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Renewable versus nonrenewable resources: an analysis of volatility in futures prices

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This study outlines a new approach for differentiating commodity futures based on their exhaustibility. Various aspects of volatility in the futures prices of renewable resources (palm oil, coffee, soya beans, rice, wheat and corn) and nonrenewable resources (zinc, aluminium, natural gas, gold, crude oil and copper) are studied, exploring whether volatility is greater in the former than in the latter. We use a generalised autoregressive conditional heteroskedasticity (GARCH) model to test our main hypothesis that the volatility in futures prices for renewable resources has recently been equal to or greater than the volatility in futures prices for nonrenewable resources. Our key findings suggest that futures prices for some renewable resources have greater variance than those for benchmark crude oil in a simulated GARCH series. We extend our analysis using a nonlinear vector smooth transition autoregressive (VSTAR) model to test for the existence of a shifting-mean tendency in the commodity series that we researched. We show that transition from a stable to a volatile regime is more abrupt for renewable resources.

Key words: futures, GARCH, renewable resources, volatility, vector smooth transition autoregressive.

1. Introduction

Fluctuations in commodity prices are of serious concern to exporters and importers across industries. This paper concentrates on the persistent volatility in related financial products, namely, commodity futures. According to the literature, futures prices are the optimal forecast of the spot prices (e.g. Chinn and Coibion 2014) and therefore an appropriate tool for evaluating volatility patterns of commodities. Bhardwaj *et al*. (2015) show that commodity spot prices are affected by a seasonality factor and exhibit predictable mean reversion. Such a factor is anticipated by the futures prices and therefore does not have an affect on it. Our analysis relies on continuous futures prices with a rollover feature of the contract (data obtained via the Bloomberg Terminal).

The volatility of prices for commodities futures has been analysed by various researchers across different periods. One early analysis of commodities' volatility based on their renewability is offered in a report by the U.S. National Academy of Sciences (Weiss 1962). A majority of the studies (e.g.

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Verleger 1993; Fleming and Ostdiek 1999; Regnier 2007) argue that prices for crude oil and natural gas are more volatile than those for other products.

During some periods, trading in commodity futures is cross-linked and causes significant co-movements. This pattern has been noticed by a number of researchers (e.g. Du *et al.* 2011; Jebabli *et al.* 2014), as trading in oil futures directly affects trading in other commodities. Such correlation could eventually lead to volatility spilling over from oil futures to different commodities. However, increased volatility may be a result of other fundamental factors, such as exhaustibility. The goal of this paper was to explore how volatility differs across commodity groups based on their exhaustibility feature.

For the purposes of this analysis, following conventional usage, we define renewables as resources (agricultural commodities) that can be physically replenished over time or reused, such as palm oil, corn, wheat, soya beans, coffee and rice. In contrast, nonrenewable (exhaustible) resources are those that are physically limited and cannot be reproduced over time, including aluminium, zinc, natural gas, gold, crude oil and copper. Uneven but overall rising demand for renewable resources, the rising frequency of extreme weather events, the active use of agricultural products for energy purposes and other factors have had a significant impact on agricultural commodity prices. A number of studies suggest that usage of agricultural products in biofuels production is a key demand curve shift factor (e.g. Ajanovic 2011; Huchet-Bourdon 2011).

The baseline GARCH (1,1) model is the main empirical method used for testing our core hypothesis. The hypothesis is that recent volatility of futures prices for the renewable resources examined has been equal to or greater than volatility of futures prices for nonrenewable resources. As the data also exhibit nonlinearity, we also use nonlinear vector smooth transition autoregressive (VSTAR) modelling to compare the transition speed from one regime to other for different resources.

The rest of the paper is structured as follows. Following a review of the literature in Section 2, we proceed in Section 3 to a discussion of the data in the time and frequency domains, in order to provide a clear picture of the selected futures. Section 4 describes the empirical methodology, which includes GARCH modelling and nonlinear VSTAR analysis applied on the selected futures. The obtained results are described in Section 5 for calculated variances and means of renewable and nonrenewable resources, and conclusions follow in Section 6. Appendixes are presented in Supporting Information.

2. Literature review

The problem of volatility in the price of a variety of products has been analysed in different ways. For example, Pindyck (1999) examined volatility in the price of oil, coal and natural gas over a long time horizon, with the main finding that the price of crude oil is much more volatile than that for natural gas and coal. Volatility in the prices of agricultural products has also been analysed extensively. Huchet-Bourdon (2011) found that volatility in the price of agricultural commodities was higher in the period 2006–2009 than in the 1990s and that variance tests also showed a significant increase in volatility in 2008 for almost all commodities.

