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SPECULATION IMPACT ON AGRICULTURAL AND OTHER COMMODITY PRICE MOVEMENTS: BEFORE AND DURING THE COVID-19 PANDEMIC

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Abstract. Motivated by recent commodity price fluctuations and spikes, we examine whether speculation in commodity markets destabilizes the price of agricultural and other commodities. For full 1986–2021 and post-2020 data, we use the Granger non-causality test with a one- to two-week time lag to assess this impact. For commodities market speculation, we utilize both short-term and long-term measurements, which are often employed by other researchers. In our study, we use weekly returns on wheat, soybean, corn, and oats futures from the major US commodities markets as well as two additional commodities for comparison reasons: oil and gold. Our research found that speculative indices and return volatility increased in the oil and gold commodity markets after 2020, but not in the agricultural markets. The non-causality test found that there is no one-way causal effect from speculation to returns as evaluated by the four speculation indicators. Most of the time, returns have a one-way causal effect on speculation. Oil, oats, and notably wheat, provided a few instances of feedback relationships. As a result, we conclude that rising speculation cannot be blamed for price spikes or booms, or that the relationship is at best questionable.

Keywords: financial speculation, commodity futures markets, Granger causality, agricultural commodity futures.
JEL code: C58, G13, Q02

Introduction

Commodity futures are used to hedge against price risks when producing these commodities. In the previous two decades, the fast growth of commodity markets has been accompanied by commodity price volatility and spikes, which has sparked a lot of controversy in academic literature about what caused them. Many researchers investigate if commodities prices and their volatility are explained solely by fundamental supply and demand factors or if there is a role for speculative volumes and other factors unrelated to price risk hedging. However, according to many authors, there is no clear academic consensus on the shape and direction of this impact, and speculation may be explained by the movement of prices rather than vice versa (Wimmer et al., 2021; Ludwig, 2019). In addition, some researchers suggest that non-commercial trading does not necessarily disrupt markets, but rather increases liquidity (Haase and Huss, 2018; Wellenreuther and Voelzke, 2019). On the other hand, the excess amount of speculative activity may lead to market instability if these market participants behave differently from ordinary users who hedge against underlying price risk and exhibit herd behavior. For example, short-term speculation has a higher and statistically significant influence on return volatility in less liquid markets, such as cattle or cotton (Algieri and Leccadito, 2019). Many recent studies have been conducted to determine what drives co-movement across various commodities markets, notably during the COVID-19 pandemic (Borgards et al., 2021; Hung, 2021). These authors, however, do not include typical metrics of speculation, such as short-term or long-term speculation indices, or their influence on commodity prices. This is especially crucial for agricultural commodity price speculation, as market destabilizing effects may jeopardize food security and farmers' income stability. In fewer recent studies, agricultural commodities are also used as well. Therefore, the aim of this research is to compare whether speculation in commodity markets, as measured by several indices, causes price changes and how this effect has changed during the pandemic period of 2020. To begin with, we are concentrating on agricultural commodities that have been understudied, but we are also including metal and energy futures in our study as a baseline for comparison.

