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Fiscal Policy Regimes in Resource-Rich Economies*

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We analyse fiscal policy in resource-rich economies using a novel Bayesian regime-switching panel model. The identified regimes capture pro- or counter-cyclical fiscal behaviour, while the switches between the regimes have the interpretation of changes in fiscal policy. Applying the model to sixteen oil-producing economies, we show that fiscal policy has alternated between a procyclical and countercyclical regime multiple times over the sample. Furthermore, we find fiscal policy to be the most volatile in the procyclical regime and that the probability of being in the procyclical regime is higher for OPEC countries rather than non-OPEC countries. We also show that following either an increase or decrease in oil revenues, the growth in government expenditure mostly increases, suggesting there is an upward bias in expenditures in oil-producing countries. These are new findings in the literature.

JEL-codes: C11, C33, C51, E62, Q43

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

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1 Introduction

During recent years, oil price volatility has increased substantially. As oil is often a significant source of revenue in resource-rich economies, such large, unpredictable changes in oil prices can have a major impact on fiscal balances in these countries. To smooth spending over the business cycle, resource-rich countries are therefore advised to save parts of their windfall gains for rainy days. This will entail government spending to be operated countercyclically, thereby sheltering the economy from fluctuations in revenues and preventing over-spending by the government, see Barro, 1979 for a standard Neoclassical model. Anecdotal evidence, however, suggests that fiscal policy in many oil-rich countries is procyclical, so that public spending increases in the boom. This exacerbates the business cycle, leaving these countries more vulnerable to cuts when oil prices decline (c.f. IMF, 2020). The problem seems to be especially worrisome for countries where oil revenue constitutes a large component of total government revenues. For example, during the oil price collapse in 2015, the fiscal balance in many significant oil-producing economies deteriorated sharply, forcing many to cut spending in order to compensate for the decline in oil revenues (see, e.g., IMF, 2015).

Few studies have consistently analysed fiscal policy over the business cycles in oil-producing countries, but those that do mainly confirm that fiscal policy is procyclical, see for instance, Sturm, Gurtner, and Gonzalez-Alegre (2009); Lopez-Murphy and Villafuerte (2010); Erbil (2011) and Bova, Medas, and Poghosyan (2016).[1] Similar conclusions are also found in Céspedes and Velasco (2014), although they emphasise that the procyclicality has declined somewhat over time and attribute this to the fact that many countries have adopted fiscal policy rules recently.

One important caveat of the above-mentioned studies is that their findings will be dependent on the sample under study. As there may be a variety of shocks hitting the economy in different periods, this can affect the results. Countries also adopt fiscal rules in response to changing economic conditions, making fiscal policy design particularly complex, see Schaechter, Kinda, Budina, and Weber (2012) for an international overview, and Bjørnland and Thorsrud (2019) for an analysis of fiscal policy during changing rules in Norway. Furthermore, the conduct of fiscal policy may not necessarily be symmetric over the different phases of the cycle, as is the implied assumption in models that rely on constant parameters. For example, fiscal policy may be procyclical during commodity price booms but countercyclical when commodity prices fall, as emphasized by Arezki and Ismail (2013).[2]

[1]See Ilzetzki and Végh (2008) for a study of fiscal policy in developing countries, which also finds evidence of procyclical fiscal policy.

[2]Analysing thirty-two oil-exporting countries using panel data, Arezki and Ismail (2013) show that current

To better understand the conduct of fiscal policy, these aspects call for flexible models that allow fiscal policy to change over time. Models that assume constant parameters or that compare the conduct of fiscal policy on exogenously given sub-periods may yield biased results. Therefore, in this paper we take a different approach. To account for the time-varying nature, we assume that fiscal policy can switch between regimes of procyclical and countercyclical behaviour over the sample. Furthermore, to accommodate for that fact that policy could be asymmetric between commodity booms and busts, we will allow fiscal policy to be operated differently in the different cyclical phases. In particular, in line with Arezki and Ismail (2013), we open up for the possibility that fiscal policy can be expansionary in both booms and busts, i.e., that fiscal policy is procyclical when government oil revenues increase, but downward sticky, i.e., countercyclical, when the revenues fall (or vice versa). For this purpose, we propose a novel Bayesian Markov-switching panel model in which the parameters change between the procyclical and countercyclical fiscal policy regimes over time according to a Markov process. The panel data framework is particularly suitable for these issues, as we can allow for a large sample of countries to be modelled together. Furthermore, as the sample often varies from country to country, we can solve this by estimating an unbalanced panel where the number of observations can vary depending on the availability of the data series. Finally, in line with most recent literature, we make use of Bayesian inference and prior distribution to estimate our model (see, for example, Canova and Ciccarelli, 2004; Canova and Ciccarelli, 2009; Koop and Korobilis, 2013; Feldkircher, Huber, Koop, and Pfarrhofer, 2022).[3]

A highly debated issue in the economic literature is the identification of fiscal policy in structural analysis. Different methodologies have been used to identify fiscal policy shocks or systematic fiscal responses, see for instance Blanchard and Perotti (2002), Mertens and Ravn (2010), Ramey (2011), Leeper, Richter, and Walker (2012), Mertens and Ravn (2012) and Leeper, Walker, and Yang (2013) for important contributions to the literature. While some studies have been criticised for their indirect identification methods such as recursive identification schemes, (c.f., Blanchard and Perotti, 2002), it can also been pointed out that it is difficult to systematically compare fiscal policy across studies, as each typically focus on only a few countries and variables at a time.

Here, we instead focus on fiscal policy regimes using a panel of countries and variables. The fiscal policy regimes will capture pro- or countercyclical fiscal behaviour, while the switches between the regimes will have the interpretation of changes in fiscal policy. In

spending increases during booms, but is downwardly sticky in the busts. They argue that this could relate to the political pressures that governments in resource-rich countries face, making it easier to increase public spending during commodity price booms rather than cut spending during commodity price busts.

[3] To deal with the unbalanced panel and to avoid overfitting issues, we will assume a hierarchical prior to model heterogeneity across panel units, including different sample sizes.

so doing, our framework focuses on fiscal policy changes upon which policymakers can exert more control. Furthermore, rather than splitting the sample arbitrarily, and then analysing whether fiscal policy has become more or less procyclical after the split, we introduce a methodology that allows us to infer *when* fiscal policy has been procyclical or countercyclical over the sample.

To identify the regimes, we propose to employ sign restrictions. In particular, we identify different regimes by imposing prior restrictions on the regime-specific parameters of the variables of interest. Previous economic literature identifying economic shocks in structural vector autoregressions (SVARs) has used different identifying assumptions that lead to point- or set-identification of a common causal parameter of interest. Usual assumptions include causal ordering restrictions, long-run neutrality restrictions and Bayesian prior restrictions. Subsets of these assumptions, such as sign restrictions that we use here, will deliver set-identified impulse responses.[4]

We relate to the literature on Markov-switching models, where the parameters are usually strictly identified (see Allman, Matias, and Rhodes, 2009), but the likelihood is invariant to the permutation of the regime labelling. Previous studies have proposed different alternatives for dealing with this problem.[5] 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., recessions and expansions) of the business cycle (see, for example, Billio, Casarin, Ravazzolo, and Van Dijk, 2016). We adopt this latter approach and impose sign restrictions on the regime-specific intercepts of the variables of interest. In particular, we restrict the sign of the intercepts of government oil revenues and non-oil fiscal balance. However, their volatility, as well as the intercept and volatility of the other endogenous variables, will remain unrestricted.

In line with Lopez-Murphy and Villafuerte (2010) and Erbil (2011), our identifying restrictions assume that fiscal policy is procyclical when increased oil revenues are met by negative changes in the non-oil fiscal balance, (i.e., changes in government expenditures exceed changes in non-oil government revenues). In particular, an increase in oil revenues, following higher oil prices, can imply increased (net) financial savings and/or an increase in government spending (not financed by increases in non-oil revenue, but by the oil revenues). In this case, fiscal policy would be exacerbating cyclical fluctuations in the

[4]See Giacomini, Kitagawa, and Volpicella (2022) for a detailed discussion.

[5]See Frühwirth-Schnatter (2006) for a review.

economy. In contrast, a countercyclical fiscal policy regime corresponds to the case in which the change in the non-oil fiscal balance is positive when oil revenues are increasing, (i.e., changes in non-oil revenues exceed changes in government expenditures). In this case, fiscal policy would be dampening cyclical fluctuations in the economy. Having imposed the economic identification constraints, these will be naturally incorporated within the parameter estimates through the prior-posterior updating. To the best of our knowledge, this is the first study that proposes a Bayesian Markov-switching panel model to analyse fiscal policy over the cycles.

Our model is applied to 16 developing economies that are also the richest oil producing countries across the globe. We include countries where oil rents account for more than 5% of GDP over the sample 1990-2016. Our sample includes countries in the Organization of the Petroleum Exporting Countries (OPEC), as well as non-OPEC countries. Oil exports from these countries corresponds to 74% of the world oil exports. 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 and the real exchange rate, which are important variables for capturing the economic conditions 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 have three main findings. First, we find that there are multiple periods over the sample when fiscal policy alternates between a procyclical and a countercyclical regime. Hence, studies that try to analyse fiscal policy using constant parameters, or that deal with the time-varying changes using a split sample framework, will misrepresent the changing pattern of how fiscal policy is operated in commodity booms and busts. Second, the probability of being in the procyclical fiscal policy regime is higher for the OPEC countries than for the non-OPEC countries. This result indicates that, on average, OPEC economies are less able to shelter their economies from fluctuations in oil revenues than non-OPEC countries. Third, the timing of the procyclical and countercyclial pattern varies between the countries, as is clearly illustrated in the cases of Russia and Saudi-Arabia. However, in some periods, fiscal policy has been predominately procyclical across all countries. These include the Asian financial crisis in 1996/97, the oil price surge between 2002 and 2005 and the aftermath of the global financial crisis.

Our paper contributes to several strands of the literature. First, by proposing a Bayesian Markov-switching panel model to identify fiscal policy regimes, we contribute to the empirical literature that analyses the effect of fiscal policy, as discussed above. However, in contrast to these studies, our econometric framework does not assume indirect exclusion or expectations-based restrictions to identify fiscal policy, but relies instead on a minimum set of direct restrictions based on actual data. Second, we contribute to the literature on Markov-Switching SVAR models (e.g., Rubio-Ramirez, Waggoner, and Zha, 2006; Lanne, Lütkepohl, and Maciejowska, 2010; Netsunajev, 2013) by extending the use of identifying restrictions on the switching parameters to the panel SVAR models. Finally, we contribute in general to the panel data literature, (see e.g., Billio, Casarin, Ravazzolo, and Van Dijk, 2016; Casarin, Foroni, Marcellino, and Ravazzolo, 2019; Agudze, Billio, Casarin, and Ravazzolo, 2022, for key contributions) by analysing several countries together, despite different samples. This is possible because we follow a Bayesian approach with hierarchical prior distributions to deal with overfitting issues in high dimensional models.

The remainder of the paper is structured as follows. Section 2 presents the data, while Section 3 describes the model and the estimation procedure. In Section 4, we present the empirical results, focusing on the estimated parameters of the fiscal policy regimes, the regime probabilities for the whole panel of countries and details for two important oil producers: Russia and Saudi Arabia. The concluding remarks are found in Section 5.

