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Jumps and volatility dynamics in agricultural commodity spot prices

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ABSTRACT
The spot commodities market exhibits both extreme volatility and price spikes, which lead to heavy-tailed distributions of price change and autocorrelation. This article uses various Lévy jump models to capture these features in a panel of agricultural commodities observed between January 1990 and February 2014. The results show that Levy jump models outperform the continuous Gaussian model. Our results prove that assuming a constant volatility or even a deterministic volatility and drift structure of agricultural commodity spot prices is not realistic and is less efficient than the stochastic assumption. The findings demonstrate an interesting correlation between volatility and jumps for a given commodity *i,* but no relationship between the volatility of commodity *i* and the probability of jumps of commodity *j*.

KEYWORDS
Agricultural commodities; heavy tails; regime switching; normal inverse Gaussian; volatility

MSC CLASSIFICATION
60J10; 91B25; 91G30

JEL CLASSIFICATION
G10; G12; G15.

I. Introduction

Since the 1990s, trading in agricultural commodities has been steadily increasing. Commodity markets are characterized by periods of volatility, with fluctuation over time (Pindyck 2004). Empirical evidence suggests that commodities prices movements have fat-tailed distribution and exhibit sudden and unexpected price jumps. The jump added in the stochastic process for commodity prices accommodates large price changes resulting from important news about supply and demand on the market. Hilliard and Reis (1999) were among the first authors to document the jump phenomenon on financial commodity markets . Koekebakker and Lien (2004) show volatility and price jumps in wheat future and options. Schmitz, Wang, and Kimn (2014) use a stochastic volatility with jumps models to fit the empirical pricing data. However, the link between jumps and volatility remains vague.

Understanding the behaviour of volatility is important for several reasons: (i) volatility can affect market variables such as the marginal value of storage and the marginal cost of production, (ii) volatility can lead to inflation pressures, by causing a downward structural break in terms of trade of commodity-exporting countries, or by increasing prices in importing countries and (iii) volatility is relevant to the formulation of economic policy in developing countries that are usually heavy exporters of a small number of primary commodities. Seasonality is an important feature of agricultural commodity prices, a feature that is generally not shared by financial assets. This article analyses the patterns of price evolution in agricultural commodity markets. Our aim is to obtain a better understanding of the evolution and distribution of prices over time and to discuss the different models that can be used to describe volatility in commodity markets.

This article shows that the spot commodities market exhibits both extreme volatility and price spikes that lead to heavy-tailed distributions of price changes. Our article does not address the causes and consequences of price volatility but instead provides a technical analysis of the extent of volatility exhibited by agricultural commodity prices, and how volatility and jumps are related. To do so, we study the prices of several agricultural commodities (beef, cocoa, corn, cotton, hides of cattle, palm oil, soybeans and sugar) between January 1990 and February 2014 and investigate whether there is any correlation between them over this period. This article uses a collection of statistical methods to study the following: (i) the presence of jumps in spot commodity prices, (ii) the presence of heavy-tailed distributions in the agricultural commodities market and (iii) evidence of changes in price volatility for the spot price dynamic.

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To address these objectives, we use a panel of jump model (i) including Lévy jump models. This class of models allows us to fit heavy tails and asymmetric distributions. We prove that models with heavy-tails distributions such as the Lévy model outperform the continuous Gaussian model. We also use (ii) a regime-switching approach to exhibit structural breaks in the price dynamic in terms of volatility and mean long-term trend and (iii) moving volatility studies to examine the local change in the level of volatility. We finally consider the link between volatility and jumps for each commodity to see whether volatility for a given commodity can increase the probability of jumps for another commodity.

This article is related to the large literature on volatility in commodity markets. Yang, Haigh, and Leatham (2001) indicated that agricultural liberalization has caused an increase in price volatility. Gilbert and Varangis (2004) studied cocoa prices in West Africa and showed that the volatility is explained by the alignment of domestic prices with world cocoa prices, with the latter being more volatile. Tang and Xiong (2010) explained the increase in the price volatility of nonenergy commodities by noting the increasing correlation with oil prices resulting from the financialization of the commodity markets since the early 2000s. According to Guilleminot, Ohana, and Ohana (2012), the new investment patterns in the commodity derivative markets and the rise of algorithmic trading, which represents more than 50% of transactions, result in disconnected price movements from physical fundamentals and increased price volatility. Hernandez and Torero (2010) found that changes in futures prices lead to changes in spot prices more often than the reverse. Kat and Oomen (2007) found that for many commodities, futures returns and volatility can vary considerably over different phases of the business cycle and under different monetary conditions. Other studies show significant degrees of autocorrelation between commodities (Kat and Oomen 2007; Chong and Miffre 2010). Boroumand et al. (2014) show that agricultural commodity prices are correlated and that there exists a hidden relation between them. Knowledge of the dynamics of spot prices is important for real and financial asset valuation and risk management for commodities, producers and consumers.

This article is of interest to researchers and people concerned with the volatility of markets (such as brokers, quants, or traders) for several reasons. Understanding key trends in the commodities markets is important because misperceptions about the causes of volatility can lead to poor policy decisions or poor portfolio optimization. Episodes of prolonged price volatility generate uncertainty and increase the risks of productive activities; adverse volatility can also have adverse macroeconomic consequences in developing countries whose growth is commodity dependent. First, our article identifies different periods of volatility and shows that there are more jumps in the 2010–2014 period than in the 1990s or the 2000s. This statement is important because many studies – Gilbert (2006), Gilbert and Morgan (2010) and Sumner (2009) – focus on analysing volatility during the 2006–2008 period, which was characterized by a price surge. An interesting result from Gilbert and Morgan (2010), who studied the volatility of 19 commodities between 1970 and 2009, and from Sumner (2009), who studied the volatility for two commodities between 1866 and 2008, is that the volatility of commodities tends to be lower in the 1990s and the 2000s than in the 1970s, for example. Our article shows that there are indeed frequent periods of jumps and spikes, but that volatility tends to increase in the 2010s. Our article uses Lèvy jump processes to identify volatility. This article then uses a regime-switching model to characterize periods of high volatility and regimes of standard volatility. Such a model is useful not only to identify periods of volatility but also to estimate the probability of moving from a standard volatility to a regime of Levy jumps. Finally, the use of a 1-month moving volatility interval is interesting to identify excesses of volatility, not necessarily in Shiller's sense.[1] Our results show that volatility increases the probability of a jump for a given commodity but that there are no real links, with few exceptions, between the volatility of a given commodity i and jumps of another commodity j.

This article proceeds as follows. The next section discusses the data set and descriptive statistics. Section II presents evidence of jumps from the statistical distribution. Section III introduces the regime-switching approach. Section IV analyses the link between jumps and volatility over the period. A conclusion follows the discussion.

[1]Shiller (1981) considers excess volatility to be price movements that are excessive relative to changes in fundamentals, i.e., supply or demand shocks greater than what the efficient market hypothesis would predict.

II. Data & descriptive statistics

Data

We study the prices of eight agricultural commodities – beef, cocoa, corn, cotton, hides of cattle, palm oil, soybeans and sugar – using monthly data between January 1994 and February 2014. Data are available on the website of the Institut National de la Statistique et des Etudes Economiques (INSEE).[2] Table 1 presents descriptive statistics for each commodity. A quick examination of the means and SD indicates which commodities experience the most volatile behaviour. The SD represents, for example, more than one-third of the mean of cocoa, cotton, soybeans, palm oil, corn and sugar, but only a small share of the average price of beef and the hides of cattle. Figure 1 shows the evolution of prices for the different commodities. Once again, the graphs show more or less intensive volatility patterns. In the long term, the price of beef shows a clear tendency to increase, but the short-term evolution does not show large ups and downs. On the contrary, the price of cocoa exhibited different tendencies: the price is decreasing between 1998 and 2000 and between 2002 and 2004, whereas it is increasing between 2000 and 2002 and between 2004 and 2006; from 2006 onward, there are several waves of sharp increases and decreases, thus revealing a pattern of high volatility. An overall examination of the graphs shows that all commodities are characterized by more volatile prices after 2004. The log returns of the variable are also used to obtain a better description of the volatility. Figure 2 plots these evolutions. The graphs included in Figure 2 provide a good overview of the volatility in the commodity markets. For example, hides of cattle do not experience a great deal of volatility except in the beginning of 2005, when the price suddenly falls. However, we can observe sudden jumps over the time interval for most commodities. For example, soybeans experience sudden changes in its price throughout the period, with large decreases in 2003 and 2005. Jumps and spikes are observed for all commodities in different periods.

III. Heavy-tailed distribution of agricultural log return prices

In this section, we compare the goodness of fit of several models that have heavy tails against the Gaussian model (i.e., a Brownian distribution where the noise follows a Gaussian distribution).

Heavy-tailed distributions

It has been accepted that financial and economic asset returns are not normally distributed; rather, the empirical observations exhibit excess kurtosis. This heavy-tailed behaviour of the distribution of price changes has also been observed in various energy or commodity markets. However, there are no reports of heavy-tailed behaviour of agricultural commodity prices.

In particular, (log) returns generally exhibit lighter tails than first differences of prices themselves. Following Weron (2006), we fit Gaussian and three relatively popular and versatile classes of

Table 1. Descriptive statistics (290 observations).

