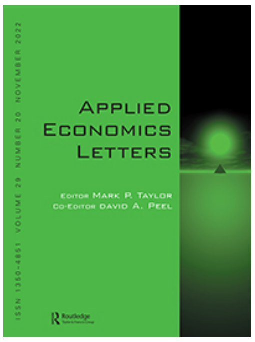

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ARTICLE

Wars, cartels and COVID-19: regime switching in commodity prices

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ABSTRACT
Commodity prices are extremely volatile, and volatility itself fluctuates over time. Using data from 1959 to 2022, we estimate a 3-state Markov-switching model to identify expansions and contractions in oil and copper price volatility. We found a transition from a low to a medium variance regime for the oil price, in 1979, reflecting changes in the oil market structure. In addition, we identify infrequent and short-lived episodes of unusually high oil price volatility. For copper, there is no transition across regimes, and episodes of high volatility are not synchronized with the periods of high volatility in oil prices. We found that oil prices are much more volatile than copper prices in all states. Oil prices react more strongly to market cartelization, war episodes, and global demand shifts, like the 2008 Great Recession and the COVID-19.

KEYWORDS
Commodity price volatility; Markov-switching; oil and copper prices

JEL CLASSIFICATIONS
C11; Q02; Q35

I. Introduction

Commodity prices are extremely volatile, and volatility itself fluctuates over time (Pindyck 2004). This volatility has consequences for both the global economy and commodity markets themselves. In a seminal contribution, Hamilton (1983) concluded that U.S. recessions, since World War II, have been preceded by dramatic increases in the price of crude petroleum. This is true also for other developed economies for which the volatility of oil price, and other commodities, like copper, constitute a source of economic fluctuations (see Figure 1). For developing economies, which are commodity producers, there is evidence that higher volatility of commodity terms of trade harms growth (see Cavalcanti, Mohaddes, and Raissi (2015) and Arezki et al. (2014) among others).

Given the relevance of commodity prices, understanding the sources of their fluctuation has been an ongoing quest for policymakers and scholars. The consensus is that, in general, demand shocks tend to dominate supply shocks in determining the spot prices in these markets.[1]

Despite recent advances, there is little understanding about potential, and continuous, regime shifts in the mean and volatility of commodity prices.[2] In this paper, we fill this gap in the literature and contribute in two dimensions. First, using Hamilton's (1989) methodology, we develop a 3-state Markov-switching model to estimate expansions and contractions in the volatility and mean of oil and copper prices. [3] We estimate our model using Bayesian techniques, because it is better suited to handling transition probabilities. In contrast, the classical method has difficulty in estimating transition probabilities accurately (see Jiang (2020) and Hamilton (2010)). Second, we determine the impact of the COVID-19 pandemic and the 2022 Ukrainian war on the volatility of commodity prices. Some recent contributions, like Ahmed and Sarkodie (2021), are restricted to a very short sample which excludes both the

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[1]Kilian (2009), Kilian and Murphy (2012), and Lippi and Nobili (2012) found that oil price movements have been driven mainly by a combination of global aggregate demand shocks and precautionary demand shocks, rather than oil supply shocks, as was commonly believed. Caldara et al., (2019), and Christiane and Hamilton, (2019) found a larger impact of supply shocks but also conclude that demand shocks play an important role in explaining oil price fluctuation. In the case of copper and other metals, Jacks and Stuermer (2020) concluded that, as in the case of oil, demand shocks are the main drivers of price fluctuations.

[2]Dvir and Rogoff (2010) and Dvir and Rogoff (2014), using annual data from 1861 to 2008, found strong evidence of changes in persistence and volatility of oil price across three well-defined periods or, as they called it, *three epochs*. However, these changes are a one-off event. Episodes of high, medium, and low volatility do not coexist in a given time frame.

[3]We restrict our attention to these two important commodities. The analysis, however, is general enough and hence, it can be extended to other commodity prices, which may be relevant for a particular group of countries.

