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Macroeconomic Conditions, Speculation, and Commodity Futures Returns

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Abstract: This paper examines the dynamic relationships between speculative activities, commodity returns, and macroeconomic conditions across five sectors compassing 29 commodities. Using weekly data spanning from January 2000 to July 2023, we construct comprehensive measures of commodity market speculation across five sectors and examine their sector-specific impact on returns through advanced econometric methods, including dynamic conditional correlation models, quantile regressions, Markov-switching models, and time-varying Granger causality tests. Our results reveal that the impact of speculative activities on commodity futures returns is conditional on the commodity sector and prevailing macroeconomic conditions. Moreover, the relationship between macroeconomic factors, speculative activities, and commodity futures returns is time varying. Among the macroeconomic variables, the financial stress indicator, as measured by the St. Louis Fed Financial Stress Index, shows a significant ability to predict commodity futures returns. The relationship between speculation and commodity returns is bi-directional across all sectors.

Keywords: commodities; commodity futures; speculation; speculative activity; macroeconomic factors

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1. Introduction

Understanding the drivers of commodity price movements is important for a wide range of stakeholders, including consumers, investors, and policymakers. In this paper, we examine whether commodity prices are influenced by macroeconomic fundamentals, speculative activities, or both using weekly data.

Speculation in commodity markets is influenced by macroeconomic conditions, such as demand and supply shocks, perceived risk situations, inflation, and interest rates. To fully understand the impact of the dynamic nature of the relationship among these variables, we must consider the fact that most commodities are traded in more than one exchange, and the prices of most commodities within the sector are more closely related due to their substitutability and complementary properties (Casassus et al., 2013). Most previous studies look at the speculation of a commodity in one market and do not consider the co-movement of commodity prices within a sector. This study aims to fill this gap by computing aggregate speculation measures in each sector and examining the impact of the speculation and various macroeconomic variables on commodity returns across five diverse sectors. We examine how macroeconomic variables and speculation collectively impact commodity futures market dynamics using weekly data on 29 commodities, 12 macroeconomic variables, and speculation measures from 1 January 2000 to 31 July 2023. Our research builds upon the current literature related to speculation, macroeconomic conditions, and commodity futures in several ways.

First, we create a measure of commodity speculation that aggregates speculative activity on a specific commodity across all tradeable exchanges. Then, we find the speculation measure for a specific commodity sector by adding speculation measures across all commodities within the sector. Our unique approach provides a more comprehensive assessment of speculative activities than previous studies. Second, we incorporate a broad range of macroeconomic variables at a weekly frequency and examine the impact of individual macroeconomic variables and the joint impact of these macroeconomic variables. Third, we use different econometric methods, such as dynamic conditional correlation (DCC) models, quantile regressions, Markov-switching models, and time-varying Granger causality tests. This methodological diversity creates a robust analysis of the complex interactions between macroeconomic conditions, speculative activities, and commodity futures returns. Fourth, we emphasize the dynamic and time-sensitive relationships between macroeconomic variables, speculative activities, and commodity futures returns. Finally, we provide detailed, sector-specific insights into how different commodity sectors respond to macroeconomic conditions and speculative pressures. This analysis highlights the unique dynamics of each sector and helps us understand the sectoral drivers of commodity price movements. This insight is useful for a wide range of stakeholders, including investors, policymakers, and researchers.

Overall, we summarize our key insights as follows: First, conditional on the commodity sector and market conditions, speculative activities have a time-varying negative impact on commodity futures returns. This finding highlights the non-uniform effects of speculative activities across sectors and over time. Second, the macroeconomic indicator related to financial stress, such as the St. Louis Fed Financial Stress Index, is the most significant predictor of commodity futures returns, highlighting the crucial role of financial market conditions in commodity pricing. Third, speculation has a stronger negative impact on commodity returns during high-return periods than in low-return periods. Fourth, speculation has a statistically significant impact on commodity returns in all sectors except the livestock sector, both in the low- and high-volatility periods. Fifth, and finally, we highlight the bi-directional dynamic nature of the relationships between speculative activities and commodity futures returns at a weekly frequency. We also observe sector-specific variations in speculation and commodity returns.

Our work adds to the extant literature debate on the impact of speculation and macroeconomic conditions on commodity futures returns and provides useful findings for developing effective investment strategies and regulatory policies. Our finding of a negative relationship between excess speculation and commodity returns aligns with the existing literature that highlights the destabilizing effects of speculative activity in certain contexts. For example, Bohl et al. (2021) demonstrate that excess speculation impairs informational efficiency and leads to price distortions and lower returns. Similarly, Tang and Xiong (2012) find that speculative intensity, particularly from index trading, contributes to excess co-movements and price deviations from fundamentals, negatively impacting returns. Singleton (2014) also shows that speculative booms can lead to price overshooting, followed by corrections that suppress returns. Furthermore, we emphasize the need for sector-specific investment approaches, since different sectors react differently to macroeconomic and speculative pressures. Our results also demonstrate the critical role of financial stress as a predictor of commodity futures returns and advocate for a dynamic analysis of commodity markets for investors. Additionally, with its dual role, speculation enhances market efficiency and price discovery but can also cause price distortions and increase volatility. For regulators, our results also highlight the importance of understanding the dynamic relationship between speculation and commodity prices in different sectors.

The remainder of this paper is structured as follows: Section 2 provides a review of the related literature, and Section 3 outlines our data sources and variable construction methodologies. Section 4 explains the econometric approaches employed for our analysis. Section 5 presents the empirical findings and discusses their policy implications. Section 6 concludes with a discussion of our findings and future research avenues.

2. Literature Review

Commodity fundamentals—supply and demand shocks, production levels, and inventories—and the macroeconomic uncertainty that engulfs them play a crucial role in determining commodity prices over the long term (Ahmed, 2023; Tsvetanov et al., 2016; Xiao & Wang, 2022). Yet, there is a debate that shocks orthogonal to global demand and supply contribute to a commodity boom/bust cycle (Kabundi & Zahid, 2023). Research by Bohl et al. (2021) shows strong evidence that speculators do impair the informational efficiency of commodity futures markets. Specifically, both excess speculation and market share, primarily driven by long-short commodity investors, negatively affect price informativeness. Furthermore, rising correlations between equity and commodity returns can be traced to the activities of speculators, particularly hedge funds, who actively trade in both markets (Büyüksahin et al., 2009). Tang and Xiong (2012) find that the futures prices of indexed non-energy commodities became much more correlated with oil prices post-2004, concurrent with the rapid growth of index fund investment. Similarly, Pen and Sévi (2018) find similar evidence of speculative intensity being a driver of time-varying excess co-movement among unrelated commodity prices; Kang et al. (2023) confirm that these findings hold in even more recent sample years. In a recent study, Da et al. (2023) present evidence that commodity index trading, an advent of financialization, results in "price overshoots and reversals" among commodities only traded in the index.[1] The rationale is that index trading spreads nonfundamental noise to all commodities that are indexed.

Still, other studies document a relationship between speculator positions and prices/returns but find stabilizing effects instead, such has dampened volatility and improved price discovery (Brunetti et al., 2016; Manera et al., 2016). Perhaps the most ardent critics on the role of speculation in the commodities markets are academics Scott Irwin and Dwight Sanders. They argue that money flows, no matter the size, do not necessarily impact futures prices, noting that attacks on the idea of speculation come about during periods of dramatic volatility (Sanders & Irwin, 2010). Boyd et al. (2018) provide an extensive survey of the literature on speculation and financialization in the commodity markets, contending that "on balance, the majority of empirical evidence presented by academic researchers insufficiently links index fund positions [speculators] to commodity returns." Similarly, Haase and Huss (2018) survey the literature on the relationship between financial speculation and its impact on commodity futures prices. Their overall summary findings indicate that the number of studies both supporting and contradicting the effects of speculation are roughly the same but that "the results shift against the criticized effects if the studies use direct measures of speculation, except for price".

While empirical evidence shows a mix of findings regarding speculation and commodity returns, more recent academic studies have attempted to model the theoretical implications of speculation resulting from financialization (Baker, 2020; Basak & Pavlova, 2016; Goldstein & Yang, 2022; Sockin & Xiong, 2015). Of note, Cheng and Xiong (2014) discuss how the economic mechanisms of risk sharing and information discovering have been transformed by an increase in speculative capital. Specifically, speculation may distort price discovery due to informational frictions and create transitory booms in the market, as traders cannot distinguish between price increases from fundamentals and speculation. Singleton (2014) also highlights that informational friction with speculative activity may induce commodity prices to drift from fundamental values, resulting in booms and busts.[2] Tang and Xiong (2012) highlight that the prospects of risk sharing and hedging pressure can be improved as new market participants act as liquidity providers; yet, Acharya et al. (2013) note that these investors possess time-varying risk appetites due to investment constraints, mandates, and the potential of financial distress, which can have an inverse impact on liquidity. Similarly, as noted by Cheng et al. (2015), CITs and hedge funds react negatively in times of distress and will de-gross, transmitting the flow of risk back to commercial hedgers.

The existing literature has extensively explored the individual roles of macroeconomic conditions and speculative activities in commodity markets, but a comprehensive, integrated analysis of how these factors interact dynamically to influence commodity returns across sectors remains largely absent. Furthermore, prior research often treats these relationships as static or uniform across commodities, overlooking their time-varying and sector-specific nature. In this study, we address these gaps by constructing an integrated framework that examines the joint influence of macroeconomic conditions and speculative activities on the returns of commodity futures. To capture the dynamic and heterogeneous nature of these interactions, we employ time-varying and sector-specific analyses. This approach not only advances theoretical understanding but also provides practical insights for policymakers and investors, highlighting the importance of tailored strategies to regulate speculation and mitigate risks in commodity markets.

3. Data and Variable Construction

3.1. Data

Daily price data for 29 specific commodities are obtained from Barchart.[3] The 29 commodities are divided into five distinct sectors: foods and fibers, grains and oilseeds, livestock, energy, and precious metals. The foods and fibers sector includes cocoa, coffee, orange juice, sugar #11, cotton #2, and lumber. The grains and oilseeds sector is comprised of barley, canola, corn, oats, rough rice, soybeans, soybean meal, soybean oil, and wheat. The livestock sector contains feeder cattle, live cattle, lean hogs, and Class III milk. The energy sector is made up of WTI crude oil, heating oil, unleaded gasoline, natural gas, and blend stock gasoline. Finally, the precious metals sector includes copper, gold, palladium, platinum, and silver.

Daily financial data for the S&P 500 Volatility Index (VIX) is similarly obtained from Barchart, while the Bull/Bear ratio and forward earnings for the S&P 500 Index are collected from Yardeni Research.

Several weekly macroeconomic variables are gathered from the Federal Reserve Bank of St. Louis, including the yield spread (the difference between AAA- and BAA-rated corporate bond rates), the Fed National Financial Conditions Index, the federal funds effective rate, the St. Louis Fed Financial Stress Index, the Economic Policy Uncertainty Index, and the Equity Market-Related Economic Uncertainty Index. Additionally, the Baltic Dry Index is obtained from investing.com, the Aruoba–Diebold–Scotti Index (ADS index) from the Federal Reserve Bank of Philadelphia, and the Office of Financial Research Financial Stress Index (OFR FSI) from the Office of Financial Research.

Finally, data on the long and short positions held by large traders, both commercial and non-commercial, in various commodity markets are retrieved from the Commodity Futures Trading Commission (CFTC).

