prior distribution is not tractable and this calls for the use of posterior approximation methods. In this paper we apply MCMC and derive the following Gibbs sampling algorithm.

Let us define $\boldsymbol{\gamma}_{i(-k)} = (\boldsymbol{\gamma}_{i1}, \ldots, \boldsymbol{\gamma}_{ik-1}, \boldsymbol{\gamma}_{ik+1}, \ldots, \boldsymbol{\gamma}_{iK})$ and $\Sigma_{i(-k)} = (\Sigma_{i1}, \ldots, \Sigma_{ik-1}, \Sigma_{ik+1}, \ldots, \Sigma_{iK})$. The first block in the Gibbs sampler is:

(i) for $i = 1, \ldots, N$, draw $\boldsymbol{\gamma}_{i0}$ from $f(\boldsymbol{\gamma}_{i0}|\mathbf{y}_i, \Xi_i, \mathbf{d}_k, \boldsymbol{\gamma}_i, \Sigma_i, \boldsymbol{\lambda}_0)$;

The second block consists of the following steps:

(ii) for $i = 1, \ldots, N$ and $k = 1, \ldots, K$ draw:

- (ii.a) $\boldsymbol{\gamma}_{ik}$ from $f(\boldsymbol{\gamma}_{ik}|\mathbf{y}_i, \Xi_i, \boldsymbol{\gamma}_{i0}, \boldsymbol{\gamma}_{i(-k)}, \Sigma, \boldsymbol{\lambda}_k)$;
- (ii.b) Σ_{ik}^{-1} from $f(\Sigma_{ik}^{-1}|\mathbf{y}_i, \Xi_i, \boldsymbol{\gamma}_{i0}, \boldsymbol{\gamma}_i, \Sigma_{i(-k)})$;
- (ii.c) $(\pi_{i,1k}, \ldots, \pi_{i,K-1\,k})$ from $f(\boldsymbol{\pi}_i|\mathbf{y}_i, \Xi_i, \boldsymbol{\gamma}_{i0}, \boldsymbol{\gamma}_i)$;
- (ii.d) d_{ik} from $p(d_{ik} = j) \propto p_k f(\boldsymbol{\gamma}_{ik}|\boldsymbol{\lambda}_{jk}, \underline{\Sigma}_{jk})$, $j = 1, 2$.

In the third block, the Gibbs sampler iterates for $k = 1, \ldots, K$: (iii.a) draw $\boldsymbol{\lambda}_{jk}$ from $f(\boldsymbol{\lambda}_k|\mathbf{d}_k, \boldsymbol{\gamma}_k, \Sigma_k)$, $j = 1, 2$ and (iii.b) draw p_k from $p(p_k|\mathbf{d}_k)$.

In the fourth block, the sampler generates: (v) $\boldsymbol{\lambda}_0$ from $f(\boldsymbol{\lambda}_0|\boldsymbol{\gamma}_0, \Sigma_0)$ and (iv) Ξ from $p(\Xi|\mathbf{y}_{1:T}, \boldsymbol{\gamma}, \Sigma, \boldsymbol{\alpha})$. Further details on full conditional distributions and their sampling methods are given in Appendix A.

4 Empirical results

Below we present the empirical results. Our main question is to analyse when fiscal policy is procyclical or countercyclical, and characterise the behaviour in the regimes. We first summarise the posterior estimates across all the countries. Then we investigate the estimated results for the three selected countries in more detail: Norway, Russia and Saudi Arabia, as they represent oil producers and exporters in OECD, non-OECD and OPEC (and non-OECD) respectively.

4.1 Posterior estimates - Mean and volatility

We start this section by presenting intercept and volatility posterior means in the procyclical and countercyclical regimes for all countries, before showing some more details for the three selected countries: Norway, Russia and Saudi Arabia.

4.1.1 Panel results

Figures 2 and 3 show the scatter plots of the intercepts posterior means (a_i; left panels) and the volatility posterior means (σ_i; right panels) for the following variables: growth in government expenditures and non-oil fiscal balance, both plotted against growth in government oil revenues (Figures 2 (a) and (b), respectively) and growth in public employment and the real exchange rate, also both plotted against growth in government oil revenues (Figures 3 (a) and (b), respectively).[5] In all figures, the red dots represent the countercyclical regime whereas the blue dots the procyclical regime. Moreover, our estimates distinguish between OECD (empty dots) and non-OECD (coloured dots) countries. Note that, due to the restrictions imposed, for the procyclical regime, the intercepts for government oil revenues are all normalized to be positive, while in the countercyclical regime, the intercepts for government oil revenues are all normalized to be negative. This is clearly visible reading of the left panels in all the graphs.

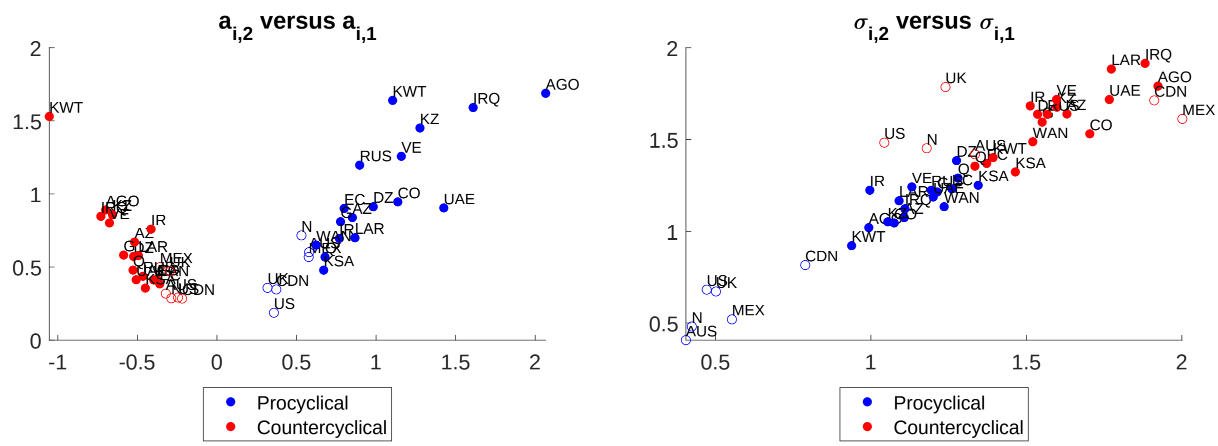
Starting with government expenditures in Figure 2 (a), we note from the right panel that the posterior for volatility is higher in the countercyclical regime than in the procyclical regime. Furthermore, volatility estimates in the procyclical regime are always smaller for OECD countries than for non-OECD countries. For the countercyclical regime, however, results are more mixed, suggesting that both OECD and non-OECD countries are able to pursue quite expansionary policies when revenues fall. These are new results in the literature.

We further note from the left panel that the intercepts for government expenditures are more dispersed in the procyclical regime than in the countercyclical regime, where the dots are more clustered. Hence, spending varies more between the countries when fiscal policy is procyclical than countercyclical. We also note, that, independent of the regimes, government spending tends to be more excessive in the non-OECD countries than in the OECD countries (as the coloured dots are ordered above the empty dots)

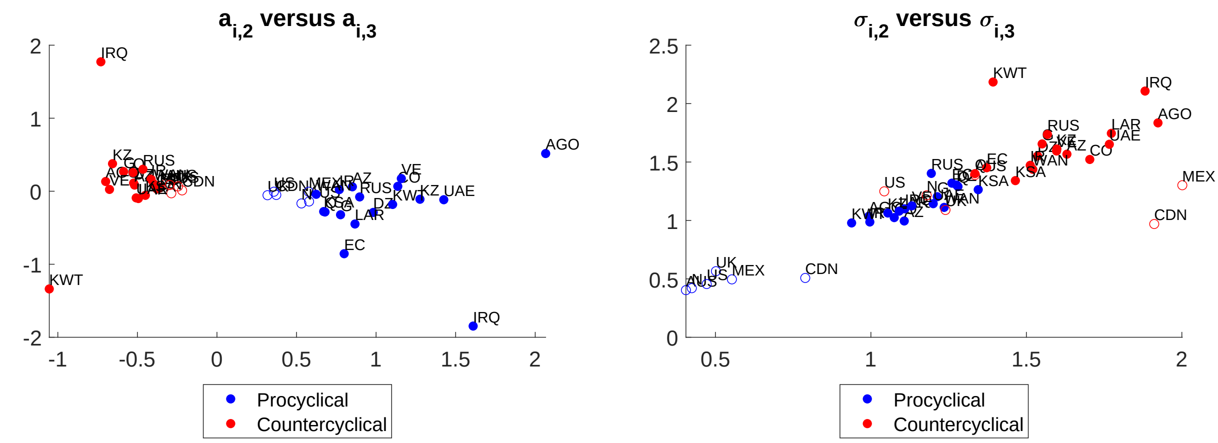
Figure 2 (b) displays non-oil fiscal balance relative to government oil revenues. The figure confirms the main picture from above, although the results for non-oil fiscal balance are less dispersed than what we saw for government expenditures in both regimes above.

[5]As emphasized, government oil revenues, government expenditures and the non-oil fiscal balance are measured relative to GDP, while government employment is measured relative to total employment.

