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Article

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Cogent Economics & Finance

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Suggested Citation: Chalid, Dony Abdul; Handika, Ranga (2022) : Comovement and contagion in commodity markets, Cogent Economics & Finance, ISSN 2332-2039, Taylor & Francis, Abingdon, Vol. 10, Iss. 1, pp. 1-27,
<https://doi.org/10.1080/23322039.2022.2064079>

This Version is available at:

<https://hdl.handle.net/10419/303632>

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To cite this article: Dony Abdul Chalid & Rangga Handika (2022) Comovement and contagion in commodity markets, Cogent Economics & Finance, 10:1, 2064079, DOI: [10.1080/23322039.2022.2064079](https://doi.org/10.1080/23322039.2022.2064079)

To link to this article: <https://doi.org/10.1080/23322039.2022.2064079>



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Received: 08 January 2022
Accepted: 02 April 2022

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FINANCIAL ECONOMICS | RESEARCH ARTICLE

Comovement and contagion in commodity markets

Dony Abdul Chalid^{1*} and Rangga Handika²

Abstract: This article investigates comovement and contagions in the commodities markets. We examine the comovement by analyzing the unconditional correlation coefficients. We document that commodities tend to partially integrate. We perform contagion tests by identifying coexceedances and estimating multinomial logit to explain the joint occurrence of those coexceedances. We document that commodities price changes tend to affect the probability of both positive and negative coexceedances. Overall, we conclude that there are comovement and contagions among commodities. However, the degrees of comovement and contagion are different among commodities and between positive and negative extreme returns. The contagion among commodities is asymmetric.

Subjects: Statistics for Business, Finance & Economics; Economics; Finance

Keywords: Commodity markets; Correlation; Comovement; Contagion; Multinomial logit

1. Introduction

There is a tremendous increase in investments in commodity markets. According to Basu and Miffre (2013), institutional investments in commodity markets have increased from \$18 billion in 2003 to \$250 billion in 2010. Basak and Pavlova (2016) also document that investments in commodity futures have increased from \$15 billion in 2003 to over \$200 billion in 2008. Overall, we can conclude that commodities markets have transformed into alternative investments (indeed, this perception is similar to Vivian & Wohar, 2012; Algieri & Leccadito, 2017). These

ABOUT THE AUTHOR

Our major research cluster is financial markets. Specifically, we are interested in analyzing and evaluating portfolios. One of the research sub-fields is examining the risk and return of commodities portfolios. We have worked and published a research manuscript investigating a risk component - GARCH volatility - in the commodities market. A thorough study of this volatility analysis inspires us to study hedging benefits (a further risk-return analysis) of commodities portfolios. We document that for stock portfolio managers, adding commodities will generate a more conservative strategy, whereas for bond and/or FX portfolio managers, adding commodities will generate a more aggressive strategy. Then, we examine another risk of commodities - whether there is another independencies risk - comovement and contagions. This manuscript will contribute to our bigger research theme in the commodities portfolio.

PUBLIC INTEREST STATEMENT

We are now living in an interconnected world. A consequence of interconnection is the contagion effect. Like a disease, a commodity could also transmit its properties into another commodity's properties. Using statistical methods inspired by the biological definition of contagion, we investigate contagions in the commodities markets. We find that there are contagions among commodities. However, the degrees of contagion are different and asymmetric among commodities. An investment manager shall carefully weigh this contagion risk when investing funds in the commodity markets.

phenomena are called the financialization of commodity markets (see also, Tang & Xiong, 2012; Cheng & Xiong, 2014).

There are at least two thoughtful risk management questions given the financialization of commodity markets. First, as more investors consider commodities as investments, do commodities integrate? Second, is there any potential diversification benefit by investing among commodities? Those two questions are indeed related. A strong argument explaining the relationship comes from Elliott et al. (2014). They argue that there is no contagion without integration. This implies that integration tends to lead contagion. Therefore, a study assessing the degree of contagion will likely answer whether commodities integrate and possess (or have less) diversification benefits. If the commodities integrate, they tend to be more dependent. This dependence causes high comovement, even contagion, among commodities; thus, there would be less diversification benefits at all.

In financial markets, a number of studies investigate financial networks and financial contagion (see, Ait-Sahalia et al., 2015; Allen & Gale, 2000; Bae et al., 2003; Brusco & Castiglionesi, 2007; Elliott et al., 2014; Kodres & Pritsker, 2002; Leitner, 2005; Pasquariello, 2007). Financial institutions tend to have strong dependencies. Thus, it is intuitive to think that a problem in a financial institution will spread quickly to other financial institutions. Suppose that a bank is suddenly shut down for any reason. Since a bank generally holds many positions with other banks, other banks will be affected and could also experience serious trouble. A recent example is the collapse of Lehman Brothers.

As commodity markets become financialized, the question whether commodities integrate arises. Contagion and integration are closely related. Therefore, we can infer the integration of commodity markets by investigating the contagion in commodity markets. Understanding the degree of contagion in commodity markets is essential because we can explore whether the diversification benefits exist in commodity markets. This knowledge of diversification benefits is essential for investors wishing to develop a portfolio containing commodities.

There are a number of studies on contagion in commodity markets (for instance, Algieri & Leccadito, 2017; Andriosopoulos et al., 2017; Ayadi et al., 2021; Chevallier & Ielpo, 2013; Ferrer et al., 2018; Han et al., 2015; Ignatieva & Ponomareva, 2017; Ji et al., 2017; Kang et al., 2017; Malik & Umar, 2019; Naeem et al., 2020; Nagayev et al., 2016; Nazlioglu et al., 2013; Reboredo et al., 2014; Yip et al., 2017; Zainudin & Mohamad, 2021). However, most of these studies investigate the contagion between commodities and economic variables. None of these studies investigate the contagion *among* commodities. While recent work from Han et al. (2015) and Zhou and Huang (2020) examine the price link between commodities, their scope is limited to the contagion between energy and/or agriculture commodities. Chevallier and Ielpo (2013) and Ji et al. (2017) also exclusively focus on risk spillover rather than price contagion among commodities. Likewise, recent papers by Adhikari and Putnam (2019), Cai et al. (2019), Nguyen and Prokopczuk (2019), Yahya et al. (2019), Zhu et al. (2019), and Nguyen et al. (2020) investigate only comovement or dependence (not contagion) among commodities. Umar et al. (2022) examine comovement (but not contagion) between commodities with the focus on energy as the leading series. Balcilar et al. (2021) examine the joint connectedness between oil and other agricultural commodities. This paper fills the research gap by investigating the contagion *among* commodities. We analyze both comovement and contagion (similar but different concepts) in commodity markets using methods that handle heteroskedasticity bias and resemble the biological definition of contagion.