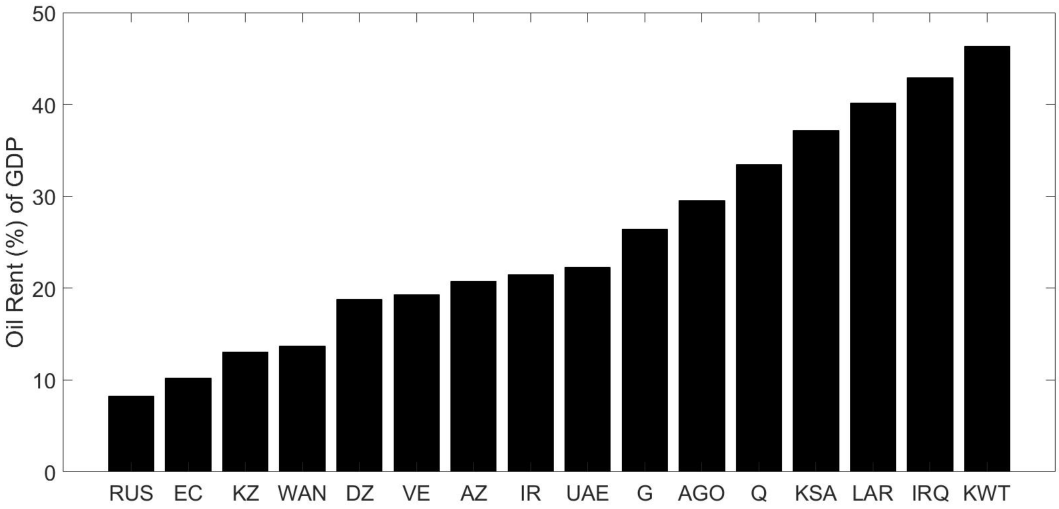
2 Data

We consider the following 16 resource-rich countries: Algeria, Angola, Azerbaijan, Ecuador, Gabon, Iran, Iraq, Kazakhstan, Kuwait, Libya, Nigeria, Qatar, Russia, Saudi Arabia, UAE, and Venezuela. These countries are major oil and gas producers and petroleum also counts for a major share of these economies. In particular, in this study we include the countries with the highest oil rents (as percentages of GDP) worldwide.[6] Figure 1 shows the average share of oil rent as share of GDP for this set of countries during the period 1990-2016. As we can observe from the figure, the majority of countries have an oil rent as share of GDP that is above 20%. In this regard, the shares of Saudi Arabia, Libya, Kuwait and Iraq are notable and above 35%. The shares of UAE, Azerbaijan, Iran, Gabon, Qatar and Angola are between 20% and 35%. The remaining countries have shares that are below 20%. These numbers indicate that our set of countries is composed of resource-rich economies that are also heavily dependent on oil. Consequently, it is likely that fiscal policy in these countries will be largely affected by swings in the price of this commodity.

As described in Kaminsky, Reinhart, and Vegh (2004), many indicators can be used

[6]According to the definition of the World Bank: "Oil rents are the difference between the value of crude oil production at regional prices and total costs of production" (see World Bank World Development Indicators, 1960-2020, 27th Edition, DOI:10.5257/wb/wdi/2022Q1).

Figure 1. Oil rents as percentage of GDP



Source: World Bank, World Development Indicators. *Notes:* The values in the figure are average shares for the countries during the period 1990-2016. Acronyms are as follows: Algeria (DZ), Angola (AGO), Azerbaijan (AZ), Ecuador (EC), Gabon (G), Iran (IR), Iraq (IRQ), Kazakhstan (KZ), Kuwait (KWT), Libya (LAR), Nigeria (WAN), Qatar (Q), Russia (RUS), Saudi Arabia (KSA), United Arab Emirates (UAE), Venezuela (VE).

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: the growth rate of total government expenditure ($y_{i1,t}$); the growth rate of government oil revenues ($y_{i2,t}$); the growth rate of non-oil fiscal balance ($y_{i3,t}$) and the growth rate of public employment relative to total employment ($y_{i4,t}$). We also include the growth rate of the real oil price ($y_{i5,t}$), which may capture common shocks in the oil market, and the growth rate of the real exchange rate ($y_{i6,t}$), which is important for capturing the changes in the economic conditions in the resource-rich economies.

In total we have 81 variables in our model for the sample period 1990:Q3-2016:Q4. The data series are collected from both international and national data sources, and the sample varies according to the data availability of each country. Accordingly, our dataset is unbalanced. All data series are expressed in terms of quarterly growth.[7] 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 A reports a detailed explanation on how we constructed all the variables used in the empirical analysis.

In the online Appendix A, we report descriptive statistics for the data series that

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

are used to estimate our model. We note that most variables show a large variability. Furthermore, most of the data series are also moderately skewed. We also observe that most of the moments are different from those of a normal distribution. We also graph the time-series for all countries in online Appendix A. While there are some similarities across countries, the graphs illustrate clearly that there are some important country differences, suggesting that both idiosyncratic shocks and policies matter. The figures also clearly show that we have different sample sizes across variables and countries, which induced us to adopt a panel analysis framework with an unbalanced panel.

3 Model

We jointly model all variables using a VAR framework, see for instance 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 the exchange of information across units and thus is well suited to 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 of them, our parameter restrictions identify procyclical and countercyclical regimes. The resulting panel Markov-switching VAR (PMS-VAR) model is applied to make inference on the cyclical fiscal policy of the countries listed in the previous section.

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

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 $k = 1, \ldots, K$, $i = 1, \ldots, N$, and $t = \tau_i, \ldots, T_i$. The vector of indicators $\boldsymbol{\xi}_{it} = (\xi_{i1t}, \ldots, \xi_{iKt})'$ collects information about the realisations of the i-th unit-specific

Markov chain over the sample period. Using these indicator variables, parameter shifts can be written as:

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

where $\mathbf{a}_{i,k} = (a_{i1,k}, \ldots, a_{iM,k})' \in \mathbb{R}^M$ 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 $\bar{\mathbf{x}}_{i0t} = (\mathbf{y}'_{it-1}, \ldots, \mathbf{y}'_{it-P})'$ and $\bar{\mathbf{x}}_{ikt} = 1$, $k = 1, \ldots, K$. The PMS-VAR in equation (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 $\boldsymbol{\gamma}_{i0} \in \mathbb{R}^{MM_0}$, $\boldsymbol{\gamma}_{ik} \in \mathbb{R}^M$, $k = 1, \ldots, K$, $i = 1, \ldots, N$, 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 hierarchical prior to model heterogeneity across panel units, including different sample sizes, and to avoid overfitting issues. For regime identification, we impose a minimum set of constraints on the parameter intercepts. Rather than developing ad hoc assumptions, our restrictions are based on the data series that we use to estimate our model. In the following section, we discuss our regime identification and we provide a summary of the parameter estimation.[8]

3.2 Regimes identification

As emphasised above, the fiscal regimes will be identified by imposing prior restrictions on the regime-specific intercepts of the variables of interest. Accordingly, we deal with the identification issue associated with label switching by imposing identification constraints on the parameters. This practice is followed to a large extent in macroeconomics (see, for example, Billio, Casarin, Ravazzolo, and Van Dijk, 2016). These prior restrictions follow from economic identification constraints and they will be naturally incorporated within the parameter estimates through the prior-posterior updating.[9] By restricting the parameter space through the use of priors, we avoid the largely criticised indirect identification methods, such as the recursive (zero) identification scheme (see, for example, Blanchard and Perotti, 2002 for example and Ramey, 2011 for a critique). In doing so, we will make

[8] Full details of the parameter estimation are provided in Appendix B.

[9] The parameters of our MS model are strict-identified (see, for example, Allman, Matias, and Rhodes, 2009).

explicit use of Bayesian inference and prior distribution to estimate our model (see, for example, Canova and Ciccarelli, 2004; Canova and Ciccarelli, 2009; Koop and Korobilis, 2013; Feldkircher, Huber, Koop, and Pfarrhofer, 2022).

In our model, regime switches are interpreted as changes in fiscal policy. Regarding economic intuition, we will examine to what extent a change in oil revenues leads to procyclical or countercyclical fiscal policy. In doing, the first challenge is to include relevant fiscal variables so as to identify the different regimes. As described in Kaminsky, Reinhart, and Vegh (2004), it may be necessary to include several indicators to evaluate the degree of procyclical or countercyclical fiscal policy in different countries. One of the advantages of the panel data model used here is precisely that we can investigate several variables at the same time, possibly allowing for more robust conclusions. For this reason we include non-oil fiscal balance, government expenditure, public employment (as a share of total employment), the real oil price and the real exchange rate, together with oil revenues. These are all relevant variables for examining fiscal policy in oil-rich countries (see, for instance, Kaminsky, Reinhart, and Vegh, 2004; Lopez-Murphy and Villafuerte, 2010; Bjørnland and Thorsrud, 2016 and Bjørnland and Thorsrud, 2019).

Next, we determine how we can identify the different fiscal policy regimes. Typically, in oil-rich countries, fiscal policy is said to be procyclical if government revenues and spending move in the same direction as oil prices, which leads to an expansionary fiscal policy that further stimulates economic growth, and vice versa when oil prices fall. One challenge when analysing fiscal policy in this way is that oil prices are quite volatile, whereas public spending only changes gradually due to implementation lags and the gradual phase in of oil revenues (see, for example, Bjørnland and Thorsrud, 2019 for an analysis of fiscal policy in Norway). Furthermore, the conduct of fiscal policy may be asymmetric over the cycles. As discussed in the introduction, Arezki and Ismail (2013) show theoretically and empirically how government expenditure increases during economic booms, but is not cut equally in the busts. They also find limited evidence that fiscal rules have helped reduce the degree of responsiveness of fiscal policy and that the bias in the fiscal response to commodity price shocks may explain the tendency for the level of the real exchange rate to remain elevated in commodity-rich countries following a decrease in commodity prices.

To better analyse the government's fiscal position after adjusting for the volatility of oil prices and the impact of oil revenues on the overall budget, we examine the non-oil fiscal balance. This is a measure of the fiscal position of a government, which excludes revenues and expenditures related to the production and export of oil. In oil-rich countries, oil revenues can be a major source of government revenue and fluctuations in oil prices can have a significant impact on the government's budget. As a result, the non-oil fiscal balance provides a better indication of the government's underlying fiscal position. This indicator is also a reasonable measure of the injection (or use) of oil revenue in the economy and the level of fiscal effort. In particular, if oil revenues increase (during a boom in oil prices) this can lead to either (*i*) increased (net) financial savings (the change in the overall balance), and/or (*ii*) an increase in government spending (not financed by increases in non-oil revenue).

