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# Oil and macroeconomic (in)stability\*

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*We analyze the role of oil price volatility in reducing U.S. macroeconomic instability. Using a regime-switching structural model we revisit the timing of the Great Moderation and the sources of changes in the volatility of macroeconomic variables. We find that smaller or fewer oil price shocks did not play a major role in explaining the Great Moderation. Instead oil price shocks are recurrent sources of macroeconomic fluctuations. The most important factor reducing macroeconomic variability is a decline in the volatility of other structural shocks (demand and supply). A change to a more responsive monetary policy regime also played a role. (JEL C11, E32, E42 Q43)*

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# 1 Introduction

Has declining oil price volatility contributed to a more stable macroeconomic environment since the mid-1980s, or, do high and volatile oil prices still make a material contribution to recessions? The views are diverse. According to [Hamilton \(2009\)](#), the run-up of oil prices in 2007-08 had very similar contractionary effects on the U.S. economy as earlier oil price shocks (such as in the 1970s), and should therefore be added to the list of recessions to which oil prices appear to have made a material contribution.<sup>1</sup> Others argue for a reduced role for oil as a cause of recessions the last decade(s). For instance, [Nakov and Pescatori \(2010\)](#) and [Blanchard and Gali \(2008\)](#) analyze the U.S. prior to and post 1984, and find that less volatile oil sector shocks (i.e., good luck) can explain a significant part of the volatility reduction of inflation and GDP growth post 1984, a period commonly referred to as the Great Moderation in the economic literature. In addition, better (or more effective) monetary policy (i.e., good policy) has also played an important role, in particular for reducing volatility of inflation.

Common to studies such as [Nakov and Pescatori \(2010\)](#) and [Blanchard and Gali \(2008\)](#), is the fact that they analyze volatility of oil price shocks and the effectiveness of monetary policy by comparing macroeconomic performance before and after a given break point in time (typically 1984). There are several reasons why analyzing the relationship between oil price volatility and macroeconomic volatility in a split sample framework such as this may give misleading results. First, while the persistent decline in macroeconomic volatility since the mid 1980s is well documented, see among others [Kim and Nelson \(1999a\)](#), [McConnell and Perez-Quiros \(2000\)](#), [Stock and Watson \(2003\)](#) and [Canova et al. \(2007\)](#), it is not clear whether there has been a systematic reduction in oil price volatility that coincides with this Great Moderation. Instead, large fluctuations in the oil price seem to be a recurrent

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<sup>1</sup>Since the seminal paper by [Hamilton \(1983\)](#), a large body of literature has appeared documenting a significant negative relationship between oil price increases and economic activity in a number of different countries (see, e.g., [Burbidge and Harrison \(1984\)](#), [Gisser and Goodwin \(1986\)](#), [Hamilton \(1996, 2003, 2009\)](#) and [Bjørnland \(2000\)](#) among many others). Higher energy prices typically lead to an increase in production costs and inflation, thereby reducing overall demand, output and trade in the economy.

feature of the economic environment, but with a sharp increase in volatility in the first quarter of 1974 standing out, see Figure 1.<sup>2</sup> Second, policy may also have changed multiple times in the last decades. For instance [Bikbov and Chernov \(2013\)](#) show that although policymakers were less concerned with the stabilization of inflation in the 1970s than from the mid 1980s, during several brief periods in the 1990s and 2000s has the stabilization of inflation also prompted less concern. And when agents are aware of the possibility of such regime changes, their beliefs will matter for the law of motion underlying the economy, see e.g., [Bianchi \(2013\)](#).

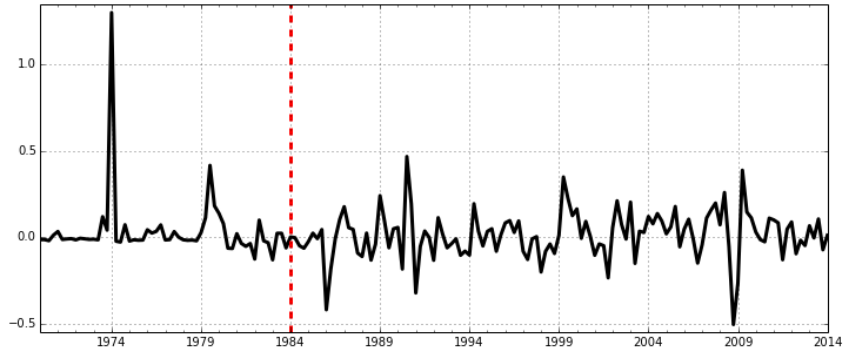
This paper instead analyzes the role of oil price volatility in reducing macroeconomic instability using a Markov Switching Rational Expectation (MSRE) New-Keynesian model. The model accommodates regime-switching behavior in shocks to oil prices, macro variables as well as in monetary policy responses. With the structural model we revisit the timing of the Great Moderation (if any) and the sources of changes in the volatility of macroeconomic variables. In so doing, we make use of new solution algorithms, see [Maih \(2014\)](#). The algorithms rely on Newton methods which extend [Farmer et al. \(2011\)](#). The model is estimated using Bayesian techniques accommodating different regimes or states within one model. We estimate models where the sets of parameters switch independently, or in combination with the other parameter sets, allowing for a simultaneous inference on both the policy parameters and the stochastic volatilities.

There are by now several papers that analyze the so called good policy versus good luck hypothesis using a regime switching framework, see e.g. [Sims and Zha \(2006\)](#), [Liu et al. \(2011\)](#) and [Baele et al. \(2015\)](#). While none of these papers analyze the effect of oil price volatility directly, oil price shocks are often suggested candidates for the heightened volatility of the 1970s, see in particular [Sims and Zha \(2006\)](#). We contribute to this literature by examining the role of oil price volatility explicitly, allowing also for regime switching in other demand and supply shocks and in policy responses using the MSRE model.

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<sup>2</sup>In 1974, OPEC announced an embargo on oil export to some countries supporting Israel during the Syrian and Egypt led attack on Israel. This led to a fall in oil production and almost a doubling in oil prices in the first quarter of 1974.

**Figure 1. Percentage change in the real price of oil (WTI)**



*Note: The figure shows the quarterly percentage change in the real price of oil. The vertical red line is plotted for 1984Q1.*

Furthermore, and in contrast to [Blanchard and Gali \(2008\)](#) and [Nakov and Pescatori \(2010\)](#), we allow oil prices to be endogenously determined by macroeconomic shocks. This follows [Kilian \(2009\)](#) that suggests there is a “reverse causality” from the macroeconomy to oil prices. In particular, he finds that if the increase in the oil price is driven by an increased demand for oil associated with fluctuations in global activity and not disruptions of supply capacity, economic activity may not be negatively affected, at least not in the short run. Corroborating results are shown in [Lippi and Nobili \(2012\)](#) and [Aastveit et al. \(2014\)](#), among others. Hence, it would seem important to allow for different shocks to affect oil prices when examining the consequences of an oil price increase on the U.S. economy.

Finally, while our focus is to nest the good luck and good policy hypothesis with the hypothesis of reduced oil price volatility, there are alternative hypotheses for explaining the rise of macroeconomic stability since the mid-1980s. In particular, the share of oil in consumption and production in the industrialized world is smaller today than it was in the 1970s, suggesting a dampened effect of oil prices on the macroeconomy, see [Blanchard and Gali \(2008\)](#) and [Nakov and Pescatori \(2010\)](#) among others. For completeness, we also examine this, and some other related hypotheses, in a Markov Switching framework in the end.

We have three major findings. First, our results support regime switching behaviour in monetary policy, U.S. shock volatility and oil price shock volatility. The model that performs best is the model where all three sets of parameters are allowed to change. Hence, both good luck and good policy matter.

Second, we find no break in oil price volatility to coincide with the Great Moderation, nor do we find that a dampening of the transmission of oil price shocks matter. Instead, we find several short periods of heightened oil price volatility throughout the whole sample, many of them preceding the dated NBER recessions. If anything, the post-1984 period has had more episodes of high oil price volatility than the pre-1984 period. According to our results, then, we cannot argue that a decline in oil price volatility was a factor in the reduced volatility of other U.S. macroeconomic variables post-1984. Instead, we confirm the relevance of oil as a recurrent source of macroeconomic fluctuations, not only in the past but also in recent times.

Third, the most important factor reducing macroeconomic variability is a decline in the volatility of structural shocks (demand and supply). In all the model variants, the break date is estimated to occur in 1986. That is not to say there were no spurs of volatility since then. However, these periods of heightened macroeconomic volatility have been much briefer, maybe because in addition a more credible monetary policy regime, responding more strongly to inflation, was in place since 1981/1982.

Going forward, if indeed the recurrent spikes in oil prices are causal factors contributing to economic downturns, the Federal Reserve should pay attention to the short-run implications. We find no evidence that the effects of these spikes have been smaller since monetary policy became more credible. Quite the contrary. Thus, the evidence presented here suggests that the Federal Reserve should give careful consideration to the possible consequences of shocks to commodity prices when designing monetary policy.

The remainder of the paper is structured as follows. Section 2 describes the New-Keynesian model, and the general framework for the MSRE model. In Section 3 we present the results and demonstrate that our baseline model is preferred, while Section 4 shows that the results are robust to alternative specifications. Section 5 concludes.

## 2 A regime switching New-Keynesian model

The model we use relates to [Blanchard and Gali \(2008\)](#). It is a standard small scale New-Keynesian model, consisting of an IS-equation, a forward looking New-Keynesian Phillips curve, a Taylor rule, and an oil price equation. We differ from the setup in [Blanchard and Gali \(2008\)](#) in three respects: (i) We allow for feedback from the macroeconomy to the oil price; (ii) we assume a more general Taylor rule (allowing for interest rate smoothing); and, importantly, (iii) we allow for regime switches in the parameters and the shock volatilities. We deliberately focus on a small-scale model, so as to allow for rich dynamics from the time-varying specification. This also facilitates comparison with previous studies analyzing the role of oil prices for macroeconomic stability in constant-parameter models.

In the setup described below, we allow for three regimes, which could be a composite of states from different Markov chains. The first chain governs the general macroeconomic volatility and is denoted  $\mathcal{S}_t^m$ . The second chain governs the policy parameters, and is denoted  $\mathcal{S}_t^p$ . Lastly, we include a chain that governs the volatility of shocks to the oil price. We denote this by  $\mathcal{S}_t^o$ . More details on the specification and estimation of the Markov chains will be provided in the subsequent sections below.<sup>3</sup>

### 2.1 The log-linearized model

Below we specify the main equations of the log-linearized model. Additional details can be found in [Appendix A](#). Small letters denote logarithms of the variable. We start by specifying the IS-equation for the output gap ( $y_t$ ) that governs the demand side of the economy

$$y_t = \mathbb{E}_t[y_{t+1}] - (r_t - \mathbb{E}_t[\pi_{t+1}]) + \Lambda s_t + z_{d,t}, \quad (1)$$

where  $r_t$  is the interest rate,  $\pi_t$  is inflation,  $s_t$  is the real price of oil and  $\Lambda$  captures the direct effect of oil prices to the output gap. This equation is

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<sup>3</sup>In [section 4.3](#), we also examine some alternative hypothesis for the Great Moderation; such as whether a smaller share of oil in consumption and production may have weakened the transmission of oil price shocks over time. We find that such hypothesis play a minor role for describing the data.

derived from the intertemporal Euler equation that relates optimal consumption today to expected consumption tomorrow.  $\Lambda \geq 0$  illustrates that ceteris paribus, a rise in  $s_t$  make firms substitute away from oil and towards labour. This factor substitution implies higher output (GDP) because labour, not oil, represents value added, see [Blanchard and Gali \(2008\)](#).

