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MODELLING AND FORECASTING ENERGY MARKET CYCLES: A GENERALIZED SMOOTH TRANSITION APPROACH

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Modelling and Forecasting Energy Market Cycles: A Generalized Smooth Transition Approach

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Abstract

In this paper we investigate the dynamic features of energy commodity prices. Using a generalized smooth transition model (GSTAR) we show that dynamic symmetry in price cycles in the energy markets is strongly rejected. Further, our results show that the proposed model performs well when compared to other linear and nonlinear specifications in a out-of-sample forecasting exercise.

Keywords: energy price commodity price cycles, dynamic asymmetries, nonlinear models, forecasting.

JEL Classification: C10, C22, C53, E32, E37.

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1 Introduction

Fluctuations in energy markets and their impact on the economic system have attracted much attention among economists. It has been shown that energy commodity prices exhibit a range of features such as mean reversion in the long run, volatility clustering, and strong persistence (see the excellent survey by Ederington et al., 2011 and the references therein). But much less attention has been paid to modeling and forecasting asymmetries in energy commodities price cycles. Most of the empirical literature make use of, vector autoregression (VAR), structural VAR models, Granger causality, and several GARCH-type models to analyze supply and demand fluctuations in relation to the business cycle (see, among other, Krichene, 2002; Kilian, 2009; Lippi and Nobili, 2012; Primiceri, 2005; Conrad et al., 2014). Yet, well-established literature on the cyclical behavior of macroeconomic variables suggests that the nonlinearity of commodity energy prices should stem from the asymmetric properties of energy market determinants like GDP, exchange rates, or interest rates.

Against this background, in this paper, we investigate the dynamic behavior in fossil fuel markets. Following the business cycle literature, to which this paper is closely related, we define "boom" and "busts" as extensive periods of time when prices are rising below or above their long-run equilibrium. Questions of interest are: What are the characteristic features of the energy commodity price cycles? Do boom periods last longer than bust periods? Or are troughs deeper than peaks? A closely related question is therefore: What kind of econometric model would best be able to capture the cyclical features of energy prices? Also, do other commodity price dynamics resemble energy commodity prices?

With this target in mind the empirical investigation proceeds in three stages. We start our analysis by testing for asymmetries in the fossil fuel price cycles. In this paper, we focus on two types of asymmetries that may or not occur simultaneously in the energy market cycles: steepness and deepness. As Sichel (1993) points out, steepness occurs when contraction periods are steeper than expansion periods, or vice-versa. Steepness asymmetry relates to the rate of change (slope) of a series, on the other side, deepness asymmetry pertains the levels of the series and it occurs when troughs are deeper than peaks are tall, or vice versa. Accordingly, we test for asymmetric behavior in the energy prices under consideration by using the non-parametric Triples test of Randles et al. (1980). The examination of asymmetry constitutes an important preliminary exercise since in the presence of asymmetry, models assuming symmetry are misspecified and can lead to incorrect inferences being drawn (see for example Blatt, 1980). Therefore, evidence of asymmetrical behavior may help to inform alternative model specifications for the determination of fuel fossil prices. In our case, the Triples test revealed evidence of asymmetric price adjustment in all series of energy prices under consideration.

Evidence of dynamic asymmetries in energy prices opens the question of how to model the data. Accordingly, we proceed to the second step of our investigation and examine the issue of modeling the price series under consideration. To this end, the generalized smooth transition model (GSTAR) suggested by Canepa and Zanetti Chini (2016) (and see also Zanetti Chini, 2018; Canepa et al. 2020; Canepa et al., 2022) is used to estimate energy price dynamics for the sample under consideration. The authors propose a STAR-type model where the logistic smooth transition function has two parameters governing the two tails of the sigmoid function in the nonlinear component of the model. The advantage of the proposed parametrization with respect to the ordinary smooth transition models (STAR) is that the resulting specification can model the tails of the logistic function independently and the rate of change in the left tail of the transition function can be different from the counterpart in the right tail.

Regime-switching models have been often used in the literature to capture cyclicality in energy prices. Applications of these types of models are popular for analyzing the oil market dynamics. In these models, the asymmetry is accommodated by assuming that spot prices evolve according to a piecewise linear autoregression where the transition between states is controlled by a transition variable. Along with a transition variable, a transition mechanism that controls the way the system moves from one state to another has to be specified. In the literature, different transition variables and several types of transition mechanisms have been used to capture the characteristic features of the spot price data-generating processes. For example, Huang et al. (2005) use a threshold model to investigate the impacts of oil price changes and their volatility on economic activity. Röthig and Chiarella (2007) used smooth transition regression models to explore nonlinearities in the response of speculators' trading activity to price changes using weekly data sets of the live cattle, corn, and lean hog futures. On the other side, Bildirici and Ersin (2015) introduced nonlinearity in the conditional variance by specifying the LSTAR-GARCH model to analyze oil prices. STAR-type models allow the dynamic of energy prices to evolve according to a smooth transition between regimes that depends on the sign and magnitude of past realization (see Chan and Tong, 1986). Consensus literature share in common that energy prices are persistent (see Fallahi et al., 2016) and slowly mean reverting (see Kumar Narayan et al., 2010). The low speed of transition between different regimes observed in energy prices supports the choice of smooth transition models. However, these types of nonlinear models rely on symmetric transition functions to capture oscillations from the conditional mean of the energy price series. In this paper, we postulate that although STAR-type models efficiently describe nonlinearity in energy price growth rates (steepness), the logistic transition function commonly used in empirical models may not be suitable to capture dynamic asymmetries in the levels of price cycles (deepness). Accordingly, the GSTAR model is adopted to accommodate departures from symmetry and nonlinearity.

A model specification able to capture the characteristic features of the data-generating process should also be able to produce superior forecasting performance. Accordingly, in the next stage of our investigation, we consider whether forecasting using the GSTAR model leads to important improvements over forecasting with alternative linear and nonlinear models. In the literature, the issue of the forecasting performance of nonlinear models is still an open question. For example, de Albuquerquemello et al. (2018) showed that STAR-type models outperformed VAR, ARIMA, and RW benchmarks both in-sample and out-of-sample for crude oil prices (see also Wang et al., 2017; Huang et al., 2009). On the other side, Rubaszek et al. (2020) found that accounting for nonlinearities did not improve out-of-sample forecasts.

The present paper extends the existing literature in several ways. First, it examines asymmetrical behavior in energy commodity price cycles. We believe that this is the first study that formally tests for cycle asymmetries in the energy markets. Related studies that investigate the turning points mostly draw inferences making use of descriptive statistics, correlation analysis, or dating algorithms (see Cashin et al., 2002). The issue of testing for asymmetric behavior has been largely under-investigated in the literature. Yet, in the presence of asymmetry, models assuming symmetry are misspecified and can lead to incorrect inferences being drawn.

Second, the GSTAR model reveals several insights into the patterns of the energy markets under consideration. In particular, it is found that during expansion periods energy prices deviate from their mean at a logarithmic rate, whereas they return to the equilibrium level at a exponential rate. This implies that the duration of expansion phases exceeds the duration of contraction periods with the amplitude of price increase in booms greater than that of busts. However, crude oil prices feature more extreme cycles with long periods of booms punctuated by sudden rebounds in subsequent booms. The findings of this type of asymmetry are compatible with the model of asymmetric price adjustment where positive demand shocks have a greater relative impact on prices than negative shocks (see Deaton and Laroque, 1992).

Third, many commodity price cycles display characteristic features similar to energy commodities. Analyzing causal relations between energy and other commodity price markets is outside the scope of this paper. However, the fact that the GSTAR model successfully fitted the fuel fossil prices under consideration suggests that the model may be suitable to fit other commodity prices.

Finally, the out-of-sample forecast comparison of the GSTAR with alternative models suggests that the model has superior forecasting properties with respect to other linear and nonlinear specifications. This is especially the case at short horizons.

The remainder of this paper proceeds as follows. In Section 2 a brief review of the literature is given. In section 3 the specification, and estimation of the proposed nonlinear model are presented. In Section 4 the empirical results are described. Section 5 investigates the properties of several other commodities prices. Finally, in Section 6 some concluding remarks are offered.

2 Asymmetries in the Energy Market Commodities

In the literature widely acknowledged empirical evidence on energy market fluctuations has prompted economists to deliver theoretical models to explain this phenomenon. Broadly speaking three strands of research can be identified. A first line of research suggests modeling asymmetries in the energy commodity price cycles in the demand and supply framework where fluctuations in supply are coupled with low demand elasticity for energy commodities. One of the first papers dealing with energy cycles is the study by Gustafson (1958) who introduced rational decision-making behavior in relation to optimal storage decisions. Building on this seminal work Samuelson (1971) showed that the optimal storage model was able to generate a nonlinear first-order Markov process for prices. Subsequent theoretical literature, such as Deaton and Laroque (1992 and 1996) introduced rational expectations into the competitive storage model to explain deviations from equilibrium price. The author introduced a non-negativity constraint on inventories to explain non-linear dynamic behavior in prices of storable commodities (see also Pindyck, 2004; Dvir and Rogoff, 2010). More recent literature suggests that fluctuations in energy prices are closely related to demand and supply misalignment where strong demand is coupled with inelastic supply to create asymmetric cycles. In this respect, Kilian (2009) found that oil price fluctuations since the 1970s have been driven mainly by a combination of aggregate demand and pre-cautionary demand shocks, rather than supply shocks. Similar results are found in Hamilton (2009) where it is suggested that the sharp increase in oil price seen in 2007-08 was mainly driven by strong demand due to the expansion in the global economy that followed stagnation in the supply in 2005-07. Similarly, Kilian and Murphy (2014) showed that the surge in the real price of oil between 2003 and mid-2008 was the cumulative effect of flow demand shocks.