One strand of literature that expanded after the Global Financial Crisis of 2007–2009 concerns the effect of fluctuation in crude oil prices on energy and nonenergy commodity futures. Baffes (2007) and Baffes and Haniotis (2010), for example, using econometric tools, show the potential effects of high oil prices on energy and nonenergy commodities. Baffes (2007) showed that during the period 1960–2005 an increase of 10 per cent in the price of crude oil increased the price of nonenergy commodities by 1.6 per cent. Baffes and Haniotis (2010) indicated that the financial crisis strengthened this relationship, in that an increase of 10 per cent in the oil price now increases nonenergy prices by 2.6 per cent. Manera *et al.* (2012) tested spillover effects from energy commodities trade to agricultural commodity futures. The main findings of their multivariate GARCH model illustrated the dependence of agricultural commodities on trading in energy futures.

Enders and Holt (2013) applied econometric modelling (vector autoregression (VAR)) to an analysis of energy and grain prices. The authors identified a mean-shifting pattern in the group of commodities that they researched. The trend towards mean switching is evident in real energy prices, whereas in agricultural products, it is not clear. As also mentioned in Bernard *et al.* (2012), futures for renewables do not show this trend but have very high volatility.

Knittel and Pindyck (2013) analysed oil prices and determined that speculation is not the key driver of futures prices, although speculative behaviour is consistent with data on production, consumption, inventory change and changes in yields. The empirical analysis carried out by Hamilton and Wu (2013) accords with that finding.

The proliferation of index funds in the market for commodity futures is yet another factor in volatility. Basak and Pavlova (2013) noted that the price increase is higher for futures included in an index fund than it is for nonindexed funds, perhaps because institutional investors care more about index performance and therefore want to keep the price higher. In a similar vein, empirical works by Singleton (2012) and Tang and Xiong (2012) identified increased volatility for index-traded futures. Pooling several commodities in an index that is traded on an exchange is one manifestation of the financialisation of commodities. In contrast, Bohl and Stephan (2013) conducted an empirical analysis of futures contracts, studying the effect on six heavily traded agricultural and energy commodities. They concluded that the increased financialisation of raw material markets did not increase volatility in commodity futures.

Clearly, the relevant literature on the subject is very rich, so we can only capture some of the main studies pertaining to our research. One common theme across these studies is the financial interconnectivity between different commodity groups. However, to the best of our knowledge, no studies have compared financial volatility in commodity futures based on their exhaustibility. We attempt such a comparison in this study.

3. Analysis in time and frequency domains

The reason we selected these particular commodities for our study was the dominance of these products on the market as a share of international trade. According to the literature (Agnolucci 2008; Gevorkyan and Gevorkyan 2012), of all the nonrenewable resources, crude oil and gold are believed to have the greatest socio-economic significance. Other nonrenewables, such as natural gas, zinc, aluminium and copper, are important as well. All of them are included in our sample based on their exhaustibility. In terms of renewables, corn, wheat and rice are critical agricultural (renewable) commodities for a number of countries (e.g. the United States of America, member states in the European Union and Southeast Asian countries), and our sample includes them as well as palm oil, soya beans and coffee. Commodities in each group have been selected based on their total trading value and significance on the global scale.

Fluctuation in the price of crude oil futures has also contributed to price swings for other renewable and nonrenewable resources. Some of those jumps in volatility have been the most severe since the Global Financial Crisis, as seen in Figures 1 and 2. Palm oil, crude oil and copper have very similar patterns; they reached a peak in 2009 and then collapsed, with a gradual rebound to previous levels by 2012. However, coffee, wheat and corn do not have identifiable patterns; their price movement has been more unpredictable

