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Jumps in Energy and Non-Energy Commodities

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Abstract

Jumps in the price process of assets represent a sort of tail risk and are found to affect many aspects of asset pricing, volatility modelling, and asset allocation. In this paper, we detect price jumps in the realized volatility series of a wide set of commodity futures and find evidence of a jumpy behaviour, especially in energy and agricultural commodities. We examine whether the realized volatilities of commodity futures jump together and find evidence that co-jumping is significant and generally clustered within the commodity groups, suggesting some sort of segmentation regarding the tail risk behaviour across energy, agricultural, and metals commodities. Additional analysis shows that price jumps and macroeconomic news surprises tend to occur together in specific commodities such as crude oil, which confirms earlier findings about the sensitivity of crude oil to news about the economy.

Keywords: Realized volatility; energy and non-energy commodities; jumps; co-jumps; macroeconomic news

1. Introduction

The commodity markets have grown to become an important investment destination for various investors, portfolio managers, hedgers, and other risk managers (Bessler and Wolff, 2015; Rehman et al., 2019; Ali et al., 2020). Their characteristics and activities also matter to commodity producers who rely on the commodity markets as the main outlet for pricing their transaction activities, including hedging operations. Interestingly, volatility jumps are not uncommon in commodity markets that have experienced booms and busts over the last two decades and increased integration resulting from, among other things, biofuel expansion (Ji et al., 2018) and financialization (Tang and Xiong, 2012)[1].

The seminal work of Barndorff-Nielsen and Shephard (2004) emphasizes the importance of jumps, which can reflect, according to Bates (2000), crash risk, i.e. tail risk. Motivated by the availability of high-frequency data, numerous later studies (e.g., Corsi et al., 2010; Charles and Darné, 2017; Ma et al., 2017; Huang, 2016; Zhu et al., 2017; Gkillas et al., 2018; Da Fonseca and Ignatieva, 2019) examine the jumps in various asset classes, providing important evidence of the impact of jumps on assets. It is often argued that the volatility of asset prices can be jumpy due to the presence of extreme shocks such as economic, financial, and geo-political events. For example, Lahaye et al. (2011) indicate that macroeconomic news might be a relevant driver of jumps in financial markets. Interestingly, Eraker (2004) and Driessen and Maenhout (2013) indicate that volatility jumps are important and have an impact on assets.

The volatility of commodities is the subject of numerous studies focusing on modelling techniques, spillovers, and connectedness (Creti et al., 2013; Nazlioglu et al., 2013; Beckmann and Czudaj, 2014; Mensi et al., 2014; Sadorsky, 2014). However, less attention is given to jumps and co-jumps in the commodity markets that constitute various groups such as energy, agricultural, and metals (see, among others, Chevallier and Ielpo (2014) and Sévi (2014), who overview the jump activities in commodity markets). Charles and Darné (2017) focus on jumps in crude oil while forecasting volatility, whereas Bouri (2019) detects price discontinuities in the sovereign risk of oil exporters and relate them to price discontinuities in crude oil. As argued by Da Fonseca and Ignatieva (2019), most of the existing literature considers the jumps in a single asset, highlighting the need to extend

[1] See Ji et al. (2018) for a discussion of the role of biofuel expansion in intensifying the link between energy and agricultural commodities; while Tang and Xiong (2012) focus on the financialization of commodities.

the literature to cover the jump activity among several assets. Much recently, Nguyen and Prokopczuk (2019) consider the price jumps in commodity markets within a calendar month and report evidence that jumps are rare events. However, studies examining jumps in the price process of the realized volatility of commodity prices are unprecedented. Given this, and the above discussion, we extend the related literature by analyzing jumps and co-jumps in the price process of the realized volatility of commodity markets. Specifically, we detect the price jump behaviour in a wide set of commodity futures via the approach of Laurent et al. (2016), which is conducted within GARCH-based models. Then, we uncover evidence of co-jumps by applying various approaches. Finally, we examine whether jumps and co-jumps are associated with macroeconomic news surprises.

Uncovering these issues is essential for financial derivatives, given that the jump activity of a financial product can be closely related to that of its underlying asset. For example, most advanced options pricing models now take into account jump activity (e.g., Driessen and Maenhout, 2013). Uncovering jump behaviour is also particularly important in the framework of hedging the risk of a derivative product and enhancing the volatility of prediction models. For example, Corsi et al. (2010) and Ma et al. (2017) indicate that jumps can increase future volatility.

Our main results show that the realized volatility of most commodity futures is subject to jumps and that there is a significant and positive contemporaneous association across the jumps, especially in the agricultural commodity. Further analysis shows that jumps tend to be associated with macroeconomic news surprises, especially for crude oil.

The rest of the paper is split into four sections. Section 2 describes the construction of daily realized data on various commodities futures. Section 3 presents the methods used to estimate jumps and capture co-jumps. Section 4 focuses on the empirical results. Section 5 concludes.

2. Data

Data on daily annualized realized volatility of 16 commodity futures contracts are collected from the Risk Lab of Professor Dacheng Xiu[2]. As in Liu et al. (2015)[3], we opt for the daily realized volatility that is based on 5-minute log returns, defined as follows:

[2] http://dachxiu.chicagobooth.edu/#risklab.

[3] The authors show that it is very difficult to beat the forecasting ability of the 5-minute realized variance measure.

$$\text{Realized Volatility}_t = \sum_{j=1}^{M} R_{t,j}^2 \quad (1)$$

where, $R_{t,j}$ denotes the jth intraday return of day t, M is the total number of observations in a trading day t, and $M = 1/\Delta$, with Δ representing the sampling frequency. The use of the 5-min data also mitigates the noise effects arising from the market structure (Andersen et al., 2012; Sévi, 2014). As for the use of realized volatility, it overcomes the issue of setting the form of the model (Hu et al., 2019).

Table 1. Statistics of daily realized volatility

	Mean	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ADF p-value
Cocoa	0.2425	1.1937	0.0013	0.0897	1.7929	14.5301	14829.25***	0.010
Coffee	0.2794	0.9153	0.0971	0.0841	1.4107	7.3553	2738.89***	0.000
Copper	0.2431	1.3105	0.0026	0.1347	2.8340	14.2217	16075.29***	0.000
Corn	0.2393	1.7592	0.0564	0.1181	2.6102	20.5128	33965.59***	0.000
Heating oil	0.2642	0.9615	0.0800	0.1269	1.6726	6.3683	2292.02***	0.000
Gold	0.1629	0.7550	0.0532	0.0796	2.5374	12.6298	12051.17***	0.000
Crude oil	0.3227	1.0633	0.0864	0.1648	1.7184	6.2924	2303.752***	0.010
Natural gas	0.3982	1.6977	0.1200	0.1595	1.7901	9.6380	5785.303***	0.000
Orange juice	0.2992	1.6048	0.0001	0.1544	1.6785	10.3134	6586.187***	0.000
Palladium	0.3006	2.0966	0.0005	0.1483	2.7668	19.3117	30176.24***	0.000
Platinum	0.2144	1.1790	0.0002	0.1000	3.7442	23.7608	49540.84***	0.000
Silver	0.2873	1.7645	0.0994	0.1472	2.8348	16.7103	22387.69***	0.000
Soybean	0.2038	0.8543	0.0643	0.0853	2.1256	10.3664	7357.123***	0.000
Soybean meal	0.2419	1.2156	0.0572	0.0961	1.9853	11.4756	8909.82***	0.000
Sugar	0.2815	1.0295	0.0470	0.1058	0.9241	5.5704	1019.395***	0.000
Wheat	0.2845	1.4487	0.0904	0.1082	2.0992	14.1625	14465.75***	0.000

Note: The sample period is 22 September 2008 to 16 April 2019, leading to 2,441 daily common observations.