A simple approach to examine a contagion is calculating the correlation among variables. However, this method is not sufficiently robust (at least according to Bae et al., 2003). Bae et al. (2003) argue that it is not appropriate to use correlations to evaluate the different impacts of large returns. The propagation of large returns is hidden in correlation measures because correlation gives equal weight to small and large returns. Thus, a few days of large returns might be hidden by

Table 1. Detailed information on the sixteen sampled financialized commodities

NO	Commodity	Contract	Category
1	Crude Oil (COI)	Crude Oil-WTI Spot Cushing US\$/BBL	Energy
2	Heating Oil (HOI)	Heating Oil DEU Exc. Tax E/kL	Energy
3	Natural Gas (NGA)	Natural Gas, West Texas US\$/MMBTU	Energy
4	Gold (GOL)	Gold Bullion LBM US\$/Troy Ounce	Metal
5	Silver (SIL)	Silver, Handy&Harman (NY) US\$/Troy OZ	Metal
6	Copper (COP)	LME-Copper Grade A Cash US\$/MT	Metal
7	Platinum (PLA)	London Platinum Free Market \$/Troy oz	Metal
8	Palladium (PAL)	Palladium US\$/Troy Ounce	Metal
9	Corn (COR)	Corn No. 2 Yellow U \$/Bushel	Grain
10	Soybeans (SOY)	US Soybeans KCity US\$/BSH	Grain
11	Kansas Wheat (WHE)	HRW Wheat K.City Terminal US\$/BSH	Grain
12	Oats (OAT)	Oats, No. 2 Milling Minneapolis \$/Bu	Grain
13	Coffee (COF)	Coffee-Brazilian (NY) Cents/lb	Soft
14	Cotton (COT)	Cotton,1 1/16Str Low - Midl,Memph \$/Lb	Soft
15	Sugar (SUG)	Raw Sugar-ISA Daily Price c/lb	Soft
16	Cocoa (COC)	Cocoa-ICCO Daily Price US \$/MT	Soft

numerous days of small returns. Furthermore, the definition of contagion is not straightforward (Forbes & Rigobon, 2002), and there were at least 124 empirical studies on financial market contagion in different journals from 1990 to 2016 (Seth & Panda, 2018). These findings demonstrate that investigation contagion is not simple. In this article, we perform the contagion in commodity markets by examining the comovement among commodities and then utilize the contagion test. Our methods in examining the comovement closely follow Forbes and Rigobon (2002) by analyzing the unconditional correlation coefficients and Chan et al. (2007) by comparing the correlations between within-category and outside-category commodities. Our contagion tests closely follow Bae et al. (2003) by performing two steps: i) identifying coexceedances (extreme returns) and ii) performing multinomial logit to explain joint occurrence of those coexceedances. However, our work is different from theirs since we focus on the contagion *among* commodities, while they focus on the contagion *across* and *within* countries.

This paper contributes to the literature by investigating the contagion among commodities. Assessing the contagion in commodity markets enables us to know not only whether commodities

integrate but also whether commodities have diversification benefits. If the contagion exists, the commodities integrate and have less diversification benefits. On the other hand, if the contagion does not exist, the commodities do not integrate and have diversification benefits by investing among commodities. The remainder of the paper is organized as follows. Section 2 explains the data. Section 3 describes the method. Section 4 discusses the empirical results. Section 5 concludes.

2. Data

Our sample includes daily series of sixteen commodity prices. The sixteen commodities were listed in Tang and Xiong (2012).

Table 1 describes further details about each commodity used in our sample. We obtained the data from Datastream. Our sample includes the commodities daily series from 1 January 1999 to 1 November 2017. The starting sample period is inspired by the fact that commodity futures have emerged as a popular asset class for many financial institutions (Han et al., 2015; Tang & Xiong, 2012). Tang and Xiong (2012) further noted that commodity markets tended to be fragmented from each other and from outside financial markets before 1999. They also observed that many institutions considered commodities as new asset classes after the 1999's equity market shock. We end our sample in 2017 because we focus on the existence of the long-term impact of exogenous risks in the commodity markets. Those exogenous risks are clearly identified as geopolitical and trade policy uncertainties (see, C. Yang et al., 2022).

3. Method

There are a number of contagion and cointegration tests, including Bai et al. (2018), Fry-McKibbin et al. (2019), and Bai et al. (2018) test deals with the nonlinear causality for multivariate variables, and Fry-McKibbin et al. (2019) test deals with coskewness, cokurtosis, and covolatility contagions. Our first focus here is filtering the heteroskedasticity biases in the comovement among commodities. It is not uncommon to find heteroskedasticity in commodity markets (Cavaliere et al., 2015; Liu & Tang, 2011). An appropriate test to filter such biases is Forbes and Rigobon (2002). Our second focus here is to examine financial contagion using the contagion test that is inspired by epidemiology research on contagious diseases. A financial contagion test that is close to the biological contagion analysis is Bae et al. (2003), who use multinomial logistic analysis.

3.1. Comovement

The first step of our analysis is calculating the correlation among commodities. Calculating the correlation enables us to examine the linkages among commodities. However, simple correlation coefficients are conditional on market volatility (Forbes & Rigobon, 2002). Therefore, during a high volatility period, estimates of correlation coefficients tend to be biased upward. Forbes and Rigobon (2002) develop a procedure to adjust the bias. Furthermore, Chan et al. (2007) propose a more robust approach to compare the correlations between within-category and outside-category commodities.

We follow Forbes and Rigobon (2002) in calculating the adjusted correlation coefficient as follows

$$\rho_A = \frac{\rho}{\sqrt{1 + \delta[1 - \rho^2]}} \text{ whereas } \delta = \frac{\sigma^h}{\sigma^l} - 1 \quad (1)$$

where ρ_A refers to the adjusted correlation coefficient, ρ refers to the unadjusted correlation coefficient, σ^h denotes the average standard deviation (volatility) of two commodities during a high variance period, and σ^l denotes the average standard deviation (volatility) of two commodities during a low-variance period. The low-variance period refers to the period of relative market stability, and the high-variance period refers to the period of market turmoil directly after a shock

or crisis. Following their definition, we defined the high-variance period as the period from 15 September 2008 to 16 October 2012. The high-variance period reflects the highest observed volatility in commodity markets (Han et al., 2015). Then, we use t-tests to evaluate whether there is a significant increase of both unadjusted and adjusted correlation coefficients during the high-variance period as follows:

$$H_0: \rho^l \leq \rho^h \quad H_0: \rho_A^l \leq \rho_A^h$$

AND (2)

$$H_1: \rho^l > \rho^h \quad H_1: \rho_A^l > \rho_A^h$$

If both the null hypotheses are not rejected, we conclude that there is no contagion, only interdependence.