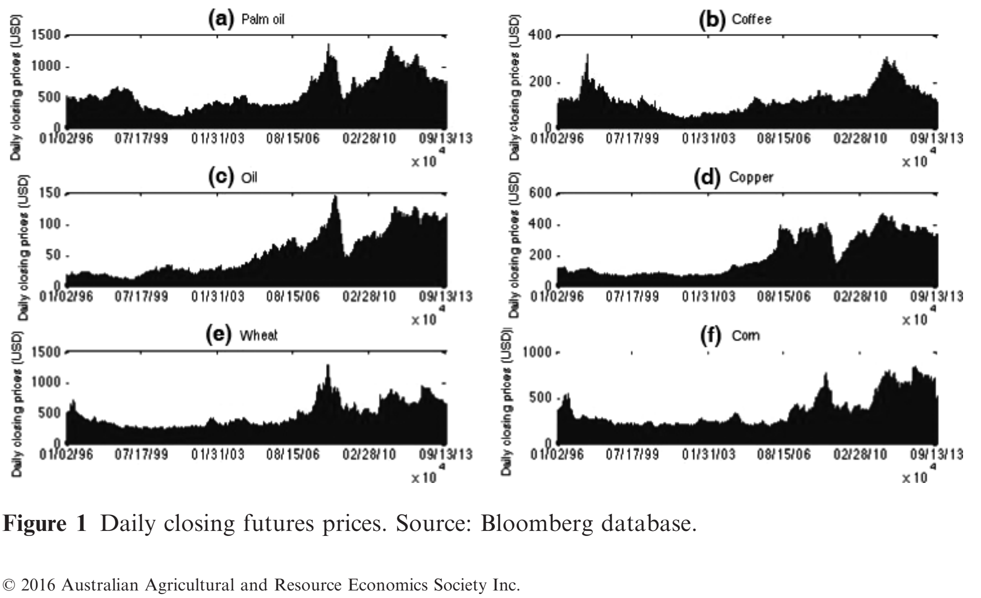

Figure 1 Daily closing futures prices. Source: Bloomberg database.

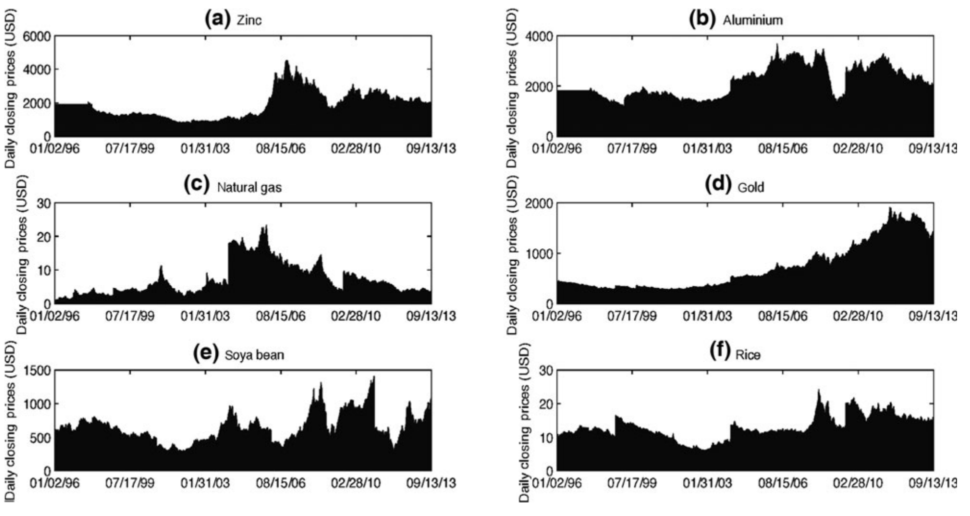

Figure 2 Daily closing futures prices (cont'd). Source: Bloomberg database.

over the past decade. The price of gold has risen continuously for the past twenty years. However, soya beans and rice are at roughly the same price as they were about two decades ago.

While Figures 1 and 2 do not give a precise comparison between the volatility of renewable and nonrenewable resources, each commodity in the sample shows high levels of instability in time series and stochastic movement. Separately, we analyse available data and compare time-domain and frequency-domain observations. In other words, the information seen in the time domain can be extended in a more detailed way in a frequency-domain representation or spectral analysis.

Data can be transformed from time to frequency domains using a Fourier transformation in an analysis of time series. Spectral analysis, as defined by Hamilton (1994), determines the importance of cycles of different frequencies in accounting for the behaviour of the series analysed. The frequencies of the data can be analysed with the help of a spectral density function, defined as a Fourier transformation of the autocovariance function, according to Hamilton (1994, p. 153, equation 6.1.2).

Table 1 lists the estimated length of the cycle for the resources selected in terms of days. Nonrenewable resources (i.e. oil, copper, natural gas and aluminium) characteristically show a longer cycle period than do the renewable resources examined here. In addition, grains, such as wheat, corn and rice, have the shortest time cycle in the researched period. The differences in the cyclicality of the selected futures can be attributed to the technical components and the process of replenishing and extracting the commodities. Crude oil, for example, can be extracted all year round and is not affected by seasonality. However, grains are sensitive to changes in climate. Analysis of the length of each individual cycle is presented for analytical purposes in order to have full picture of the commodity futures researched.

