EVALUATING THE FACTORS THAT IMPACT THE RETURNS ON AGRICULTURAL AND OTHER COMMODITY FUTURES CONTRACTS: THE INFLUENCE OF FINANCIAL SPECULATION

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Abstract

This study examines the impact of financial speculation on the returns and volatility of agricultural and other commodity futures before and after the COVID-19 pandemic, contributing to the debate on whether speculative trading amplifies or mitigates market instability in increasingly financialized commodity markets (Alaminos et al., 2024; Chiu & Chou, 2022). Using weekly data and applying Granger non-causality tests together with generalised autoregressive conditional heteroskedasticity (GARCH) and threshold generalised autoregressive conditional heteroskedasticity (TGARCH) models, the analysis shows that commodity returns either lead speculative activity or exhibit no significant causal relationship, indicating that speculation does not drive price dynamics. Speculation affects return volatility only in crude oil and gold markets, where the effect is stabilizing, while agricultural commodities show no statistically significant volatility response. Macroeconomic variables, particularly the Goldman Sachs Commodity Index (GSCI) index, strongly shape returns across all commodities, and volatility increased notably during the post-2020 period. Overall, the findings suggest that commodity price behaviour is primarily driven by fundamental and macroeconomic conditions rather than speculative pressures, and that speculation does not amplify volatility in agricultural markets even during periods of heightened global uncertainty.

Keywords: Agricultural Commodities, Futures, Financial Speculation, Return Volatility, Commodities

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1. INTRODUCTION

The contemporary economic environment is marked by geopolitical tensions, food and energy insecurity, high inflation, elevated debt, volatile currencies, and shifting capital flows, all of which heighten concerns about global food security and agricultural price dynamics (Algieri et al., 2023). Beyond fundamental supply–demand forces, many studies emphasise developments within major commodity futures markets, which link agricultural and energy commodities through production and price interdependencies (Conrad, 2023; Singhal & Tarp, 2025; Boateng et al., 2022). These markets have become increasingly shaped by financialization — driven by cross-country integration, new financial instruments, and market liberalisation (Hrabynska et al., 2022). The rapid expansion of global futures trading illustrates this trend, while globalisation amplifies the influence of speculative activity on world food prices (Bohmann et al., 2019; Guo & Tanaka, 2022). Financialization also affects agricultural producers, who increasingly rely on futures contracts to hedge price risks (Rl & Mishra, 2022).

Speculation attracts continued attention because it may amplify volatility, especially during periods of macroeconomic stress (Djamal & Saida, 2025). Recent evidence shows that speculative dynamics have grown more prominent within commodity markets as financialization deepens, and even cryptocurrency speculation can transmit shocks to commodities (Alaminos et al., 2024; Mosbey et al., 2024). These developments have prompted calls for tighter regulatory oversight (Chiu & Chou, 2022). Empirical studies, however, remain divided, with many reporting mixed or insignificant effects of speculation (Haase et al., 2016). Much of the existing research focuses on the 2008 financial crisis or pre-COVID periods of relative stability, whereas post-pandemic commodity market disruptions are far less examined. Recent legal scholarship also highlights growing disputes over how speculation is defined and regulated across jurisdictions (Ramos-Munoz, 2025).

Against this background, this research aims to evaluate the impact of financial speculation on agricultural and other commodity futures returns before and after the COVID-19 pandemic and to assess whether speculation amplifies the influence of fundamental market factors.

The paper is structured as follows. Section 2 reviews the theoretical and empirical literature on speculation and commodity price behaviour. Section 3 describes the data and methodology, including the construction of the speculation index and the econometric models. Section 4 presents the empirical results for the full sample and the post-COVID-19 period. Section 5 discusses the findings in the context of previous research, and Section 6 concludes with the main implications and directions for future work.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Speculation in commodity futures markets is broadly understood as taking risky positions to profit from price movements or opening non-hedging positions over longer horizons, typically undertaken by non-commercial participants such as index funds (Soana et al., 2020; Andreasson et al., 2016). Traditional theories explain their role through storage cost and hedging pressure mechanisms, whereby speculators help producers avoid storage costs and absorb risk premia arising from imbalances in commercial positions, consistent with Keynes' normal backwardation. However, financialization increasingly reshapes these dynamics: it has reduced risk premia and managed-futures returns, weakened food security, especially in wheat and soybean markets, strengthened commodity–equity comovements, increased the influence of non-commercial traders, and shifted the futures–spot basis (Carter & Revoredo-Giha, 2023; Manogna & Kulkarni, 2024; Kang et al., 2023). Even emerging agricultural markets exhibit early signs of financialization, though spillovers remain limited and commodities still support diversification (Acikgoz et al., 2023). Trader behavior also matters — index traders behave passively while non-reportable and trend-following traders shape returns — and speculators enhance liquidity and price discovery (Sun et al., 2023; Shao & Li, 2025; Borgards & Czudaj, 2022). Nonetheless, spot prices continue to reflect fundamental factors such as gross domestic product, industry output, inflation, and money supply, particularly where financialization reinforces the dominance of fundamentals (Ye et al., 2021; Galán-Gutiérrez & Martín-García, 2022). When speculative activity grows beyond liquidity needs, prices may deviate from supply-demand expectations, motivating behavioral perspectives showing that overreactions are frequent and that sentiment-driven strategies can amplify volatility while rational switching can stabilize markets (Algieri et al., 2023; Borgards et al., 2021; Di Francesco & Hommes, 2025).