For completeness of the paper, we provide a brief description of each macroeconomic variable included in the paper:

i. The yield spread measures the difference between the yield of AAA-rated corporate bonds and the yield of BAA-rated corporate bonds. It captures changes in credit risk perceptions and broader economic sentiment.
ii. The Fed National Financial Conditions Index (NFCI) captures the overall health of the financial system by analyzing stress in money, debt, and equity markets. It provides insights into whether financial conditions are tight or loose, which directly impacts market behaviors, including commodity speculation.
iii. The federal funds effective rate is the overnight interest rate at which banks lend reserves to each other.
iv. The St. Louis Fed Financial Stress Index (STLFSI) aggregates indicators like interest rates, yield spreads, and market volatility to assess stress levels in the financial system. High-stress values signal financial instability, which can reduce commodity demand and heighten speculative activity in uncertain environments.
v. The Economic Policy Uncertainty Index (EPU) quantifies uncertainty in economic policy based on news coverage and other sources. Elevated uncertainty can influence investment and spending decisions, often leading to increased commodity price volatility, as commodities are viewed as hedges during uncertain times.
vi. The Equity Market-Related Economic Uncertainty Index (EMUI) focuses specifically on uncertainty within equity markets. It reflects investor sentiment and perceived risk, with high uncertainty often leading to shifts in capital toward commodities as alternative or safer investments.
vii. The Baltic Dry Index (BDI) measures global shipping costs for raw materials. It is often viewed as a leading indicator of global trade and industrial activity. Rising shipping costs typically signal strong demand for raw materials, which can drive up commodity prices.
viii. The Aruoba–Diebold–Scotti (ADS) Index provides a real-time assessment of U.S. economic conditions using high-frequency data like employment and production. Positive values indicate above-average activity, while negative values suggest weaker economic conditions, directly impacting commodity demand.
ix. The Office of Financial Research Financial Stress Index (OFR FSI) evaluates systemic risks in financial markets by analyzing credit spreads, market volatility, and funding conditions. High financial stress levels can suppress economic activity and influence speculative behavior in commodities.
x. The S&P 500 Volatility Index (VIX) measures expected volatility in the S&P 500, often termed the "fear gauge." Higher values indicate increased market uncertainty and risk aversion, which can lead to greater speculative activity in commodities as a hedging mechanism.
xi. The Bull/Bear ratio tracks investor sentiment by comparing bullish to bearish outlooks. High bullish sentiment often correlates with increased investment and commodity demand, while bearish sentiment signals cautious market behavior.
xii. Forward earnings for the S&P 500 reflect analysts' projections of corporate earnings over the next 12 months, serving as a barometer of market optimism about future economic growth. Rising forward earnings suggest confidence in economic expansion, which supports higher commodity demand.

3.2. Commodity Sector Returns

Individual commodity futures return series are created following Miffre and Rallis (2007). We roll the daily futures prices of the nearby contract to the next-nearby contract 30 days prior to the maturity of the nearby contract. The daily return series for each commodity future is subsequently compounded to a weekly frequency, on a Tuesday-to-

Tuesday basis, to match the weekly trader position data reported by the CFTC. The weekly return series for each of the five commodity sectors is calculated as the price-weighted average of all sector constituents.

3.3. Macroeconomic Variables

We use two techniques to identify the overall state and trend of the global economy using twelve macroeconomic variables. First, we use the Bayesian model averaging (BMA) method (Hoeting et al., 1999; Steel, 2020) to identify important predictors within each sector from the compilation of twelve macroeconomic variables. Second, we apply principal component analysis (PCA) to convert the original twelve macroeconomic variables into principal components, which are then utilized in the subsequent regression analysis. The first two principal components, in order of significance, are utilized in all regression specifications.

3.4. Excess Speculation

Data from the Commitment of Traders (COT) reports are utilized to calculate Working's T index (Working, 1960) of commodity excess speculation. This index assumes that hedgers' total positions indicate the intrinsic demand for hedging. It measures speculation exceeding the minimal level needed to balance long and short hedging positions as "excess". A high T index or its volatility signals excess speculation.

Furthermore, COT data classify traders into commercial hedgers, non-commercial hedgers, and small traders. Commercial hedgers use the futures market to hedge inherent commodity price risks, while speculators aim to profit from price movements. Following previous works (Büyükşahin & Robe, 2014; Sanders & Irwin, 2010; Working, 1960), we calculate the excess speculation for each commodity traded in the ith market as follows:

$$\text{Excess Speculation}_{I,t} = \begin{cases} \frac{SS_i}{HS_{I,t}+HL_{I,t}} \text{ if } HS_{I,t} \geq HL_{I,t} \\ \frac{SL_i}{HS_{I,t}+HL_{I,t}} \text{ if } HS_{I,t} < HL_{I,t} \end{cases} \tag{1}$$

where SS (speculative short) refers to the total non-commercial short positions, SL (speculative long) refers to the total non-commercial long positions, HS (hedging short) refers to the total commercial short positions, and HL (hedging long) refers to the total commercial long positions. Excess speculation is calculated for each commodity across all markets where it is traded and then aggregated. For instance, if coffee is traded on three exchanges (e.g., the Coffee, Sugar and Cocoa Exchange, ICE Futures U.S., and the New York Board of Trade), we compute the excess speculation for each exchange and sum the values to find the total excess speculation in the coffee futures markets.

After computing the total excess speculation for each individual commodity, we aggregate the excess speculation across all commodity constituents for a given sector. For example, the measure of excess speculation for the foods and fibers sector is calculated as the sum of the total excess speculation for cocoa, coffee, orange juice, sugar #11, cotton #2, and lumber. Specifically, we calculate commodity sector excess speculation as follows:

$$\text{Speculation in i}^{\text{th}} \text{ sector} = \sum_{j=1}^{n} \text{Excess Speculation}_{j,t} \tag{2}$$

where $\text{Excess Speculation}_{j,t}$ refers to the excess speculation of the jth commodity at time t.

4. Methodology

4.1. Bayesian Model Averaging

BMA is a statistical technique used to address model uncertainty by averaging over a set of possible models rather than selecting a single best model (Steel, 2020). BMA calculates the posterior probability for each model given the data, which is then used to weight the models in the averaging process. Instead of relying on a single model, BMA averages the results over multiple plausible models to account for model uncertainty. This method leads to improved predictive performance and more robust statistical inferences by incorporating the uncertainty associated with model selection.

We consider many possible models using sector returns as the dependent variable and the macroeconomic variables as independent variables. We identify a few predictors using the probability of a macroeconomic variable being included in a model across all the models considered. Then, the true predictors are used in the subsequent regression, in conjunction with our measure of excess speculation.

4.2. Principle Component Analysis

We use PCA to explain the variance–covariance nature of the 12 macroeconomic variables previously discussed. PCA is a statistical method that converts a set of correlated variables into a set of uncorrelated variables through orthogonal transformation (Rencher & Christensen, 2012). Its significance is that it reduces higher dimensional data into a small number of principal components that carry sufficient information of the original larger set of correlated variables. Given the original 12-dimension, mean-centered random vector of macroeconomic variables, X, with the corresponding covariance matrix, S, such that $\Sigma = \frac{1}{n}X'X$, the ith sample principal component can be obtained by solving the following problem:

$$\mathrm{Var}\ (Y_i) = \max_{\alpha_i} \alpha_i' \Sigma \alpha_i \text{ subject to } \alpha_i' \alpha_i = 1 \tag{3}$$

where α_i is a 1×12 vector for the ith principal component such that α_i is not a zero vector. To find the principal components that have the maximum variance subject to the condition of being orthogonal to any previous principal component, we solve the following:

$$\alpha_i = \lambda_i \alpha_i \tag{4}$$

where λ_i is an eigenvalue corresponding to the eigenvector of Σ. Since Σ is 12×12, there will be 12 eigenvalues, such that $\lambda_{12} \geq \lambda_{11} \geq \ldots \geq \lambda_1 \geq 0$, and 12 corresponding eigenvectors. We only consider the first two principal components, which account for more than 95% of the total variance in the original 12 macroeconomic variables.

4.3. Regression Models

We use four econometric tools to examine the relationship between excess speculation and commodity returns. They include the dynamic conditional correlation (DCC) model (Engle, 2002), quantile regression model, Markov-switching model(s), and Vector Autoregressive (VAR)-based time-varying Granger Causality model.

4.3.1. DCC Model

In order to implement the DCC model of Engle (2002), we first utilize the following mean equation to obtain estimates of the conditional mean for returns and speculation:

$$y_t = \mathrm{Intercept} + \beta p_t + \epsilon_t \tag{5}$$

where $y_t = \begin{bmatrix} r_{1t} \\ s_{1t} \end{bmatrix}$, and $\epsilon_t = \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix}$. Here, r_t is a vector of returns, s_t is a vector of speculation measures, p_t is a vector of the first principles obtained from principal components analysis, β is an estimated coefficient on the first principal component, and ϵ_{it} is a residual series.

The volatility models of the return and speculation series are modeled as follows:

$$\epsilon_t = \Sigma^{\frac{1}{2}} \nu_t \tag{6}$$

where the $\nu_t = \begin{bmatrix} \nu_{1t} \\ \nu_{2t} \end{bmatrix}$ are independent and identically distributed (i.i.d.) 2-dimensional bivariate random vectors with mean vector 0 and covariance matrix I, so that the conditional covariance matrix of r_t and s_t, given information up to time $t-1$, is $\Sigma = \begin{bmatrix} h_{11t} & h_{12t} \\ h_{21t} & h_{22t} \end{bmatrix}$. The diagonal elements of Σ evolve according to a univariate GARCH model, $h_{iit} = \alpha_{i0} + \alpha_{i1}\epsilon^2_{it-1} + \beta_{i1}h_{iit-1}$, and the off-diagonal elements are modeled as a non-linear function of diagonal terms, $h_{ijt} = \rho_{ijt}\sqrt{h_{iit}h_{jjt}}$, in which ρ_{ijt} follows a dynamic process specified by Engle (2002). The $\Sigma^{\frac{1}{2}}$ denotes the positive–definite square root matrix of Σ.

The conditional covariance matrix for the DCC model is specified as follows:

$$\Sigma_t = D_t^{1/2} R_t D_t^{1/2} \tag{7}$$

where $D_t^{1/2} = \begin{bmatrix} \sqrt{h_{11t}} & 0 \\ 0 & \sqrt{h_{11t}} \end{bmatrix}$ and R_t are a matrix of conditional quasicorrelations.

$$R_t = dia(Q_t)^{-\frac{1}{2}}\, Q_t\, dia(Q_t)^{-\frac{1}{2}} \tag{8}$$

where the elements of the matrix Q_t follow a standard GARCH(1,1) model, specified as follows:

$$Q_t = (1 - \lambda_1 - \lambda_2)\overline{R} + \lambda_1 z_{t-1} z'_{t-1} + \lambda_2 Q_{t-1} \tag{9}$$

where λ_i are time-invariant parameters for estimation and $\overline{R}$ is an unconditional correlation matrix of z_{it}, in which $z_{it} = \epsilon_{it}/\sqrt{h_{it}}$ is a standardized error term.

To handle heavy tails in the returns, we use a multivariate Student's t-distribution for the innovations in the DCC model. The parameters of the DCC model are computed by using the maximum log-likelihood estimation method.