The inflation dynamics in the model is governed by a forward-looking New-Keynesian Phillips curve

$$\pi_t = \beta \mathbb{E}_t[\pi_{t+1}] + \kappa y_t + \Gamma s_t + z_{s,t}, \quad (2)$$

where  $\beta$  is the subjective discount factor,  $\kappa$  is the effect on inflation from a change in the output gap, and  $\Gamma$  gives the direct effect from oil prices to inflation (i.e., an oil price markup). Note that the oil price markup enters the Phillips curve like a cost-push term.  $\Gamma \geq 0$  determines the effect on domestic markups of a rise in  $s_t$ . A rise in  $s_t$  leads to higher marginal cost of production, and when prices are sticky, to a temporary decline in the markup of firms. Firms raise prices in an attempt to stabilize the markup. Thus, higher oil price translates into producer price inflation, see [Blanchard and Gali \(2008\)](#).

Both the demand,  $(z_{d,t})$ , and the supply shifter,  $(z_{s,t})$ , are given as AR(1) processes

$$z_{d,t} = \rho_d z_{d,t-1} + \epsilon_{d,t}, \quad \text{where } \epsilon_{d,t} \sim N\left(0, \sigma_d (\mathcal{S}_t^m)^2\right) \quad (3)$$

$$z_{s,t} = \rho_s z_{s,t-1} + \epsilon_{s,t}, \quad \text{and } \epsilon_{s,t} \sim N\left(0, \sigma_s (\mathcal{S}_t^m)^2\right) \quad (4)$$

where  $\rho_d$  is the persistence of the shock to the IS-equation and  $\rho_s$  is the persistence of the shock to the Phillips equation.<sup>4</sup> The shock specification for the IS and Phillips curves specify that the demand and supply shocks follow the same chain,  $\mathcal{S}_t^m$ , i.e., they will switch together (but not necessarily in the same direction).

Monetary policy is governed by a Taylor rule of the following form

$$r_t = \rho_r (\mathcal{S}_t^p) r_{t-1} + (1 - \rho_r (\mathcal{S}_t^p)) \left[ \phi_\pi (\mathcal{S}_t^p) \pi_t + \phi_y (\mathcal{S}_t^p) y_t \right] + \sigma_r \epsilon_{r,t}, \quad (5)$$

<sup>4</sup>We also estimate the IS-equation and the Phillips curve equation as hybrid functions, allowing for both backward- and forward-looking terms. In this case the demand and supply shifter will be  $N(0, 1)$ . Results are robust to such changes.



where  $\phi_\pi$  and  $\phi_y$  are parameters governing the central banks responsiveness to inflation and the output gap respectively. The parameter  $\rho_r$  gives the rate of interest rate smoothing over time and  $\epsilon_{r,t} \sim N(0, \sigma_r^2)$  is a monetary policy shock. Importantly, we allow all parameters that the monetary authorities may have control over to switch throughout the sample. The policy parameters follow the same chain,  $\mathcal{S}_t^p$ , implying they will switch together, (albeit not necessarily in the same direction).<sup>5</sup>

Blanchard and Gali (2008) model the oil price process as an AR(1) process. Here, we also allow the oil price to respond to macroeconomic shocks. As motivated above, Kilian (2009) and others have shown that changes in demand can be an important oil price driver. We will therefore assume that the oil important country (the U.S.) is large and potentially can affect oil prices through increased consumption.<sup>6</sup> To account for such a simultaneity, we allow for a direct feedback effect from the output gap to the oil price

$$s_t = \rho_o s_{t-1} + \zeta y_t + \epsilon_{o,t}, \quad \text{where } \epsilon_{o,t} \sim i.i.d.N\left(0, \sigma_o(\mathcal{S}_t^o)^2\right), \quad (6)$$

$\rho_o$  is a persistence parameter and  $\zeta$  gives the feedback from the macroeconomy (i.e., the output gap) to the oil price. The notation used for the variance makes it clear that the volatility of an oil price shock can vary according to different regimes,  $\mathcal{S}_t^o$ .

## 2.2 Markov Switching Rational Expectation framework

The model outlined above can be cast in a general Markov Switching Rational Expectation (MSRE) framework. Below we lay out the general framework for this MSRE model. All models in this paper are estimated using Bayesian methods, and the computations for solving and estimating the models are

<sup>5</sup>In Section 4.3, we also estimate a model where we allow the variance of the monetary policy shock,  $\sigma_r$ , to also switch. Our main results remain invariant to this augmentation.

<sup>6</sup>We approximate the world economy with the U.S. output gap. We believe this to be a realistic approximation inasmuch as U.S. is the main consumer of petroleum products and an important driver of the oil price during the sample period. Having said that, since the start of the century, emerging economies, China in particular, have increased consumption of natural resources and thereby also potentially affected the oil price, see Aastveit et al. (2014). Still, Section 4 demonstrates that our results are robust to alternative measures of global activity.

performed using the RISE toolbox.<sup>7</sup> The advantage of these procedures is that the likelihood is evaluated at each point in time under the different regimes. This information, through a Bayesian filtering scheme, is used to update the probabilities of being in different states. So even if there was only one outlying observation (such as the oil price shock of 1974), the estimation procedure would still pick it up, perhaps as a change in volatility.

To allow for regime switching in the parameters and shock processes, we first cast the New Keynesian model into the general MSRE system given by

$$\mathbb{E}_t \left\{ \mathbf{A}^+(\mathcal{S}_{t+1})\mathbf{x}_{t+1} + \mathbf{A}^0(\mathcal{S}_t)\mathbf{x}_t + \mathbf{A}^-(\mathcal{S}_t)\mathbf{x}_{t-1} + \mathbf{B}(\mathcal{S}_t)\boldsymbol{\epsilon}_t \right\} = 0, \quad (7)$$

where the vector  $\mathbf{x}_t \in \mathbb{R}^{n \times 1}$  contains the  $n$  endogenous variables, and the vector  $\boldsymbol{\epsilon}_t \in \mathbb{R}^{l \times 1}$  contains the  $l$  structural shocks, where  $\boldsymbol{\epsilon}_t \sim i.i.d.N(\mathbf{0}, \mathbf{I}_l)$ . The parameter matrices take the following form,  $\mathbf{A}^+(\mathcal{S}_{t+1}), \mathbf{A}^0(\mathcal{S}_t), \mathbf{A}^-(\mathcal{S}_t) \in \mathbb{R}^{n \times n}$  and  $\mathbf{B}(\mathcal{S}_t) \in \mathbb{R}^{n \times l}$ , where  $\mathcal{S}_t$  denotes the different states of the system. That is, the MSRE framework allows the model economy to be in different regimes at certain times. Each regime can be described as a specific state where the economy is governed by certain separate rules specific for that state. In general, we can have  $h$  different regimes so that  $\mathcal{S}_t \in \{1, 2, \dots, h\}$ . The probabilities of moving between regimes are given by a transition probability matrix

$$\mathcal{P} = [p_{\mathcal{S}_t, \mathcal{S}_{t+1}}] = \begin{bmatrix} p_{11} & \cdots & p_{1h} \\ \vdots & \ddots & \vdots \\ p_{h1} & \cdots & p_{hh} \end{bmatrix}, \quad \text{where } \sum_{j=1}^h p_{ij} = 1 \quad \forall i.$$

where the probability  $p_{ij} = Pr(\mathcal{S}_{t+1} = j | \mathcal{S}_t = i)$ , is the probability of moving from regime  $i$  this period into regime  $j$  the next period. We assume that the agents in the economy know the transition probability matrix, and form expectations as follows:

$$\mathbb{E}_t \left[ \mathbf{A}^+(\mathcal{S}_{t+1})\mathbf{x}_{t+1}(\mathcal{S}_{t+1}) \middle| \mathcal{S}_t = i \right] = \sum_{j=1}^h p_{ij} \mathbb{E}_t \mathbf{A}^+(\mathcal{S}_{t+1} = j)\mathbf{x}_{t+1}(\mathcal{S}_{t+1} = j, \mathcal{S}_t = i). \quad (8)$$

<sup>7</sup>RISE; ‘‘Rationality In Switching Environments’’ is a toolbox for Matlab developed by Junior Maih. See [Maih \(2014\)](#) for further details.

The agents' expectations of the future  $\mathbf{x}$  vector are a weighted sum over all the possible states of the world. A general solution to the system is given in equation (7)

$$\mathbf{x}_t(\mathcal{S}_t, \mathcal{S}_{t-1}) = \mathbf{T}(\mathcal{S}_t)\mathbf{x}_{t-1}(\mathcal{S}_{t-1}, \mathcal{S}_{t-2}) + \mathbf{R}(\mathcal{S}_t)\epsilon_t. \quad (9)$$

In this system the parameters are allowed to switch and the traditional stability concept for constant parameters cannot be used. We use instead a concept from the engineering literature: mean square stability (MSS), see [Svensson and Williams \(2005\)](#) and [Farmer et al. \(2011\)](#).<sup>8</sup> We let the number of possible states be  $h$ , and the transition probability matrix,  $\mathcal{P}$ , be of size  $h \times h$ . Consider the solution to the MSRE system in equation (7) given by equation (9). If for any initial condition  $\mathbf{x}_0$  there exist a  $\boldsymbol{\mu}$  and a  $\boldsymbol{\Sigma}$  independently of  $\mathbf{x}_0$  such that

$$\lim_{t \rightarrow \infty} \|\mathbb{E}[\mathbf{x}_t] - \boldsymbol{\mu}\| = \mathbf{0} \quad \text{and} \quad \lim_{t \rightarrow \infty} \|\mathbb{E}[\mathbf{x}_t \mathbf{x}_t^\top] - \boldsymbol{\Sigma}\| = \mathbf{0},^9$$

then the system satisfies MSS. This is a requirement that the first and second order moments of the stochastic process,  $\{\mathbf{x}_t\}_{t=0}^\infty$ , are finite.

### 2.3 Data and Bayesian estimation

The data series are quarterly and span the periods 1970Q1 – 2014Q1. The observed variables are the U.S. output gap ( $y_t$ ), the U.S. inflation rate ( $\pi_t$ ), the U.S. interest rate ( $r_t$ ), and the real price of crude oil ( $s_t$ ). The U.S. output gap is calculated using a Hodrick-Prescott (HP) filter on U.S. real GDP.<sup>10</sup> The inflation rate is calculated as the first difference of the logarithm of the U.S. GDP deflator;  $\pi_t = \log(P_t) - \log(P_{t-1})$ . For the interest rate we observe the Federal Funds Rate. This series is quarterly but the values are

<sup>8</sup>See [do Valle Costa et al. \(2006\)](#), page 36, for a detailed definition.

<sup>9</sup>To check if these conditions are satisfied, a necessary and sufficient condition is that the matrix  $\Xi$  given by

$$\Xi \equiv (\mathcal{P} \otimes \mathbf{I}_{n^2}) \cdot \text{diag}[\mathbf{T}(\mathcal{S}_t = 1) \otimes \mathbf{T}(\mathcal{S}_t = 2) \otimes \cdots \otimes \mathbf{T}(\mathcal{S}_t = h)],$$

has all its eigenvalues inside the unit circle.