Accordingly, we define fiscal policy in oil producing countries as expansionary (or contractionary) when we observe a negative (or positive) non-oil fiscal balance. This definition focuses on fiscal policy changes over which policymakers can exert more control. As a consequence, a procyclical fiscal regime occurs when a positive (negative) change in government oil revenues leads to an expansionary (or contractionary) fiscal policy. Such a regime can be interpreted as a "spend as you go" fiscal regime. On the contrary, a countercyclical fiscal regime occurs when an expansionary (or contractionary) fiscal policy is associated with a negative (or positive) change in government oil revenues. This can be interpreted as a fiscal regime of saving for a "rainy day" (i.e., spend more during recessions). More formally:

$$\begin{aligned}
\text{Gov. Oil Rev.} + \text{Non-Oil Gov. Rev.} - \text{Gov. Exp.} &= \text{Overall Bal.} \\
\Delta\text{Overall Bal.} = \Delta\text{Gov. Oil Rev.} + \Delta\text{Non-Oil Gov. Rev.} &- \Delta\text{Gov. Exp.} \\
\Delta\text{Gov. Oil Rev.} = \Delta\text{Overall Bal.} + \Delta\text{Gov. Exp.} &- \Delta\text{Non-Oil Gov. Rev.} \\
\Delta\text{Gov. Oil Rev.} = \Delta\text{Overall Bal.} &- (\Delta\text{Non-Oil Fis. Bal.}) \\
\Delta\text{Gov. Oil Rev.} = \text{Savings} &+ \text{Use} \qquad (3)
\end{aligned}$$

where ΔX represents the growth rate of variable X expressed in quarterly terms.

By this definition, we may potentially see four regimes, $K = 4$. We can have two regimes characterised by procyclical fiscal policy (related to an increase or decrease in oil revenues) and two regimes characterised by countercyclical fiscal policy (related to an increase or a decrease in oil revenues). Accordingly, we can allow for asymmetric responses following an increase or decrease in oil revenues.

Our restrictions are placed on the intercept parameters $a_i(s_{i\,t})$ only, whereas autoregressive components are left unrestricted. There exists extensive empirical evidence for these choices (see, for example, Clements and Krolzig, 1998; Krolzig et al., 2000; Billio, Casarin, Ravazzolo, and van Dijk, 2012 and Baştürk, Çakmakli, Ceyhan, and Van Dijk, 2014). Volatility parameters are also left unrestricted. Therefore, our approach assumes a minimum set of restrictions and it allows us to investigate to what extent the different regimes can be characterized by different volatility.

Table 1. Regime identification scheme

Variables			Fiscal Regimes Identification			
Label	Description	Intercept	Countercyclical 1 ($k = 1$)	Countercyclical 2 ($k = 2$)	Procyclical 1 ($k = 3$)	Procyclical 2 ($k = 4$)
y_{i1t}	Δ Gov. Exp.	a_{i1k}	NA	NA	NA	NA
y_{i2t}	Δ Gov. Oil Rev.	a_{i2k}	+	-	-	+
y_{i3t}	Δ Non-Oil Fiscal Bal.	a_{i3k}	+	-	+	-
y_{i4t}	Δ Public Emp. / Total Emp.	a_{i4k}	NA	NA	NA	NA
y_{i5t}	Δ Real Oil Price	a_{i5k}	NA	NA	NA	NA
y_{i6t}	Δ Real Exchange Rate	a_{i6k}	NA	NA	NA	NA

Notes: The regime identification scheme in the above table is common to all countries $i = 1, \ldots, 16$, based on the intercepts a_{ijk} of the variables $j = 1, \ldots, 6$ and regime $k = 1, 2, 3, 4$.

Table 1 summarises the chosen restrictions on the intercepts of the growth rate of non-oil fiscal balance and the growth rate of government oil revenues in order to identify the two regimes. For the other variables, the intercept parameters are left unrestricted.

3.3 Parameter estimation

A Gibbs sampler is used for posterior approximation (see, for example, Krolzig, 1997; Frühwirth-Schnatter, 2006; Canova and Ciccarelli, 2009; Billio, Casarin, Ravazzolo, and Van Dijk, 2016; Agudze, Billio, Casarin, and Ravazzolo, 2022; Casarin, Foroni, Marcellino, and Ravazzolo, 2019). The sampler iterates over different blocks of unit-specific parameters in equation (2).

We define $\mathbf{y}_i = \text{vec}\left((\mathbf{y}_{i1}, \ldots, \mathbf{y}_{iT_i})\right)$ as the MT_i-dimensional vector of observations collected over time for the i-th unit of the panel and $\mathbf{y} = \text{vec}\left((\mathbf{y}_1, \ldots, \mathbf{y}_N)'\right)$ as the $(\sum_i^N MT_i)$-dimensional vector of observations collected over time and panel units. Moreover, we define $\boldsymbol{\xi} = \text{vec}\left((\Xi_1, \ldots, \Xi_N)\right)$ as the $(\sum_i^N KT_i)$-dimensional vector of allocation variables, with $\Xi_i = (\boldsymbol{\xi}_{i1}, \ldots, \boldsymbol{\xi}_{iT})$. The vector of regression coefficients is defined as $\boldsymbol{\gamma} = \text{vec}\left((\boldsymbol{\gamma}_1, \ldots, \boldsymbol{\gamma}_N)\right)$, where $\boldsymbol{\gamma}_i = \text{vec}\left((\boldsymbol{\gamma}_{i0}, \boldsymbol{\gamma}_{i1}, \ldots, \boldsymbol{\gamma}_{iK})\right)$. Moreover, we define 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 with the PMS-VAR model, writes as:

$$p(\mathbf{y}, \boldsymbol{\xi} | \boldsymbol{\gamma}, \Sigma, \boldsymbol{\pi}) = \prod_{i=1}^{N} p(\mathbf{y}_i, \boldsymbol{\xi} | \boldsymbol{\gamma}_i, \Sigma_i, \boldsymbol{\pi}_i) \tag{4}$$

where:

$$p(\mathbf{y}_i, \boldsymbol{\xi}|\boldsymbol{\gamma}_i, \Sigma_i, \boldsymbol{\pi}_i) = (2\pi)^{-\frac{T_i M}{2}} \prod_{t=\tau_i}^{T_i} |\Sigma_i(s_{it})|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}\mathbf{u}_{it}'\Sigma_i(s_{it})^{-1}\mathbf{u}_{it}\right\} \prod_{k,l=1}^{K} \pi_{i,kl}^{\xi_{ikt}\xi_{ilt-1}} \quad (5)$$

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 with 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 conditional posterior distribution of the parameter $\boldsymbol{\gamma}_{i0}$ is a normal density with the mean and variance values given in equation (B.9) in Appendix B.

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 $f(\boldsymbol{\gamma}_{ik}|\mathbf{y}_i, \Xi_i, \boldsymbol{\gamma}_{i0}, \boldsymbol{\gamma}_{i(-k)}, \Sigma, \boldsymbol{\lambda}_k)$. The conditional posterior distribution of the parameter $\boldsymbol{\gamma}_{ik}$ is a normal density with the mean and variance values given in (B.10) in Appendix B.

(ii.b) Σ_{ik}^{-1} from $f(\Sigma_{ik}^{-1}|\mathbf{y}_i, \Xi_i, \boldsymbol{\gamma}_{i0}, \boldsymbol{\gamma}_i, \Sigma_{i(-k)})$. The conditional posterior distribution of the parameter Σ_{ik}^{-1} is a Wishart density with scale and location values given in equation (B.11) in Appendix B.

(ii.c) $(\pi_{i,1k}, \ldots, \pi_{i,K-1\,k})$ from a Dirichlet distribution $f(\boldsymbol{\pi}_{ik}|\mathbf{y}_i, \Xi_i, \boldsymbol{\gamma}_{i0}, \boldsymbol{\gamma}_i)$.

In the third block, the Gibbs sampler generates for each regime $k = 1, \ldots, K$ and unit $i = 1, \ldots, N$:

- (iii.a) $\boldsymbol{\lambda}_0$ from the normal distribution $f(\boldsymbol{\lambda}_0|\gamma_0, \Sigma_0)$ given in equation (B.12) in Appendix B;

- (iii.b) the mixture allocation variable d_{ik} from $p(d_{ik} = j) \propto p_k f(\boldsymbol{\gamma}_{ik}|\boldsymbol{\lambda}_{jk}, \underline{\Sigma}_{jk})$, $j = 1, 2$;

- (iii.c) the location of the mixture components $\boldsymbol{\lambda}_{jk}$ from the normal distribution $f(\boldsymbol{\lambda}_{jk}|\mathbf{d}_k, \boldsymbol{\gamma}_k, \Sigma_k)$ given in equation (B.13) in Appendix B for $j = 1, 2$;

- (iii.d) the allocation probability p_k from a beta distribution $p(p_k|\mathbf{d}_k)$.

In the last block, the Gibbs sampler generates Ξ from the posterior $p(\Xi|\mathbf{y}_{1:T}, \boldsymbol{\gamma}, \Sigma, \boldsymbol{\alpha})$ by standard Forward Filtering Backward Sampling for each unit i of the panel given the other unit hidden states (e.g., see Billio, Casarin, Ravazzolo, and Van Dijk, 2016). Further details are given in Appendix B.

4 Empirical results

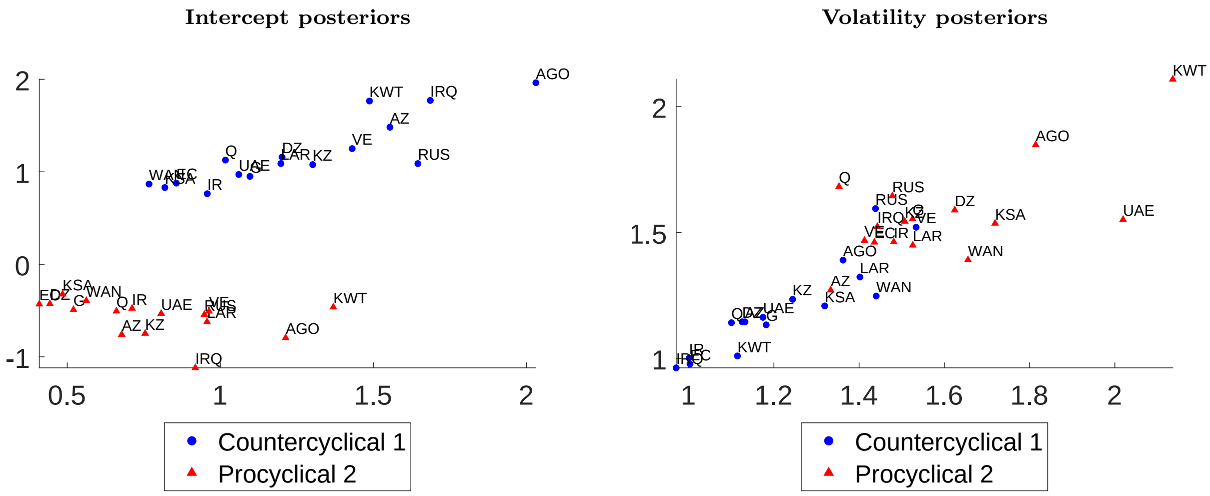
Below, we present the empirical results for the overall panel of countries. Our main focus is to characterise the behaviour of the fiscal policy regimes, before examining the periods in which fiscal policy was procyclical or countercyclical. We do so by first summarising the posterior estimates and then turning to describe the regime probabilities. Finally, we focus on fiscal policy in two major oil economies, namely Russia and Saudi Arabia.