A second strand of literature relates the energy price cycles directly to the business cycles. This strand of literature maintains that interest rates, inflation, and exchange rates affect energy prices, oil prices in particular. For example, Barsky and Kilian (2002, 2004) investigate the relationships between U.S. monetary policy, economic growth, and oil prices from the 1970s to the early 2000s. The authors noted that the sharp increase in the price of oil in 1973-1974 and 1979-1980 were both preceded by sustained economic expansion and abnormally low real interest rates, whereas the global recession in 1982 coincided with a sharp contraction in oil prices. In the same vein, Akram (2009) postulated that oil price increases in response to negative interest rate shocks. However, the author also suggested that US dollar exchange rate shocks caused oil prices to respond asymmetrically, with oil prices responding positively to negative shocks to the value of the dollar. These results are also shared in Sauter and Awerbuch (2003), Chen (2009), Cologni and Manera (2008), Herrera and Pesavento (2009), and Lizardo and Mollick (2010); Bernanke et al. (1997).

Finally, the third strand of literature shares in common that conflicts economic, uncertainty, and geopolitical events are largely responsible for energy price fluctuations. It is generally agreed that conflicts in major oil-producing regions, disruptions in supply chains, or changes in government policies can create price volatility and contribute to the duration of price cycles. For example, Agnello et al. (2020) examine the role of geopolitical tensions and weather conditions in commodity price cycle duration and found that greater economic policy uncertainty, a rise in military conflicts, and an increase in world rainfalls reduce the commodity price booms, whereas the duration of busts is closely related with the deterioration of the world's economic activity, unfavorable climate changes, and military conflicts. Similarly, Kassouri (2022) reported that political, military, financial, and economic shocks play a crucial role in creating large fluctuations in oil consumption (see also Zhang et al., 2023; Dogan et al. 2021; Majeed, et al. 2021).

While the cyclicality of energy prices is well documented in the economic literature, not much is known regarding the statistical properties of energy price cycles. In a rare study, Cashin et al. (2002) examined the properties of the real prices of 36 commodities and suggested that the asymmetry was a characteristic feature of commodity price cycles with slumps exceeding the duration of booms. Evidence of state-dependent asymmetric adjustments and nonlinearity in the speed of the mean reversion to the equilibrium price was also found in Balcilar et al. (2014), Huang et al., (2005), and Ferderer (1996). On the other side, evidence of structural breaks and bubbles in the energy price series was found in Kisswani and Nusair (2013), Alvarez-Ramirez et al. (2015), and Cuestas and Regis (2010), among others.

Such stylized facts reveal that asymmetries that have long been known in the business cycle literature, are also a feature of the energy market cycles. These findings have significant implications for the financial stability of the countries involved. This is because the presence of positive duration dependence found in Agnello et al. (2020) implies that periods of sustained price expansion are increasingly likely to terminate and signal an unsustainable departure from fundamental price valuation. Contractions often act as adjustment periods after long expansions, this implies that the longer the expansion, the deeper and more painful the subsequent contraction (Alqaralleh and Canepa, 2020).

3 The Econometric Model

In this section we focus on modelling energy prices using the GSTAR model. Below we briefly describe the econometric model that is considered in our analysis. We refer the readers to the work of Zanetti Chini (2018) for details on the dynamic asymmetric specification, see also Teräsvirta et al. (2005) for details on smooth transition models.

Let Δy_t be a realization of a the energy price changes (i.e. $\Delta y_t = y_t - y_{t-1}$) observed at $t = 1-p$, $1-(p-1), .., -1, 0, 1, T-1, T$. Then, the univariate process $\{y_t\}_t^T$ can be specified using the following model

$$\Delta y_t = \phi' z_t + \theta' z_t G(\gamma, h(c_k, s_t)) + \epsilon_t, \qquad \epsilon_t \sim I.I.D.(0, \sigma^2) \tag{1}$$

$$G(\gamma, h(c_k, s_t)) = \left(1 + \exp\left\{-\prod_{k=1}^{K} h\left(c_k, s_t\right)\right\}\right)^{-1}. \tag{2}$$

In Eq. (1)-(2) the vectors $z_t = (1, \Delta y_{t-1}, \ldots, \Delta y_{t-p})'$, $\phi = (\phi_0, \phi_1, \ldots, \phi_p)'$, $\theta = (\theta_0, \theta_1, \ldots, \theta_p)'$ are parameter vectors. The process $\{\epsilon_t\}_t^T$ in Eq. (1) is assumed to be a martingale difference sequence with respect to the history of the time series up to time $t-1$, denoted as $\Omega_{t-1} = [\Delta y_{1-(p-a)}, \Delta y_{t-p}]$, with $E[\epsilon_t|\Omega_{t-1}] = 0$ and $E[\epsilon_t^2|\Omega_{t-1}] = \sigma^2$. The expression $G(\tilde{\gamma}, h(c_k, s_t))$ defines the transition function, which is assumed to be continuously differentiable with respect to the scale parameters $\tilde{\gamma} \in (\gamma_1, \gamma_2)$ and bounded between 0 and 1. Also, $G(\tilde{\gamma}, h(c_k, s_t))$ is continuous in the function $h(c_k, s_t)$ and $h(c_k, s_t)$

is strictly increasing in the transition variable s_t. The transition variable s_t is assumed to be a lagged endogenous variable, that is, $s_t = \Delta y_{t-d}$ for a certain integer $d > 0$. The parameters $c_k \in \{1, 2\}$ are the location parameters. Defining $\eta_t = (s_t - c)$ in Eq. (2) we have

$$h(\eta_t) = \left\{ \begin{array}{ll} \gamma_1^{-1} \exp\left(\gamma_1 |\eta_t| - 1\right) & \text{if } \gamma_1 > 0 \\ 0 & \text{if } \gamma_1 = 0 \\ \gamma_1^{-1} \log\left(1 - \gamma_1 |\eta_t|\right) & \text{if } \gamma_1 < 0 \end{array} \right\}, \tag{3}$$

for $\eta_t \geq 0$ ($\mu > 1/2$) and

$$h(\eta_t) = \left\{ \begin{array}{ll} \gamma_2^{-1} \exp\left(\gamma_2 |\eta_t| - 1\right) & \text{if } \gamma_2 > 0 \\ 0 & \text{if } \gamma_2 = 0 \\ \gamma_2^{-1} \log\left(1 - \gamma_2 |\eta_t|\right) & \text{if } \gamma_2 < 0 \end{array} \right\}, \tag{4}$$

for $\eta_t < 0$ ($\mu < 1/2$).

Asymmetric behavior in energy price dynamics is introduced in the model by Eq. (3)-(4). In particular, Eq. (3) models the higher tail of the probability function, whereas Eq. (4) models the lower tail of the probability function. Note that in Eq. (3) and (4) the asymmetric behavior is captured by the slope parameters in $\tilde{\gamma}$. In particular, the speed of the transition between the expansion and contraction regimes in the fossil fuel prices is controlled by the slope parameters $\tilde{\gamma}$. If the vector $\tilde{\gamma} > 0$, the function $h(\eta_{k,t})$ is an exponential rescaling which increases more quickly than a standard logistic function. On the other hand, if $\tilde{\gamma} < 0$, the function $h(\eta_{k,t})$ is a logarithmic rescaling which increases more slowly than a standard logistic function.

Different choices of the transition function $G(\tilde{\gamma}, h(c_k, s_t))$ give rise to different types of regime-switching behavior. In this paper we assume $k = 1$ in Eq. (2), that is we assume that the transition function is a generalized logistic, since the literature on the topic largely support the use of a logistic transition function. In this peculiar case, the parameters on the right hand side of Eq. (1) change monotonically as a function of s_t from ϕ to $\phi + \theta$ and the corresponding transition function is given by

$$G\left(\tilde{\gamma}, h\left(\eta_{1,t}\right)\right) = \left(1 + \exp\left\{ \begin{array}{l} -h\left(\eta_{1,t}\right) I_{(\gamma_1 \leq 0, \gamma_2 \leq 0)} + h\left(\eta_{1,t}\right) I_{(\gamma_1 \leq 0, \gamma_2 > 0)} \\ +h\left(\eta_{1,t}\right) I_{(\gamma_1 > 0, \gamma_2 \leq 0)} + h\left(\eta_{1,t}\right) I_{(\gamma_1 > 0, \gamma_2 > 0)} \end{array} \right\}\right)^{-1} \tag{5}$$

with $h(\eta_{1,t})$ given in Eq. (3)-(4) and $I(\cdot)$ is an indicator function. This parametrization can be interpreted as an endogenous shock on the vector of lagged observable that produces a change in the velocity in which the energy prices passes from a lower extreme to a higher extreme.