<sup>10</sup>We also analyze and document robustness to the HP filtering using other data transformations.

annualized, so we calculate quarterly values. The real oil price is defined as  $S_t = P_{o,t}/P_t$ , where  $P_{o,t}$  is the nominal price of oil, and  $s_t = p_{o,t} - p_t$ . For the price of oil we use the West Texas Intermediate (WTI) divided by the U.S. GDP deflator. The series were downloaded from the FRED database.<sup>11</sup> All data are demeaned before the estimation.

In order to estimate the model, the likelihood has to be computed. Due to the presence of unobserved variables, the likelihood has to be computed using a filtering procedure. The switching process makes the standard Kalman filter inappropriate in this case because the information up to time  $t$  includes all the history of the states of the Markov chains. An ideal filtering procedure should take into account all possible paths, multiplied by the number of states at each iteration. This is infeasible. Instead, we use a filter that limits the number of states that are carried forward at each iteration of the Kalman filter. The filter is a combination of [Hamilton \(1994\)](#) and [Kim and Nelson \(1999b\)](#), but with some modifications, see [Maih \(2014\)](#) for details.

The likelihood obtained from the filtering procedure is then combined with the prior density of the parameters to form the posterior kernel. This posterior kernel is maximized to get the posterior mode. The full posterior distribution is calculated using Markov Chain Monte Carlo (MCMC) methods. To find the mode we use a stochastic grid search algorithm, which is derivative-free, then the regions where the global peak might lie is located. The global peak is reached using a Newton-based optimization procedure. This procedure can be computational heavy, especially if the posterior kernel has many peaks, see [Maih \(2014\)](#) for details.

### 3 Results

We present here the results from estimating the MSRE New-Keynesian model. We first compare model performance for the eight different models, before detailing the chosen model framework and implied results.

<sup>11</sup>See <http://research.stlouisfed.org/fred2/>. In the FRED database, the real GDP series is denoted *gdp1*, the GDP deflator is named *gdpdef*, the Federal funds rate is named *fedfunds* and the WTI series is named *oilprice*.

### 3.1 Model selection

From the three independent Markov chains described above, we get eight potential model combinations; The first model,  $\mathcal{M}_1$ , is a model without any parameter switching, i.e., constant parameters model. It is our starting point, from which the other models will be evaluated against.  $\mathcal{M}_2$  refers to a model allowing for switching in macroeconomic volatility, i.e., the variance of the structural shocks to the IS-equation and to the Phillips equation, and with the states of the economy denoted  $\mathcal{S}_t = \mathcal{S}_t^m$ . The third model,  $\mathcal{M}_3$ , allows for switching in oil volatility, i.e., the variance of the structural shocks to the oil price;  $\mathcal{S}_t = \mathcal{S}_t^o$ .  $\mathcal{M}_4$  refers to a model allowing for switching in policy parameters;  $\mathcal{S}_t = \mathcal{S}_t^p$ . The remaining four models are combinations of the above mentioned states.  $\mathcal{M}_5$  allows for switching in both macroeconomic volatility and oil price volatility;  $\mathcal{S}_t = \{\mathcal{S}_t^m, \mathcal{S}_t^o\}$ .  $\mathcal{M}_6$  allows for switching in macroeconomic volatility and policy;  $\mathcal{S}_t = \{\mathcal{S}_t^m, \mathcal{S}_t^p\}$ .  $\mathcal{M}_7$  admits switching in oil price volatility and policy;  $\mathcal{S}_t = \{\mathcal{S}_t^o, \mathcal{S}_t^p\}$ . Finally,  $\mathcal{M}_8$ , allows for switching in macroeconomic volatility, oil price volatility, and policy;  $\mathcal{S}_t = \{\mathcal{S}_t^m, \mathcal{S}_t^o, \mathcal{S}_t^p\}$ . Thus, the different specifications will differ with respect to which parameter sets are allowed to switch. This implies that all models will be nested, allowing us to evaluate which of these specifications are most important in explaining the data.

We adopt the convention that the variance in regime 1 is higher than the variance in regime 2 for the structural shocks:

$$\sigma_d(\mathcal{S}_t^m = 1) \geq \sigma_d(\mathcal{S}_t^m = 2),$$

$$\sigma_o(\mathcal{S}_t^o = 1) \geq \sigma_o(\mathcal{S}_t^o = 2).$$

where the first specification refers to the macroeconomic volatility regime (normalised so that macroeconomic volatility is high when volatility of shocks to the IS-equation are the highest) and the second equation defines the oil price volatility regime. Finally, we define a high monetary policy response regime as the periods where the monetary authorities respond the most to inflation:

$$\phi_\pi(\mathcal{S}_t^p = 1) \geq \phi_\pi(\mathcal{S}_t^p = 2).$$

This specification assumes the policy responses to switch together, but does not restrict the other responses to be high or low in the same regime.

The model specification is uncertain. To evaluate whether a regime switching model gives an accurate description of the data relative to a constant parameter model, we use a statistical criterion to decide what specification is preferred. In particular, we compute the Laplace approximation of the log Marginal Data Density (MDD) for the constant parameter model which we then compare with all the seven alternative regime switching models.<sup>12</sup>

Table 1 displays results and ranking of models based on the MDD. Details of prior and posterior distributions are given below. Importantly, however, we keep the priors constant when comparing performance across models. Clearly, the worst performing model is,  $\mathcal{M}_1$ , the model with constant parameters. The results show that by letting the variance of the shocks to the U.S. macroeconomic variables switch (model  $\mathcal{M}_2$ ), we get the largest improvement in the MDD. Allowing for switches in oil price volatility ( $\mathcal{M}_3$ ), improves the MDD substantially as well, while allowing for switches in the Taylor rule ( $\mathcal{M}_4$ ) yields the least important improvement, but still an improvement. In the end, the model that suggests the largest improvement in MDD is the model that allows all three chains to switch, i.e., model  $\mathcal{M}_8$ . In the following we denote this as the baseline model and present details below.<sup>13</sup>

## 3.2 Priors and parameter estimates

Table 2 displays prior and posterior distributions for the baseline model,  $\mathcal{M}_8$ . We report 90 percent probability intervals for both the priors and the posteriors together with the mean for the posterior. When choosing the priors, we use related literature for guidance. There are by now several studies that estimate a Markov-switching model with switches in volatility and policy, see e.g. Bianchi (2013) and Liu et al. (2011). Our work is novel in estimating a model with oil prices, so here we lack guidance. Our starting point in

<sup>12</sup>Recall, with three independent Markov chains (oil volatility, macroeconomic volatility, and policy parameters), we will have eight possible model combinations, ranging from a constant parameter model ( $\mathcal{M}_1$ ) to model ( $\mathcal{M}_8$ ) where all three regimes are allowed to change.

<sup>13</sup>Details on all the various models can be given on request.

**Table 1. Model performance**

Model	Description	Switching parameters	Log-MDD	Rank
$\mathcal{M}_1$	No parameter switching.	–	2250	#8
$\mathcal{M}_2$	The volatility of the demand and supply shocks can change.	$\sigma_d, \sigma_s$	2291	#4
$\mathcal{M}_3$	The variance of the oil price shock can change.	$\sigma_o$	2272	#6
$\mathcal{M}_4$	The Taylor rule can change.	$\phi_\pi, \phi_y, \rho_r$	2253	#7
$\mathcal{M}_5$	$\mathcal{M}_2$ and $\mathcal{M}_3$ together.	$\sigma_d, \sigma_s, \sigma_o$	2325	#2
$\mathcal{M}_6$	$\mathcal{M}_2$ and $\mathcal{M}_4$ together.	$\sigma_d, \sigma_s, \phi_\pi, \phi_y, \rho_r$	2295	#3
$\mathcal{M}_7$	$\mathcal{M}_3$ and $\mathcal{M}_4$ together.	$\phi_\pi, \phi_y, \rho_r, \sigma_o$	2293	#5
$\mathcal{M}_8$	$\mathcal{M}_2, \mathcal{M}_3$ and $\mathcal{M}_4$ together.	$\sigma_d, \sigma_s, \phi_\pi, \phi_y, \rho_r, \sigma_o$	2332	#1

*Note: The table reports model performance using the logarithm of the marginal data density, for the eight different models. The last column shows how the different models are ranked.*

our choice of oil specific priors is the calibration done in [Blanchard and Gali \(2008\)](#). We do not choose very restrictive priors, and we strive to capture most parameter values that are estimated in similar studies.

For the subjective discount factor,  $\beta$ , we choose the bounds so that the parameter lies within the interval  $[0.96, 1.00]$ .<sup>14</sup> For the persistence parameters,  $\rho_d$ ,  $\rho_s$ , and  $\rho_o$ , we use an almost uniform prior, implemented using a Beta distribution.<sup>15</sup> For the parameters  $\kappa$ ,  $\Lambda$  and  $\Gamma$  we base our priors on the calibration in [Blanchard and Gali \(2008\)](#). For the policy parameters, there are several studies we can relate to.<sup>16</sup> For the inflation response we use a Gamma prior with a 90 percent probability interval between 0.50 and 3.50; for the output response we use a Gamma prior with a 90 percent probability interval between 0.05 and 1.50; and lastly, for the interest rate smoothing parameter we choose a Beta prior with a 90 percent probability interval between

<sup>14</sup>To ease the computations we estimate a transformation of  $\beta$ , given by  $\tilde{\beta} \equiv 100(\beta^{-1} - 1)$ .  $\tilde{\beta}$  follows a Gamma distribution where we choose the bounds so that the 90 percent probability interval of  $\tilde{\beta}$  is  $[0.2, 4.0]$ .

<sup>15</sup>We use a Beta distribution instead of a uniform distribution as we want to avoid values of the persistence parameter equal to 1.

<sup>16</sup>For a linear Taylor rule see [Liu et al. \(2011\)](#), while for a Taylor rule with switching more in line with our setup, see [Bianchi \(2013\)](#).

0.05 and 0.95. For the shock volatilities we set priors based on the volatility of an subsample of the data. The priors for the transition probability matrix are set according to similar studies, e.g. [Bianchi \(2013\)](#). The priors are given in the rows 2–4 in [Table 2](#).

We start by describing the results for the constant parameters. First, we estimate the subjective discount factor,  $\beta$ , to 0.97, which corresponds to a quarterly rate of interest of 3 percent. The persistence parameters  $\rho_d$ ,  $\rho_s$ , and  $\rho_o$ , are, in line with many other studies, estimated to be fairly high: 0.91, 0.75, and 0.97 respectively.  $\kappa$  is estimated to be 0.06, emphasizing a substantial response in inflation to the output gap.  $\Lambda$  and  $\Gamma$  are estimated to be 0.0007 and 0.0006, suggesting a non-negligible response in the output gap and inflation to oil price variation. Finally, we find  $\zeta$  to be 0.45, suggesting a simultaneous response in the oil price to macroeconomic conditions, a feature also found in many empirical studies such as [Kilian \(2009\)](#).

Turning to the parameters governing the high and low macroeconomic volatility regime, we find a clear difference between the various regimes. In particular, the standard deviation of demand shocks is found to be three times higher in the high volatility regime than in the low volatility regime. Further, the standard deviation of supply shocks switches in the same direction as the demand shock, and is estimated to be more than twice the size in the high relative to the low volatility regime. Overall we find the probability of moving from high to low volatility regime to be 10 percent, which is slightly higher than moving from the low to high volatility regime (8 percent). Based on these numbers, we can also calculate the expected duration times of each regime over this specific sample. Doing so we find the high macroeconomic volatility regime is expected to last for 10.4 quarters, while the low volatility regime lasts 12 quarters.