4.1 Posterior estimates of intercept and volatility for the overall panel

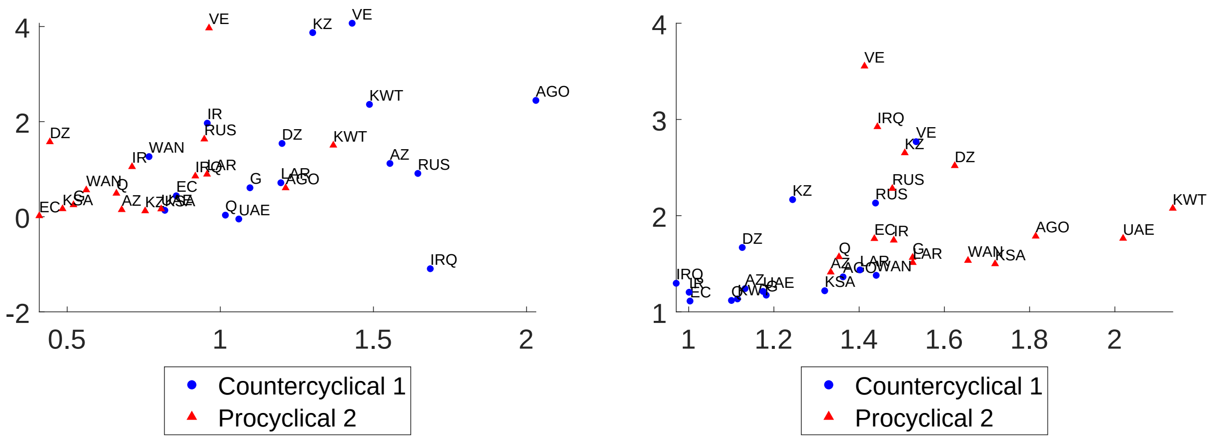
We start this section by presenting intercept and volatility posteriors. Here, we focus on the means of the posteriors, while the complete distributions are reported in online Appendix B. Following the identification proposed in Section 3, we distinguish between a procyclical and a countercyclical regime, for decreasing or increasing oil revenues. Hence, we have four regimes. To recap, we assume that a procyclical fiscal policy regime is a scenario in which expansionary (or contractionary) fiscal policy, measured by a negative (or positive) change in the non-oil fiscal balance, is associated with a positive (or negative) change in government oil revenues. In either case, fiscal policy would be exacerbating cyclical fluctuations in the economy. On the other hand, a countercyclical fiscal policy regime is a scenario in which expansionary (or contractionary) fiscal policy is associated with a negative (or positive) change in the non-oil fiscal balance and a negative (or positive) change in government oil revenues. In these cases, fiscal policy would be dampening cyclical fluctuations in the economy.

First, we examine the regimes with a positive change in government oil revenues in Figures 2 and 3, followed by a negative change in government oil revenues in Figures 4 and 5. In all figures, the left panels refer to the intercept posterior estimates (a_i), whereas the right panels refer to the volatility posterior estimates (σ_i). All figures show scatter plots of selected variables plotted against government oil revenues. In particular, Figure 2, panel (a) focuses on non-oil fiscal balance, whereas panel (b) focuses on government expenditures. Figure 3, panel (a) displays the results for public employment, whereas panel (b) focuses on the real exchange rate. In Figures 2-5, the blue dots represent the

Figure 2. Positive change in government oil revenues



(a) Non-oil fiscal balance (vertical axis) plotted against government oil revenues (horizontal axis)



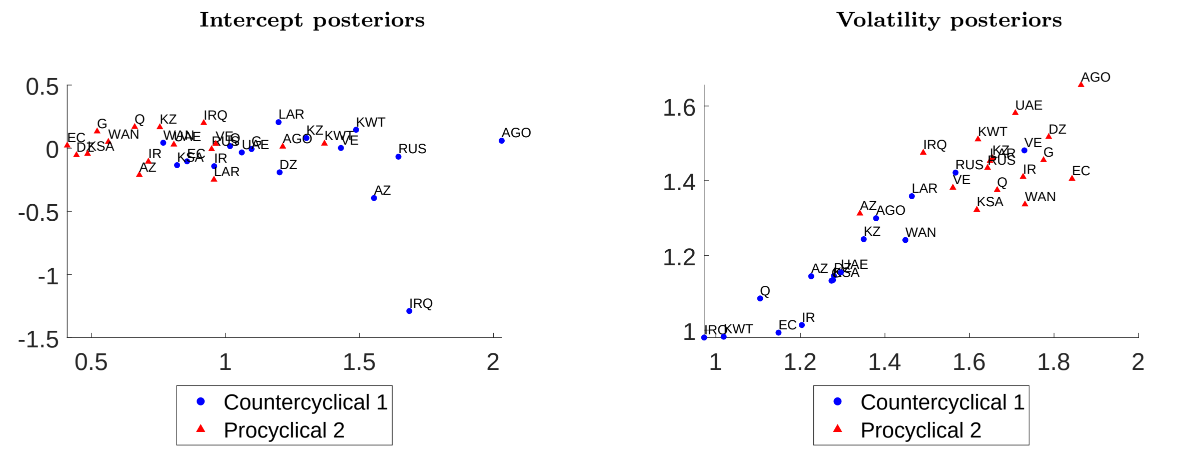
(b) Total government expenditure (vertical axis) plotted against government oil revenues (horizontal axis)

Notes: Intercept posteriors (left panels) and volatility posteriors (right panels) for the growth in non-oil fiscal balance (top row) and the growth in total government expenditure (bottom row), both plotted against growth in government oil revenues. Blue dots represent the countercyclical regime 1 ($k = 1$, as defined in Table 1), whereas the red triangles refer to the procyclical regime 2 ($k = 4$, as defined in Table 1). Acronyms are as follows: Algeria (DZ), Angola (AGO), Azerbaijan (AZ), Ecuador (EC), Gabon (G), Iran (IR), Iraq (IRQ), Kazakhstan (KZ), Kuwait (KWT), Libya (LAR), Nigeria (WAN), Qatar (Q), Russia (RUS), Saudi Arabia (KSA), United Arab Emirates (UAE), Venezuela (VE).

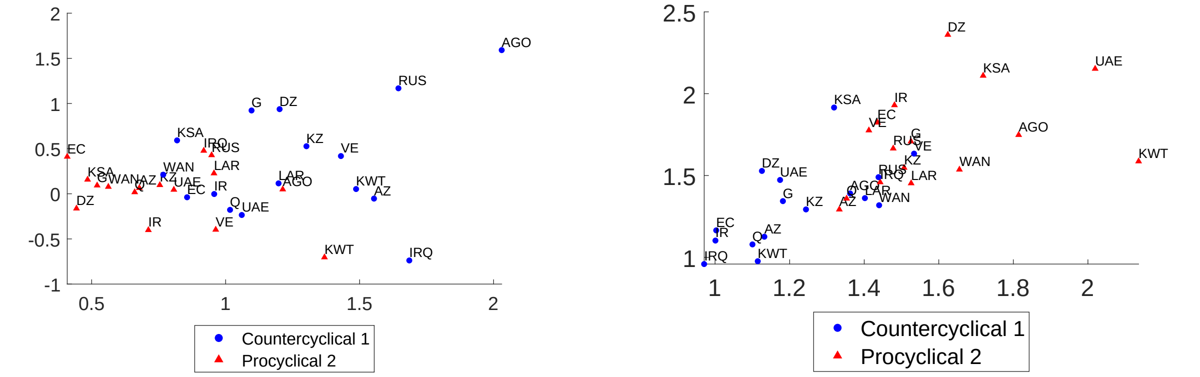
countercyclical regime 1 ($k = 1$, as defined in Table 1), whereas the red triangles refer to the procyclical regime 2 ($k = 4$, as defined in Table 1).

Starting with Figure 2 (a), from the right panel, we note that the posterior estimates

Figure 3. Positive change in government oil revenues



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



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

Notes: Intercept posteriors (left panels) and volatility posteriors (right panels) for the growth in the public employment ratio (top row) and the real exchange rate (bottom row), both plotted against the growth in government oil revenues. Blue dots represent the countercyclical regime 1 ($k = 1$, as defined in Table 1), whereas the red triangles refer to the procyclical regime 2 ($k = 4$, as defined in Table 1). Acronyms are as follows: Algeria (DZ), Angola (AGO), Azerbaijan (AZ), Ecuador (EC), Gabon (G), Iran (IR), Iraq (IRQ), Kazakhstan (KZ), Kuwait (KWT), Libya (LAR), Nigeria (WAN), Qatar (Q), Russia (RUS), Saudi Arabia (KSA), United Arab Emirates (UAE), Venezuela (VE).

for volatility of the non-oil fiscal balance are higher in the procyclical regime than in the countercyclical regime. The countries that show the highest volatility in the procyclical regime are Kuwait, Angola, Qatar and Russia. This result suggests that an increase in oil revenues in these countries is associated with large changes in the volatility of the non-oil fiscal balance in the procyclical regime.

Turning to the left panel, we observe a clear difference in the regimes. In line with our imposed identifying assumption, the growth in non-oil fiscal balance falls in the procyclical regime, but is positive in the countercyclical regime. Interestingly, we note a more dispersed response in the intercept estimates in the countercyclical regime, where countries such as Kuwait, Angola, Iraq, Azerbaijan, Venezuela and Russia have the largest growth in the non-oil fiscal balance.

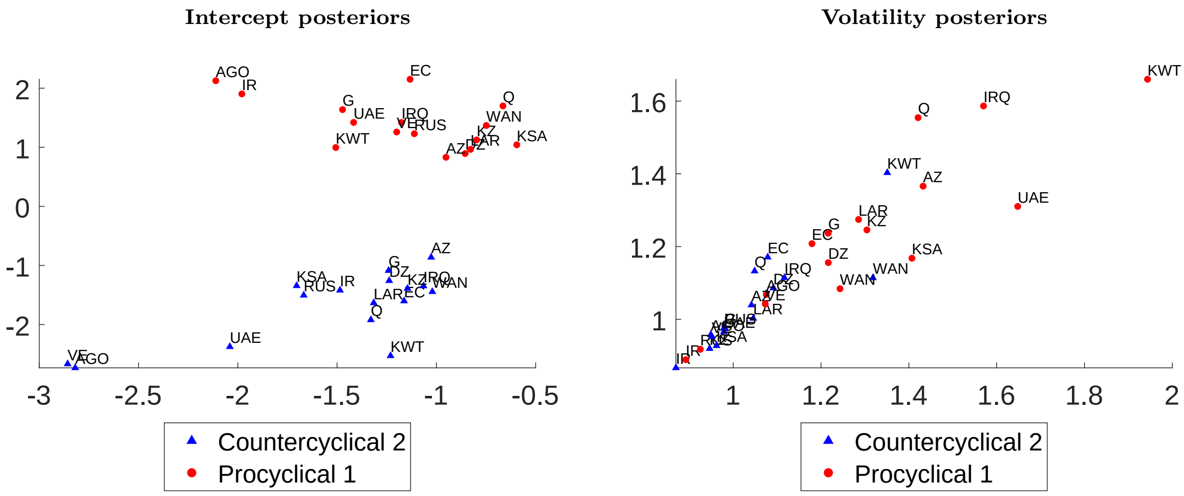
Turning to government expenditure in Figure 2 (b), we confirm the main picture from above: from the right panel, we observe that the posterior for volatility is higher in the procyclical regime than in the countercyclical regime. The countries that experience the highest volatility in the procyclical regime are Venezuela, Iraq, Kazakhstan, Algeria and Russia. This result suggests that an increase in oil revenues in these countries causes the most volatile changes in their government spending in the procyclical regime. The left panel of the same figure shows that the intercepts for government expenditure are mostly positive in both regimes, although they are more dispersed in the countercyclical regime.