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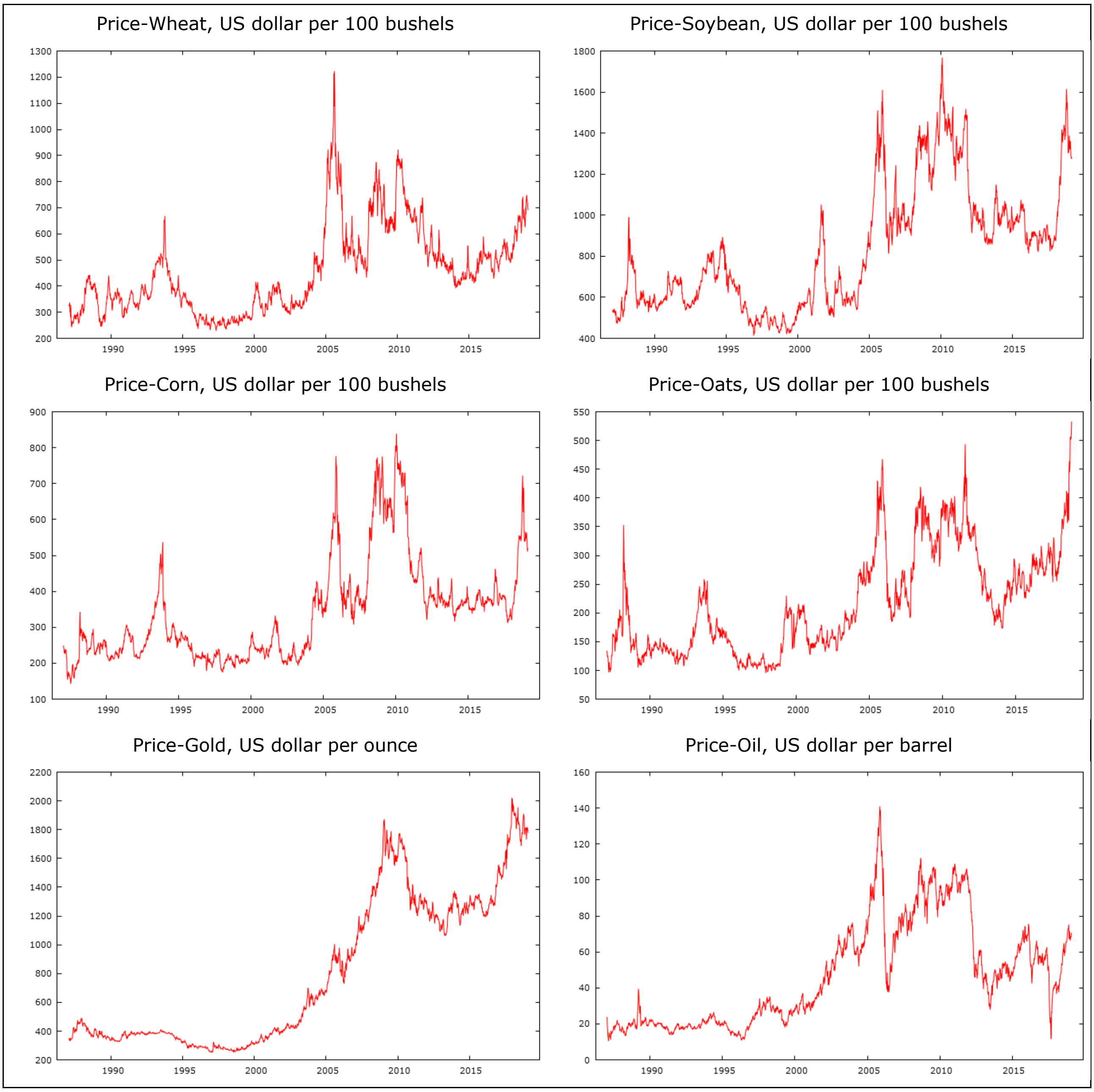
Data

Our research looks at four agricultural commodities: wheat, corn, soybeans, and oats, as well as two additional commodities: crude oil and gold. These agricultural futures are traded on the Chicago Board of Trade, whereas gold and crude oil futures are traded on the New York Mercantile Exchange. Barchart provides us with data on continuous futures prices, total open interest, and trading volume. We use the Commodity Futures Trading Commission's Commitments of Traders data to collect the number of non-commercial and commercial traders' positions. We gather weekly data from January 15, 1986, until September 21, 2021. The sample is separated into two subsamples: the full sample and after 2020. Throughout this time span, all commodities' prices have risen (Figure 1).



Source: author's calculations based on CBOT and NYMEX data, 2021

Fig. 1. **Prices of commodities (1986, January–September 2021)**

Methodology

We employ the Granger non-causality test to look at causal linkages between price and speculation, as well as the Augmented Dickey-Fueller test to check for time series stationarity. We employ four independent variables: the short-term speculation indicator TV/OI, long-term speculation indicators, the Working T index of excessive speculation, non-commercial long ratio (IL), and non-commercial short ratio (IS). We use the natural log of futures prices to generate a price return series (Formula 1). This variable is often used by others to better describe the movement of prices (Wimmer et al., 2021).

$$R_r = \ln\left(\frac{P_t}{P_{t-1}}\right) \times 100. \tag{1}$$

where: R_t is the price for a continuous futures contract, P_t is the futures price, and ln is the natural logarithm.