Regarding oil price shocks, we confirm again a substantial difference between the high and low volatility regimes. In particular, a standard deviation shock to the oil price in the high volatility regime is 26 percent while it is 7 percent in the low volatility regime. Furthermore, the probability of moving from the high to the low oil price volatility regime is 14 percent, which is twice as high as the probability of moving from low to high oil price volatility regime. In line with this, the expected duration time in the high oil volatility



**Table 2. Prior and posterior distributions for the model  $\mathcal{M}_8$**

Parameter	<u>Prior distribution</u>		<u>Posterior distribution</u>	
	Distribution	5%–95%	Mean	5%–95%
<b>Constant parameters:</b>				
$\beta$	Gamma	0.96–1.00	<b>0.97</b>	0.93–1.00
$\kappa$	Beta	0.05–0.30	<b>0.06</b>	0.01–0.21
$\zeta$	Uniform	0.05–2.00	<b>0.45</b>	0.03–0.92
$\rho_d$	Beta	0.05–0.95	<b>0.91</b>	0.87–0.96
$\rho_s$	Beta	0.05–0.95	<b>0.75</b>	0.66–0.97
$\rho_o$	Beta	0.05–0.95	<b>0.97</b>	0.95–0.99
$100\sigma_r$	Inv. Gamma	0.05–1.00	<b>0.20</b>	0.18–0.27
$100\Lambda$	Gamma	0.01–1.00	<b>0.07</b>	0.00–0.26
$100\Gamma$	Gamma	0.01–1.00	<b>0.06</b>	0.03–0.53
<b>Switching macro volatility:</b>				
$100\sigma_d(\mathcal{S}_t^m = 1)$	Inv. Gamma	0.05–1.00	<b>0.42</b>	0.27–0.53
$100\sigma_d(\mathcal{S}_t^m = 2)$	Inv. Gamma	0.05–1.00	<b>0.14</b>	0.08–0.19
$100\sigma_s(\mathcal{S}_t^m = 1)$	Inv. Gamma	0.05–1.00	<b>0.15</b>	0.10–0.26
$100\sigma_s(\mathcal{S}_t^m = 2)$	Inv. Gamma	0.05–1.00	<b>0.05</b>	0.04–0.10
$p_{12}^m$	Beta	0.05–0.15	<b>0.10</b>	0.06–0.14
$p_{21}^m$	Beta	0.05–0.15	<b>0.08</b>	0.05–0.13
<b>Switching oil volatility:</b>				
$\sigma_o(\mathcal{S}_t^o = 1)$	Inv. Gamma	0.05–1.00	<b>0.26</b>	0.20–0.35
$\sigma_o(\mathcal{S}_t^o = 2)$	Inv. Gamma	0.05–1.00	<b>0.07</b>	0.06–0.08
$p_{12}^o$	Beta	0.05–0.15	<b>0.14</b>	0.09–0.20
$p_{21}^o$	Beta	0.05–0.15	<b>0.07</b>	0.05–0.11
<b>Switching policy:</b>				
$\phi_\pi(\mathcal{S}_t^p = 1)$	Gamma	0.50–3.50	<b>1.96</b>	1.43–3.35
$\phi_\pi(\mathcal{S}_t^p = 2)$	Gamma	0.50–3.50	<b>1.54</b>	1.28–1.81
$\phi_y(\mathcal{S}_t^p = 1)$	Gamma	0.05–1.50	<b>0.05</b>	0.03–0.15
$\phi_y(\mathcal{S}_t^p = 2)$	Gamma	0.05–1.50	<b>0.74</b>	0.16–1.02
$\rho_r(\mathcal{S}_t^p = 1)$	Beta	0.05–0.95	<b>0.33</b>	0.17–0.84
$\rho_r(\mathcal{S}_t^p = 2)$	Beta	0.05–0.95	<b>0.85</b>	0.71–0.91
$p_{12}^p$	Beta	0.05–0.15	<b>0.07</b>	0.03–0.16
$p_{21}^p$	Beta	0.05–0.15	<b>0.15</b>	0.05–0.24

*Note: Model  $\mathcal{M}_8$  allows for switching in the macroeconomic volatility, oil price volatility, and policy;  $\mathcal{S}_t = \{\mathcal{S}_t^m, \mathcal{S}_t^o, \mathcal{S}_t^p\}$ . The posterior is simulated using a Metropolis Hastings algorithm. The results are from one single chain where we use 100 000 draws. We use a burn in of 10 percent.*

regime will be 7.3 quarters, increasing to 13.6 quarters in the low volatility regime.

Finally, we also find a substantial difference between the parameters governing the policy regimes. In particular, the policy response to inflation is estimated to be 1.96 in the high policy response regime, while it is 1.54 in the low response regime. The response to the output gap, however, moves in the other direction. The response is low (0.05) when policymakers are responding strongly to inflation (denoted the high response regime), and high (0.74) in the low response (to inflation) regime. Note also that the interest rate smoothing parameter is estimated to be 0.33 in the high response regime, and 0.85 in the low response regime. This implies that the relative difference between the parameters in the high and low policy regimes will be even larger. Finally, the probability of moving from the low to the high response regime is 15 percent, more than twice as high as the probability of moving from a high to low response regime. Consistent with this, the regime with the longest duration is the high monetary response regime with an expected duration of 14.6 quarters.

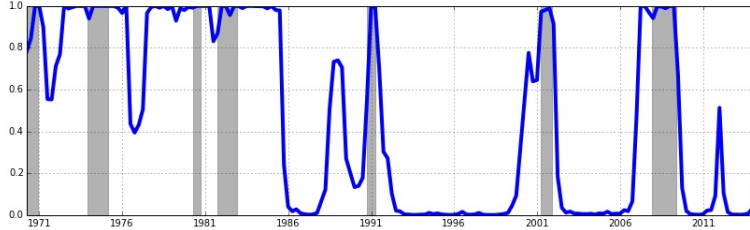
### 3.3 Smoothed regime probabilities

The smoothed probabilities for the model are plotted in Figure 2. Panel 2a shows the smoothed probabilities for being in the high macroeconomic volatility regime. We identify a regime with high volatility in the structural macroeconomic shocks (i.e., shocks to the IS curve and to the Phillips curve) for the periods prior to 1986. That is, throughout the 1970s and until 1986, the economy is in a regime of high macroeconomic volatility. From 1986, the economy moves into a low volatility regime. The shift from the high to the low volatility regime in the middle 1980s is in line with the literature on the Great Moderation, see e.g. [Bianchi \(2013\)](#) and [Liu et al. \(2011\)](#), although we find that the shift to a low macroeconomic volatility regime occurred 1-2 years than in the above mentioned studies. In addition, we identify some short periods of heightened volatility after 1986, mostly coinciding with the NBER recessions.

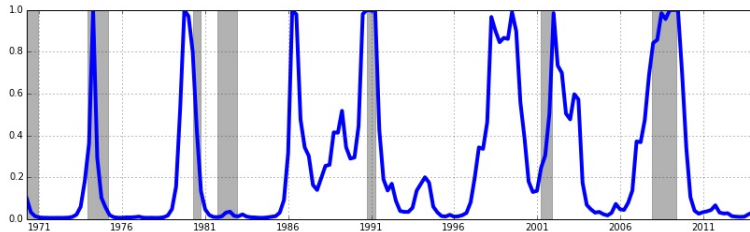
Panel 2b shows the smoothed probabilities for the high oil price volatil-

**Figure 2. Smoothed probabilities for model  $\mathcal{M}_8$**

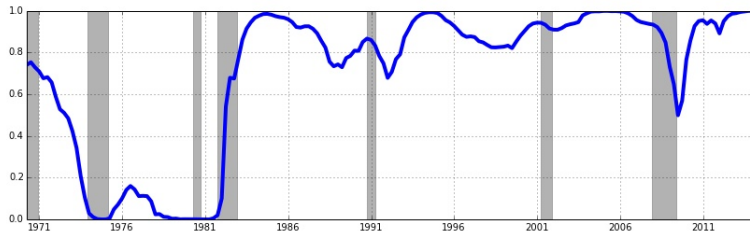
(a) Probability of being in the high macroeconomic volatility regime



(b) Probability of being in the high oil price volatility regime



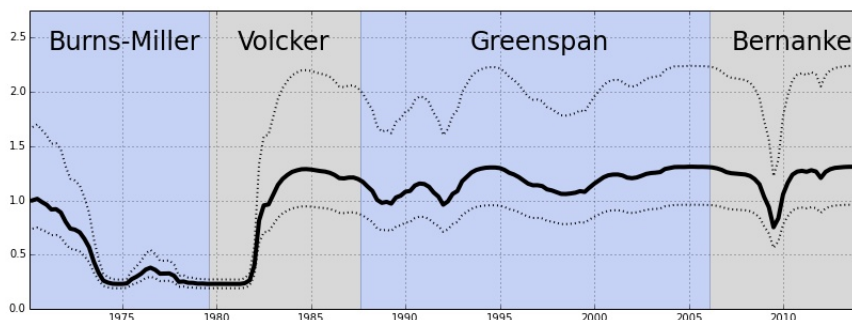
(c) Probability of being in the high policy response regime



*Note: Panel (a) presents the smoothed probabilities for being in the high macroeconomic volatility regime. Panel (b) presents the smoothed probabilities for being in the high monetary policy response regime. Panel (c) presents the smoothed probabilities for being in the high oil volatility regime. The shaded areas correspond to the dated NBER recessions.*

ity regime. A quick glance at the figure suggests there is no support for the hypothesis that a fall in oil price volatility coincided with the decline in macroeconomic instability from the mid-1980s (the start of the Great Moderation) noted in many previous studies. Instead, we find that the oil price has displayed several periods of heightened volatility throughout the sample, many of them coinciding with the NBER recessions. Thus, we reject the notion put forward in [Nakov and Pescatori \(2010\)](#) and [Blanchard and Gali](#)

**Figure 3.** The inflation response,  $(1 - \rho_r)\phi_\pi$ .



*Note:* The figure plots the initial response to inflation over time as the Taylor rule parameters for the high and low response regime weighted using the smoothed probabilities for being in the high monetary policy response regime.

(2008), that, based on a split sample, argue that reduced oil price volatility has contributed to increase macroeconomic stability over time.<sup>17</sup>

Looking at the graph in more detail, we identify seven periods where the structural shocks to the oil price are in a high volatility state. Interestingly, these episodes correspond well with the historical oil price shocks identified in Hamilton (2013). The *first* and *second* episodes are well-known distinct spurs of high oil price volatility: the 1973–1974 OPEC embargo; and the 1978 Iranian revolution followed by the Iran-Iraq war of 1980. Both episodes led to a fall in world oil production, an increase in oil prices and a gasoline shortage in the U.S., see Hamilton (2013) for more details. Between 1981 and 1985, Saudi Arabia held production down to stimulate the price of oil, until, in 1986 they brought production up again, which led in turn to a collapse in the oil price. This sharp fall in 1986 coincides with our *third* episode. The *fourth* episode in 1990/1991, coincides with the first Persian Gulf war during which Iraqi production collapsed and oil prices again shot up. The *fifth* episode is slightly more persistent than the previous episodes and coincides with the East Asian Crisis around 1997/1998 and what Hamilton (2013) calls a period

<sup>17</sup> Herrera and Pesavento (2009) also analyze the contribution of oil prices shocks and systematic monetary policy to the Great Moderation by splitting the sample. They report that an oil price shock had a larger and longer-lived effect on output and inflation in the pre-Volcker period. They also find that systematic monetary policy helped stabilize the economy during the 1970s, but had no effect after the mid-1980s.

of resumed growth.<sup>18</sup> The *sixth* episode coincides with the Venezuelan unrest and the second Persian Gulf war 2001/2002. The *seventh* episode, 2007–2009, coincides with what [Hamilton \(2013\)](#) calls a period of growing demand and stagnant supply. The probability of a high oil price volatility regime shoots up before the last NBER recession, suggesting high oil price volatility may also have played a role here.