Figure 2. Scatter plots of the estimates for mean (left) and volatility (right) of total government expenditure and non-oil fiscal balance, both plotted versus government oil revenues



(a) Total government expenditure (vertical axis) versus government oil revenues (horizontal axis)

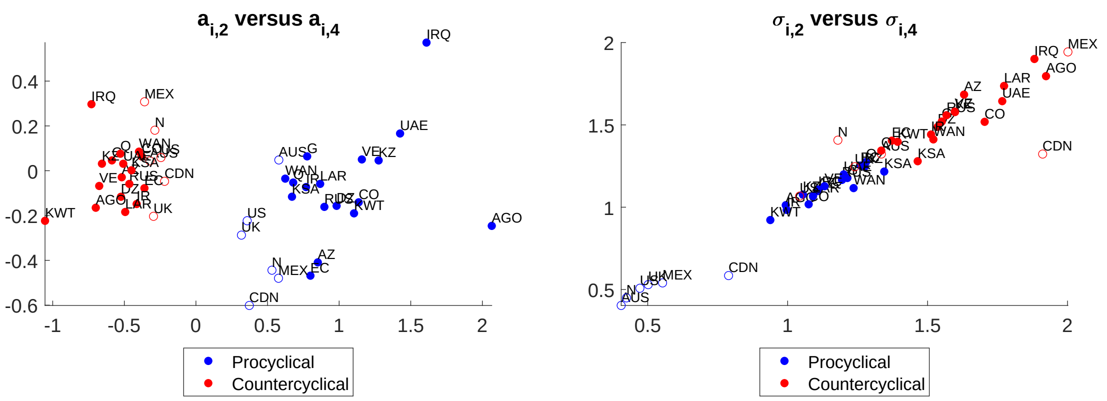


(b) Non-oil fiscal balance (vertical axis) versus government oil revenues (horizontal axis)

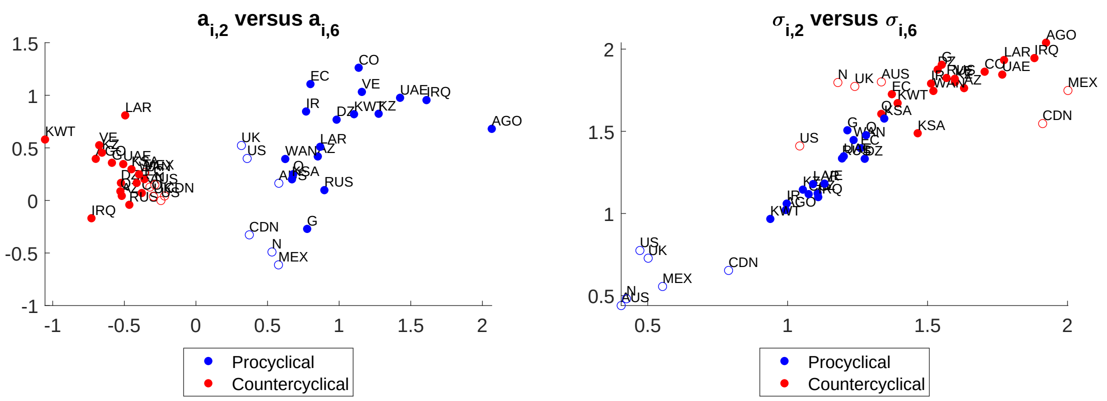
Notes: Intercepts posterior means (a_i; left panels) and the the volatility posterior means (σ_i; right panels) for growth in total government expenditure and non-oil fiscal balance, both plotted against growth in government oil revenues. Government oil revenues and government expenditure are measured relative to GDP. We distinguish between OECD (empty dots) and non-OECD (coloured dots) countries.

Still, volatility in the countercyclical regime is higher than in the procyclical regime. Note also some outliers, such as Iraq, that has a large negative mean value in the procyclical regime and a large positive mean value in the countercyclical regime. The recent war and the dependence on foreign support during the war, and in particular before oil revenues were restored, can probably explain these results.

Figure 3. Scatter plots of the estimates for mean (left) and volatility (right) of public employment and the real exchange rates, both plotted against government oil revenues



(a) Public employment/total employment (vertical axis) versus government oil revenues (horizontal axis)



(b) Real exchange rate (vertical axis) versus government oil revenues (horizontal axis)

Notes: Intercepts posterior means (a_i; left panels) and the the volatility posterior means (σ_i; right panels) for growth in public employment (relative to total employment) and the real exchange rate, both plotted against growth in government oil revenues. We distinguish between OECD (empty dots) and non-OECD (coloured dots) countries.

Turning to the right panel in Figure 3 (a), we confirm again the main picture from above for public employment, namely that volatility is higher in the countercyclical regime than in the procyclical regime, and that the variation tends to be higher in non-OECD countries than in OECD countries. We also note from the left panel, that while public employment responses are clustered around zero in the countercyclical regimes (showing little variation), results are much more dispersed in the procyclical regime.[6] This indicates

[6]This suggests that for OECD countries, public employment falls relative to total employment in the pro-

heterogeneity across countries in response to increased government oil revenues.

Finally, Figure 3 (b), displays the responses in real exchange rates in the procyclical and countercyclical regimes. Focusing on the intercept values, we note that in the countercyclical regime, the exchange rates mostly depreciate (increase) when government oil revenues fall, while in the procyclical regime, results vary: in OECD countries such as Canada, Norway and Mexico, the exchange rate appreciates when government oil revenues increase, while for the other countries, the exchange rate mostly depreciates, although with a lot of variations between countries. The results for Norway are interesting, as they suggest that despite having adopted a fiscal rule, the exchange rate has not been sheltered, consistent with the conclusion also made in Bjørnland and Thorsrud (2019). Finally, we note that, during procyclical periods, there is a larger volatility of the real exchange rate for non-OECD countries than for OECD countries. In general, the countercyclical regimes are associated with a more volatile exchange rate than the procyclical regimes.

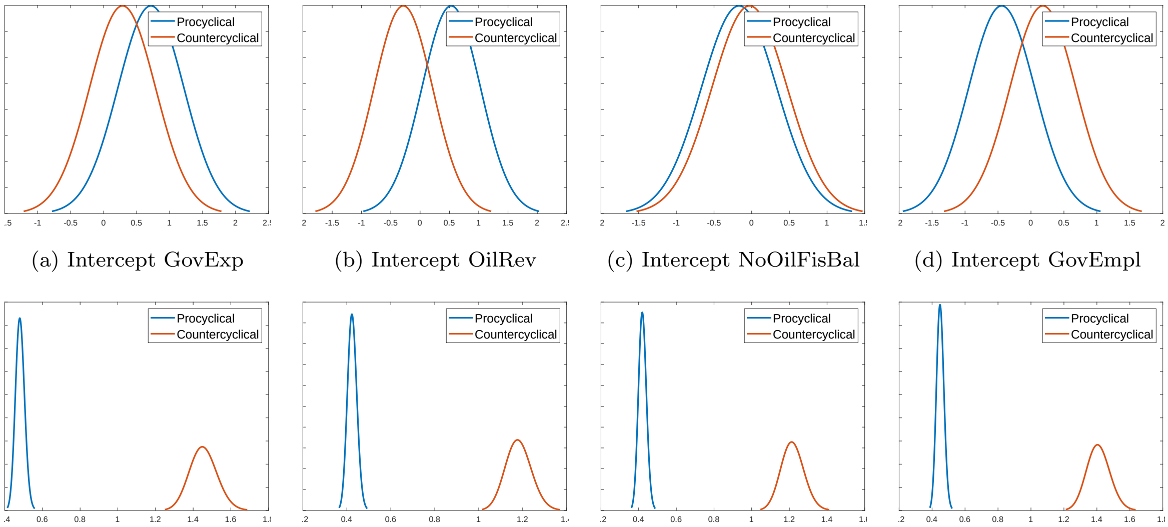
Hence, our first conclusion emphasizes that volatility is higher in the countercyclical fiscal policy regimes than in the procyclical regimes. Our empirical findings therefore show a clear distinction between the two regimes. Moreover, fiscal policy tends to be more volatile in non-OECD countries than in OECD countries, in particular in the procyclical regime. These results essentially support our strategy of estimating two regimes. By only restricting the mean response, we are able to identify systematic differences in volatility in the two regimes, and across countries. Doing so, we have encountered new facts about fiscal policy in oil rich countries.

4.1.2 Details for Norway, Russia and Saudi Arabia

Having seen results for the whole panel, we provide some details about the posterior estimates of the model intercepts and volatility for three selected countries: Norway, Russia and Saudi Arabia in Figures 4-6 respectively. Results for other countries are given in the online Appendix. As discussed above, we choose to focus on Norway, Russia and Saudi Arabia since they are large oil exporters, both in terms of share of world oil production, but also the relative size of oil in the country. However, the countries are diverse in other aspects: Norway is an OECD member, while Russia and Saudi Arabia are not. Moreover, Saudi Arabia is an OPEC member, whereas the other two countries are not. Hence, here we can examine similarities and differences between OECD, non-OECD and OPEC countries. We focus on four variables from our panel: total government

cyclical regime, while for most non-OECD countries, public employment responds little or even increases relative to total employment. For many OECD countries, a rise in oil revenues increases both public and private employment (suggesting little variation in the ratio), while for non-OECD countries, public employment relative to total employment generally increases.