The sample period is 22 September 2008 to 16 April 2019, as dictated by the availability of some commodity futures. In total, there are 2,441 daily common observations[4]. The statistics from Table 1 show that natural gas has the highest mean, followed by light crude oil. Conversely, the lowest mean is for gold. The largest standard deviation is reported for light crude oil, while the lowest

[4] More details on the construction of daily realized volatility are given at http://dachxiu.chicagobooth.edu/#risklab.

standard deviation is for gold. There is evidence of excess kurtosis and positive skewness. Given that our empirical methods require stationary data, we employ the augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979). Results show that the levels of all the realized volatility series are stationary. Accordingly, our empirical analyses are conducted with level series, otherwise taking the first difference of stationary series may lead to spurious estimates of the volatility modelling and dependencies with other series (Gupta et al., 2015). Figure A1 in the appendix draws the daily realized volatility of the 16 commodity futures contracts under study. Regarding the correlation matrix among the 16 daily realized volatilities, it is given in Table 2. The highest positive correlations are between light crude oil and heating oil (0.7999), and corn and wheat (0.7765). The lowest negative correlation is between cocoa and coffee (-0.1093). Finally, the weakest correlations are between coffee and heating oil (0.0087), and coffee and orange juice (0.0250).

3. Methodology

3.1. The jump test of Laurent et al. (2016)

We follow Laurent et al. (2016)[5] by testing for additive jumps in AR-GARCH-GJR models[6]. Random returns (r_t) are described by an AR(1)-GARCH(1,1) model:

$$r_t = \mu_t + \alpha\, r_{t-1} + \varepsilon_t \tag{2}$$

$$\varepsilon_t = \sigma_t z_t \text{ and } z_t \sim i.i.d.\ N(0,1) \tag{3}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{4}$$

where μ_t is the conditional mean of the random returns (r_t), z_t is the white noise process, and σ_t^2 is the conditional variance of r_t.

[5] According to Laurent et al. (2016), their test is comparable to the non-parametric jump tests of Lee and Mykland (2008).

[6] To account for potential asymmetry, Laurent et al. (2016) extend their semi-parametric test for additive jumps in AR-GARCH models to AR -GARCH-GJR models. However, our results remain qualitatively the same if we apply the AR- AR-GARCH-GJR model.

Table 2. Correlation matrix

	Cocoa	Coffee	Copper	Corn	Heating_oil	Gold	Crude_oil	Natural gas	Orange juice	Palladium	Platinum	Silver	Soybean	Soybean meal	Sugar
Cocoa	1														
Coffee	-0.1093	1													
Copper	0.3503	0.074	1												
Corn	0.2109	0.1325	0.5429	1											
Heating oil	0.2353	0.0087	0.656	0.3787	1										
Gold	0.1442	0.0532	0.6496	0.453	0.5469	1									
Crude oil	0.2685	0.0586	0.7078	0.3808	0.7999	0.4926	1								
Natural gas	0.1729	0.1059	0.3398	0.2331	0.3542	0.2237	0.3978	1							
Orange juice	0.0752	0.025	0.1303	0.1788	0.1405	0.1317	0.1478	0.141	1						
Palladium	0.2459	0.026	0.5831	0.3629	0.4335	0.4397	0.4679	0.2288	0.1358	1					
Platinum	0.2683	0.0544	0.757	0.4475	0.5743	0.6383	0.6049	0.2595	0.1556	0.6394	1				
Silver	0.1817	0.1353	0.7044	0.5181	0.4272	0.6501	0.4909	0.2232	0.1451	0.5628	0.7123	1			
Soybean	0.2462	0.1002	0.6493	0.7955	0.4683	0.5144	0.4617	0.2707	0.1694	0.4075	0.5797	0.5461	1		
Soybean meal	0.1503	0.0967	0.527	0.7421	0.3732	0.453	0.3467	0.2464	0.158	0.3216	0.4809	0.4775	0.9243	1	
Sugar	0.2660	0.0516	0.33	0.3007	0.2682	0.128	0.2798	0.1905	0.0584	0.3189	0.2425	0.2499	0.2524	0.1934	1
Wheat	0.2578	0.1322	0.5091	0.7765	0.3683	0.364	0.3711	0.1555	0.114	0.362	0.4001	0.4713	0.7063	0.6245	0.396

Notes: We provide here the pair-wise correlation coefficients based on the full sample period (22 September 2008 to 16 April 2019).

Adding an independent jump component $a_t I_t$ to r_t, it follows that:

$$r_t^* = r_t + a_t I_t \tag{5}$$

where r_t^* is the observed returns, I_t, is a binary variable (it takes value of 1 if there is a jump on day *t* and 0 otherwise), and a_t reflects the jump size. Laurent et al. (2016) show that the conditional variance at $t+1$ (σ_{t+1}^2) is not affected by $a_t I_t$.

We then obtain the estimates of μ_t and r_t, $\tilde{\mu}_t$ and $\tilde{\sigma}_t$ respectively[7]. Notably, they are robust to potential jumps $a_t I_t$.

Considering the standardized return on day *t* as:

$$\tilde{J}_t = \frac{r_t^* - \tilde{\mu}_t}{\tilde{\sigma}_t} \tag{6}$$

To detect jump, we test the null hypothesis H_0: $a_t I_t = 0$, against the alternative H_1: $a_t I_t \neq 0$. H_0 is rejected if $\max_T |\tilde{J}_t| > g_{T,\lambda}$, where $\max_T$ is the maximum of $|\tilde{J}_t|$ for $t = 1, \ldots, T,$ and $g_{T,\lambda}$ is the critical value. If H_0 is rejected, the following binary variable is suggested:

$$\tilde{I}_t = I(|\tilde{J}_t| > g_{T,\lambda}) \tag{7}$$

where I(.) is the indicator function, with $\tilde{I}_t$ equal to 1 if there is a jump on day *t*.

3.2. Co-jump analysis

We examine co-jumps among the realized volatility series via the coexceedance rule. To this end, we define the cojumps as the jumps occurring among more than half of the number of series under study (Ma et al., 2019), in our context it is eight (16/2 = 8).

$$\sum_{i=1}^{8} I\left(\mathrm{Jump}_{t,i} > 0\right) \begin{cases} = 8 \text{ cojump} \\ \leq 1 \text{ Nocojump} \end{cases} \tag{8}$$

[7] See Laurent et al. (2016) for auxiliary specification for the conditional variance to limit the effect of $a_t I_t$ on the estimation of the parameters of the GARCH-based model.

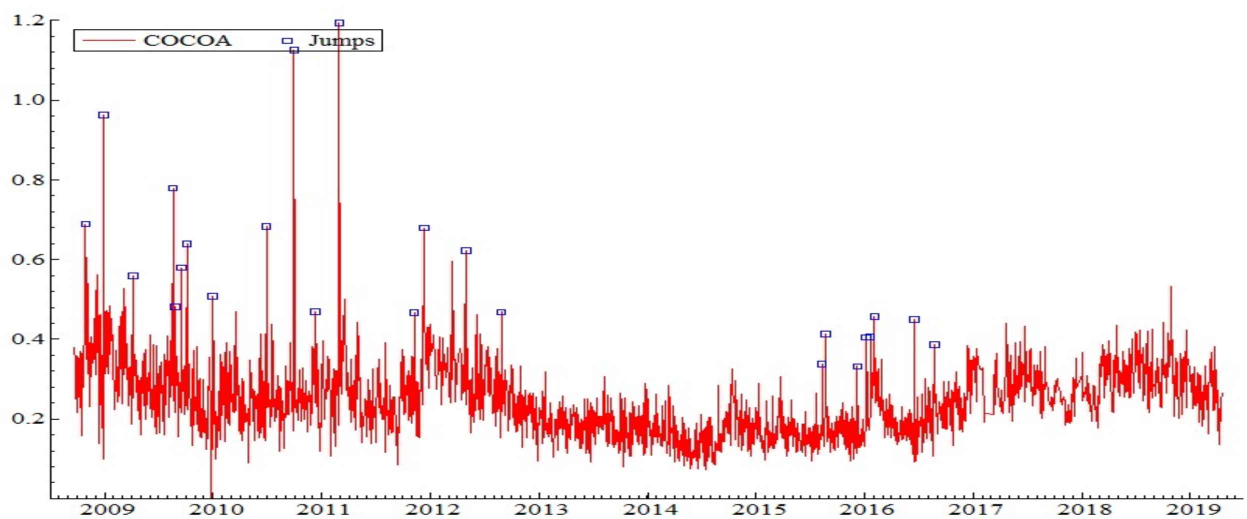
where the $I(\text{Jump}_{t,i} > 0)$ is an indication function that takes the value of 1 when a jump is detected in commodity i on day t.