The right panel of Figure 3 (a) once again confirms that volatility for public employment is higher in the procyclical regime than in the countercyclical regime. We also note from the left panel that while public employment responses are clustered around zero in the procyclical regime (showing little variation), results are again slightly more dispersed in the countercyclical regime, with some countries having reductions in public employment, whereas others have increases. This indicates heterogeneity across countries in response to increased government oil revenues in this fiscal policy regime.

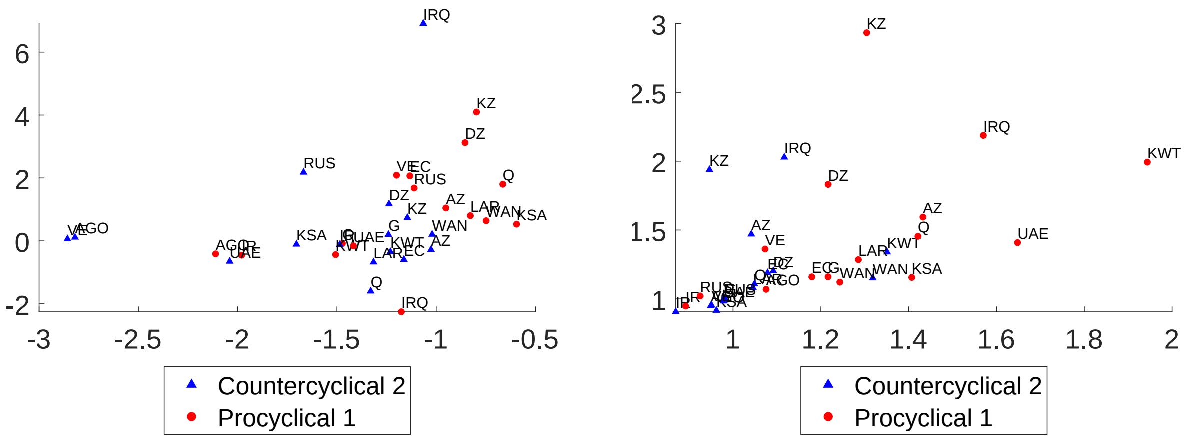
Figure 3 (b) displays the responses of the real exchange rate in the procyclical and countercyclical regimes. Focusing on the intercept values in the left panel, we note that in the procyclical regime the exchange rates mostly appreciate (increase) when government oil revenues increase, with the exception of Algeria, Iran, Kuwait and Venezuela, where their exchange rates depreciate. In the countercyclical regime, the intercepts of the exchange rate are more dispersed: most countries experience large appreciations with the exceptions of Iraq, Qatar and the UAE. Finally, from the right panel, we note that the procyclical regime is associated with more volatile exchange rate changes than the countercyclical regime.

Having investigated fiscal regimes when oil revenues are increasing, we now turn to the regimes when oil revenues are declining (Figures 4 and 5). Starting with Figure 4 (a), the left panel shows, in line with our identifying restrictions, that when oil revenues fall, non-oil fiscal balance increases in the procyclical regime and declines in the countercyclical regime. Compared to the case when oil revenues increased, we observe that heterogeneity is smaller across regimes, although the countercyclical regime is still the most dispersed. The right panel shows that when oil revenues fall, volatility is higher in the procyclical

Figure 4. Negative change in government oil revenues



(a) Non-oil fiscal balance (vertical axis) plotted against government oil revenues (horizontal axis)



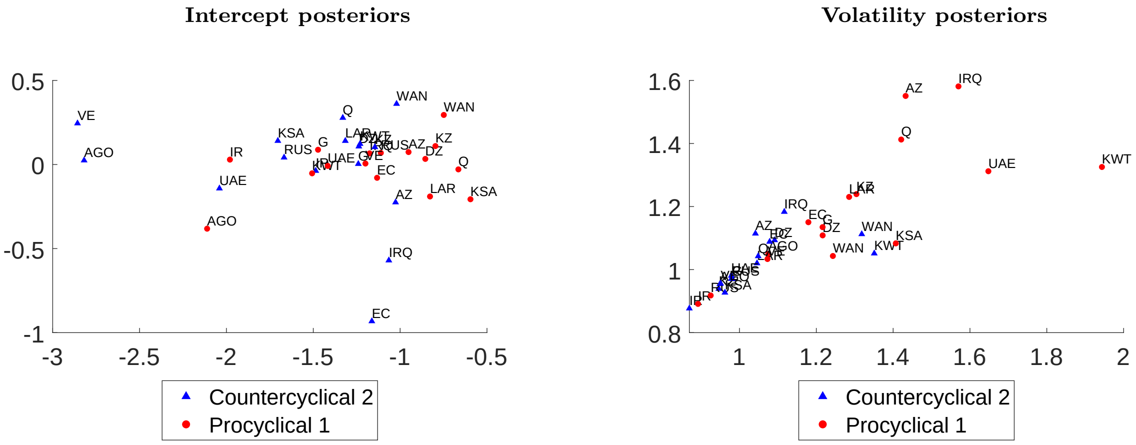
(b) Total government expenditure (vertical axis) plotted against government oil revenues (horizontal axis)

Notes: Intercept posteriors (left panels) and volatility posteriors (right panels) for the growth in non-oil fiscal balance (top row) and total government expenditure (bottom row), both plotted against growth in government oil revenues. Blue triangles represent the countercyclical regime 2 ($k = 2$, as defined in Table 1), whereas the red dots the procyclical regime 1 ($k = 3$, as defined in Table 1). Acronyms are as follows: Algeria (DZ), Angola (AGO), Azerbaijan (AZ), Ecuador (EC), Gabon (G), Iran (IR), Iraq (IRQ), Kazakhstan (KZ), Kuwait (KWT), Libya (LAR), Nigeria (WAN), Qatar (Q), Russia (RUS), Saudi Arabia (KSA), United Arab Emirates (UAE), Venezuela (VE).

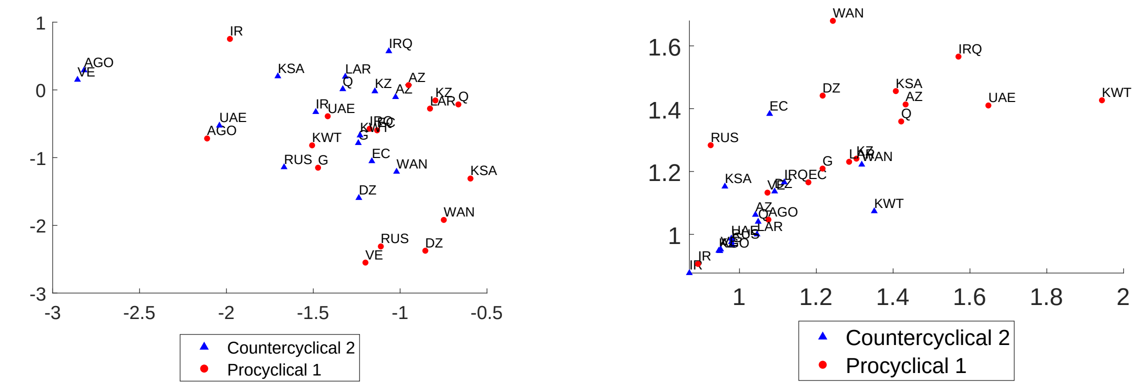
regime compared to the countercyclical regime. Kuwait, Iraq and Qatar are the countries that show the highest volatility.

Turning to government spending in Figure 4 (b), the right panel indicates again that

Figure 5. Negative change in government oil revenues



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



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

Notes: Intercepts posteriors (left panels) and volatility posteriors (right panels) for the growth in the public employment ratio (top row) and the real exchange rate (bottom row), both plotted against the growth in government oil revenues. Blue triangles represent the countercyclical regime 2 ($k = 2$, as defined in Table 1), whereas the red dots the procyclical regime 1 ($k = 3$, as defined in Table 1). Acronyms are as follows: Algeria (DZ), Angola (AGO), Azerbaijan (AZ), Ecuador (EC), Gabon (G), Iran (IR), Iraq (IRQ), Kazakhstan (KZ), Kuwait (KWT), Libya (LAR), Nigeria (WAN), Qatar (Q), Russia (RUS), Saudi Arabia (KSA), United Arab Emirates (UAE), Venezuela (VE).

the volatility of government spending is higher in the procyclical regime than in the countercyclical regime. This is particularly evident for Kazakhstan, Iraq, Kuwait and Algeria. Thus, government spending varies greatly in response to lower oil revenues in the procyclical regime for these countries. From the left panel, we observe a strong heterogeneity in terms of government spending across countries both in the procyclical and countercyclical regimes. In particular, when oil revenues fall, there is no clear evidence that government expenditures are cut. This is consistent with the results in Arezki and Bruckner (2010) and Arezki and Ismail (2013).

From the right panel of Figure 5 (a), we observe that the volatility of public employment is higher in the procyclical regime than in the countercyclical regime. In particular, Azerbaijan, Iraq and Qatar display the highest volatility. This implies that, for these countries, when oil revenues decrease, public employment relative to total employment tends to change substantially in the procyclical regime. The left panel shows that most countries are dispersed across zero, suggesting no typical pattern for public employment (relative to total employment) when oil revenues fall.

Finally, the left panel of Figure 5 (b) shows that in almost all countries, the exchange rate depreciates when oil revenues fall and there seems to be no clear difference between the procyclical and countercyclical regimes. From the right panel, however, we still see that the procyclical regime has the highest volatility.