TV/OI is a short-term speculation indicator also known as the scalping index (Formula 2). Trading turnover, on the other hand, shows the intensity of speculative activity, whilst open positions reflect the total amount of hedging activity (Bohl et al., 2018). Shear (2020) claims that because speculators have a short trading horizon and trade often, the volume of speculation influences the volume of trade.

$$\mathrm{S}_t = \frac{TV_t}{OI_t}. \tag{2}$$

where: S_t is the short-term speculation index, TV_t is futures trade volume, and OI_t is open interest.

Next, we use the Working T index of speculation to measure excessive speculation in agricultural commodity markets (Working, 1960). The Working's T index is used in futures market research to assess the excess of non-commercial positions (index funds positions) over commercial positions (agricultural producers' and consumers' positions) (Büyükşahin and Robe, 2014). This index's value must be less than one. If it equals 1, all market positions are considered commercial:

$$T_t = \begin{cases} 1 + \frac{SS_t}{HL_t + HS_t} \text{ if}(\mathrm{HS_t} \geq \mathrm{HL_t}), \\ 1 + \frac{SL_t}{HL_t + HS_t} \text{ if}(\mathrm{HL_t} > HS_t). \end{cases} \tag{3}$$

where: T_t is the Working's T index for excessive speculation, SS_t are non-commercial short positions, SL_t are non-commercial long positions, HS_t are commercial short positions, and HL_t are commercial long positions.

We also use another long-term speculative index – the ratio of non-commercial long positions:

$$\mathrm{IL}_t = \frac{SL_t}{HL_t + SL_t}. \tag{4}$$

where: IL_t is the ratio of non-commercial long positions, SL_t are non-commercial long positions, and SL_t are non-commercial long positions, HL_t are commercial long positions.

And finally, we use the ratio of non-commercial short positions to show the number of hedgers that hedge against decreasing prices and are not producers of the type of product.

$$\mathrm{IS}_t = \frac{SS_t}{HS_t + SS_t}. \tag{5}$$

where: IS_t is the ratio of non-commercial short positions, SS_t are non-commercial short positions, SS_t are non-commercial short positions, HS_t are commercial short positions.

When evaluating time series, it is critical that their statistical features and distribution remain constant – autocorrelation, mean, and variance. Therefore, we then run an augmented Dickey-Fuller test to see if the time series is stationary. As proposed by Said and Dickey (1984), the test employs a constant, a trend,

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and a number of time lags (Formula 6). This allows one to determine if the time series is stationary by considering (and adjusting the data to) the long-term determinative trend. The statistical hypothesis in this case is H0: the time series has a unit root φ = 0.

$$\Delta Y_t = \alpha + \beta t + \varphi Y_{t-1} + \sum_{i=1}^{j} \theta_i \Delta Y_{t-i} + u_t \tag{6}$$

where: Y_t is the dependent variable return on futures contracts, φ, θ, α, β are model parameters, u_t is the residual error, Δ is the change in the first order, *i* is the time lag, and *j* is the number of lags.

Even though selected time series may be correlated, that does not necessarily indicate causation. Therefore, we use the Granger non-causality test for speculative indices and prices or returns if prices are not stationary. The Granger Causation Test is expressed as two autoregressive equations (Formulae 7 and 8). The model's first equality allows you to check that the speculative index is not driving prices or returns on a product's futures contracts (Formula 7). The model's second equation allows you to determine whether prices or futures returns are not a reason to speculate in the market (Formula 8). Using the methods presented by Granger (1969), it is determined which time series can best explain the next time series for a given number of time lags. We form hypotheses about causality relationships. H0: $\alpha_i = 0$. Speculation does not cause returns; H0: $\beta_i = 0$. Returns do not cause speculation. There are situations when both time series show statistically significant effects, yet the variables are defined by feedback.

$$\mathrm{Y}_t = \alpha_0 + \sum_{i=1}^{j} \alpha_1 Y_{t-i} + \sum_{i=1}^{j} \alpha_i X_{t-i} + \varepsilon_t. \tag{7}$$

$$\mathrm{X}_t = \beta_0 + \sum_{i=1}^{j} \beta_1 X_{t-i} + \sum_{i=1}^{j} \beta_i Y_{t-i} + \omega_t. \tag{8}$$

where: Y_t is the dependent variable return on futures contracts, X_t is an independent variable index of speculative activities, $\beta_{0,1,2}$, $\alpha_{0,1,2}$ are model parameters, ε_t, ω_t are residual errors, *i* is the time lag, and *j* is the number of time lags.