4.3.2. Quantile Regression

A quantile regression extends the classic regression model and provides a suite of alternative methods to explore the entire conditional distribution of a response variable (Koenker & Bassett, 1978). It provides a comprehensive analysis by estimating various conditional quantiles, offering insights into data structure and heterogeneity that standard mean regressions may overlook (Koenker, 2017); a quantile regression is also robust to outliers, skewness, and heteroscedasticity. The quantile regression to examine the impact of macroeconomic variables and excess speculation on commodity sector returns is as follows:

$$Q_\theta(y_t|x_t) = \beta(\theta)x_t + \epsilon_t \tag{10}$$

where $0 < \theta < 1$, $Q_\theta(y_t|x_t)$ denotes the conditional quantile function of commodity returns, $\beta(\theta)$ a vector of parameter estimates, x_t is a matrix of macroeconomic variables and excess speculation measures, and ϵ_t is an error term for data in the θth quantile. Equation (10) is set up as linear and is solved with linear programming techniques, as outlined by Koenker (2005). We estimate five regressions at the 10th, 25th, 50th, 75th, and 90th percentiles and perform a comparison of the estimates.

4.3.3. Markov-Switching Models

Markov-switching models are particularly useful in examining the relationship between speculation and commodity returns due to their ability to capture the dynamic and non-linear nature of the relationship. Our dynamic model is specified in the following form:

$$y_t = \mu_{s_t} + x_t\beta + z_t\theta_{s_t} + \epsilon_s \tag{11}$$

where y_t is the returns on a commodity, μ_{s_t} is the state-dependent intercept, x_t is a vector of exogenous variables with state-invariant coefficients β, z_t is a vector of exogenous variables with state-dependent coefficients θ_{s_t}, and ϵ_s is an i.i.d. normal error with a mean of 0 and state-dependent variance σ^2. Based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) model selection criteria, we fit a two-state dynamic model with state-dependent variances.

4.3.4. Time-Varying Granger Causality Tests

Granger causality tests for each equation are performed in the following bivariate VAR(m) model:

$$y_t = \beta x_t + \epsilon_t \tag{12}$$

where $y_t = [r_t,\ s_t]$ represents a matrix of commodity sector returns and excess speculation, x_t represents lag values of the commodity returns and financial speculation, β is a vector of estimated coefficients on the lag values of the independent variables, and ϵ_t is serially uncorrelated error terms.

After fitting a VAR(4) model, we use the Wald test to determine whether one variable "Granger-causes" another. Excess speculation is said to Granger-cause commodity sector returns if, given past values of commodity returns, past values of excess speculation help predict future returns. The Wald test statistic evaluates the null hypothesis that the estimated coefficients on the lagged values of excess speculation are jointly zero. If we fail to reject the null hypothesis, we conclude that excess speculation does not Granger-cause commodity returns. Similarly, we apply the Wald test to determine if past values of commodity sector returns provide additional predictive information about excess speculation beyond what is offered by past values of excess speculation alone. If this is the case, we say that commodity sector returns Granger-cause excess speculation.

For the time-varying Granger causality tests, we use the methodology previously developed (Shi et al., 2019; Shi et al., 2018). This test uses the Wald test statistic from the bivariate VAR(m) model specified in Equation (12) and is based on recursive testing algorithms. These algorithms compute a sequence of Granger causality test statistics for each time period of interest.

Three algorithms are used to generate this series of test statistics: the forward expanding (FE) window, the rolling (RO) window, and the recursive evolving (RE) window algorithms (see Baum et al., 2022, for details). In the FE algorithm, the Wald test statistic is initially calculated using a minimum window length. Then, the sample size is gradually expanded by adding one observation at a time until the entire dataset is included, at which point the final Wald test statistic is computed. This systematic expansion ensures a comprehensive analysis, incorporating information from the entire sample into the test statistic.

In the RO algorithm, a fixed-size window of 'n' moves through the sample, advancing one observation at a time. At each step, a Wald test statistic is calculated for the data within the window. Under the RE algorithm, a test regression is performed for every possible subsample of size 'n' or larger, using the observation of interest as the common endpoint of all subsamples. This process is iteratively applied, with each point in the sample serving as the observation of interest, while maintaining the minimum window size constraint. Consequently, each observation in the sample, except for those in the initial subsample that establishes the minimum window size, will have an associated set of Wald test statistics.

The maximum FE statistic is identified as the largest value in the first row of the matrix. The maximum RO statistic corresponds to the largest value along the main diagonal of the matrix. The maximum RE statistic is determined by finding the largest value within the entire upper triangular portion of the matrix. The inference for the test of the null hypothesis is whether excess speculation (or commodity sector returns) does not Granger-cause commodity returns (or excess speculation) at any point during the sample period. The alternative hypothesis suggests evidence of Granger causality at some point in the sample, based on the empirical distribution of the test statistics computed under the null hypothesis through bootstrapping. If the test statistics exceed the 95th or 99th percentiles, the null hypothesis of no Granger causality is rejected at the 5% or 1% significance levels, respectively.

5. Empirical Results

5.1. Descriptive Statistics

Table 1 provides an overview of the descriptive statistics for various variables included in the analysis, offering insights into the central tendency, dispersion, and distribution of the data. The table includes sector returns, the principal components derived from macroeconomic variables, and measures of excess speculation. The variables are summarized using several statistical metrics, including the number of observations (N), mean, standard deviation (S.D.), 25th percentile (25th %), median, and 75th percentile (75th %). The sector returns cover different commodity sectors such as foods and fibers, grains and oilseeds, livestock, energy, and precious metals. The mean returns are positive for all sectors, indicating overall growth during the period studied. Notably, the energy sector exhibits the highest mean return (0.10) but also the highest standard deviation (5.27), reflecting significant volatility. In contrast, foods and fibers and precious metals have the same mean return (0.12), yet the precious metals sector shows less volatility (S.D. of 3.62) compared to foods and fibers (S.D. of 4.48).

Table 1. Descriptive statistics.

	N	Mean	S.D.	25th %	Median	75th %
Sector Returns						
Foods and fibers	1229	0.12	4.48	−2.69	0.07	2.89
Grains and oilseeds	1229	0.09	2.99	−1.70	0.07	1.87
Livestock	1229	0.08	3.39	−1.38	0.10	1.66
Energy	1229	0.10	5.27	−2.46	0.36	3.13
Precious metals	1229	0.12	3.62	−1.67	0.32	2.13
Principal Components						
PC #1	1229	0.00	2.34	−1.46	−0.58	0.72
PC #2	1229	0.00	1.15	−0.69	−0.04	0.51
Excess Speculation						
SPE foods and fibers	1229	1.10	0.39	0.80	1.10	1.35
SPE grains and oilseeds	1229	1.10	0.46	0.71	0.99	1.48
SPE livestock	1229	0.98	0.42	0.78	0.90	1.09
SPE energy	1229	0.48	0.27	0.29	0.44	0.70
SPE precious metals	1229	0.76	0.40	0.45	0.66	0.98

This table shows the descriptive statistics of weekly commodity sector returns, principal components, and excess speculation. The sample period spans from 1 January 2000 to 31 July 2023. PC #1 and PC #2 represent the first and second principal components from the set of 12 macroeconomic variables. SPE refers to excess speculation for a given sector.

Principal components, represented as PC #1 and PC #2, are derived from a set of 12 macroeconomic variables and serve to reduce data dimensionality while retaining most of the variance. These components have mean values close to zero, a typical outcome of the principal component analysis (PCA) process, and their standard deviations indicate the spread of the component scores. The excess speculation measures provide insights into speculative activities across different sectors. The foods and fibers and grains and oilseeds sectors exhibit the highest mean excess speculation values (1.10), suggesting a higher level of speculative activity. Conversely, the energy sector displays the lowest mean excess speculation (0.48), indicating relatively lower speculative activity compared to other sectors.

Table 2 presents the pairwise correlation coefficients among commodity sector returns, the first two principal components, and excess speculation measures. Among sector returns, foods and fibers and grains and oilseeds show a significant positive correlation (0.14) at the 1% level, suggesting some degree of co-movement. However, livestock returns do not exhibit significant correlations with other sectors, indicating independent behavior. Energy and precious metals returns are positively correlated with several other sectors and principal components, highlighting their interconnectedness within the commodity markets.

Table 2. Pairwise correlations.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Foods and fibers	1.00											
(2) Grains and oilseeds	0.14 ***	1.00										
(3) Livestock	−0.01	0.00	1.00									
(4) Energy	0.14 ***	0.25 ***	0.04	1.00								
(5) Precious metals	0.19 ***	0.28 ***	−0.01	0.29 ***	1.00							
(6) PC #1	−0.02	−0.05 *	−0.04	−0.13 ***	−0.03	1.00						
(7) PC #2	−0.03	−0.05 *	0.01	−0.05 *	−0.02	0.00	1.00					
(8) SPE foods and fibers	0.01	0.00	−0.04	−0.05 *	−0.01	0.00	−0.21 ***	1.00				
(9) SPE grains and oilseeds	−0.02	−0.08 ***	−0.02	−0.04	−0.05 *	−0.22 ***	0.10 ***	0.33 ***	1.00			
(10) SPE livestock	0.03	−0.04	0.00	−0.03	0.01	−0.02	−0.09 ***	−0.08 ***	−0.13 ***	1.00		
(11) SPE energy	−0.03	−0.03	−0.02	−0.02	−0.04	−0.27 ***	0.31 ***	0.24 ***	0.58 ***	−0.21 ***	1.00	
(12) SPE precious metals	−0.02	−0.03	0.00	−0.05 *	−0.05 *	−0.13 ***	0.04	0.21 ***	0.45 ***	−0.03	0.49 ***	1.00

This table shows the pairwise correlations between commodity sector returns, the first two principal components, and excess speculation. PC #1 and PC #2 represent the first and second principal components from the set of 12 macroeconomic variables. SPE refers to excess speculation for a given sector. The asterisks *** and * represent significance levels at 1%, 5%, and 10%, respectively.

Regarding principal components, PC #1 has a significant negative correlation with energy returns (−0.13) at the 1% level, implying that higher macroeconomic principal component values are associated with lower energy returns. PC #2 shows weaker and less significant correlations with sector returns, suggesting a lesser impact of the second principal component on commodity returns. Excess speculation measures reveal mixed correlations with sector returns. For instance, the excess speculation in foods and fibers shows a positive but not significant correlation with its returns (0.01). On the other hand, the grains and oilseeds and energy sectors display significant negative correlations between excess speculation and returns, indicating that higher speculative activity is associated with lower returns in these sectors. These insights underline the complex relationships between speculative activities and market returns across different commodity sectors.

5.2. Bayesian Model Averaging (BMA)

We used posterior inclusion probabilities (PIPs) in the BMA framework to identify the key macroeconomic drivers of commodity returns from the list of our twelve macroeconomic variables (yield spread, Fed National Financial Conditions Index (NFCI), federal funds effective rate, St. Louis Fed Financial Stress Index (STLFSI), Economic Policy Uncertainty Index (EPU), Equity Market-Related Economic Uncertainty Index (EMUI), Baltic Dry Index (BDI), Aruoba–Diebold–Scotti (ADS) Index, Office of Financial Research Financial Stress Index (OFR FSI), S&P 500 Volatility Index (VIX), Bull/Bear ratio, and forward earnings for the S&P 500).