Table 1 Periodicity of the data (per day)

	Renewable resources					
	Palm oil	Coffee	Soya beans	Rice	Wheat	Corn
Cycle length	402.34	312.5	320.31	101.56	191.41	195.31
	Nonrenewable resources					
	Zinc	Aluminium	Natural gas	Gold	Oil	Copper
Cycle length	218.75	488.28	496.09	234.38	496.09	495.07

We further extend the spectral analysis with an estimation of harmonic regression and determination of the harmonic coefficients. Harmonic analysis is one type of spectral analysis (another is periodogram analysis), which involves estimating the amplitude and the phase of a cycle that best fits the time-series data.

As emphasised by Warner (1998), harmonic analysis can be used as one estimation method in the frequency domain where the cycle length of the data is known. Formally, the harmonic regression is a summation of the sinusoidal and cosine functions, where a_i, b_i and ω_i (where $\omega_i = 2\pi/r_i$) are constant parameters that are unknown and need to be estimated. An example is given by

$$y_t = \sum_{i=1}^{k} \left(a_i \sin\left(\frac{2\pi}{r_i}(t - t_0)\right) + b_i \cos\left(\frac{2\pi}{r_i}(t - t_0)\right)\right). \tag{1}$$

In Equation (1), the number of harmonics k is typically assumed to equal 6 for consistency. According to Artis *et al*. (2007), the estimated coefficients a_i and b_i are the harmonic representation in the frequency domain of the data, and r_i represents the time period. For additional references on the use of the method, see Bloomfield (2000).

We start by applying a fast Fourier transformation to the detrended data. This method picks up periods for the harmonic fit, which have the highest power. Power spectral density describes how the power of a signal or time series will be distributed over the different frequencies.

Values for the harmonic analysis are in the Appendix S1. All the estimates of the harmonic analysis were obtained using Equation (1), as defined above. Coefficients a_i and b_i were estimated to determine the 'best estimate' to be fitted on the detrended data and are presented in Appendix Table S1 for the sample commodities. Coefficients a_i and b_i are constant parameters, required for the harmonic fitting on the detrended time series.

The values of these coefficients vary significantly. For our purposes, a number of simulations were conducted, reducing dispersion in the coefficients for different harmonics values. Estimated harmonic coefficients are fitted on the detrended data and presented in Appendix Figures S1–S6 for the commodities selected. The significance of corn, wheat, palm oil and soya beans fitting based on the smaller time period (the length of the last cycle), presented in number of days, can be noted. Such significance is represented by the higher values of the coefficients a_i and b_i in Appendix Table S1. Also, the lower right panels of Figures 1, Appendix Figures 5 and 6 are corresponding with the Table 1 results, where the fitted harmonics are not able to capture all the volatility in the actual data.

Presenting analysed data in the time and frequency domains reveals some underlying processes in the formation of futures prices for renewable and nonrenewable resources. Therefore, in our analysis, we identify some common patterns in price discovery for the commodity futures we researched.

4. Empirical methodology

The period researched is from 2 January 1996 to 12 September 2013 (all data accessed via Bloomberg). Appendix Table S2 reports descriptive statistics for 4,618 daily observations for each commodity. The standard deviation is significant for the majority of the renewable resources (except for coffee). Zinc, aluminium and gold have the highest standard deviation among the nonrenewable resources.

Pretesting the data, we find that the futures price series shows the presence of a unit root (test results are omitted for brevity). All observations are converted into a series of log returns, with the first observation excluded. That helps to eliminate the unit-root problem.

In order to test our hypothesis, we first need to compare the variances for different commodities. According to the literature (e.g. Manera *et al*. 2012), GARCH (1,1) is one of the better approaches for estimating specified simulations, accounting for the conditional and unconditional variances. In order to apply GARCH methodology to compare volatility across commodities, we first conduct autoregressive conditional heteroscedasticity (ARCH) tests.

4.1 Pretesting

The ARCH effects can be determined by conducting visual (i.e. autocorrelation function (ACF)) and Ljung-Box tests (Portmanteau-Q). The ACF results on the returns and normalised errors are plotted in Appendix Figures S7–S9. The dependence structure is revealed on the ACF for the normalised errors, with significant dependencies on the first and fifth lags, indicating the presence of nonlinear and conditional dependencies.