The GSTAR nests several well known linear and non-linear models. First, the model in (1) with the transition function in (5) implies that the GSTAR model reduces to a one-parameter symmetric logistic STAR model (see Teräsvirta (1994)) with slope $\gamma_1 = \gamma_2 = \gamma$. However, with respect to the STAR model a clear advantage of the indicator functions in (5) is that slope parameters are not constrained. Positiveness of the slope parameter is an identifying condition which was a crucial assumption in Teräsvirta (1994). Second, the transition function in (5) nests an indicator function $I_{(s_t > c)}$ when $\tilde{\gamma} \to +\infty$. Therefore, the GSTAR reduces to the model in Tong (1983) when $\tilde{\gamma} \to +\infty$ and it becomes a straight line around 1/2 for each s_t when $\tilde{\gamma} \to -\infty$. Finally, the GSTAR model nests a linear AR model when $\tilde{\gamma}$ is a null vector. In this case $h(\eta_t)$ in (5) reduces to a simpler function given by

$$\tilde{h}(\eta_t) = \left\{ \begin{array}{ll} \gamma_1^{-1} \exp\left(\gamma_1 \left|\eta_t\right| - 1\right) & \text{if } \gamma_1 > 0 \\ 0 & \text{if } \gamma_1 = 0 \\ \gamma_1^{-1} \log\left(1 - \gamma_1 \left|\eta_t\right|\right) & \text{if } \gamma_1 < 0 \end{array} \right\},$$

for $\eta_t \geq 0$ $(\mu > 1/2)$ and

$$\tilde{h}(\eta_t) = \left\{ \begin{array}{ll} \gamma_2^{-1} \exp\left(\gamma_2 \left|\eta_t\right| - 1\right) & \text{if } \gamma_2 > 0 \\ 0 & \text{if } \gamma_2 = 0 \\ \gamma_2^{-1} \log\left(1 - \gamma_2 \left|\eta_t\right|\right) & \text{if } \gamma_2 < 0 \end{array} \right\},$$

for $\eta_t < 0$ $(\mu < 1/2)$. This special case is used below to construct a test for the null of linearity against the alternative hypothesis of dynamic asymmetry.

Estimating the GSTAR model involves the use of conditional least squares, that is concentrating the sum of square residuals function with respect to the vectors θ and ϕ, that is minimizing:

$$SSR = \sum_{t=1}^{T} (\Delta y_t - \hat{\psi}' x_t') \tag{6}$$

where

$$\hat{\psi} = [\hat{\phi}, \hat{\theta}] = \left(\sum_{t=1}^{T} x_t'(\tilde{\gamma}, c) x_t(\gamma, c) \right)^{-1} \left(\sum_{t=1}^{T} x_t'(\tilde{\gamma}, c) \Delta y_t \right),$$

and

$$x_t(\hat{\gamma}, \hat{c}) = \left[z_t z_t' G\left(\hat{\gamma}, h\left(\hat{c}, s_t\right)\right) \right].$$

Note that under the assumption that the vectors $\tilde{\gamma}$ and c are known and fixed, the GSTAR model is linear in the vectors θ and ϕ. Therefore, the nonlinear least square minimization problem reduces to a minimization on three (or four) parameters and can be solved via a grid search over γ_1, γ_2 and c.

Before the estimated GSTAR model can be accepted as adequate, it should be subjected to misspecification tests. Some important hypotheses which should be tested are the hypotheses that there is no residual correlation, no remaining nonlinearity and parameter constancy. These tests are discussed in details in Canepa and Zanetti Chini (2016).

Forecasting with the GSTAR Model

Once that an econometric model has been specified one may want to use it to make forecast. The fact that we use a nonlinear model to handle asymmetry in the energy markets has some practical implications. When energy prices are being forecasted using nonlinear models, the estimated forecast densities are asymmetric. This makes multiperiod forecasting less straightforward than linear models.

Consider the case where Δy_t is described by the model in Eq. (1), that is,

$$\Delta y_t = F\left(z_t;\Omega_t\right) + \epsilon_t \tag{7}$$

where is given by $F\left(z_t;\Omega_t\right) = \phi' z_t + \theta' z_t G(\gamma, h(c_k, s_t))$.

Let $\Delta y^f_{t+h|t} = E[\Delta y_{t+h}|\mathcal{I}_t]$ the optimal point forecast of $y|_{t+h}$ made at time t on the base of the past information $\mathcal{I}_t$ up until that time. Based on Eq. (7), the one step-ahead forecast for Δy_{t+1} is given by

$$\Delta y^f_{t+1|t} = E(\Delta y_{t+1}|\mathcal{I}_t) = E\left\{F\left(z^f_{t+1};\Omega_t\right) + \epsilon_{t+1}|\mathcal{I}_t\right\} = E\left\{F\left(z^f_{t+1};\Omega_t\right)|\mathcal{I}_t\right\}, \tag{8}$$

where $z^f_{t+1} = (1, \Delta y_t + \epsilon_t, \Delta y_{t-1}, \ldots, \Delta y_{t-(p-1)})'$. Similarly, for the two step-ahead forecast period we have

$$\Delta y^f_{t+2|t} = E(\Delta y_{t+2}|\mathcal{I}_t) = E\left(F\left(z^f_{t+2};\Omega_t\right) + \epsilon_{t+2}|\mathcal{I}_t\right) = E\left\{F\left(z^f_{t+2};\Omega_t\right)|\mathcal{I}_t\right\},$$

where $z^f_{t+2} = (1, \Delta y_{t+1} + \epsilon_{t+1}, \Delta y_t, \ldots, \Delta y_{t-(p-2)})'$. The exact expression for equation (8) is

$$\Delta y^f_{t+2|t} = E\left(F\left(z^f_{t+2};\Omega_t\right)|\mathcal{I}_t\right) = \int_{-\infty}^{\infty} F\left(z^f_{t+2};\Omega_t\right) d\Phi\left(\omega\right) d\omega, \tag{9}$$

where $\Phi\left(\omega\right)$ is the cumulate density function of ϵ_{t+1}. Note that if in Eq. (3)-(4) the vector $\tilde{\gamma}$ is a null vector, then the h-step-ahead forecast can be obtained recursively in a manner similar to Eq. (8). This the so called "skeleton extrapolation" approach, that in the case of nonlinear models would yield biased forecasts (see for example Granger and Terasvirta, 1993). For the GSTAR model, when the forecast horizon increases, the multi-step ahead forecast is not available in closed form, but it can be computed by numerical integration. If Eq. (9) is solved by numerical integration for the model in Eq. (1) with $p = 1$ and $d = 1$ the two-steps ahead forecast is given by

$$\begin{aligned} \Delta y^f_{t+2|t} &= \int_{-\infty}^{\infty} [\phi_0 + \phi_1(\Delta y^f_{t+1|t} + \omega) + (\theta_0 + \theta_1\left(\Delta y^f_{t+1|t} + \omega\right) \\ & \times \left(1 + \exp - \{h(c_1, \omega)\right\} d\Phi\left(\omega\right) d\omega\right), \end{aligned} \tag{10}$$

where

$$h(c_1, \omega) = \left\{ \begin{array}{ll} \gamma_1^{-1} \exp(\gamma^{-1}\left(\Delta y_{t+1|t} + \omega - c_1 - 1\right), & \text{if } \gamma_1 > 0 \\ \omega - c_1, & \text{if } \gamma_1 = 0 \\ -\gamma_1^{-1} \log(1 - \gamma_1 + \left(\Delta y_{t+1|t} + \omega - c_1\right)), & \text{if } \gamma_1 < 0 \end{array} \right\} \tag{11}$$

for $h(c, \omega) > 1/2$ and

$$h(c_1, s_t) = \left\{ \begin{array}{ll} \gamma_2^{-1} \exp(\gamma^{-1}\left(\Delta y_{t+1|t} + \omega - c_1 - 1\right), & \text{if } \gamma_2 > 0 \\ \omega - c_1, & \text{if } \gamma_2 = 0 \\ -\gamma_2^{-1} \log(1 - \gamma_1 + \left(\Delta y_{t+1|t} + \omega - c_1\right)), & \text{if } \gamma_2 < 0 \end{array} \right\} \tag{12}$$

for $h(c_1, \omega) < 1/2$. Solving the integral in Eq. (10) is relatively easy, however an exact expression for $E[\Delta y_{t+h}|\mathcal{I}_t]$ would involve solving an $h-1$ dimensional integral which is rather time consuming. A less cumbersome approach to obtain a multi-step ahead energy price forecast is by using numerical methods to approximate the integral in Eq. (10). This leaves three possibilities open. The first possibility is to ignore the error term ε_{t+1} and just use the skeleton as suggested in Granger and Teräsvirta (1993). However, this is a rather naive method and it would lead to forecast bias in Eq. (10). A second method is to use the Monte Carlo simulation approach. For Eq. (10), this involves drawing a sample of N independent errors $\left\{\hat{\varepsilon}_{t+1}^{(1)}, ..., \hat{\varepsilon}_{t+1}^{(N)}\right\}$ and compute the Monte Carlo forecast

$$\Delta y_{t+2|t}^{MC} = \frac{1}{N} \sum_{i=1}^{N} g^{MC} \left(z_{t+1|t}^{f}; \xi \right),$$

where ξ is the vector of estimated parameters. As $N \to \infty$ the forecast is asymptotically unbiased by the weak law of large numbers. A possible limitation of the Monte Carlo approach is that it requires assumptions on the distribution of the errors terms. A third possibility is to use bootstrap method to obtain a bootstrap analogue of $\Delta y_{t+2|t}^{f}$ by resampling from the estimated residuals with replacement

$$\Delta y_{t+2|t}^{B} = \frac{1}{N^B} \sum_{B=1}^{N_B} g^{B} \left(z_{t+1|t}^{f}; \boldsymbol{\xi} \right).$$

The procedure can thus easily be replicated to obtain the $h > 2$ steps ahead forecast. In our case, we adopt the moving block-bootstrap method and resample blocks of residuals with block length $b = 10$ and $B = 10,000$ replications to avoid making assumption the distribution of the estimated residuals. Non parametric bootstrap procedures were successfully used in Lundberg et al. (2003) (see also Zanetti Chini, 2018) to forecast STAR-type models. Given that these models are nested in the GSTAR model considered in this work below we follow these authors and generate the h-steps ahead forecast of energy commodity prices by using the block bootstrap procedure to generate the empirical analogue of $\Delta y_{t+h|t}^{f}$, say $\Delta y_{t+h|t}^{B}$.