Based on the higher values of PIP, we find that the STLFSI and yield spread are the most significant macroeconomic predictors of the foods and fibers sector returns. The BMA analysis reveals that none of the macroeconomic variables strongly influence the grains and oilseeds sector returns. The highest PIP for the STLFSI is only 0.15761, indicating weak evidence of its importance. Most other variables have very low PIPs and statistically insignificant coefficients, suggesting minimal impact. For livestock sector returns, we find that the ADS and STLFSI are the most significant macroeconomic predictors, with moderate inclusion probabilities. However, their PIPs and coefficient estimates indicate that the relationships are not strong and are surrounded by considerable uncertainty.

Similarly, we find the STLFSI, OFR FSI, and NFCI to be the most significant macroeconomic predictors for energy sector returns. The STLFSI has a very high inclusion probability and a strong negative impact on energy sector returns. The OFR FSI and NFCI also have relatively high inclusion probabilities, indicating their importance, but their coefficients show more uncertainty. Most other macroeconomic variables have low PIPs and statistically insignificant coefficients, suggesting minimal impact on energy sector returns. Finally, the BMA analysis for precious metals sector returns identifies the STLFSI and Yield spread as the most significant macroeconomic predictors. The STLFSI has a very high inclusion probability and a strong negative impact, while yield spread has a similarly high inclusion probability and a strong positive impact on precious metals sector returns. Most other macroeconomic variables have low PIPs and statistically insignificant coefficients.

Across all sectors, the STLFSI consistently appeared to be a significant predictor with varying influences on returns. Other macroeconomic variables generally had lower PIPs and less impact, suggesting that only a few key variables significantly drive commodity returns.

5.3. Principal Component Analysis

Our empirical analysis starts with a detailed examination of the 12 initial macroeconomic variables, where we employed PCA to derive 'k' linear combinations. To ensure the stability and constancy of the covariance and correlation of these variables, we first examine each one for stationarity. In cases where the variables were nonstationary, we applied differencing to achieve stationarity. Our computation of the principal components was conducted using both the variance–covariance matrix and the correlation matrix. This process yielded different sets of principal components; however, our subsequent analyses revealed that these differences did not significantly impact the results. Consequently, we selected the principal components derived from the correlation matrix for further regression analyses. Guided by the principles outlined by Rencher and Christensen (2012, p. 423), we chose to retain the first two principal components, as they collectively account for over 97% of the total variance in the original macroeconomic variables.

5.4. DCC Model Analysis

The estimates from the DCC model are presented in Table 3. Each column in Table 3 presents the DCC model's estimated parameters. The coefficient estimates for the first principal component (PC #1) and intercept are from the mean model. The coefficient estimates for ARCH, GARCH, and the intercept are from the univariate GARCH model. The remaining coefficient estimates are from the DCC model specified in Equation (9).

Table 3. Estimates from dynamic conditional correlation multivariate GARCH models.

	Foods and Fibers	Grains and Oilseeds	Livestock	Energy	Precious Metals
			Panel A Dependent Variable: Returns		
PC #1	−0.0535 *	−0.0456	−0.0740 ***	−0.1627 ***	−0.0408
	(0.0844)	(0.2229)	(0.0029)	(0.0051)	(0.2561)
Intercept	−0.0749	0.0945	−0.0228	0.0637	0.1143 *
	(0.2247)	(0.1845)	(0.6944)	(0.5560)	(0.0891)
ARCH	0.0671 **	0.1420 ***	0.0520 ***	0.0784 ***	0.0781 ***
	(0.0242)	(0.0000)	(0.0002)	(0.0000)	(0.0000)
GARCH	0.8984 ***	0.8202 ***	0.9391 ***	0.9143 ***	0.9097 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Intercept	0.2079	0.4135 ***	0.0664	0.2182	0.1322 **
	(0.2139)	(0.0036)	(0.1132)	(0.1111)	(0.0441)
			Panel B Dependent Variable: Speculation		
PC #1	−0.0007	0.0005	−0.0007	−0.0003	−0.0003
	(0.4842)	(0.4488)	(0.4937)	(0.3563)	(0.6423)
Intercept	0.0004	0.0016	0.0007	0.0005	0.0006
	(0.8572)	(0.4266)	(0.7741)	(0.4713)	(0.7242)
ARCH	0.2026 ***	0.0812 ***	0.2072 ***	0.0597 ***	0.1285 ***
	(0.0001)	(0.0003)	(0.0001)	(0.0001)	(0.0000)
GARCH	0.7296 ***	0.8996 ***	0.7138 ***	0.9287 ***	0.8730 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Intercept	0.0008 **	0.0001 *	0.0009 **	0.0000	0.0001 *
	(0.0148)	(0.0882)	(0.0119)	(0.1206)	(0.0893)
Conditional Correlation	−0.1655 ***	−0.2700 ***	−0.0450	0.0298	−0.3931 **
	(0.0002)	(0.0000)	(0.2048)	(0.79)	(0.0000)
λ_1	0.0163	0.0362 **	0.0085	0.0367	0.0311 ***
	(0.1562)	(0.0122)	(0.4835)	(0.0974)	(0.0004)
λ_2	0.9363 ***	0.8824 ***	0.9243 ***	0.8066 ***	0.9493 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

This table presents the estimation results of dynamic conditional correlation (DCC) multivariate GARCH models for the relationship between sectoral returns and excess speculation within five sectors: foods and fibers, grains and oilseeds, livestock, energy, and precious metals. The dependent variables are sectoral returns and measures of speculation, with PC #1 representing the principal component derived from macroeconomic variables. The table reports coefficients for the mean equations (PC #1 and intercept), variance equations (ARCH, GARCH, and intercept), and conditional correlations. The adjustment parameters λ_1 and λ_2 are also included *p*-values are reported in parentheses. The asterisks ***, **, and * represent significance levels at 1%, 5%, and 10%, respectively.

In the second column (Panel A), we observe that the first principal component derived from macroeconomic variables shows a slightly negative and statistically significant effect on the foods and fibers sector, livestock, and precious metal sector returns, with negligible impact on grains and oilseeds returns. We observe the statistically significant negative coefficients for energy (−0.1627), foods and fibers (−0.0535), and livestock (−0.0740), indicating that macroeconomic shocks negatively impact returns in these sectors. However, the coefficients for grains and oilseeds and precious metals are insignificant, suggesting that macroeconomic factors do not significantly influence their returns. All sector returns and excess speculation exhibit significant volatility clustering, indicated by the significant ARCH and GARCH terms.

In Panel B, we observe insignificant coefficients on PC #1 for all sectors, suggesting no meaningful relationship between macroeconomic variables and speculation levels. We observe positive and significant ARCH and GARCH terms across all sectors. The conditional correlations show significant negative relationships for foods and fibers (−0.1655), grains and oilseeds (−0.2700), and precious metals (−0.3931). In contrast, livestock (−0.0450) and energy (0.0298) show insignificant correlations. The significant λ_1 and λ_2 confirm the presence of dynamic conditional correlations, indicating that the correlation between returns and speculation changes over time.

The dynamic conditional correlations between sector returns (foods and fibers, grains and oilseeds, livestock, energy, and precious metals) and excess speculation within that specific sector are plotted in Figure 1. The correlations vary significantly over time, reflecting the dynamic nature of market conditions and investor behavior. The energy sector exhibits a mostly positive correlation, indicating that higher speculation generally corresponds with higher returns. In contrast, the grains and oilseeds and precious metals sectors show predominantly negative correlations, suggesting that increased speculation is often associated with lower returns. The foods and fibers and livestock sectors display no strong long-term relationship, with correlations fluctuating around zero.

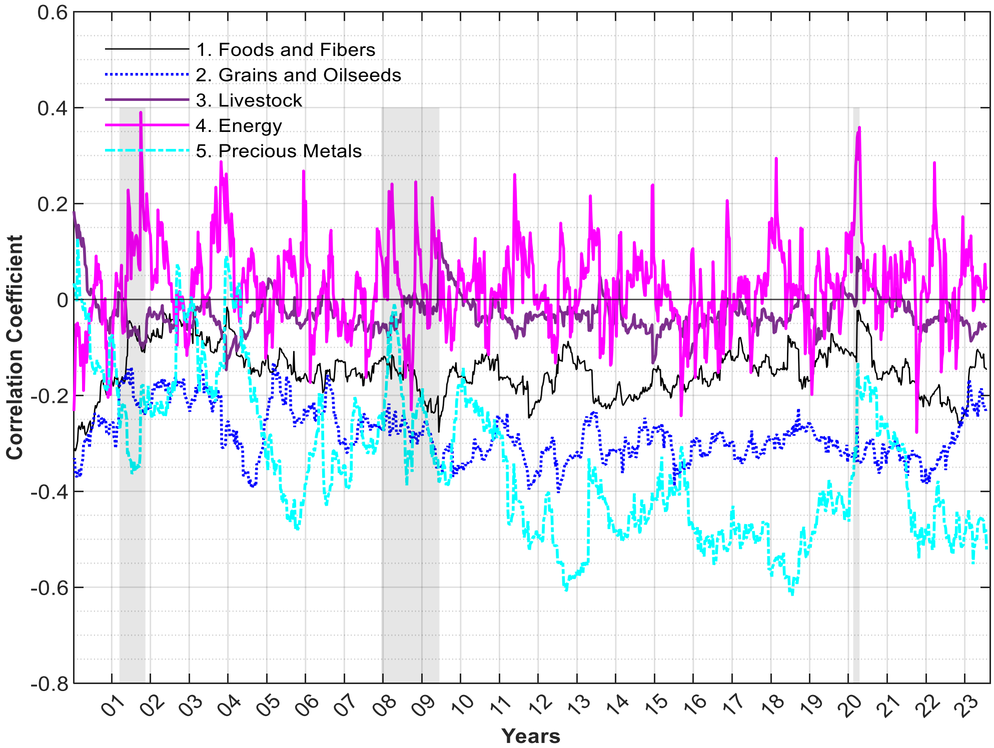

Figure 1. Dynamic conditional correlation between sector returns and excess speculation. This chart shows the dynamic conditional correlation between each of the five commodity sector returns and the sector's measure of excess speculation.

The differing correlations between speculation and returns across commodity sectors stem from their unique market dynamics. In the energy sector, positive correlations may arise because speculation aligns with geopolitical risks, inelastic demand, and broader investment strategies, driving prices upward. In contrast, grains and oilseeds face negative correlations as speculation can disrupt prices away from fundamentals, amplify oversupply, or trigger regulatory interventions. Precious metals also show negative correlations due to their safe-haven nature, where speculative activity often leads to unsustainable price spikes followed by corrections. These sector-specific drivers explain the variation in speculative impact on returns. These insights highlight the importance of understanding sector-specific relationships to inform investment strategies, risk management, and the impact of speculative activities on returns.

The results from the DCC model highlight the need for sector-specific and adaptive regulatory frameworks to address the diverse impacts of speculation and macroeconomic conditions on commodity markets. Policies should focus on mitigating speculation-driven distortions in sensitive sectors like grains and oilseeds and precious metals while supporting their role in enhancing market efficiency in resilient sectors like energy. Real-time monitoring and transparency in speculative trading are crucial to reducing informational frictions and volatility clustering. These measures can promote market stability, improve price discovery, and protect critical markets from excessive risk.