Statistics	Cocoa	Cotton	Hides of cattle	Soybeans
Maximum	3448.10	229.70	107.00	1702.70
Minimum	716.70	37.40	34.50	412.20
Mean	1671.33	73.24	83.05	772.18
Variance	447,104.89	648.63	114.10	98,856.50
SD	668.66	25.47	10.68	314.41
Skewness	247,301,289.49	45,522.02	−1512.18	36,052,761.99
Kurtosis	528,172,780,853.58	6,202,720.89	95,918.45	30,916,047,038.93
	Palm oil	Corn	Sugar	Beef
Maximum	1284.30	803.50	32.10	221.60
Minimum	226.50	178.30	4.80	89.30
Mean	567.55	328.08	12.23	126.59
Variance	58,782.14	23,544.26	32.31	757.69
SD	242.45	153.44	5.68	27.53
Skewness	14,196,087.57	5,335,812.067	262.73	19,295.80
Kurtosis	11,434,022,559.70	2,249,531,485.02	4864.58	1,814,075.88

[2]http://www.insee.fr/fr/bases-de-donnees/bsweb/theme.asp?id=18

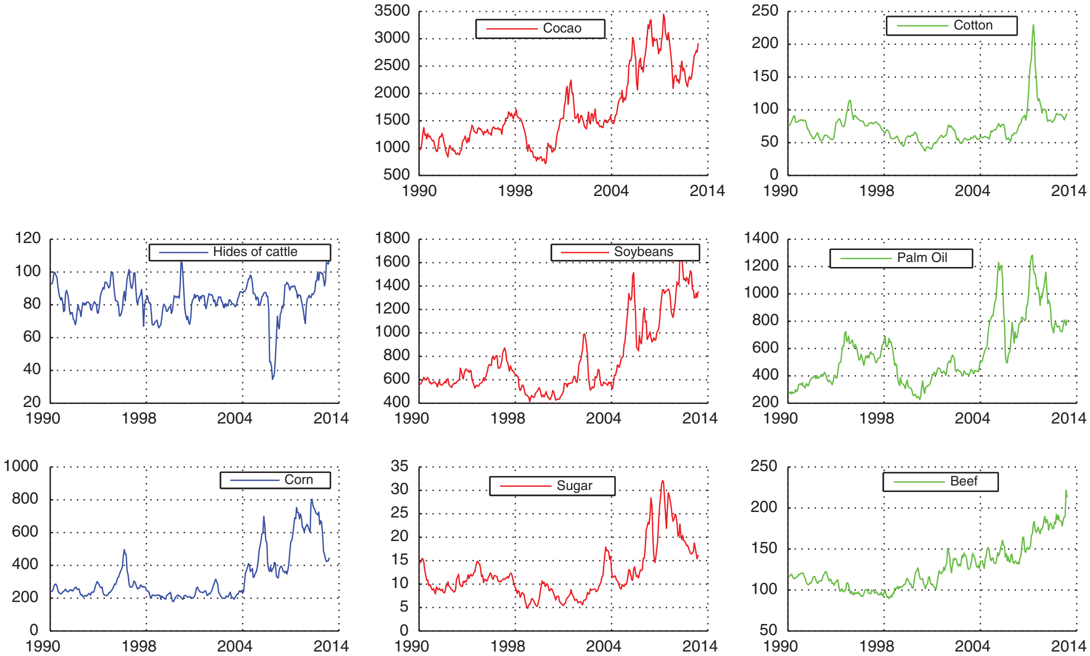

Figure 1. Prices of agricultural commodities between January 1990 and February 2014.

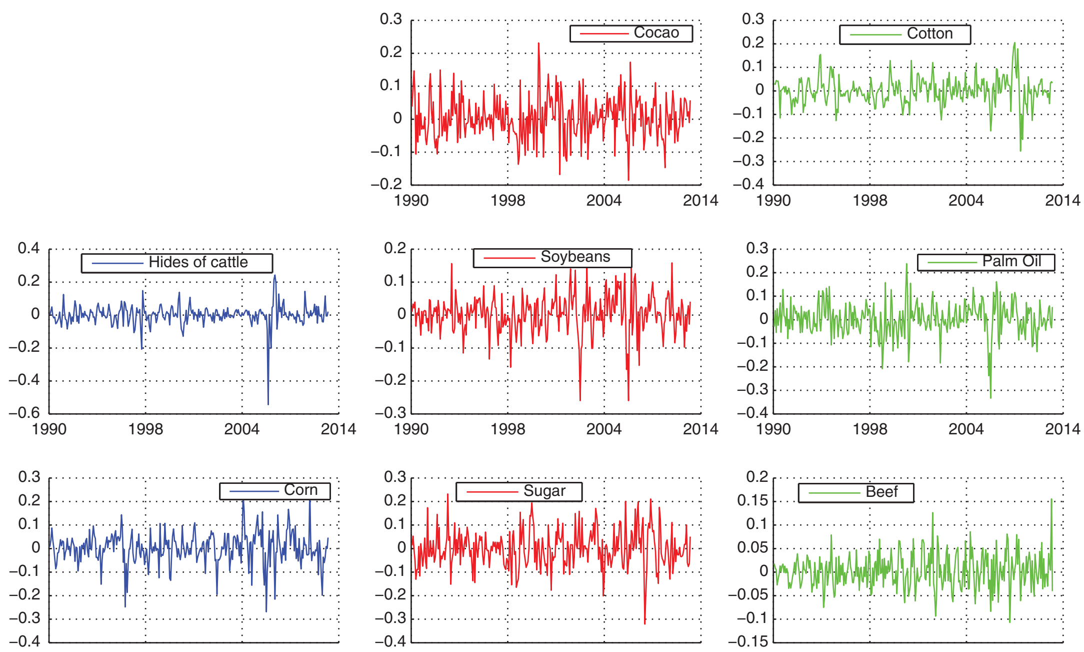

Figure 2. Log returns of Agricols commodities between January 1990 and February 2014.

heavy-tailed distributions – hyperbolic, normal inverse Gaussian (NIG) and α-stable – to agricultural commodity prices changes from the eight markets. Calibrations of the hyperbolic and NIG distributions are performed via a maximum likelihood method, as their probability density functions (PDFs) are given in the explicit form in the sequel.

Definition 3.1. *The PDFs of a hyperbolic random variable X are given by*

$$f_H(x) = \frac{\sqrt{\alpha^2 - \beta^2}}{2\alpha\delta K_1(\delta\sqrt{\alpha^2 - \beta^2})} e^{-\alpha\sqrt{\delta^2 + (x-\mu)^2} + \beta(x-\mu)} \tag{3.1}$$

Definition 3.2. *The PDFs of an NIG random variable X are given by*

$$f_{NIG}(x) = \frac{\alpha\delta}{\pi} e^{-\delta\sqrt{\alpha^2-\beta^2}+\beta(x-\mu)} \frac{K_1(\alpha\sqrt{\delta^2+(x-\mu)^2}))}{\sqrt{\delta^2+(x-\mu)^2}}. \quad (3.2)$$

Remark 3.1. *Both laws are characterized by four parameters* $(\alpha, \beta, \delta, \mu)$ *and can be interpreted as having a different effect on the shape of the distribution:*

α – *tail heaviness with steepness.*
β – *skewness (with* $0 \leq |\beta| < \alpha$*).*
δ – *scale (* > 0*).*
μ – *location.*

Remark 3.2. *The four parameters* $(\alpha, \beta, \delta, \mu)$ *also have an economic or financial interpretation. For the two first parameters, we have*

- α – *the smaller it is (close to zero), the greater the likelihood of intense jumps and spikes in the market. Thus, a value of* α *near-zero indicates evidence of a jump and spike in the agricultural commodity spot price.*
- β – *the sign of* β *reflects the asymmetry of the distribution. Hence, a negative value means that changes in the dynamic prices are greater in negative profit than in positive profit. If we combine this result with a* α *close to zero, we find that the extreme values and, thus, extreme losses are greater in negative than in positive profits. Thus, we lose more money than we win.*

Statistical tests

We propose several statistical tests to measure the goodness of fit of each possible distribution against the real one given by the data.

Kolmogorov–Smirnov test

The Kolmogorov–Smirnov test is a form of minimum distance estimation that is used as a parametric test of the equality of a one-dimensional probability distribution compared with a reference probability. The Kolmogorov–Smirnov statistic, D_n, where n is the sample size, quantifies a distance between the empirical distribution function (EDF) of the sample $F_n(\Delta z)$ and the cumulative distribution function (CDF) of a reference distribution $F(\Delta z)$. The EDF $F_n(\Delta z)$ for n i.i.d. observations Δz_i is defined as

$$F_n(\Delta z) = \sum_{i=1}^{n} 1(\Delta z_i \leq \Delta z),$$

where $1(\Delta z_i \leq \Delta z)$ is the indicator function equal to 1 if $\Delta z_i \leq \Delta z$ and 0 otherwise. The Kolmogorov–Smirnov statistic for a given CDF $F(\Delta z)$ is

$$D_n = \sup_z |F_n(\Delta z) - F(\Delta z)|,$$

where $\sup_z$ denotes the supremum with respect to the parameter z. These values can be found in Table 2.

Table 2. Goodness-of-fit statistics for each commodity's log return prices (the best one for each statistic is in bold).