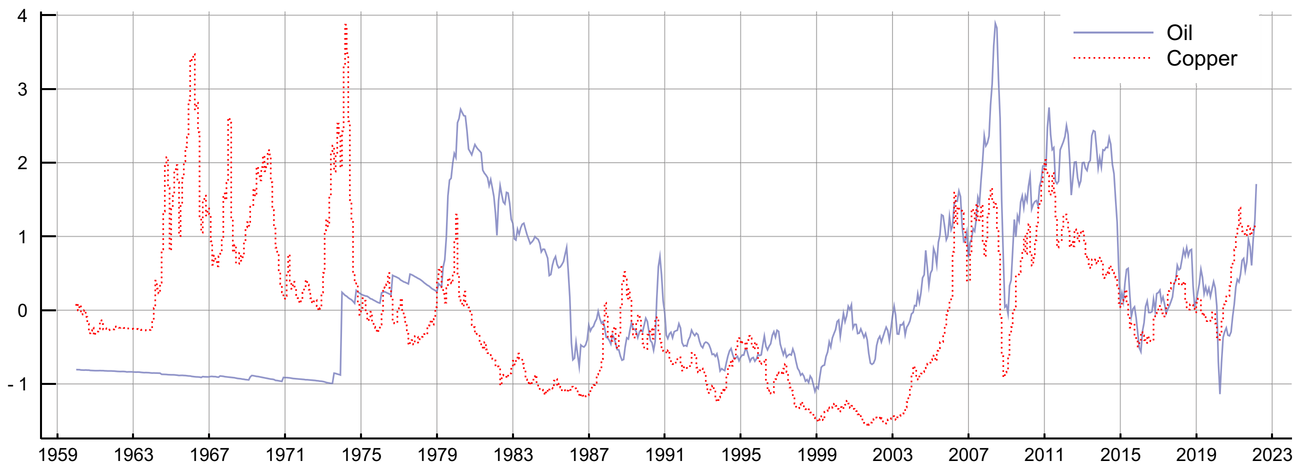

Figure 1. Real price of oil and copper (1960.1–2022.3). The price is normalized with respect to the average and the standard deviation: $p_{s,t} = (p_t - \overline{p})/\sigma$. Prices are WTI Spot Crude Oil Price (dollar per barrel) and BML Refined Copper (dollar per pound), both deflated by USA CPI index. Source: FRED, Federal Reserve Bank of ST. Louis.

Ukrainian war and part of the COVID-19 pandemic episode.

We found that oil prices are much more volatile than copper prices in any possible state. We found a transition from a low to a medium variance regime for the oil price in 1979. We identify infrequent and short-lived episodes of unusually high oil price volatility, related to oil supply disruptions and demand shifts. More specifically, oil prices react more strongly to market cartelization, war episodes, and global demand shifts, like the 2008 Great Recession and the COVID-19. In the case of copper, there is no transition, and episodes of high volatility are not synchronized with periods of high volatility in oil prices. Hence, oil and copper prices may be correlated, but their volatility regimes are remarkably different.

This paper is organized as follows. In Section II, we present a 3-State Markov-Switching model, whose relevant coefficients are estimated through Bayesian techniques. Section III compares the results of estimating these models, in a monthly frequency, for oil and copper price. Finally, Section IV concludes.

II. A 3-state Markov-switching model

Regime switching models characterize the properties of time series in different states. Models in which switching among regimes occurs stochastically, according to a Markov process, are called Markov regime switching models. The Markov switching model is due to Hamilton89 and has been widely applied in economics and finance.[4]

We follow Hamilton (1989) and propose a tractable approach to modelling changes in regime as the outcome of a discrete-state Markov process. The mean and the variance of the real price of oil and copper are parameterized in terms of an unobserved state variable that follows a 3-state Markov process with unknown transition probabilities. We want to determine the probability that the variance of either, the price of oil or copper is, at any point in time, in a given state. [5]

As in Garcia and Perron (1996), we employ and AR(2) process:

$$\left(y_t - \mu_{S_t}\right) = \phi_1\left(y_{t-1} - \mu_{S_{t-1}}\right) + \phi_2\left(y_{t-2} - \mu_{S_{t-2}}\right) + \sigma(S_t)\in_t \tag{1}$$

where the mean μ and the standard deviation of the process, σ, depend on the regime at time t, indexed by S_t. The term, $\in_t$ is a sequence of i.i.d. $N(0,1)$ random variables. The state-dependent means and variances are specified linearly as:

[4]For a more comprehensive exposition of this method, see Hamilton (1994), Kim and Nelson (1999) and Fruhwirth-Schnatter (2004).