5.5. Quantile Regression Results

To better understand the relationship between commodity sector returns and excess speculation at different points in the conditional distribution of returns, we utilize a quantile regression. The use of a quantile regression makes our approach robust to outliers, allows us to examine the nature of the relationship using location and scale parameters of the model, and avoids assumptions about the parametric distribution of regression error (Koenker, 2005). Table 4 shows the parameter estimates and associated *p*-values (in parentheses) from the quantile regression at the 25th, 50th, and 75th percentiles. The dependent variable is commodity sector returns for all specifications. The independent variable, which captures macroeconomic conditions, varies in each panel. In Panel A, we present estimates using the St. Louis Fed Financial Stress Index (Fed FSI), and in Panel B, we present estimates using the first principal component (PC #1). The variable of interest in each regression specification is excess speculation. The results show that the quantile regression coefficients vary across quantiles and conform according to the test of coefficient equality across quantiles.

Table 4. Quantile regression estimates.

	Foods and Fibers	Grains and Oilseeds	Livestock	Energy	Precious Metals
Panel A					
25th %					
Fed FSI	−0.3969 ***	−0.4273 ***	−0.2142 ***	−1.2027 ***	−0.5332 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Excess speculation	−0.2012	−0.1446	0.5713 ***	−0.2492	−0.4416
	(0.25)	(0.45)	(0.00)	(0.72)	(0.08)
Constant	−1.3038 ***	−1.2088 ***	−1.9738 ***	−2.4666 ***	−1.2190 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
50th %					
Fed FSI	−0.1764 *	−0.3274 **	−0.1991 **	−0.7772 ***	−0.2768
	(0.03)	(0.00)	(0.00)	(0.00)	(0.08)
Excess speculation	−0.4528	−0.5241 **	0.3111 *	−1.5900 **	−0.6402 *
	(0.07)	(0.00)	(0.01)	(0.00)	(0.01)
Constant	0.4544	0.5242 *	−0.3397 *	1.0891 ***	0.7344 ***
	(0.12)	(0.03)	(0.02)	(0.00)	(0.00)
75th %					
Fed FSI	−0.1077	−0.0277	−0.1525 *	−0.1783	0.0436
	(0.44)	(0.87)	(0.03)	(0.43)	(0.79)
Excess Speculation	−0.5212 *	−0.8083 ***	0.1872	−1.8769 ***	−0.6135 **
	(0.02)	(0.00)	(0.21)	(0.00)	(0.01)
Constant	1.9960 ***	2.3636 ***	1.1159 ***	3.5818 ***	2.2712 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Panel B					
25th %					
First PC	−0.1514 **	−0.1736 ***	−0.1206 ***	−0.5997 ***	−0.2570 ***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Excess speculation	−0.1846	−0.2362	0.5647 ***	−1.0093	−0.4878
	(0.26)	(0.24)	(0.00)	(0.25)	(0.08)
Constant	−1.3122 ***	−1.1431 ***	−1.9746 ***	−2.1643 ***	−1.2523 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
50th %					
First PC	−0.0512	−0.1110 **	−0.0908 **	−0.3601 **	−0.0509
	(0.23)	(0.01)	(0.01)	(0.00)	(0.53)
Excess speculation	−0.3817	−0.5710 ***	0.3209 *	−1.9235 **	−0.6263 *
	(0.11)	(0.00)	(0.02)	(0.00)	(0.01)
Constant	0.3735	0.6161 **	−0.3856 *	1.1721 ***	0.7208 ***
	(0.18)	(0.01)	(0.02)	(0.00)	(0.00)
75th %					
First PC	0.0093	0.0177	−0.0734 *	−0.0503	0.1206
	(0.86)	(0.79)	(0.03)	(0.60)	(0.09)
Excess speculation	−0.4807	−0.7654 ***	0.1267	−1.9390 ***	−0.6921 ***
	(0.07)	(0.00)	(0.40)	(0.00)	(0.00)
Constant	1.9449 ***	2.3309 ***	1.1633 ***	3.6089 ***	2.3907 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

This table shows the coefficient estimates from the 25th, 50th, and 75th quantile regressions, as specified in Equation (10). The dependent variable in each equation is commodity sector returns. In Panel A, the independent variables are the Financial Stress Index (Fed FSI) and excess speculation. In Panel B, the independent variables are the first principal component, excess speculation, and an autoregressive term. *p*-values are reported in parentheses. The asterisks ***, **, and * represent significance levels at 1%, 5%, and 10%, respectively.

Regardless of the variable that represents macroeconomic conditions, it typically has a negative sign, implying an inverse impact on commodity sector returns. Looking at the Fed FSI, generally, its coefficient is statistically significant in the lowest quartile, but that significance begins to deteriorate as you move into higher quartiles. Furthermore, the magnitude of the coefficient estimate for the Fed FSI declines in absolute value as we move from the lower quartile to the higher quartile. Similar results are observed with PC #1 in Panel B.

The measure of excess speculation is generally negative, implying an inverse impact on commodity sector returns, and statistically significant (mostly in upper quartiles). The impact of excess speculation on return sectors is heterogenous across quantiles. For example, in the grains and oilseeds sector, the incremental effect of excess speculation on weekly returns is −0.2362% in the 25th percentile, intensifying to −0.57% in the 50th percentile, and further intensifying to −0.7654% in the 75th percentile.

The quantile regression findings highlight the need for policies that address the performance-dependent and sector-specific impacts of macroeconomic conditions and speculative activities on commodity markets. Regulators should prioritize stabilizing markets during downturns, as macroeconomic stress has the strongest adverse effects at lower quantiles. Measures such as dynamic position limits and enhanced transparency in speculative trading can help mitigate excessive volatility during bullish periods, where speculation tends to amplify risks. Sector-specific approaches are crucial, particularly for energy and precious metals, which are more sensitive to external shocks and speculative pressures. These targeted and adaptive policies can enhance market stability and protect critical sectors from disproportionate risks.

5.6. Markov-Switching Regression Results

We investigate the presence of regime-switching behavior in commodity sector returns and excess speculation. To this end, we employ a Markov-switching model, considering one to three regimes. The optimal model is determined by employing information criteria such as the Schwarz Information Criterion (SIC), AIC, Likelihood Ratio Test, and Hannan–Quinn (HQ) Information Criterion. Our findings indicate that a model with two regimes with varying variance is the most suitable.

Table 5 presents the results derived from Markov-switching models, as specified in Equation (11). The dependent variable utilized in each equation is commodity sector returns, while the independent variables include the measure of speculation and one of the measures of financial condition and lag returns.

The results from Table 5 show regime-dependent dynamics between sectoral commodity returns, macroeconomic indicators, and excess speculation, with notable variations across sectors. For example, the coefficient on the Financial Stress Index (Fed FSI) indicates the negative relationship between financial stress and sectoral returns, with sectors like energy (−20.76) and precious metals (−10.09) showing greater sensitivity compared to foods and fibers (−0.38) and grains and oilseeds (−0.19). This highlights the varying impact of financial stress across commodity sectors, emphasizing the heightened vulnerability of speculative and hedging markets to macroeconomic uncertainty. Transition probabilities (e.g., P11 = 0.927 for foods and fibers and 0.993 for livestock) indicate high persistence in specific regimes, while variances (e.g., Sigma = 4.18 for energy and 2.27 for livestock) capture differences in volatility across states. These results illustrate the heterogeneous effects of financial stress and excess speculation on commodity returns, highlighting the need for tailored strategies to address sector-specific risks under varying market conditions. These findings emphasize the dynamic and non-linear interactions between macroeconomic conditions, speculative activities, and sectoral returns, providing important insights into the complex behavior of commodity markets.

Table 5. Markov-switching dynamic regression estimates.

	Foods and Fibers	Grains and Oilseeds	Livestock	Energy	Precious Metals
			Panel A		
μ_1	−0.3841 **	−0.1958 **	−0.0349	−20.7569 ***	−10.0868 ***
	(0.1568)	(0.0772)	(0.0656)	(2.0313)	(1.3601)
μ_2	2.0407 ***	2.2458 ***	11.3326 ***	0.1919	0.2334 ***
	(0.5163)	(0.5803)	(1.0720)	(0.1215)	(0.0729)
Sigma	2.1256	2.0975	2.2677	4.1786	2.4752
	(0.0814)	(0.0651)	(0.0474)	(0.0887)	(0.0545)
P11	0.9267	0.9699	0.9937	0.2729	0.1846
	(0.0405)	(0.0173)	(0.0026)	(0.1733)	(0.1651)
P21	0.4447	0.2605	0.8089	0.0044	0.0114
	(0.1313)	(0.1624)	(0.1368)	(0.0022)	(0.0037)
Fed FSI	−0.3184 ***	−0.3228 ***		−0.5295 ***	−0.1174
	(0.0756)	(0.0567)		(0.1118)	(0.0820)
Dependent lag	−0.0904 **	−0.1429 ***	−0.0127	0.0039	−0.0468
	(0.0412)	(0.0327)	(0.0309)	(0.0312)	(0.0335)
Excess speculation	−1.8741 ***	−6.3615 ***	0.0922	−1.6054 ***	−9.3249 ***
	(0.5476)	(0.6918)	(0.1795)	(0.5847)	(0.7771)
ADS Index			0.3555 ***		
			(0.0352)		
			Panel B		
μ_1	−0.3345 **	−0.2087 ***	0.4393	−21.7343 ***	−9.4944 ***
	(0.1691)	(0.0787)	(0.3784)	(2.5913)	(1.0913)
μ_2	2.0693 ***	2.0574 ***	−0.3404 *	0.1667	0.2555 ***
	(0.6276)	(0.4784)	(0.1755)	(0.1233)	(0.0725)
Sigma	2.1645	2.1173	2.4548	4.2155	2.4610
	(0.0841)	(0.0576)	(0.0588)	(0.0915)	(0.0535)
P11		0.9701	0.0000	0.2998	0.2806
	(0.0424)	(0.0149)	(0.0000)	(0.1963)	(0.1404)
P21	0.4593	0.2364	0.5921	0.0038	0.0127
	(0.1534)	(0.1182)	(0.3910)	(0.0024)	(0.0039)
PC #1	−0.1097 ***	−0.1243 ***	−0.1126 ***	−0.1504 ***	0.0227
	(0.0355)	(0.0277)	(0.0300)	(0.0544)	(0.0414)
Auto lag	−0.0731 *	−0.1355 ***		0.0036	−0.0442
	(0.0423)	(0.0328)		(0.0336)	(0.0361)
Excess speculation	−1.8259 ***	−6.3308 ***	0.0767	−1.7931 ***	−9.2439 ***
	(0.5514)	(0.6921)	(0.1967)	(0.3390)	(0.7588)

This table shows the coefficient estimates from Markov-switching models, as specified in Equation (11). The dependent variable in each equation is commodity sector returns. In Panel A, the independent variables are the Financial Stress Index (Fed FSI) and excess speculation. In Panel B, the independent variables are the first principal component, excess speculation, and an autoregressive term. P11 represents the probability of staying in State 1, and P21 represents the probability of staying in State 2. *p*-values are reported in parentheses. The asterisks ***, **, and * represent significance levels at 1%, 5%, and 10%, respectively.