The Ljung-Box test for serial autocorrelation in the squared returns is conducted, with the null hypothesis of no serial autocorrelations. Table 2 summarises the results and rejects the null hypothesis, in favour of the presence of ARCH effects. Lagrange Multiplier test results with the *P*-values

Table 2 GARCH pretesting of squared returns

Futures	Ljung-Box/Portmanteau-Q	*P*-value	LM test	*P*-value
Renewable resources				
Palm oil	11,020.3	0.0	705.9	0.0
Coffee	8,335.2	0.0	316.4	0.0
Wheat	6,983.3	0.0	793.3	0.0
Corn	5,265.2	0.0	22.4	0.0
Soya beans	4,711.7	0.0	8.0	0.0
Rice	4,627.4	0.0	100.0	0.0
Nonrenewable resources				
Zinc	6,834.0	0.0	211.3	0.0
Aluminium	4,779.4	0.0	22.2	0.0
Natural gas	4,939.1	0.0	42.0	0.0
Gold	4,849.7	0.0	33.7	0.0
Oil	9,179.0	0.0	552.5	0.0
Copper	11,011.1	0.0	688.3	0.0

are also reported in Table 2. These tests also reflect evidence of ARCH effects in the series.

In sum, ARCH effects are identified in the data set; therefore, the GARCH (1,1) methodology can be applied. We develop this methodology below. In the process, consistent with the GARCH approach, we estimate the best-fitting autoregressive model, compute error-term autocorrelations and then test for significance.

4.2 Econometric specifications

4.2.1 GARCH (1,1)

As shown in the previous section, all our data series, according to the Ljung-Box test, have ARCH effects in the residuals. Therefore, we can switch to a generalised conditional heteroskedasticity (GARCH) model, which also depends on the number of lags included. The GARCH methodology allows the comparison of variances that are simulated through modelling techniques and, in some cases, serve as reliable predictions. That characteristic of the GARCH approach makes it relevant to our analysis.

Bollerslev (1986) introduced an extension to Engle's (1982) ARCH models. Bollerslev *et al.* (1994) showed that the GARCH (1,1) specification worked well in most applied situations. A standard GARCH (1,1) model for daily returns is given by

$$r_t = \mu_t + \epsilon_t = \mu_t + \sigma_t z_t, \quad z_t \sim NID(0,1)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2,$$

where μ_t denotes the conditional mean and σ_t^2 is the conditional variance with parameter restrictions $\alpha_0 > 0$, $\alpha_1 > 0$, $\beta > 0$ and $\alpha_1 + \beta < 1$. In Appendix Table S1, we see that our sample mean is quite small, with its standard deviation of the estimated series. Therefore, we set the conditional mean equal to zero, following Wei *et al*. (2010). As seen in the literature (e.g. Agnolucci 2008), a more complicated GARCH specification does not seem to improve on the widely used GARCH (1,1).

Because the goal of our research was to compare the volatility of futures prices for different commodity groups, we first estimate GARCH parameters and then conduct some diagnostic testing, ensuring the model's good fit with the data. We then compare variances, kurtosis and skewness of the distribution of the simulated GARCH returns. Comparison of those distributions and their variances between renewable and nonrenewable futures prices serves as an indicator of futures price volatility. According to the analysis in Bohl and Stephan (2013), speculation in futures markets does not destabilise spot prices for commodities but, rather, correlates with them. The dynamics of the movements are also the same in futures and spot markets. Therefore, we can assume that what happens in futures markets, also happens in spot markets. Nonlinear VSTAR methodology is applied to obtain a comparison of the speed of transition from low- to high-volatility regimes.

4.2.2 Nonlinear VSTAR

According to some research (e.g. Enders and Holt 2013), there is a mean-shifting tendency across energy commodities (oil, copper, gold, etc.). However, across agricultural commodities, such an obvious mean-shifting pattern has not been yet discovered. Therefore, in this study, we extend the empirical analysis and implement a nonlinear VSTAR.

The advantage of VSTAR is that it allows for either smooth or abrupt regime switching (from low- to high-volatility regime and the reverse) based on the observed nonlinear data. The linearity of the financial time series is always questionable, particularly if the observations researched cover a period of financial or economic crisis.

The VSTAR method was originally proposed by Terasvirta (1994) and extended to a bivariate model by Terasvirta and Yang (2014). VSTAR methodology is also used in Schleer and Semmler (2013). Below we show the adjustments that were made on the complete version of the applied model of Terasvirta and Yang (2014).