Then, we follow Chan et al. (2007) in comparing the correlations between within-category and outside-category commodities. First, we calculate the average pairwise correlations between commodity c 's return and the return on each of the other commodities of its category (CAT):

$$\rho_{ci,CAT} = \frac{\sum_{cj \in CAT, cj \neq ci} \rho_{ci,cj}}{N - 1} \quad (3)$$

where $\rho_{ci,cj}$ is the time-series correlation between the return on commodity i (ci) and commodity j (cj), and N denotes the number of commodities in the category. Then, the average pairwise correlation between commodity i 's return and the return of all other commodities in different categories is calculated as follows:

$$\Phi_{ci,CAT} = \frac{\sum_{cj \notin ci} \rho_{ci,cj}}{K - N} \quad (4)$$

where K denotes the number of all commodities in our sample. We then calculate the average within-category correlation over all commodities in the sample as follows:

$$\bar{\rho}_{CAT} = \frac{\sum_{i=1}^K \rho_{ci,CAT}}{K} \quad (5)$$

The average correlation between a commodity and other commodities in different categories is calculated as follows

$$\bar{\Phi}_{CAT} = \frac{\sum_{i=1}^K \Phi_{ci,CAT}}{K} \quad (6)$$

Finally, similar to the hypotheses in equation (2), we compare the values of and assess the degree to which the commodity category distinguishes between similar and dissimilar commodities:

$$H_0: \bar{\rho}_{CAT} \leq \bar{\Phi}_{CAT}$$

(7)

$$H_1: \bar{\rho}_{CAT} > \bar{\Phi}_{CAT}$$

If the null hypothesis is not rejected, we conclude that there is no comovement difference between within-category and outside-category commodities.

3.2. Contagion

The second step in our analysis is performing the contagion test. Our contagion test here follows Bae et al. (2003). First, we identify the extreme returns, i.e., exceedances, of the commodities in a category. We define the extreme return, or exceedance, as a return either below (above) the 5th (95th) quantile of the commodity's return distribution. Note that two exceedances mean one coexceedances, three exceedances mean 2 coexceedances, and so on. We should note that the exceedances in terms of extreme positive or negative returns in a particular commodity can be modeled as a dichotomous variable. However, our analysis investigating the coexceedances to capture contagion among commodities requires classification as a polychotomous variable. A popular approach to estimate the probabilities associated with events captured in a polychotomous variable is the multinomial logistic regression model (Bae et al., 2003). Equation (8) is our model investigating the contagion among commodities.

$$P(\text{COECO}_t = X) = \frac{1}{1 + \sum_{y=1}^z \exp(\beta_y \overline{RET}_{t,CATy})} \quad (8)$$

where $P(\text{COECO}_t = X)$ refers to the X number of coexceedances (in our case, X equals 0, 1, 2 ... m), $\overline{RET}_{t,CATy}$ denotes the average return of commodities in different categories at time t . Then, equation (8) is estimated using the following maximum likelihood expression (Hill et al., 2011; Greene, 2017):

$$LNL = \sum_{p=1}^q \sum_{X=0}^m d_{pX} \ln(\text{Prob}(\text{COECO}_t = X | \sum_{y=1}^z \exp(\beta_y \overline{RET}_{t,CATy}))) \quad (9)$$

where L is the log-likelihood function for a sample of q observations, and d_{pX} refers to an indicator variable where alternative X occurs at observation p . We follow Kleiber and Zeileis (2008) and Bilder and Loughin (2015) for the estimation procedure of the multinomial logit model and the postestimation analysis. Note that if the numbers of coexceedances are only 0 and 1, we use the logistic regression instead.

4. Empirical results

Table 2 presents the descriptive statistics of daily price changes for the sixteen commodities.

We find that the averages of daily price changes range from 0.0236 percent (cotton) to 0.1970 percent (natural gas). The volatilities of the daily price changes range from 0.0645 (natural gas) to 0.010 (gold). We can see that natural gas has the highest average return followed by crude oil, while that for cotton has the lowest. Note that the averages of daily price changes for the commodities tend to be zero. Regarding risk, as measured in the standard deviation of returns, the natural gas return also has the highest value followed by heating oil, while that for gold return has the lowest. This finding implies that gold was the superior investment asset of the six commodities due to possessing a higher risk reward ratio during the sample period. The skewness and kurtosis measures demonstrate that all the distributions of returns exhibit fat tails. All of the Jarque–Bera statistics for returns are positive and statistically significant, indicating non-normalities. Overall, the descriptive statistics of our sample commodities are similar to other papers on commodities (for example, Algieri & Leccadito, 2017; Han et al., 2015; Nagayev et al., 2016).

Table 3 presents the estimated conditional (unadjusted) correlation coefficients, whereas Table 4 presents the estimated unconditional (adjusted—equation (1)) correlation coefficients for

Table 2. Descriptive statistics of daily price changes for the sixteen commodities

Category	Energy								Metal							
	COI	HOI	NGA	GOL	SIL	COP	PLA	PAL								
Commodity																
Mean	0.0597%	0.0416%	0.1970%	0.0364%	0.0419%	0.0452%	0.0296%	0.0446%								
Std Dev	0.0241	0.0173	0.0645	0.0110	0.0185	0.0165	0.0144	0.0209								
Max	0.2371	0.2419	1.6204	0.0766	0.1464	0.1244	0.0879	0.1716								
Min	-0.1582	-0.2133	-0.6228	-0.0966	-0.1219	-0.0984	-0.1587	-0.1636								
Skewness	0.2144	0.7745	4.5598	-0.1588	-0.3404	0.0508	-0.5038	-0.0401								
Kurtosis	8.20	45.18	103.94	8.99	8.57	7.56	10.96	8.98								
JB-test	5.583	3,64,764	21,02,910	7,371	6,457	4,256	13,176	7,326								
# of observation	4,913	4,913	4,913	4,913	4,913	4,913	4,913	4,913								
Category	Grain								Soft							
Commodity	COR	SOY	WHE	OAT	COF	COT	SUG	COC								
Mean	0.0268%	0.0264%	0.0255%	0.0503%	0.0250%	0.0236%	0.0348%	0.0240%								
Std Dev	0.0187	0.0171	0.0182	0.0250	0.0220	0.0202	0.0213	0.0183								
Max	0.1152	0.1339	0.1910	0.2879	0.2377	0.1000	0.1527	0.2138								
Min	-0.1142	-0.1371	-0.1646	-0.2260	-0.2391	-0.0988	-0.1759	-0.1754								
Skewness	0.0028	-0.3154	0.2867	0.7145	0.3413	0.1451	-0.0698	0.2290								
Kurtosis	6.08	11.18	10.65	25.58	13.97	4.82	6.66	17.05								
JB-test	1,942	13,780	12,045	1,04,762	24,714	695	2,749	40,429								
# of observation	4,913	4,913	4,913	4,913	4,913	4,913	4,913	4,913								

commodities daily returns. Overall, the conditional correlation coefficients tend to be positive, and the highest value is noted for the correlation between gold and silver (0.6837) followed by that between platinum and palladium (0.5865). Likewise, the unconditional correlation coefficients tend to be positive, and the highest is the correlation between gold and silver (0.6142) followed by that between platinum and palladium (0.5526). We should note that only those two correlations are greater than 0.5 for both conditional and unconditional correlations. We also note that there is no significant difference between conditional and unconditional correlations. These findings indicate that 1) the dependence among commodities are not so strong and 2) the heteroskedasticity biases are not so high at least compared with the biases in the stock markets (as observed by Forbes & Rigobon, 2002).

We argue that the lower biases in commodities are due to the heterogeneity characteristics.