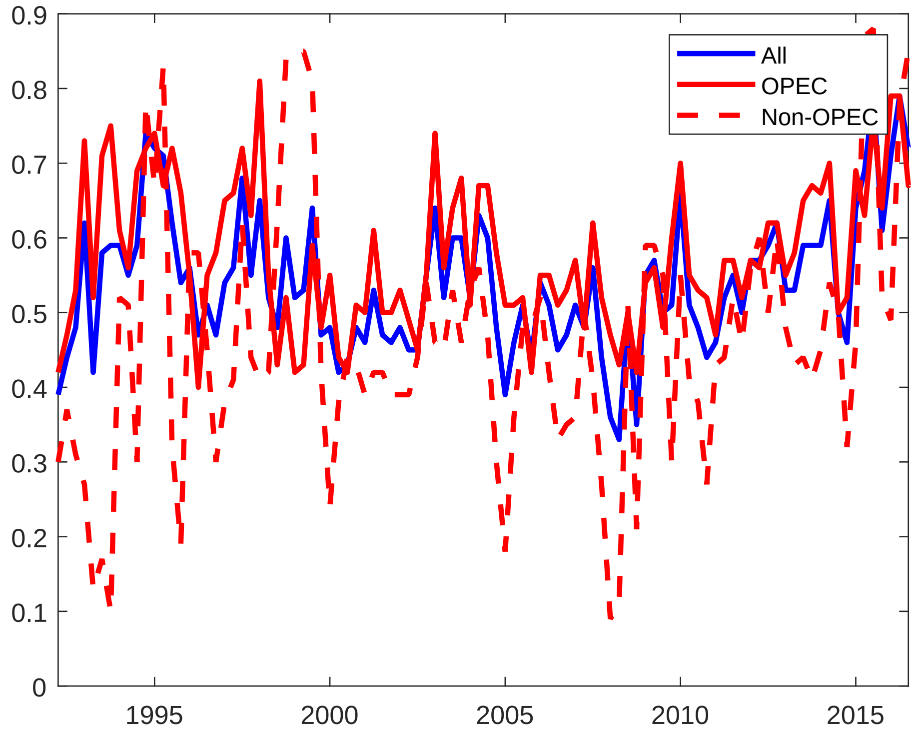
To summarise, by simply restricting the intercept responses of few variables, we have been able to identify systematic differences in the pro- and countercyclical regimes. By doing so, we have encountered new facts about fiscal policy in oil-rich countries. In particular, we show that volatility is higher in the procyclical fiscal policy regime than in the countercyclical regime and that the procyclical behaviour exacerbates (rather than smooths) the cycles. We also show that, following either an increase or decrease in oil revenues, the growth in government expenditure mostly increases. This result suggests that there is an upward bias in expenditures, in line with the model predictions of Arezki and Bruckner (2010). We also find that the exchange rate mostly appreciates following an increase in oil revenues, but depreciates when oil revenues fall, independent of the regime. We find no particular pattern for public employment. Our findings illustrate that most countries are not able to smooth spending and save more during the booms, thereby exacerbating the business cycles.

4.2 Regime probabilities for all countries

Next, we turn to the description of the regime probabilities. In particular, we focus on the probability of being in the procyclical fiscal policy regime when oil revenues are increasing, i.e., procyclical regime 2 ($k = 4$, as defined in Table 1). Figure 6 shows the probabilities of being in this regime, aggregated across all countries (solid blue line), across OPEC countries (solid red line) and across non-OPEC countries (dashed red line).

Three main findings stand out. First, for all countries, there are multiple periods when fiscal policy alternated between a procyclical and a countercyclical regime over the sample. Hence, we find no evidence that fiscal policy has been mostly procyclical over the

Figure 6. Aggregate probabilities of the procyclical regime 2 ($k = 4$ regime) when oil revenues are increasing, for all countries, OPEC and non-OPEC countries



Notes: Average regime probability of being in the procyclical fiscal policy regime 2 ($k = 4$ regime) aggregated across all countries (solid blue line), OPEC countries (solid red line) and non-OPEC countries (dashed red line).

last few decades, as suggested by Lopez-Murphy and Villafuerte (2010), as well as 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 countries have alternated between procyclical and countercyclical regimes over the sample.

Second, for the entire sample, the probability of being in the procyclical fiscal policy regime when oil revenues are increasing is higher for the OPEC countries than for the non-OPEC countries. This result indicates that, on average, OPEC economies were less able to shelter their economies from fluctuations in oil revenues than non-OPEC countries. Moreover, we observe that the average regime probabilities in the OPEC and non-OPEC countries have divergent patterns prior to the 2000s. Indeed, the correlation coefficient between the procyclical probabilities of OPEC and non-OPEC economies prior to 2000 corresponds to -0.26, but it is positive and equal to 0.54 thereafter, i.e., during the commodity boom from the 2000s.

Finally, at least three periods deserve closer scrutiny. The first period corresponds to the intensifying of the Asian financial crisis (1996:Q4-1997:Q4). Over this period, the higher real oil price induced an increase in the oil revenues in these resource-rich countries. Accordingly, the OPEC countries first increased their spending in response to this crisis, so fiscal policy became more procyclical. A similar pattern was observed in non-OPEC countries one year later. The second period relates to the oil price surge between 2002 and 2005, which was caused by the increase in oil demand from emerging and oil importing countries (notably, China and India), c.f. Aastveit, Bjørnland, and Thorsrud (2015). During this period, all countries observed a large increase in their oil revenues and, as a consequence, fiscal policy became more procyclical, exacerbating the business cycles in the countries. Finally, the last period that stands out relates to the aftermath of the global financial crisis when the real oil price and oil revenues bounced back from the end of 2009. In this period, both groups of countries, and in particular OPEC countries, adopted a more procyclical fiscal policy. While the expansionary fiscal policy may have prevented a deepening of the recession in countries that had the fiscal space, it also most likely contributed to the recovery of the overall global economy following the global financial crisis.

4.3 Fiscal policy in Russia and Saudi Arabia

In the previous section, we analysed the results for the whole panel of countries. Here, we provide some more detail about the regime probabilities for two selected countries: Russia and Saudi Arabia.[10] We focus on these two countries since they are the largest oil producers in our sample, measured by their share of world oil production.[11] Moreover, these countries are interesting to compare for additional reasons: Saudi Arabia is an OPEC member, whereas Russia is not. Hence, although both are large enough to move prices when they change their production volumes, there will be different mechanisms in the price setting. These countries are also diverse in terms of their trade. While 82% of Saudi Arabia's exports came from minerals, fuels, ores and salts over the sample,[12] Russia had a higher level of diversification: in our sample period on average, Russia's share of exports related to minerals, fuels, ores and salts was just 50%. However, since 2010 this share has increased to 60%.[13]

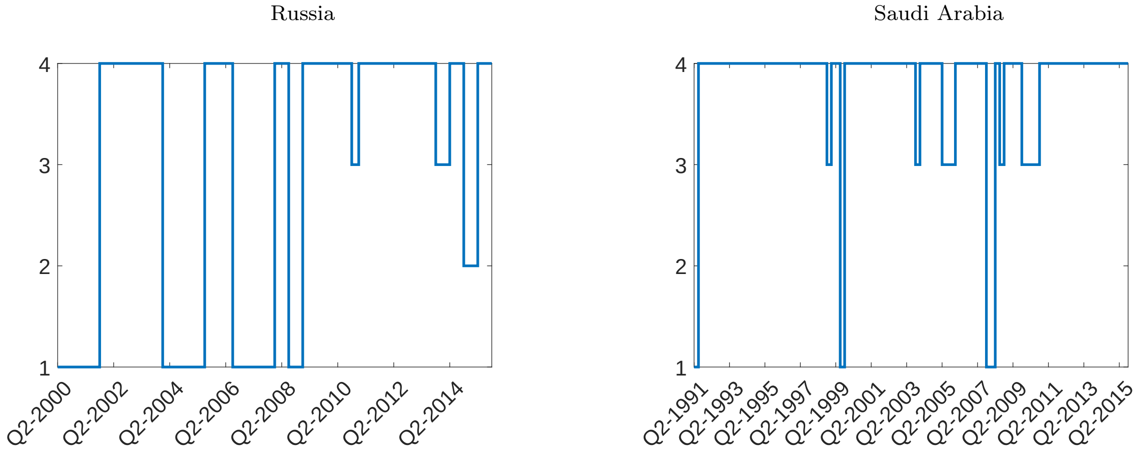
[10] We show results for the remaining countries of our sample in online Appendix C.

[11] During the period 1992-2016, Russia and Saudi Arabia's shares of world oil production were 12% and 13%, respectively.

[12] Vision 2030 aims to diversify the Saudi Arabian economy and its exports CEDA (2016).

[13] See the Comtrade database (UN, 2023) for more details about the current gross exports disaggregated by product type for Russia and Saudi Arabia. The sample period of these data corresponds to 1995-2016.

Figure 7. Fiscal policy regime for Russia and Saudi Arabia



Notes: The blue line is the probability of being in the following fiscal policy regimes: countercyclical 1 ($k = 1$), countercyclical 2 ($k = 2$), procyclical 1 ($k = 3$) and procyclical 2 ($k = 4$).

Figure 7 shows the probability of being in the different regimes in the two countries. As defined in Table 1, we have four regimes: countercyclical 1 ($k = 1$), countercyclical 2 ($k = 2$), procyclical 1 ($k = 3$) and procyclical 2 ($k = 4$). Note that the regimes for $k = 1$ and 4 are defined for increasing oil revenues, while regimes for $k = 2$ and 3 are defined for decreasing oil revenues. Starting with the regime probabilities for Russia (left panel of Figure 7), we note that before 2010 the fiscal policy in Russia alternated between the countercyclical 1 ($k = 1$) and procyclical 2 ($k = 4$) regimes multiple times. Two periods stand out. In 2002/2003, pressures for fiscal relaxation to finance costly reforms increased in line with an increased oil tax windfall (IMF, 2004), leading to a procyclical fiscal policy. Between 2004 and 2006, however, fiscal policy became countercyclical. From 2006, fiscal policy was again procyclical, propelled by large terms-of-trade gains, and Russian real GDP growth accelerated in line with increased government oil revenues, setting the stage for procyclical fiscal spending. Since 2010, fiscal policy in Russia has been largely procyclical with the predominance of the regime $k = 4$. In response to the global financial crisis, the Russian government adopted an expansionary fiscal policy that almost entirely took the form of permanent measures (IMF, 2010). More recently, the doubling of oil prices following the oil price collapse in 2014 laid the foundation for a recovery that was also supported by a more expansionary fiscal stance. During this period, the share of government expenditure increased (IMF, 2017).

Turning to the results for Saudi Arabia, the right panel of Figure 7 shows that the country has predominately adopted a procyclical fiscal policy. The procyclical fiscal regime that has been dominant relates to high oil revenues and a negative non-oil fiscal balance, i.e., procyclical 2 regime ($k = 4$). This fiscal regime was dominant without interruption over the 1990s. According to SAMA (1995), during this period Saudi Arabia saw a growth in the economy that was mainly attributed to the growth in the government sector through procyclical fiscal spendings. In the early 2000s, the Saudi economy experienced record high growth rates in all its sectors, including the government sector, benefiting from a notable rise in oil prices and revenues (SAMA, 2004). During the global financial crisis, oil revenues declined, leading to the procyclical ($k = 3$) regime (low oil revenues and positive non-oil fiscal balance). After 2010, the procyclical behaviour in fiscal policy was due to an increase in oil prices and subsequent enlarged fiscal spending (SAMA, 2011). More recently, both the oil sector, GDP and expenditures increased, as Saudi Arabia's average daily production of oil also rose, in line with increased oil prices and subsequent pumped oil revenues (SAMA, 2017).

To sum up, while both countries are predominately in a procyclical fiscal policy regime, at least after the financial crisis, Russia alternated between the procyclical and countercyclical fiscal policy regimes prior to 2010. Furthermore, 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 attempt to analyse fiscal policy across countries using, say, a split sample framework, will misrepresent the changing pattern of how fiscal policy alternates between procyclical and countercyclical regimes.

5 Conclusion

The significant changes in oil prices that the world has witnessed over the last few 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 idea that fiscal policy is stable over the sample and instead analyse to what extent fiscal policy can switch between procyclical and countercyclical fiscal policy regimes over the cycles. 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. We use parameter restrictions to identify procyclical and countercyclical fiscal policy regimes and evaluate the response of fiscal policy within the different regimes. We rely on data for a large set of oil-exporting countries in order to identify their fiscal regimes based on intercept restrictions.