The VSTAR model has transition functions, where $G_t^i(.)$ is a diagonal matrix of transition functions such that different transition functions across regimes can be modelled:

$$G_t^i(.) = diag\{g(s_{1it}|\gamma_{i1,i1}), \ldots, g(s_{kit}|\gamma_{ik}, c_{ik})\}, \tag{2}$$

for $i = 1, \ldots, m - 1$, where m determines the number of transitions across equations and $G_t^m = 0, G_t^0 = I_k$. The diagonal elements of G_t^i in Equation (2) are logistic functions of their transition variables:

$$g(s_{ijt}|\gamma_{ij}, c_{ij}) = \left[1 + \exp\left(-\gamma_{ij}(s_{ijt} - c_{ij})\right)\right]^{-1}, \quad \gamma_{ij} > 0. \tag{3}$$

In Equation (3), γ_{ij} is the slope parameter, or the smoothness parameter, determining the shape of the function or the smoothness of the transition. Another important parameter, c_{ij}, is a location parameter determining the mid-point of the transition. Equation (3) is a continuous (for $\gamma_{ij} > \infty$), monotonically increasing sigmoid function of its argument s_{jt} (transition variable) and bounded between zero and one, according to Terasvirta and Yang (2014). As pointed out by Schleer and Semmler (2013), the slope parameter γ_{ij}, and thereby the VSTAR model, is redefined by

$$\gamma_{ij} = \exp(\upsilon_{ij}), \tag{4}$$

where υ_{ij} is the parameter to be estimated following Schleer and Semmler (2013).

To construct the grid, we need to redefine γ_{ij}, because one can build an equidistant grid in the dimension of υ_{ij}. According to Terasvirta (2004), to make γ a scale-free parameter, it is divided by the standard deviation of the transition variable when the parameters of the VSTAR model are estimated.

Estimation of the VSTAR model requires conducting a linearity test, defining the specification and providing results evaluation (for some results, see the subsection on Pretesting). Linearity testing is a very important part of a model specification. If a transition variable proves to be linear, then there is no need to apply a VSTAR model. In our estimation, we rely on the Rao statistical test and choose a respective lag of the transition variable with minimised P-values.

Consistent with Terasvirta and Yang (2014), we select the lag length using the Schwartz information criterion based on a linear VAR model and estimate the model by maximum likelihood. In our calculations, we find results with respect to γ and c by using 0.5 and 40 for the slope parameter γ. As in the approach used by Schleer and Semmler (2013), we define the location parameter c for the grid as a function of the transition speed: $C = f(\gamma)$. Therefore, when γ is very high, it implies a low number of observations around the threshold. In this case, we use a truncated sample of observations of the transition variable for the location parameter c.

Finally, the model can be evaluated in many ways, as there are different options to show that the estimated VSTAR model does not exhibit serially correlated error terms. The impulse response analysis is chosen in this paper to validate the results of the estimated VSTAR model. Overall, the goal of the VSTAR estimation is to show the speed of the transition from one regime to another for commodity futures and whether such a shift is abrupt or smooth for renewable and nonrenewable resources.

5. Results

5.1 GARCH (1,1)

Estimation results for renewable and nonrenewable resources based on the conditional likelihood function are summarised in Table 3. We report the estimated value of the parameters – α_1 and $\beta 1$ – and the constant α_0 estimated for each individual series and fitted to the data set. The log-likelihood values are also reported in Table 3. Appendix Figure 12 depicts a series of estimated squared residuals, computing estimated parameters in Table 3.

The horizontal (red) line in Appendix Figure 11 represents the unconditional variance of the series, used to initialise the computation process. As can be seen with respect to crude oil and palm oil, high volatility is captured during the period of the financial meltdown in 2007–2009. In particular, the price of coffee experienced a spike in volatility in 1998.

The visual test, via the ACF of squared returns, shows the squared series to have significant autocorrelations (Appendix Figures S7 and S8) for the selected commodities, with the statistical confirmation achieved through Ljung-Box/Portmanteau and Lagrange Multiplier diagnostic test statistics, as seen in Table 4. The high level of significance for both tests and the sample autocorrelation functions for standardised squared returns for the majority of resources indicate that the estimated coefficients do produce GARCH effects. Low *P*-values indicate that GARCH modelling was selected correctly for our estimations. The fit of the simulated values on the observed returns of kernel densities is illustrated in Appendix Figures S13 and S14.

Table 5 presents descriptive statistics of the simulated GARCH series returns for renewable and nonrenewable resources.