Unlike financial assets, commodities tend to be heterogenous (Ausubel, 2006; Fleurbaey & Tadenuma, 2007; Pereira et al., 2017) and more independent (Fleurbaey & Tadenuma, 2007). We should also note that commodities are not only representatives of market relations but also nonmarket relations (Lapavitsas, 2004). Nonmarket relations do not shrink inexorably, thus reducing the biases. The estimated conditional correlation coefficients for the high-variance (from 15 September 2008 to 16 October 2012) and low-variance (from 4 January 1999 to 12 September 2008 and from 17 October 2012 to 1 November 2017) periods are shown in Tables 5 and 6, respectively. Table 7 reports the t-values for one-tailed t-tests examining whether the cross-commodity conditional correlation coefficient during the high-variance period is significantly greater than that during the low-variance period (hypotheses in equation (2)).

We can observe several apparent patterns here. First, the significant increase in the conditional correlation coefficient during the high variance period occurs only in 63 (or 52.5 percent) pairs of commodities. This finding implies that financial contagion occurred only to (slightly above) half of the commodities. This finding also indicates that commodities tend to be resilient assets during a highly volatile market. We document that commodities have better diversification benefits than stocks given the following reasons: 1) stock markets experience significant dependences during global financial crisis (Wang et al., 2017), and 2) commodities exhibit low synchronization with the stock market (Pereira et al., 2017). Second, platinum and palladium tend to be the most contagious commodities because the 13 (out of other 15) other commodities experience significant increase in the conditional correlation coefficient during the high-variance period when paired with them. The next contagious commodity is oat (11 out of other 15) followed by corn and cotton (10 out of other 15). Third, natural gas (4 out of other 15), followed by gold and coffee (5 out of other 15), tends to be the least contagious. We can conclude that 1) commodities tend to partially integrate, 2) natural gas, gold and coffee are good portfolio diversifiers because they experience few significant increases in the conditional correlation coefficient, even during highly volatile markets, and 3) platinum and palladium are bad portfolio diversifiers because they experience many significant increases in the conditional correlation coefficient during highly volatile markets. There are two practical implications here. First, as a portfolio manager, I would use different commodities as diversifiers because commodities are partially integrated. Second, I would add a kind of commodity to our existing portfolio depending on our portfolio's objectives, whether an aggressive or conservative strategy.

As noted in our discussion in section 3.1, these contagion tests may be inaccurate due to heteroskedasticity bias in the correlation coefficient. According to Forbes and Rigobon (2002), the estimated increases in the conditional correlation coefficient could reflect either an increase in cross-market linkages and/or increased market volatility. In our analysis, the market refers to commodity market. To control the heteroskedasticity bias, we repeat our analysis but use the correction in equation (1) to adjust for the bias. The estimated unconditional correlation coefficients for the high-variance (from 15 September 2008 to 16 October 2012) and low variance (from 4 January 1999 to 12 September 2008 and from 17 October 2012 to 1 November 2017) periods are

Table 3. The estimated conditional (unadjusted) correlation coefficients for daily return among sixteen commodities

Conditional correlation coefficients

Commodity	COI	HOI	NGA	GOL	SIL	COP	PLA	PAL	COR	SOY	WHE	OAT	COF	COT	SUG	COC
COI																
HOI	-0.0102															
NGA	0.0370	-0.0212														
GOL	0.1626	0.0018	0.0487													
SIL	0.2211	-0.0136	0.0626	0.6837												
COP	0.2912	-0.0227	0.0234	0.2848	0.4004											
PLA	0.1144	-0.0347	0.0634	0.4360	0.4076	0.2390										
PAL	0.1102	-0.0107	0.0509	0.3191	0.3410	0.2418	0.5865									
COR	0.1863	-0.0245	0.0446	0.0960	0.1663	0.1813	0.1075	0.0967								
SOY	0.0027	-0.0028	0.0389	0.0346	0.0616	0.0202	0.0947	0.0663	0.0135							
WHE	-0.0027	0.0046	0.0388	0.0417	0.0536	0.0156	0.0779	0.0815	0.0244	0.3791						
OAT	0.0599	0.0009	0.0336	0.0483	0.0713	0.0773	0.0569	0.0316	0.2886	0.0396	0.0375					
COF	0.0644	0.0141	0.0291	0.0514	0.0675	0.0149	0.0759	0.0797	0.0267	0.0757	0.0979	0.0457				
COT	0.1581	-0.0076	0.0346	0.0924	0.1313	0.1779	0.0824	0.0706	0.1881	-0.0082	0.0125	0.0853	0.0402			
SUG	0.1416	-0.0029	0.0322	0.0754	0.1152	0.1507	0.0755	0.0801	0.1238	0.0401	0.0188	0.0709	0.0679	0.1124		
COC	0.0308	0.0154	-0.0189	0.0456	0.0622	0.0125	0.0492	0.0541	0.0128	0.0666	0.0611	0.0373	0.0832	0.0287	0.0038	

Table 4. The estimated unconditional (adjusted) correlation coefficients for daily return among sixteen commodities

Unconditional correlation coefficients

Commodity	COI	HOI	NGA	GOL	SIL	COP	PLA	PAL	COR	SOY	WHE	OAT	COF	COT	SUG	COC
COI																
HOI	-0.0098															
NGA	0.0359	-0.0217														
GOL	0.1439	0.0018	0.0479													
SIL	0.1899	-0.0125	0.0598	0.6142												
COP	0.2510	-0.0210	0.0224	0.2387	0.3321											
PLA	0.1031	-0.0348	0.0627	0.3985	0.3565	0.2055										
PAL	0.0991	-0.0105	0.0499	0.2884	0.2977	0.2093	0.5516									
COR	0.1622	-0.0231	0.0429	0.0817	0.1377	0.1498	0.0940	0.0847								
SOY	0.0024	-0.0029	0.0387	0.0319	0.0539	0.0177	0.0891	0.0617	0.0120							
WHE	-0.0024	0.0044	0.0376	0.0360	0.0447	0.0129	0.0689	0.0722	0.0207	0.3476						
OAT	0.0571	0.0009	0.0340	0.0470	0.0657	0.0715	0.0560	0.0306	0.2719	0.0395	0.0356					
COF	0.0646	0.0159	0.0303	0.0537	0.0656	0.0146	0.0799	0.0816	0.0264	0.0806	0.0982	0.0496				
COT	0.1403	-0.0073	0.0337	0.0811	0.1113	0.1508	0.0739	0.0632	0.1626	-0.0075	0.0108	0.0815	0.0405			
SUG	0.1286	-0.0029	0.0317	0.0684	0.1002	0.1313	0.0698	0.0736	0.1097	0.0377	0.0168	0.0693	0.0702	0.1017		
COC	0.0283	0.0157	-0.0188	0.0422	0.0547	0.0110	0.0464	0.0505	0.0115	0.0640	0.0555	0.0372	0.0884	0.0263	0.0036	

Table 5. The estimated unadjusted (conditional) correlation during the high-variance period (from 15 September 2008 to 16 October 2012)
Unadjusted (conditional) correlation during high variance period (from 15 September 2008 to 16 October 2012)