We find that there are multiple periods over the sample when fiscal policy alternates between a procyclical and a countercyclical regime. Hence, studies that try to analyse fiscal policy using a split sample framework will misrepresent the changing pattern of how fiscal policy is operated. Moreover, our results indicate that, for all countries, fiscal variables (government spending, non-oil fiscal balance and public employment) and the real exchange rate are more volatile in the procyclical regime than in the countercyclical regime, and that OPEC countries have a higher probability of being in the procyclical regimes. We also find that following either an increase or decrease in oil revenues, the growth in government expenditures mostly increases, confirming the model predictions in Arezki and Bruckner (2010) of an upward bias in government spending in oil-rich countries. Hence, by only restricting the intercept responses of few variables, we have been able to identify systematic differences in the fiscal policy regimes and across countries. By doing so, we have encountered new facts about fiscal policy in oil-rich countries.

References

Aastveit, K. A., H. C. Bjørnland, and L. A. Thorsrud (2015): "What Drives Oil Prices? Emerging versus Developed Economies," *Journal of Applied Econometrics*, 30(7), 1013–1028.

Agudze, K. M., M. Billio, R. Casarin, and F. Ravazzolo (2022): "Markov Switching Panel with Endogenous Synchronization Effects," *Journal of Econometrics*, 230(2), 281–298.

Albert, J. H., and S. Chib (1993): "Bayes Inference via Gibbs Sampling of Autoregressive Time Series Subject to Markov Mean and Variance Shifts," *Journal of Business and Economic Statistics*, 11, 1–15.

Allman, E., C. Matias, and J. Rhodes (2009): "Identifiability of Parameters in Latent Structure Models with Many Observed Variables," *The Annals of Statistics*, 37(6A), 3099–3132.

Arezki, R., and M. Bruckner (2010): "International Commodity Price Shocks, Democracy, and External Debt," *International Monetary Fund*.

Arezki, R., and K. Ismail (2013): "Boom-Bust Cycle, Asymmetrical Fiscal Response and the Dutch Disease," *Journal of Development Economics*, 101, 256–267.

Barro, R. J. (1979): "On the Determination of Public Debt," *Journal of Political Economy*, 87, 940–971.

Baştürk, N., C. Çakmakli, S. P. Ceyhan, and H. K. Van Dijk (2014): "Posterior-Predictive Evidence on US Inflation Using Extended New Keynesian Phillips Curve Models with Non-Filtered Data," *Journal of Applied Econometrics*, 29(7), 1164–1182.

Billio, M., R. Casarin, F. Ravazzolo, and H. Van Dijk (2016): "Interactions between Eurozone and US Booms and Busts: A Bayesian Panel Markov-Switching VAR Model," *Journal of Applied Econometrics*, 31(7), 1352–1370.

Billio, M., R. Casarin, F. Ravazzolo, and H. K. van Dijk (2012): "Combination Schemes for Turning Point Predictions," *The Quarterly Review of Economics and Finance*, 52(4), 402–412.

Bjørnland, H. C., and L. A. Thorsrud (2016): "Boom or Gloom? Examining the Dutch Disease in Two-Speed Economies," *Economic Journal*, 126(598), 2219–2256.

Bjørnland, H. C., and L. A. Thorsrud (2019): "Commodity Prices and Fiscal Policy Design: Procyclical Despite a Rule," *Journal of Applied Econometrics*, 34(2), 161–180.

Blanchard, O., and R. Perotti (2002): "An Empirical Characterization of the Dynamic Effects of Changes in Government Spending and Taxes on Output," *the Quarterly Journal of Economics*, 117(4), 1329–1368.

Bova, E., P. Medas, and T. Poghosyan (2016): "Macroeconomic Stability in Resource-Rich Countries: The Role of Fiscal Policy," Working Paper 2016/16/36, IMF.

Canova, F., and M. Ciccarelli (2004): "Forecasting and Turning Point Predictions in a Bayesian Panel VAR model," *Journal of Econometrics*, 120(2), 327–359.

Canova, F., and M. Ciccarelli (2009): "Estimating Multicountry VAR Models," *International Economic Review*, 50(3), 929–959.

Carter, C. K., and R. Kohn (1994): "On Gibbs Sampling for State Space Models," *Biometrika*, 81(3), 541–553.

Casarin, R., C. Foroni, M. Marcellino, and F. Ravazzolo (2019): "Uncertainty Through the Lenses of a Mixed-Frequency Bayesian Panel Markov Switching Model," *Annals of Applied Statistics*, 12(4), 2559–2586.

CEDA (2016): "Saudi Vision 2030," Discussion paper, Kingdom of Saudi Arabia, Council of Economic and Development Affairs.

Celeux, G. (1998): "Bayesian Inference for Mixture: The Label Switching Problem," Preprint INRIA.

Céspedes, L., and A. Velasco (2014): "Was This Time Different? Fiscal Policy in Commodity Republics," *Journal of Development Economics*, 106, 92–106.

Clements, M. P., and H.-M. Krolzig (1998): "A Comparison of the Forecast Performance of Markov-Switching and Threshold Autoregressive Models of US GNP," *The Econometrics Journal*, 1(1), 47–75.

Di Fonzo, T., and M. Marini (2012): "On the Extrapolation with the Denton Proportional Benchmarking Method," *IMF Working Papers*.

Erbil, N. (2011): "Is Fiscal Policy Procyclical in Developing Oil-Producing Countries?," IMF Working Paper 171.

Feldkircher, M., F. Huber, G. Koop, and M. Pfarrhofer (2022): “Approximate Inference and Forecasting in Huge-Dimensional Multycountry VARs,” *International Economic Review*, 63(4), 1625–1658.

Frühwirth-Schnatter, S. (2001): “Markov Chain Monte Carlo Estimation of Classical and Dynamic Switching and Mixture Models,” *Journal of the American Statistical Association*, 96(453), 194–209.

Frühwirth-Schnatter, S. (2001): “Markov Chain Monte Carlo Estimation of Classical and Dynamic Switching and Mixture Models,” *Journal of the American Statistical Association*, 96(453), 194–209.

Frühwirth-Schnatter, S. (2006): *Finite Mixture and Markov Switching Models*. Springer.

Frühwirth-Schnatter, S. (2006): “Mixture and Markov-Swithing Models,” *Springer*.

Giacomini, R., T. Kitagawa, and A. Volpicella (2022): “Uncertain Identification,” *Quantitative Economics*, 13(1), 95–123.

Ilzetzki, E., and C. A. Végh (2008): “Procyclical Fiscal Policy in Developing Countries: Truth or Fiction?,” Discussion paper, National Bureau of Economic Research.

IMF (2004): “Russian Federation: Article IV Consultation,” Discussion paper, IMF Country Report, International Monetary Fund.

——— (2010): “Russian Federation: Article IV Consultation,” Discussion paper, IMF Country Report, International Monetary Fund.

——— (2015): “The Commodities Roller Coaster: A Fiscal Framework for Uncertain Times,” Discussion paper, IMF Fiscal Monitor, International Monetary Fund.

——— (2017): “Russian Federation: Article IV Consultation,” Discussion paper, IMF Country Report, International Monetary Fund.

——— (2020): “Fiscal Policy Responses to the Sharp Decline in Oil Prices,” Discussion paper, IMF Fiscal Affairs, International Monetary Fund.

Kaminsky, G. L., C. M. Reinhart, and C. A. Vegh (2004): “When it Rains, it Pours: Procyclical Capital Flows and Macroeconomic Policies,” *NBER Macroeconomics Annual, MIT Press*, 19.

Koop, G., and D. Korobilis (2013): “Large Time-Varying Parameter VARs,” *Journal of Econometrics*, 177(2), 185–198.

Krolzig, H.-M. (1997): "Markov Switching Vector Autoregressions. Modelling, Statistical Inference and Application to Business Cycle Analysis," *Springer*.

Krolzig, H.-M., et al. (2000): "Predicting Markov-Switching Vector Autoregressive Processes," *Nuffield College Oxford*.

Lanne, M., H. Lütkepohl, and K. Maciejowska (2010): "Structural Vector Autoregressions with Markov Switching," *Journal of Economic Dynamics and Control*, 34(2), 121–131.

Leeper, E. M., A. W. Richter, and T. B. Walker (2012): "Quantitative Effects of Fiscal Foresight," *American Economic Journal: Economic Policy*, 4(2), 115–144.

Leeper, E. M., T. B. Walker, and S.-C. S. Yang (2013): "Fiscal Foresight and Information Flows," *Econometrica*, 81(3), 1115–1145.

Lopez-Murphy, P., and M. Villafuerte (2010): "Fiscal Policy in Oil Producing Countries during the Recent Oil Price Cycle," IMF Working Papers WP/10/28.

Mertens, K., and M. O. Ravn (2010): "Measuring the Impact of Fiscal Policy in the Face of Anticipation: a Structural VAR Approach," *The Economic Journal*, 120(544), 393–413.

——— (2012): "Empirical Evidence on the Aggregate Effects of Anticipated and Unanticipated US Tax Policy Shocks," *American Economic Journal: Economic Policy*, 4(2), 145–181.

Netsunajev, A. (2013): "Reaction to Technology Shocks in Markov-Switching Structural VARs: Identification via Heteroskedasticity," *Journal of Macroeconomics*, 36, 51–62.

Ramey, V. A. (2011): "Identifying Government Spending Shocks: It's All in the Timing," *The Quarterly Journal of Economics*, 126(1), 1–50.

Rubio-Ramirez, J. F., D. Waggoner, and T. Zha (2006): "Markov-Switching Structural Vector Autoregressions: Theory and Application," Computing in Economics and Finance 2006 69, Society for Computational Economics.

SAMA (1995): "Thirty-Second Annual Report," Discussion paper, Saudi Arabian Monetary Agency, Research and Statistics Department.

——— (2004): "Forty Annual Report," Discussion paper, Saudi Arabian Monetary Agency, Research and Statistics Department.

——— (2011): "Forty-Seven Annual Report," Discussion paper, Saudi Arabian Monetary Agency, Research and Statistics Department.

——— (2017): "Fifty-Third Annual Report," Discussion paper, Saudi Arabian Monetary Agency, Research and Statistics Department.

Schaechter, M. A., M. T. Kinda, M. N. Budina, and A. Weber (2012): "Fiscal Rules in Response to the Crisis: Toward the Next-Generation Rules: A New Dataset," *International Monetary Fund*.

Shephard, N. (1994): "Partial Non-Gaussian State Space," *Biometrika*, 81, 115–131.

Sturm, M., F. J. Gurtner, and J. Gonzalez-Alegre (2009): "Fiscal Policy Challenges in Oil-Exporting Countries-A Review of Key Issues," *ECB Occasional paper*, (104).

UN (2023): "United Nations Comtrade Database," Discussion paper, United Nations, Trade Statistics.

A 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 A.1-A.4. Here, we provide the information about the construction of the observed series.

Growth Rate of Total Government Expenditure. Data for Azerbaijan and Kazakhstan are obtained from the IMF Country Reports. Data for 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: 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 A.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), 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).

All data series are expressed in terms of quarterly growth.