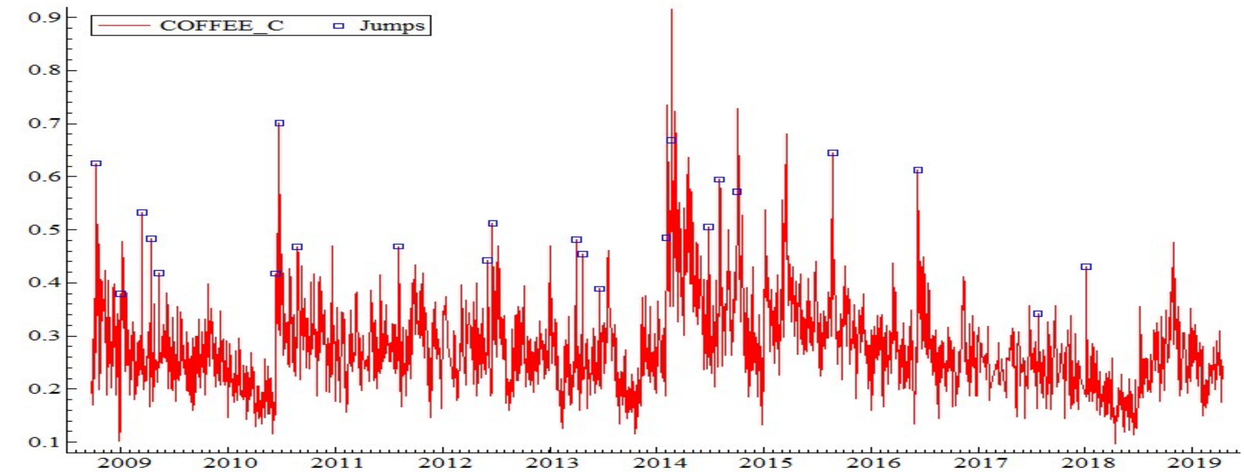
4. Empirics

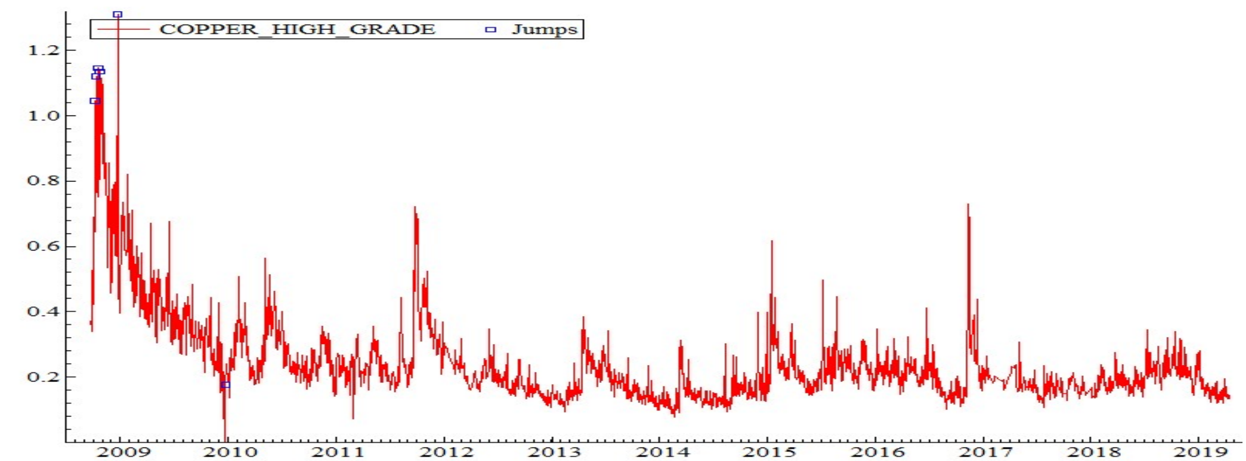
4.1. Results of the jump test of Laurent et al. (2016)

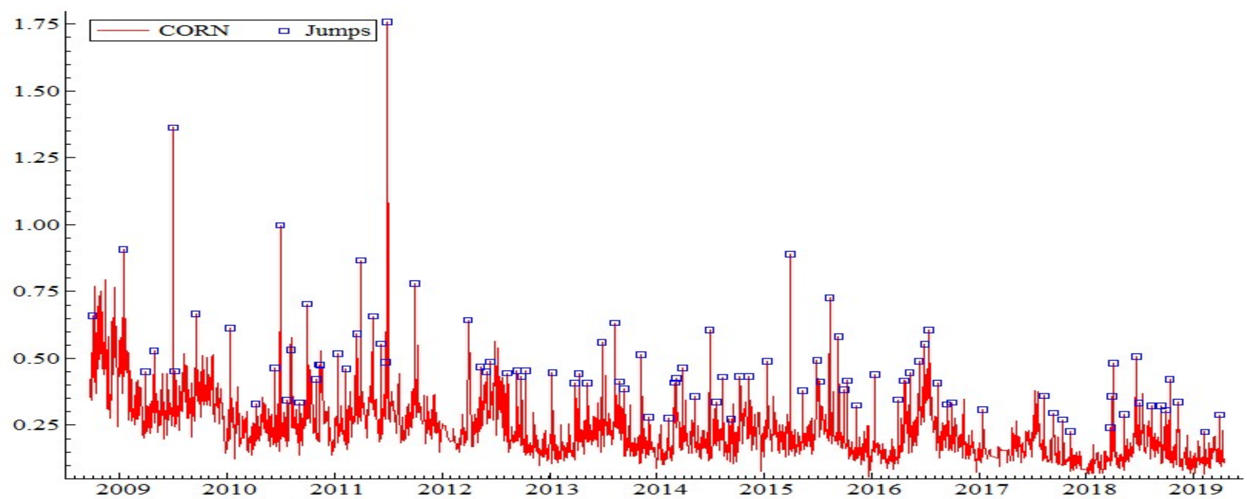
Figure 1 provides the plots of jumps on the realized volatility of the 16 commodity futures, while the statistics of the detected jumps are given in Table 3. The highest number of jumps is observed in the daily realized volatility of corn (94) and soybean meal (69), representing 3.85% and 2.83% of days. Furthermore, most jumps occur in 2016 and 2009-2010. Among the energy commodity group, the realized volatility of light crude oil experiences jumpy behaviour 53 times, representing 2.17% of the time. These findings not only imply evidence of infrequent large volatility shocks but might also point to the need to account for such large volatility shocks in any modelling involving the realized volatility of corn, soybean meal, or light crude oil. Further results show that gold appears the least jumpy, followed by heating oil and sugar.