Research results and discussion

We start our analysis by providing descriptive statistics for all six commodities (Table 1). The volatility of returns described by standard deviation is largest for oil futures, whereas the smallest is for gold. Agricultural commodities, in terms of standard deviation of returns, fall between these two commodities. When analysing agricultural commodities, the largest volatility of returns is for oats and the smallest for soybean futures. The results are similar when analysing post-2020 data. The variance of returns has increased in oats, gold, and especially oil futures, while it has decreased in other agricultural commodities.

The mean value of the short-term speculative index S is the highest for soybean futures and the smallest for oat futures. However, the mean value of the short-term speculative index is higher for gold and oil futures than for agricultural ones when analysing post-2020 data. The mean value of the long-term speculative index T is the highest for wheat futures and the smallest for oil futures, and it roughly remained the same while analysing both time samples. The mean value of the speculative index IL is the highest for gold futures and the smallest for oil futures. When analysing post-2020 data, the mean value of the IL speculative index is higher for gold and oil futures than for agricultural ones. The mean value of the speculative index IS is the highest for wheat futures and the smallest for oat futures. In summary, our analysis shows that speculative indices are becoming more intense in oil and gold commodities using post-2020 data.

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Table 1

Commodity futures: Descriptive statistics and ADF test results

Variable	**Wheat**		**Soybean**		**Corn**		**Oats**		**Gold**		**Oil**	
	full sample	post-2020	full sample	post-2020	full sample	post-2020	full sample	post-2020	full sample	post-2020	full sample	post-2020
P, price of futures contract, euro												
Average	457	603	832	1141	342	452	219	344	796	1791	47	50
ADF, p-value	0.18	0.12	0.12	0.91	0.09	0.61	0.20	0.99	0.72	0.66	0.13	0.12
R, return on futures contract, percent												
St. deviation	4.07	3.59	3.44	2.86	3.98	3.89	5.17	5.36	2.27	2.63	5.68	12.25
ADF, p-value	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
S, index of short-term speculation												
Average	0.36	0.33	0.49	0.27	0.31	0.23	0.22	0.12	0.33	0.53	0.37	0.48
ADF, p-value	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
T, index of excessive speculation												
Average	1.24	1.34	1.12	1.08	1.13	1.11	1.09	1.02	1.13	1.14	1.08	1.08
ADF, p-value	<0.01	0.04	<0.01	0.98	<0.01	0.74	<0.01	0.16	<0.01	0.07	0.02	0.12
IL, non-commercial long position ratio												
Average	0.37	0.46	0.35	0.36	0.31	0.35	0.40	0.59	0.46	0.72	0.25	0.47
ADF, p-value	<0.01	0.29	<0.01	>0.99	<0.01	0.60	<0.01	0.01	0.06	0.29	<0.01	0.77
IS, non-commercial short position ratio												
Average	0.34	0.39	0.20	0.12	0.20	0.19	0.12	0.03	0.22	0.16	0.13	0.11
ADF, p-value	<0.01	0.03	<0.01	0.99	<0.01	0.64	<0.01	0.17	<0.01	0.10	<0.01	0.06

Source: author's calculations based on CBOT and NYMEX data, 2021

If we look at the ADF test results, all time series but absolute price are stationary when using a full-time sample and have p-values of below 0.1 (see Table 1). When using post-2020 data, long-term speculative indices are usually non-stationary, especially for soybean and corn futures. The results of the ADF test using constants and trends show that return time series are better suited for further analysis of causality than absolute values of prices. Therefore, we look at how speculation indices explain return time series instead of price. Returns are calculated as the difference between the prices of continuous futures contracts in the next week and the prices of those contracts in the previous week.