[5]Multiple logistic regression is a different statistical technique used when the probability of a dichotomous outcome, such as the presence or absence of a consumer choice, needs to be estimated. This approach is used in Boccia and Sarnacchiaro (2020), but is difficult to extend it to computing a non dichotomic outcome, as in this paper.

$$\mu_{S_t} = \mu_1 S_{1t} + \mu_2 S_{2t} + \mu_3 S_{3t} \quad (2)$$

$$\sigma^2_{S_t} = \sigma^2_1 S_{1t} + \sigma^2_2 S_{2t} + \sigma^2_3 S_{3t} \quad (3)$$

As stressed by Garcia and Perron (1996), to make the model tractable, the stochastic process for the variable S_t should be specified. We follow Hamilton (1989) and model S_t as the outcome of an unobserved discrete-time, discrete-state Markov process. In the case of three-state, first-order Markov process, the transition probabilities are given by:

$$S_{jt} = 1,\ \text{if}\ S_t = j,\ \text{and}\ S_{jt} = 0,\ \text{otherwise. For}\, j = 1, 2, 3 \quad (4)$$

$$Pr[S_t = j | S_{t-1} = i] = p_{ij}, \quad i, j = 1, 2, 3 \quad (5)$$

and

$$\sum_{j=1}^{3} p_{ij} = 1 \quad (6)$$

Gibbs-sampling

As in Albert and Chib (1993) and Kim and Nelson (1999), we implement a Bayesian estimation framework in which the unobserved states, one for each point in time, are treated as missing data and then analysed via the simulation tool of Gibbs sampling. Under this method, the conditional posterior distribution of the parameters, given the states, and the conditional posterior distribution of the states, given the parameters, all have a form amenable to Monte Carlo sampling.

This approach generates marginal posterior distributions for all parameters of interest. The random variables to be drawn via the Gibbs-sampling are the states, $\tilde{S}_T = [S_1, S_2, \ldots S_T]'$, the set of variances, $\tilde{\sigma}^2 = [\sigma^2_1, \sigma^2_2, \sigma^2_3]'$, the mean $\tilde{\mu} = [\mu^2_1, \mu^2_2, \mu^2_3]'$, the transition probabilities, $\tilde{p} = [p_{11}, p_{12}, p_{21}, p_{22}, p_{31}, p_{32}]'$ and the autoregressive coefficients, $\tilde{\phi} = [\phi_1, \phi_2]'$. To insure the identification of the model, within the Gibbs-sampling framework, the constraint that $\mu_1 < \mu_2 < \mu_3$ is included in Equation (2). Given this constraint, there is no need to restrict the values of the variances, σ^2_1, σ^2_2 and σ^2_3.

In our case, the Gibbs-sampling procedure is given by successive iterations of five steps detailed by Kim and Nelson (1999).

(1) Generate $\tilde{S}_T$, conditional on $\tilde{\sigma}^2, \tilde{p}, \tilde{\mu}, \tilde{\phi}$, and $\tilde{y}_T$.
(2) Generate $\tilde{p}$, conditional on $\tilde{S}_T$.
(3) Generate $\tilde{\sigma}^2$, conditional on $\tilde{\mu}$, $\tilde{\phi}$, $\tilde{S}_T$ and $\tilde{y}_T$
(4) Generate $\tilde{\mu}$, conditional on $\tilde{\sigma}^2$, $\tilde{\phi}$, $\tilde{S}_T$ and $\tilde{y}_T$
(5) Generate $\tilde{\phi}$, conditional on $\tilde{\sigma}^2$, $\tilde{\mu}$, $\tilde{S}_T$ and $\tilde{y}_T$

To simulate the posterior distribution of the state variable $\tilde{S}_T$ we use the specification of the multi-move Gibb-sampling $g(\tilde{S}_T | \tilde{y}_T) = g(S_T | \tilde{y}_T) \prod_{t=1}^{T-1} g(S_t | S_{t+1} | \tilde{y}_t)$ were $\tilde{y} = [y_1, \cdots, y_t]'$. Using the Hamilton (1989) filter to get $g(S_t | \tilde{y}_t)$ and $g(S_t | \tilde{y}_{t-1})$, then we can obtain S_t from $g(S_t | S_{t+1}, \tilde{y}_t) \propto g(S_{t+1} | S_t) g(S_t | \tilde{y}_t)$. The corresponding conditional posterior distributions of p_{ii}, σ_1, $\tilde{\mu}$ and $\tilde{\phi}$ are:

$$p_{ii} | \tilde{S}_T \sim beta(u_{ii} + n_{ii}, \overline{u}_{ii} + \overline{n}_{ii}), \mathrm{i} = 1, 2, 3 \quad (7)$$

$$\sigma^2_1 | \tilde{y}_T, \tilde{S}_T, h_2, h_3 \sim IG\left(\frac{v_1 + T}{2}, \frac{\delta_1 + \sum_{t=1}^{T} Y^2_{1t}}{2}\right) \quad (8)$$

$$\tilde{\mu} | \tilde{\sigma}^2, \tilde{\phi}, \tilde{S}_T, \tilde{y}_T \sim N(a_1, A_1)_{I[\mu_1 < \mu_2 < \mu_3]} \quad (9)$$

$$\tilde{\phi} | \tilde{\sigma}^2, \tilde{\mu}, \tilde{S}_T, \tilde{y}_T \sim N(b_1, B_1)_{I[\phi(L) \in s]} \quad (10)$$

Where u_{ii}, $\overline{u}_{ii}$, v_1 and δ_1 are the known hyper-parameters of the priors and their values are chosen ex ante. n_{ii} and $\overline{n}_{ii}$, $i = 1, 2, 3$, are the total number of transitions from state $S_{t-1} = i$ to $S_t = i$ and $S_{t-1} = i$ to $S_t \neq i$ respectively. The posterior variance of $i = 2, 3$ is $\sigma^2_i = f(\sigma^2_1, h_i)$ with $h_i \sim IG\left(\frac{v_i + T_i}{2}, \frac{\delta_i + \sum^{N_i} Y^2_{it}}{2}\right)_{I[h_i > 1]}$. Additionally, the mean and variance in $\tilde{\mu}$ and $\tilde{\phi}$ are defined by $a_1 = (A_0^{-1} + \tilde{S}^{*\prime}_T \tilde{S}^*_T)^{-1} (A_0^{-1} a_0 + \tilde{S}^{*\prime}_T \tilde{y}^*_T)$, $A_1 = (A_0^{-1} + \tilde{S}^{*\prime}_T \tilde{S}^*_T)^{-1}$, $b_1 = (B_0^{-1} + X'X)^{-1} (B_0^{-1} b_0 + X' \tilde{y}^{**}_T)$, $B_1 = (B_0^{-1} + X'X)^{-1}$, $\{a_0, A_0, b_0, B_0\}$ are known hyperparameters of the prior distribution and $I[\cdot]$ refers to an indicator function.

III. Results

We found that oil price volatility is remarkably different across three, well defined, regimes (Table 1).[6] We identify a regime of low price volatility (LV) in which the variance is $\sigma_1^2 =$ 0.096%, a period of medium volatility (MV) where $\sigma_3^2 = 46.9\%$ and a period of high volatility (HV) where $\sigma_2^2 = 525.9\%$. Our model is able to identify these regimes clearly: in each case, the posterior 95% confidence interval, for each estimated variance, does not overlap with the other intervals.

The smoothed probabilities, in Figure 2, show the likelihood that the oil price is in a given volatility regime at each point in time. We found two persistent states across time. The first one, a LV regime, is prevalent from 1948 to 1979. The second one is a MV regime which is present, mostly, from 1979 to 2021. Our results are consistent with the structural break in oil price volatility reported in Dvir and Rogoff (2010), Dvir and Rogoff (2014), Kilian (2010) and previous contributions. This break in volatility is attributed to changes in the oil market structure in the mid-1970s. Since we use monthly data and allow for the possibility of discrete changes in the volatility regime, we are able to provide further insights on this regime change. First, the transition from a LV regime to a MV one happened in January 1979 and not in the mid-1970s, as much of the literature suggests. Second, before 1979 there were several episodes in which the price of oil moved between the LV and MV regimes, as shown in the first and second panel of Figure 2.

We identify a HV regime that is characterized by infrequent and short-lived episodes of unusually high oil price volatility (third panel of Figure 2). There have been five well-identified episodes of HV from the mid-1970s until today.

The first episode of HV is from January to February 1974. This reflects a spike in oil price due to the oil embargo the Organization of Arab Petroleum Exporting Countries (OAPEC) placed on the United States. Previously, in August 1973, there had been an increase in the probability of being in a HV regime, which is related to tensions in the Middle East. In general, the literature, identifies 1974 as when the shift in oil price volatility occurred. Our results tend to support this hypothesis but only partially: in 1974, the oil price volatility increased substantially but only for a brief period. It was only in January 1979 that the volatility of oil prices moved to a HV regime due to the oil crisis in the aftermath of the Iranian Revolution.