Panel [2c](#) shows the smoothed probabilities for the high monetary policy response regime. There is a widespread belief that the more Hawkish policy imposed by the Chair of Federal Reserve Paul Volcker helped bring down the high inflation that persisted during the 1970s, see e.g. [Clarida et al. \(2000\)](#) and [Lubik and Schorfheide \(2004\)](#). Our results support this view that the FED’s response to inflation grew stronger after Volcker took office. More specifically, we identify a switch to a more hawkish regime around 1982. A similar shift to a more responsive policy regime around that time was also found by [Bianchi \(2013\)](#) and [Baele et al. \(2015\)](#). The regime is in place until the end of the financial crisis, when the probability of being in the hawkish regime declines to less than 0.5 percent.

[Figure 3](#) illustrates our results further. In that figure we graph the Taylor rule coefficient on inflation during the periods of the different Chairs of the Federal Reserve. There is a clear shift towards a higher inflation response during the Volcker period, since which it has remained fairly stable, interrupted briefly by Chairman Ben Bernanke’s intervention during the global financial crisis.

To sum up, we nest the “Good luck” hypothesis and find that a reduction in volatility of demand and supply shocks coincides with the general decline in volatility in the U.S. economy, although not before 1986. Further, the volatility reduction is not permanent, and we also identify some brief periods of high macroeconomic volatility throughout the 1990s and 2000s. We also nest the “Good policy” hypothesis, and find that the FED moved into a regime of responding more strongly to inflation around 1982. As to the oil price, we do not find declining oil price volatility to play a separate role for the observed volatility reduction in the U.S. economy.

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<sup>18</sup>During this period the oil price fell below \$12, the lowest price since 1972.

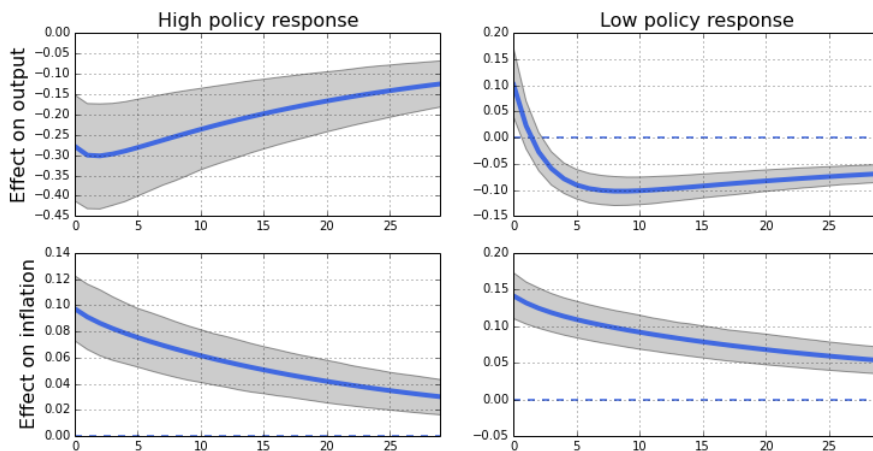
### 3.4 Oil and the macroeconomy

Having observed the coinciding pattern of heightened oil price volatility and the NBER-dated U.S. recession, a natural follow up question is how an oil price shock affects the macroeconomy in the different policy regimes. More specifically, is it the oil price shocks that depress output over time, or are the recessions that followed the severe oil shocks instead caused by the Federal Reserve's contractionary response to inflationary concerns? [Bernanke et al. \(1997\)](#) presented key evidence supporting this latter view, demonstrating that, had it not been for the Federal funds rate responses (of an increased interest rate) to the oil shock, the economic downturns might have been largely avoided.

Figure 4 goes a long way in answering these questions. It displays the responses associated with the oil price shock to output and inflation in both the high and low monetary response regimes. The oil price is normalized to increase with 24 percent on impact, corresponding to a one standard deviation shock in the high oil price volatility regime. The figure has two take-away points. First, independent of whether monetary policy is in the low or high monetary policy regimes, inflation increases and output eventually falls for a prolonged period of time following an adverse oil price shock. This suggests an independent role for oil price shocks in past and present NBER dated recessions, in line with the arguments put forward in [Hamilton \(2009\)](#).

Second, the negative effect on output of an oil price shock is magnified when the policymakers are in the high policy response regimes. In particular, when monetary policy is responding more aggressively to inflation, output falls by more than 0.3 percent within a year, compared to the 0.1 percent decline in the low policy response regime. The reason, of course, is that the increase in interest rates, although effectively curbing inflation, will exacerbate the oil-led contraction of the economy. Thus, and in line with results of [Bernanke et al. \(1997\)](#), the effect of an oil price shock is most severe in the high policy response regime, whereas for inflation the opposite is the case. However, as it turns out, since the policymakers have been in the high response regime since the early 1980s, oil price shocks have been most contractionary for the U.S. economy in the period of the Great Moderation, and

Figure 4. The effects of an oil price shock



Note: The effects of a one standard deviation oil price shock in the high oil price volatility regime (24 percent) to output and inflation. The 67.5 percent credible bands are plotted.

not just in the Volcker area as suggested in [Bernanke et al. \(1997\)](#).

## 4 Extensions

We began this paper by questioning whether a reduction in oil price volatility could be partly responsible for the Great Moderation, that is, a period of stable economic conditions from the mid-1980s. Our results suggest that, contrary to common perception, there is no support for the role of oil price shocks in reducing macroeconomic instability. Instead we find the usual suspects of “Good luck” and “Good policy” in explaining the Great Moderation. There are, however, alternative hypotheses for explaining the rise of macroeconomic stability since the mid-1980s. Below we examine two of these hypothesis before addressing other extensions related to model specification and estimation.

### 4.1 Declining oil dependence

The share of oil in consumption and production in the industrialized world is today smaller than it was in the 1970s. [Blanchard and Gali \(2008\)](#) argue that these declining oil shares play an important role in explaining the

reduced impact of oil prices on output and inflation over time. [Nakov and Pescatori \(2010\)](#) also argue that the transmission of oil price volatility has been dampened since the mid-1980s, thereby contributing effectively to the Great Moderation.<sup>19</sup>

To examine the hypothesis of a reduced transmission (or dependence) of the oil price shocks, we allow the parameters  $\Lambda$  and  $\Gamma$  that govern the response in respectively output and inflation to an oil price shock to switch. We denote model  $\mathcal{M}_9$  as the model that allows for switching only in the oil-macroeconomic response, and normalize the high dependence regime to be a regime where the transmission of oil price shocks to inflation is the largest. We also add switching in the oil-macroeconomic dependence to our main model  $\mathcal{M}_8$  and call this model  $\mathcal{M}_{10}$ . Model  $\mathcal{M}_{10}$  is then a model with 4 different Markov chains meaning that we have a total of 16 possible regimes.

The results (see [Table 3](#) in [Appendix B.1](#) for details) suggest that allowing for switches in only  $\Lambda$  and  $\Gamma$  (model  $\mathcal{M}_9$ ), produces a much worse performance (in terms of MDD) than our constant specification in model  $\mathcal{M}_1$ , and is therefore a poor explanation of the changing volatility in the macroeconomic data. For model  $\mathcal{M}_{10}$ , the performance also falls relative to our best performing model  $\mathcal{M}_8$ , but the difference is now minor, suggesting that switching in the macroeconomic dependence may add new features to the baseline regime switching model deserving of attention.

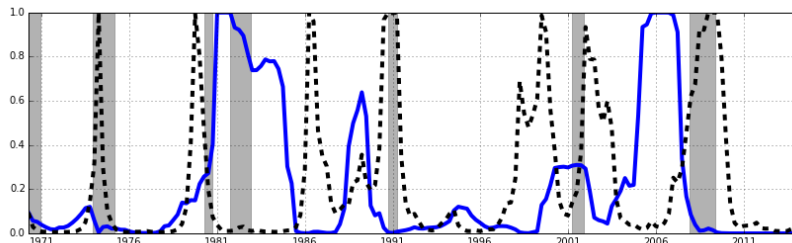
To illustrate this, [Figure 5](#) plots the smoothed probabilities for being in the high oil dependence regime together with the probability of being in the high oil price volatility regime.<sup>20</sup> The figure shows the economy has been in the low oil dependence regime during most of the period. Further, the low oil dependence regime is close to our baseline with respect to the estimated parameter values for  $\Lambda$  and  $\Gamma$ . Interestingly, we note that the probability of being in the high oil dependence regime increases in between the high oil volatility periods. This is most notable in the early 1980s, briefly in 1989, and then again from 2003 to 2007. As oil prices have increased, so has also the

<sup>19</sup>Again, in their model this is measured by splitting the sample and comparing model performance in the two samples.

<sup>20</sup>The baseline results are robust to this additional regime, with the exception that the hawkish policy regime declines somewhat during the mid-1990s, see [Appendix B.1](#).



**Figure 5. Probability of being in the high oil dependence regime**



*Note: The figure shows the smoothed probabilities for being in the high oil dependence regime. Shaded areas are NBER recessions and the black dashed line gives the probability of being in the high oil price volatility regime.*

share of energy goods and services in total consumption, see [Hamilton \(2009\)](#). To the extent that we observe a marked fall in oil dependence from the mid-1980s, it could therefore in part be in response to the reduced consumption shares in this period. Yet, impulse responses plotted in [Appendix B.1](#) show that, irrespectively of the oil dependence regimes, an oil price shock still has a substantial and significant contractionary effect on output and inflation, although more so in the high oil dependence regimes.

## 4.2 Volatility of monetary policy shocks

In our baseline model we allow the policy parameters in the Taylor rule to change, but keep the volatility of monetary policy shocks,  $\sigma_r$ , constant in all periods. This is in contrast to [Liu et al. \(2011\)](#), [Bianchi \(2013\)](#), and [Baele et al. \(2015\)](#), who argue that volatility of monetary policy shocks (i.e., discretionary policy) should also be allowed to change.<sup>21</sup> One reason for this choice, is that during recessions or after large shocks (such as the oil price shocks), the Fed is more willing to deviate from its interest rate rule. This could then also explain an important part of the change in macroeconomic dynamics. However, since we are including oil prices explicitly in the model, thereby allowing the Fed to respond to oil prices via its effect on output and inflation, policy errors due to omitted variables may be of less concern.

<sup>21</sup>In the case of [Liu et al. \(2011\)](#), only discretionary policy is allowed to change, at the cost of leaving the systematic policy (the Taylor rule coefficients) unchanged over the sample.