Empirical evidence on speculation's impact remains mixed. Many studies find no significant effects on price levels or volatility, while others document stabilizing or destabilizing effects (Wellenreuther & Voelzke, 2019; Staugaitis & Christauskas, 2023; Bohl & Sulewski, 2019; Grosche, 2014). Destabilizing findings often arise when using the trade volume (TV)/open interest (OI) index as a proxy for short-term speculation (Bohl et al., 2018). Bubble-focused studies similarly report mixed evidence across commodities, and non-causality tests produce inconsistent outcomes (Etienne et al., 2017; Long & Guo, 2022; Chen et al., 2023; Czudaj, 2019). Recent contributions highlight more complex volatility effects and show that speculation may dominate fundamental forces in cross-market spillovers, particularly in emerging economies (Bonnier, 2021; Pasquariello & Wang, 2024). Sentiment-driven long-short traders generate significant short-term profits, and widespread alignment with momentum strategies may impair diversification (Borgards & Czudaj, 2023; Uhl, 2025). Evidence from Chinese, Indian, and EU markets is similarly mixed, often constrained by limited position data (Bohl et al., 2018; Khan & Ejaz, 2024). Overall, destabilizing effects appear modest and concentrated in older or thinly traded markets such as pork, sugar, and soybean before 2010 (Algieri, 2016; Soana et al., 2020; Palazzi et al., 2020; Haase et al., 2019). Broader reviews confirm that empirical outcomes depend heavily on methodology, with Granger-causality tests typically showing weak effects and correlation or spread-based approaches finding stronger price impacts (Haase et al., 2016; Conrad, 2023; Kupabado & Kaehler, 2025).

During periods of economic stress, many studies conclude that fundamentals and macroeconomic forces drive commodity price dynamics. Prior crises were largely explained by supply-demand factors, macro-financial conditions, and lagged volatility (Behmiri et al., 2019; Lu et al., 2019; Büyüksahin & Robe, 2014). The influence of speculation can depend on sector-specific conditions and broader financial stress, while several studies find little to no speculative impact even in turbulent periods (Adhikari & Putnam, 2025; Hachula & Rieth, 2020). Crisis conditions also strengthen market interdependence (Behmiri et al., 2019). In energy markets, speculation-driven shocks matter mainly in high-volatility regimes, with mixed evidence on whether speculation amplifies or buffers uncertainty. Agricultural markets have experienced bubble episodes during past crises, and extreme conditions can intensify commodity-equity interactions or reduce trader positions due to policy uncertainty (Alam et al., 2022; Xiao & Wang, 2022; Chen et al., 2023; Makkonen et al., 2021; Du & Dong, 2023). During the COVID-19 era, markets exhibited stronger co-movement and volatility, though spillovers were smaller than during the financial crisis (Ahmed & Sarkodie, 2021; Cao & Cheng, 2021). Pandemic-era spillovers still intensified relative to pre-COVID periods, and stock-to-commodity linkages strengthened, while rising case counts hindered economic conditions (Hung, 2021; Wen et al., 2021; Jiang et al., 2022). Evidence on speculative dynamics during COVID-19 is limited: cross-speculative pressure appears weak, yet extreme risk events may accelerate speculative transmission across markets (Fan et al., 2022; Wang et al., 2022).

The study focuses on agricultural commodities, but as mentioned before, energy prices play an important role in the formation of agricultural prices. Therefore, the study also involves crude oil futures and, for comparison reasons, gold futures. In this research, we analyse the newest data on agricultural and other commodity markets, including the COVID-19 pandemic period and after (the post-2020 time frame). Next, we form the first hypothesis of our research:

H1: Speculation does cause returns from futures contracts.

We also, similarly to Bohl and Sulewski (2019), emphasise not only the level of commodity prices but also return volatility:

H2: Speculation does affect futures return volatility.

As previously indicated, a number of macroeconomic variables influence commodity prices, so it is crucial to consider the impact of speculation alongside other factors. Seasonality is crucial when it comes to agricultural markets (da Silveira et al., 2017). The impact of seasonality on return volatility, which is frequently observed in agricultural markets and is highlighted by other researchers (Supriya & Mamilla, 2022), is also examined in our research. For example, the price of grain futures tends to be more volatile before the harvest. According to Karali and Ramirez (2014), volatility in the prices of energy products is also characterised by seasonality (higher volatility in March–November) and the effect of the day of the week. Therefore, the third hypothesis of our research can be described as:

H3: Speculation amplifies futures return volatility during months in which returns are most volatile.

3. MATERIALS AND METHODS

3.1. Data

The study analyses five commodities, of which three are agricultural commodities. The main focus of this research is agricultural commodities, but for comparison reasons, we also use two additional commodities. All commodities included in the study are soft red winter wheat futures, soybean futures, corn futures, crude oil (West Texas Intermediate) futures, and gold futures. Selected futures contracts: 1) are liquid; 2) have a long history of trading; 3) were used in other authors' research. All agricultural commodities are traded on the Chicago Board of Trade (CBOT), whereas crude oil and gold are traded on the New York Mercantile Exchange (NYMEX). The study uses weekly data, which ranges from October 15, 1992, to June 27, 2023. Data on commercial and non-commercial positions necessary to estimate the Working's T index is gathered from weekly reports on the commitment of traders. The study is divided into two subperiods: the all-time sample and the time period post-2020 (starting on January 7, 2020). The study also includes four indicators reflecting the macroeconomic environment: the major US stock index Standard and Poor's 500 (S&P 500), the commodity index S&P Goldman Sachs Commodity Index (GSCI), the 10-Year U.S. Bond Yield, and the U.S. Dollar Index. The data was collected using financial data platforms such as Bloomberg and Barchart. Calculations are made using the software Gretl.

3.2. Method

The study uses time series analysis to further investigate speculation's impact on returns from different commodity futures contracts. The study uses typical methods used in time series analysis: summary statistics, the augmented Dickey-Fuller (ADF) test, the Granger non-causality test, and generalised autoregressive conditional heteroskedasticity (GARCH) modeling.

The dependent variable is the return from futures contracts. Returns are calculated as the logarithmic difference between prices at moments t and t - 1. Returns, unlike prices, are more stationary and better suited for modelling using GARCH and Granger techniques.