	Kolmogorov			
Commodity	Gaussian	Hyperbolic	NIG	Alpha-stable
Cocoa	0.6577	**0.4437**	0.4532	0.5171
Cotton	1.0459	0.4293	**0.4277**	0.4622
Hides of Cattle	1.9642	0.5603	**0.4350**	0.7661
Soybeans	1.1611	**0.5100**	0.5473	0.7549
Palm Oil	1.1010	0.4950	**0.4559**	0.5071
Corn	1.1931	0.4877	**0.4153**	0.4629
Sugar	1.0547	**0.5342**	0.5638	0.7043
Beef	0.7802	0.4360	**0.4305**	0.4850
	Anderson–Darling			
Commodity	Gaussian	Hyperbolic	NIG	Alpha-stable
Cocoa	0.4169	**0.1526**	0.1567	0.2273
Cotton	1.9313	0.1656	**0.1436**	0.2313
Hides of Cattle	9.5282	0.4312	**0.2029**	0.4294
Soybeans	1.9549	0.2248	**0.2088**	0.3407
Palm Oil	1.5124	0.2482	**0.2338**	0.2505
Corn	2.3740	0.2391	**0.1822**	0.1908
Sugar	1.1131	**0.2566**	0.2881	0.5672
Beef	0.5153	0.1220	**0.1211**	0.1414

According to the Kolmogorov–Smirnov test, the null hypothesis of equality between the empirical distribution probability of our model and a reference probability is rejected at the level α if

$$\sqrt{n}D_n > K_\alpha$$

where K_α is found from

$$P(K \leq K_\alpha) = 1 - \alpha.$$

K is a random variable following the Kolmogorov distribution with a CDF given by

$$P(K \leq x) = \frac{2\pi}{x}\sum_{i=1}^{\infty}\exp\left(-\frac{(2i-1)^2\pi^2}{8x^2}\right).$$

Cramer–von Mises

Another popular class of measures of discrepancy is given by the Cramer–von Mises family. Thus, we provide a two-sample Cramer–von Mises goodness-of-fit hypothesis test. This test determines whether independent random samples are drawn from the same underlying distribution.

$$Q_n = n\int_{-\infty}^{\infty}(F_n(\Delta z) - F(\Delta z))^2\Psi(\Delta z)dF(\Delta z) \tag{3.3}$$

where $\Psi(\Delta z)$ is a suitable function that gives weights to the squared difference

$$(F_n(\Delta z) - F(\Delta z))^2$$

when

$$\Psi(\Delta z) = \Psi(\Delta z) = \frac{1}{F(\Delta z)(1 - F(\Delta z))}$$

Equation (3.3) yields the Anderson–Darling statistic, which may be treated as a weighted Kolmogorov statistic that places more weight on the differences in the tails of the distributions.

The decision rules are the same as for the Kolmogorov–Smirnov test. When applied to our model, this test yields the results shown in Table 2.

Goodness of fit

In this section, we discuss which of the theoretical distributions better fits the observed distribution of prices. To do so, we compare the Gaussian distribution to three distributions accounting for jumps. We evaluate the Kolmogorov–Smirnov statistic and the Anderson–Darling statistic. Naturally, the lower the values, the better the fit. The obtained values are given in Table 2. The NIG distribution appears to yield the best fit, not only visually (where it recovers the power-law tail; see the QQplots in the next subsection) but also in terms of the goodness-of-fit statistics. The Gaussian laws largely underestimate the tails of the distribution.

The goodness-of-fit statistics leave no doubt that the price distributions in all markets have much heavier tails than the Gaussian law.

QQplot

The heavy-tailed nature of the phenomenon is clearly apparent. The fits of the Gaussian distribution compared with the NIG distribution to price changes are presented in Figures 3 and 4. In the left columns, we plot the QQplot of the log returns residual versus the NIG distribution, and in the right columns, the QQplot versus a Gaussian distribution is shown. We clearly see that the NIG distribution fits the empirical distribution much better than the Gaussian one, especially in the extreme values, which is proof of the heavy tails of the distribution.

Cumulative distributions

Figures 5–8 plot the CDFs obtained by each fitted model of the previous section with respect to the EDF. Each boxplot includes the CDF for the Gaussian (light blue line), hyperbolic (red line), NIG (pink line) and alpha-stable (dark blue line) models. We clearly see on the box plot that the Gaussian model differs from the EDF (the dark blue dotted line) on both the left and right sides of the distribution for nearly all of the agricultural commodity spot prices. By contrast, the heavy-tailed distributions, especially the NIG distribution, fit very well with the EDF of the log returns of agricultural commodity spot prices for each market. To underline the potential differences between the Gaussian and NIG CDF, we included black boxes identifying the major gaps between the Gaussian distribution and the NIG and heavy-tailed distribution.

Distribution parameters estimated for log returns

In the appendix, Tables A1–A8 present the estimated parameters for each commodity price. We show in the previous section that the NIG

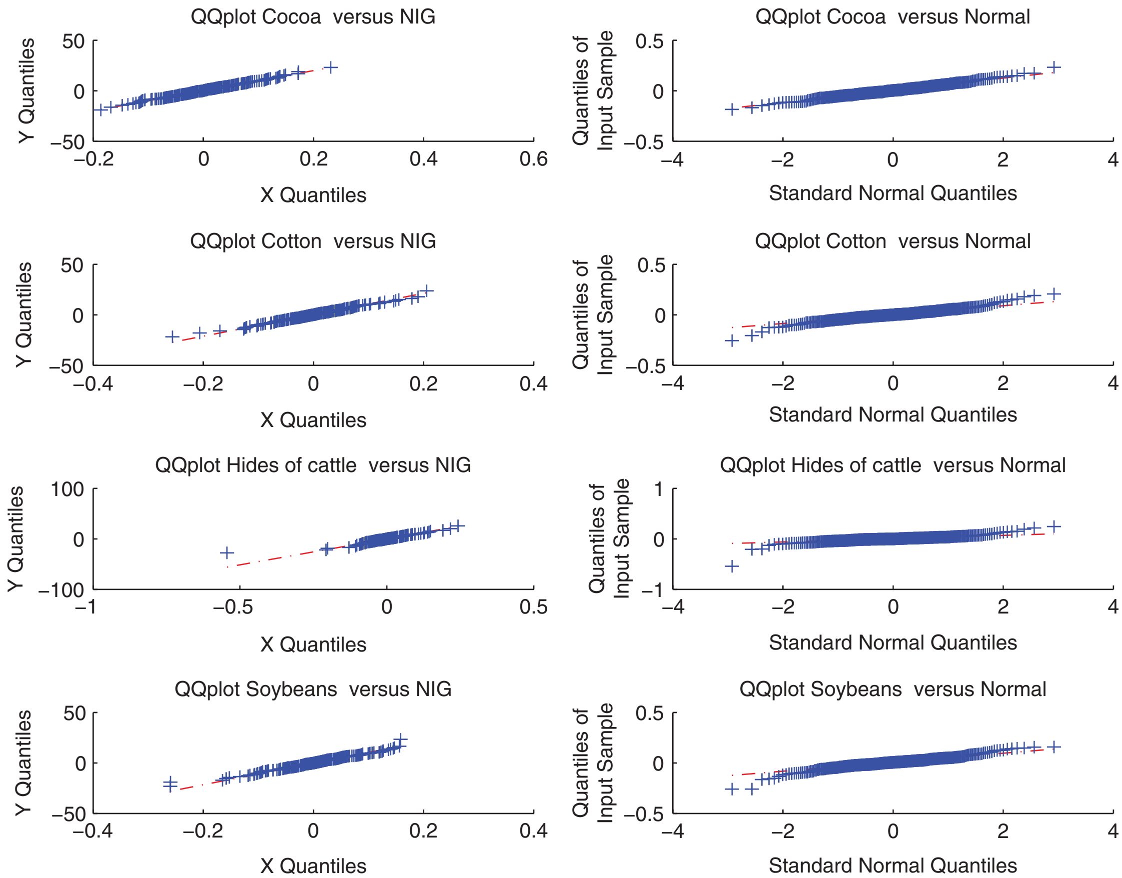

Figure 3. QQplot of the log returns versus normal and NIG distributions.

distribution is the best fit to log returns. If we examine the estimated NIG parameters, we observe that the values of the parameter α are always less than 0.57 and very close to zero (less than 0.2 for six of the eight commodities).

Our results show that although the Gaussian distribution is widely used to model asset volatility, it is rarely suitable to explain extreme events that are controlled by the tail of the distribution. Movements in the commodities markets are sometimes abrupt and jump-like. In fact, the Levy jump processes are more efficient to understand the evolution of commodity prices.

IV. Regime-switching approach

In this section, we use regime-switching models to obtain a better understanding of jumps across time. Regime-switching models demonstrate that nonlinear regime-switching time-series models might provide good models of agricultural commodity price dynamics. The underlying idea behind this Markov regime-switching scheme is to model the observed stochastic behaviour of a specific time series by two (or more) separate states or regimes with different underlying processes. In other words, the parameters of the underlying process may change for a certain period of time and then revert back to their original structure. Thus, regime-switching models separate time series into different phases called regimes. For each regime, one can define separate and independent underlying price processes. The mechanism of switching between states is assumed to be governed by an unobserved random variable X_t, which will be a homogeneous Markov chain.

The agricultural commodity price is assumed to exhibit either low or very high volatility at each point in time, depending on the regime $X_t = 1$ or $X_t = 2$. Consequently, we have a probability law that governs the transition from one state to another. The price processes linked to each of the two regimes are assumed to be independent of each