4 Data and Empirical Results

The data under consideration are related to monthly energy prices from 1987:05 to 2023:06. Specifically, we consider the spot price for Brent oil (Brent), West Texas Intermediate Oil (WTO_t), coal ($COAL_t$) and natural gas (GAS_t). Note that, due to data availability the prices series for COAL and GAS were considered from 1990:1 to 2023:06.

In Fig. 1 a)-d) the estimated Kernel density functions of the energy price series in levels (in the log) are plotted against a Normal distribution. If the data-generating process of energy markets were well represented by a martingale difference stochastic process, then the estimated Kernel density function should look like the Normal distribution represented in bold. However, if contraction and expansion phases were not mirror images of each other, then a martingale different process such as a pure random walk process or an autoregressive model would fail the target. This is because in these models the probability of observing a peak and a trough occurring are identical by construction. Therefore, in Fig. 1 a)-d) departures from the symmetric distribution may provide evidence of asymmetric cycles.

From Fig. 1 a)-d) it appears that the estimated densities may well be described by a convex combination of a mixture of normal distributions with a shape that suggests two separate modes: the lower part of the distribution embodying most of the observations, and another upper part covering the highest values of the series. A first look at the data, therefore indicates that the linear model with Gaussian innovations would not be able to describe the characteristic features of the generating process of the energy markets under consideration.

Figure 1: a)-f) plot the density functions of the different series against a Normal distribution. Note that s denotes the standard deviation of the Normal.

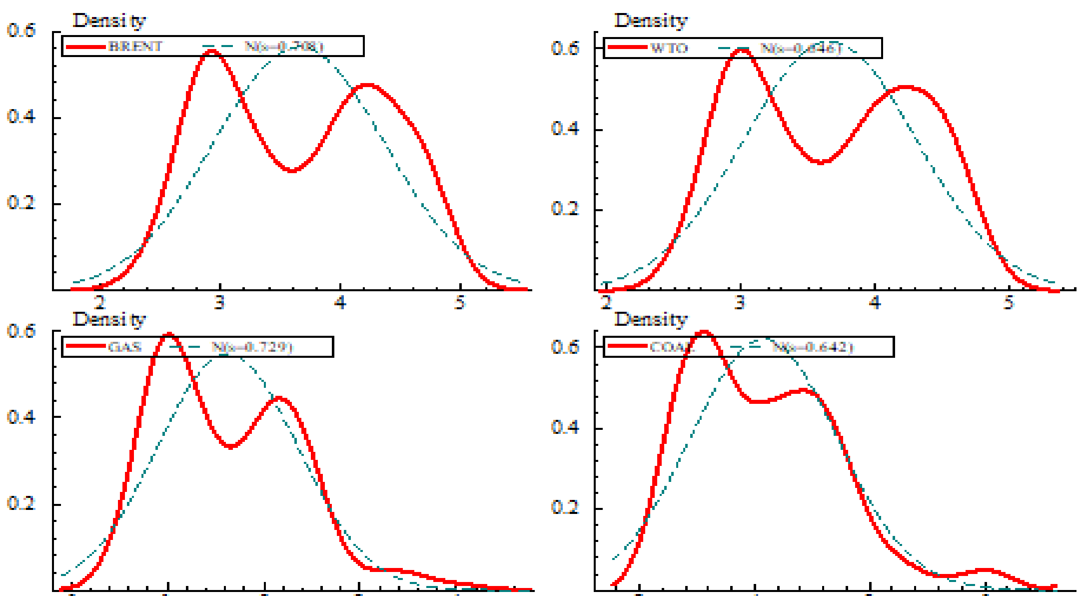

Figure 1: a)-d) plot the density functions of the different series against a Normal distribution. Note that s denotes the standard deviation of the Normal.

A closer look at the plot of the estimated density functions suggests that the distributions of the two crude oil price series are quite different from the other fossil fuel series. From Fig. 1 a)-b) it appears that the crude oil price series are clearly bimodal with a probability density function that may be derived by the convolution of two Normal distributions: a first a Normal random variable with higher mean and smaller variance and a second Normal distribution that features lower mean and larger variance. In addition, the two components are quite far apart from each other (i.e. the mean of the two distributions are quite different from each other). This suggests that oil price cycles are highly asymmetrical with deep troughs and contractions that are steeper than expansions. Looking now at Fig. c)-d), the plot of the estimated Kernel densities for the natural gas and coal series, they also feature the characteristic of a bimodal distribution, but to a lesser extent: the mixture components and the weights for the latter series are more balanced and the estimated Kernel densities are less asymmetric with respect to those of the oil prices. This is particularly true for the coal prices. Overall, a first look at these series indicates that all the energy market price under consideration experience asymmetric cycles, however, the asymmetries seems to be more accentuated for the crude oil price series.

4.1 Testing for Asymmetries in the Energy Market Cycles

To investigate possible asymmetries in the energy commodity market cycles the Triples test suggested by Randles et al. (1980) has been used. Loosely speaking, the test is based on the principle that if a time series exhibits steepness, then its first differences should exhibit negative skewness. On the other hand, if a time series exhibits deepness, then it should exhibit negative skewness relative to the mean or trend. Therefore, a test for steepness can be computed by using the series in the first difference, whereas a test for deepness can be based on the coefficient of skewness of the energy price series in levels (see Randles et al.,1980 for more details).

Table 1 shows the calculated test statistics and relative p-values. In particular, the second column in Table 1 displays the calculated Triples test obtained using the logs of the energy price series. The fourth column reports the same test statistic but calculated using the logs of the first differences of the fossil fuel price series. In both cases, under the null hypothesis, the distribution of the energy price series is symmetric around the unknown median against the alternative of asymmetry. Therefore, failure to reject the null hypothesis implies symmetry. The asymptotic reference distribution of the test is a standard normal random variable. Note that Randles et al. (1980) suggest detrending the series before calculate the test statistic. In our case, the Christiano and Fitzgerald (2003) filter[1] has been used to filter the series of energy prices taken in natural logs.

Table 1. Triples test statistic for symmetry (deepness and steepness).

Energy Market	Deepness		Steepness	
	Triples Test	p-value	Triples Test	p-value
$BRENT_t$	-2.897	0.004	-1.861	0.063
WTO_t	-1.980	0.048	-1.674	0.094
GAS_t	4.241	0.000	0.602	0.547
$COAL_t$	4.919	0.000	1.408	0.159

[1] Note that in their original work Randles *et al.* (1980) use the filter suggested in Hodrick and Prescott (1997) to filter the series prior to testing for asymmetry. However, Hamilton (2018) shows that this filter has several limitations and introduces spurious dynamic relations that have no basis in the underlying data-generating process. For this reason the filter in Christiano and Fitzgerald (2003) has been used in this work.

Note: The acronyms stand for: Brent oil (BRENT), west Texas intermediate oil (WTO), coal (COAL), and natural gas (GAS). Deepness refers to asymmetry in the level of detrended data. Steepness refers to asymmetry in the first difference of the detrended data. The null hypothesis is symmetry; and the under the alternative the series presents asymmetry. The Triples test statistic is asymptotically $N(0,1)$ and the p-values are those of a standard Normal distribution.

From Table 1 it appears that the Triples test detects asymmetric deepness in all the series under consideration since the test statistic is significant at 1% or 5% for the price series in levels. However, the test is significant for the detrended series in first differences only for the two crude oil price series, whilst at 10%. This implies that for crude oil the rate of change of prices is different in the contraction and expansion phases of the cycles.

4.2 Estimation Results

The modeling procedure adopted involves determining the dynamic structure of the series of energy price changes in the first place. In our case, for each energy price series, the maximal lag order of the $AR(p)$ model has been chosen by using the Bayesian information criterion and the Portmanteau test for serial correlation. Then, the second step prior to starting the estimation procedure is to test if the data support the hypothesis of nonlinearity. A natural way of doing it is to perform a test of linearity and check if the model in Eq. (5) reduces to a linear autoregressive model. This can be done by using the LM principle, however, the distribution of such a test would not be identified under the null hypothesis since the parameters $\tilde{\gamma}$ and c in Eq. (5) are not identified under the null. The identification problem can be solved by using a Taylor series approximation to reparametrize the transition function in Eq. (5).