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Table 2

Estimates of Granger's non-causality test using the short-term speculation index

Commodity/hypothesis	Time lag	Full data		2020–2021		Results
		p-value	Coefficient	p-value	Coefficient	
Wheat, R does not cause S	1	0.6315	0.0004	0.2836	−0.0035	Accept
	2	0.1149	−0.0015	0.5526	−0.0019	
Wheat, S does not cause R	1	0.7620	0.1922	0.4683	−2.7852	Accept
	2	0.9309	0.0550	0.8300	0.8116	
Soybean, R does not cause S	1	0.3956	0.0011	0.4412	0.0021	Reject/accept
	2	0.0142	−0.0032	0.5953	−0.0015	
Soybean, S does not cause R	1	0.3969	−0.3836	0.6718	1.8703	Accept
	2	0.4435	0.3466	0.0675	8.1351	
Corn, R does not cause S	1	0.1874	0.0010	0.9159	0.0002	Accept
	2	0.0856	−0.0013	0.9254	0.0002	
Corn, S does not cause R	1	0.2026	1.0148	0.8748	−0.7803	Accept
	2	0.1747	−1.0773	0.7980	−1.2469	
Oats, R does not cause S	1	0.6072	−0.0004	0.1415	−0.0021	Accept
	2	0.9025	−0.0001	0.3734	−0.0013	
Oats, S does not cause R	1	0.3778	0.6864	0.1196	−14.7645	Accept
	2	0.8372	0.1600	0.3908	7.8866	
Oil, R does not cause S	1	0.1057	−0.0009	0.1077	−0.0031	Reject/accept
	2	0.0032	0.0016	0.3091	0.0019	
Oil, S does not cause R	1	0.0427	−2.2403	0.7053	−2.9300	Reject/accept
	2	0.0006	3.7714	0.0656	13.8189	
Gold, R does not cause S	1	0.0540	0.0033	0.1512	0.0012	Accept
	2	0.5544	−0.0010	0.9660	0.0001	
Gold, S does not cause R	1	0.2747	0.3712	0.1243	2.0581	Accept
	2	0.2346	−0.4035	0.2885	−1.4275	

Source: author's calculations based on CBOT and NYMEX data, 2021

We then present the results of the Granger non-causality test. To begin, we look at the short-term speculation index TV/OI (denoted by S) and its relationship with return (denoted by R) (Table 2). Wheat, corn, oats, and gold futures all have parameters with p-values larger than 0.05, indicating that neither return nor speculation cause one another and that these time series are uncorrelated. Both hypotheses have p-values below 0.05 when analysing the full sample of oil futures market data, showing that there is a feedback relationship between return and short-term speculation. It is also worth noticing that the p-value is larger for the hypothesis that oil returns do not cause short-term speculation in these markets and with both time lags. However, this effect in the oil market is not observed when analysing post-2020 data. For soybean futures, the hypothesis that returns do not cause speculation can be rejected with a p-value of 0.0142 when analysing full data with a two-week time lag. Therefore, returns better explain short-term speculation. To sum up, there is no evidence that in any of these cases, short-term speculation has a significant one-directional effect on returns.

Table 3

Estimates of Granger's non-causality test using the Working-T speculation index

Commodity/hypothesis	Time lag	Full data		2020–2021		Results
		p-value	Coefficient	p-value	Coefficient	
Wheat, R does not cause T	1	<0.0001	−0.0010	0.7292	−0.0004	Reject/accept
	2	0.3750	−0.0002	0.7124	0.0004	
Wheat, T does not cause R	1	0.0472	5.7814	0.1134	22.3122	Reject/accept
	2	0.0694	−5.2803	0.5399	−8.6600	
Soybean, R does not cause T	1	<0.0001	−0.0009	0.2108	0.0004	Reject/accept
	2	0.0057	−0.0005	0.3817	−0.0003	
Soybean, T does not cause R	1	0.5470	−2.2031	0.6034	17.1921	Accept
	2	0.7084	1.3590	0.3848	−27.8897	
Corn, R does not cause T	1	<0.0001	−0.0012	0.9041	−0.0001	Reject/accept
	2	0.1037	−0.0002	0.4143	−0.0002	
Corn, T does not cause R	1	0.8930	−0.5505	0.8919	5.3530	Accept
	2	0.8949	0.5373	0.8034	−9.7059	
Oats, R does not cause T	1	<0.0001	−0.0006	0.9728	−0.0001	Reject/accept
	2	0.0012	−0.0005	0.4878	0.0002	
Oats, T does not cause R	1	0.1447	6.1610	0.5545	24.9217	Accept
	2	0.3772	−3.7319	0.5450	26.8553	
Oil, R does not cause T	1	0.2839	−0.0001	0.3865	0.0001	Reject/accept
	2	0.0005	−0.0002	0.0616	−0.0001	
Oil, T does not cause R	1	0.3510	12.0921	0.3097	−155.5790	Accept
	2	0.4404	−10.0001	0.2681	163.2180	
Gold, R does not cause T	1	<0.0001	−0.0013	0.1512	0.0012	Reject/accept
	2	0.1171	−0.0005	0.9660	0.0001	
Gold, T does not cause R	1	0.5864	1.0963	0.3028	−16.6963	Accept
	2	0.8565	−0.3643	0.3976	13.6622	