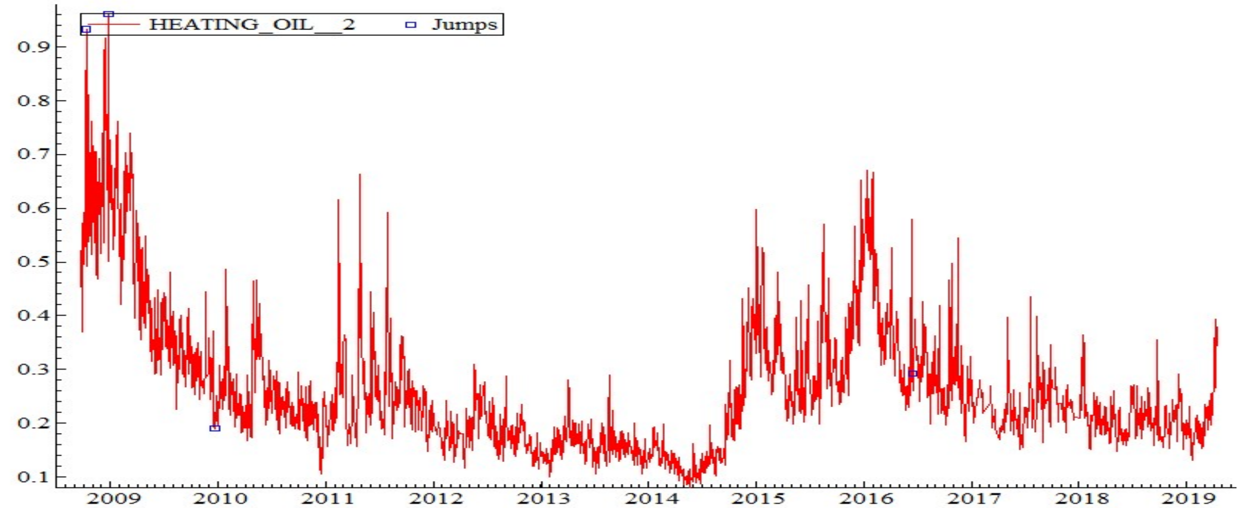
Figure 1. Plots of jumps in the realized volatility of the 16 series

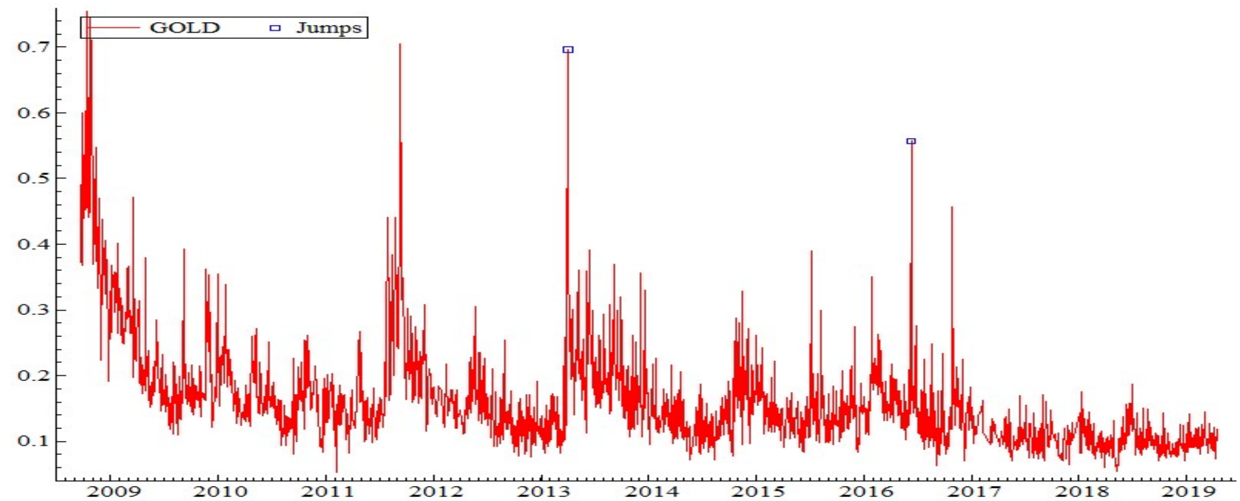


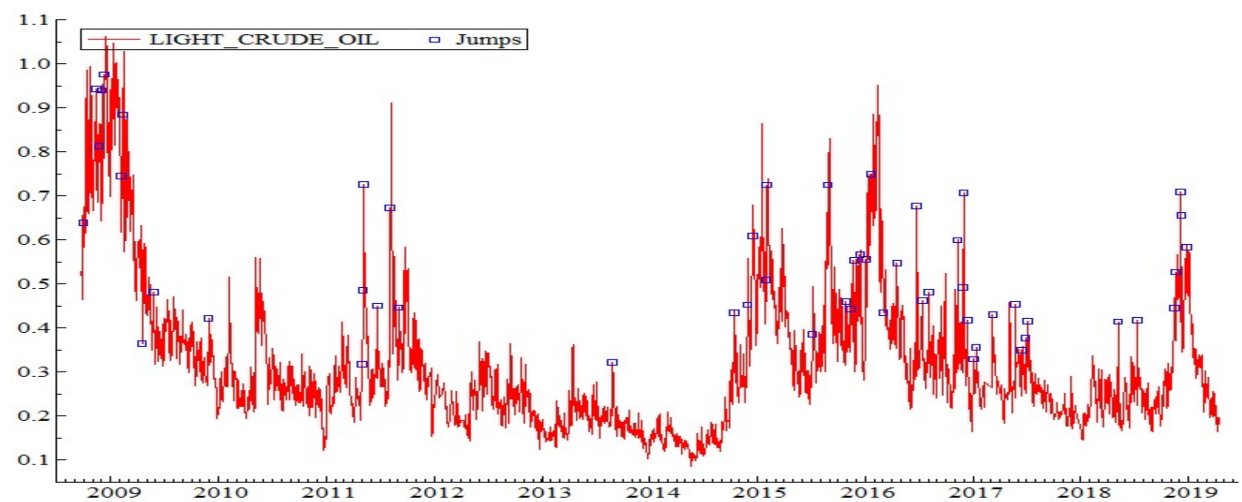

COFFEE_C
Jumps
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019

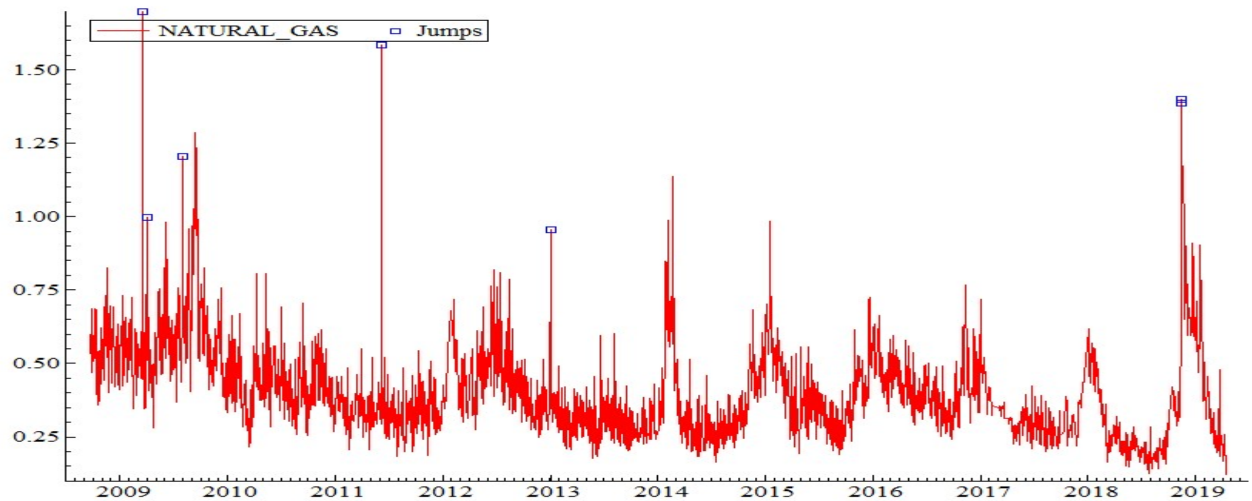

COPPER_HIGH_GRADE
Jumps
1.2
1.0
0.8
0.6
0.4
0.2
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019