Figure 4. Posterior distribution for intercept and volatility estimates for Norway



(a) Intercept GovExp (b) Intercept OilRev (c) Intercept NoOilFisBal (d) Intercept GovEmpl

(e) Volatility GovExp (f) Volatility OilRev (g) Volatility NoOilFisBal (h) Volatility GovEmpl

Notes: GovExp total government expenditure/GDP; OilRev government oil revenues/GDP; NoOilFisBal non-oil fiscal balance/GDP; GovEmpl public employment/total employment;

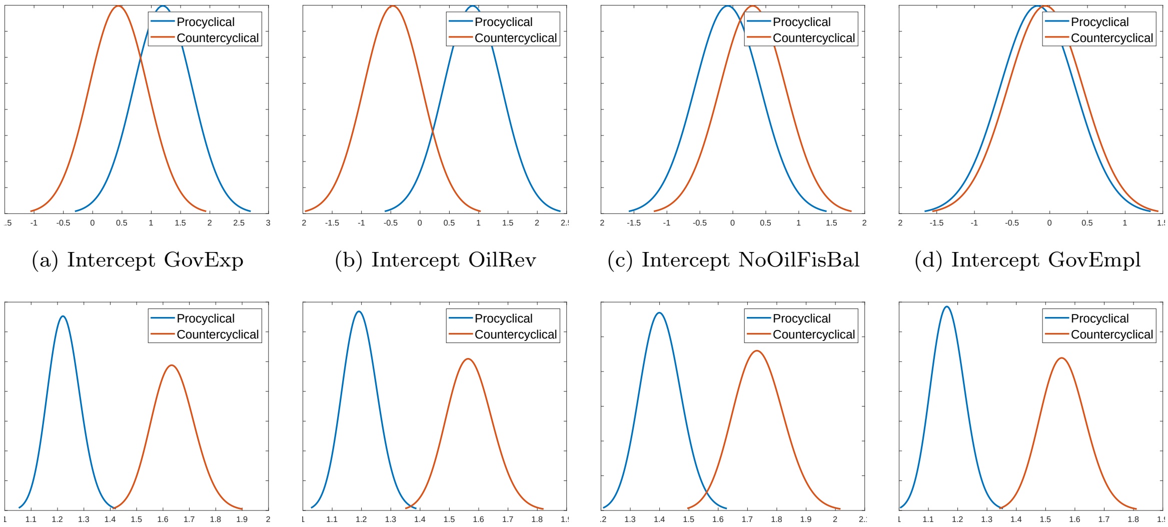
expenditure, government oil revenues, non-oil fiscal balance and public employment. In each figure, panel (a) - (d) present the intercept estimates, while figures (e) - (h) present the volatility estimates.

Starting with the estimated intercepts for the government oil revenues and expenditures, see panel (a) and (b) respectively of Figures 4-6, we note that most of the intercepts are well identified: the estimated intercepts are positive in the procyclical regime, while in the countercyclical regime, the posterior density have larger mass in the negative interval. The exception is Saudi Arabia, where the procyclical and countercyclical regimes for government expenditures are overlapping. The strongest identification is achieved for Russia, where there are clear distinctions between the regimes.

Turning to the estimated intercepts for non-oil fiscal balance and public employment, see panels (c) and (d) respectively of Figures 4-6, the posteriors in the two regimes are more overlapping. The exception is public employment in Norway, where the posterior distributions for public employment is different between the two regimes: Procyclical intercepts have negative values whereas countercyclical intercepts assume positive values. This result confirms evidence in Bjørnland and Thorsrud (2019) that indicates a tendency from Norway to increase public employment to mitigate effects of declines in oil revenues during countercyclical policies.

Regarding volatility, the posterior distribution for the three countries shows some distinct similarities. In particular, for all countries, there are clear differences in the

Figure 5. Posterior distribution for intercept and volatility estimates for Russia

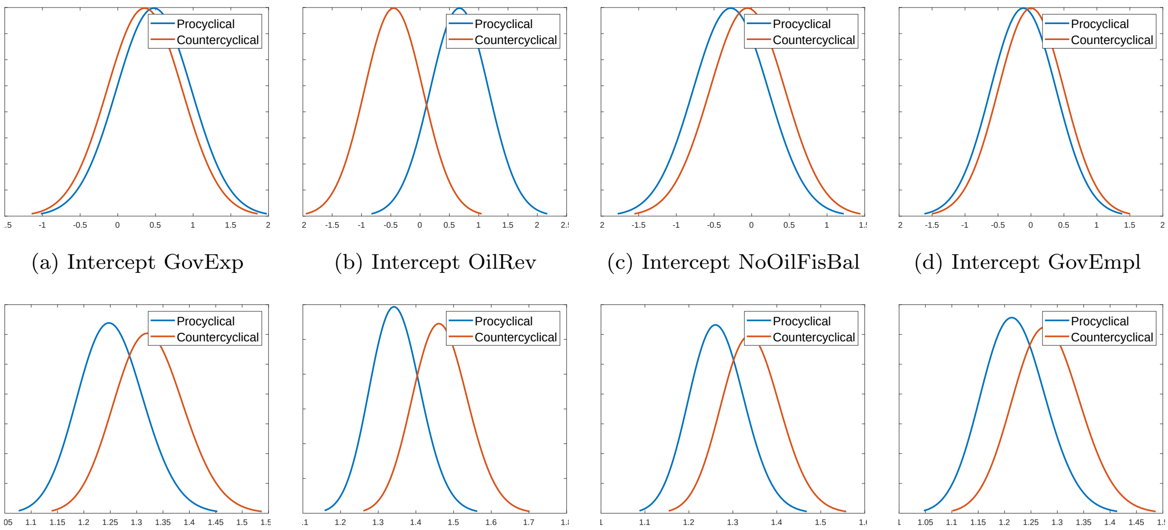


(a) Intercept GovExp (b) Intercept OilRev (c) Intercept NoOilFisBal (d) Intercept GovEmpl

(e) Volatility GovExp (f) Volatility OilRev (g) Volatility NoOilFisBal (h) Volatility GovEmpl

Notes: GovExp total government expenditure/GDP; OilRev government oil revenues/GDP; NoOilFisBal non-oil fiscal balance/GDP; GovEmpl public employment/total employment;

Figure 6. Posterior distribution for intercept and volatility estimates for Saudi Arabia



(a) Intercept GovExp (b) Intercept OilRev (c) Intercept NoOilFisBal (d) Intercept GovEmpl

(e) Volatility GovExp (f) Volatility OilRev (g) Volatility NoOilFisBal (h) Volatility GovEmpl

Notes: GovExp total government expenditure/GDP; OilRev government oil revenues/GDP; NoOilFisBal non-oil fiscal balance/GDP; GovEmpl public employment/total employment;

distribution of volatility between the two regimes: in general, volatility is higher during the countercyclical regimes than during the procyclical periods. This is in particularly notable for Norway, followed by Russia and Saudi Arabia. Furthermore, for Norway, the distribution is much more dispersed during the countercyclical regime than during the procyclical regime. This is not the case for Russia and Saudi Arabia, where the posterior distribution is similarly shaped in the two regimes.

To sum up, we have seen that the data supports the hypothesis that variations in the intercepts are associated with major differences in volatilities among the two regimes. These results support our model set-up of identifying fiscal policy through a regime switching framework. Still, we have seen that Norway (an OECD country) stands out by having the most profound differences between the procyclical and the countercyclical regimes, whereas Russia and Saudi Arabia (Non-OECD, and for Saudi Arabia, also OPEC, countries) are more similar. This supports the conclusion made in the previous section.

4.2 Regime probabilities

We turn now to describe the regime probabilities, defined here as the probabilities of being in the procyclical fiscal policy regime. We start by plotting the probabilities across groups of countries. In particular, Figure 7 shows the probabilities of being in a procyclical fiscal policy regime, aggregated over OECD countries (solid blue line), non-OECD countries (solid red line) and OPEC countries (dashed red line).

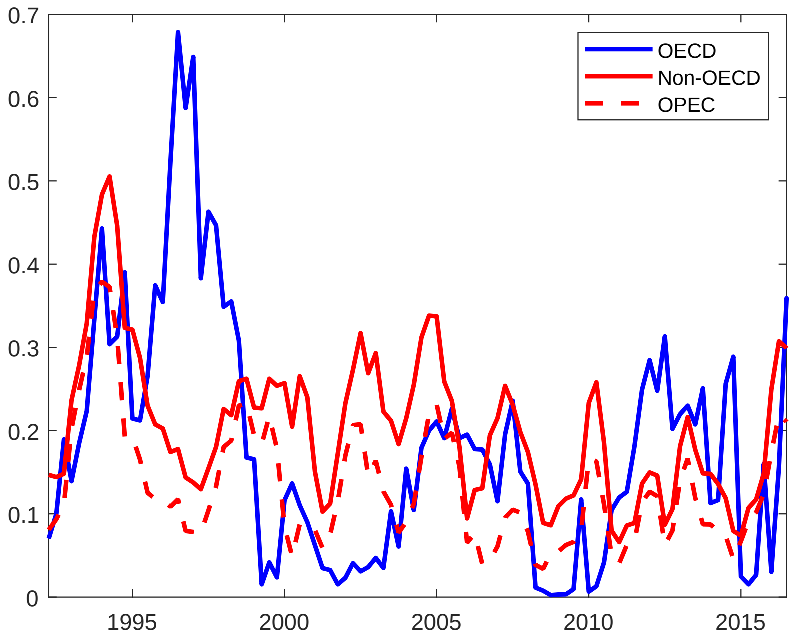
Two findings stand out. First, for all groups of countries, there are multiple periods when fiscal policy is in a procyclical regime over the sample. Hence, we find no evidence that fiscal policy has been mostly procyclical during the last decades, as suggested by Lopez-Murphy and Villafuerte (2010) or Bova, Medas, and Poghosyan (2016), or that fiscal policy has been less procyclical over time, as found in Céspedes and Velasco (2014). Instead, we find all countries to alternate between procyclical and countercyclical regimes over the sample.

Second, the average regime probabilities between OPEC countries and non-OECD countries (red and dashed red lines) have very similar patterns, as opposed to OECD countries (blue line). In particular, the correlation coefficient between the procyclical probabilities of non-OECD and OPEC countries is as high as 0.89. On the other hand, the pattern of fiscal policy in OECD countries is largely unrelated with those of non-OECD and OPEC countries. More specifically, the correlation coefficient between the procyclical probabilities of OECD and non-OECD countries is 0.17, whereas the correlation coefficient between OECD and OPEC countries is 0.22.