Comm odity	COI	HOI	NGA	GOL	STL	COP	PLA	PAL	COR	SOY	WHE	OAT	COF	COT	SUG	COC
COI																
HOI	-0.0525															
NGA	0.0450	-0.1279														
GOL	0.2569	-0.0162	0.0428													
STL	0.3546	-0.0532	0.0871	0.6779												
COP	0.5215	-0.0864	0.0569	0.2970	0.4503											
PLA	0.2104	-0.0781	0.1178	0.4958	0.5144	0.3484										
PAL	0.2580	-0.0752	0.1600	0.3858	0.4587	0.3780	0.7314									
COR	0.3442	-0.1110	0.1133	0.1360	0.2417	0.3354	0.1620	0.1835								
SOY	-0.0314	-0.0061	-0.0003	0.0407	0.0936	0.0023	0.1674	0.1461	0.0472							
WHE	-0.0377	-0.0319	0.0846	0.0801	0.0873	0.0100	0.1757	0.1753	0.0446	0.5586						
OAT	0.1324	-0.0790	0.0736	0.0730	0.1260	0.1421	0.1575	0.1341	0.4284	0.1443	0.1278					
COF	0.0717	-0.0205	0.0604	0.0878	0.1143	0.0591	0.1411	0.1572	0.0233	0.2188	0.2382	0.0920				
COT	0.3097	-0.0841	0.0294	0.1475	0.2124	0.3290	0.1542	0.1565	0.2983	-0.0312	0.0008	0.1997	0.0411			
SUG	0.2752	-0.0356	0.0776	0.0711	0.1790	0.2783	0.0985	0.1279	0.2741	0.0570	0.0161	0.1364	0.0984	0.2048		
COC	0.0466	0.0201	0.0030	0.0987	0.0834	0.0397	0.1221	0.1043	0.0274	0.1747	0.1591	0.0816	0.1664	0.0543	-0.0157	

Table 6. The estimated unadjusted (conditional) correlation during the low-variance period (from 4 January 1999 to 12 September 2008 AND from 17 October 2012 to 1 November 2017)

Unadjusted (conditional) correlation during low variance period (from 4 January 1999 to 12 September 2008 AND from 17 October 2012 to 1 November 2017)																
Commodity	COI	HOI	NGA	GOL	SIL	COP	PLA	PAL	COR	SOY	WHE	OAT	COF	COT	SUG	COC
	COI															
	HOI	0.0023														
	NGA	0.0345	0.0037													
	GOL	0.1191	0.0077	0.0516												
	SIL	0.1514	0.0003	0.0543	0.6891											
N	COP	0.1677	-0.0003	0.0098	0.2793	0.3680										
	PLA	0.0747	-0.0229	0.0461	0.4109	0.3587	0.1863									
	PAL	0.0477	0.0077	0.0150	0.2893	0.2833	0.1734	0.5291								
	COR	0.1083	0.0037	0.0187	0.0748	0.1209	0.0874	0.0827	0.0555							
	SOY	0.0157	-0.0020	0.0506	0.0323	0.0478	0.0291	0.0688	0.0372	-0.0009						
	WHE	0.0139	0.0165	0.0223	0.0224	0.0342	0.0189	0.0346	0.0389	0.0135	0.3084					
	OAT	0.0363	0.0189	0.0232	0.0403	0.0514	0.0535	0.0258	-0.0011	0.2426	0.0096	0.0059				
	COF	0.0646	0.0201	0.0231	0.0434	0.0574	0.0020	0.0619	0.0627	0.0289	0.0451	0.0633	0.0370			
	COT	0.0895	0.0157	0.0368	0.0661	0.0876	0.0950	0.0520	0.0333	0.1324	0.0007	0.0180	0.0474	0.0413		
	SUG	0.0873	0.0061	0.0179	0.0772	0.0849	0.0889	0.0667	0.0613	0.0557	0.0341	0.0199	0.0511	0.0621	0.0740	
	COC	0.0249	0.0143	-0.0254	0.0249	0.0538	0.0001	0.0235	0.0361	0.0068	0.0315	0.0219	0.0248	0.0660	0.0190	0.0107

Table 7. The t-values for one-tailed t-tests examining whether the cross-commodity conditional correlation coefficient during the high-variance period is significantly greater than during the low-variance period

Test Statistics

Commodity	COI	HOI	NGA	GOL	SIL	COP	PLA	PAL	COR	SOY	WHE	OAT	COF	COT	SUG	COC
COI																
HOI	1.26															
NGA	0.24	3.05														
GOL	3.30	0.55	0.20													
SIL	5.03	1.24	0.76	0.48												
COP	9.43	1.99	1.09	0.45	2.28											
PLA	3.20	1.28	1.67	2.47	4.46	4.04										
PAL	4.99	1.92	3.38	2.51	4.72	5.13	7.91									
COR	5.77	2.66	2.19	1.43	2.89	6.03	1.86	3.00								
SOY	1.09	0.10	1.18	0.19	1.06	0.62	2.31	2.54	1.11							
WHE	1.19	1.12	1.44	1.33	1.23	0.21	3.30	3.19	0.72	7.20						
OAT	2.23	2.26	1.16	0.76	1.73	2.06	3.07	3.14	4.85	3.13	2.83					
COF	0.16	0.94	0.86	1.03	1.32	1.32	1.85	2.21	0.13	4.09	4.14	1.27				
COT	5.32	2.31	0.17	1.90	2.95	5.68	2.38	2.87	4.02	0.74	0.40	3.58	0.01			
SUG	4.50	0.96	1.38	0.14	2.21	4.54	0.74	1.55	5.20	0.53	0.09	1.99	0.84	3.08		
COC	0.50	0.13	0.65	1.71	0.69	0.91	2.29	1.58	0.48	3.34	3.19	1.31	2.35	0.81	0.61	

shown in [Tables 8 and 9](#), respectively. [Table 10](#) reports the t-values for one-tailed t-tests examining whether the cross-commodity unconditional correlation coefficient during the high-variance period is significantly greater than that during the low-variance period (hypotheses in equation (2)).

We observe similar apparent patterns here. First, the significant increase in the conditional correlation coefficient during the high-variance period occurs only in 60 (or 50 percent) pairs of commodities. This finding implies that financial contagion occurred only to (slightly above) half of the commodities. This finding also indicates that commodities tend to be resilient assets during highly volatile markets. Our analysis reveals no significant difference between conditional and unconditional correlation coefficients. This finding implies that the heteroskedasticity bias is not significant, at least compared with the bias in the stock market. This finding is consistent with our argument stating that the lower biases in commodities are due to the heterogeneity characteristics. Second, palladium tends to be the most contagious commodity because the 13 (out of other 15) other commodities experience significant increases in the unconditional correlation coefficient during the high variance period when paired together. The next contagious commodity is platinum (12 out of other 15) followed by oat and cotton (10 out of other 15). Third, natural gas and gold (4 out of other 15) followed by coffee (5 out of other 15) tend to be the least contagious commodities. We can conclude that 1) commodities tend to partially integrate, 2) natural gas, gold and coffee are good portfolio diversifiers because they experience few significant increases in the conditional correlation coefficient, even during highly volatile markets, and 3) platinum and palladium are bad portfolio diversifiers because they experience many significant increases in the conditional correlation coefficient during highly volatile markets. There are two practical implications here. First, as a portfolio manager, I would use different commodities as diversifiers because commodities are partially integrated. Second, I might use a commodity to reduce the heteroskedasticity bias in our existing stock portfolio.