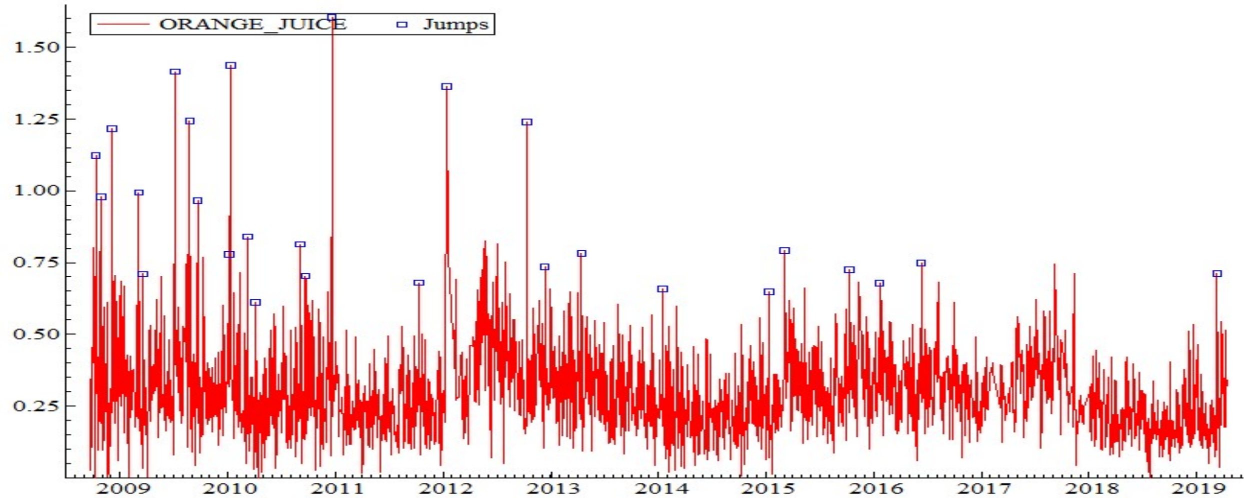

CORN
Jumps
1.75
1.50
1.25
1.00
0.75
0.50
0.25
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019