By constructing 68% high density posterior (HDP) of the state probabilities, we confirm that procyclical fiscal policies for OECD and non-OECD countries are statistically different in several periods.[7] From Figure 7, we see that there are in particular three periods that stand out. The first period is in the aftermath of the Asian crisis (1996:Q4-

[7] The 68% HDP can be obtained at request. We also not that the 68% HDP of the state probabilities are on average statistically the same the 89% interval.

Figure 7. Aggregate procyclical fiscal policy probabilities for OECD, non-OECD and OPEC countries



Note: Average regime probability of being in a procyclical fiscal policy regime aggregated over OECD countries (solid blue line), non-OECD countries (solid red line) and OPEC countries (dashed red line).

1997:Q3). The resource rich OECD countries relaxed their fiscal policy in response to the crisis, so fiscal policy became procyclical. Contemporaneously, government oil revenues in these countries increased due to the higher real oil price. The second period is the oil price surge between 2002 and 2007 that was caused by the increase in oil demand from emerging countries (notably China and India). During this period, non-OECD countries saw a large increase in their oil revenues and contemporaneously they increased their government spending (became more procyclical). Finally, the last period that stands out relates to the oil price plunge that occurred from 2008:Q3 and the subsequent oil price recovery from 2009/2010. All countries experienced at first a large fall in their government oil revenues and became less procyclical, but OECD countries in particular. From 2010, however, non-OECD countries stand out by becoming more procyclical as revenues increased.

To sum up, our estimated results imply that non-OECD and OPEC countries have very similar patterns in fiscal policy as opposed to OECD countries. A notable exception, however, is the recovery following oil price decline in 2014/2015, when fiscal policy in all countries moves in the same direction of being more procyclical as oil prices increase.

These results suggest that our approach of analysing fiscal policy through procyclical and countercyclical regimes in different countries is meaningful. We do not know a priori whether oil exporter/producer countries have the same probabilities of being in certain fiscal policy regimes. We have seen, however, that while countries within certain groups tend to behave similarly, there are huge differences across groups. In particular, OECD countries behave differently than non-OECD and OPEC countries during the procyclical regimes.

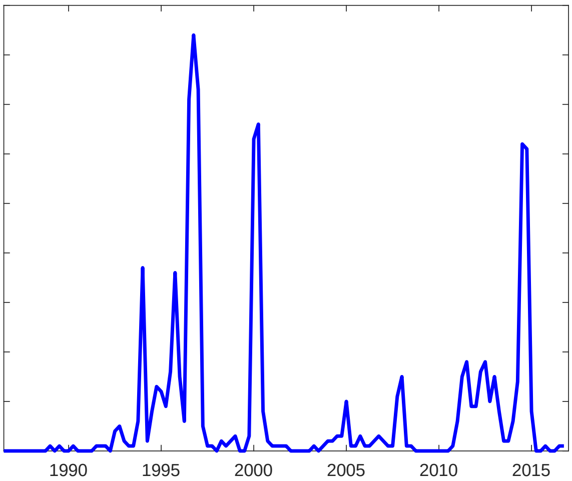
4.2.1 Regime probabilities - Norway, Russia and Saudi Arabia

We now turn to examine in more details the probability of being in a procyclical fiscal policy regime for Norway, Russia and Saudi Arabia in Figure 8, panels (a)-(c), respectively. Starting with Norway, we note from Figure 8 (a) that fiscal policy was procyclical during the middle and late 1990s, during the turn of the millennium, and increasingly so from 2011/2012, and until 2015. This pattern relates well to certain know episodes: the first and most prolonged period in the 1990s relates to the recovery after the Scandinavian bank and real estate crisis, which led to increased government spendings and a substantial widening of the deficit. The second period came after oil revenues started to pour into the economy, and spending picked up. In 2001 the spending rule was adopted, to shelter the economy from the procyclical behaviour.[8] With a few brief exceptions, spending was countercyclical during the first half of the decade. As expected, fiscal policy was also countercyclical during the great recession in 2008/2009, but became procyclical again in line with the increased oil revenues as the economy recovered. This pattern of procyclical fiscal policy is consistent with that which was found in Bjørnland and Thorsrud (2016).

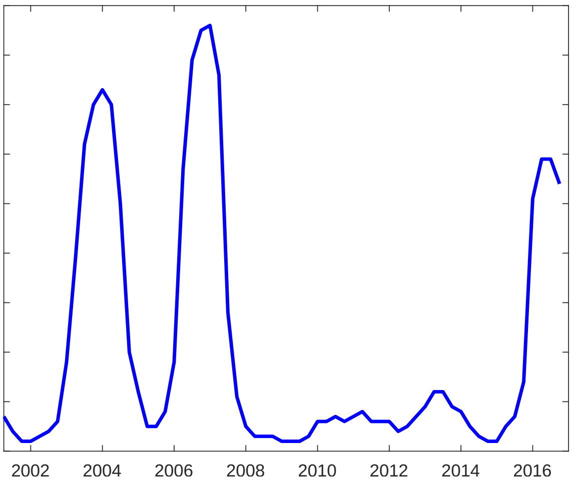
Turning to Russia, see Figure 8 (b), we note that the probabilities that fiscal policy is procyclical were high during 2003/2004, 2006/2007 and in 2015/2016. In 2003/2004, pressures for fiscal relaxation to finance reforms increased, taking advantage of the oil tax windfall to accelerate costly reforms (IMF, 2004). At the same time, less of the revenues from oil taxes were saved. In 2006, propelled by large terms-of-trade gains, Russian real GDP growth accelerated in line with increased government oil revenues, setting the stage for procyclical fiscal spending. In 2016, the recovery in oil prices eased the recession in Russia following the oil price decline in 2014. The doubling of oil prices during the year laid the foundation for a recovery that was also supported by a more expansionary fiscal stance. The rebound of the economy gathered further momentum by the end of 2016, at the same time, the share of government expenditure on GDP increased (IMF, 2017).

[8]The rule specified that the government should spend the expected real return of the fund, that was set to be 4% of the fund value. Subsequently, the rule has been revised down to 3%, see also Bjørnland and Thorsrud (2019) for details.

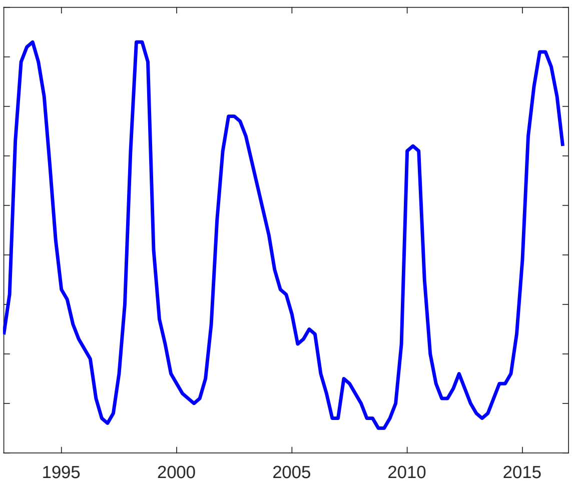
Figure 8. Procyclical fiscal policy probabilities



(a) Norway



(b) Russia



(c) Saudi Arabia

Note: The blue line is the probability of being in a procyclical fiscal policy regime.

Figure 8 (c) shows results for Saudi Arabia. The probabilities that fiscal policy is procyclical were high in many periods: 1993/1994, 1997/1998, 2002/2003, 2010, and 2015/2016. In the early and late 1990s, the Saudi economy showed marked resilience in the face of the depressed condition in the world oil market. The increase in the economy was partly attributed to the growth in government sector through procyclical fiscal spendings (SAMA, 1995). In 2004, the Saudi economy experienced record high growth rates in all its sectors, benefiting from a notable rise in oil prices. The oil sector increased by 32% and total government expenditure increased by 11% (SAMA, 2004). In 2010, the Saudi economy recorded strong growth as global economic recovery lifted up oil prices and enlarged fiscal spending by the government. The economy experienced a rise of 46% in total government revenue compared to 2009. Government expenditure went up by 10% compared to 2009 (SAMA, 2011). Finally, in 2015/2016, both the oil sector, GDP and expenditures increased, as Saudi Arabia's average daily production of oil also rose, in line with the increased oil prices (SAMA, 2017).

To sum up, we have seen that there are multiple periods when fiscal policy is in a procyclical regime over the sample, and these periods fit well with known historical episodes of increased oil revenues and overall growth. While there are some similarities in the timing of the switches between the regimes, i.e., the recovery after the oil price decline of 2014/2015, there are many country specific episodes that need to be accounted for. Hence, studies that try to analyse fiscal policy across countries using, say, a split sample framework, will misrepresent the changing pattern of how fiscal policy alternate between procyclical and countercyclical regimes. In line with this, we have found no evidence that fiscal policy in oil rich countries is mostly procyclical, as suggested by Lopez-Murphy and Villafuerte (2010) or Bova, Medas, and Poghosyan (2016), or that fiscal policy has been less procyclical over time, as found in Céspedes and Velasco (2014). Instead, we find that the probability of being in a procyclical regime varies over the sample.

5 Conclusion

Huge plunges in oil prices that the world has witnessed the last decades, represent an opportune moment to review how oil-rich countries are conducting fiscal policy in order to manage their resource wealth. In this regard, our paper tries to answer the following question: how do oil-rich countries conduct fiscal policy in light of huge oil price volatility? This question is particularly relevant as there are large costs associated with sharp and unpredictable swings in oil prices and, in turn, oil revenues, for the oil-rich countries. Hence, if not well managed, oil price volatility can destabilise such economies through fiscal policy and undermine their long-term growth.