The independent variable, the Working's T index, is calculated as the number of outstanding non-commercial positions in the commodity market that offset commercial positions (Eq. (1)) (Working, 1960). The index, therefore, reflects the degree of excess speculation at any given time: it equals one when all long or short positions are held by commercial traders, and exceeds one when speculative positions dominate. We employ the Working's T index because it remains one of the most widely used and conceptually transparent measures of speculative pressure, directly comparing speculative open interest to hedging demand. Recent evidence further supports its validity as a proxy for aggregate speculation across commodity-futures markets, including under changing macroeconomic conditions (Adhikari & Putnam, 2025). Compared with alternative proxies such as the TV/OI ratio or non-commercial net positions, the Working's T index provides a more direct and theoretically grounded measure of excess speculative activity relative to commercial hedging needs.

$$S_t = \begin{cases} 1 + \dfrac{NS_t}{CL_t + CS_t} & \text{if}(CS_t \geq CL_t) \\ 1 + \dfrac{NL_t}{CL_t + CS_t} & \text{if}(CL_t > CS_t) \end{cases} \tag{1}$$

where, S_t is the Working's T index of excessive financial speculation, NL_t and NS_t are long and short non-commercial positions, CL_t and CS_t are long and short commercial positions, and t is the time period (week).

After providing summary statistics, time series are tested for stationarity using the ADF test with a constant and a trend. If the p-value is lower than 0.05, the time series is considered stationary, and no unit root is present.

The Granger non-causality test is then used to estimate whether time-lag returns explain speculation better than vice versa (Eq. (2) and (3)). Parameters for vector autoregression (VAR) equations are estimated between two endogenous variables: returns and speculation. The optimal time lag for each commodity is calculated using the lowest information criteria value. Next, p-values must be estimated for each parameter. This allows us to test two statistical conditions: 1) $\alpha_2 = 0$, indicating that speculation does not affect returns; and 2) $\beta_2 = 0$, indicating that returns do not affect speculation. If only the second condition ($\beta_2 = 0$) is accepted, research hypothesis *H1* can be accepted, implying that speculation causes returns in futures contracts.

$$R_t = \alpha_0 + \sum_{i=1}^{j} \alpha_{1i} R_{t-i} + \sum_{i=1}^{j} \alpha_{2i} S_{t-i} + \varepsilon_t. \tag{2}$$

$$S_t = \beta_0 + \sum_{i=1}^{j} \beta_{1i} S_{t-i} + \sum_{i=1}^{j} \beta_{2i} R_{t-i} + \omega_t. \tag{3}$$

where, R_t is the return on commodity futures contracts, S_t is the Working's T index of financial speculation, $\alpha_{0,1,2}$ and $\beta_{0,1,2}$ are model parameters, ε_t and ω_t are residual errors, i is the time lag, j is the number of time lags, and t is the time period.

Next, we employ GARCH modelling to test for speculation's impact on return conditional volatility. We use a one-week lag GARCH (1,1) main model that consists of two equations: the mean equation, which consists of return (-1) and constant; and the variance lag, which consists of parameters alpha, beta, constant, and speculation. The models are similar to those of other authors who analysed return volatility (Czudaj, 2019; Alexiou & Rompolis, 2022). In the variance equation, parameter alpha captures variance autoregression, while beta reflects generalized variance persistence. We include the speculation index as an exogenous factor in the variance equation and incorporate major macroeconomic determinants into the main equation. Beyond the standard GARCH model, we also estimate an expanded threshold generalised autoregressive conditional heteroskedasticity (TGARCH) specification, where the variance equation includes the parameter omega, indicating whether shocks from the previous period have asymmetric (positive or negative) effects on conditional return volatility. To enhance transparency and strengthen the robustness of model selection, GARCH-family models were chosen using a combination of information criteria — Akaike information criterion (AIC), Bayesian information criterion (BIC) and Hannan–Quinn information criterion (HQC) — and diagnostic checks of standardized residuals. We tested alternative lag structures and distributional assumptions (normal, student-t) to ensure that results were not driven by specification choices. The preferred models were those that simultaneously minimized information criteria and eliminated residual autocorrelation and remaining ARCH effects. Furthermore, we re-estimated key models using both GARCH and TGARCH variants to confirm that the main conclusions remained stable across different volatility specifications, underscoring the overall robustness of the empirical findings.

Finally, we propose an extended GARCH model (Eq. (4) and (5)), also adding seasonality to the variance equation. For each commodity, we choose a month in which returns are most volatile and then place it into the variance equation as a time dummy variable. This enables us to evaluate the effect of seasonality on agricultural commodity return volatility as well as test the *H3* that returns from agricultural commodities are amplified by speculation during months when returns are most volatile. To evaluate research hypothesis *H3*, we test the statistical condition that $\beta_6 = 0$. To evaluate research hypothesis *H2*, we test the statistical condition that $\beta_4 = 0$.

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + u_t \tag{4}$$

$$h_t^2 = \beta_0 + \beta_1 u_{t-1}^2 + \beta_2 h_{t-1}^2 + \beta_3 u_{t-1}^2 d_{t-1} + \beta_4 S_{t-1} + \beta_5 D_{t-1} + \beta_6 D_{t-1} S_{t-1} \tag{5}$$

where, R_t is returns from futures contracts. The mean equation also consists of parameters α_0, α_1 and an error term u_t which has a variance of h^2. The conditional variance h_t^2 is then provided in the variance equation, where β_0 is the constant, $\beta_1 u_{t-1}^2$ is the residual effect (alpha), $\beta_2 h_{t-1}^2$ is the variance effect (beta). $\beta_3 u_{t-1}^2 d_{t-1}$ is the asymmetric component (gamma) (the parameter

$d_t = 1$ if $u_{t-1} < 0$ and $d_t = 0$ otherwise). We also use an external variable $\beta_5 D_{t-1}$ in the variance equation to assess the direct effect of a month on conditional volatility, $\beta_4 S_{t-1}$ is the effect of financial speculation, and $\beta_6 D_{t-1} S_{t-1}$ is the combined effect of the speculation index and month.