In Table 2 the linearity test, the estimated parameters with the relative standard errors, and the misspecification tests are reported. In particular, the second and the third columns report the estimation results for the two crude oil price series (i.e. $BRENT_t$ and WTO_t), whereas the fourth to the sixth columns relate the results for the other fuel prices (i.e.$COAL_t$, and GAS_t), respectively.

Looking at the top panel of Table 2, on the basis of the empirical p-values reported for the linearity test, the null hypothesis of nonlinearity can be rejected for all energy price series at 1% and 5% significance levels, thus confirming our conjecture that a nonlinear specification needs to be used to model the data at hand.

Coming to the estimation results, from the middle panel of Table 2 it appears that energy price changes are persistent since most of the estimated autoregressive coefficients, ϕ_i and θ_i (for $i = 1, ..., 3$), are significantly different from zero. These results are consistent with the findings in Ghoshray (2011) where evidence of high levels of persistence in energy prices is found (see also Gil-Alana et al., 2020; Haldrup and Nielsen, 2006; Martin-Valmayor et al., 2023; Martin-Valmayor and Gil-Alana, 2022).

The estimated parameters γ_1 and γ_2 for are significantly different from zero for all energy price series. These estimated coefficients give an indication of the speed of the transition between boom and bust regimes, as well as the size of the cyclical peaks and troughs in the energy markets for the period under consideration. In particular, with regard to the signs of these coefficients it is observed that the parameters γ_1 are all negative, whereas γ_2 are all positive. This implies that the energy price series go through contraction phases at an accelerating pace until they reach a local minimum, after which they start to recover with fast decreasing acceleration until they smoothly recover the peak. The speed of the transition from one regime to the other regime increases in periods of energy price contractions at a rate greater than the one which would be consistent with a standard logistic curve (i.e. the exponential rescale of the logistic function is used for contraction periods), but the rate of change of prices in expansion phases is slower than one which would be consistent with a standard logistic function (i.e. the logarithmic rescale of the logistic function is assumed for expansion periods). This implies that when improving economic conditions boosts energy commodity demand above the long-run equilibrium, prices slowly start rising above their expected level. On the other hand, energy prices fall rapidly when the economic conditions worsen and the economic output is below potential. These results are in line with Kilian and Murphy (2014) where it was found that cumulated positive demand shocks push up prices, but will have a small effect on output. In contrast, negative nominal demand shocks have a relatively larger impact on prices than on oil production.

Concerning the magnitude of the estimated γ_1 and γ_2 it appears that the estimated parameters for γ_2 are smaller than γ_1 in modulus for all the series under consideration. This is consistent with the pro-cyclical nature of energy prices described above. However, the estimated coefficients $|\gamma_2|$for natural gas and coal are much greater than those of the two crude oil price series. This implies that the speed of the transition between the boom and bust phases of the former group is much faster than the latter group. The relatively small magnitude of the estimated $|\gamma_2|$ parameters for the oil price series implies that the series are much more persistent during expansion phases with respect to the other fossil fuels, whereas the same is not true during contraction phases. Overall, from Table 2, it appears that the duration of oil price expansions is much longer for oil prices, whereas the contraction periods have roughly similar lengths. These results are consistent with Fig. 1 where it is shown that the plot of the density function for oil prices looks much more asymmetric than those of the other fossil fuels.

Note that the relatively small estimates of γ_1 and γ_2 indicate that other types of nonlinear models in the class of regime switching, such as the Markov switching or the TAR models, are may not be suitable for capturing the energy market dynamics since these models assume that $\gamma_1 = \gamma_2 \longrightarrow \infty$, thus implying a sudden transition between one regime and the next, by assumption. Coming now to parameter c, this indicates the halfway point between the boom and bust phases of the energy markets. In Table 2 the estimated parameter c is statistically significant at the 5% level.

Table 2. Estimation results for energy price series.

	$BRENT_t$	WTO_t	GAS_t	$COAL_t$
Linearity Tests (p-values)				
	0.001	0.000	0.006	0.007
Estimated Parameters				
ϕ_1	-0.072^{**} (0.011)	0.230^{**} (0.012)	0.093^{**} (0.013)	0.296^{**} (0.014)
ϕ_2	0.340^{**} (0.033)	-0.106^{**} (0.021)	-0.075^{**} (0.011)	0.106^{**} (0.016)
ϕ_3	-0.084^{**} (0.007)	-0.164^{**} (0.020)	-0.313^{**} (0.011)	0.183^{**} (0.019)
θ_1	0.223^{**} (0.061)	0.136^{**} (0.040)	-0.277^{**} (0.014)	0.110^{**} (0.029)
θ_2	-0.668^{**} (0.010)	0.109^{**} (0.010)	0.595^{**} (0.067)	-0.220^{**} (0.072)
θ_3	0.065^{**} (0.015)	0.195^{**} (0.091)	0.086 (0.165)	0.067^{**} (0.024)
γ_1	-5.151^{**} (0.386)	-7.151^{**} (0.807)	-7.150^{**} (0.337)	-6.159^{**} (0.499)
γ_2	0.750^{**} (0.188)	1.246 (0.331)	3.250^{**} (0.352)	3.150^{**} (0.399)
c	11.27^{**} (0.133)	-2.456^{**} (0.298)	12.856^{**} (0.178)	7.052^{**} (0.164)
Log Likelihood	-384.19	-387.65	-779.55	-388.73
Diagnostic Tests (p-values)				
LM test for no Corr.	0.452	0.2556	0.126	0.188
LM Test for no Rem. Asy.	0.240	0.3361	0.103	0.114
LM Test for Par. Const.	0.223	0.5673	0.902	0.560

The top part of the table reports the estimated parameters for the GSTAR model and p-values for the misspecification tests are given in the bottom panel. The diagnostic statistics are: $i)$ the LM tests for the hypothesis that there is no serial correlation against the q-order autoregression, $ii)$ the LM test for the hypothesis that there is no remaining asymmetry, $iii)$ the LM test for parameter constancy. Note: ** and * indicate significance level at 5% and 10%, respectively

Figure 2 a)-d) reports the estimated transition functions for the energy markets under consideration plotted against the transition variable (s_t) with one dot for every observation (note that a single dot may represent more than one observation). The plot of the estimated transition functions illustrates the degree of asymmetry of the sigmoid function.

From Fig. 2 a)-d) we notice that the acceleration of the transition is abrupt in the first half and moderate in the second half, which is also consistent with the description of deep cycles from the result of the Triples test in Table 1. The shape of the transition functions reflects the different signs of the estimated slope parameters in Table 2: the negative sign of γ_1 corresponds to an exponential rescaling of the segment 0-0.5 of the vertical axis, whereas the positive γ_2 produces a logarithmic transformation of the upper portion of the estimated transition function.

The plot of the estimated transition functions sheds further light on the degree of asymmetry of the sigmoid function. For the Brent crude oil prices, most of the observations lie in the upper part of the graph, corresponding to the segment between 0.5-0.8 of the vertical axis, while the remaining are in the extreme regime. This reveals the strong procyclical nature of the oil prices with the series increasing more often than it decreases. The plot of the estimated transition of the WTO price series is similar to that of the Brent. However, a less accentuated asymmetrical behavior can be noticed for the natural gas and coal series as the number of observations is more equally distributed between the upper and the lower segment of the estimated transition function.

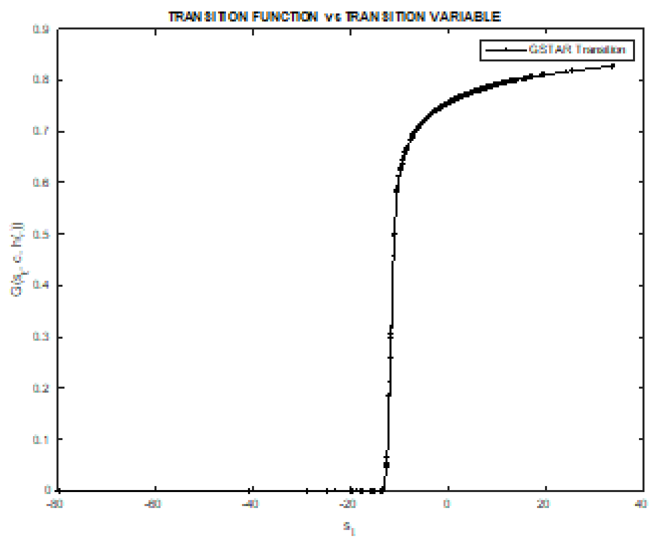

Figure 1. Estimated transition function for BRENT oil prices and the transition variables. .

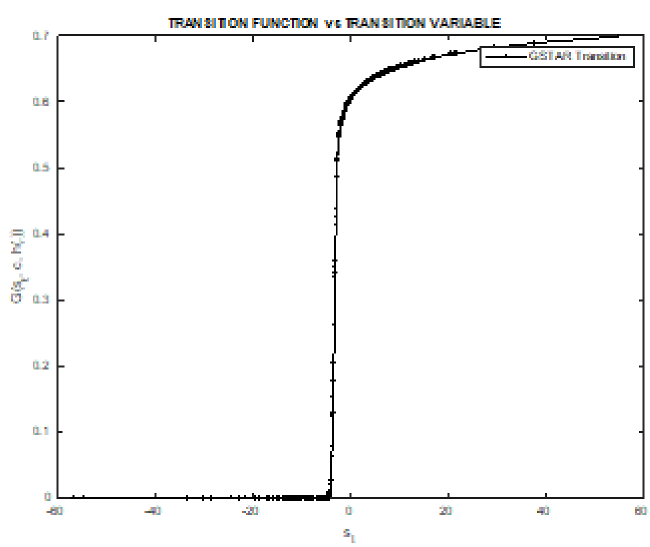

Figure 2. Estimated transition function for WTO crude oil prices and the transition variables. .