Table 1. Estimation results: 3-State model for oil price (1948.01–2022.03).

			Posterior		
Parameter	Density	Prior Mean	Mean	95% posterior interval	
p_{11}	Beta	0.90	0.943	0.92	0.964
p_{12}	Beta	0.05	0.042	0.001	0.073
p_{13}	Beta	0.05	0.014	0.001	0.066
p_{21}	Beta	0.05	0.239	0.010	0.402
p_{22}	Beta	0.90	0.646	0.494	0.836
p_{23}	Beta	0.05	0.115	0.036	0.262
p_{31}	Beta	0.10	0.009	0.000	0.0430
p_{32}	Beta	0.10	0.011	0.003	0.023
p_{33}	Beta	0.80	0.980	0.941	0.996
ϕ_1	Normal	0.00	0.286	0.173	0.375
ϕ_2	Normal	0.00	−0.003	−0.012	0.012
σ_1^2	InvGamma	1.00	0.096	0.070	0.099
σ_2^2	InvGamma	5.00	525.925	319.426	1057.253
σ_3^2	InvGamma	8.00	46.874	40.646	53.159
μ_1	Normal	0.00	−0.255	−0.295	−0.216
μ_2	Normal	0.00	0.017	−0.438	0.561
μ_3	Normal	0.00	0.520	−0.027	1.142

[6]See Appendix for details on the estimation procedure and specifications.