Still, it is interesting to examine the role of discretionary (unsystematic) monetary policy in reducing overall macroeconomic volatility. In so doing we follow [Baele et al. \(2015\)](#) in letting  $\sigma_r$  switch according to its own independent Markov chain. That is, we allow the origins of the shocks to be different. Results suggest that allowing for changing volatility in unsystematic policy gives no value added once we have allowed for oil price volatility to switch. Hence, our results remain robust, see [Figure 8](#) in [Appendix B.2](#).

### 4.3 Additional model extensions and robustness tests

We have estimated the model using a number of alternative data compositions and model specifications. As described in greater detail in [Appendix C.1](#), the main conclusions of the paper are robust to all of these alternatives. Below, we provide a brief summary.

First, we estimate the models using a truncated estimation sample, excluding data from 2007:Q1. This alternative experiment excludes the financial crisis and the period thereafter from the sample. One argument for excluding this period is that during the financial crisis and after, monetary policy assumed a form our model cannot account for (zero-lower bound, quantitative easing). Another argument is that while our set-up is for an oil importing country, lately, the U.S. has relied more on home produced oil and gas and is therefore less dependent on imports. This could change the results. Excluding the last few years, still we find that the importance of macroeconomic volatility is prevalent. In fact, the responses obtained using the truncated sample are not significantly different from each other. If anything, the results based on the truncated estimation sample are stronger, in line with what we suggested here, see [Figure 9](#) in [Appendix C.1](#).

Second, the output gap is not observed. As discussed in [Appendix C.1](#), the results reported in [Section 3](#) are not affected by changing how we measure this variable, using, for instance, a band-pass filter.

Third, [Aastveit et al. \(2014\)](#) has shown that demand from emerging countries has been an important driver of the oil price the last decade. To test the implication of this, we include an index of global demand (OECD) directly. Results do not change much using this index, most likely as the business cycles

have been synchronized in the OECD.

We have also conducted a series of other robustness checks, for which details can be provided on request. In particular, the inclusion/exclusion of alternative measures of inflation, additional lags in the Phillips and IS curve will potentially also affect the estimates. Still, the main results are robust to estimating the models using these alternative representations. Lastly, our results seem robust to different prior specifications.

## 5 Conclusion

This paper revisits the role of oil price volatility in reducing general macroeconomic volatility by estimating Markov Switching Rational Expectation New-Keynesian models that accommodate regime-switching behavior in shocks to oil prices, macro variables as well as in monetary policy. With the structural model we revisit the timing of the Great Moderation (if any) and the sources of changes in the volatility of macroeconomic variables. We have three major findings. First, our results support regime switching in monetary policy, U.S. shock volatility and oil price shock volatility. The best fit model is when both the volatility of shocks and systematic monetary policy are allowed to change. Hence, both good luck and good policy matter.

Second, we do not find a break in oil price volatility from the mid-1980s that coincides with the Great Moderation. What we find instead is several short periods of heightened oil price volatility throughout the whole sample, many of them preceding the dated NBER recession. If anything, the post-1984 period has had more episodes of high volatility than the pre-1984 period. Hence, according to our results, we cannot argue that declining oil price volatility was a factor in the reduced volatility of other U.S. macroeconomic variables. Instead, and in contrast to common perceptions, we confirm the relevance of oil as a recurrent source of macroeconomic fluctuations.

Third, the most important factor reducing macroeconomic variability is the decline in volatility of structural shocks (demand and supply). In all the model variants, the break date is estimated to occur in 1986. That is not to say there has not been any spurs of volatility since then. However, these periods of heightened macroeconomic volatility have been much briefer.

Thus, if indeed the recurrent spikes in oil prices are causal factors contributing to economic downturns, the Federal Reserve should give careful consideration to the possible consequences of shocks to commodity prices when designing monetary policy.

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# Appendices

## For Online Publication

### Appendix A The New-Keynesian model

The model we use is in most respects a standard New-Keynesian model extended to include an oil sector. The model is based on the model developed in [Blanchard and Gali \(2008\)](#). Because we follow their model so closely, we refer to that paper for details. Here we lay out the fundamental equations for the log-linearized model outlined in [Section 2](#).

#### Households

We start from the households that have the following objective

$$\max_{\{C_{H,t}, C_{o,t}, B_t, N_t\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left( \log C_t - \frac{N_t^{1+\varphi}}{1+\varphi} \right), \quad (\text{A.1})$$

where consumption  $C_t$  is a combination of home produced goods  $C_{H,t}$  and consumption of imported oil,  $C_{o,t}$ .  $B_t$  is a one-period risk-less bond that pays one unit of domestic currency in the next period.  $N_t$  is hours worked. The parameter  $\beta$  is the subjective discount factor and  $\varphi$  is the inverse of the Frisch labor supply elasticity. Consumption of non-oil goods is a CES aggregate of different varieties on the unit measure given by  $C_{H,t} \equiv \left( \int_0^1 C_{H,t}(i)^{\frac{\varepsilon-1}{\varepsilon}} di \right)^{\frac{\varepsilon}{\varepsilon-1}}$ , where  $\varepsilon$  is the elasticity of substitution between domestic goods.

The aggregate consumption basket is given by

$$C_t \equiv \left( \frac{C_{o,t}}{\chi} \right)^\chi \left( \frac{C_{H,t}}{1-\chi} \right)^{1-\chi} = \Theta_\chi C_{o,t}^\chi C_{H,t}^{1-\chi}, \quad (\text{A.2})$$

where  $C_{o,t}$  is consumption of oil,  $\Theta_\chi \equiv \chi^{-\chi}(1-\chi)^{-(1-\chi)}$  and  $\chi$  is the oil share in the consumption basket. The household faces the one period budget constraint given by

$$P_{H,t}C_{H,t} + P_{o,t}C_{o,t} + Q_tB_t = W_tN_t + B_{t-1} + \Pi_t, \quad (\text{A.3})$$

where  $P_{H,t}$  is a domestic price index given by  $P_{H,t} \equiv \left( \int_0^1 P_{H,t}(i)^{1-\varepsilon} di \right)^{\frac{1}{1-\varepsilon}}$ .  $P_{o,t}$  is the price of imported oil in domestic currency.  $W_t$  is the nominal wage,



$Q_t$  is the price of the one-period nominal risk-less domestic bond,  $B_t$ , and  $\Pi_t$  is gross profits.

Let's define the CPI as  $P_t \equiv P_{o,t}^\chi P_{H,t}^{1-\chi}$ . By solving the household problem we get the intertemporal Euler equation

$$Q_t = \beta \mathbb{E}_t \left\{ \frac{C_t}{C_{t+1}} \frac{P_t}{P_{t+1}} \right\}, \quad (\text{A.4})$$

which governs the allocation of consumption over time. We also get the optimality condition governing the allocation of labor and consumption

$$\frac{W_t}{P_t} = C_t N_t^\varphi. \quad (\text{A.5})$$

## Firms

We have a continuum of firm  $i$  on the unit interval, all producing a differentiated good using the following production function

$$Q_t(i) = A_t O_t(i)^{\alpha_o} N_t(i)^{\alpha_n} \quad \text{where } \alpha_o + \alpha_n \leq 1. \quad (\text{A.6})$$

$O_t(i)$  and  $N_t(i)$  are oil and labor input for firm  $i$  respectively. The level of technology is constant across firms and given by  $A_t$ , the parameters  $\alpha_o$  and  $\alpha_n$  are the oil share and labor share in production respectively. Aggregate gross output is defined as

$$Q_t \equiv \left( \int_0^1 Q_t(i)^{\frac{\epsilon-1}{\epsilon}} di \right)^{\frac{\epsilon}{\epsilon-1}}.$$

We assume Calvo pricing where a fraction  $1 - \theta$  of the firms can reset their price every period. Optimal price setting by firms gives the following first order condition

$$\mathbb{E}_t \left\{ \sum_{k=0}^{\infty} \theta^k \Lambda_{t,t+k} Q_{t+k|t} (P_t^* - \mathcal{M}^P \Psi_{t+k|t}) \right\} = 0,$$

where  $P_t^*$  is the price set by the firms that can change the price.  $Q_{t+k|t}$  and  $\Psi_{t+k|t}$  are the output and the marginal cost for a firm in period  $t+k$  that last reset its price at time  $t$ .  $\Lambda_{t,t+k}$  is the stochastic discount factor between period  $t$  and  $t+1$  and  $\mathcal{M}^P = \frac{\epsilon}{\epsilon-1}$  is the steady state gross markup. The parameter  $\theta$  is the probability that the firm must keep the price fixed for one more period. Solving for the optimal price gives

$$P_{H,t}^* = \mathcal{M}^P \mathbb{E}_t \left\{ \frac{\sum_{k=0}^{\infty} \theta^k \beta^k P_{H,t+k}^\epsilon \Psi_{t+k|t}^r}{\sum_{k=0}^{\infty} \theta^k \beta^k P_{H,t+k}^{\epsilon-1}} \right\}. \quad (\text{A.7})$$

## Aggregate relationships

Gross domestic product,  $Y_t$  is defined as

$$P_t Y_t \equiv P_{H,t} Q_t - P_{o,t} O_t. \quad (\text{A.8})$$

In equilibrium with balanced trade,  $B_t = 0$ , the total value of consumption is equal to the total value of output minus the total value of imported oil.

$$P_t C_t = P_{H,t} Q_t - P_{o,t} O_t.$$

## Monetary authorities

We assume that monetary authorities set the interest rate according to the following rule

$$\frac{R_t}{\bar{R}} = \left( \frac{R_{t-1}}{\bar{R}} \right)^{\rho_r} \left( \left( \frac{P_t}{P_{t-1}} \right)^{\phi_\pi} \left( \frac{Y_t}{\bar{Y}} \right)^{\phi_y} \right)^{1-\rho_r} e^{\epsilon_{r,t}}, \quad (\text{A.9})$$

where  $R_t$  is the gross interest rate,  $\bar{R}$  is steady state gross interest rate, and  $\bar{Y}$  is steady state output. This rule says that the monetary authorities care about both price stability and that the output gap is closed, and they respond to inflation according to the parameter  $\phi_\pi$  and to the output gap according to  $\phi_y$ . We allow for interest rate smoothing according to the parameter  $\rho_r$  and  $\epsilon_{r,t}$  is a monetary policy shock.

## The importance of oil

The model includes oil both as a factor in production and as a consumption good. We do not specify a production sector for oil, in the model developed by [Blanchard and Gali \(2008\)](#) the oil price is assumed to follow an AR(1):

$$s_t = \rho_o s_{t-1} + \varepsilon_{o,t}. \quad (\text{A.10})$$

We augment this AR(1) model to allow for demand factors as possible drivers of the oil price. In our model we use the following specification for the oil price

$$s_t = \rho_o s_{t-1} + \zeta y_t + \varepsilon_{o,t}, \quad (\text{A.11})$$

where  $\zeta$  measures the direct effect of chance in the output gap on the real price of oil.

## Appendix B Additional Figures and Tables: Alternative hypothesis

Below we show results from examining two alternative hypotheses for the reduction in macroeconomic volatility from the mid-1980s. Section B.1 first examines whether the economy has become less dependent on oil, while Section B.2 examines whether (discretionary) monetary policy has become less volatile.

### B.1 Declining oil dependence

One alternative explanation in the literature on the Great Moderation is that the economy has become less dependent on oil, i.e., the oil share in both production and consumption has fallen over time. This is one of the hypotheses examined by Blanchard and Gali (2008). The parameters governing the oil dependence of the economy are  $\Lambda$  and  $\Gamma$ . It can be shown that both parameters are increasing in the oil share in production as in the oil share in consumption. The alternative hypothesis that oil has a dampening effect on the macroeconomy over time can then be tested by letting parameters  $\Lambda$  and  $\Gamma$  change over time.