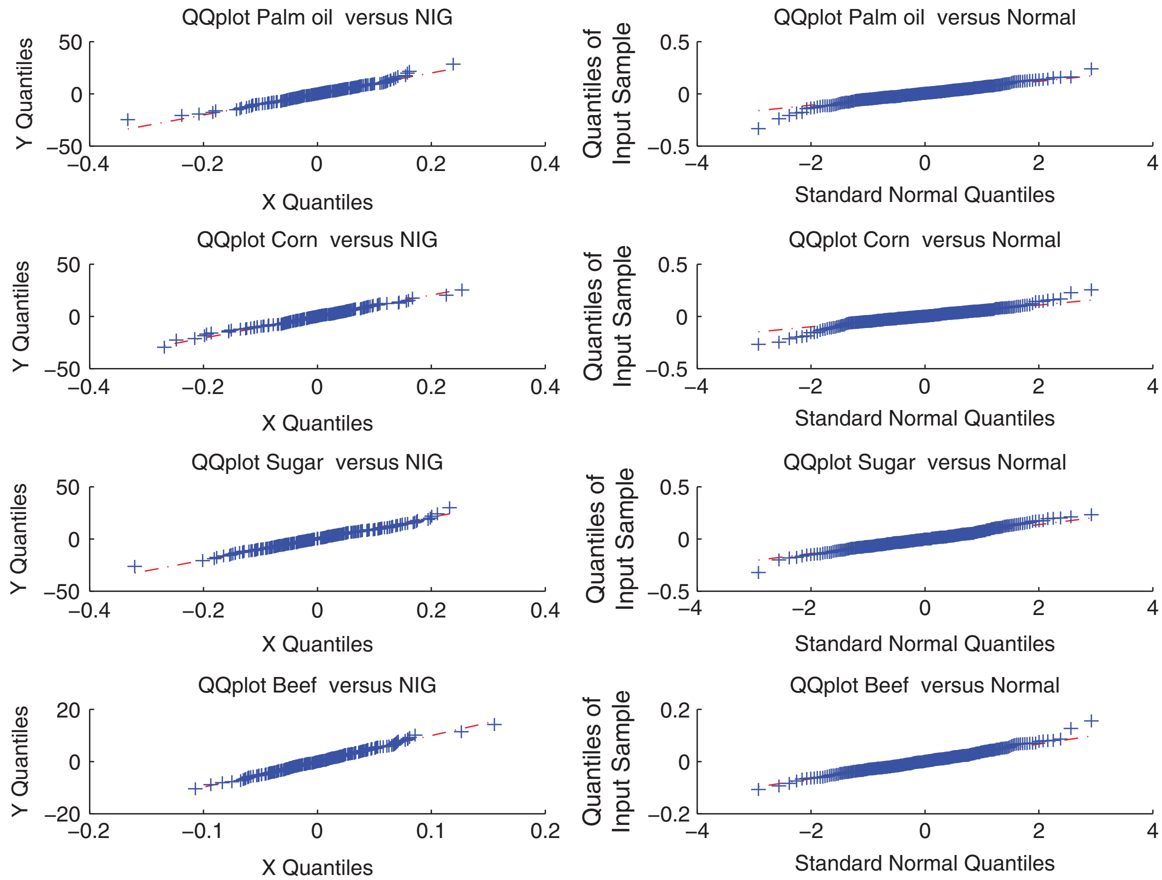

Figure 4. QQplot of the log returns versus normal and NIG distributions.

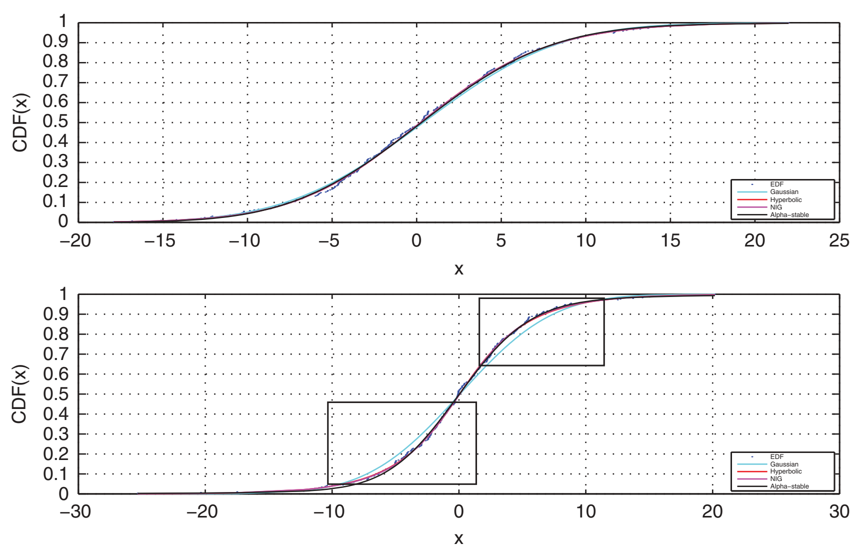

Figure 5. Cumulative distribution function fit for cocoa (on top) and cotton (on bottom).

other. The transition matrix Q contains the probabilities q_{ij} of switching from state i at time t to state j at time $t+1$ for $i, j \in \{1, 2\}$.

Remark 4.3. *The idea behind the different states of the model is that each state refers to an economic behaviour or an economic situation. Typically, in a*

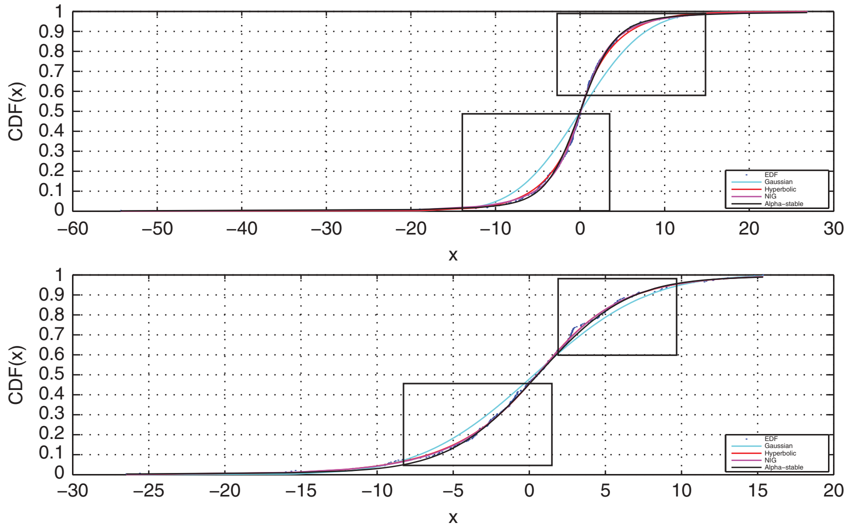

Figure 6. Cumulative distribution function fit for hides of cattle (on top) and soybeans (on bottom).

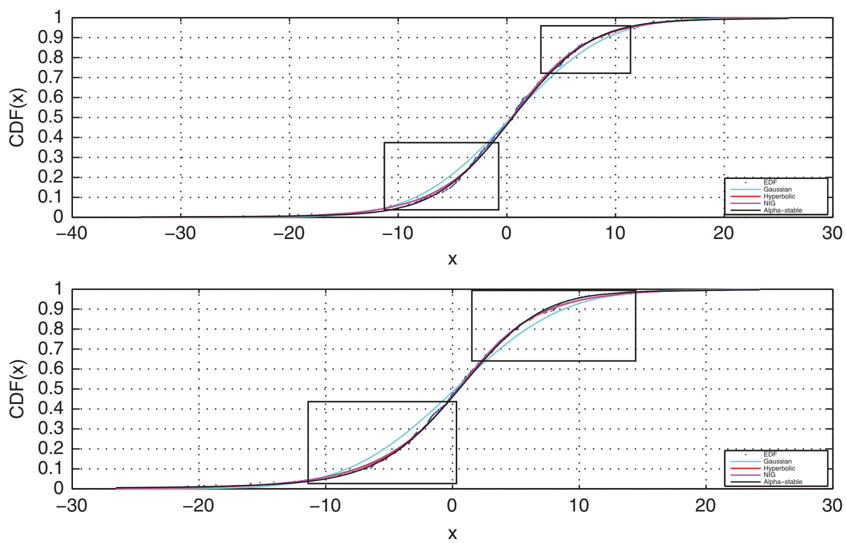

Figure 7. Cumulative distribution function fit for palm oil (on top) and corn (on bottom).

two-regime case, we can identify the two states as follows:

(1) *the standard regime when $X_t = 1$. It models a 'normal' economic situation.*
(2) *the jump regime or high-volatility state when $X_t = 2$. It models a sudden variation in the price dynamics.*

The use of regime-switching models is important to identify the frequency and intensity of the volatility regimes of a time series. We would expect commodities to experience frequent periods of price jumps, with a jump regime lasting for some time.

Results

Thus far, we have considered only jump diffusions. In this section, we check to determine whether other processes also fulfil the modelling requirements of parsimony and statistical adequacy. The Markov regime-switching models seem to be a good candidate to measure and highlight some jump and

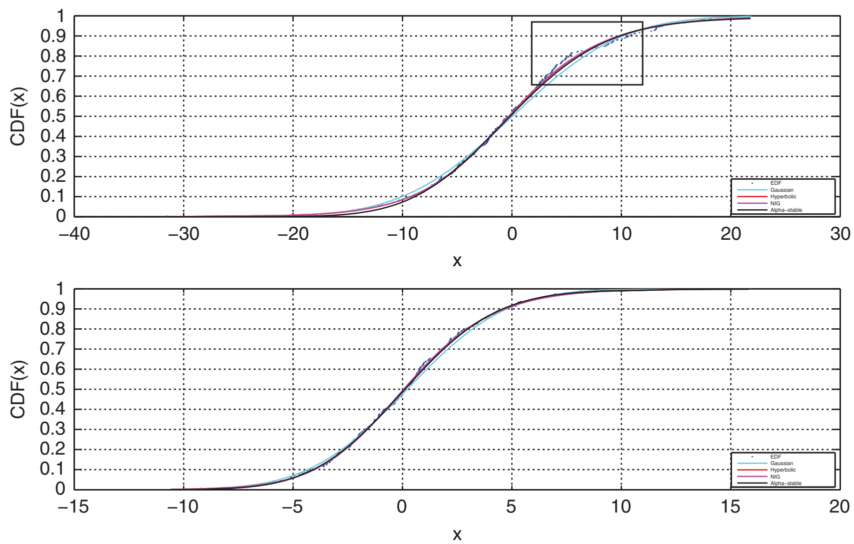

Figure 8. Cumulative distribution functions fit for sugar (on top) and beef (on bottom).

dynamic breaks in the behaviour of the prices of agricultural commodities. We fit a regime-switching model to the log returns of agricultural commodities between January 1990 and February 2014. The two-regime specification is given by the following stochastic dynamic:

$$dP_t = \left(c_{X_t} - \beta_{X_t} P_t\right) dt + \sigma_{X_t} dW_t$$

where X_t is a homogeneous Markov chain (see Goutte (2014) for more details regarding regime-switching modelling).