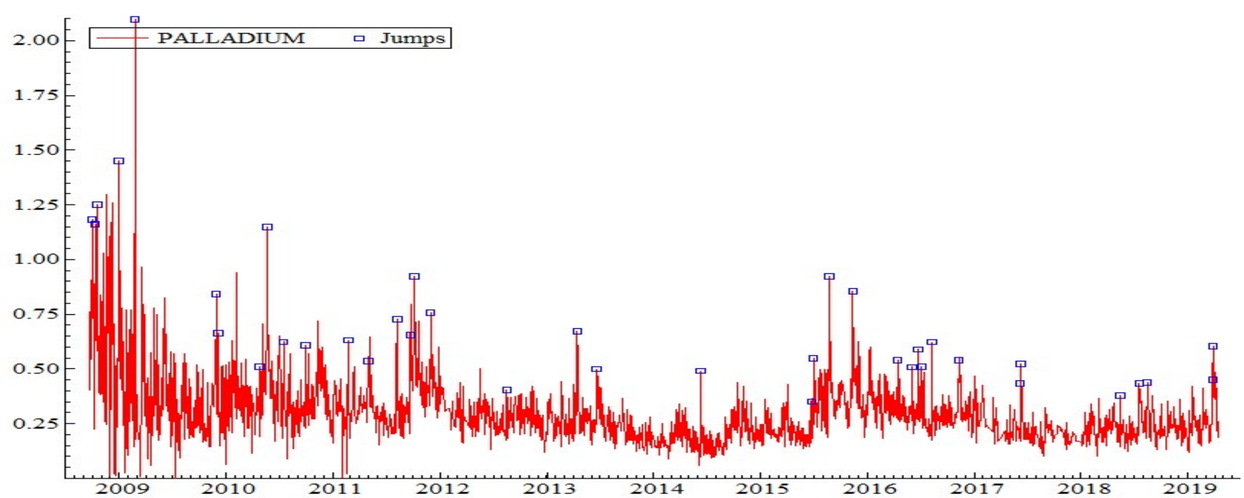

HEATING_OIL__2
Jumps

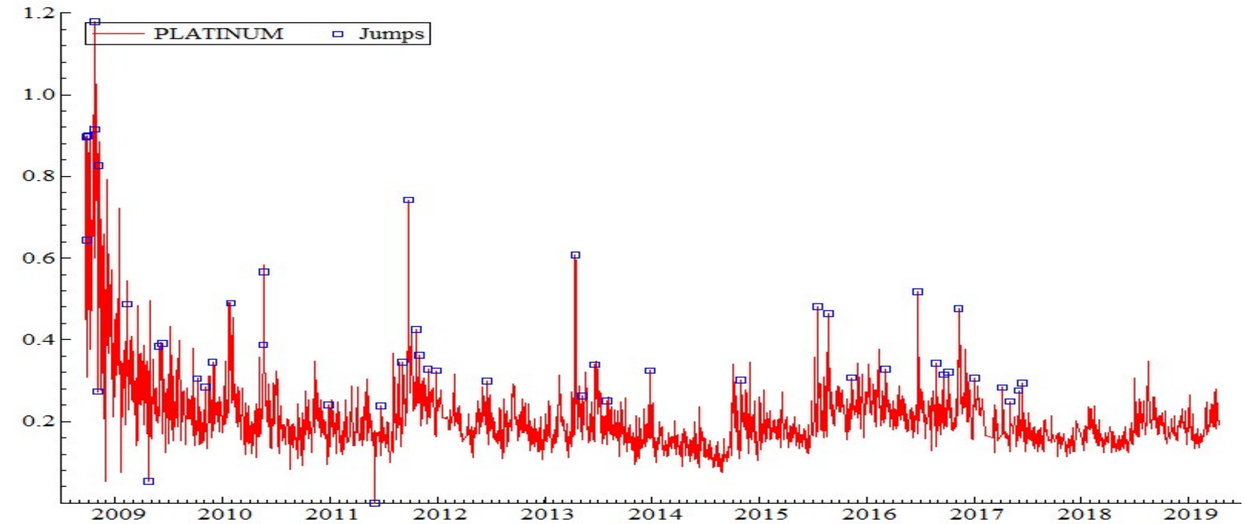

GOLD
Jumps

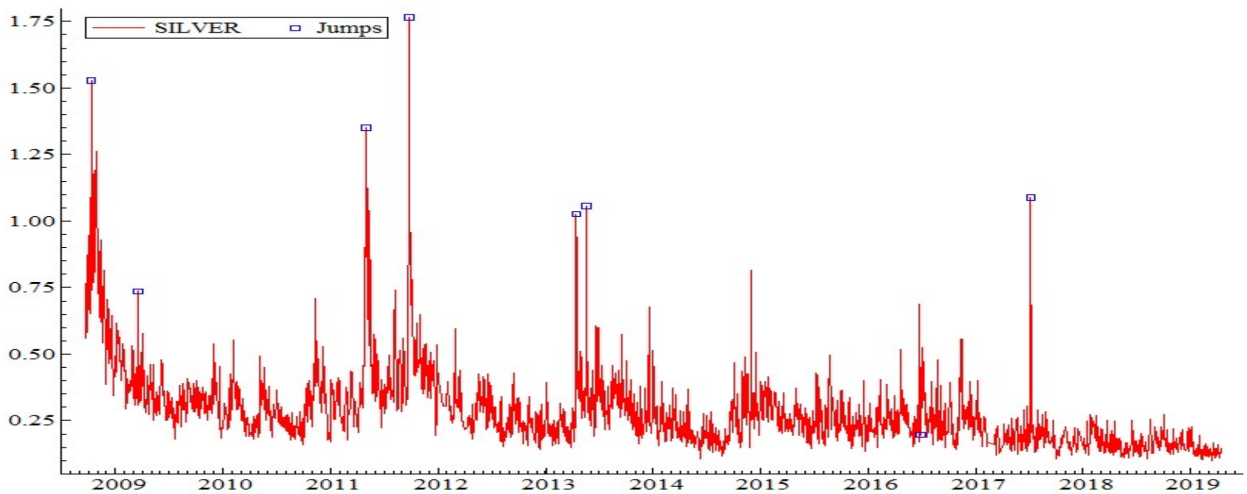

LIGHT_CRUDE_OIL
Jumps

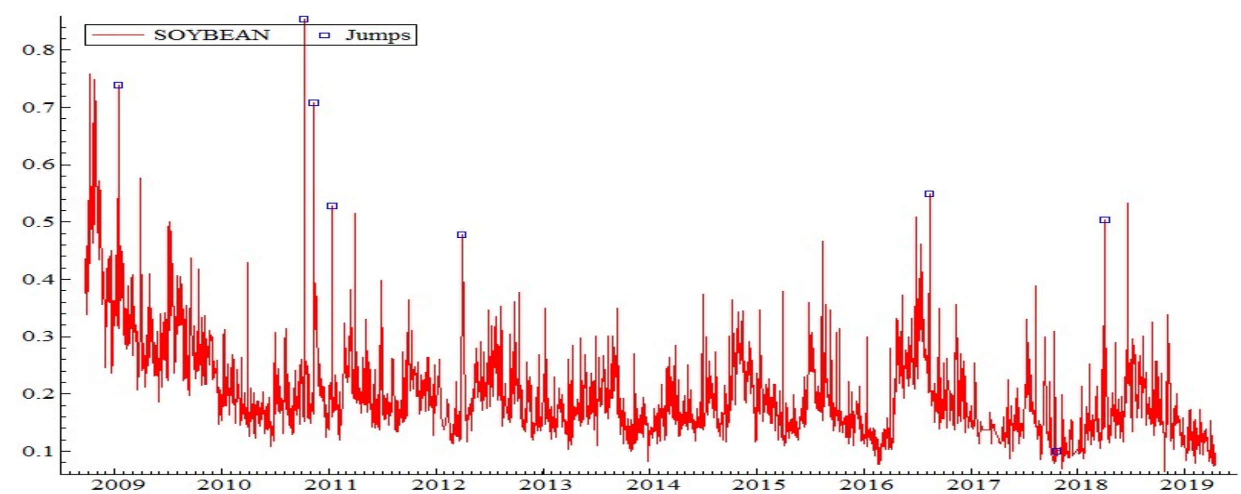

NATURAL_GAS
Jumps

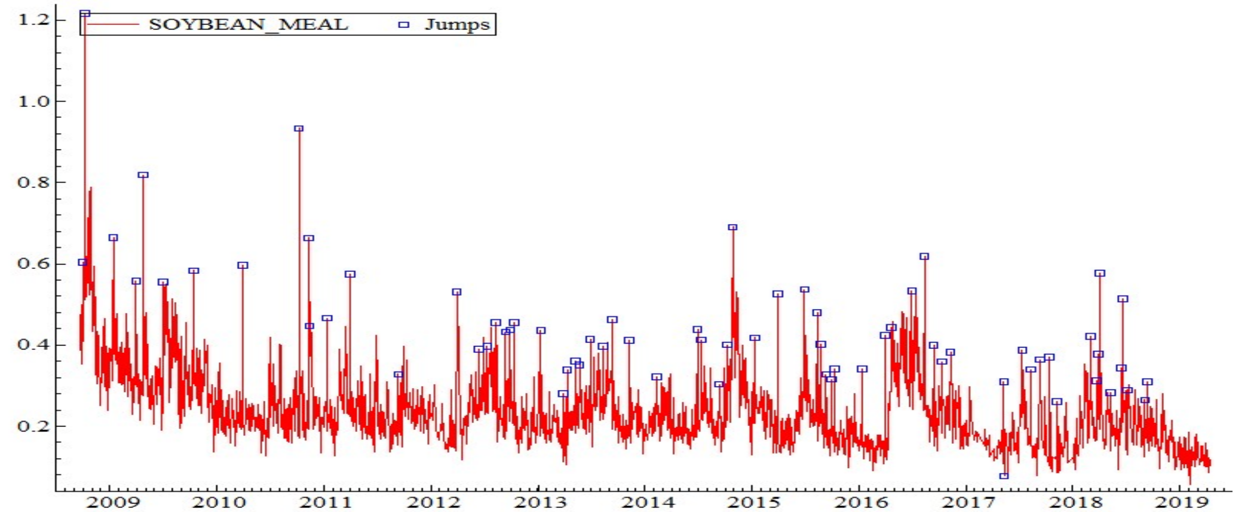

ORANGE_JUICE
Jumps

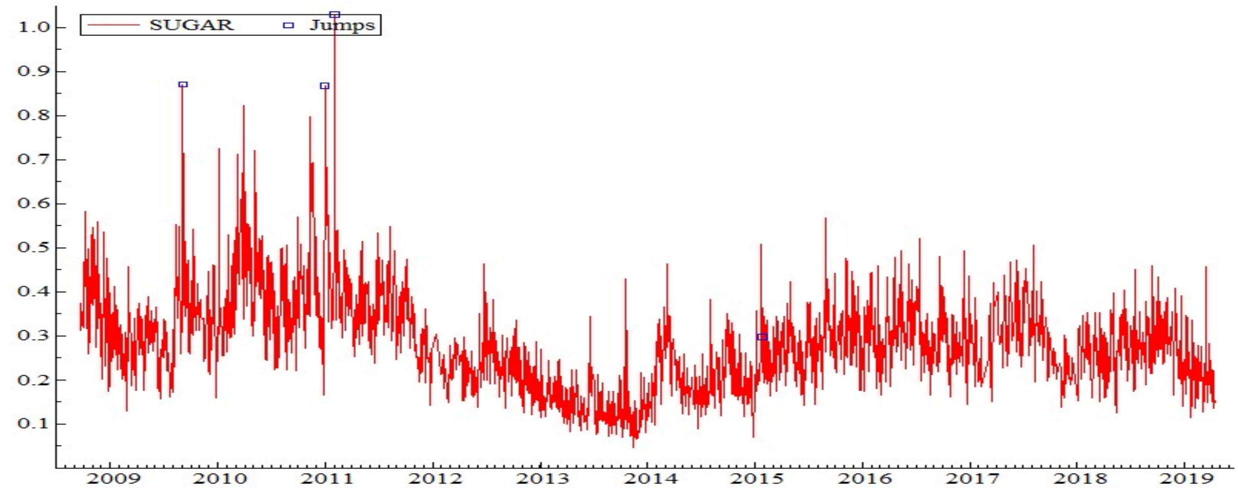

PALLADIUM
Jumps


PLATINUM
Jumps
1.2
1.0
0.8
0.6
0.4
0.2
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019


SILVER
Jumps
1.75
1.50
1.25
1.00
0.75
0.50
0.25
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019