We proceed then to estimate our model in which we allow for switching in the effect from oil prices to the macroeconomy. We denote model  $\mathcal{M}_9$  as the model that allows for switching in oil dependence, and normalize the high dependence regime to be  $\mathcal{S}_t = \mathcal{S}_t^{mo} = 2$  such that

$$\Gamma(\mathcal{S}^{mo} = 2) \geq \Gamma(\mathcal{S}^{mo} = 1).$$

This gives us a model with two possible regimes, one where movements in the oil price have a relatively large effect on the macroeconomy (dependence is high), and one where this effect is relatively small (dependence is low).

We also estimate a model where, in addition to letting  $\Lambda$  and  $\Gamma$  switch, we allow for all the different regimes as in our baseline model  $\mathcal{M}_8$ . We call this specification model  $\mathcal{M}_{10}$ . In this specification the state of the economy can be written as  $\mathcal{S}_t = \{\mathcal{S}_t^m, \mathcal{S}_t^o, \mathcal{S}_t^p, \mathcal{S}_t^{mo}\}$  and we have a total of 16 different regimes into which the economy can move. In Table 3 we report the model

**Table 3. Model performance - Alternative hypothesis**

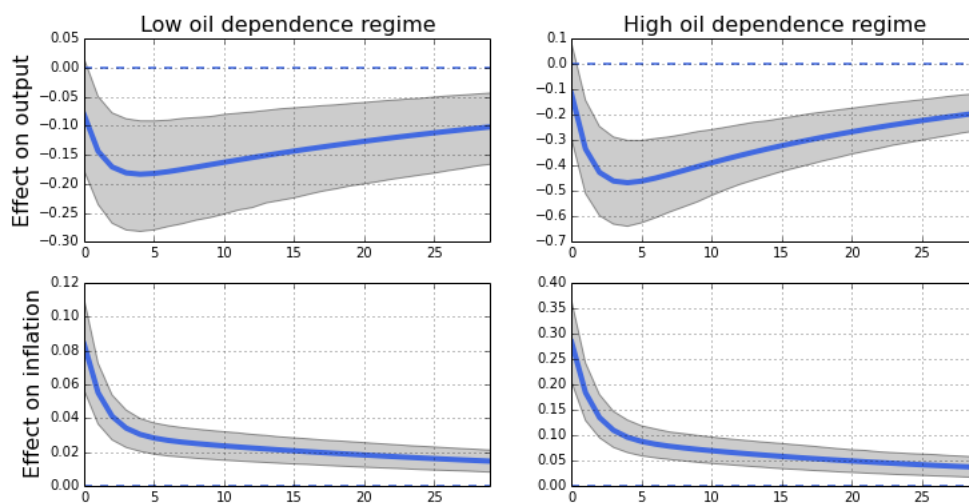
Model	Description	Switching parameters	Log-MDD	Rank
$\mathcal{M}_9$	The parameters in front of the oil price in the IS- and Phillips equation can change.	$\Gamma, \Lambda$	2212	#10
$\mathcal{M}_{10}$	A combination of $\mathcal{M}_2, \mathcal{M}_3, \mathcal{M}_4$ and $\mathcal{M}_9$ .	$\sigma_d, \sigma_s, \phi_\pi, \phi_y, \rho_r, \sigma_o, \Gamma, \Lambda$	2297	#3

*Note: The table reports the model performance, using the logarithm of the marginal data density, for the models allowing for switching in the oil-macro response. The last column shows how the two models are ranked compared to the models  $\mathcal{M}_1 - \mathcal{M}_8$ .*

performance of these two alternative hypothesis. We find that allowing for switches in only  $\Lambda$  and  $\Gamma$  (model  $\mathcal{M}_9$ ), performs much worse than our constant specification in model  $\mathcal{M}_1$  based on the MDD, and is therefore a poor explanation of the changing volatility in the macroeconomic data.

For model  $\mathcal{M}_{10}$ , the performance also falls relative to our best performing model  $\mathcal{M}_8$ , but the difference is minor, suggesting that switching in oil dependence may add new features to the baseline model, deserving of attention. The smoothed probabilities for model  $\mathcal{M}_{10}$  are plotted in Figure 6. We also graph the impulse responses to an oil price shock in the high and low dependence regime in Figure 7. Interestingly, we find an oil price shock to have a substantial and significant effect on output and inflation in both regimes, but even more so when oil dependence is high. In particular, following a one standard deviation oil price shock (normalised to increase oil prices by 24 percent, as in the high oil price volatility regime), output gradually falls by close to 0.5 percent and inflation increases with 0.3 percentage points. A similarly sized shock in the low dependence regime eventually reduces output by close to 0.2 percent, and increases inflation with 0.09 percentage points.

Figure 7. The effects of an oil price shock



Note: The effects of a one standard deviation oil price shock (24 percent) to output and inflation. The 67.5 percent credible bands are plotted.

## B.2 Switching in the volatility of monetary policy shocks

Some papers specifying Markov-switching models with a Taylor rule also allow for switching in the volatility of monetary policy shocks. There are different ways of modeling the possibility of a switch in the parameter  $\sigma_r$ . [Bianchi \(2013\)](#) uses two different Markov chains to estimate switching, one for structural parameters and one for volatility parameters. This means that he is bundling all volatility parameters together and forcing them to switch together. The volatility of monetary policy shocks must therefore switch together with the general macroeconomic volatility in the model. Another approach is suggested by [Baele et al. \(2015\)](#). Here, the volatility of the different shocks switch according to different and independent Markov chains. This implies that the volatility regime of the monetary policy shocks is independent of the other regimes in the model.

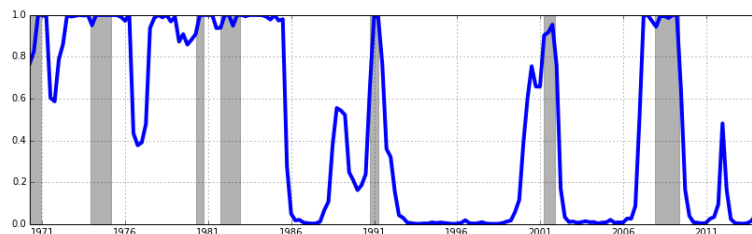
Since we have shown that the origins of the shocks are very different, we follow [Baele et al. \(2015\)](#) by letting the volatility of unsystematic monetary policy ( $\sigma_r$ ) switch according to its own chain. We define the chain that governs volatility of monetary policy shocks as  $\mathcal{S}_t^r \in \{0, 1\}$ . The Taylor rule can be written in this specification as

$$r_t = \rho_r(\mathcal{S}_t^p)r_{t-1} + (1 - \rho_r(\mathcal{S}_t^p)) \left[ \phi_\pi(\mathcal{S}_t^p)\pi_t + \phi_y(\mathcal{S}_t^p)y_t \right] + \sigma_r(\mathcal{S}_t^r)\epsilon_{r,t}. \quad (\text{B.1})$$

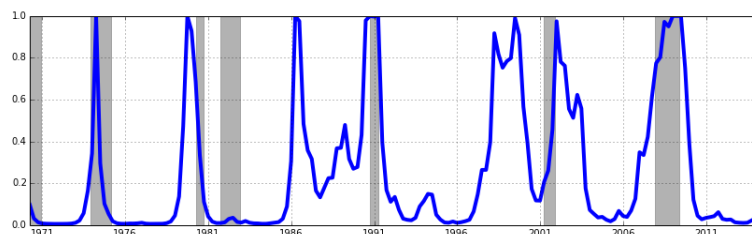
Results are given in [Figure 8](#). The figure shows that our results remain robust. Letting monetary policy switch on its own does not give any value added, once we have allowed for volatility in oil price shock and in demand and supply shocks.

**Figure 8. Smoothed probabilities**

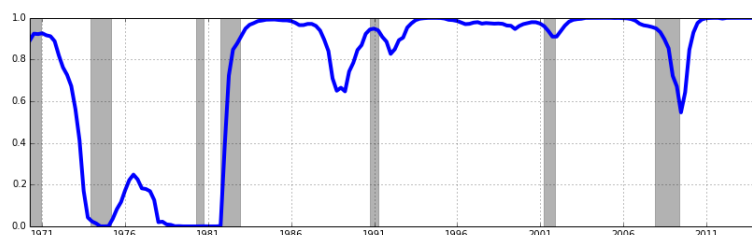
(a) Probability of being in the high macroeconomic volatility regime



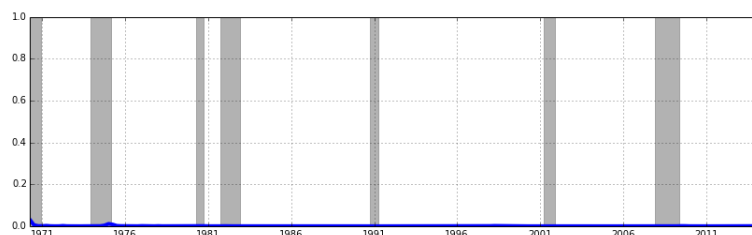
(b) Probability of being in the high oil price volatility regime



(c) Probability of being in the high policy response regime



(d) Probability of being in the high monetary policy volatility regime



*Note: The smoothed probabilities for being in the various regimes in the model where we also allow for switching in the volatility of monetary policy shocks.*

## Appendix C Robustness

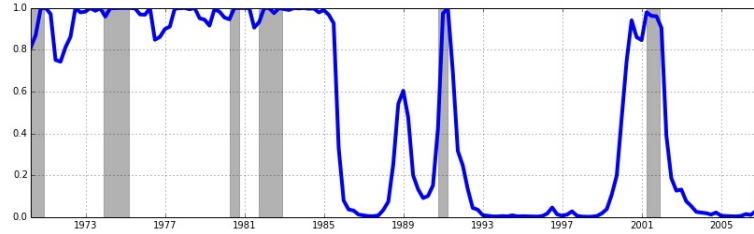
### C.1 Estimation of truncated sample

We analyze our results with a view to establishing their robustness to a truncated sample ending before the financial crisis. From 2007, the U.S. experienced a recession. Oil prices were also fluctuating wildly and the monetary policy regime was different (zero-lower bound). We want to examine whether these events influence our results. We therefore stop the estimation in the last quarter of 2006. The smoothed probabilities for the estimated model on the pre-2007 data sample is plotted in Figure 9. Results are robust to the truncated sample.