We can see that the analysis using unconditional correlation coefficients is similar with that of using conditional correlation coefficients. Overall, we can conclude that 1) commodities tend to partially integrate, and 2) natural gas, gold and coffee are good portfolio diversifiers, whereas platinum and palladium are bad portfolio diversifiers. Platinum is not only a bad portfolio diversifier but also demonstrated a speculative bubble (Emekter et al., 2012). Palladium is similar to platinum given their similar chemical characteristics (Kotzé et al., 2019; Rane, 2019). Gold is proven as a safe haven nature because gold protects investors by providing a fall back during harsh investment periods (Pereira et al., 2017).

Natural gas and coffee are good portfolio diversifiers because they have small net spillover (Chevallier & Ielpo, 2013). Coffee is also a good portfolio diversifier because it exhibits stationarity after multiple structural breaks (C. H. Yang et al., 2012).

We then compare the correlations between within-category and outside-category commodities using Equations (3), (4), (5), (6) and (7).

[Table 11](#) reports the conditional and unconditional correlations within a category (as expressed in Equation (3)), outside a category (as expressed in Equation (4)), the average within a category (as expressed in Equation (5)), the average outside a category (as expressed in Equation (6)), and the t-values for one-tailed t-tests examining whether the average within category correlation coefficient is significantly greater than the average outside category correlation coefficient. There are several patterns according to [Table 11](#). First, almost all metals and grains (silver is the exception) have higher correlation coefficients within category than outside category correlation coefficients. Second, on the other hand, all energies have lower within category than outside category correlation coefficients. Third, regarding softs, coffee and cocoa have lower whereas cotton and sugar have higher within category than outside category correlation coefficients. Fourth, although the average within category correlation coefficient is greater than the average

Table 8. The estimated adjusted (unconditional) correlation during the high-variance period (from 15 September 2008 to 16 October 2012)
 Adjusted (unconditional) correlation during high variance period (from 15 September 2008 to 16 October 2012)

Commodity	COI	HOI	NGA	GOL	SIL	COP	PLA	PAL	COR	SOY	WHE	OAT	COF	COT	SUG	COC
COI																
HOI	-0.0504															
NGA	0.0437	-0.1304														
GOL	0.2284	-0.0160	0.0420													
SIL	0.3078	-0.0491	0.0831	0.6081												
COP	0.4618	-0.0800	0.0544	0.2493	0.3764											
PLA	0.1902	-0.0782	0.1164	0.4558	0.4562	0.3024										
PAL	0.2333	-0.0737	0.1568	0.3504	0.4057	0.3309	0.6998									
COR	0.3029	-0.1045	0.1092	0.1160	0.2012	0.2808	0.1419	0.1613								
SOY	-0.0288	-0.0062	-0.0003	0.0375	0.0821	0.0020	0.1577	0.1361	0.0421							
WHE	-0.0330	-0.0304	0.0820	0.0691	0.0729	0.0083	0.1560	0.1556	0.0379	0.5203						
OAT	0.1263	-0.0828	0.0743	0.0710	0.1163	0.1315	0.1550	0.1300	0.4060	0.1439	0.1213					
COF	0.0718	-0.0231	0.0629	0.0918	0.1110	0.0577	0.1485	0.1608	0.0230	0.2322	0.2389	0.0998				
COT	0.2770	-0.0810	0.0286	0.1296	0.1807	0.2820	0.1386	0.1403	0.2597	-0.0285	0.0007	0.1911	0.0414			
SUG	0.2512	-0.0352	0.0764	0.0645	0.1562	0.2441	0.0911	0.1176	0.2445	0.0537	0.0144	0.1334	0.1018	0.1858		
COC	0.0428	0.0204	0.0030	0.0914	0.0734	0.0350	0.1153	0.0974	0.0246	0.1680	0.1448	0.0814	0.1766	0.0498	-0.0148	

Table 9. The estimated adjusted (unconditional) correlation during the low-variance period (from 4 January 1999 to 12 September 2008 AND from 17 October 2012 to 1 November 2017)

Adjusted (unconditional) correlation during low variance period (from 4 January 1999 to 12 September 2008 AND from 17 October 2012 to 1 November 2017)

Commodity	COI	HOI	NGA	GOL	SIL	COP	PLA	PAL	COR	SOY	WHE	OAT	COF	COT	SUG	COC
COI																
HOI	0.0022															
NGA	0.0335	0.0038														
GOL	0.1053	0.0076	0.0507													
SIL	0.1296	0.0003	0.0518	0.6198												
COP	0.1435	-0.0003	0.0093	0.2340	0.3038											
PLA	0.0673	-0.0230	0.0455	0.3747	0.3120	0.1597										
PAL	0.0429	0.0076	0.0147	0.2610	0.2462	0.1496	0.4948									
COR	0.0941	0.0035	0.0180	0.0637	0.0999	0.0719	0.0722	0.0486								
SOY	0.0144	-0.0020	0.0504	0.0298	0.0419	0.0255	0.0647	0.0346	-0.0008							
WHE	0.0122	0.0157	0.0216	0.0193	0.0285	0.0157	0.0306	0.0344	0.0115	0.2815						
OAT	0.0346	0.0198	0.0235	0.0391	0.0474	0.0495	0.0254	-0.0010	0.2282	0.0096	0.0056					
COF	0.0647	0.0227	0.0240	0.0454	0.0557	0.0020	0.0652	0.0641	0.0286	0.0480	0.0635	0.0401				
COT	0.0793	0.0151	0.0358	0.0579	0.0741	0.0803	0.0466	0.0298	0.1142	0.0006	0.0157	0.0452	0.0416			
SUG	0.0792	0.0061	0.0176	0.0700	0.0738	0.0773	0.0616	0.0563	0.0493	0.0321	0.0178	0.0499	0.0642	0.0669		
COC	0.0229	0.0146	-0.0253	0.0231	0.0474	0.0001	0.0221	0.0337	0.0061	0.0303	0.0199	0.0248	0.0702	0.0174	0.0101	

Table 10. The t-values for one-tailed t-tests examining whether the cross-commodity unconditional correlation coefficient during the high-variance period is significantly greater than that during the low-variance period