SOYBEAN
Jumps
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019


SOYBEAN_MEAL
Jumps
1.2
1.0
0.8
0.6
0.4
0.2
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019


SUGAR
Jumps
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019

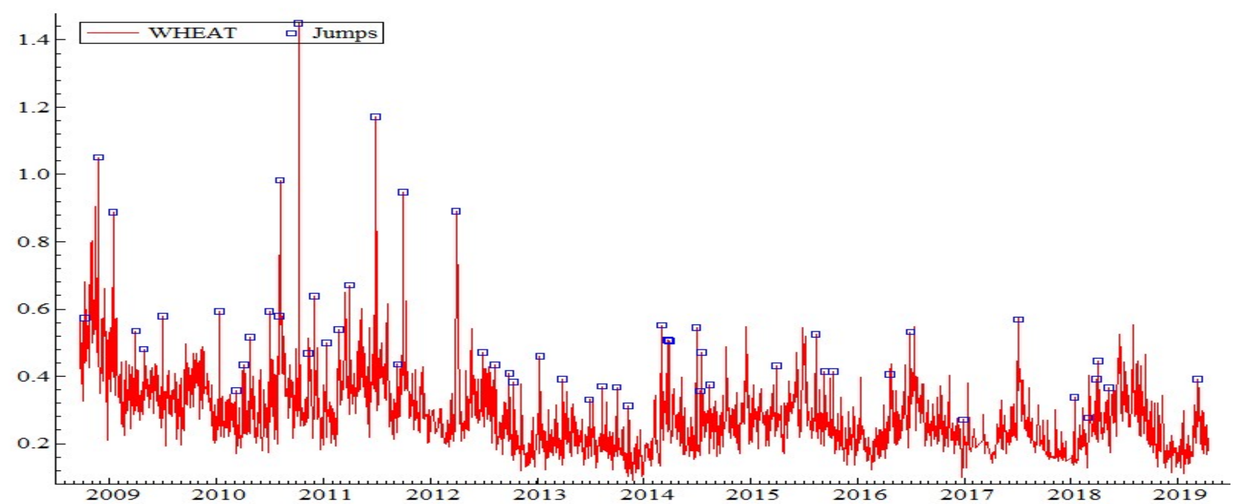

WHEAT
Jumps
1.4
1.2
1.0
0.8
0.6
0.4
0.2
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019

Table 3. Statistics of jumps

	Cocoa	Coffee	Copper	Corn	Heating_oil	Gold	Crude_oil	Natural gas	Orange juice	Palladium	Platinum	Silver	Soybean	Soybean meal	Sugar	Wheat	**Sum**
Panel A: Number of jumps																	
2008	2	2	5	1	0	2	5	0	3	4	7	1	0	2	0	2	**36**
2009	6	3	1	6	0	1	5	3	5	3	7	1	1	5	1	4	**52**
2010	3	3	0	11	0	0	0	0	7	4	4	0	2	4	1	10	**49**
2011	3	1	0	9	0	0	6	1	1	6	8	2	1	3	1	6	**48**
2012	2	2	0	8	0	0	0	0	3	1	1	0	1	7	0	5	**30**
2013	0	3	0	10	1	0	1	1	1	2	5	2	0	9	0	6	**41**
2014	0	5	0	11	0	0	3	0	1	1	1	0	0	6	0	7	**35**
2015	3	1	0	10	0	0	8	0	3	4	3	0	0	8	1	4	**45**
2016	5	1	0	10	1	1	11	0	2	6	6	1	1	8	0	3	**56**
2017	0	1	0	5	0	0	7	0	0	2	5	1	1	7	0	1	**30**
2018	0	1	0	11	0	0	7	2	0	3	0	0	1	10	0	5	**40**
2019	0	0	0	2	0	0	0	0	1	2	0	0	0	0	0	1	**6**
Sum	**24**	**23**	**6**	**94**	**4**	**2**	**53**	**7**	**27**	**38**	**47**	**8**	**8**	**69**	**4**	**54**	**468**
Panel B: % of days with jumps																	
2008	2.86%	2.86%	7.14%	1.43%	0.00%	2.86%	7.14%	0.00%	4.29%	5.71%	10.00%	1.43%	0.00%	2.86%	0.00%	2.86%	
2009	0.84%	0.84%	2.11%	0.42%	0.00%	0.84%	2.11%	0.00%	1.27%	1.69%	2.95%	0.42%	0.00%	0.84%	0.00%	0.84%	
2010	1.20%	1.20%	0.00%	4.40%	0.00%	0.00%	0.00%	0.00%	2.80%	1.60%	1.60%	0.00%	0.80%	1.60%	0.40%	4.00%	
2011	1.42%	0.47%	0.00%	4.25%	0.00%	0.00%	2.83%	0.47%	0.47%	2.83%	3.77%	0.94%	0.47%	1.42%	0.47%	2.83%	
2012	0.94%	0.94%	0.00%	3.76%	0.00%	0.00%	0.00%	0.00%	1.41%	0.47%	0.47%	0.00%	0.47%	3.29%	0.00%	2.35%	
2013	0.00%	1.20%	0.00%	4.02%	0.40%	0.00%	0.40%	0.40%	0.40%	0.80%	2.01%	0.80%	0.00%	3.61%	0.00%	2.41%	
2014	0.00%	2.01%	0.00%	4.42%	0.00%	0.00%	1.20%	0.00%	0.40%	0.40%	0.40%	0.00%	0.00%	2.41%	0.00%	2.81%	
2015	1.20%	0.40%	0.00%	3.98%	0.00%	0.00%	3.19%	0.00%	1.20%	1.59%	1.20%	0.00%	0.00%	3.19%	0.40%	1.59%	
2016	1.98%	0.40%	0.00%	3.97%	0.40%	0.40%	4.37%	0.00%	0.79%	2.38%	2.38%	0.40%	0.40%	3.17%	0.00%	1.19%	
2017	0.00%	0.68%	0.00%	3.40%	0.00%	0.00%	4.76%	0.00%	0.00%	1.36%	3.40%	0.68%	0.68%	4.76%	0.00%	0.68%	
2018	0.00%	0.42%	0.00%	4.60%	0.00%	0.00%	2.93%	0.84%	0.00%	1.26%	0.00%	0.00%	0.42%	4.18%	0.00%	2.09%	
2019	0.00%	0.00%	0.00%	2.78%	0.00%	0.00%	0.00%	0.00%	1.39%	2.78%	0.00%	0.00%	0.00%	0.00%	0.00%	1.39%	
Total	**0.98%**	**0.94%**	**0.25%**	**3.85%**	**0.16%**	**0.08%**	**2.17%**	**0.29%**	**1.11%**	**1.56%**	**1.93%**	**0.33%**	**0.33%**	**2.83%**	**0.16%**	**2.21%**	

Panel C: Number of days with co-jumps in agricultural (i.e., simultaneous jumps in at least four agricultural commodities)	
2008	0
2009	1
2010	1
2011	1
2012	2
2013	0
2014	0
2015	1
2016	0
2017	0
2018	1
2019	0
Total	**7**

Notes: Panel A of this table presents the number of jumps detected in the realized volatility series. Panel B provides the percentage (%) of days with jumps, where the corresponding % for 2008 and 2019 covers only 70 and 72 days, respectively. This means that comparison between that % in 2008 and 2019 and each of years from 2009 to 2018 must be made with caution. The total % is the average % of days with jumps over the sample period. Panel C provides the number of days when at least four series jump together in the agricultural group of commodities.