Tables 3–10 summarize the estimated results for our two-state regime-switching model with mean-reverting process for spikes applied to each agricultural commodity price. We especially focus on the probability q_{ii} of prices remaining in a given regime once they are in and on the unconditional probabilities $P(X_t = i)$, i.e., the repartition of regimes over our time series. The probability of remaining in the baseline regime is very high ($P(R_t = 1)$>0.9) for cocoa, hides of cattle and palm oil, for instance. Other commodities, such as cotton and beef experience, also have a high probability of remaining in the baseline regime. The probability of remaining in the jump regime ($P(R_t = 2)$>0.9) is also high for some commodities, such as cocoa and palm oil, thus confirming the presence of periods characterized by continuous jumps. Considering the unconditional probabilities, we find that cocoa, soybeans, sugar and beef have high probabilities of being in the jump regime (40%, 48%, 60% and 50%, respectively). Therefore, the jump regime state is not marginal but a real economic state reflecting the price dynamic behaviour.

Figures 9–16 graph the log returns (in the upper part of the figure) and the probability of being in the

Table 5. Hides of cattle.

State	β_i	c_i	σ_i^2	$\mathbb{E}$	$Var[P_{t,i}]$	q_{ii}	$P(X_t = i)$
Standard	0.6742	0.0000	0.0011	0.0000	0.0013	0.9724	0.8916
Jump	0.7388	0.0021	0.0214	0.0029	0.0230	0.7731	0.1084

Table 3. Cocoa.

State	β_i	c_i	σ_i^2	$\mathbb{E}$	$Var[P_{t,i}]$	q_{ii}	$P(X_t = i)$
Standard	0.81746	0.00251	0.00520	0.00308	0.00537	0.97268	0.60011
Jump	0.95394	0.00464	0.00162	0.00487	0.00163	0.95901	0.39989

Table 4. Cotton.

State	β_i	c_i	σ_i^2	$\mathbb{E}$	$Var[P_{t,i}]$	q_{ii}	$P(X_t = i)$
Standard	0.5309	−0.0013	0.00085	−0.0024	0.0011	0.8817	0.6195
Jump	0.4608	0.0029	0.0049	0.0064	0.0070	0.8074	0.3805

Table 6. Soybeans.

State	β_i	c_i	σ_i^2	$\mathbb{E}$	$Var[P_{t,i}]$	q_{ii}	$P(X_t = i)$
Standard	0.8916	0.0065	0.0008	0.0073	0.0008	0.6674	0.5158
Jump	0.5296	−0.0019	0.0051	−0.0037	0.0066	0.6457	0.4842

Table 7. Palm oil.

State	β_i	c_i	σ_i^2	$\mathbb{E}$	$Var[P_{t,i}]$	q_{ii}	$P(X_t = i)$
Standard	0.8118	0.0076	0.0026	0.0093	0.0027	0.9789	0.8075
Jump	0.6998	−0.0136	0.0111	−0.0194	0.0122	0.9115	0.1925

Table 8. Corn.

State	β_i	c_i	σ_i^2	$\mathbb{E}$	$Var[P_{t,i}]$	q_{ii}	$P(X_t = i)$
Standard	0.7155	0.0076	0.0015	0.0106	0.0016	0.7958	0.7561
Jump	0.5744	−0.0176	0.0111	−0.0307	0.0135	0.3672	0.2439

Table 9. Sugar.

State	β_i	c_i	σ_i^2	$\mathbb{E}$	$Var[P_{t,i}]$	q_{ii}	$P(X_t = i)$
Standard	0.8353	−0.0132	0.0020	−0.0158	0.0020	0.7257	0.3984
Jump	0.6577	0.0086	0.0079	0.0131	0.0089	0.8184	0.6016

Table 10. Beef.

State	β_i	c_i	σ_i^2	$\mathbb{E}$	$Var[P_{t,i}]$	q_{ii}	$P(X_t = i)$
Standard	0.9497	−0.0023	0.0006	−0.0025	0.0006	0.8225	0.4976
Jump	0.8518	0.0058	0.0018	0.0068	0.0019	0.8242	0.5024

jump regime (in the lower part of the graph). The plotted line of the log returns can be drawn either in blue (standard regime) or in red (jump regime). Log returns are plotted in red when the probability of being in the jump regime is higher than 0.9, corresponding to a 90% likelihood of being in the above-mentioned regime. Figures 9–16 show that the high probabilities of being in the jump regime appear in blocks, i.e. there are some periods of jump regimes and some periods characterized by a standard evolution of commodity prices. This is especially observable for cocoa, cotton, hides of cattle, palm oil and beef. Corn, sugar and soybeans are characterized by more frequent regime changes during the studied period. In our opinion, these commodities are noisy because they are used as an input in agricultural production. Corn is even used to produce ethanol, which can explain its higher volatility in

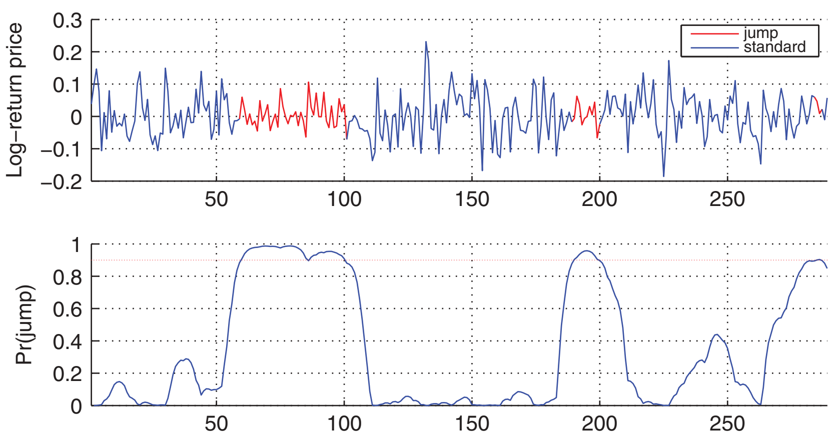

Figure 9. Cocoa.

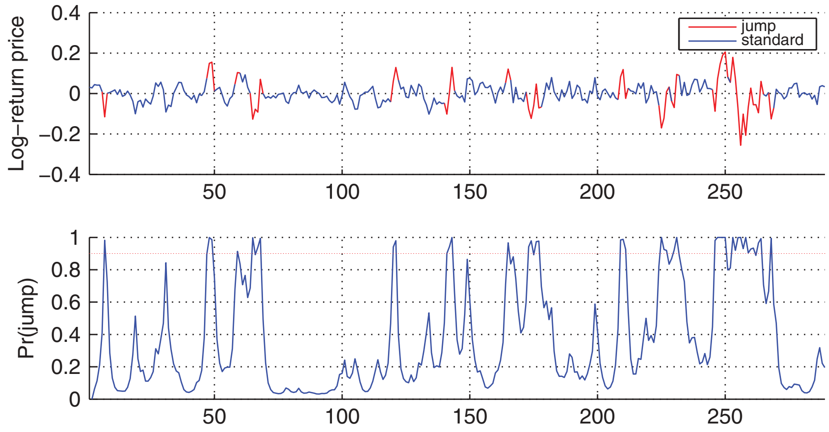

Figure 10. Cotton.

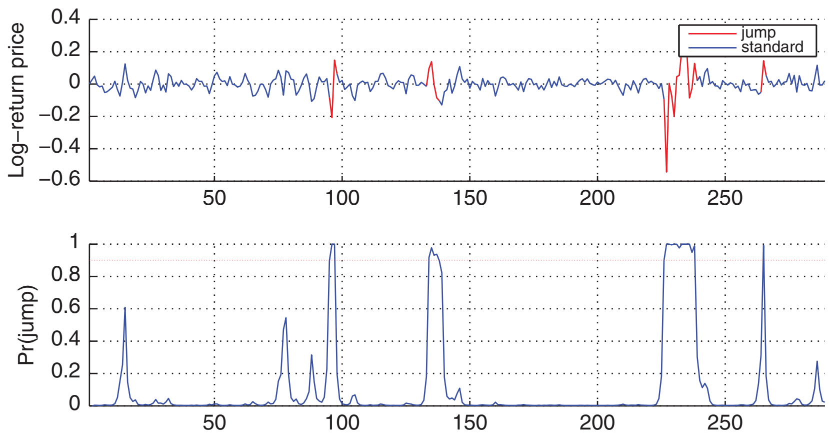

Figure 11. Hides of cattle.

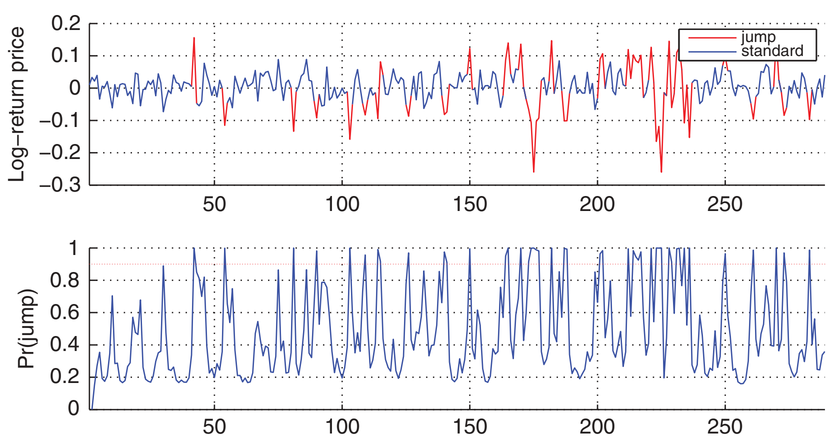

Figure 12. Soybeans.

the observed period. Unlike jump diffusions, the most interesting aspect of using the regime-switching model is that it allows consecutive spikes in a very natural way, as plotted in Figures 9–16. The results show that commodities do not systematically experience jump regimes in the same periods even if some trends can be observed: in the year 2009, most commodities are in the jump regime, whereas the

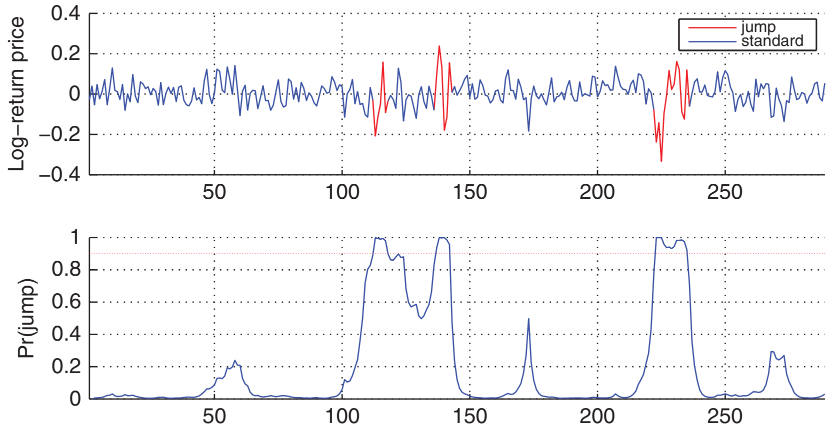

Figure 13. Palm oil.