The key critical estimation factor in this paper is the variance in the futures price. The results show that variance for the top three renewables is the following: soya bean (88.012), corn (5.629) and coffee (5.544); and for

Table 3 Estimated GARCH (1,1) parameters

Futures	α_0	α_1	β_1	Log-likelihood values
Renewable resources				
Palm oil	0.037759	0.08270	0.90563	8,398.1
Coffee	0.124275	0.04871	0.92863	10,252.9
Wheat	0.049948	0.03561	0.95207	9,545.0
Corn	0.042807	0.06394	0.92994	9,192.7
Soya beans	2.809641	0.80635	0.18769	10,741.7
Rice	0.035372	0.04516	0.95484	8,466.1
Nonrenewable resources				
Zinc	0.002444	0.06548	0.93452	7,843.3
Aluminium	0.001191	0.11126	0.88874	6,846.3
Natural gas	0.066259	0.05104	0.94896	12,074.0
Gold	0.019484	0.10128	0.89872	6,676.2
Oil	0.036580	0.04392	0.94859	9,799.8
Copper	0.027259	0.04182	0.94936	8,804.2

Table 4 Diagnostic testing of standardised returns generated with GARCH parameter estimated

Futures	Ljung-Box/Portmanteau-Q	*P*-value	LM test	*P*-value
Renewable resources				
Palm oil	5,412.4	0.0	166.8	0.0
Coffee	4,711.9	0.2	82.0	0.0
Wheat	4,621.7	0.5	34.3	0.0
Corn	4,763.7	0.1	44.9	0.0
Soya beans	4,639.6	0.2	3.0	0.5
Rice	4,591.2	0.3	0.9	0.5
Nonrenewable resources				
Zinc	4,557.2	0.5	58.7	0.0
Aluminium	4,523.2	0.6	22.8	0.1
Natural gas	4,602.3	0.4	0.2	0.6
Gold	4,631.9	0.2	3.2	0.6
Oil	5,196.8	0.0	180.1	0.0
Copper	5,064.1	0.0	136.6	0.0

Table 5 Descriptive statistics: simulated GARCH returns

Futures	Mean	Variance	Skewness	Kurtosis
Renewable resources				
Palm oil	−0.034	3.444	+0.209	2.47
Coffee	−0.007	5.544	+0.047	0.20
Wheat	0.009	4.631	−0.071	0.42
Corn	−0.047	5.629	+0.015	1.54
Soya beans	−0.121	88.012	−8.932	32.19
Rice	−0.123	2.450	−0.021	5.47
Nonrenewable resources				
Zinc	−0.032	2.790	+0.145	3.56
Aluminium	−0.003	1.760	+0.155	5.78
Natural gas	0.325	22.383	+0.306	8.32
Gold	0.028	3.646	+0.072	3.09
Oil	0.022	5.266	+0.018	0.75
Copper	0.019	2.773	−0.006	0.29

nonrenewables: the highest are natural gas (22.383), oil (5.266) and gold (3.646). According to Table 5, coffee has a slightly higher variance than crude oil. The skewness and kurtosis of coffee are also much greater than those for crude oil. Nonrenewable resources such as copper and aluminium have the lowest variances out of all the futures analysed here. Soya beans have the highest variance of both the renewables and nonrenewables in the sample.

Therefore, the results in Table 5 support our hypothesis, at least for the particular resources analysed. Computing the average of the six variances separately for renewable and nonrenewable resources, the variances for renewable resources are significantly higher (18.3 versus 6.4).

As shown in Enders and Holt (2013), nonrenewable resources tend to trade around the mean, once a new mean is established. However, renewable futures trade independently of the mean, which is in constant adjustment, and thereby more volatility is created. Therefore, in view of this analysis, it is also important to compare the speed of transition from low- to high-volatility regime for different commodity groups and determine the type of transition function for them. This methodology will provide additional comparisons between renewable and nonrenewable resources for the most recent period.

5.2 Nonlinear VSTAR

The transition variable in the VSTAR case is presented by the futures price of the commodity. Overall, there are 1,272 observations of monthly data. As mentioned above, data for the futures price come from the Bloomberg database.

Due to the existing trend in some futures data, the Hodrick–Prescott filter is applied to the financial time series. According to Ravn and Uhlig (2002) and others, the chosen lambda (γ) parameter for the smoothing of monthly data is 129,600.