Source: author's calculations based on CBOT and NYMEX data, 2021

Next, we analyse causal relationships between returns and the long-term Working-T index of excessive speculation (Table 3). The only case where there are mixed results is wheat futures. There is a feedback relationship using a one-week lag when analysing full data for wheat. However, the hypothesis that returns have no effect on speculation is rejected at a much smaller p-value (it is 0.0001 as compared to 0.0472). For all other products, returns have a one-directional effect on excessive speculation. However, p-values of below 0.05 are only present when analysing full data, and post-2020 data time series are uncorrelated. It is also worth mentioning that in all cases where there is a rejected hypothesis that returns do not cause speculation, coefficient values are negative, meaning that an increase in returns reduces the excessive amount of speculation. In addition, all products except for oil have a one-day week with a smaller p-value than the two-week lag. This may show that a one-week lag is best used to explain returns. To sum up, returns explain long-term speculation better than vice versa for all six product groups.

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Table 4

Estimates of Granger's non-causality test using the IL speculation index

Commodity/hypothesis	Time lag	Full data		2020–2021		Results
		p-value	Coefficient	p-value	Coefficient	
Wheat, R does not cause IL	1	<0.0001	0.0012	0.1233	0.0010	Reject/accept
	2	0.9877	−0.0001	0.3636	0.0005	
Wheat, IL does not cause R	1	0.0386	−4.9552	0.4584	−17.3080	Reject/accept
	2	0.0440	4.7661	0.8574	4.2399	
Soybean, R does not cause IL	1	0.0003	0.0010	0.4770	0.0005	Reject/accept
	2	0.2747	0.0003	0.5680	0.0004	
Soybean, IL does not cause R	1	0.6359	−1.3037	0.9820	−0.4688	Accept
	2	0.5915	1.4568	0.7950	5.2782	
Corn, R does not cause IL	1	<0.0001	0.0007	0.5616	−0.0002	Reject/accept
	2	0.2890	0.0002	0.4767	0.0003	
Corn, IL does not cause R	1	0.3757	3.8711	0.9931	0.2906	Accept
	2	0.3841	−3.7568	0.8530	6.1590	
Oats, R does not cause IL	1	<0.0001	0.0011	0.2423	0.0015	Reject/accept
	2	0.0161	0.0006	0.7479	0.0004	
Oats, IL does not cause R	1	0.1212	−3.8633	0.1598	−16.0849	Accept
	2	0.2533	2.8487	0.9713	0.4307	
Oil, R does not cause IL	1	0.0006	0.0003	0.7977	0.0001	Reject/accept
	2	0.4978	−0.0001	0.0612	0.0002	
Oil, IL does not cause R	1	0.3928	−6.0013	0.3383	−93.1182	Accept
	2	0.4100	5.7817	0.0908	170.2730	
Gold, R does not cause IL	1	0.0009	0.0019	0.0405	−0.0014	Reject
	2	0.8687	−0.0001	0.9090	−0.0001	
Gold, IL does not cause R	1	0.3374	−1.3688	0.3968	16.5168	Accept
	2	0.2529	1.6157	0.1271	−29.3208	

Source: author's calculations based on CBOT and NYMEX data, 2021

Next, we analyse the causal relationships between returns and long non-commercial positions (Table 4). The wheat futures market is the only case where the results show a feedback relationship. When using a one-week lag, the p-value of return has no effect on speculation and is lower than vice versa (0.0001 compared to 0.0386). When using a two-week lag, we can only reject the hypothesis that speculation has no effect on returns (the p-value is 0.0440), but a week-two lag has a higher p-value compared to a week-one. Furthermore, the coefficient sigh for one-week and two-week lags differs – for one-week, it is negative (-4.9552) and for two-weeks, it is positive (4.7661). For all other agricultural products, returns better explain long-term speculative positions than vice versa. However, only gold kept the same direction of causality when analysing post-2020 data as well. One-week lag of returns better explains speculation than two-week lag, and coefficient values are positive for all cases except for gold when analysing post-2020 data. To sum up, returns explain non-commercial long positions better than vice versa for all six product groups.