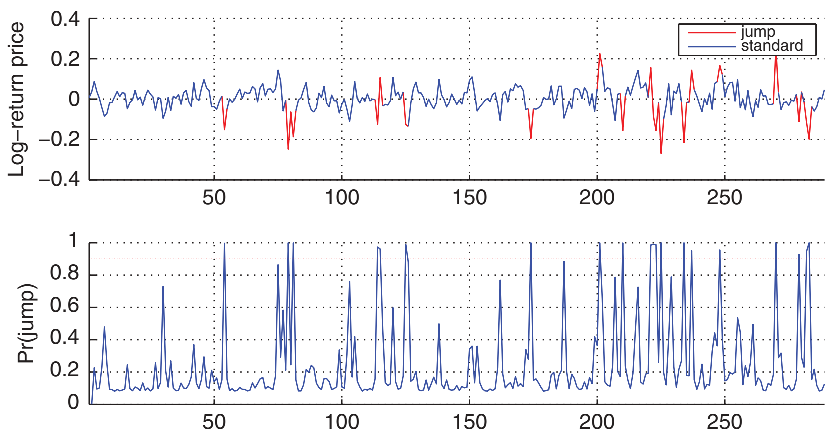

Figure 14. Corn.

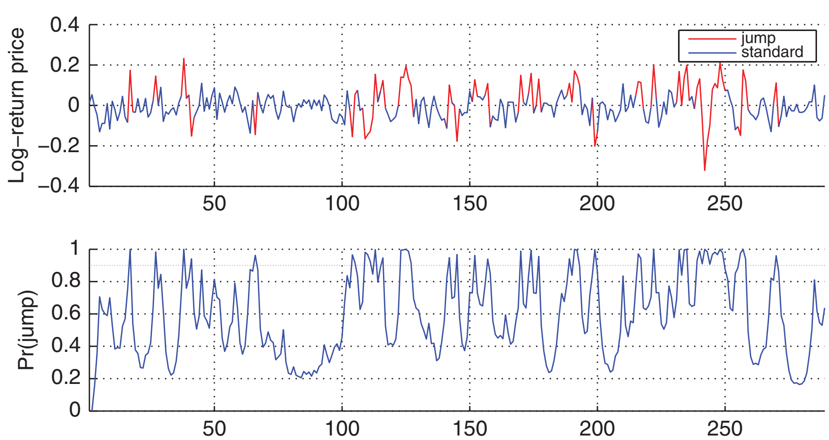

Figure 15. Sugar.

2009–2014 period is characterized by more-frequent jump regimes compared with those observed in the earlier periods.

Table 11 shows the number of jumps for each commodity. Commodities usually undergo some periods of several jumps in a row. In most cases, periods of frequent jumps capitalize more than a third of all jumps. The longest periods of jumps are correlated for cocoa and cotton, palm oil and hides of cattle, and sugar and beef. Most

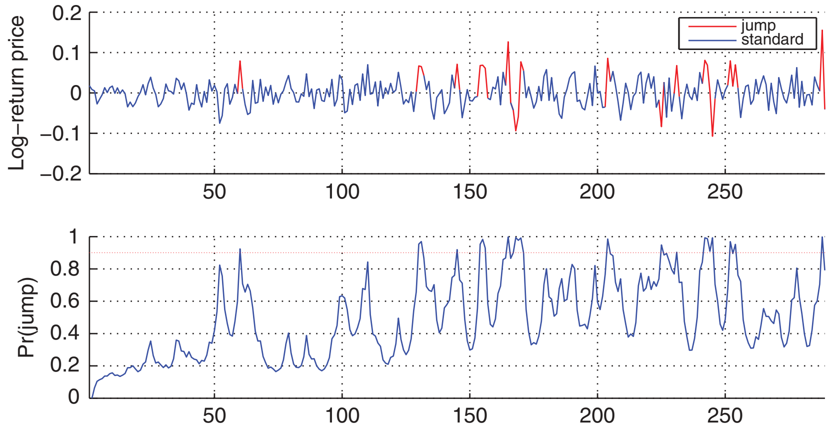

Figure 16. Beef.

Table 11. Jump intensity and persistence.

Commodity	# Jumps	Max. Jumps in a Row	Longest Jumps	Periods w/o Jumps (mean)	Jumps Duration (mean)
Cocoa	48	25	January1995–January1997	42.17	11.67
Cotton	25	3	June–August1995	20.23	2.08
Hides of Cattle	15	11	December2008-–October2009	68.25	5
Soybeans	16	4	June–September2004	24.72	1.6
Palm Oil	21	11	September2008–July2009	66.75	7
Corn	4	2	June–July2007	71	1.33
Sugar	22	10	December2009–September2010	29.56	2.75
Beef	8	3	March–May2010	56	2

commodities are characterized by a limited number of jumps: jumps occur less than 10% of the time, only cocoa and sugar are characterized by more frequent jumps, occurring, respectively, 10.7% and 16.67% of the time. Jump periods are not so frequent but tend to be long-lasting: they tend to occur every 20–70 months and they can last between 1 month and a year on average. Jumps are thus not frequent but they can last for long periods.

In the appendix, we report the table of correlations for jumps for all commodities. Results show that there is very little correlation between commodities' jumps. Jumps between commodities do not seem to be related. In the next section, we investigate whether volatility is linked to the jump patterns of commodities.

V. Jumps and volatility dynamics

This section studies the evolution of volatility across time. Figures 17–24 plot the log returns and the interval of monthly volatility. The interval is computed as [−1 SE; +1 SE]. When the log price

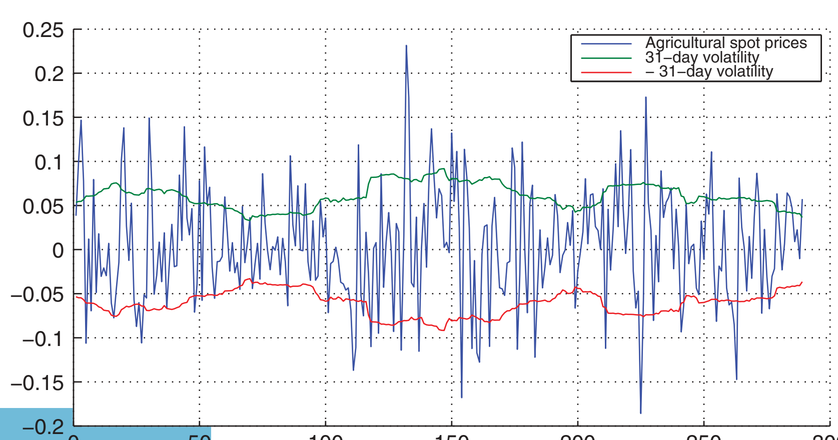

Figure 17. Cocoa.

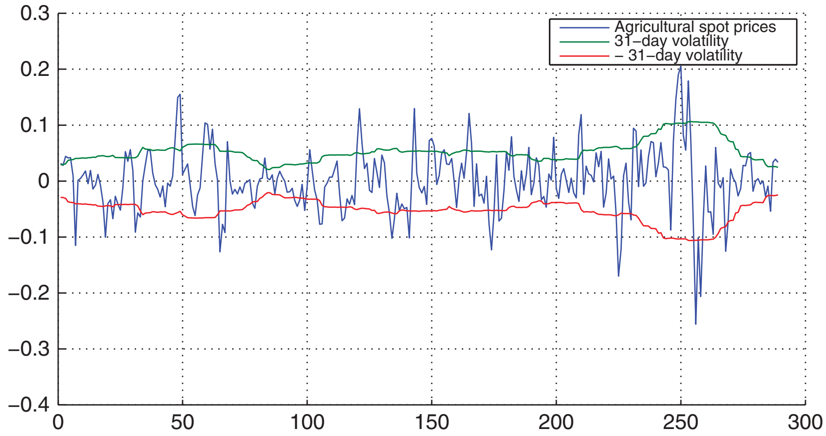

Figure 18. Cotton.

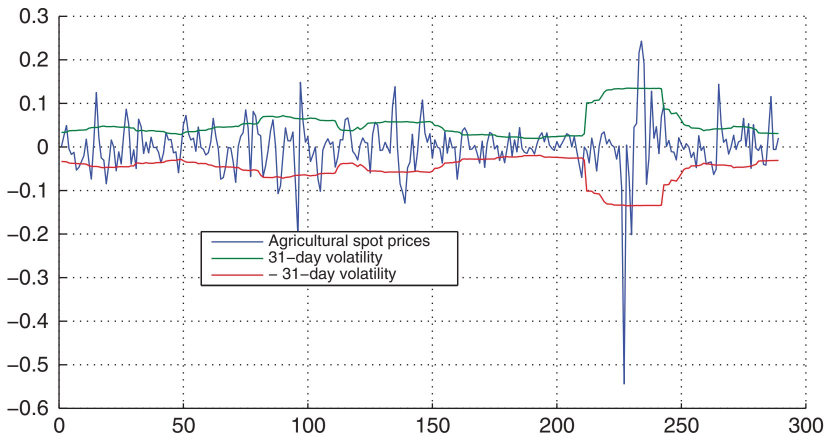

Figure 19. Hides of cattle.