Test Statistics

Commodity	COI	HOI	NGA	GOL	SIL	COP	PLA	PAL	COR	SOY	WHE	OAT	COF	COT	SUG	COC
COI																
HOI	1.21															
NGA	0.24	3.11														
GOL	2.93	0.55	0.20													
SIL	4.33	1.14	0.73	0.43												
COP	8.19	1.84	1.04	0.37	1.90											
PLA	2.89	1.28	1.65	2.26	3.92	3.48										
PAL	4.49	1.88	3.31	2.28	4.13	4.46	7.48									
COR	5.04	2.50	2.11	1.22	2.39	4.99	1.63	2.63								
SOY	1.00	0.10	1.17	0.18	0.93	0.54	2.17	2.36	0.99							
WHE	1.04	1.06	1.40	1.15	1.03	0.17	2.92	2.83	0.61	6.63						
OAT	2.13	2.37	1.18	0.74	1.60	1.91	3.02	3.04	4.58	3.12	2.68					
COF	0.16	1.06	0.90	1.08	1.28	1.29	1.94	2.26	0.13	4.35	4.15	1.38				
COT	4.73	2.22	0.17	1.67	2.50	4.83	2.14	2.57	3.48	0.67	0.35	3.42	0.01			
SUG	4.09	0.95	1.36	0.13	1.93	3.96	0.68	1.43	4.62	0.50	0.08	1.94	0.87	2.79		
COC	0.46	0.13	0.65	1.58	0.60	0.80	2.16	1.48	0.43	3.21	2.90	1.31	2.50	0.75	0.57	

outside category correlation coefficient, the one-tailed t-tests reveal that the differences are not statistically significant for both conditional and unconditional correlation coefficients. We can conclude that 1) metal and grain commodities tend to integrate, whereas energy commodities do not tend to integrate; 2) the integration of soft commodities is inconclusive; 3) there is no significant difference of comovement between within a category and outside a category in commodity markets; 4) (again) the heteroskedasticity bias is not significant for commodities.

Our results in [Table 11](#) can be explained as follows. First, recall that commodities are heterogeneous (Ausubel, 2006; Fleurbaey & Tadenuma, 2007; Pereira et al., 2017). Second, metal commodities offer much less diversification potential for equity investors (Pereira et al., 2017). Third, grain commodities have spillover risks (Ji et al., 2017) and the highest directional spillover effects (Chevallier & Ielpo, 2013). This property of commodities is due to seasonality factors (Pereira et al., 2017) or is highly dependent on climate (Adhikari & Putnam, 2019). Fourth, both metal and grain commodities have strong correlations (Cai et al., 2019). Fifth, energy commodities have different behaviors on spillover effects (Uddin et al., 2018). Sixth, we should note that i) soft commodities showed no jump comovement and ii) jumps for many soft commodities are even negatively correlated to Goldman Sachs Commodity Index jumps (Nguyen & Prokopczuk, 2019). Seventh, our insignificant difference of comovement between within category and outside category commodity markets is somewhat significant in light of the results of Adhikari and Putnam (2019) who also reported statistical insignificance.

The next step is performing a multinomial logit analysis. First, the exceedance and coexceedances were identified as defined in section 3.2. We then estimated a multinomial logit model as expressed in Equation (8). Recall that if the numbers of coexceedances are only 0 and 1, we use logistic regression instead. [Table 12](#) reports the multinomial logit (or logit) regression results for positive coexceedances in the four different commodity categories. According to [Table 12](#), slightly more covariates (14 out of 27—excluding intercepts) tend to be statistically significant. This finding demonstrates that the probability of positive coexceedances is somewhat affected by the other categories price changes in the commodity markets. We can also see that softs tend to be contagious to metals and grains, metals tend to be contagious to energies, and energies and grains tend to be contagious to softs. However, energies do not tend to be contagious to grains.

[Table 13](#) reports the multinomial logit (or logit) regression results for negative coexceedances in the four different commodity categories. According to [Table 13](#), most of the covariates (17 out of 27—excluding intercepts) tend to be statistically significant. This finding demonstrates that the probability of negative coexceedances is affected by the other categories price changes in the commodity markets. We can also see that softs tend to be contagious to grains, metals tend to be contagious to energies, and grains tend to be contagious to softs. However, energies do not tend to be contagious to grains.

Overall, we document that commodity price changes tend to affect the probability of both positive and negative coexceedances. We also observe that a positive daily change tends to increase the probability of positive coexceedances, and a negative daily change tends to increase the probability of negative coexceedances. This finding indicates that contagion exists in both directions, i.e., positive and negative extreme events. Therefore, there is a contagion in the commodity markets. As a portfolio manager, I would need to carefully evaluate the commodities' diversification benefits and contagion costs as financial instruments. On one side, commodities bring diversification benefits. On the other side, commodities have contagion effects.

Further analysis based on AIC values and the multinomial (or merely) logit models demonstrate that the contagion is stronger for negative coexceedances. This finding implies that commodities tend to be contagious in negative rather than positive extreme returns. This asymmetric contagion is somewhat similar to that reported by Amonlirdviman and Carvalho (2010). They find that

Table 11. The conditional and unconditional correlations within a category (as expressed in equation (3)), outside a category (as expressed in equation (4)), the average within a category (as expressed in equation (5)), the average outside a category (as expressed in equation (6)), and the t-values for one-tailed t-tests examining whether the average within category correlation coefficient is significantly greater than the average outside category correlation coefficient

Conditional correlations					
Category	Commodity	Equation (3)	Equation (4)	Eq (5)	Eq (6)
		Within	Outside	Average Within	Average Outside
		Category	Category	Category	Category
Energy	COI	0.0134	0.1185	0.1701	0.1045
	HOI	-0.0157	-0.0064		
	NGA	0.0079	0.0371		
Metal	GOL	0.4309	0.0635		
	SIL	0.4582	0.7535		
	COP	0.2915	0.0857		
	PLA	0.4173	0.0694		
	PAL	0.3721	0.0646		
Grain	COR	0.1088	0.1005		
	SOY	0.1441	0.0409		
	WHE	0.1470	0.0418		
	OAT	0.1219	0.0516		
Soft	COF	0.0638	0.0536		
	COT	0.0604	0.0848		
	SUG	0.0614	0.0768		
	COC	0.0386	0.0357		

(Continued)

Table 11. (Continued)						
Conditional correlations						
Category	Commodity	Equation (3)		Equation (4)		Eq (5)
		Within	Outside	Eq (6)		Test Statistics
		Unconditional correlations				
Category	Commodity	Eq (3)	Eq (4)	Eq (5)	Eq (6)	Test Statistics
		Within	Outside	Average Within	Average Outside	Test Statistics
		Category	Category	Category	Category	
Energy	COI	0.0131	0.1052	0.1535	0.0933	0.16
	HOI	-0.0157	-0.0059			
	NGA	0.0071	0.0364			
Metal	GOL	0.3849	0.0578			
	SIL	0.4001	0.6555			
	COP	0.2464	0.0738			
	PLA	0.3780	0.0645			
	PAL	0.3368	0.0597			
Grain	COR	0.1015	0.0867			
	SOY	0.1330	0.0390			
	WHE	0.1346	0.0380			
	OAT	0.1156	0.0500			
Soft	COF	0.0664	0.0551			
	COT	0.0562	0.0745			

(Continued)

Table 11. (Continued)

Conditional correlations						
Category	Commodity	Equation (3)	Equation (4)	Eq (5)	Eq (6)	Test Statistics
		Within	Outside	Average Within	Average Outside	
	SUG	0.0585	0.0695			
	COC	0.0395	0.0332			

Table 12. Result of the multinomial logit (or logit) regression results for positive coexceedances in the four different commodity categories. The asterisk indicates a significant covariate at the *) 10 percent significance level, **) 5 percent significance level, ***) 1 percent significance level