In addition to the chosen Granger non-causality tests and GARCH-family models, several alternative methodological approaches could also be used to study the relationship between speculation and commodity returns. Methods such as exponential generalized autoregressive conditional heteroskedasticity (EGARCH), GARCH dynamic conditional correlation (DCC), modified Granger tests, or nonlinear causality frameworks may provide further insights, especially in capturing asymmetric or time-varying dynamics. Although these approaches were not implemented in this study, they represent suitable alternatives for future research.

4. RESULTS

4.1. Descriptive statistics and test for time series unit root

First, we provide descriptive statistics for price and speculation index in Table 1 for all five commodities: wheat (W), soybean (S), corn (C), crude oil (O), and gold (G). The dynamics of these variables are shown in Figure A.1. All commodity prices have increased in the post-2020 timeframe. Speculation has increased in wheat and gold commodity futures. However, speculation in soybean and corn futures used to be higher in the past than in the post-2020 timeframe. Speculation in crude oil markets remained similar between both time periods. Prices of non-agricultural commodities used in the study were more volatile according to the standard deviation compared to agricultural commodities by mean values (standard deviation, %), except for gold, during the post-2020 timeframe.

Table 1. Summary statistics for commodity futures prices and speculation index

Commodity†	*Mean*	*Median*	*Min*	*Max*	*SD*	*SD%*	*Skewness*	*Kurtosis*
Price W1	492.06	465.25	231.50	1286.50	187.24	38.05	0.93	0.64
Price W2	716.15	697.12	491.00	1286.50	162.71	22.72	1.11	1.30
Spec W1	1.26	1.24	1.03	1.64	0.12	9.76	0.54	-0.36
Spec W2	1.36	1.35	1.22	1.56	0.06	4.62	0.93	1.01
Price S1	893.20	873.00	413.75	1768.20	328.84	36.82	0.54	-0.76
Price S2	1304.20	1378.60	824.25	1728.20	254.17	19.49	-0.54	-0.81
Spec S1	1.12	1.11	1.02	1.38	0.07	5.80	1.03	0.86
Spec S2	1.08	1.07	1.03	1.19	0.03	3.07	1.14	1.46
Price C1	372.00	354.50	175.50	838.75	155.54	41.81	0.96	0.01
Price C2	550.84	573.38	312.00	801.50	133.83	24.30	-0.32	-0.96
Spec C1	1.14	1.12	1.01	1.46	0.09	7.58	0.90	0.37
Spec C2	1.10	1.08	1.03	1.25	0.06	5.73	0.81	-0.78
Price O1	52.57	49.73	11.12	140.97	29.38	55.87	0.44	-0.87
Price O2	68.32	70.99	11.57	123.70	23.01	33.68	-0.10	-0.39
Spec O1	1.08	1.07	1.00	1.25	0.04	4.12	0.60	0.06
Spec O2	1.07	1.07	1.03	1.12	0.01	1.39	0.54	0.65
Price G1	900.72	819.60	254.10	2043.30	557.84	61.93	0.35	-1.34
Price G2	1816.90	1813.80	1525.80	2043.30	109.29	6.02	-0.23	-0.09
Spec G1	1.15	1.13	1.01	1.66	0.09	8.09	1.62	3.87
Spec G2	1.19	1.18	1.05	1.47	0.08	6.94	0.91	1.26

Note: † commodity names with 1 indicate the full-time frame, with 2 the post-2020 time frame. SD is the standard deviation, and SD% is the standard deviation as a percentage of the mean.
Source: Authors' calculations using CBOT and NYMEX data.

Next, in Table 2, we provide results for the ADF test using constant and constant with trend. This table also includes returns calculated as logarithmic differences in prices. Here we can see that returns are stationary for all commodity groups. Prices, in most cases, do have a unit root, as p-values are above 0.05. Therefore, further analysis uses returns instead of price. The speculation index is also stationary using one or the other model in most cases, except for crude oil using full sample data and corn and gold using post-2020 data.

Table 2. The augmented Dickey-Fuller test results

Commodity, ADF test type	*Price*		*Return*		*Speculation*	
	Full sample	*Post-2020*	*Full sample*	*Post-2020*	*Full sample*	*Post-2020*
W, test w/ const.	0.2047	0.3179	< 0.0001	< 0.0001	0.0442	0.0250
W, test w/ const., trend	0.1486	0.5891	< 0.0001	< 0.0001	0.0011	0.0319
S, test w/ const.	0.3552	0.5384	< 0.0001	< 0.0001	0.0000	0.0270
S, test w/ const., trend	0.1676	0.8645	< 0.0001	< 0.0001	0.0000	0.1253
C, test w/ const.	0.1426	0.5701	< 0.0001	< 0.0001	0.0026	0.3415
C, test w/ const., trend	0.0958	0.7848	< 0.0001	< 0.0001	0.0000	0.9853
O, test w/ const.	0.2273	0.6890	< 0.0001	< 0.0001	0.1968	0.0333
O, test w/ const., trend	0.1699	0.6580	< 0.0001	< 0.0001	0.1770	0.0881
G, test w/ const.	0.9574	0.0445	< 0.0001	< 0.0001	0.0000	0.0784
G, test w/ const., trend	0.5839	0.1698	< 0.0001	< 0.0001	0.0000	0.1245

Source: Authors' calculations using CBOT and NYMEX data.

4.2. Granger non-causality test results

To determine the optimal lag structure, preliminary autoregressive (AR) models were estimated, indicating a one-week lag for all commodities except corn, which requires two weeks (Table A.1). The Granger non-causality results (Table 3) show that, in the full sample, returns generally lead speculation, with crude oil being the only market showing no significant causal relationship in either direction. In the post-2020 period, both hypotheses are accepted across all commodities, confirming the absence of statistically significant causality. Although soybean and wheat display slightly stronger evidence that speculation may explain returns, these effects are also insignificant.