In this paper we divert from the notion that fiscal policy is conducted in the same way over the sample, and analyse instead whether fiscal policy can switch between procyclical and countercyclical fiscal policy regimes. For this purpose, we propose a Bayesian Markov switching panel model where parameters change between the procyclical and countercyclical fiscal policy regimes over time according to a Markov process. Then we use parameter restrictions to identify procyclical and countercyclical fiscal policy regimes and evaluate fiscal policy's response in the different regimes. We use mixed frequency data for a large set of oil-exporting (OECD and non-OECD) countries in order to identify their fiscal regimes based on intercept restrictions.

We have three main findings. First, we find that there are multiple periods when fiscal policy is in a procyclical regime during the sample. Hence, studies that try to analyse fiscal policy using a split sample framework will misrepresent the changing pattern of how fiscal policy alternates between procyclical and countercyclical regimes. Second, for all countries, government oil revenues and expenditures are always more volatile in the countercyclical regime than in the procyclical regime. Third, in the procyclical regime, fiscal policy is always more volatile in the non-OECD (including OPEC) countries than in the OECD countries. Hence, during the booming periods, when government oil revenues increase, the OECD countries are able to smooth spending and save more than the non-OECD countries. Our results emphasize that it is both possible and important to separate a procyclical regime from a countercyclical regime. Doing so, we have been able to encounter new facts about fiscal policy in oil-rich countries.

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A Model inference

This section provides the prior distributions and posterior distributions. For the latter, we provide the main steps in Appendix A.2 and the detailed derivation in Appendix A.3.

A.1 Prior distributions

We assume a mixture prior, which allows us to model heterogeneity between panel units, in combination with a hierarchical specification strategy, which allows us to avoid overfitting issues. For the coefficients of the PMS-VAR regression we assume:

$$\begin{aligned} \boldsymbol{\gamma}_{i0} &\overset{iid}{\sim} \mathcal{N}_{MM_0}(\boldsymbol{\lambda}_0, \underline{\Sigma}_{i0}), \quad i = 1, \dots, N && \text{(A.1)} \\ \boldsymbol{\lambda}_0 &\sim \mathcal{N}_{MM_0}(\underline{\boldsymbol{\lambda}}_0, \underline{\Sigma}_0) && \text{(A.2)} \end{aligned}$$

whereas for the intercepts we assume:

$$\begin{aligned} \boldsymbol{\gamma}_{ik} &\overset{iid}{\sim} p_k \mathcal{N}_M(\boldsymbol{\lambda}_{1k}, \underline{\Sigma}_{1k}) + (1 - p_k)\mathcal{N}_M(\boldsymbol{\lambda}_{2k}, \underline{\Sigma}_{2k}), \quad i = 1, \dots, N && \text{(A.3)} \\ \boldsymbol{\lambda}_{jk} &\overset{iid}{\sim} \mathcal{N}_M(\underline{\boldsymbol{\lambda}}_k, \underline{\Sigma}_k), \quad j = 1, 2 && \text{(A.4)} \\ p_k &\overset{iid}{\sim} \mathcal{B}e(a, b) && \text{(A.5)} \end{aligned}$$

with $k = 1, \dots, K$, and for the inverse covariance matrix Σ_{ik}^{-1} we assume independent Wishart priors:

$$\Sigma_{ik}^{-1} \overset{iid}{\sim} \mathcal{W}_M(\underline{\nu}_k, \underline{\Upsilon}_k), \quad i = 1, \dots, N, \; k = 1, \dots, K. \tag{A.6}$$

Therefore, the hierarchical prior specification we apply allows for country i specific priors that hierarchically depend on all the $N-$countries. As we show in the full posterior derivation in Appendix A.3, this assumption allows us to combine the country i specific likelihood with the information for all the other countries.

When using Markov-switching processes, one has to deal with the identification issue associated with label switching. See, for example, Frühwirth-Schnatter (2001) for a discussion on the effects that the label switching and the lack of identification have on the results of MCMC-based Bayesian inference. In the literature, different routes have been proposed for dealing with this problem (see Frühwirth-Schnatter, 2006 for a review). One efficient approach is the permutation sampler (see Frühwirth-Schnatter, 2001), which can be applied under the assumption of exchangeability of the posterior density. This assumption is satisfied when one assumes symmetric priors on the transition probabilities of the switching process. As an alternative one may impose identification constraints on the parameters. This practice is followed to a large extent in macroeconomics and it is related to the natural interpretation of the different regimes as different phases (e.g. recession and expansion) of the business cycle. We follow this latter approach and include constraints on the intercept terms of two equations of the system (see Section 3.2).

A.2 Posterior approximation

A Gibbs sampler is used for posterior approximation (Krolzig, 1997; Frühwirth-Schnatter, 2006; Canova and Ciccarelli, 2009; Billio, Casarin, Ravazzolo, and Van Dijk, 2016; Agudze, Billio, Casarin, and Ravazzolo, 2018; Casarin, Foroni, Marcellino, and Ravazzolo, 2019). The sampler iterates over different blocks of unit-specific parameters in equation (2).

Let $\mathbf{y}_i = \mathrm{vec}\left((\mathbf{y}_{i1}, \ldots, \mathbf{y}_{iT})\right)$ be the MT_i-dimensional vector of observations collected over time for the i-th unit of the panel, $\mathbf{y} = \mathrm{vec}\left((\mathbf{y}_1, \ldots, \mathbf{y}_N)'\right)$ the $(\sum_{i=1}^N MT_i)$-dimensional vector of observations collected over time and panel units and $\boldsymbol{\xi} = \mathrm{vec}\left((\Xi_1, \ldots, \Xi_N)\right)$ the $(\sum_i^N KT_i)$-dimensional vector of allocation variables, with $\Xi_i = (\boldsymbol{\xi}_{i1}, \ldots, \boldsymbol{\xi}_{iT})$. We define the vector of regression coefficients, $\boldsymbol{\gamma} = \mathrm{vec}\left((\boldsymbol{\gamma}_1, \ldots, \boldsymbol{\gamma}_N)\right)$ where $\boldsymbol{\gamma}_i = \mathrm{vec}\left((\boldsymbol{\gamma}_{i0}, \boldsymbol{\gamma}_{i1}, \ldots, \boldsymbol{\gamma}_{iK})\right)$, the set of covariance matrices, $\Sigma = (\Sigma_1, \ldots, \Sigma_N)$, and the transition probability vector, $\boldsymbol{\pi} = \mathrm{vec}\left((\boldsymbol{\pi}_1, \ldots, \boldsymbol{\pi}_N)\right)$ where $\boldsymbol{\pi}_i$ is a K-dimensional transition matrix.

Under the conditional independence assumption, the complete data likelihood function, associated to the PMS-VAR model, writes as:

$$p(\mathbf{y}, \boldsymbol{\xi} | \boldsymbol{\gamma}, \Sigma, \boldsymbol{\pi}) = \prod_{i=1}^{N} p(\mathbf{y}_i, \boldsymbol{\xi} | \boldsymbol{\gamma}_i, \Sigma_i, \boldsymbol{\pi}_i) \tag{A.7}$$

where

$$p(\mathbf{y}_i, \boldsymbol{\xi} | \boldsymbol{\gamma}_i, \Sigma_i, \boldsymbol{\pi}_i) = (2\pi)^{-\frac{TM}{2}} \prod_{t=\tau_i}^{T_i} |\Sigma_i(s_{it})|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}\mathbf{u}_{it}'\Sigma_i(s_{it})^{-1}\mathbf{u}_{it}\right\} \prod_{k,l=1}^{K} \pi_{i,kl}^{\xi_{ikt}\xi_{ilt-1}} \tag{A.8}$$

with $\mathbf{u}_{it} = \mathbf{y}_{it} - ((1, \boldsymbol{\xi}_{it}') \otimes I_M) X_{it} \boldsymbol{\gamma}_i$ and $X_{it} = (\boldsymbol{\iota}_K \otimes (I_M \otimes \bar{\mathbf{x}}_{i0t}'), I_{KM})$. The joint posterior distribution associated to the likelihood function and the prior distribution is not tractable and this calls for the use of posterior approximation methods. In this paper we apply MCMC and derive the following Gibbs sampling algorithm.

Let us define $\boldsymbol{\gamma}_{i(-k)} = (\boldsymbol{\gamma}_{i1}, \ldots, \boldsymbol{\gamma}_{ik-1}, \boldsymbol{\gamma}_{ik+1}, \ldots, \boldsymbol{\gamma}_{iK})$ and $\Sigma_{i(-k)} = (\Sigma_{i1}, \ldots, \Sigma_{ik-1}, \Sigma_{ik+1}, \ldots, \Sigma_{iK})$. The first block in the Gibbs sampler is:

(i) for $i = 1, \ldots, N$, draw $\boldsymbol{\gamma}_{i0}$ from $f(\boldsymbol{\gamma}_{i0} | \mathbf{y}_i, \Xi_i, \mathbf{d}_k, \boldsymbol{\gamma}_i, \Sigma_i, \boldsymbol{\lambda}_0)$;

The second block consists of the following steps:

(ii) for $i = 1, \ldots, N$ and $k = 1, \ldots, K$ draw:

- (ii.a) $\boldsymbol{\gamma}_{ik}$ from $f(\boldsymbol{\gamma}_{ik} | \mathbf{y}_i, \Xi_i, \boldsymbol{\gamma}_{i0}, \boldsymbol{\gamma}_{i(-k)}, \Sigma, \boldsymbol{\lambda}_k)$;
- (ii.b) Σ_{ik}^{-1} from $f(\Sigma_{ik}^{-1} | \mathbf{y}_i, \Xi_i, \boldsymbol{\gamma}_{i0}, \boldsymbol{\gamma}_i, \Sigma_{i(-k)})$;
- (ii.c) $(\pi_{i,1k}, \ldots, \pi_{i,K-1\,k})$ from $f(\boldsymbol{\pi}_i | \mathbf{y}_i, \Xi_i, \boldsymbol{\gamma}_{i0}, \boldsymbol{\gamma}_i)$;
- (ii.d) d_{ik} from $p(d_{ik} = j) \propto p_k f(\boldsymbol{\gamma}_{ik} | \boldsymbol{\lambda}_{jk}, \underline{\Sigma}_{jk})$, $j = 1, 2$.