The Markov-switching regression analysis reveals that commodity sector returns exhibit regime-dependent dynamics influenced by macroeconomic conditions and speculative activities. Financial stress, measured by the Fed Financial Stress Index (Fed FSI), has a significantly negative impact on returns, with the energy and precious metals sectors showing the greatest sensitivity, underscoring their heightened vulnerability to economic uncertainty. Transition probabilities indicate high persistence in State 1 for foods and fibers, grains and oilseeds, and livestock sectors and in State 2 for energy and precious metals sectors. Excess speculation amplifies risks differently across sectors, with the grains and oilseeds and precious metals sectors showing pronounced negative effects. These findings highlight the importance of tailored, sector-specific strategies to manage the risks associated with macroeconomic uncertainty and speculative activity.

5.7. Time-Varying Granger Causality Test Results

Table 6 presents the findings from the time-varying Granger causality tests. We employ a VAR model with four lags ($p = 4$) and one lag for the lag-augmented component (d = 1). The initial column presents the sector returns used in the VAR model, and the subsequent column illustrates the causality direction using an arrow (→). For example, a statistically significant coefficient for "Speculation → Returns" indicates that fluctuations in excess speculation Granger-cause variations in the sector's commodity returns. The third, fourth, and fifth columns present the Max Wald FE, Max Wald RO, and Max Wald

RE statistics, respectively. These statistics are computed using the forward expanding window, rolling window, and recursive evolving window approaches. We adopt a minimum window size of 72 observations. The bootstrap test statistics are shown with the 95th and 99th percentiles in parentheses and brackets, respectively. These values are derived from 499 replications over a year to maintain control size, emphasizing the Wald tests' robustness against heteroskedasticity.

Table 6. Wald tests of time-varying Granger causality.

Sectors	Direction of Causality	Max Wald FE	Max Wald RO	Max Wald RE
Foods and fibers	Speculation → Returns	9.563	27.947	31.949
		(8.284)	(8.636)	(9.394)
		[12.679]	[13.533]	[14.521]
	Returns → Speculation	19.47	35.698	39.625
		(12.836)	(12.661)	(13.861)
		[18.438]	[16.553]	[19.407]
Grains and oilseeds	Speculation → Returns	7.709	33.618	36.584
		(9.826)	(9.847)	(10.21)
		[15.539]	[17.268]	[18.54]
	Returns → Speculation	68.578	64.675	68.808
		(14.734)	(15.763)	(16.242)
		[20.394]	[21.767]	[22.886]
Livestock	Speculation → Returns	18.789	59.187	59.645
		(13.919)	(14.062)	(14.495)
		[18.188]	[19.329]	[19.541]
	Returns → Speculation	14.487	36.215	36.215
		(18.996)	(18.825)	(19.693)
		[25.442]	[24.336]	[26.779]
Energy	Speculation → Returns	5.462	37.821	42.997
		(7.742)	(8.648)	(9.286)
		[11.777]	[11.568]	[12.08]
	Returns → Speculation	9.987	24.404	25.714
		(8.516)	(8.48)	(9.869)
		[14.292]	[14.001]	[14.998]
Precious metals	Speculation → Returns	10.071	34.599	34.781
		(8.987)	(9.186)	(9.4)
		[13.715]	[12.69]	[14.168]
	Returns → Speculation	24.428	38.944	41.467
		(9.359)	(10.193)	(10.61)
		[14.619]	[14.695]	[14.971]

This table shows the results from the time-varying Granger causality tests. The underlying VAR model is fit with $p = 4$ lags and with d = 1 lag. FE, RO, and RE represent test statistics computed using the forward expanding, rolling window, and recursive evolving window algorithms, respectively. The minimum window size is set at 72 observations. The 95th and 99th percentiles of the empirical distribution of the bootstrap test statistics are shown in parentheses and brackets, respectively, and are based on 499 replications with a one-year period to control for size.

To evaluate the null hypothesis of no time-varying Granger causality, the test statistics are compared to the bootstrapped critical values at the 5% and 1% significance thresholds. When a test statistic exceeds the 95th percentile of the bootstrapped empirical distribution, the null hypothesis is rejected in favor of the alternative hypothesis at the 5% level. Similarly, if a test statistic surpasses the 99th percentile of the bootstrapped empirical distribution, we reject the null hypothesis at the 1% level, indicating the presence of causality. Conversely, if the test statistics are below these critical values, we do not reject the null hypothesis, indicating no evidence of time-varying causality.

The results for the full sample indicate that we fail to reject the null hypothesis of no Granger causality between financial stress and commodity returns in both directions. Specifically, for the hypothesis that speculation does not Granger-cause returns in the grains and oilseeds sector, the test statistic values (max Wald FE, max Wald RO, and max Wald RE) are 7.71, 33.62, and 36.58, respectively. The 99th percentile critical values for these statistics are 15.54, 17.27, and 18.54. Since the calculated test statistics exceed the critical values, we reject the null hypothesis and conclude that changes in speculation do Granger-cause changes in returns for the grains and oilseeds sector. Similarly, for the hypothesis that commodity returns in the grains and oilseeds sector do not Granger-cause speculation, the max Wald FE, max Wald RO, and max Wald RE values are 68.58, 64.66, and 68.81, respectively. These values significantly exceed their corresponding 99th percentile critical values of 20.39, 21.77, and 22.89, leading us to reject the null hypothesis. Thus, we observe bi-directional causation between speculation and returns in the grains and oilseeds sector.

The bi-directional relationship between excess speculation and commodity sector returns is consistent across all sectors. This indicates that changes in commodity prices can impact various economic and financial market factors, such as asset values, inflation rates, interest rates, exchange rates, and liquidity. These factors, in turn, can drive excess speculation.

We also include plots of time-varying Granger causality test statistics in Appendix A. These figures illustrate three sequences of test statistics, calculated using forward expanding windows, rolling windows, and recursive evolving window algorithms (plotted as Forward, Rolling, and Recursive, respectively). The plots demonstrate that Granger-causal relationships vary significantly across different sample periods and are influenced by the specific recursive algorithm applied.

In essence, the empirical results show that financial stress indicators, like the St. Louis Fed Financial Stress Index, play a crucial role in predicting commodity futures returns, highlighting the significant impact of macroeconomic stability on commodity prices. Our analysis also reveals that the relationship between macroeconomic indicators, speculative actions, and commodity returns is dynamic and varies over time, depending on the specific period and econometric methods used. Additionally, the effects of macroeconomic conditions and speculation differ across commodity sectors, emphasizing the importance of sector-specific dynamics in analyzing commodity futures markets. The role of speculation varies based on the market sector and prevailing macroeconomic conditions, presenting a complex and influence on commodity market dynamics.

Furthermore, the time-varying Granger causality analysis shows the dynamic relationship between speculation and commodity returns and reveals a bi-directional causality across sectors. This indicates that speculation and price movements are mutually reinforcing, reflecting the feedback loops inherent in commodity markets. It also highlights sector-specific variations in how speculation interacts with returns and emphasizes the need for targeted analysis to understand these unique dynamics. The findings also show the evolving nature of these relationships, driven by changes in macroeconomic conditions and market environments, which necessitate flexible and adaptive approaches to market regulation and risk management.

6. Concluding Remarks

This paper uses weekly data to explore the dynamic relationships between macroeconomic conditions, speculative activities, and commodity futures returns over a span of more than two decades. Using a combination of advanced econometric methodologies—including dynamic conditional correlation (DCC) models, quantile regression, Markov-switching models, and time-varying Granger causality tests—we thoroughly examine sector-specific dynamics across commodity markets.

Our empirical results show that speculative activities have a complex and dual impact on commodity futures returns. The effects of speculative activity vary significantly across sectors. For example, in the grains and oilseeds sector, increased speculation is often associated with reduced returns, while in other sectors, such as energy, the relationship is less consistent. Furthermore, the dynamic and time-sensitive nature of speculation highlights the need for continuous monitoring and adaptive strategies by market participants and policymakers. Furthermore, financial stress indicators, such as the FED FSI and the EPU

Index, emerge as significant predictors of commodity futures returns, underscoring the crucial role of financial market conditions in commodity pricing.

The insights presented here are valuable for investors, policymakers, and researchers. However, our study's limitations also present opportunities for future research to deepen our understanding of these critical economic relationships and to refine strategies for market participants and regulators alike. For instance, our analysis includes 12 macroeconomic variables, but broader considerations like geopolitical tensions or climate risks could deepen insights. Additionally, the impact of regulatory changes on speculation and returns remains unquantified, highlighting an area for detailed investigation to assess how these policies influence market dynamics. Finally, examining the relationship among macroeconomic variables, speculative activity measures, and commodity returns in a multivariate dynamic framework could provide deeper insights into these complex relationships.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

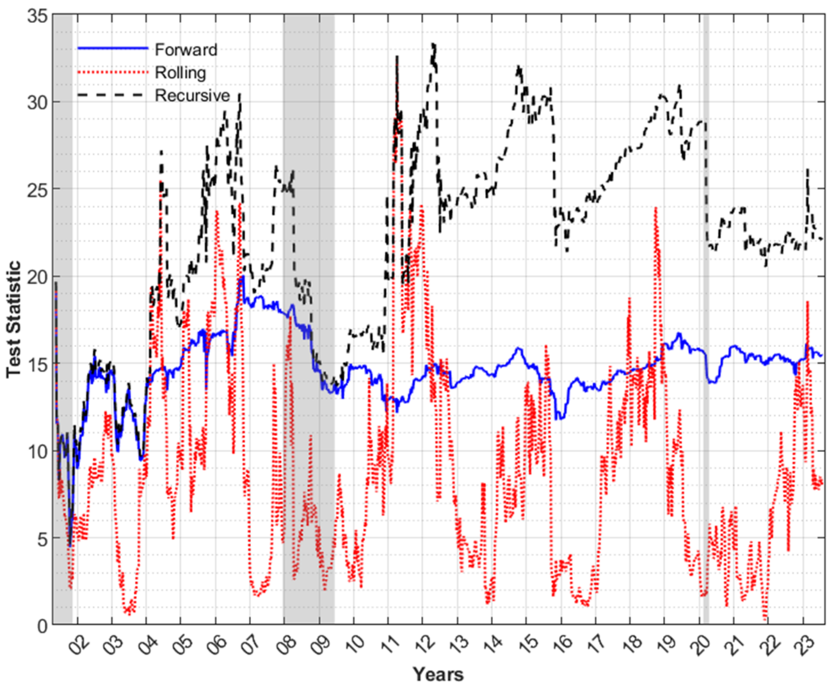

Figure A1. Forward, rolling, and recursive time-varying Granger causality test statistics. This chart shows that the direction of causality being tested runs from sector returns of foods and fibers to excess speculation.