4.2. Results of co-jump

Unreported results show no evidence of co-jumping among the 16 realized volatility series, given that, at most, only five realized volatility series jump together. This finding adds to our understanding of the link between various groups of commodities (e.g., Ji et al., 2018), suggesting that the association between energy and non-energy commodities doesn't extend to jumps in the price process of the realized of commodity markets. In other words, the occurrence of extreme tail risk, as represented by jumps (Bates, 2000) is somewhat independent between energy and non-energy commodities. However, looking at the clusters of commodities, the results for co-jumps differ (see Panel C). In fact, after dividing the commodities into three groups (energy, metals, and agricultural), there is evidence of co-jumping, especially among the agricultural commodities (cocoa, coffee, corn, orange juice, soybean, soybean meal, sugar, and wheat). The results reported in Table 3 Panel C show a correlation among jumps in agricultural commodities. This result is not surprising given that most of the jumps were found in this group of commodities[8]. In general, the empirical literature points to the role of macroeconomic news in driving jumps and co-jumps (e.g., Lahaye and Neely, 2011).

4.3. Further analysis – Jumps and macroeconomic news surprises

We further examine whether macroeconomic news surprises[9] from the US are associated with the occurrence of jumps and co-jumps. We use changes in the macroeconomic news surprises index and a binary variable taking the value of taking the value of 1 in the occurrence of macroeconomic news surprises and 0 otherwise. The results, reported in Table 4, shows that jumps and macroeconomic news surprises tend to occur together in some cases, especially for crude oil, corn, wheat, and platinum. In contrast, independence is noted between jumps and macroeconomic news surprises for some metals such as gold, silver, and copper, which is somewhat consistent with prior findings on the safe-haven role of gold and some other metals (e.g., Roache and Rossi, 2010). Furthermore, unreported results show no significant evidence that co-jumps, which mostly occur in agricultural commodities, are tied to macroeconomic news surprises. This new finding from the

[8] In their study focusing on returns, Nguyen and Prokopczuk (2019) find that jump correlations is irregular among various commodities.

[9] We use data from Scotti (2016), available at: https://sites.google.com/site/chiarascottifrb/research/surprise-and-uncertainty-indexes. However, it ends on 23 August 2018.

commodity markets contradicts earlier evidence from Lahaye et al. (2011) which associates economic news and co-jumps in multiple forex markets.

We further split the macroeconomic news surprises into positive and negative components via another binary variable taking the value of 1 if the macroeconomic news surprises are positive and 0 otherwise. This is based on the rationale that jumps in specific commodities such as crude oil might be driven more by positive macroeconomic news surprises than negative ones, whereas safe-have assets like gold might be more driven by negative macroeconomic news surprises. Results from the last line of Table 4 indicate that jumps and positive macroeconomic news surprises tend to occur together in some cases, especially for crude oil (Elder et al., 2013), and to a lesser extent for corn. In contrast, jumps and negative macroeconomic news surprises tend to occur together in some other cases, especially for Cocoa and platinum.

The above results extend our understanding of the factors driving the realized volatility of some strategic commodities such as oil prices. Specifically, the results suggest that macroeconomic news surprises matter to the jump behaviour of crude oil, confirming prior studies (e.g., Elder et al., 2013).

5. Concluding remarks

Given that risk-averse investors are likely to select low volatile assets, it is crucial to understand the jump behaviour that represents a kind of tail-risk (Oliva and Renò, 2018), especially the jump behaviour in asset volatility (Eraker, 2004). In this paper, we consider the commodity markets that represent a major investment destination for portfolio and risk managers and a market outlet for commodity producers. Empirical analyses indicate evidence of jumps in the realized volatility of 16 commodity futures, especially agricultural commodities such as corn and soybean meal and in crude oil. It is therefore crucial to account for the presence of such large volatility shocks in any modelling involving the realized volatility of those three commodities. In fact, accounting for that has important implications regarding option pricing and risk management (Driessen and Maenhout, 2013; Charles and Darné, 2017). Further analyses indicate the lack of co-jumping among the commodities. However, considering agricultural commodities, we find strong evidence of contemporaneous co-jumping in this cluster of commodities, which suggests that the occurrence of a jump in the realized volatility of one

Table 4. Jumps matched with macroeconomic news surprises

Variable	Cocoa	Coffee	Copper	Corn	Heating oil	Gold	Crude oil	Natural gas	Orange juice
	9/16/2009	3/12/2009	10/16/2008	9/15/2009	12/24/2008	4/1/2013	9/29/2008	8/3/2009	9/3/2010
	3/1/2011	6/11/2010	12/23/2009	9/3/2010	6/14/2016		2/6/2009	1/2/2013	
	4/30/2012	8/5/2011		11/1/2010			5/2/2011		
		4/1/2013		9/30/2011			5/6/2011		
		2/3/2014		3/30/2012			8/5/2011		
		8/1/2014		6/1/2012			9/2/2011		
		1/3/2018		9/28/2012			10/15/2014		
				11/8/2013			12/15/2014		
				3/3/2014			1/30/2015		
				3/7/2014			2/2/2015		
				8/12/2016			8/28/2015		
				9/30/2016			1/4/2016		
				3/29/2018			11/30/2016		
				6/29/2018			1/3/2017		
							6/14/2017		
Number of matched jumps	3	7	2	14	2	1	15	2	1
Number of matched positive jumps	3	2	0	8	1	0	9	1	1

Note: *Number* is the number of days showing an association between jumps and macroeconomic news surprises.

Table 4 continued

Variable	Palladium	Platinum	Silver	Soybean	Soybean meal	Sugar	Wheat
	10/16/2008	9/29/2008	5/2/2011	10/8/2010	10/8/2010	9/4/2009	8/2/2010
	12/4/2009	11/3/2008	7/7/2017	3/30/2012	3/30/2012		8/6/2010
	5/2/2011	6/11/2009		8/12/2016	9/28/2012		10/8/2010
	6/12/2014	6/1/2011			11/8/2013		12/1/2010
	6/25/2015	7/31/2013			8/12/2016		9/30/2011
	7/1/2015	10/31/2014			5/12/2017		3/30/2012
	11/13/2015	3/4/2016			3/1/2018		6/29/2012
	6/3/2016	10/7/2016			3/29/2018		9/28/2012
	5/15/2018	1/3/2017			6/15/2018		11/8/2013
	8/15/2018	4/7/2017			7/6/2018		3/3/2014
		6/1/2017					8/15/2014
		6/14/2017					1/12/2018
							3/29/2018
Number of matched jumps	10	12	2	3	10	1	13
Number of matched positive jumps	6	5	2	0	4	0	7

Note: *Number* is the number of days showing an association between jumps and macroeconomic news surprises.

agricultural commodity futures series increases with the occurrence of a jump in other realized volatility series. Further analysis shows that jumps in some commodities, especially crude oil, are closely tied to macroeconomic news surprises. From our above analyses emerge some policy implications. A first implication concerns the importance to incorporate co-jumps when studying the volatility dynamics of agricultural commodities within multivariate models to uncover evidence of spillovers or connectedness. In this regard, previous studies (e.g., Driessen and Maenhout, 2013) point to the need to account for jumps when making trades that involve volatility or jumps[10], which in turn might result in some diversification gains. A second implication concerns the evidence of dependence between jumps in some commodities and macroeconomic news surprises, which suggests the need for market participants to keep a close eye on macroeconomic news and the need to model jumps and macroeconomic news surprises, especially for crude oil. A natural extension of our work would be the use of a different approach allowing for the decomposition of realized volatility, as in Masrorkhah Lehnert (2017). Future research could also consider dynamic asset allocation models while accounting for the occurrence of jumps and co-jumps in the realized volatility (Oliva and Renò, 2018). Other extensions can be made to our analyses by constructing more complex networks of jump risk as in Hu et al. (2019), while accounting for the role of macroeconomic news.

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[10] Driessen and Maenhout (2013) indicate the possibility to this via trading options or via investing in hedge funds.

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APPENDIX

Figure A1. Plots of the daily realized volatility of commodity futures