In the third block, the Gibbs sampler iterates for $k = 1, \dots, K$: (iii.a) draw $\boldsymbol{\lambda}_{jk}$ from $f(\boldsymbol{\lambda}_k|\mathbf{d}_k, \boldsymbol{\gamma}_k, \Sigma_k)$, $j = 1, 2$ and (iii.b) draw p_k from $p(p_k|\mathbf{d}_k)$.

In the fourth block, the sampler generates: (v) $\boldsymbol{\lambda}_0$ from $f(\boldsymbol{\lambda}_0|\boldsymbol{\gamma}_0, \Sigma_0)$ and (iv) Ξ from $p(\Xi|\mathbf{y}_{1:T}, \boldsymbol{\gamma}, \Sigma, \boldsymbol{\alpha})$. Further details on the full conditional distributions and their sampling methods are given in the following section.

A.3 Full conditional distributions

The full conditional distribution of the PMS-VAR coefficients $\boldsymbol{\gamma}_{i0}$ is a normal with density function:

$$
\begin{aligned}
f(\boldsymbol{\gamma}_{i0}|\mathbf{y}_i, \Xi_i, \boldsymbol{\gamma}_i, \Sigma_i, \boldsymbol{\lambda}_0) &\propto \exp\left\{-\frac{1}{2}\boldsymbol{\gamma}_{i0}'\left(\sum_{t=\tau_i}^{T_i}(I_M \otimes \bar{\mathbf{x}}_{i0t}')'\Sigma_{it}^{-1}(I_M \otimes \bar{\mathbf{x}}_{i0t}')\underline{\Sigma}_{i0}^{-1}\right)\boldsymbol{\gamma}_{i0}\right\} \cdot \\
&\quad \cdot \exp\left\{\boldsymbol{\gamma}_{i0}\left(\sum_{t=1}^{T}(I_M \otimes \bar{\mathbf{x}}_{i0t}')'\Sigma_{it}^{-1}\mathbf{y}_{i0t} + \underline{\Sigma}_{i0}^{-1}\boldsymbol{\lambda}_0\right)\right\} \\
&\propto \mathcal{N}_{MM_0}(\bar{\boldsymbol{\gamma}}_{i0}, \bar{\Sigma}_{i0})
\end{aligned} \tag{A.9}
$$

where $\mathbf{y}_{i0t} = \mathbf{y}_{it} - (\xi_{i1t}\boldsymbol{\gamma}_{i1} + \ldots + \xi_{iKt}\boldsymbol{\gamma}_{iK})$, $\bar{\boldsymbol{\gamma}}_{i0} = \bar{\Sigma}_{i0}(\underline{\Sigma}_{i0}^{-1}\boldsymbol{\lambda}_0 + \sum_{t=\tau_i}^{T_i}(I_M \otimes \bar{\mathbf{x}}_{i0t}')'\Sigma_{it}^{-1}(I_M \otimes \bar{\mathbf{x}}_{i0t}'))$ and $\bar{\Sigma}_{i0}^{-1} = (\underline{\Sigma}_{i0}^{-1} + \sum_{t=\tau_i}^{T_i}(I_M \otimes \bar{\mathbf{x}}_{i0t}')'\Sigma_{it}^{-1}(I_M \otimes \bar{\mathbf{x}}_{i0t}'))$.

The full conditional distributions of the PMS-VAR intercepts $\boldsymbol{\gamma}_{ik}$, with $k = 1, \dots, K$ are normal with density function:

$$
\begin{aligned}
&f(\boldsymbol{\gamma}_{ik}|\mathbf{y}_i, \Xi_i, d_{ik}, \boldsymbol{\gamma}_{i0}, \boldsymbol{\gamma}_{i(-k)}, \Sigma, \boldsymbol{\lambda}_k) \propto \\
&\propto \exp\left\{-\frac{1}{2}\boldsymbol{\gamma}_i'\left(T_{ik}\Sigma_k^{-1} + \underline{\Sigma}_{d_{ik}k}^{-1}\right)\boldsymbol{\gamma}_i + \boldsymbol{\gamma}_i'\left(\sum_{t\in\mathcal{T}_{ik}}\Sigma_{it}^{-1}\mathbf{y}_{ikt} + \underline{\Sigma}_{ik}^{-1}\boldsymbol{\lambda}_{d_{ik}k}\right)\right\} \\
&\propto \mathcal{N}_M(\bar{\boldsymbol{\gamma}}_{ik}, \bar{\Sigma}_{ik})
\end{aligned} \tag{A.10}
$$

with $\bar{\boldsymbol{\gamma}}_{ik} = \bar{\Sigma}_{ik}^{-1}(\underline{\Sigma}_{d_{ik}k}^{-1}\boldsymbol{\lambda}_{d_{ik}k} + \sum_{t\in\mathcal{T}_{ik}}\Sigma_{it}^{-1}\mathbf{y}_{it})$ and $\bar{\Sigma}_{ik}^{-1} = (\underline{\Sigma}_{d_{ik}k}^{-1} + T_{ik}\Sigma_{it}^{-1})$, where we defined $\mathcal{T}_{ik} = \{t|\xi_{ikt} = 1, t = \tau_i, \dots, T_i\}$, $T_{ik} = \text{Card}(\mathcal{T}_{ik})$, and $\mathbf{y}_{ikt} = \mathbf{y}_{it} - (I_M \otimes \bar{\mathbf{x}}_{i0t}')\boldsymbol{\gamma}_{i0}$. An accept/reject method is applied to account for the identification constraints on $\boldsymbol{\gamma}_{ik}$, $k = 1, \dots, K$ (see, e.g., Celeux, 1998; Frühwirth-Schnatter, 2001).

The full conditional distributions of the regime-dependent inverse variance-covariance matrix Σ_{ik}^{-1}, $k = 1, \dots, K$, are Wishart distributions with density:

$$
\begin{aligned}
&f(\Sigma_{ik}^{-1}|\mathbf{y}_i, \Xi_i, \boldsymbol{\gamma}_{i0}, \boldsymbol{\gamma}_i, \Sigma_{i(-k)}) \propto \\
&\propto |\Sigma_{ik}^{-1}|^{\frac{\nu_k + T_{ik} - M - 1}{2}} \exp\left\{-\frac{1}{2}\text{tr}\left(\left(\underline{\Upsilon}_k^{-1} + \sum_{t\in\mathcal{T}_{ik}}\mathbf{u}_{ikt}\mathbf{u}_{ikt}'\right)\Sigma_{ik}^{-1}\right)\right\} \\
&\propto \mathcal{W}_M(\bar{\nu}_{ik}, \bar{\Upsilon}_{ik})
\end{aligned} \tag{A.11}
$$

where $\mathbf{u}_{ikt} = \mathbf{y}_{it} - (I_M \otimes \bar{\mathbf{x}}'_{i0t})\boldsymbol{\gamma}_{i0} - \boldsymbol{\gamma}_{ik}$, $\bar{\nu}_{ik} = \underline{\nu}_k + T_{ik}$ and $\bar{\Upsilon}_{ik}^{-1} = \underline{\Upsilon}_k^{-1} + \sum_{t \in \mathcal{T}_{ik}} \mathbf{u}_{ikt}\mathbf{u}'_{ikt}$.

The full conditional distribution of the parameter $\boldsymbol{\lambda}_0$, of the third stage of the hierarchical structure, is a normal distribution with density function:

$$
\begin{aligned}
& f(\boldsymbol{\lambda}_0 | \gamma_0, \Sigma_0) \propto \\
& \propto \exp\left\{ -\frac{1}{2} \left[\boldsymbol{\lambda}'_0 \left(\sum_{i=1}^{N} \underline{\Sigma}_{i0}^{-1} + \underline{\Sigma}_0^{-1} \right) \boldsymbol{\lambda}_0 - 2\boldsymbol{\lambda}'_0 \left(\sum_{i=1}^{N} \underline{\Sigma}_{i0}^{-1} \boldsymbol{\gamma}_{i0} + \underline{\Sigma}_0^{-1} \underline{\boldsymbol{\lambda}}_0 \right) \right] \right\} \\
& \propto \mathcal{N}_{MM_0}(\bar{\boldsymbol{\lambda}}_0, \bar{\Sigma}_0)
\end{aligned} \tag{A.12}
$$

where $\bar{\Sigma}_0^{-1} = \sum_{i=1}^{N} \underline{\Sigma}_{i0}^{-1} + \underline{\Sigma}_0^{-1}$ and $\bar{\boldsymbol{\lambda}}_0 = \bar{\Sigma}_0 \left(\sum_{i=1}^{N} \underline{\Sigma}_{i0}^{-1} \boldsymbol{\gamma}_{i0} + \underline{\Sigma}_0^{-1} \underline{\boldsymbol{\lambda}}_0 \right)$.