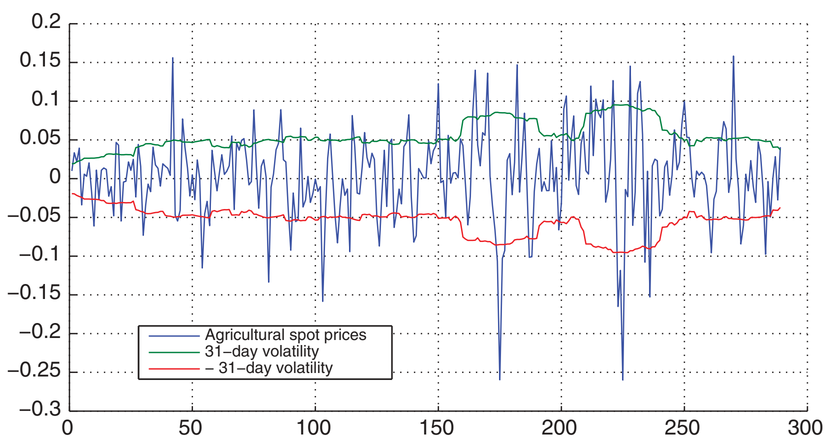

Figure 20. Soybeans.

difference goes above or beyond the volatility interval, this means that the regime switches from the standard volatility regime to the jump regime. As we can observe, volatility is not constant; the higher the volatility interval is, the more jumps there are. Such a graphical analysis allows us to analyse volatility in a dynamic pattern with a moving volatility rather than focusing on the deviation

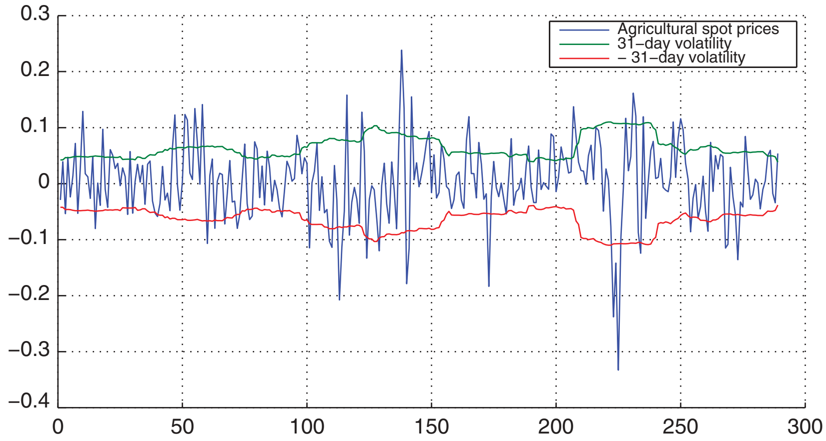

Figure 21. Palm oil.

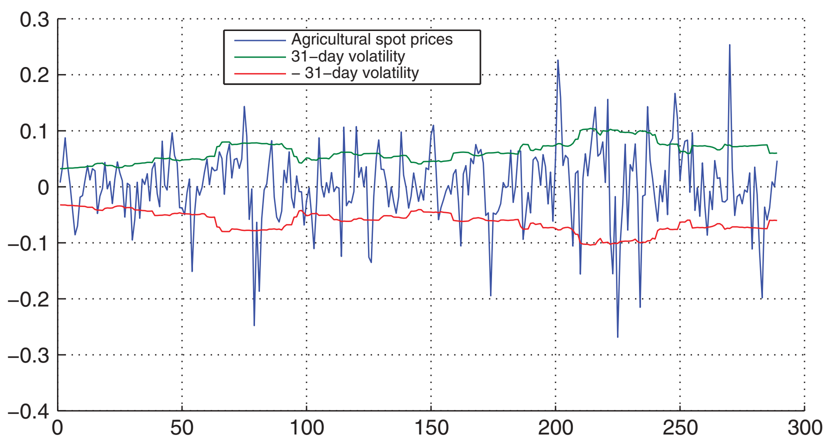

Figure 22. Corn.

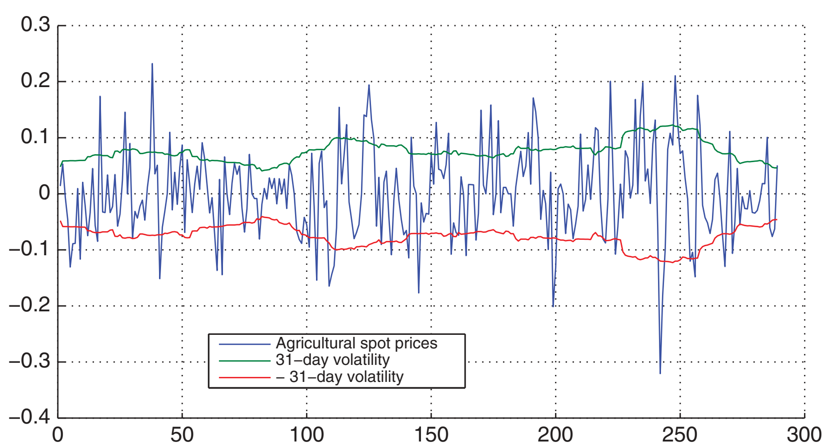

Figure 23. Sugar.

from the mean of the entire period. Using this graphical analysis shows that agricultural commodities often experience jumps in their prices, but there tends to be a quick return to a convenient level of volatility, as spikes are usually observed for a single period.

Table 12 shows the number of volatility for each commodity. Commodities usually undergo some

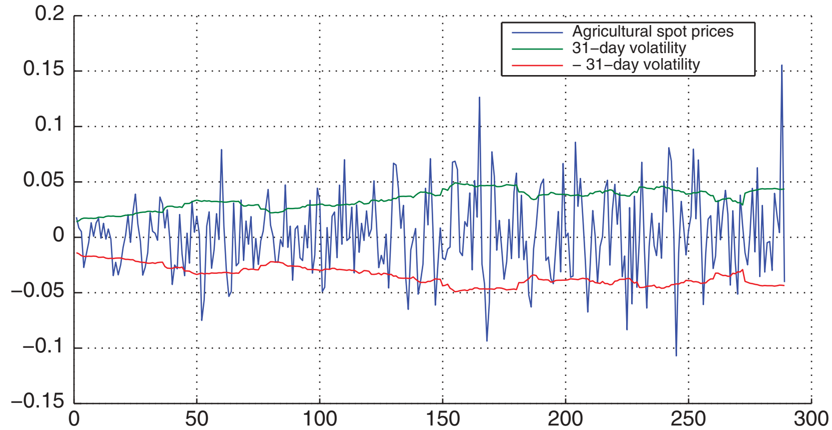

Figure 24. Beef.

periods of several months of volatility in a row, which are sometimes correlated such as cocoa and hides of cattle, and corn and soybeans. Periods of volatility are relatively short and frequent. Most commodities are characterized by a limited number of periods of volatility; they overall represent less than 15% of the observed period, but they tend to occur frequently, every 9–15 months in our data set, and to be short-lasting, usually between 1 and 2 months.

Table 13 depicts the correlation between commodities' volatility and jumps. The numbers in bold show the correlation between a given commodity volatility and jumps experienced for each period. The other numbers are the results of the correlation between the volatility of a given commodity with the presence of jumps of another commodity. The table shows that the correlation between volatility and jumps for a given commodity is in most cases above 0.3 while it is low for most of the intersections between commodities.

In order to investigate the potential links between volatility and jumps, and the potential correlation existing between commodities, we then run a simple probit model :

$$J_i = \beta_0 + \beta V_i + \eta_i \tag{5.4}$$

where V_i is a dummy variable equal to one if a jump is observed and 0 otherwise, $\beta$is the vector of coefficients, $V_i$is the vector of volatility covariates for commodity i,

Table 12. Volatility and persistence.

Commodity	# Vol. Periods	Max Periods with Vol.	Longest Period of Vol.	Periods w/o Vol. (mean)	Duration of Vol. (mean)
Cocoa	34	5	Feb–June 1994; Aug–Dec 2011	12.09	1.7
Cotton	36	4	May–Aug 1995; Oct 2013–Jan 2014	12	1.71
Hides of Cattle	31	4	Nov 2011–Feb 2012	11.21	1.42
Soybeans	25	4	June–Sep 1991; June–Sep 2004; June–Sep 2010	13.84	1.39
Palm Oil	34	6	May–Oct 2001	9.77	1.36
Corn	22	4	June–Sep 2010	15.65	1.85
Sugar	31	5	Mar–July 2000; Sept 2013–Jan 2014	12.85	1.55
Beef	26	4	Apr–July 1991; Mar–June 1998; Dec 2003–Mar 2004	13.84	2.6

Table 13. Table of correlation between commodities' volatility and jumps.

Volatility/Jumps	Beef	Corn	Cocoa	Cotton	Hides of Cattle	Sugar	Palm Oil	Soybeans
Beef	**0.3842**	−0.0381	−0.0072	−0.00682	0.0907	−0.0085	−0.0150	−0.0651
Corn	−0.00049	**0.4461**	−0.1627	0.0612	−0.0865	0.0206	0.0322	0.2648
Cocoa	0.0051	0.066	**−0.104**	0.1019	−0.0407	−0.0282	−0.0015	0.0181
Cotton	0.0012	0.0401	0.0449	**0.3503**	0.0808	0.002	0.0609	0.0261
Hides of Cattle	−0.0598	0.0680	0.0411	0.0637	**0.1711**	0.0189	0.0861	−0.1249
Sugar	0.0488	0.0588	0.0264	0.0504	0.0085	**0.5478**	0.0212	0.0302
Palm Oil	0.0420	−0.0362	0.0546	0.0407	0.0628	−0.0251	**0.285**	0.1234
Soybeans	0.058	0.2186	−0.0982	−0.0014	−0.0141	0.0189	0.1415	**0.5922**

Table 14. Probit estimation: jump and volatility.