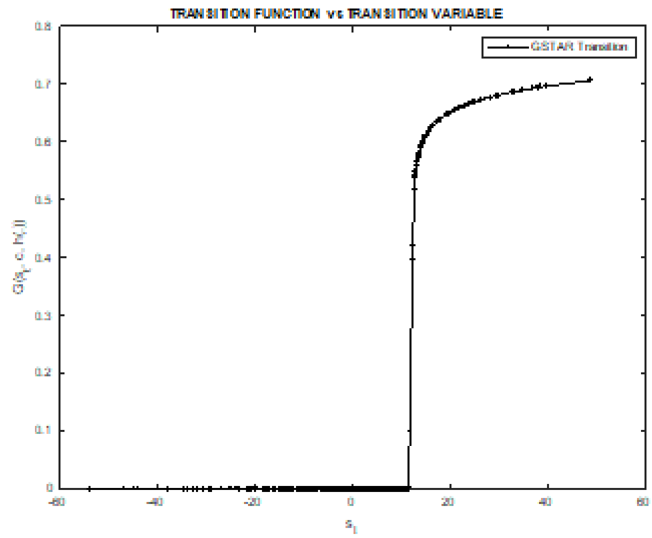

Figure 3. Estimated transition function for natural gas prices and the transition variables.

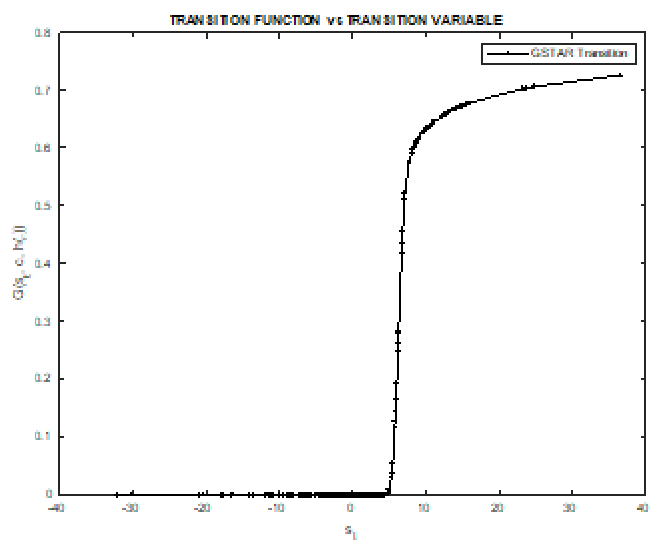

Figure 4. Estimated transition function for coal prices and the transition variables.

Once the model has been estimated, we evaluate the goodness of fit of the model using the misspecification tests suggested by Canepa and Zanetti Chini (2016). In particular, the diagnostic statistics considered are: *i*) the LM test for the hypothesis that there is no serial correlation against the fourth order autoregression (for $q = 4$), *ii*) the LM test for the hypothesis that there is no remaining asymmetry, *iii*) the LM test for parameter constancy. The p-values of the tests are reported in the bottom panel of Table 2. Looking at the results of the misspecification tests it emerges that the test statistic does not reject the null hypothesis of no autocorrelation against q-order autoregression for all estimated models.

There is also no evidence of remaining asymmetry since the LM test does not reject the null hypothesis for all the estimated models. Similarly, the LM test for parameter constancy does not reject the null hypothesis at the 5% significant level for all the estimated models. Overall, the results in Table 2 suggest that the estimated models do not suffer from misspecification problems.

4.3 Forecast Results

In the previous section we presented the estimation results of the GSTAR model. In this section we evaluate the forecasting properties of the model. With this target in mind the commodity price series were split onto two subsamples: a pre-forecast period (for $t = 1, ..., T_{s-1}$) from which the model was estimated and a forecast period $t = T^s, \ldots, T$ with $T^s = t + h$. Then h-step-ahead forecasts were computed and compared with the pre-forecast period. The forecast period under consideration was $h = \{1, 3, 6, 12\}$. Note that, below we only report the results relating to the aggregated data of the Brent price series. The analysis for the other energy commodity price series revealed similar results. For this reason, the output is not reported, but available from the authors on request.

We compare a linear $AR(p)$, and the LSTAR with the GSTAR model in their out-of-sample point forecasts. These models, which are nested in the GSTAR specification, have been popular in forecasting energy commodity prices. For example, the LSTAR specification was used by Röthig and Chiarella (2007) to forecast energy prices (see also de Albuquerquemello et al., 2018). Along with these models, an AR-Markov switching model and an AR-GARCH(1,1) have been considered (see Appendix for details). These specifications were successfully used to predict oil prices in Zou and Chen (2013) and Marchese et al., 2020, (see also Lin et al., 2020; Alizadeh et al., 2008).

Our analysis expands beyond the traditional point forecasts to include density forecasts. Recent studies report that nonlinear models produce superior interval and density forecasts with respect to linear models, although inferior point forecasts (see, for example, Rapach and Wohar, 2006). It is therefore of interest to see how the models considered in this paper compare in their predictive accuracy.

a) Point Forecasts Measures

For the out-of-sample forecast, for robustness, we compare the results of four different measures. Namely, the mean forecast error (MFE), the root mean square forecast error (RMSFE), the symmetric mean absolute percentage error (sMAPE) and the median relative absolute error (mRAE). The four performance measures are calculated as follows:

$$\begin{aligned}
MFE_h &= \frac{1}{T-h-T^s+1}\sum_{t=T^s}^{T-h}\left(\Delta y_{t+h}-\Delta \hat{y}_{t+h|t}\right), \\
sMAPE_h &= \frac{100|\Delta y_{t+h}-\Delta \hat{y}_{t+h}|}{0.5(\Delta y_{t+h}-\Delta \hat{y}^j_{t+h|t})}, \\
mRAE_h &= \frac{|\Delta y_{t+h}-\Delta \hat{y}_{t+h}|}{|\Delta y_{t+h}-\Delta \hat{y}^{(1)}_{t+h}|}, \text{ with (1) indexing the benchmark model;} \\
RMSFE_h &= \frac{1}{T-h-T^s+1}\sum_{t=T^s}^{T-h}\left(\Delta y_{t+h}-\Delta \hat{y}_{t+h|t}\right)^2.
\end{aligned}$$

b) Density Forecast Measures

The literature on the aggregation of density forecasts focuses on the so-called scoring rules (see, for example, Geweke and Amisano, 2011). These are functions that enable the forecaster to aggregate the set of conditional predictive densities. As regards point forecasting, the out-of-sample forecast comparisons based on four different scoring rules were used for aggregating the $T-T^s-h+1$ predictive densities produced by the same forecasting exercise:

The logarithmic score (LogS):

$$LogS_{j,h} = \frac{1}{T-h-T^s+1}\sum_{t=T^s}^{T-h}\log f^j_{t+h|t},$$

which corresponds to a Kullback-Liebler distance from the true density; models with higher LogS are preferred.

The quadratic score, somewhat the equivalent of the MSFE in point forecasting, is defined as:

$$QRS_{j,h} = \frac{1}{T-h-T^s+1}\sum_{t=T^s}^{T-h}\sum_{k=1}^{K}\left(f^j_{t+h|t}-d_{kt}\right)^2,$$

where $d_{kt} = 1$if $k=t$ and 0 otherwise; models with lower QSR are preferred.

The (aggregate) continuous-ranked probability score (CRPS), equivalent to the sMAPE, is defined as:

$$CRPS_{j,h} = \frac{1}{T-h-T^s+1}\times\sum_{t=T^s}^{T-h}\left(\left|f_{t-h}-f^j_{t+h|t}\right|-0.5\left|f_{t-h}-f^{'}_{t+h|t}\right|\right),$$

where f and $f\prime$ are independent random draws from the predictive density and $f_{t+h|t}$ is the observed; models with lower CRPS are preferred.

Finally, the quantile score (qS), which can be obtained if $f^j_{t+h|t}$ is replaced with a predictive α-level quantile $q^{\alpha}_{t+h|t}$ in Eq. (8) (and the logarithmic function is removed); this score is used in risk analysis because it provides information about deviations from the true tail of the distribution.

Table 3. Forecasting energy prices: point and density predictive performances for Brent oil.