Table 3. Granger non-causality test results

N	*Variable*	*β*	*p*	*N*	*Variable*	*β*	*p*
Full sample				***Post-2020***			
W	S (-1)	0.7860	0.3495	W	S (-1)	2.9091	0.6172
W	R (-1)	-0.0009	< 0.0001	W	R (-1)	-0.0001	0.9941
S	S (-1)	-1.0142	0.4279	S	S (-1)	-6.9525	0.3155
S	R (-1)	-0.0008	< 0.0001	S	R (-1)	-0.0001	0.6268
C	S (-1)	-0.4863	0.6608	C	S (-1)	6.4747	0.7711
C	R (-1)	-0.0013	< 0.0001	C	S (-2)	-11.3631	0.6065
				C	All lags of S	-	0.4853
				C	R (-1)	0.0004	0.1452
				C	R (-2)	-0.0005	0.0778
				C	All lags of R	-	0.0959
O	S (-1)	1.4116	0.6452	O	S (-1)	15.6093	0.7483
O	R (-1)	-0.0001	0.1076	O	R (-1)	0.0001	0.5261
G	S (-1)	0.8291	0.1663	G	S (-1)	0.7957	0.7011
G	R (-1)	-0.0017	< 0.0001	G	R (-1)	-0.0012	0.1467

Source: Author's calculations using CBOT and NYMEX data.

4.3. GARCH and TGARCH results

Table 4 reports the full-sample GARCH and TGARCH results. Macroeconomic variables in the mean equation show that the GSCI index significantly affects all commodity returns, with the strongest effect in wheat and the weakest in gold; soybean returns are additionally linked to the S&P 500. The USD index is significant for all commodities — positive only for crude oil — while bond yields matter only for gold. The speculation index reduces return variance but is significant only for gold and oil. All commodities exhibit strong volatility clustering (beta), and asymmetric effects (gamma) are significant except for corn and gold, with crude oil showing the only positive asymmetry. TGARCH provides a better model fit based on information criteria.

Table 4. GARCH and TGARCH parameter estimates for the main model

Name	*W(G)*	*W(T)*	*S(G)*	*S(T)*	*C(G)*	*C(T)*	*O(G)*	*O(T)*	*G(G)*	*G(T)*
Mean equation										
Constant	0.007	0.078	0.043	0.083	0.107	0.100	-0.046	-0.11*	0.101	0.102
Δln(*SP*)	-4.072	-1.273	4.073	5.962*	-2.988	-2.923	-2.440	-3.79*	-2.798	-1.962
Δln(*GSCI*)	35.90*	35.49*	29.46*	30.29*	30.60*	31.85*	147.6*	146.7*	15.74*	14.55*
Δln(*Bond*)	0.229	-0.063	-0.292	-1.339	-0.823	-2.157	1.796	0.524	-12.7*	-12.5*
Δln(*USD*)	-33.3*	-34.9*	-25.3*	-26.1*	-20.4*	-17.0*	17.39*	17.82*	-69.2*	-71.7*
R (-1)	-0.009	-0.005	-0.016	-0.007	-0.017	-0.008	-0.032	-0.037	-0.023	-0.014
Variance equation										
Constant	2.434	2.602*	1.600	0.674	3.279*	1.947*	1.290	1.296*	0.664*	0.532*
S (-1)	-0.571	-0.457	-0.764	-0.183	-1.900	-0.816	-0.745	-0.80*	-0.41*	-0.30*
Alpha	0.094*	0.086*	0.097*	0.094*	0.144*	0.148*	0.181*	0.151*	0.065*	0.074*
Beta	0.793*	0.798*	0.829*	0.881*	0.780*	0.810*	0.715*	0.807*	0.882*	0.892*
Gamma		-0.68*		-0.48*		-0.050		0.591*		-0.203
Information criteria										
BIC	8847.6	8846.2	8089.4	8083.0	8513.9	8511.7	6729.9	6700.9	6507.1	6509.3
AIC	8793.9	8787.0	8035.7	8023.9	8460.2	8452.5	6676.2	6641.8	6453.4	6450.2
HQC	8813.9	8809.0	8055.7	8045.8	8480.1	8474.5	6696.2	6663.7	6473.3	6472.1

*Note: * indicates p-values below 0.05.*
Source: Authors' calculations using CBOT and NYMEX data.

Table A.2 presents the post-2020 GARCH results. Because of limited observations, only the standard GARCH model converges for this period. The GSCI index significantly affects all commodity returns except gold, with the strongest impact in wheat. Gold returns instead respond to the S&P 500, USD index, and bond yields. The speculation index reduces return variance but is significant only for gold. Volatility clustering (beta) appears only in corn, crude oil, and gold futures.

4.4. GARCH and TGARCH results using seasonality

Table A.3 shows that agricultural commodity returns are most volatile in June, while crude oil peaks in February and gold in September, though the latter effects are not statistically significant. Table 5 presents the seasonality-adjusted model, where the mean equation and volatility parameters (beta and gamma) remain consistent with the non-seasonal specification. Only soybean, corn, and gold display significant seasonal volatility via the month dummy. Speculation does not significantly affect volatility, nor does it amplify volatility during high-volatility months, indicating that return variability is driven primarily by fundamental rather than speculative factors.