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Table 5

Estimates of the Granger non-causality test using the IS speculation index

Commodity/hypothesis	Time lag	Full data		2020–2021		Results
		p-value	Coefficient	p-value	Coefficient	
Wheat, R does not cause IS	1	<0.0001	−0.0017	0.2309	−0.0012	Reject/accept
	2	0.9429	−0.0001	0.9758	0.0001	
Wheat, IS does not cause R	1	0.0079	7.0253	0.1924	26.4106	Reject/accept
	2	0.0166	−6.2827	0.7584	−6.2074	
Soybean, R does not cause IS	1	<0.0001	−0.0013	0.2128	0.0007	Reject/accept
	2	0.2885	−0.0002	0.3048	−0.0006	
Soybean, IS does not cause R	1	0.2148	−3.5723	0.3635	18.4651	Accept
	2	0.2034	3.6150	0.2133	−24.5903	
Corn, R does not cause IS	1	<0.0001	−0.0014	0.5729	−0.0001	Reject/accept
	2	0.7097	−0.0001	0.6084	−0.0002	
Corn, IS does not cause R	1	0.5296	2.0806	0.8243	−5.7141	Accept
	2	0.7022	−1.2498	0.8600	4.5192	
Oats, R does not cause IS	1	<0.0001	−0.0009	0.9512	0.0001	Reject/accept
	2	0.0005	−0.0006	0.5758	0.0002	
Oats, IS does not cause R	1	0.0201	8.8196	0.5827	18.0465	Reject/accept
	2	0.1018	−6.2162	0.5107	22.8173	
Oil, R does not cause IS	1	0.0053	−0.0002	0.4378	0.0001	Reject
	2	0.0033	−0.0002	0.0366	−0.0002	
Oil, IS does not cause R	1	0.5204	4.8456	0.3158	−116.4470	Accept
	2	0.6578	−3.3329	0.3473	104.6260	
Gold, R does not cause IS	1	0.0016	−0.0015	0.1113	0.0012	Reject/accept
	2	0.3490	−0.0004	0.9593	−0.0001	
Gold, IS does not cause R	1	0.9561	−0.0789	0.3513	−16.2193	Accept
	2	0.9350	0.1154	0.4482	13.1734	

Source: author's calculations based on CBOT and NYMEX data, 2021

Next, we analyse causal relationships between returns and short-term non-commercial positions (Table 5). The only cases where there are feedback relationships are wheat and oats futures. For both products, p-values are smaller for the return parameter, except when using two-week lag wheat futures. Here it has a p-value of 0.0166 compared to 0.9429, but for both products, p-values are higher than they are when using a one-week lag. It is also worth noticing that for wheat speculation coefficient values have different signs (parameter values are 7.0253 and -6.2827), so it is difficult to tell if speculation reduces or increases returns. All other commodities show that returns lead speculation. However, only oil kept the same direction of causality when analysing post-2020 data as well. In all cases, a one-week lag better explains speculation than a two-week lag, except for oil futures. Return coefficient values when they are statistically significant are negative, so an increase in returns reduces the ratio of non-commercial short positions. To sum up, returns explain non-commercial short positions better than returns for all six product groups.

We conclude that the Granger non-causality test can be used effectively to analyse data from major commodities futures before and after 2020. When employing long-term speculation indexes, returns almost always outperform speculation in terms of explanatory power. Except for uncorrelated results, feedback linkages, or p-values between 0.05 and 0.10, there were no occurrences of one-way causal impact from speculation to returns.

These results go in line with authors like Palazzi et al., 2020; Leone et al., 2019, who also applied similar tests and found that, in most cases, returns explain speculation better than vice versa. More speculation indicators, more detailed time periods, and more commodity futures can be used to expand the inquiry into the impact of financial speculation on agricultural and other commodity prices and returns. A continuous Granger-non-Causality test could be used in future analysis as well as focusing on less liquid markets outside of the US.