Forecast Horizon	Forecast Error Measure	AR(p)	LSTAR	MS	GSTAR	GARCH
PANEL A: Point Forecasts						
1	MFE	-0.733	-0.546	-0.542	-0.538	-0.570
3		-0.798	-0.560	-0.554	-0.509	-0.632
6		-0.940	-0.689	-0.737	-0.606	-0.840
12		-1.199	-0.923	-0.964	-0.835	-1.053
1	sMAE	0.108	0.087	0.090	0.087	0.091
3		0.154	0.097	0.098	0.097	0.960
6		0.179	0.128	0.127	0.118	0.174
12		0.209	0.170	0.170	0.160	0.209
1	mRAE	1.000	0.510	0.535	0.506	0.534
3		1.000	0.525	0.546	0.520	0.542
6		1.000	0.5639	0.550	0.523	0.560
12		1.000	0.585	0.590	0.565	0.560
1	RMSPE	0.053	0.044	0.048	0.037	0.049
3		0.059	0.054	0.049	0.046	0.056
6		0.067	0.058	0.059	0.050	0.060
12		0.074	0.068	0.070	0.068	0.069
PANEL B:Density Forecast						
1	LogS	0.015	0.016	0.018	0.018	0.000
3		0.016	0.017	0.018	0.019	0.001
6		0.019	0.019	0.019	0.020	0.001
12		0.021	0.022	0.017	0.024	0.002
1	QRS	0.014	0.008	0.009	0.007	0.011
3		0.021	0.013	0.025	0.100	0.014
6		0.026	0.014	0.025	0.012	0.015
12		0.027	0.020	0.022	0.019	0.022
1	CRPS	4.614	4.485	4.470	4.483	4.466
3		4.615	4.462	4.473	4.462	4.465
6		4.634	4.451	4.487	4.451	4.474
12		4.694	4.469	4.492	4.469	4.474
1	qS	-0.039	-0.034	-0.038	-0.021	-0.022
3		-0.004	-0.036	-0.041	-0.025	-0.024
6		-0.045	-0.042	-0.047	-0.034	-0.029
12		-0.045	-0.050	-0.050	-0.034	-0.034

The table compares RW, AR(p), LSTAR, AR-GARCH(1,1) models and the GSTAR model in their out-of-sample forecasts. In Panel A the point forecast measures are i) the mean forecast error (MFE); ii) the root mean square forecast error (RMSFE); iii) the symmetric mean absolute percentage error (sMAPE); and iv) the median relative absolute error (mRAE). In Panel B the density forecast measures are: i) the logarithmic score (LogS) SR); iii) the continuous-ranked probability score (CRPS); and iv) the quantile score (qS). The forecast horizon is 1,3,6 and 12 quarters.

Table 3 reports the results of the h-step-ahead forecasts for the forecast period $h = \{1, 3, 6, 12\}$. In Panel A the point forecast measures are reported, whereas the density forecast performance measures are reported in Panel B. In columns 1 and 2 the forecasting horizon and the forecast error measures are respectively reported, whereas in columns 3-6 the forecasting results for each module are reported. From panel A of Table 3 it is clear that, according to the point performance measures, the GSTAR model performs better than its linear and nonlinear counterparts, especially in the medium-term and long-term horizons. However, the results for the logarithmic score are mixed with the AR-GARCH(1,1) occasionally outperforming the GSTAR in the long-term horizons.

5 Do Other Commodity Cycles Resemble the Energy Market Commodities?

In Section 4, the GSTAR model detected widespread evidence of asymmetric adjustment in the energy market cycles. In particular, it was found that deepness and moderate steepness of expansion and contraction phases are the characteristic features of the energy market cycles. Consensus literature shares in common that energy market dynamics have a strong impact on other commodity prices. As Baffes (2007) points out energy price increases impact on agricultural prices as the production costs of food commodities would be expected to increase. Energy enters the production function of agricultural commodities as energy-intensive inputs, such as fertilizer and transportation. Similarly, the model in Ciaian and Kancs (2010) relates agricultural prices to energy market dynamics using a demand-supply framework where the supply of land is fixed and food demand is price-inelastic. As a result, food price dynamics are directly linked to asymmetries in the energy market cycles with agricultural commodity expansion and contraction phases lagging those of energy prices. A recent strand of literature supports the view that major demand shocks experienced by the agricultural sector over recent years arose from the demand for grains and oil seeds as biofuel feedstocks. These studies suggest that the increasing demand for biofuels as a substitute for oil had a strong impact on the demand for corn and soybean (see for example, Gilbert and Mugera, 2014).

Against this background, one question that naturally arises is: To what extent do the energy commodity price dynamics reflect the developments of other commodity prices? In other words, do other commodity markets show similar asymmetric cyclical features?

To answer these questions we consider several commodity markets and test whether the price dynamics of these commodities show characteristic features similar to those observed in the energy market. With this target in mind, we replicate the analysis in Section 4 by testing for asymmetries and nonlinearity in the commodity price cycles using the Randles et al. (1980) and Luukkonen, et al. (1988) tests, respectively. Evidence of nonlinearity indicates that nonlinear specifications should be considered when modeling and forecasting commodity prices. However, the Luukkonen, et al. (1988) test does not point toward any particular class of nonlinear model. Accordingly, to assess whether the GSTAR model is an admissible specification for commodity price series under consideration we also test for dynamic asymmetry. Following Canepa and Zanetti Chini (2016), we specify the following auxiliary regression

$$\hat{u}_t = \hat{z}_{1t}'\tilde{\beta}_1 + \sum_{j=1}^{p} \beta_{2j}\Delta y_{t-j}\Delta y_{t-d} + \sum_{j=1}^{p} \beta_{3j}\Delta y_{t-j}\Delta y_{t-d}^2 + \sum_{j=1}^{p} \beta_{4j}\Delta y_{t-j}\Delta y_{t-d}^3 + v_t \ , \tag{13}$$

where $v_t \sim I.I.D.(0, \sigma^2)$, $\tilde{\beta}_1 = (\beta_{10}, \beta_1')'$, $\beta_{10} = \phi_0 - (c/4)\theta_0$, $\beta_1 = \phi - (c/4)\theta + (1/4)\theta_0 e_d$, $e_d = (0, 0, \ldots, 0, 1, 0, \ldots, 0)'$ with the d-th element equal to unit and $T_3(G) = f_1 G + f_3 G^3$ is the third-order Taylor expansion of $G(\Xi)$ at $\tilde{\gamma} = 0$, $f_1 = \partial G(\Xi)/\partial\Xi|_{\gamma=0}$ and $f_3 = (1/6)\partial^3 G(\Xi)/\partial\Xi|_{\gamma=0}$, $G(\Xi)$ is given in the Eq. (2). To test the null hypothesis

$$\mathcal{H}_0 : \beta_{2j} = \beta_{3j} = \beta_{4j} = 0 \qquad (j = 1, \ldots, p). \tag{14}$$

in Eq. (14) the following LM statistic can be used

$$LM = (SSR_0 - SSR)/\hat{\sigma_v}^2 \ , \tag{15}$$

where SSR_0 and SSR denote the sum of the squared estimated residuals from the estimated auxiliary regression Eq. (13) and under the null and the alternative, respectively, and $\sigma_v^2 = (1/T)SSR$. Under the null hypothesis the LM test in Eq. (15) is asymptotically distributed as a χ_p^2 distribution.

Table 4 reports the three test statistics for a large range of commodities. In columns two and three the p-values for the Triples test are reported, whereas in columns four and five the p-values for the calculated test of nonlinearity and dynamic symmetry are given, respectively.

Table 4. Linearity and dynamic symmetry tests for other commodity prices.

Commodity	Deepness	Steepness	Nonlinearity test	Dynamic Symmetry
	p-value	p-value	p-value	p-value
Metals				
Aluminium	0.025	0.293	0.035	0.012
Copper	0.007	0.343	0.040	0.001
Lead	0.038	0.892	0.041	0.050
Nickel	0.222	0.481	0.603	0.759
Steel	0.389	0.542	0.471	0.268
Tin	0.317	0.925	0.931	0.997
Zinc	0.844	0.817	0.394	0.988
Grains				
Barley	0.024	0.055	0.064	0.280
Corn	0.091	0.098	0.081	0.065
Rice	0.035	0.053	0.002	0.094
Wheat	0.006	0.013	0.005	0.013
Animal Products				
Beef	0.014	0.051	0.003	0.091
Hides	0.031	0.154	0.045	0.012
Lambs	0.317	0.142	0.156	0.254
Minerals				
Iron Ore	0.014	0.178	0.003	0.027
Phosphate	0.001	0.036	0.010	0.014
Potash	0.000	0.124	0.035	0.000
Sulfur	0.562	0.428	0.907	0.939
Soft Commodities				
Cocoa	0.332	0.004	0.002	0.009
Coffee	0.000	0.017	0.007	0.026
Cotton	0.001	0.387	0.003	0.025
Palm oil	0.067	0.725	0.005	0.004
Sugar	0.000	0.448	0.023	0.039
Tea	0.709	0.147	0.902	0.998
Wool	0.865	0.135	0.633	0.992
Other Energy Commodities				
Heating Oil	0.001	0.069	0.023	0.046
Dubai Oil	0.032	0.091	0.007	0.009
Gasoline	0.067	0.145	0.047	0.078

Note: The table reports the calculated p-values for the Triples, the nonlinearity, and the dynamic asymmetry tests, respectively.

Looking at the results in Table 4, it appears that the characteristic features of other commodity price cycles are quite similar to those of energy commodities. This is particularly true for agricultural products related to ethanol production and oil seed rape for biodiesel production. Metal commodity prices such as aluminum, copper, and lead also feature asymmetric cycles. These results may be because energy commodity prices enter the aggregate production function as input cost, therefore any development in the energy market would have repercussions on the other commodities markets. However, food commodities can be used to produce substitutes for crude oil. These results seem to support the findings of Gilbert and Mugera (2014) who postulated that the recent expansion of biodiesel production has profoundly affected food commodity price dynamics.