Let $\mathbf{d}_k = (d_{1k}, \ldots, d_{Nk})$ be a collection of allocation variables, $\mathcal{D}_{jk} = \{i | d_{ik} = j, i = 1, \ldots, N\}$ the set of country indexes allocated to the j-th component of the mixture, and $D_{jk} = \text{Card}(\mathcal{D}_{jk})$ the number of countries in the j-th group. The full conditional distributions of the parameters $\boldsymbol{\lambda}_k$, $k = 1, \ldots, K$, of the third stage of the hierarchical structure, are normal distributions with density functions:

$$
\begin{aligned}
& f(\boldsymbol{\lambda}_{jk} | \mathbf{d}_k, \boldsymbol{\gamma}_k, \Sigma_k) \propto \\
& \propto \exp\left\{ -\frac{1}{2} \left[\boldsymbol{\lambda}'_{jk} \left(D_{jk} \underline{\Sigma}_{jk}^{-1} + \underline{\Sigma}_k^{-1} \right) \boldsymbol{\lambda}_{jk} - 2\boldsymbol{\lambda}'_{jk} \left(\sum_{i \in \mathcal{D}_{jk}} \underline{\Sigma}_{jk}^{-1} \boldsymbol{\gamma}_{ik} + \underline{\Sigma}_k^{-1} \underline{\boldsymbol{\lambda}}_k \right) \right] \right\} \\
& \propto \mathcal{N}_M(\bar{\boldsymbol{\lambda}}_k, \bar{\Sigma}_k)
\end{aligned} \tag{A.13}
$$

where $\bar{\Sigma}_k^{-1} = \sum_{i \in \mathcal{D}_{jk}} \underline{\Sigma}_{jk}^{-1} + \underline{\Sigma}_k^{-1}$ and $\bar{\boldsymbol{\lambda}}_k = \bar{\Sigma}_k \left(\sum_{i \in \mathcal{D}_{jk}} \underline{\Sigma}_{jk}^{-1} \boldsymbol{\gamma}_{ik} + \underline{\Sigma}_k^{-1} \underline{\boldsymbol{\lambda}}_k \right)$.

A.3.1 Allocation variable full conditional distributions

To sample the hidden states, we propose a multi-move strategy. In Krolzig (1997) a multi-move Gibbs sampler (see Carter and Kohn, 1994; Shephard, 1994) is presented for Markov-switching vector autoregressive models as an alternative to the single-move Gibbs sampler introduced, for example, in Albert and Chib (1993). The multi-move procedure, also known as a forward-filtering backward sampling (FFBS) algorithm, is particularly useful in a highly parameterised model, because it can improve the mixing of the MCMC chain over a large parameter space, thus leading to a more efficient posterior approximation. Unfortunately, the FFBS does not apply easily to our model due to the presence of the chain interaction mechanism. In fact, the FFBS should be iterated jointly for all the Markov-switching processes of the panel implying large matrix operations and, therefore, a high computational cost. We follow a different route and apply here the FFBS to the unit-specific chains, conditioning on the sampled value of other chains in the panel.

B Data Description

As we explained in the main body of the paper, our dataset is unbalanced. In particular, the data sample varies according to the data availability of each country and our data are at quarterly frequency. The data sources and sample periods of all countries are summarised in Tables B.1-B.4. Here, we provide the information about the construction of the observed series.

Share of Total Government Expenditure on GDP. Both series of Total Government Expenditure and GDP for Australia, Canada, UK and US are obtained from the OECD Economic Outlook. Data for Azerbaijan and Kazakhstan are obtained from the IMF Country Reports. Data for Colombia, Kuwait, Saudi Arabia and Venezuela are obtained from the IMF World Economic Outlook. Data for Algeria, Ecuador, Gabon, Iraq, Libya and Russia are obtained from IMF World Economic Outlook and IMF Country Reports. Data for Angola are obtained from the Republica de Angola, Ministerio das Financas and US FRED. Data for the remaining countries are obtained from national sources: Statistics Norway; Banco de México; Central Bank of the Islamic Republic of Iran; Nigeria Central Bank; Qatar Central Bank; UAE Federal Competitiveness and Statistics Authority. All original series are seasonally adjusted.

Table B.1 shows data frequency for each country. For those countries for which data are available only at yearly frequency, we use the Denton method (Di Fonzo and Marini, 2012) to disaggregate data into quarterly frequency. In general, we apply the Denton method using the series of Crude Oil Production obtained from the US EIA Monthly Energy Review. There are some exceptions: Azerbaijan (for which we use the series of Petroleum Production taken from US EIA), Colombia (for which we use the series of GDP taken from the OECD Quarterly National Account), Gabon (for which we use the series of Real Effective Exchange Rate taken from IMF IFS), Russia (for which we use the series of GDP taken from the OECD Quarterly National Account) and Venezuela (for which we use the series of GDP taken from Banco Central de Venezuela).

For all countries the series of Total Government Expenditure is expressed as a share of GDP and in terms of quarterly growth.

Share of Government of Oil Revenues on GDP. The series of Government Oil Revenues for Azerbaijan, Colombia, Ecuador, Gabon, Kazakhstan, Libya and Russia are obtained from IMF Country Reports. Data for Algeria are obtained from IMF World Economic Outlook and IMF Country Reports. Data for remaining countries are obtained from national sources: Australia, Department of Industry, Innovation and Science(DIIS); Canada, Alberta Energy; Norway Statistics; UK Office National Statistics; US Bureau of Economic Analysis; Banco de México; Republica de Angola, Ministerio das Financas; Central Bank of the Islamic Republic of Iran; Kuwait Central Statistical Bureau; Nigeria Central Bank; Qatar Central Bank; Saudi Arabian Monetary Agency (SAMA); Gobierno Bolivariano de Venuezuela; UAE Federal Competitiveness and Statistics Authority. Data for Iraq are obtained from the Iraqi Ministry of Finance and US EIA. All original series are seasonally adjusted.

Table B.2 shows data frequency for each country. For those countries for which data are available only at yearly frequency, we use the Denton method (Di Fonzo and Marini, 2012) to disaggregate data into quarterly frequency. In general, we apply the Denton method using the series of Crude Oil Production. There are some exceptions: Azerbaijan (for which we use the series of Petroleum Production), Australia (for which we use the series of Total Government Revenues taken from the OECD Economic Outlook), Colombia (for which we use the series of GDP), Gabon (for which we use the series of Real Effective Exchange Rate), Russia (for which we use the series of GDP), US (for which we use the series of Corporate Income Tax Revenues taken from the US BEA) and Venezuela (for which we use the series of GDP).

For all countries, the series of Government Oil Revenues is expressed as a share of GDP and in terms of quarterly growth.

Share of Non-Oil Fiscal Balance on GDP. We define Non-Oil Fiscal Balance as:

$$NOFB = NOGR - TGE \tag{B.1}$$

where $NOGR$ corresponds to Non-Oil Government Revenues and TGE is the Total Government Expenditure. In equation B.1, we define Non-Oil Government Revenues as:

$$NOGR = TGR - GOR \tag{B.2}$$

where TGR corresponds to Total Government Revenues and GOR stands for Government Oil Revenues.

We presented above the sources for the series of Total Government Expenditure and Government Oil Revenues. The sources for the series of Total Government Revenues are the same as those for the series of Total Government Expenditure. All original series of Total Government Revenues are seasonally adjusted. In order to convert annual series into quarterly frequency, we followed the same steps that we described above for the series of Total Government Expenditure.

For all countries, the series of Non-Oil Fiscal Balance is expressed as a share of GDP and in terms of quarterly growth.

Share of Public Employment on Total Employment. The series of Public Sector Employment and Total Employment for Australia are obtained from the OECD Labour Force Statistics. Data for Canada, Norway, UK and US are obtained from OECD Economic Outlook. Data for Angola, Azerbaijan, Colombia, Ecuador, Gabon, Iraq, Kazakhstan, Nigeria and Russia are obtained from Key Indicators of the Labour Market - ILO. Data for Mexico are obtained from the OECD Labour Force Statistics, Instituto Nacional de Estadística y Geografía (INEGI) and the OECD Economic Outlook. Data for Algeria are obtained from Key Indicators of the Labour Market - ILO - and the IMF Country Report. Data for Iran are obtained from the Iran Data Portal. Data for Kuwait are obtained from the Kuwait Central Statistical Bureau and World Bank WDI. Data for Libya are obtained from IMF World Economic Outlook and IMF Country Reports. Data for Qatar are obtained from the Qatar Statistics Authority and Key Indicators of the Labour Market - ILO. Data for Saudi Arabia are obtained from SAMA and the World Bank WDI. Data for Venezuela are obtained from Gobierno Bolivariano de Venuezuela, Istituto Nacional de Estadistica. Data for the UAE are obtained from the Ministry of the Economy and Key Indicators of the Labour Market - ILO. All original series are seasonally adjusted.

Table B.3 shows data frequency for each country. For those countries for which data are available only at yearly frequency, we use the Denton method (Di Fonzo and Marini, 2012) to disaggregate data into quarterly frequency. For Algeria, Angola, Ecuador, Iraq, Kazakhstan, Kuwait, Libya, Nigeria, Qatar, Saudi Arabia and UAE we apply the Denton method using the series of Crude Oil Production. For Australia and Mexico we use the series of Total Employment. For Azerbaijan we use the series of Petroleum Production. For Gabon we use the series of Real Effective Exchange Rate. For Colombia, Russia and Venezuela we use the series of GDP.

For all countries the series of Public Sector Employment is expressed as a share of Total Employment and in terms of quarterly growth.

Real Oil Price. For the period 1947:Q1-1973:Q4 data are taken from Baumeister and Peersman (2013). From 1974:Q1 to 2017:Q3, the nominal series of US Refiners Acquisition Cost of Imported Crude Oil is taken from the US EIA Monthly Energy Review. This series is deflated by the US CPI that is obtained from US FRED (Consumer Price Index for All Urban Consumers: All Items, Index 1982-1984=100, Quarterly, Seasonally Adjusted). We merge the two samples and we express the final series of the Real Oil Price in terms of quarterly growth.