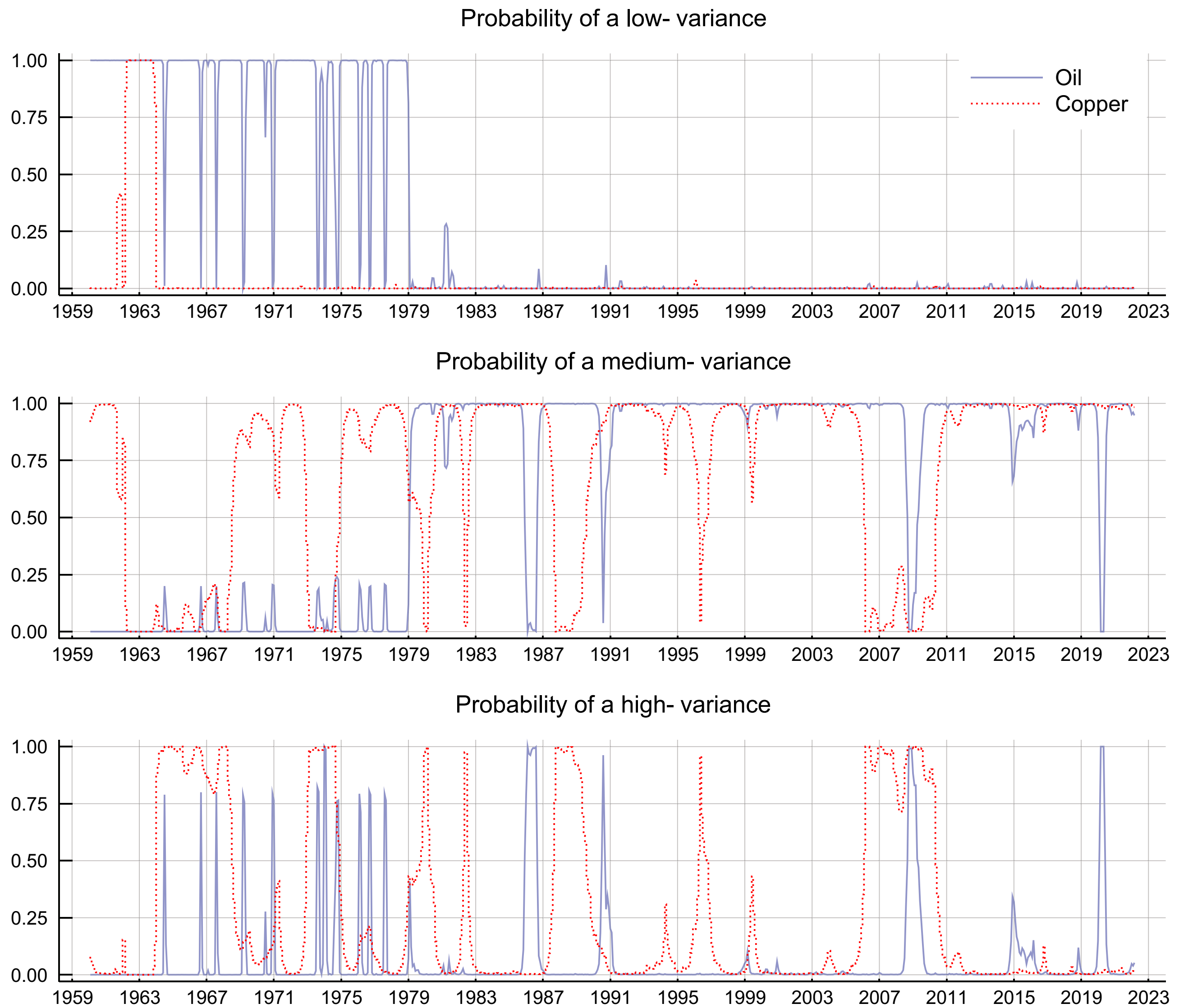

Figure 2. Smoothed probabilities: oil and copper price variance.

In short, our model identifies the 1974 oil crisis as an event that may have changed the *level* of oil prices, but not their volatility.

The second episode of HV was from January to September 1986, reflecting the oil price collapse, which was a direct consequence of increased oil supply by non-OPEC members. From July to September 1990, the third episode was linked to the Gulf War, whereas the fourth episode, from September 2008 to August 2009, was related to the price collapse during the Great Recession. The last episode, from February to June 2020, was after a rapid drop in worldwide demand for oil as governments closed businesses and restricted travel due to the COVID-19 pandemic.[7] In contrast, the Russian invasion of Ukraine, in late February 2022, increased just marginally the probability that the oil price was in a HV state (see last panel in Figure 2).

Overall, the HV episodes were dominated by supply disruptions, although contractions in demand were also present in the last two episodes. Those episodes were short-lived, with a probability of remaining in the same state of $p_{22} = 0.646$. This is well below the probabilities of remaining on the LV regime, $p_{11} = 0.943$, or in the MV regime, $p_{33} = 0.980$.

[7]On April 20th, the May 2020 contract futures price for West Texas Intermediate (WTI) plummeted from USundefined to -USundefined a barrel.

Table 2. Estimation results: 3-state model for copper price (1960.01–2022.03).

			Posterior		
Parameter	Density	Prior	Mean	95% posterior bands	
p_{11}	Beta	0.90	0.977	0.958	0.99
p_{12}	Beta	0.05	0.020	0.008	0.038
p_{13}	Beta	0.05	0.003	0.000	0.008
p_{21}	Beta	0.05	0.062	0.026	0.111
p_{22}	Beta	0.90	0.934	0.883	0.971
p_{23}	Beta	0.05	0.004	0.000	0.014
p_{31}	Beta	0.10	0.031	0.001	0.11
p_{32}	Beta	0.10	0.041	0.001	0.128
p_{33}	Beta	0.80	0.928	0.814	0.994
ϕ_1	Normal	0.00	0.359	0.295	0.425
ϕ_2	Normal	0.00	−0.099	−0.161	−0.038
σ_1^2	InvGamma	1.00	18.591	16.140	21.090
σ_2^2	InvGamma	5.00	99.596	79.998	122.952
σ_3^2	InvGamma	8.00	0.338	0.025	0.078
μ_1	Normal	0.00	−0.286	−0.565	−0.076
μ_2	Normal	0.00	−0.260	−0.666	−0.016
μ_3	Normal	0.00	−0.033	−0.146	0.067

In the case of copper, the three volatility regimes are substantially different from the ones in the oil sector in several dimensions. First, the variance of the copper price is, under any state, lower than its oil counterpart (see Tables 1 and 2). This is the case when comparing the variance's posterior mean in each regime and when comparing the posterior distribution of oil and copper variances (see Figure 3).