Table 5. GARCH and TGARCH parameter estimates for the extended model with seasonality

Name	*W(G)*	*W(T)*	*S(G)*	*S(T)*	*C(G)*	*C(T)*	*O(G)*	*O(T)*	*G(G)*	*G(T)*
Mean equation										
Constant	0.001	0.066	0.101	0.122	0.140	0.145	-0.048	-0.112	0.095*	0.103*
Δln(*SP*)	-2.811	0.141	6.718*	6.829*	0.713	0.522	-2.737	-3.716	-2.629	-1.804
Δln(*GSCI*)	35.86*	34.97*	27.30*	26.70*	29.91*	30.04*	147.3*	146.3*	15.80*	14.77*
Δln(*Bond*)	0.213	-0.316	0.239	0.015	-1.464	-2.037	1.834	0.917	-12.93	-12.6*
Δln(*USD*)	-33.1*	-34.7*	-24.8*	-26.3*	-17.9*	-16.37	16.77*	17.59*	-69.9*	-71.7*
R (-1)	-0.012	-0.009	-0.027	-0.013	-0.037	-0.040	-0.03*	-0.04*	-0.021	-0.015
Variance equation										
Constant	4.886	4.337	3.054*	1.295	3.682*	2.397*	1.255	1.269*	0.946*	0.677*
D (-1)	-8.437	-3.617	-1.98*	-0.521	-2.38*	-1.169	-0.768	-0.789	-0.65*	-0.41*
D × S (-1)	8.808	3.936	6.605	4.426	14.549	4.383	-5.440	-1.354	-0.252	-0.110
S (-1)	-1.927	-1.177	-0.475	-1.926	-6.426	-1.214	5.450	1.440	0.458	0.260
Alpha	0.102*	0.093*	0.087*	0.086*	0.093*	0.106*	0.174*	0.153*	0.068*	0.082*
Beta	0.721*	0.729*	0.781*	0.841*	0.789*	0.814*	0.728*	0.806*	0.872*	0.877*
Gamma		-0.71*		-0.58*		-0.126		0.562*		-0.252
Information criteria										
BIC	8851.5	8848.4	8007.2	8002.8	8417.9	8423.4	6739.6	6712.7	6512.8	6513.9
AIC	8787.0	8778.5	7942.7	7933.0	8353.4	8353.5	6675.1	6642.9	6448.3	6444.1
HQC	8811.0	8804.5	7966.7	7958.9	8377.3	8379.4	6699.0	6668.8	6472.3	6470.0

*Note: * indicates p-values below 0.05.*
Source: Authors' calculations using CBOT and NYMEX data.

5. DISCUSSION

5.1. Comparison with previous studies

Three main findings emerge from this study. First, Granger non-causality tests show that commodity returns either explain speculative activity or exhibit no significant relationship, consistent with earlier CME-based evidence. Similar non-causality or inverse effects were found by Etienne et al. (2017) and Smales (2022), while opposite results in soybean markets appeared only in older datasets (Haase et al., 2019).

Second, speculation influences return volatility only in crude oil and gold, with a negative effect. This aligns with Xiao and Wang (2022), who show that speculative trading in crude oil can buffer macroeconomic uncertainty, and with agricultural-market findings of stabilizing speculative effects (Bohl & Sulewski, 2019). Studies using short-term speculation measures also document destabilizing effects (Bohl et al., 2018). The stronger role of speculation in non-agricultural markets suggests that volatility originating in energy markets may spill over into agricultural commodities.

Finally, the inclusion of macroeconomic factors in the GARCH and TGARCH models produces results similar to prior work. Negative TGARCH asymmetry in wheat and soybeans mirrors findings from da Silveira et al. (2017) and the asymmetric volatility patterns documented by Baur and Dimpfl (2018). Crude oil's positive volatility asymmetry is consistent with evidence that negative shocks increase volatility more than positive ones (Galyfianakis et al., 2016). Post-2020 results also indicate increased volatility across most commodities and a strong influence from the GSCI index, aligning with evidence that commodity returns respond to COVID-19-related uncertainty and economic stress (Ahmed & Sarkodie, 2021; Hung, 2021).

5.2. Future research guidelines

Other authors who analysed commodity markets and returned volatility also applied alternative methods: the modified Granger test, exponential EGARCH, mean GARCH-M, dynamic conditional correlation GARCH DCC (Etienne et al., 2017; Czudaj, 2019; Baur & Dimpfl, 2018; Manera et al., 2016; Ma et al., 2021). These methods can also be applied in future research on financial speculation in the post-2020 time frame. Short-term speculation indicators can also be used besides the Working's T index. On the other hand, according to Wimmer et al. (2020), the methods used in the previous studies underestimated the causal relationships between positions and prices in non-commercial markets and did not sufficiently apply a nonlinear methodology for assessing causal relationships.

While our seasonality analysis focuses on identifying the single most volatile month for each commodity, this approach is designed to isolate periods in which volatility spikes most sharply and to evaluate whether speculation amplifies volatility specifically during these peak months. Although broader month-to-month or quarterly seasonality patterns were beyond the scope of this study, future work could extend this framework by modelling full seasonal cycles to capture more nuanced intra-year dynamics.

5.3. Practical implications

The results of this article are consistent with several recent studies showing that financial speculation does not inherently destabilize commodity markets. For example, recent evidence indicates that speculative behaviour in crude oil markets can buffer rather than amplify macroeconomic uncertainty (Xiao & Wang, 2022), while other work demonstrates that excess speculation may actually reduce return volatility in some contexts (Long & Guo, 2022). Further, studies documenting the informational content provided by sophisticated speculators and evidence that cross-market spillovers tend to be more strongly driven by fundamentals than by speculative pressure reinforce the view that speculation is not uniformly harmful (Borgards & Czudaj, 2023). Taken together, these insights suggest that blanket interventions — such as aggressive position limits or broad margin hikes — may restrict beneficial liquidity and impair hedging efficiency. A more effective policy approach would emphasize transparency, monitoring of large positions, and strengthening institutional environments, while allowing markets to benefit from the stabilizing and informational roles that well-capitalized speculators can provide (Algieri, 2021). In practical terms, this includes implementing enhanced real-time position reporting for major traders and adopting targeted margin adjustments only for contracts exhibiting clear signs of stress, rather than applying uniform restrictions across all markets.