5.1 Discussion

In the last few years a great deal of attention has been paid to the understanding of the price formation mechanisms of energy markets and several researchers pointed out that large fluctuations in energy commodity prices impact exchange rate (Hamilton, 1983), inflation (Bernanke et al., 1997) and economic growth (Rogoff, 2006). However, the available literature has largely neglected the very feature that most attracts the attention of investors, economists, and policymakers alike, namely, that there are extensive periods when energy prices rise and fall. Also, the steepest the rise, the more pronounced the fall, with all the dramatic consequences that a large number of empirical and theoretical works have so well explained. Accordingly, before concluding this section a question is in order: What do we learn about energy commodity price dynamics that the literature has so far missed?

First, evidence of asymmetry in Section 4 provides support against the class of linear models with symmetric distributions. However, looking at the estimation results in Section 4 it is clear that the transition function commonly used in STAR-type models may be useful to capture nonlinearity in the energy commodity price cycles, but may not be the best specification to capture asymmetric oscillations from the conditional mean. This is because the sigmoid function used in the transition equation is reflexively symmetric by construction. In this respect, Zanetti Chini (2018) shows that the logistic transition function used in the logistic STAR model is able to reproduce steepness, but not deepness. A small-scale Monte Carlo simulation experiment by Canepa et al. (2022) corroborates these results. The authors suggest that using a class of models indexed by two shape parameters that influence the symmetry and heaviness of the tails of the fitted transition equation produces a model that was better able to fit the non-central probability regions of the density function of the distribution at hand. Despite the difference in methodology, the results in Section 4 support Cashin et al. (2002) main conclusions that model specifications for energy price series should focus on two types of asymmetries simultaneously (see also Gately and Huntington, 2002). These results are also supported by theoretical business cycle literature, to which this work is closely related. For example, Sichel (1993) noted that models of asymmetric price adjustment can generate deepness (also De Long and Summers, 1998; Ball and Mankiw, 1994; Clark and Laxton, 1996).

Second, a good forecasting model should be able to capture both types of asymmetries, since superior descriptive accuracy usually delivers better forecasting properties (see Teräsvirta et al., 2005). The results in Section 4 confirm evidence in de Albuquerquemello et al. (2018) that STAR-type nonlinear models surpass their linear counterparts in relation to their accuracy, however, our findings suggest that the GSTAR model beats its competitors for point forecasting, although this superiority becomes less evident for density forecasting. Unlike Chinn and Coibion (2014) we doubt that the efficient market hypothesis can be supported for energy prices as the AR(p) model is the worst performer model.

Third, although this application focuses on energy commodity markets, from Section 5, it is clear that the GSTAR model may be a useful specification for several other commodity prices. This result highlights the fact that different types of econometric specifications have to be used for particular commodities simply to reflect their relation with the real economy. Looking forward, a multivariate modification of the GSTAR proposed in Canepa and Zanetti Chini (2016) that allows us to investigate possible correlations between commodities markets would be an interesting development.

6 Conclusion and Policy Implications

In this paper, the generalized smooth transition model proposed by Canepa and Zanetti Chini (2016) is applied to energy commodity prices to investigate the asymmetrical behavior of fossil fuel price cycles. In particular, we consider crude oil, natural gas, and coal spot prices and investigate if the GSTAR model is an admissible specification for the energy price series under consideration. The model is able to accommodate nonlinearity in the conditional mean in a highly flexible manner while the generalized logistic function preserves the smoothness of the transition function by construction. It is found that the fuel commodity prices under consideration deviate from their mean at a logarithmic rate during boom periods, whereas they return to the long-run price equilibrium level at an exponential rate. This implies that expansion phases last longer than contraction phases and peaks are higher than troughs are deep. However, gas and coal prices are found to be more procyclical than oil prices, whereas crude oil prices are more prone to extreme price drops. This may be due to a greater level of financialization of crude oil which exposes the price of the physical commodity to greater volatility (see Ellen and Zwinkels, 2010).

The GSTAR model handling the asymmetry in energy prices has several policy implications. Evidence of dynamic asymmetries suggests that economic agents face asymmetric risks. In this respect, policymakers may reduce the impact of large price fluctuations in a number of ways. For example, tightening monetary policy may be used to control inflationary pressures during sustained expansion phases. Macroprudential measures may also be implemented to manage external capital flow and international arbitrage opportunities. In this respect, Hofmann and Takats (2015) suggest that in a financially open economy monetary policy tools may be implemented along with macroprudential policies to reduce the impact of large commodity price fluctuations on the real economy (see also Bruno et al. 2017; and Cerutti et al., 2017; Kharroubi and Zampolli, 2016).

Also, for countries with high energy dependence, fiscal policy can be used to reduce fuel fossil dependence as well as carbon emissions. In this respect, fiscal policy offers a number of levers to reduce carbon emissions. For example, leveraging fiscal policy to support renewable energy investments can reduce the exposure to the procyclicality of fuel fossil prices. Carbon taxation on the production or consumption side can reduce fuel fossil dependence and mitigate climate change. Similarly, debt-financed public investments in emission-reducing infrastructure can reduce the exposition to fuel fossil commodity price cycles. Energy price fluctuations also remain a key challenge for energy-exporting countries. Governments of oil-producing countries often rely heavily on revenue from oil production. Countries may also seek to mitigate the risks of energy commodity price fluctuations on fiscal accounts through the use of financial derivatives, such as forward contracts, or the issuance of oil-linked bonds (Daniel, 2002).

APPENDIX: Estimated alternative models for Brent crude oil prices.

AR(3) Model:

$$\Delta y_t = \underset{(0.666)}{0.114} + \underset{(0.000)}{0.268^{**}}\Delta y_{t-1} + \underset{(0.062)}{0.263^{**}}\Delta y_{t-2} - \underset{(0.003)}{0.034^{**}}\Delta y_{t-3} + \varepsilon_t,$$

Log-Likelihood: -1162.843; LM test for Serial Error Correlation p-value: 0.412; Akaike info criterion: 6.093; Schwarz criterion: 6.134.

LSTAR Model:

$$\begin{aligned} y_t \quad = \quad & \underset{(0.0006)}{0.0027^{**}} + \underset{(0.113)}{0.450^{**}} y_{t-1} + \underset{(0.133)}{0.362^{*}} y_{t-2} - \underset{(0.140)}{0.138} y_{t-3} - \underset{(0.134)}{0.198} y_{t-4} \\ & + \underset{(0.0038)}{0.0040} + \underset{(0.170)}{0.484^{**}} y_{t-1} - \underset{(0.221)}{0.648^{**}} y_{t-2} - \underset{(0.222)}{0.696^{**}} y_{t-3} \\ & + \underset{(0.124)}{0.329^{**}} y_{t-4} \times \left[1 - \exp\left(-\underset{(245.22)}{5.53^{*}}\left(y_{t-4} - \underset{(0.001)}{0.020^{**}}\right)\right)\right]^{-1}, \end{aligned}$$

Log-Likelihood: -443.980; LM test for Serial Error Correlation p-value: 0.196; Akaike info criterion: 5.134; Schwarz criterion: 5.041.

Markow Switching Model:

$$\begin{aligned} y_t \quad = \quad & \underset{(0.005)}{0.090^{*}_{s1}} + \underset{(0.087)}{0.115} y_{t-1,s_1} + \underset{(0.091)}{0.185^{**}} y_{t-2,s_1} + \underset{(0.000)}{0.462^{*}} \sigma_{t,s_1}, \\ & \underset{(0.007)}{0.255^{**}_{s2}} + \underset{(0.066)}{0.292^{**}} y_{t-1,s_2} + \underset{(0.047)}{1.856^{***}} \sigma_{t,s_2}, \end{aligned}$$

The estimated transition probability matrices for s_{1t} and s_{2t} are:

$$Pr_1 = \begin{bmatrix} P\left(s_{1,t} = 1 | s_{1,t-1} = 1\right) & P\left(s_{1,t} = 1 | s_{1,t-1} = 2\right) \\ P\left(s_{1,t} = 2 | s_{1,t-1} = 1\right) & P\left(s_{1,t} = 2 | s_{1,t-1} = 2\right) \end{bmatrix} = \begin{bmatrix} \underset{(0.649)}{4.026^{**}} \\ \underset{(0.736)}{-4.612^{**}} \end{bmatrix},$$

Log-Likelihood: -1066.980; LM test for Serial Error Correlation p-value: 0.198; Akaike info criterion: 5.605; Schwarz criterion: 5.770.

AR-GARCH-M(1,1) Model:

$$\begin{aligned}\Delta y_t &= \underset{(0.152)}{-0.082} + \underset{(0.051)}{0.120^{**}} \Delta y_{t-1} + \underset{(0.069)}{0.120^{*}} \sigma_t^2 + \varepsilon_t, \\ \sigma_t^2 &= \underset{(0.038)}{0.060} + \underset{(0.053)}{0.029^{**}} u_{t-1}^2 + \underset{(0.000)}{0.782^{**}} \sigma_{t-1}^2.\end{aligned}$$

Log-Likelihood: -1043.980; LM test for Serial Error Correlation p-value: 0.578; Akaike info criterion: 5.465; Schwarz criterion: 5.547.

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