Multinomial logit regression equation (8)

$$P(COECD_{it} = X) = \frac{1}{1 + \sum_{j=1}^J \exp(\beta_j' T_{it, j})}$$

Positive Coexceedances

Coexceedances		Energy (using Logit)			Metal			Grain			Soft (using Logit)		
		Coef	t-Stat		Coef	t-Stat		Coef	t-Stat		Coef	t-Stat	
1	Intercept	-7.76	-11.57	***)	-4.30	-33.11	***)	-5.14	-26.30	***)	-6.55	-16.68	***)
	Energy				6.79	2.01	*)	4.16	0.91		-8.10	-0.62	***)
	Metal	68.64	2.84	***)				27.29	2.01	*)	55.37	3.00	
	Grain	4.59	0.10		22.64	2.37	**)				44.14	2.07	**)
	Soft	34.51	0.74		29.29	2.85	***)	26.64	1.71	*)			
2	Intercept				-5.97	-19.95	***)	-7.09	-13.69	***)			
	Energy				5.90	0.99		-19.06	-1.23				
	Metal							-28.68	-0.88				
	Grain				27.59	1.52							
	Soft				65.62	4.00	***)	67.78	2.46	**)			
3	Intercept				-6.55	-16.66	***)	-9.40	-6.19	***)			
	Energy				10.46	2.52	**)	2.75	0.10				
	Metal												
	Grain				21.66	0.87		33.32	0.56				
	Soft				68.62	3.31	***)	92.76	1.76	*)			
4	Intercept				-8.20	-9.63	***)						
	Energy				10.09	1.54							
	Metal												
	Grain				28.18	0.60							
	Soft				88.90	2.74	***)						
AIC			64.52			1,195.24			509.41		152.76		

Table 13. Result of the multinomial logit (or logit) regression results for negative coexceedances in the four different commodity categories. The asterisk indicates a significant covariate at the *) 10 percent significance level, **) 5 percent significance level, ***) 1 percent significance level

Multinomial logit regression equation (8)												$P(COE_{CO_i} = X) = \frac{1}{1 + \sum_{j=1}^3 \exp(\beta_j \overline{CO}_{(CO_i)})}$											
Negative Coexceedances																							
Coexceedances				Energy (using Logit)				Metal				Grain				Soft (using Logit)							
		Coef	t-Stat					Coef	t-Stat			Coef	t-Stat			Coef	t-Stat			Coef	t-Stat		
1	Intercept	-7.58	-12.37	***)				-4.34	-32.33	***)						-4.86	-28.28	***)			-5.80	-21.60	***)
	Energy							-5.49	-1.07							-2.77	-0.44			2.80	0.33		
	Metal	-78.45	-4.02	***)												-33.09	-3.15	***)			-36.77	-2.84	***)
	Grain	-21.56	-0.74					-30.31	-3.33	***)											-61.14	-4.53	***)
	Soft	-24.78	-0.69					-45.90	-4.64	***)						-41.11	-3.20	***)					
2	Intercept							-5.51	-23.07	***)						-7.82	-11.81	***)					
	Energy							-14.24	-2.09	**)						-8.23	-0.69						
	Metal															-61.28	-3.18	***)					
	Grain							-41.50	-3.09	***)													
	Soft							-53.40	-3.50	***)						-97.34	-3.68	***)					
3	Intercept							-6.33	-17.83	***)													
	Energy							-21.41	-2.49	**)													
	Metal																						
	Grain							-33.16	-1.44														
	Soft							-27.74	-1.04														
4	Intercept							-8.34	-9.36	***)													
	Energy							6.10	0.33														
	Metal																						
	Grain							-67.89	-1.98	*)													
	Soft							-81.40	-2.08	**)													
AIC																							
			81.51																				

correlations are higher in market downturns than in upturns. Furthermore, the asymmetric dependence is also addressed by Hameed et al. (2015) and Malceniace et al. (2019).

5. Conclusion

This article investigates comovement and contagions in the commodities markets. A simple approach to examine a contagion is calculating the correlation among variables. However, this method is neither robust nor appropriate. We examine the comovement by analyzing both the conditional and unconditional correlation coefficients and comparing the correlations between within-category and outside-category commodities. We perform contagion tests by identifying coexceedances and estimating multinomial logit to explain joint occurrence of those coexceedances.

Analyzing both conditional and unconditional (after correcting the heteroskedasticity bias) correlation coefficients, we find that 1) commodities tend to partially integrate; 2) natural gas, gold and coffee are good portfolio diversifiers, whereas platinum and palladium are bad portfolio diversifiers. We also demonstrate that our analysis using unconditional correlation coefficients is similar with that of using conditional correlation coefficients. This finding implies that the heteroskedasticity biases tend to be insignificant in commodity markets, which is different from the biases in the stock markets.

Comparing the correlations between within-category and outside-category commodities, we find that 1) metal and grain commodities tend to integrate, whereas energy commodities do not tend to integrate, 2) the integration of soft commodities is inconclusive, 3) there is no significant difference between within category and outside category comovement in commodity markets, and 4) the heteroskedasticity bias is not significant for commodities.

Estimating the multinomial logit, we find that commodity price changes tend to affect the probability of both positive and negative coexceedances. We also document that a positive daily change tends to increase the probability of positive coexceedances, and a negative daily change tends to increase the probability of negative coexceedances.

Overall, we conclude that there are comovement and contagions among commodities. The degrees of comovement and contagion however are different among categories and between positive and negative extreme returns. This difference is due to heterogeneity in commodity markets. The contagion among commodities is asymmetric and worse during negative extreme returns. These results suggest that the diversification benefit from commodities market is limited. Different type of commodity might give a different level of diversification benefit since the integration level among commodities are different. The financialization seems to drive the commodity markets to be more integrated, thus reduce the diversification benefit.

As a portfolio manager, I would need to carefully evaluate the commodities' diversification benefits and contagion costs as financial instruments. On one side, commodities bring diversification benefits. On the other side, commodities have contagion effects. This cost-benefit analysis of commodities could be interesting future research. Our study is limited to the comovement test focusing only on heteroskedasticity biases control and contagion test focusing on biological contagion (multinomial logistic analysis). A broad analysis of different focuses can contribute to the literature by analyzing comovement and contagion using different methods.

Acknowledgements

Funding: Universitas Indonesia PUTI Grant with contract number NKB-1768/UN2.RST/HKP.05.00/2020.

We also would like to thank seminar participants at the 3rd Sydney Banking and Financial Stability Conference 2019 at the University of Sydney Business School and editor and anonymous reviewers who provided valuable comments and suggestions to improve the quality of the manuscript.

Funding

This work was supported by the Universitas Indonesia [PUTI Grant NKB:1768/UN2.RST/HKP.05.00/2020].

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Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

The data that support the findings of this study are available from Datastream. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors with the permission of Datastream (subscription terms and conditions).

Citation information

Cite this article as: Comovement and contagion in commodity markets, Dony Abdul Chalid & Rangga Handika, *Cogent Economics & Finance* (2022), 10: 2064079.

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