6. CONCLUSION

In this study, we look at how financial speculation affects the returns and return volatility of agricultural and other commodity futures. Futures contracts from CBOT and NYMEX, two major US commodities markets, are used in the study. The futures of three agricultural products — wheat, soybeans, and corn — as well as two other products — crude oil and gold — are chosen to be used in the study. In order to determine whether speculation causes returns and whether it makes returns more volatile, we estimate the Working's T index of excessive financial speculation. Additionally, we provide a model that examines the effect of seasonality on return volatility and determines if financial speculation enhances return volatility during months in which futures returns are most volatile. Our analysis uses data on continuous futures contracts from October 15, 1992, to June 27, 2023.

The study made several important observations. *H1* and *H3* of the research were rejected, as there is no statistically significant evidence that financial speculation causes returns from commodity futures contracts or amplifies return volatility during months in which these commodities experience the highest return volatility. However, there is some evidence that an increase in financial speculation is followed by reduced return volatility in the crude oil and gold futures markets. Therefore, *H2* can be partially supported. In the gold market, this effect is also valid when analysing the post-2020 data. Another important finding from the study is that agricultural commodities are influenced by the commodity GSCI index, and this impact became even stronger during the post-2020 timeframe. Agricultural markets, as well as crude oil futures markets, also experience asymmetric return volatility, meaning that in agricultural markets, negative returns are followed by reduced volatility, whereas in crude oil markets, this relationship is the opposite.

The findings of our investigation have significant policy implications. According to the results of our analysis, stricter regulation is not the best course of action given the multiple benefits of financialization and speculator participation in commodity markets, such as higher market liquidity and the ability to distribute risks among commercial and non-commercial market participants.

The research has some limitations, most notably the small number of post-2020 observations resulting from the use of weekly data on financial speculation; a larger dataset based on daily information would allow greater modelling flexibility, and future research could expand the analysis to non-US markets or additional commodities, high frequency data. Nevertheless, to address the limited post-2020 sample, we rely on model specifications validated in the full-sample analysis and confirm that key relationships remain qualitatively consistent when re-estimated on the shorter subsample. We also employ robustness checks — such as alternative GARCH-family specifications and diagnostic tests — to ensure that the conclusions drawn from the post-2020 period reflect genuine underlying dynamics.

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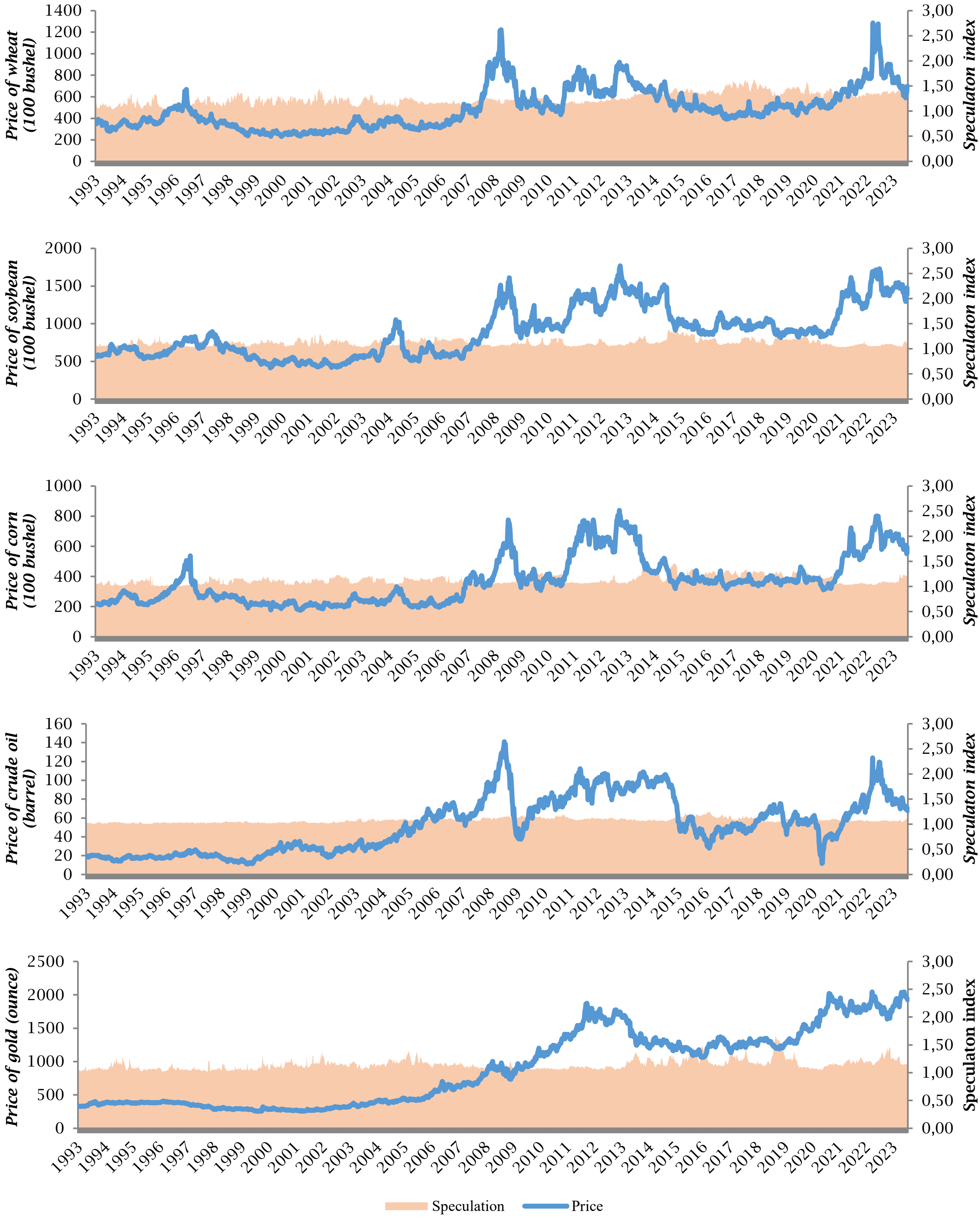
APPENDIX

Figure A.1. Commodity price and speculation dynamics from October 15, 1992, to June 27, 2023



Source: Authors' calculations using CBOT and NYMEX data.