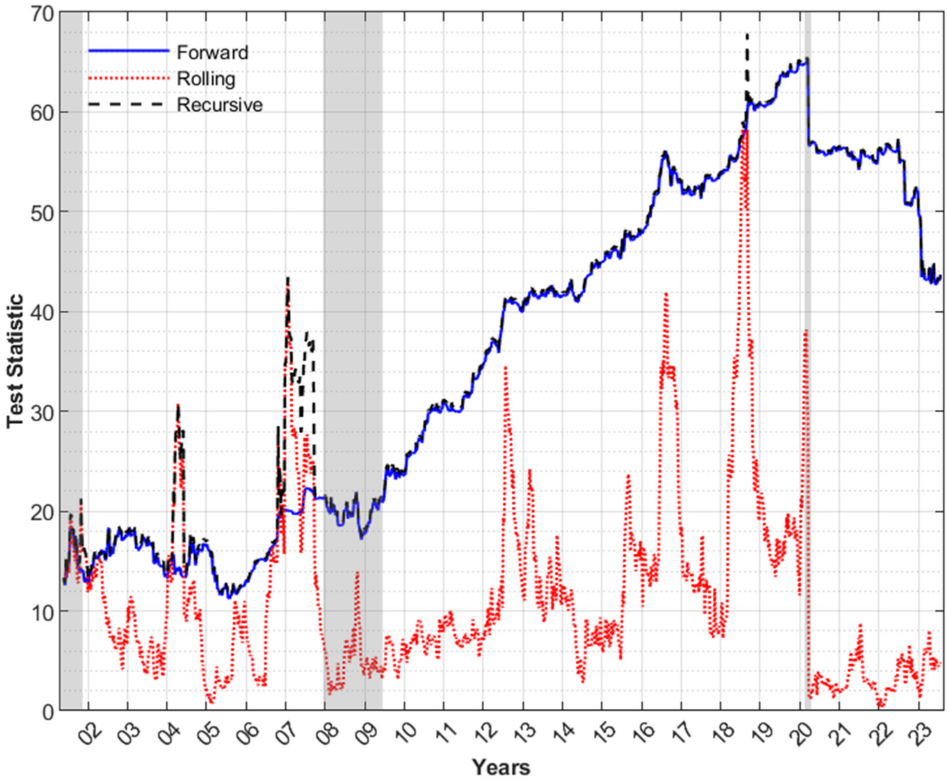

Figure A2. Forward, rolling, and recursive time-varying Granger causality test statistics. This chart shows that the direction of causality being tested runs from sector returns of grains and oilseeds to excess speculation.

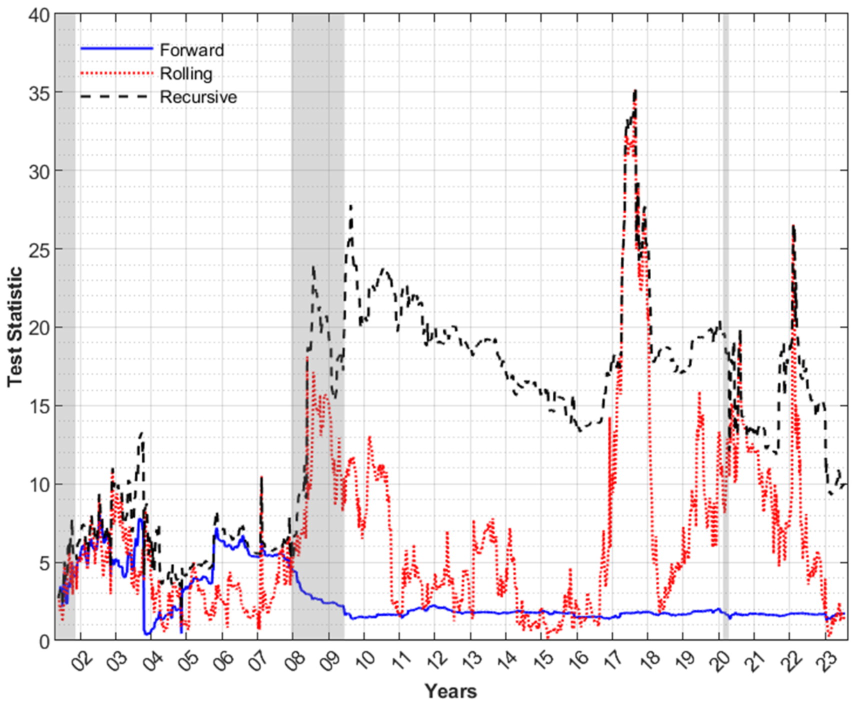

Figure A3. Forward, rolling, and recursive time-varying Granger causality test statistics. This chart shows that the direction of causality being tested runs from sector returns of livestock to excess speculation.

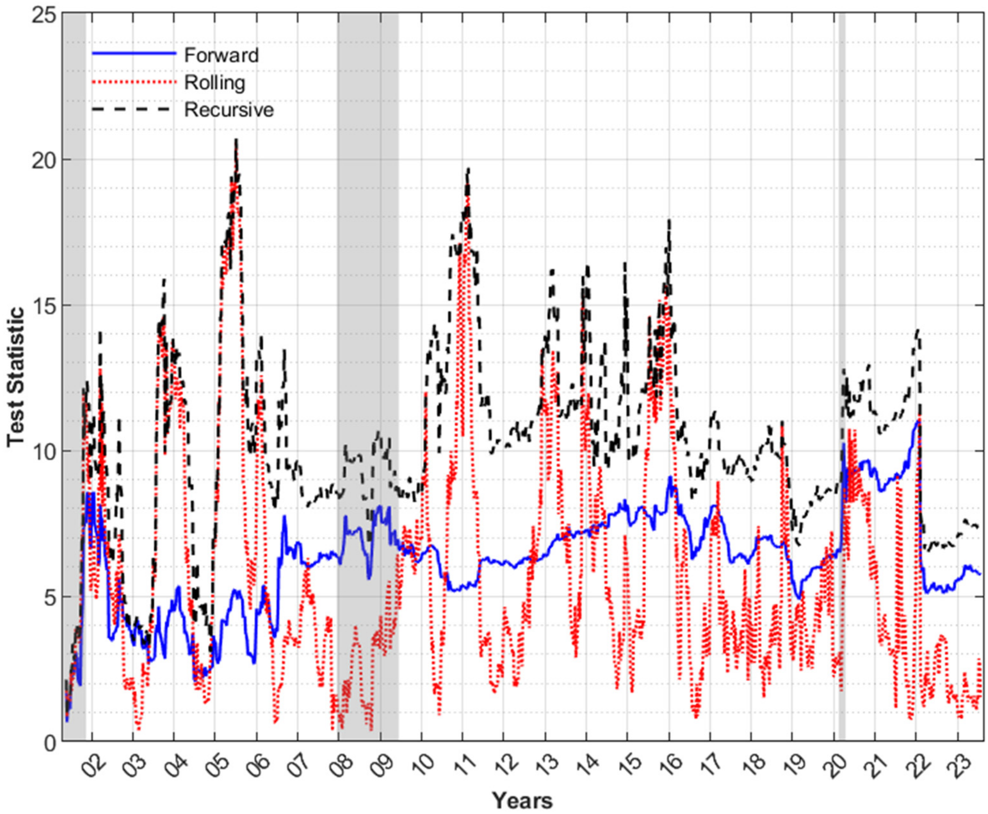

Figure A4. Forward, rolling, and recursive time-varying Granger causality test statistics. This chart shows that the direction of causality being tested runs from sector returns of energy to excess speculation.

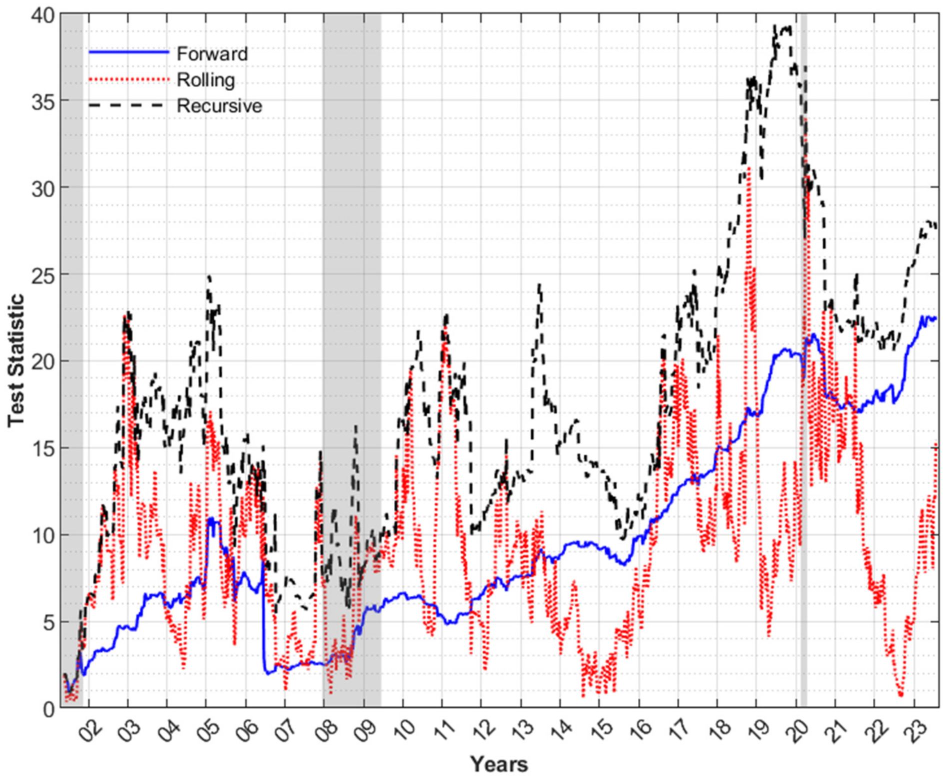

Figure A5. Forward, rolling, and recursive time-varying Granger causality test statistics. This chart shows that the direction of causality being tested runs from sector returns of precious metals to excess speculation.

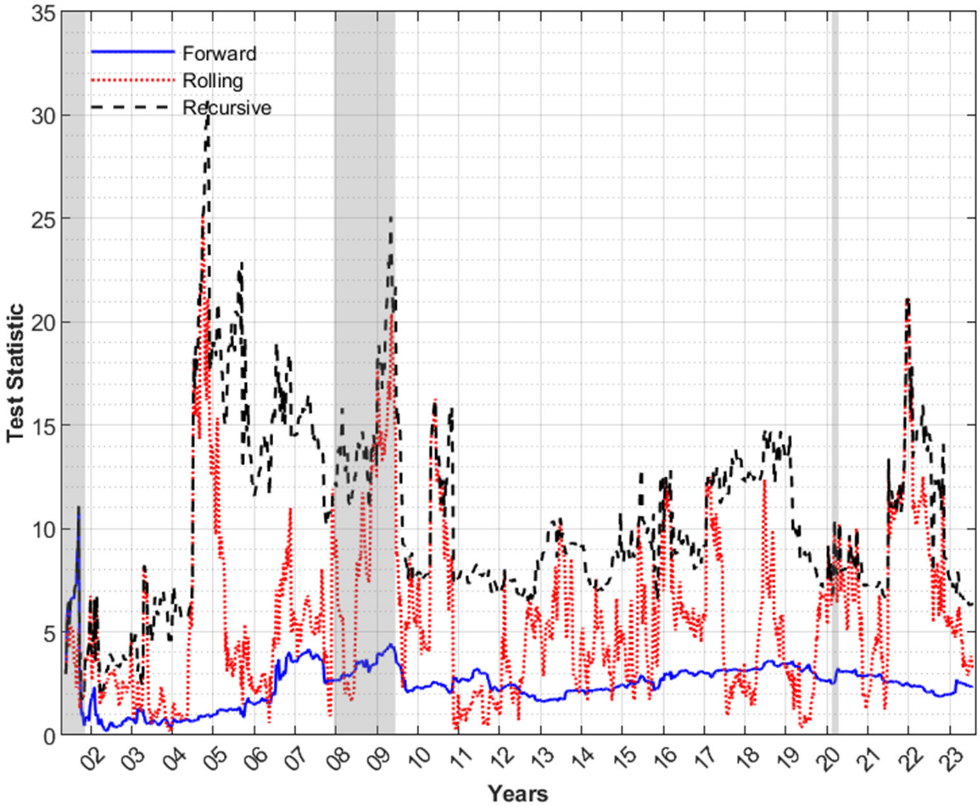

Figure A6. Forward, rolling, and recursive time-varying Granger causality test statistics. This chart shows that the direction of causality being tested runs from excess speculation to the sector returns of foods and fibers.