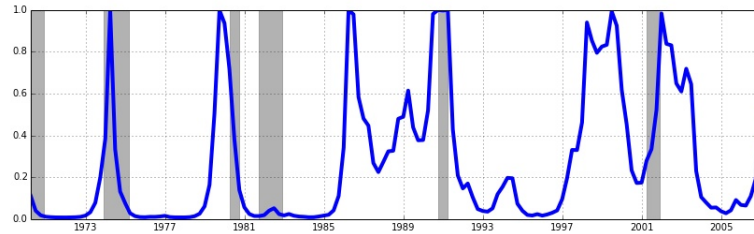


**Figure 9. Smoothed probabilities for pre-2007 data**

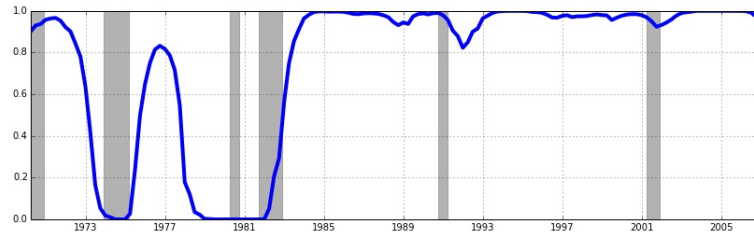
(a) Probability of being in the high macroeconomic volatility regime



(b) Probability of being in the high oil price volatility regime



(c) Probability of being in the high policy response regime



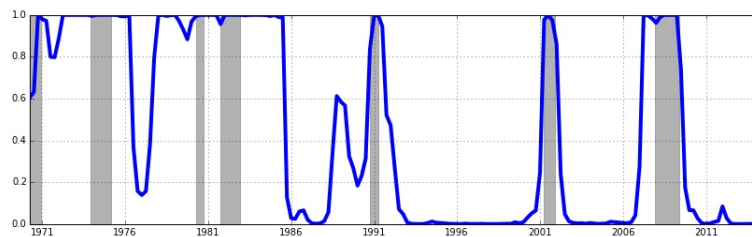
*Note: The smoothed probabilities for being in the various regimes estimated for model  $M_8$  where we stop the estimation in 2006Q4.*

## C.2 Measures of output gap

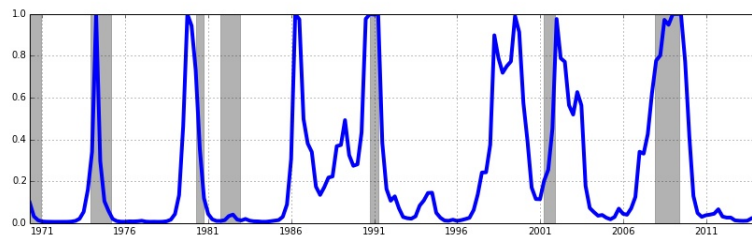
We estimate the output gap using the Baxter-King (BK) bandpass filter (see [Baxter and King \(1999\)](#)) and the Christiano-Fitzgerald (CF) asymmetric random walk filter (see [Christiano and Fitzgerald \(2003\)](#)) instead of the Hodrick-Prescott filter. The results are robust to either measure, see [Figures 10 and 11](#).

**Figure 10. Smoothed probabilities using the BK-filter**

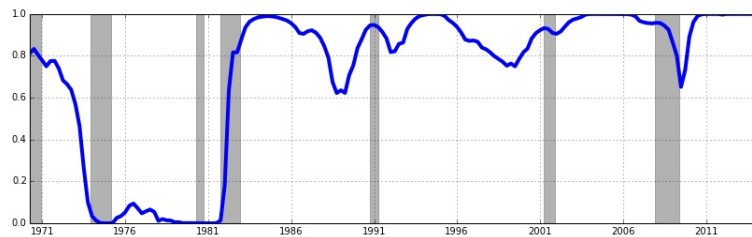
(a) Probability of being in the high macroeconomic volatility regime



(b) Probability of being in the high oil price volatility regime



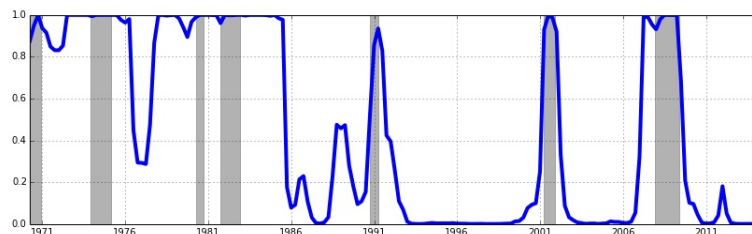
(c) Probability of being in the high policy response regime



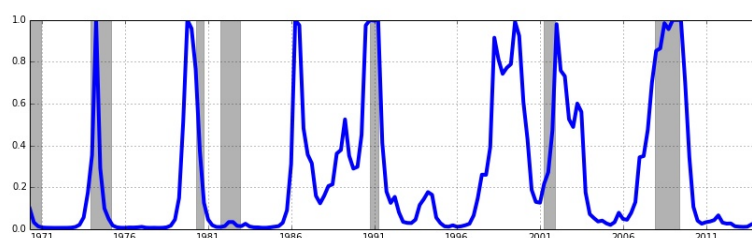
*Note: The smoothed probabilities for being in the various regimes estimated for model  $\mathcal{M}_8$  where we estimate the model using the BK-filter.*

**Figure 11. Smoothed probabilities using the CF-filter**

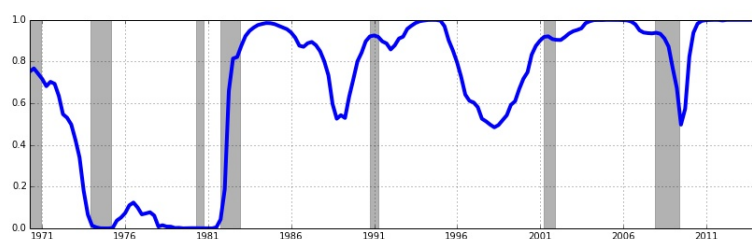
(a) Probability of being in the high macroeconomic volatility regime



(b) Probability of being in the high oil price volatility regime



(c) Probability of being in the high policy response regime



*Note: The smoothed probabilities for being in the various regimes estimated for model  $M_8$  where we estimate the model using the CF-filter.*

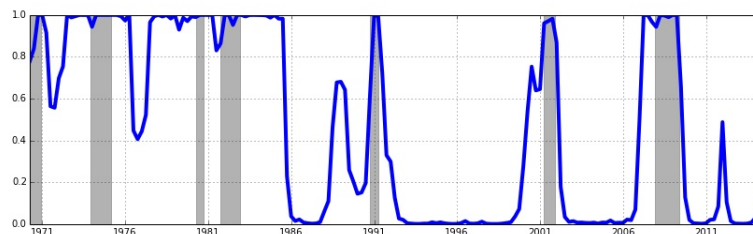
### C.3 Global output gap measure in the oil price equation

As discussed in the main part of the paper, contrary to earlier beliefs that the oil price was purely supply driven and could be treated as exogenous, many studies have shown that global demand is an important oil price driver, see e.g. [Kilian \(2009\)](#). In our baseline model we approximate global demand by the U.S. output gap. We believe this to be a reasonable approximation, especially in the early parts of our sample. We proceed then to check whether this result is robust to the inclusion of a broader output gap measure, using the OECD – Total index obtained from the OECD database. We use data on GDP denoted in real U.S. dollars with base year 2005, the data is in fixed PPPs, and seasonally adjusted.

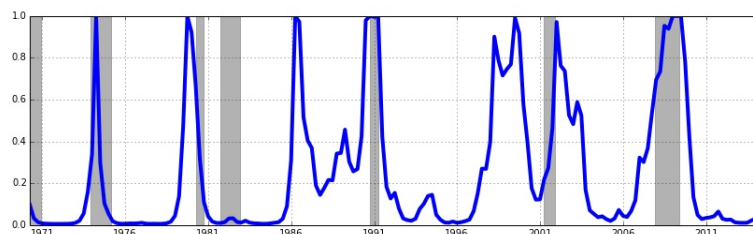
$$s_t = \rho_o s_{t-1} + \zeta y_t^{\text{OECD}} + \sigma_o(\mathcal{S}_t^o) \epsilon_{o,t} \quad (\text{C.1})$$

**Figure 12. Smoothed probabilities for model with global GDP**

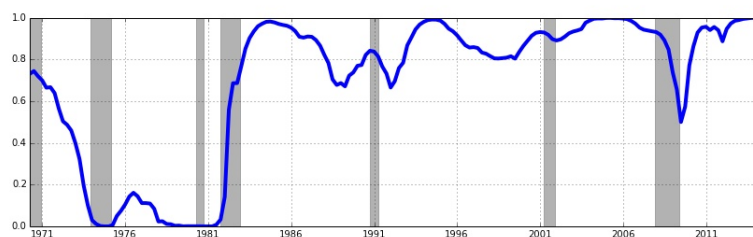
(a) Probability of being in the high macroeconomic volatility regime



(b) Probability of being in the high oil price volatility regime



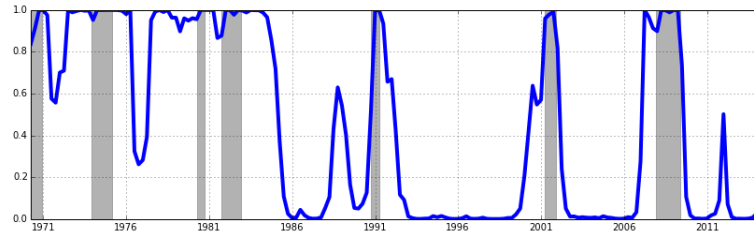
(c) Probability of being in the high policy response regime



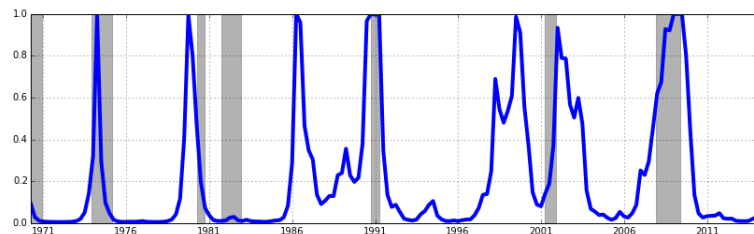
*Note: The smoothed probabilities for being in the various regimes in the model where we use global GDP in the oil price equation.*

**Figure 6. Smoothed probabilities for model  $\mathcal{M}_{10}$**

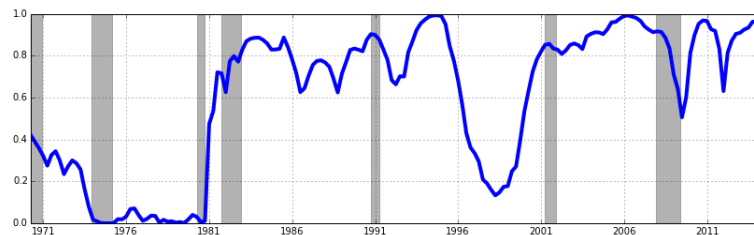
(a) Probability of being in the high macroeconomic volatility regime



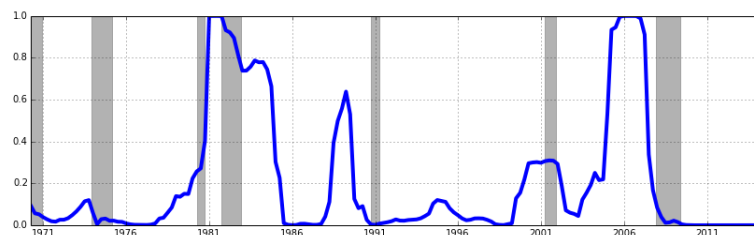
(b) Probability of being in the high oil price volatility regime



(c) Probability of being in the high policy response regime



(d) Probability of being in the high oil to macro regime



*Note: Panel (a) presents the smoothed probabilities for being in the high macroeconomic volatility regime. Panel (b) presents the smoothed probabilities for being in the high monetary policy response regime. Panel (c) presents the smoothed probabilities for being in the high oil volatility regime. Panel (d) presents the probability of being in the regime with the high oil to macro relationship.*

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