Second, in the case of copper, the LV regime is a brief period between 1961 and 1964. According to Crowson (2007) and Jacks and Stuermer (2020), global copper markets achieved a dynamic equilibrium in the late 1950s and early 1960s, expanding the supply capacity and preventing an increase in prices. This kept the price and the volatility low. Third, there is no clear prevalence of either MV or HV regimes over time: the copper price tends to

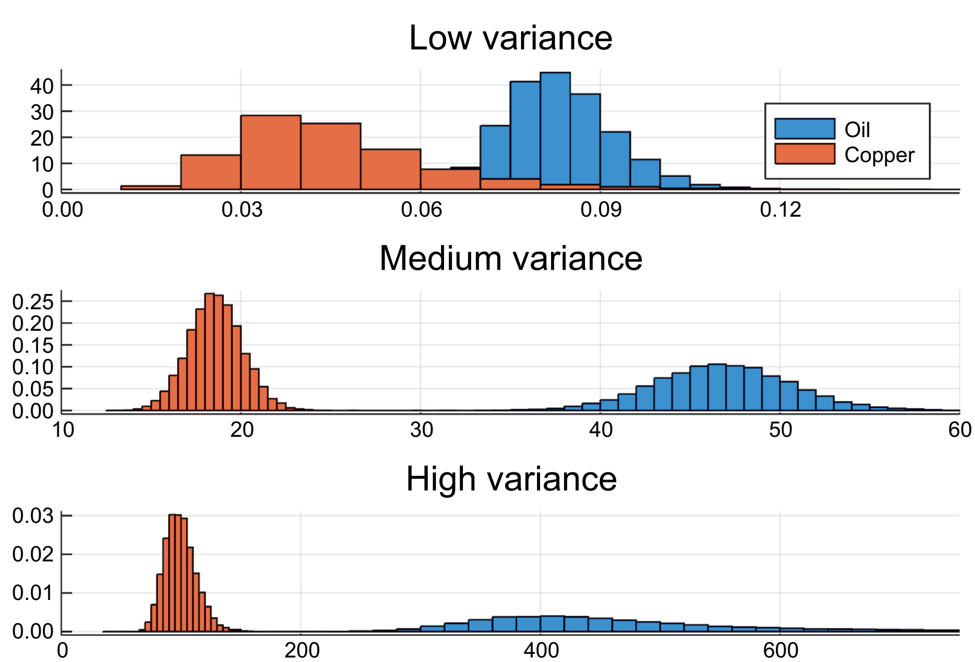

Figure 3. Posterior distribution of oil and copper prices variances.

shift constantly between those regimes.[8] Finally, the HV episodes in the copper price are not generally synchronized with the HV episodes in oil price. They only coincide in 1974 and at the beginning of the Great Recession (2008). In both cases, the episodes last longer in the case of copper.

IV. Conclusions

Movements in the real price of oil and copper are determined by shocks to global demand, precautionary motives, and disruptions in supply. Despite the fact that the relative importance of these forces is still highly debated in the case of oil, the profession has gained important insight on the main drivers of commodity prices. There is, however, little understanding about potential, and continuous, regime shifts in the mean and volatility of commodity price fluctuations.

Using data from 1959 to 2022, we estimate a 3-state Markov-switching model to identify expansions and contractions in oil and copper price volatility. We found that oil prices are much more volatile than copper prices in any possible state. We found a transition from a low to a medium variance regime for the oil price in 1979. We identify infrequent and short-lived episodes of unusually high oil price volatility, related to oil supply disruptions and demand shifts. Oil prices react more strongly to market cartelization, war episodes, and global demand shifts, like the 2008 Great Recession and the COVID-19. In contrast, the Russian invasion of Ukraine, in late February 2022, increased just marginally the probability that the oil price was in a high-volatility regime.

In the case of copper, there is no transition across volatility regimes, and episodes of high volatility are not synchronized with periods of high volatility in oil prices. Hence, oil and copper prices may be correlated, but their volatility regimes are remarkably different.

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[8]The probability of remaining in the MV and HV regime are similar: close to 0.95.

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Appendix
Specifications

We consider the price of crude oil WTI (dollar per barrel) and the London Metal Exchange refined copper price (dollar per pound) from 1948M1 to 2022M03 and 1960M1 to 2022M03 respectively. The Markov-switching model is applied to the price growth. Each model is estimated in two stages. First, we set the priors and then we use the Gibbs-sampling procedure to obtain the posterior distribution of the parameters and the states. This procedure uses 14.000 draws. The first 2.000 draws are discarded to avoid conditioning the posterior distributions on the initial draws.