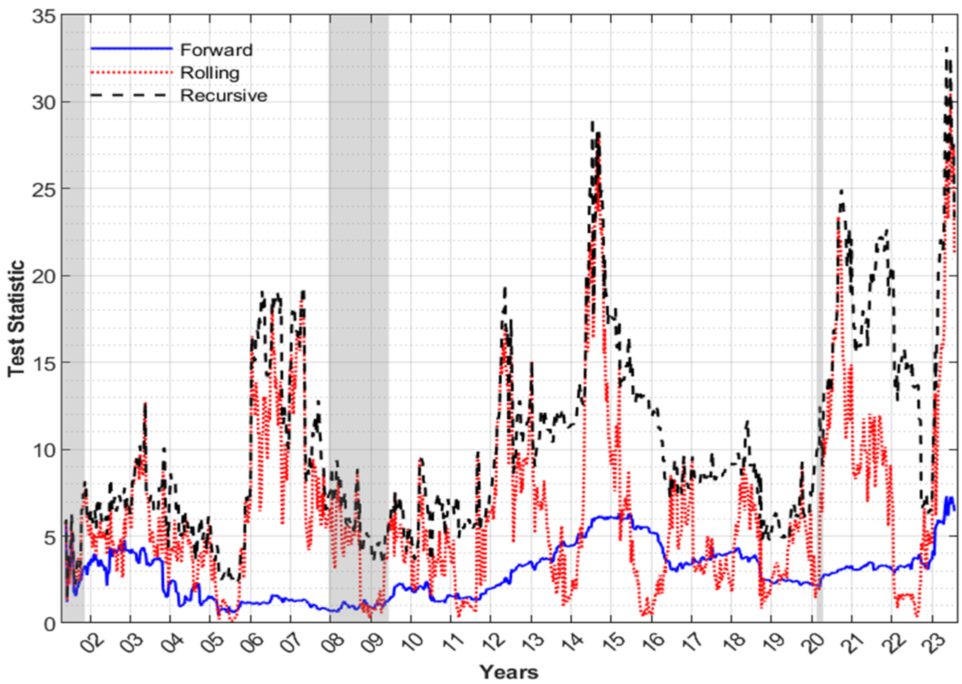

Figure A7. Forward, rolling, and recursive time-varying Granger causality test statistics. This chart shows that the direction of causality being tested runs from excess speculation to the sector returns of grains and oilseeds.

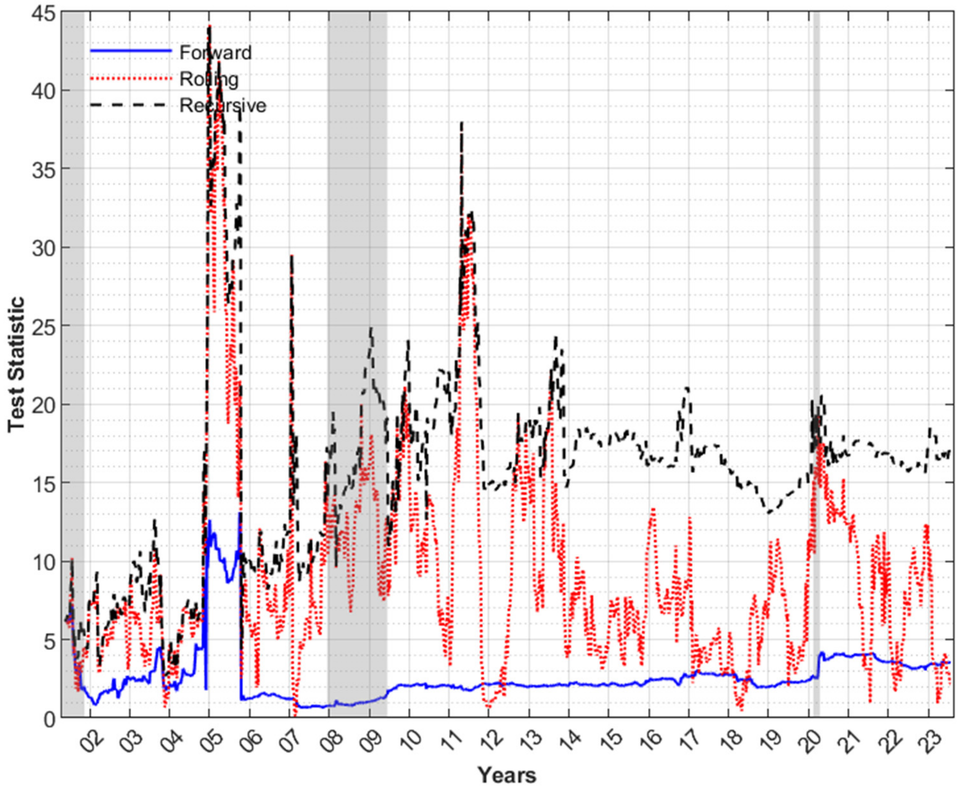

Figure A8. Forward, rolling, and recursive time-varying Granger causality test statistics. This chart shows the direction of causality being tested, which runs from excess speculation to the sector returns of livestock.

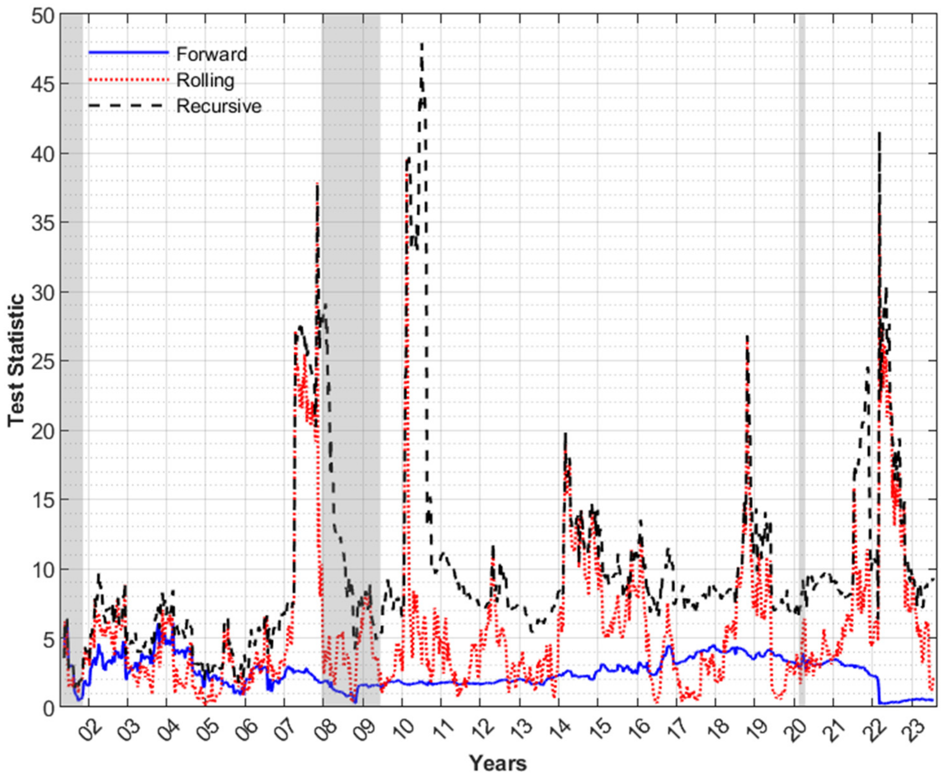

Figure A9. Forward, rolling, and recursive time-varying Granger causality test statistics. This chart shows that the direction of causality being tested runs from excess speculation to the sector returns of energy.

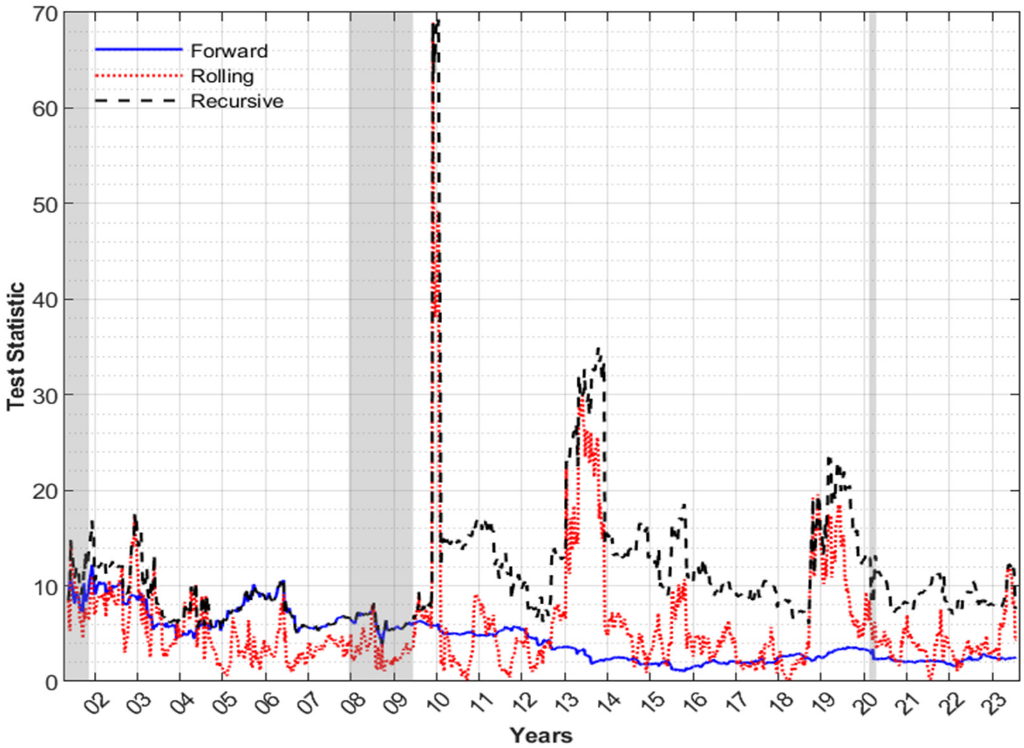

Figure A10. Forward, rolling, and recursive time-varying Granger causality test statistics. This chart shows that the direction of causality being tested runs from excess speculation to the sector returns of precious metals.

Notes

1 Here, financialization refers to the mid-2000s explosion of flows from non-commercial and non-hedging activities, deemed speculative capital, among commodity index traders (CITs) and other types of funds (Baker et al., 2018).

2 Singleton (2014) finds both economically and statistically significant effects from investor flows on oil futures prices, with the largest economic impacts coming from the growth in index positions and professionally managed spread positions. In a similar vein, Hamilton and Wu (2014) find significant changes in the risk premium of oil futures post-financialization. Specifically, the compensation to long positions has become smaller over time, which is consistent with the claim that indexed commodity investing has become more important relative to commercial hedging in determining oil futures risk premiums.

3 Data limitations constrain the commodity universe to those listed.

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