The first step in estimations is to determine the nonlinearity of the data. We compute a full-sample linearity test based on the Rao statistic. Table 6 reports the average of the *P*-values for the full sample. All data sets in general reflect nonlinearity in the time series, and linearity is rejected with a 1 per cent to 5 per cent level of significance.

Next we estimate and present the transition functions for the commodities. We also estimate the smoothing parameters γ and c as the location parameter. The results are reported in Table 7. As noted, estimated parameters have different values for all commodities.

Graphical analysis helps reinforce some of the VSTAR model's results. Appendix Figures S15–S20 show the transition function for the selected commodities, illustrating the regime shift. Smooth rather than abrupt change takes place for most commodities. Coffee, oil and corn have a very similar pattern in the transition function, where a smooth shift occurs over time. For these commodities, γ is also in the same range and shows a similar pattern.

However, the regimes for commodities such as palm oil, soya beans and natural gas show a tendency towards an abrupt switch. The results for soya

Table 6 Mean of *P*-values of linearity test (Rao statistics)

	Renewable resources					
	Palm oil	Coffee	Soya beans	Rice	Wheat	Corn
Full sample	0.025	0.043	0.035	0.001	0.042	0.031
	Nonrenewable resources					
	Zinc	Aluminium	Natural gas	Gold	Oil	Copper
Full sample	0.041	0.030	0.001	0.010	0.030	0.030

Table 7 Optimised location and slope parameter of VSTAR models

	Renewable resources					
	Palm oil	Coffee	Soya beans	Rice	Wheat	Corn
c	8.833	2.497	0.138	0.038	15.687	10.503
γ	30.0	9.319	108.063	1.180	1.163	7.459
	Nonrenewable resources					
	Zinc	Aluminium	Natural gas	Gold	Oil	Copper
c	0.149	0.106	0.168	0.074	0.529	7.170
γ	2.040	3.749	34.468	3.541	5.5111	5.060

beans and natural gas are particularly important because the high transition speed corresponds with the high variance obtained through GARCH simulations. To verify and evaluate our estimated results, we also conducted an impulse response function, however, that did not yield any significant findings (omitted here for brevity). The results, obtained here with GARCH and VSTAR modelling, are important in studying the financial time series and their subsequent influence on the macroeconomic data analysis. Our analysis and results indicate that the price of commodities futures in renewable and nonrenewable resources shows diverse and distinct trends. Therefore, it is important to further extend the research to the various commodity groups.

6. Conclusion

The excessive volatility of futures prices for renewable and nonrenewable resources has economic costs. The conventional wisdom of the majority of the previous studies is that oil prices are more volatile than prices of other commodities (e.g. Verleger 1993; Fleming and Ostdiek 1999; Regnier 2007). However, the fact that some resources are renewable and can be replenished does not necessarily mean that they will be available in the required amounts in order to keep up with the changing demand levels. A number of factors that lead to the changes in the supply of the commodities (climate change, weather fluctuations, exhaustibility feature and economic growth) are already having some impact on local economies. Active development of biofuel and environmental policies has also contributed to the adjustments in supply and demand of agricultural commodities for macroeconomic, financial, social and market-behaviour reasons. Market participants are aware of these situations and therefore adjust their holding positions accordingly, which eventually have an effect on the volatility of those products. Such uncertainty about the future supply factors can explain higher volatility of renewable resources identified in the current study. The findings of this paper strongly correlate with the conclusion drawn by the U.S. National Academy of Sciences (Weiss

1962), relating to the slow growth of the supply of renewable resources in comparison with the population growth. In addition to those concerns discussed in the Weiss (1962) report, volatility of the renewable resources, as we argue in this paper, remains a serious challenge today to sustainable development and growth.

One of the aims of this paper has been to explore whether volatility has been different for commodities that are distinguished by the renewability feature. The empirical GARCH (1,1) test conducted in this paper supports our main hypothesis – that volatility in futures prices for some renewable resources is greater than for benchmark crude oil. This paper has also provided harmonic fitting, showing the time-series dynamic and its periodicity. The length of the cycles for different futures is also presented, where exhaustible resources tend to have longer cycles than renewable ones. The nonlinear VSTAR model explored similarities in the shifts from one regime to another and in the means within the data. The results obtained suggest that such similarities exist in oil, natural gas, coffee, soya beans and corn financial futures data. These products have not only higher variance compared to other futures commodities, but also the most abrupt transition functions from low- to high-volatility regimes. We recommend that future research should focus more on macroeconomic fundamentals that underpin commodity price changes.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1. Figures and Tables.