Growth Rate of Government of Oil Revenues. The series of government oil revenues for Azerbaijan, 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: 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 A.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), Gabon (for which we use the series of real effective exchange rate), Russia (for which we use the series of GDP) and Venezuela (for which we use the series of GDP).

All data series are expressed in terms of quarterly growth.

Growth Rate of Non-Oil Fiscal Balance. As explained in the main text, we define non-oil fiscal balance as the difference between non-oil government revenues and total government expenditure, where non-oil government revenues is the difference between total government revenues and government oil revenues.

We have presented the sources for the series of total government expenditure and government oil revenues above. 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.

All data series are expressed in terms of quarterly growth.

Growth Rate of the Share of Public Employment on Total Employment. Data for Angola, Azerbaijan, Ecuador, Gabon, Iraq, Kazakhstan, Nigeria and Russia are obtained from Key Indicators of the Labour Market - ILO. 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 A.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 Azerbaijan we use the series of petroleum production. For Gabon we use the series of real effective exchange rate. For 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.

Growth Rate of the Real Oil Price. The nominal series of the 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 express the final series of the real oil price in terms of quarterly growth.

Growth Rate of the Real Exchange Rate. Data for Algeria, Ecuador, Gabon, Iran, Nigeria, Russia and Saudi Arabia are obtained from IMF IFS. Data for Angola, Azerbaijan, Iraq, Kazakhstan, Kuwait, Libya, Qatar, UAE 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 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 A.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 A.1. Total government expenditure and total government revenues data

Variable	Country	Status	Source	Sample/Frequency
Total Government Expenditure and Total Government Revenues	Algeria	OPEC	IMF World Economic Outlook & IMF Country Reports	1997-2016
	Angola	OPEC	Republica de Angola: Ministerio das Financas & US FRED	2002-2016
	Azerbaijan	NON-OPEC	IMF Country Reports	1999-2016
	Ecuador	OPEC	IMF World Economic Outlook & IMF Country Reports	1995-2016
	Gabon	OPEC	IMF World Economic Outlook & IMF Country Reports	1998-2016
	Iran	OPEC	Central Bank of the Islamic Republic of Iran	1990:Q3-2012:Q1
	Iraq	OPEC	IMF World Economic Outlook	2004-2016
	Kazakhstan	NON-OPEC	IMF Country Reports	1999-2016
	Kuwait	OPEC	IMF World Economic Outlook	1999-2014
	Libya	OPEC	IMF World Economic Outlook & IMF Country Reports	1997-2013
	Nigeria	OPEC	Nigeria Central Bank	1991-2016
	Qatar	OPEC	Qatar Central Bank	1994-2016
	Russia	NON-OPEC	IMF World Economic Outlook & IMF Country Reports	2000-2016
	Saudi Arabia	OPEC	IMF World Economic Outlook	1991-2016
	UAE	OPEC	Federal Competitiveness and Statistics Authority	2001-2016
	Venezuela	OPEC	IMF World Economic Outlook	1997-2014

Table A.2. Government oil revenues data

Variable	Country	Status	Source	Sample/Frequency
Government Oil Revenues	Algeria	OPEC	IMF World Economic Outlook & IMF Country Reports	1997-2016
	Angola	OPEC	Republica de Angola: Ministerio das Financas	2002-2016
	Azerbaijan	NON-OPEC	IMF Country Reports	1999-2016
	Ecuador	OPEC	IMF Country Reports	1995-2016
	Gabon	OPEC	IMF Country Reports	1998-2016
	Iran	OPEC	Central Bank of the Islamic Republic of Iran	1990:Q3-2012:Q1
	Iraq	OPEC	Iraqi Ministry of Finance & US EIA	2004:Q2-2016:Q4
	Kazakhstan	NON-OPEC	IMF Country Reports	1999-2016
	Kuwait	OPEC	Kuwait Central Statistical Bureau	1999-2014
	Libya	OPEC	IMF Country Reports	1997-2013
	Nigeria	OPEC	Nigeria Central Bank	1991-2016
	Qatar	OPEC	Qatar Central Bank	1994-2016
	Russia	NON-OPEC	IMF Country Reports	2000-2016
	Saudi Arabia	OPEC	Saudi Arabian Monetary Agency	1991-2016
	UAE	OPEC	Federal Competitiveness and Statistics Authority	2001-2016
	Venezuela	OPEC	Gobierno Bolivariano de Venuezuela: Istituto Nacional de Estadistica	1997-2014

Table A.3. Public sector and total employment data

Variable	Country	Status	Source	Sample/Frequency
Public Sector and Total Employment	Algeria	OPEC	ILO: Key Indicators of the Lab. Market & IMF Country Reports	1997-2016
	Angola	OPEC	ILO: Key Indicators of the Lab. Market	2002-2016
	Azerbaijan	NON-OPEC	ILO: Key Indicators of the Lab. Market	1999-2016
	Ecuador	OPEC	ILO: Key Indicators of the Lab. Market	1995-2016
	Gabon	OPEC	ILO: Key Indicators of the Lab. Market	1998-2016
	Iran	OPEC	Iran Data Portal	1990:Q3-2012:Q1
	Iraq	OPEC	ILO: Key Indicators of the Lab. Market	2004-2016
	Kazakhstan	NON-OPEC	ILO: Key Indicators of the Lab. Market	1999-2016
	Kuwait	OPEC	Kuwait Central Statistical Bureau & World Bank WDI	1999-2014
	Libya	OPEC	IMF World Economic Outlook & IMF Country Reports	1997-2013
	Nigeria	OPEC	ILO: Key Indicators of the Lab. Market	1991-2016
	Qatar	OPEC	Qatar Statistics Authority & ILO: Key Indicators of the Lab. Market	1994-2016
	Russia	NON-OPEC	ILO: Key Indicators of the Lab. Market	2000-2016
	Saudi Arabia	OPEC	Saudi Arabian Monetary Agency & World Bank WDI	1991-2016
	UAE	OPEC	Ministry of the Economy: AER 2015 & ILO: Key Indicators of the Lab. Market	2001-2016
	Venezuela	OPEC	Gobierno Bolivariano de Venuezuela: Istituto Nacional de Estadistica	1997-2014

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

Variable	Country	Status	Source	Sample/Frequency
Real Oil Price			US EIA & US FRED	1990:Q3-2016:Q4
Real Exchange Rate	Algeria	OPEC	IMF: International Financial Statistics	1997:Q2-2016:Q4
	Angola	OPEC	US FRED	2004-2015
	Azerbaijan	NON-OPEC	US FRED	1999-2014
	Ecuador	OPEC	IMF: International Financial Statistics	1995:Q2-2016:Q4
	Gabon	OPEC	IMF: International Financial Statistics	1998:Q2-2016:Q4
	Iran	OPEC	IMF: International Financial Statistics	1990:Q3-2016:Q4
	Iraq	OPEC	US FRED	2004-2014
	Kazakhstan	NON-OPEC	US FRED	1999-2014
	Kuwait	OPEC	US FRED	1999-2014
	Libya	OPEC	US FRED	1997-2010
	Nigeria	OPEC	IMF: International Financial Statistics	1991:Q2-2016:Q4
	Qatar	OPEC	US FRED	1994-2014
	Russia	NON-OPEC	IMF: International Financial Statistics	2000:Q2-2016:Q4
	Saudi Arabia	OPEC	IMF: International Financial Statistics	1991:Q2-2016:Q4
	UAE	OPEC	US FRED	2001:Q2-2017:Q3
	Venezuela	OPEC	US FRED	1997:Q2-2017:Q3

B Model inference

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

B.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:

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

whereas for the intercepts we assume:

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

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

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

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 B.3, this assumption allows us to combine the country i specific likelihood with the information for all the other countries.

For the rows of the unit-specific transition matrix, $\boldsymbol{\pi}_{ik}$, $k = 1, \ldots, K$, we use a conjugate Dirichlet distribution, i.e., $\boldsymbol{\pi}_{ik} \sim \mathcal{D}ir(c)$ with hyper-parameter c. 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).

B.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, 2022; Casarin, Foroni, Marcellino, and Ravazzolo, 2019). The sampler iterates over different blocks of unit-specific parameters in equation (2).

Let $\mathbf{y}_i = \text{vec}\left((\mathbf{y}_{i1}, \ldots, \mathbf{y}_{iT})\right)$ 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 $(\sum_{i=1}^N MT_i)$-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 with the PMS-VAR model, writes as:

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

where

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

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 with 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 $\Sigma_{i(-k)} = (\Sigma_{i1}, \ldots, \Sigma_{ik-1}, \Sigma_{ik+1}, \ldots, \Sigma_{iK})$. In the first block, the sampler draws $\boldsymbol{\gamma}_{i0}$ from $f(\boldsymbol{\gamma}_{i0} | \mathbf{y}_i, \Xi_i, \mathbf{d}_k, \boldsymbol{\gamma}_i, \Sigma_i, \boldsymbol{\lambda}_0)$, for $i = 1, \ldots, N$. In the second block, for $i = 1, \ldots, N$ and $k = 1, \ldots, K$, the sampler draws: (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 $f(\Sigma_{ik}^{-1} | \mathbf{y}_i, \Xi_i, \boldsymbol{\gamma}_{i0}, \boldsymbol{\gamma}_i, \Sigma_{i(-k)})$ and (ii.c) $(\pi_{i,1k}, \ldots, \pi_{i,K-1\,k})$ from a Dirichlet distribution $f(\boldsymbol{\pi}_{ik} | \mathbf{y}_i, \Xi_i, \boldsymbol{\gamma}_{i0}, \boldsymbol{\gamma}_i)$.

In the third block, the sampler iterates for $k = 1, \ldots, K$ the following steps: (iii.a) draw $\boldsymbol{\lambda}_0$ from $f(\boldsymbol{\lambda}_0 | \gamma_0, \Sigma_0)$; (iii.b) draw d_{ik} from $p(d_{ik} = j) \propto p_k f(\boldsymbol{\gamma}_{ik} | \boldsymbol{\lambda}_{jk}, \underline{\Sigma}_{jk})$, $j = 1, 2$; (iii.c) draw $\boldsymbol{\lambda}_{jk}$ from $f(\boldsymbol{\lambda}_k | \mathbf{d}_k, \boldsymbol{\gamma}_k, \Sigma_k)$, $j = 1, 2$; and (iii.d) draw p_k from $p(p_k | \mathbf{d}_k)$.

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

B.3 Full conditional distributions

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

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

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 $k = 1, \ldots, K$ are the normal distributions:

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

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 $\mathcal{T}_{ik} = \{t|\xi_{ikt} = 1, t = \tau_i, \ldots, T_i\}$, $T_{ik} = \text{Card}(\mathcal{T}_{ik})$, 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 $\boldsymbol{\gamma}_{ik}$, $k = 1, \ldots, K$ (see, e.g., Celeux, 1998; Frühwirth-Schnatter, 2001).

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

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

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:

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

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 $\mathbf{d}_k=(d_{1k},\dots,d_{Nk})$ be a collection of allocation variables, $\mathcal{D}_{jk}=\{i|d_{ik}=j,i=1,\dots,N\}$ 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 conditionals of the parameters $\boldsymbol{\lambda}_{jk}$, $j=1,2$ of the third stage of the hierarchical prior are the normal distributions:

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

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

B.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 that imply 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.

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