Real Exchange Rate. Data for Algeria, Australia, Canada, Colombia, Ecuador, Gabon, Iran, Mexico, Nigeria, Norway, Russia and Saudi Arabia are obtained from IMF IFS. Data for Angola, Azerbaijan, Iraq, Kazakhstan, Kuwait, Libya, Qatar, UAE, UK, US and Venezuela are obtained from US FRED. We collect the series of the Real Effective Exchange Rate for all countries, except Azerbaijan, Iraq, Kazakhstan, Kuwait, Mexico and Russia. For these countries, we collect the series of the Nominal Exchange Rate and we deflate it by the respective CPI. All original series are seasonally adjusted. Table B.4 shows data frequency for each country. For those countries for which data are available only at yearly frequency, we use the Denton method (Di Fonzo and Marini, 2012) to disaggregate data into quarterly frequency. For Angola, Iraq, Libya and Qatar, we apply the Denton method using the series of Crude Oil Production. For Azerbaijan, we use the series of Petroleum Production. For Kazakhstan, we use the series of Crude Oil Production and Government Oil Revenues. For Kuwait, we use the series of Crude Oil Production and GDP. For all countries, the series of the Real Exchange Rate are expressed in terms of quarterly growth.

Table B.1. Total government expenditure, total government revenues and GDP data

Variable	Country	Status	Source	Sample/Frequency
Total Government Expenditure, Total Government Revenues and GDP	Australia	OECD	OECD Economic Outlook No. 99	1989:Q1-2016:Q4
	Canada	OECD	OECD Economic Outlook No. 99	1970:Q1-2017:Q4
	Mexico	OECD	Banco de México	1977:Q1-2017:Q2
	Norway	OECD	Statistics Norway	1985:Q1-2017:Q2
	UK	OECD	OECD Economic Outlook No. 99	1970:Q1-2017:Q4
	US	OECD	OECD Economic Outlook No. 99	1960:Q1-2017:Q4
	Algeria	NON-OECD	IMF World Economic Outlook & IMF Country Reports	1997-2016
	Angola	NON-OECD	Republica de Angola: Ministerio das Financas & US FRED	2002-2016
	Azerbaijan	NON-OECD	IMF Country Reports	1999-2016
	Colombia	NON-OECD	IMF World Economic Outlook	1996-2015
	Ecuador	NON-OECD	IMF World Economic Outlook & IMF Country Reports	1995-2016
	Gabon	NON-OECD	IMF World Economic Outlook & IMF Country Reports	1998-2016
	Iran	NON-OECD	Central Bank of the Islamic Republic of Iran	1990:Q2-2012:Q1
	Iraq	NON-OECD	IMF World Economic Outlook	2004-2016
	Kazakhstan	NON-OECD	IMF Country Reports	1999-2016
	Kuwait	NON-OECD	IMF World Economic Outlook	1990-2017
	Libya	NON-OECD	IMF World Economic Outlook & IMF Country Reports	1997-2013
	Nigeria	NON-OECD	Nigeria Central Bank	1991-2016
	Qatar	NON-OECD	Qatar Central Bank	1991-2016
	Russia	NON-OECD	IMF World Economic Outlook & IMF Country Reports	2000-2016
	Saudi Arabia	NON-OECD	IMF World Economic Outlook	1990-2017
	UAE	NON-OECD	Federal Competitiveness and Statistics Authority	2001-2016
	Venezuela	NON-OECD	IMF World Economic Outlook	1997-2014

Table B.2. Government oil revenues data

Variable	Country	Status	Source	Sample/Frequency
Government Oil Revenues	Australia	OECD	Department of Industry, Innovation and Science	1989-2016
	Canada	OECD	Alberta Energy	1973:Q1-2016:Q4
	Mexico	OECD	Banco de México	1977:Q1-2017:Q2
	Norway	OECD	Statistics Norway	1985:Q1-2017:Q2
	UK	OECD	UK Office of National Statistics	1978:Q4-2016:Q2
	US	OECD	Bureau of Economic Analysis	1950-2015
	Algeria	NON-OECD	IMF World Economic Outlook & IMF Country Reports	1997-2016
	Angola	NON-OECD	Republica de Angola: Ministerio das Financas	2002-2016
	Azerbaijan	NON-OECD	IMF Country Reports	1999-2016
	Colombia	NON-OECD	IMF Country Reports	1996-2015
	Ecuador	NON-OECD	IMF Country Reports	1995-2016
	Gabon	NON-OECD	IMF Country Reports	1998-2016
	Iran	NON-OECD	Central Bank of the Islamic Republic of Iran	1990:Q2-2012:Q1
	Iraq	NON-OECD	Iraqi Ministry of Finance & US EIA	2004:Q1-2016:Q4
	Kazakhstan	NON-OECD	IMF Country Reports	1999-2016
	Kuwait	NON-OECD	Kuwait Central Statistical Bureau	1999-2016
	Libya	NON-OECD	IMF Country Reports	1997-2013
	Nigeria	NON-OECD	Nigeria Central Bank	1991-2016
	Qatar	NON-OECD	Qatar Central Bank	1991-2016
	Russia	NON-OECD	IMF Country Reports	2000-2016
	Saudi Arabia	NON-OECD	Saudi Arabian Monetary Agency	1969-2016
	UAE	NON-OECD	Federal Competitiveness and Statistics Authority	2001-2016
	Venezuela	NON-OECD	Gobierno Bolivariano de Venuezuela: Istituto Nacional de Estadistica	1997-2014

Table B.3. Public sector and total employment data

Variable	Country	Status	Source	Sample/Frequency
Public Sector and Total Employment	Australia	OECD	OECD Labour Force Statistics	1989-2016
	Canada	OECD	OECD Economic Outlook No. 99	1966:Q1-2017:Q4
	Mexico	OECD	OECD Labour Force Statistics, Instituto Nacional de Estadística y Geografía & OECD Economic Outlook No. 99	2000-2016
	Norway	OECD	OECD Economic Outlook No. 99	1985:Q1-2017:Q2
	UK	OECD	OECD Economic Outlook No. 99	1970:Q1-2017:Q4
	US	OECD	OECD Economic Outlook No. 99	1960:Q1-2017:Q4
	Algeria	NON-OECD	ILO: Key Indicators of the Lab. Market & IMF Country Reports	1997-2016
	Angola	NON-OECD	ILO: Key Indicators of the Lab. Market	2002-2016
	Azerbaijan	NON-OECD	ILO: Key Indicators of the Lab. Market	1999-2016
	Colombia	NON-OECD	ILO: Key Indicators of the Lab. Market	1996-2015
	Ecuador	NON-OECD	ILO: Key Indicators of the Lab. Market	1995-2016
	Gabon	NON-OECD	ILO: Key Indicators of the Lab. Market	1998-2016
	Iran	NON-OECD	Iran Data Portal	1990:Q2-2012:Q1
	Iraq	NON-OECD	ILO: Key Indicators of the Lab. Market	2004-2016
	Kazakhstan	NON-OECD	ILO: Key Indicators of the Lab. Market	1999-2016
	Kuwait	NON-OECD	Kuwait Central Statistical Bureau & World Bank WDI	1999-2016
	Libya	NON-OECD	IMF World Economic Outlook & IMF Country Reports	1997-2013
	Nigeria	NON-OECD	ILO: Key Indicators of the Lab. Market	1991-2016
	Qatar	NON-OECD	Qatar Statistics Authority & ILO: Key Indicators of the Lab. Market	1991-2016
	Russia	NON-OECD	ILO: Key Indicators of the Lab. Market	2000-2016
	Saudi Arabia	NON-OECD	Saudi Arabian Monetary Agency & World Bank WDI	1990-2016
	UAE	NON-OECD	Ministry of the Economy: AER 2015 & ILO: Key Indicators of the Lab. Market	2001-2016
	Venezuela	NON-OECD	Gobierno Bolivariano de Venuezuela: Istituto Nacional de Estadistica	1997-2014

Table B.4. Real oil price and real exchange rate data

Variable	Country	Status	Source	Sample/Frequency
Real Oil Price	All countries	OECD & NON-OECD	Baumeister and Peersman (2012), US EIA & US FRED	1960:Q1-2017:Q3
Real Exchange Rate	Australia	OECD	IMF: International Financial Statistics	1980:Q1-2016:Q4
	Canada	OECD	IMF: International Financial Statistics	1970:Q1-2016:Q4
	Mexico	OECD	IMF: International Financial Statistics	1980:Q1-2016:Q4
	Norway	OECD	IMF: International Financial Statistics	1970:Q1-2016:Q4
	UK	OECD	US FRED	1972:Q1-2017:Q3
	US	OECD	US FRED	1964:Q1-2017:Q3
	Algeria	NON-OECD	IMF: International Financial Statistics	1980:Q1-2016:Q4
	Angola	NON-OECD	US FRED	2004-2015
	Azerbaijan	NON-OECD	US FRED	1994-2014
	Colombia	NON-OECD	IMF: International Financial Statistics	1980:Q1-2016:Q4
	Ecuador	NON-OECD	IMF: International Financial Statistics	1980:Q1-2016:Q4
	Gabon	NON-OECD	IMF: International Financial Statistics	1980:Q1-2016:Q4
	Iran	NON-OECD	IMF: International Financial Statistics	1973:Q1-2016:Q4
	Iraq	NON-OECD	US FRED	1973-2014
	Kazakhstan	NON-OECD	US FRED	1999-2014
	Kuwait	NON-OECD	US FRED	1999-2014
	Libya	NON-OECD	US FRED	1980-2010
	Nigeria	NON-OECD	IMF: International Financial Statistics	1980:Q1-2016:Q4
	Qatar	NON-OECD	US FRED	1981-2014
	Russia	NON-OECD	IMF: International Financial Statistics	1994:Q1-2016:Q4
	Saudi Arabia	NON-OECD	IMF: International Financial Statistics	1980:Q1-2016:Q4
	UAE	NON-OECD	US FRED	1994:Q1-2017:Q3
	Venezuela	NON-OECD	US FRED	1994:Q1-2017:Q3

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