Table A.1. Time lag selection using the smallest information criteria values

Name	*Lag*	*AIC*	*BIC*	*HQC*	*Name*	*Lag*	*AIC*	*BIC*	*HQC*
Full sample					***Post-2020***				
W	1	1.562654	1.582872†	1.570163†	W	1	1.615977†	1.721604†	1.658797†
W	2	1.564009	1.597706	1.576524					
W	3	1.554733	1.601909	1.572254					
W	4	1.555535	1.61619	1.578062					
W	5	1,553396†	1.627529	1.580929					
S	1	0.409656	0.429874†	0.417165†	S	1	-1.226969†	-1.121342†	-1.184149†
S	2	0.407801	0.441498	0.420316					
S	3	0,405549†	0.452725	0.42307					
C	1	0.799294	0.819512†	0.806802†	C	1	-0.451635	-0.346009	-0.40882
C	2	0.800059	0.833756	0.812574	C	2	-0.543520†	-0.367476†	-0.472154†
C	3	0.793887	0.841063	0.811408					
C	4	0,791951†	0.852605	0.814477					
O	1	-0.279673	-0,259444†	-0.27216	O	1	0.663762	0.769388†	0.706581†
O	2	-0.281474	-0.24776	-0.268953	O	2	0.652313	0.828357	0.723679
O	3	-0.29084	-0.243641	-0.273310†	O	3	0.650491	0.896953	0.750403
O	4	-0.293086	-0.232401	-0.270547	O	4	0.686639	1.003518	0.815097
O	5	-0.292179	-0.218008	-0.264632	O	5	0.724192	1.11149	0.881197
O	6	-0.294304	-0.206648	-0.261749	O	6	0.664547	1.122262	0.850098
O	7	-0.293928	-0.192787	-0.256364	O	7	0.632625	1.160758	0.846722
O	8	-0.311682†	-0.197055	-0.269109	O	8	0.555636†	1.154187	0.79828
G	1	0.125721†	0.145949†	0.133234†	G	1	-0.215908†	-0.110281†	-0.173088†

Note: † indicates the smallest information criteria value.
Source: Authors' calculations using CBOT and NYMEX data.

Table A.2. GARCH estimates for the main model using the post-2020 time frame

Name	*W β*	*W p*	*S β*	*S p*	*C β*	*C p*	*O β*	*O p*	*G β*	*G p*
Mean equation										
constant	0.011	0.971	0.228	0.298	0.128	0.541	-0.244	0.047	0.254	0.066
Δln(*SP*)	-27.917	0.110	-2.259	0.811	3.355	0.710	2.993	0.854	-19.691	0.018
Δln(*GSCI*)	57.333	0.002	25.849	0.003	33.934	0.000	156.393	0.001	15.737	0.056
Δln(*Bond*)	-7.008	0.241	-0.986	0.800	-2.229	0.504	3.955	0.507	-8.914	0.023
Δln(*USD*)	10.296	0.804	-24.161	0.545	21.141	0.411	37.515	0.176	-108.36	0.000
R (-1)	0.038	0.618	-0.037	0.794	0.062	0.469	-0.008	0.926	-0.070	0.309
Variance equation										
constant	28.179	0.234	50.952	0.408	-2.847	0.793	8.407	0.757	3.987	0.019
S (-1)	-14.366	0.381	-39.919	0.475	4.661	0.632	-6.992	0.783	-2.527	0.028
alpha	0.245	0.132	0.068	0.795	0.265	0.052	0.619	0.003	0.167	0.288
beta	0.277	0.155	-0.102	0.813	0.542	0.000	0.404	0.000	0.519	0.050
Information criteria										
BIC	1081.3		935.1		974.8		867.3		762.8	
AIC	1049.3		903.1		942.8		835.2		730.7	
HQC	1062.2		916.1		955.8		848.2		743.7	

Source: Authors' calculations using CBOT and NYMEX data.

Table A.3. GARCH results using month dummy variables in the variance equation

Month	*Wheat*		*Soybean*		*Corn*		*Oil*		*Gold*	
	β	*p*	*β*	*p*	*β*	*p*	*β*	*p*	*β*	*p*
Jan	0.5363	0.4953	-0.2702	0.6854	-0.9710	0.0573	-0.7693	0.7618	0.0152	0.9455
Feb	2.8501	0.0055	-0.0168	0.9666	0.2485	0.6185	4.6556	0.1059	0.3225	0.2885
Mar	0.9937	0.4523	0.1241	0.7808	1.6795	0.0298	1.9348	0.5594	0.1178	0.8325
Apr	1.7256	0.2150	-0.0874	0.8464	-0.7518	0.3417	-1.7096	0.2967	-0.0018	0.9974
May	0.5901	0.6915	1.0269	0.1684	1.2092	0.3237	1.0815	0.4995	-0.2141	0.6358
Jun	3.1642	0.0136	4.5043	0.0104	7.0644	0.0007	1.4285	0.4474	0.0068	0.9797
Jul	-1.6805	0.0460	-1.7217	0.0577	-3.8330	0.0005	0.8350	0.6103	-0.1204	0.5086
Aug	0.6497	0.3258	-0.7925	0.2280	-0.9818	0.2412	-0.0511	0.9726	-0.1568	0.3311
Sep	1.7541	0.0502	0.7617	0.2427	1.8526	0.0708	3.4581	0.1773	1.1717	0.2015
Oct	-0.7716	0.1871	-0.7838	0.1217	-1.7044	0.0014	-0.9705	0.5595	-0.7887	0.0884
Nov	1.1695	0.1621	0.0250	0.9689	-0.2752	0.6652	3.2076	0.1616	0.0155	0.9333

Source: Authors' calculations using CBOT and NYMEX data.