Commodity Variables	(1) Full Sample	(2) Beef	(3) Corn	(4) Cocoa Jump (=1)	(5) Cotton	(6) Hides of Cattle	(7) Sugar	(8) Palm Oil	(9) Soybeans
Volatility (=1)	1.103***								
	(0.0703)								
Beef Volatility (=1)		**1.844******	0.051	−0.069	**−0.393****	0.348	−0.101	−0.017	−0.138
		(0.416)	(0.347)	(0.186)	(0.228)	(0.244)	(0.226)	(0.270)	(0.272)
Corn Volatility (=1)		−0.067	**1.936******	**−0.646****	0.096	−0.495	0.158	−0.045	**0.595****
		(0.342)	(0.346)	(0.186)	(0.228)	(0.244)	(0.226)	(0.27)	(0.272)
Cocoa Volatility (=1)		0.119	0.028	−0.298	0.341	−0.183	−0.172	0.001	−0.300
		(0.272)	(0.291)	(0.191)	(0.207)	(0.253)	(0.225)	(0.256)	(0.256)
Cotton Volatility (=1)		−0.179	0.012	0.151	**1.12******	0.161	−0.231	0.134	0.205
		(0.304)	(0.307)	(0.193)	(0.206)	(0.243)	(0.229)	(0.265)	(0.268)
Hides Volatility (=1)		−0.197	0.343	0.116	−0.026	**0.684*****	0.096	0.482	−0.549
		(0.326)	(0.310)	(0.195)	(0.212)	(0.246)	(0.215)	(0.255)	(0.309)
Sugar Volatility (=1)		0.244	0.435	0.053	0.045	−0.065	**1.869******	−0.09	0.172
		(0.292)	(0.299)	(0.192)	(0.205)	(0.228)	(0.219)	(0.234)	(0.240)
Palm Oil Volatility (=1)		0.120	−0.357	0.189	0.071	0.237	−0.325	**1.027******	0.145
		(0.297)	(0.302)	(0.191)	(0.208)	(0.222)	(0.241)	(0.223)	(0.240)
Soybeans Volatility (=1)		0.418	**0.574****	−0.193	−0.13	0.144	0.103	0.432	**1.992******
		(0.332)	(0.294)	(0.212)	(0.229)	(0.28)	(0.24)	(0.241)	(0.273)
Constant	−2.044***	−2.785***	−3.029***	−0.792***	−1.55***	−1.913***	−1.717***	−2.203***	−2.144***
	(0.12)	(0.579)	(0.441)	(0.177)	(0.183)	(0.273)	(0.246)	(0.262)	(0.27)
Pseudo R^2	0.16	0.30	0.39	0.05	0.16	0.10	0.33	0.17	0.43

All models are probits. Robust SE in parentheses with *p < 0.10, **p < 0.05 and ***p < 0.01. In model (1), dummies for commodities are included. Models (2)–(9) split the sample for each commodity. Bold values indicate the coefficients of interest.

and $is\eta_i$ the random disturbance for a given commodity i. The vector of covariates includes dummies controlling for the presence of volatility for each commodity.

Table 14 summarizes the results from the probit model. Column (1) describes the results for the full sample, where volatility and jump refer to the volatility of a given commodity i at period t. Columns (2)– (9) depict the results for each commodity taken separately in order to capture the potential effect of the volatility of all other commodities on the probability of jumps for a given commodity. Such models give us the opportunity to look at potential cross-correlations between commodities. Interesting results are reported in bold. For all commodities, except cocoa, there is a significant positive relationship between volatility and jumps. Interestingly, there is a significant negative relationship between corn and cocoa and a significant positive relationship between corn and soybeans, most probably because these commodities are usually part of the same financial products. The presence of volatility thus increases the probability of jumps.

VI. Conclusion

In the current context of highly volatile commodity prices, a better description of price movements is essential to hedge risks. In these markets, fundamentals might no longer be relevant to understand volatility. In this article, we model agricultural commodity prices to obtain a better analysis of volatility. We show that the Gaussian distribution does not fit well with the distribution of real-life prices. By contrast, distributions accounting for jumps – especially the NIG distribution – provide a good fit of the real distribution of prices. The results show that because of the volatility in the agricultural commodity markets, standard models based on a Gaussian distribution will be inefficient in understanding the evolution of prices in these markets. By contrast, models using jumps will provide a better understanding of the volatility on these markets. Indeed, extreme volatility and price spikes lead to heavy-tailed distributions of price changes. Moreover, using log returns generates lighter tails than the first differences of agricultural commodity prices themselves. We then use a regime-switching model to identify the periods in which jumps occur. We find that the probability of being in a jump regime tends to increase in the last four years and that commodity prices tend to be correlated. We finally show that volatility also evolves throughout the period and that jumps are more frequent when volatility is high for a given commodity i. However, there does not seem to be a link between the volatility of a given commodity i and the probability of experiencing a jump for commodity j.

Our results have implications for researchers focused on the study of volatility and for professionals working in the financial industry, such as analysts, brokers, quants, or traders. Indeed, by identifying the key instruments for identifying volatility, we can help investors build the right portfolios. Further studies could focus on the correlation between storage and price volatility or on the impact of price volatility on consumer utility.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix

Table A1. Cocoa.

Distribution	α	σ, δ	β	μ
Gaussian		6.3714		0.3923
Hyperbolic	0.4099	12.3620	0.0505	−1.6200
NIG	0.3757	14.8032	0.0521	−1.6803
Alpha-stable	1.9512	4.3331	0.9383	0.4591

Table A2. Cotton.

Distribution	α	σ, δ	β	μ
Gaussian		5.7298		0.0794
Hyperbolic	0.2761	2.5677	0.0027	−0.0068
NIG	0.1741	5.7014	0.0016	0.0284
Alpha-stable	1.7461	3.2891	0.2168	0.2289

Table A3. Hides of Cattle.

Distribution	α	σ, δ	β	μ
Gaussian		6.0227		0.0430
Hyperbolic	0.2765	0.0001	0.0000	0.0417
NIG	0.0905	2.9500	−0.0023	0.1182
Alpha-stable	1.5284	2.5017	0.0644	0.1139

Table A4. Soybeans.

Distribution	α	σ, δ	β	μ
Gaussian		5.8677		0.3097
Hyperbolic	0.2751	2.8697	−0.0213	1.0232
NIG	0.1814	6.1041	−0.0207	1.0115
Alpha-stable	1.7573	3.4102	−0.0444	0.5125

Table A5. Palm oil.

Distribution	α	σ, δ	β	μ
Gaussian		6.8810		0.3827
Hyperbolic	0.2488	4.6344	−0.0064	0.6758
NIG	0.1691	7.8495	−0.0075	0.7314
Alpha-stable	1.7996	4.1034	0.0543	0.5891

Table A6. Corn.

Distribution	α	σ, δ	β	μ
Gaussian		6.6708		0.2223
Hyperbolic	0.2433	3.2107	−0.0185	1.0118
NIG	0.1506	6.5299	−0.0177	0.9963
Alpha-stable	1.7247	3.7567	−0.3296	0.1565

Table A7. Sugar.

Distribution	α	σ, δ	β	μ
Gaussian		7.8720		0.0404
Hyperbolic	0.2338	7.2097	0.0274	−1.6473
NIG	0.1936	11.7236	0.0290	−1.7346
Alpha-stable	1.8539	5.0138	0.9917	0.5313

Table A8. Beef.

Distribution	α	σ, δ	β	μ
Gaussian		3.5521		0.2109
Hyperbolic	0.6679	5.4911	0.1156	−1.1765
NIG	0.5713	6.7266	0.1137	−1.1549
Alpha-stable	1.9293	2.3578	1.0000	0.2588

Table A9. Table of correlation: commodities' jumps.

Commodity	Beef	Corn	Cocoa	Cotton	Hides of Cattle	Sugar	Palm Oil	Soybeans
Beef	1							
Corn	−0.0581	1						
Cocoa	0.0388	0.088	1					
Cotton	0.0691	0.0687	0.0728	1				
Hides of Cattle	−0.0516	0.0286	0.0509	0.1773	1			
Sugar	0.0098	−0.0241	−0.0032	0.0889	0.0002	1		
Palm Oil	0.0106	0.0154	−0.0033	0.107	−0.014	0.0799	1	
Soybeans	−0.068	0.2595	0.1157	−0.0093	−0.0818	−0.0164	0.1511	1

Table A9 shows the correlation between commodities' jumps. The correlation between jumps is usually low, except for soybeans and corn, which experience a higher degree of jumps correlations.

Table A10. Table of correlation: commodities' volatility.

Commodity	Beef	Corn	Cocoa	Cotton	Hides of Cattle	Sugar	Palm Oil	Soybeans
Beef	1							
Corn	−0.0238	1						
Cocoa	−0.0964	−0.0567	1					
Cotton	0.0359	0.0423	−0.1165	1				
Hides of Cattle	−0.0205	0.0377	−0.0516	0.0095	1			
Sugar	0.0867	0.0948	−0.1156	0.0753	−0.0082	1		
Palm Oil	0.0124	0.1650	−0.141	0.125	0.4261	0.0645	1	
Soybeans	0.0268	0.3341	−0.1515	0.0937	0.1171	0.0603	0.2858	1

Table A10 shows the correlation between commodities' volatility. The correlation is usually low, except for soybeans and corn, soybeans and palm oil, which experience a medium level of correlation.