Conclusions, proposals, recommendations

1) In this study, we examine the volatility of six commodities using the Granger non-causality test to determine if speculation is a source of returns. We utilize realized weekly returns from major US commodities markets. We employ four independent variables: short-term speculation indicator TV/OI, long-term speculation indicators, the Working T index of excessive speculation, non-commercial long ratio (IL), and non-commercial short ratio (IS). The results of the ADF test reveal that the time series are, in most cases, stationary and fit for further non-causality analysis.
2) Our research has three important observations. First, using post-2020 data, study shows that speculative indices and return volatility became larger in oil and gold commodity markets, but not in agriculture markets. Second, there is no case of one-directional effect from speculation to returns measured by all four speculation indicators. in most cases returns have one-directional effect to speculation. There were few examples of feedback relationships: oil, oats and especially wheat. Third, in most cases time series of returns and speculation became uncorrelated during post-2020 period, except for gold and oil futures using long and short non-commercial ratios to describe speculation but still returns better explained these variables than vice versa.
3) The findings of our study have significant policy consequences. Financial speculation is causing futures commodities exchange authorities to impose a limit on non-commercial holdings. Our findings, like those of other authors, suggest that financial speculation has a limited impact on price level and volatility in agricultural markets, and that in certain circumstances, the reverse is true, as a rise in non-commercial holdings might be followed by smaller returns. However, we show that these associations have not altered much, and that speculation did not begin to outperform returns throughout the pandemic era.

References

1. Algieri, B. and Leccadito, A., 2019. Price Volatility and Speculative Activities in Futures Commodity Markets: A Combination of Combinations of P-Values Test. *Journal of Commodity Markets*, *13*, pp.40-54.
2. Bohl, M.T., Siklos, P.L. and Wellenreuther, C., 2018. Speculative Activity and Returns Volatility of Chinese Agricultural Commodity Futures. *Journal of Asian Economics*, *54*, pp.69-91.
3. Borgards, O., Czudaj, R.L. and Van Hoang, T.H., 2021. Price Overreactions in the Commodity Futures Market: An Intraday Analysis of the COVID-19 Pandemic Impact. *Resources Policy*, *71*, p.101966.
4. Büyükşahin, B. and Robe, M.A., 2014. Speculators, Commodities, and Cross-Market Linkages. *Journal of International Money and Finance*, *42*, pp.38-70.
5. *Futures Prices by Exchange* (2021). Retrieved: https://www.barchart.com/futures/prices-by-exchange. Access: 15.11.2021.
6. Granger, C.W., 1969. Investigating Causal Relations by Econometric Models and Cross-Spectral Methods. *Econometrica: journal of the Econometric Society*, pp.424-438.

7. Haase, M. and Huss, M., 2018. Guilty Speculators? Range-Based Conditional Volatility in a Cross-Section of Wheat Futures. *Journal of Commodity Markets*, *10*, pp.29-46.
8. Hung, N.T., 2021. Oil Prices and Agricultural Commodity Markets: Evidence From Pre and During COVID-19 Outbreak. *Resources Policy*, *73*, p.102236.
9. Leone, M., Manelli, A. and Pace, R., 2019. Commodity Market and Financial Derivative Instruments Is There a Cointegration. *J. Modern Account. Audit*, *15*, pp.185-202.
10. Ludwig, M., 2019. Speculation and Its Impact on Liquidity in Commodity Markets. *Resources Policy*, *61*, pp.532-547.
11. Palazzi, R.B., Pinto, A.C.F., Klotzle, M.C. and De Oliveira, E.M., 2020. Can We Still Blame Index Funds for the Price Movements in the Agricultural Commodities Market? *International Review of Economics & Finance*, *65*, pp.84-93.
12. Said, S.E. and Dickey, D.A., 1984. Testing for Unit Roots in Autoregressive-Moving Average Models of Unknown Order. *Biometrika*, *71*(3), pp.599-607.
13. Shear, F., 2020. Speculation and Returns' Volatility: Evidence From Pakistan Mercantile Exchange. Retrieved: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3777006. Access: 06.03.2022.
14. Wellenreuther, C. and Voelzke, J., 2019. Speculation and Volatility—A Time-Varying Approach Applied on Chinese Commodity Futures Markets. *Journal of Futures Markets*, *39*(4), pp.405-417.
15. Wimmer, T., Geyer-Klingeberg, J., Hütter, M., Schmid, F. and Rathgeber, A., 2021. The Impact of Speculation on Commodity Prices: A Meta-Granger Analysis. *Journal of Commodity Markets*, *22*, p.100148.
16. Working, H., 1960. Speculation on Hedging Markets. *Food Research Institute Studies*, *1*(1387-2016-116000), pp.185-220