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Financial Market Stress and Commodity Returns: A Dynamic Approach

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Abstract: This paper examines the relationship between commodity index returns and the Office of Financial Research Financial Stress Index (OFR FSI). Utilizing the S&P GSCI and its five sub-indices (agriculture, livestock, energy, industrial metals, and precious metals), we find that the causal relationship between financial market stress and commodity index returns is conditional on the sample period examined and the methodology employed. We also note that stress in financial markets has a negative relationship with commodity index returns during low commodity return states; however, during high commodity return states, financial market stress exhibits a positive relationship with commodity index returns. Our findings highlight the importance of considering a time-varying framework for analyzing commodity return dynamics.

Keywords: financial market stress; commodity index returns; S&P GSCI index; office of financial research financial stress index; time-varying Granger causality; Markov-switching

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1. Introduction

This paper examines the relationship between financial market stress and commodity index returns using weekly data spanning January 2000 to July 2023. Financial market stress refers to periods of instability, uncertainty, or distress, often characterized by increased volatility, liquidity shortages, and declining asset prices. We utilize the Office of Financial Research's monitoring tools (Office of Financial Research, 2023) to measure stress in global financial markets. The Office of Financial Research Financial Stress Index (OFR FSI) is a daily market-based indicator that measures stress in global financial markets. This index is constructed from 33 financial market variables, including yield spreads, valuation measures, and interest rates.

Financial market stress can affect commodity prices through various channels, including changes in demand, supply chain disruptions, and shifts in investor sentiment to impact risk premiums, price volatility, and correlations (see [1–7]). The literature on the "financialization" of commodity markets discusses the various links between the raw commodity markets and financial markets that have emerged post-2004. Of note, ref. [8] developed a theoretical model that captures the effects of a rise in institutional investors on indexed and non-indexed commodity prices. More recently, ref. [9] provided a framework that models the interactions between commodity futures prices and the real economy in a period of acute financialization. Outside of theoretical research, numerous empirical studies highlight the impact of financialization on the commodity markets. Of particular importance, ref. [10], and more recently, ref. [11], found the growing presence of financial investors has led to higher correlations between commodity prices and traditional financial markets. Since the publication of [10], an increasing number of research studies examining the economic mechanisms and effects of financialization in commodity markets have emerged (see references in [11,12]. The supposed impacts of financialization on the commodity markets are, of course, not without controversy (see [13,14]).

Early work by [15] demonstrated that financial market stress can influence the volatility and movement of commodity prices. Ref. [16] document that during periods of significant financial stress, commodity prices tend to decline on average. Ref. [5] find that higher levels of stress in financial markets, as proxied by the TED spread, are associated with weaker equity-commodity return correlations, suggesting that during periods of elevated stress, commodity returns tend to be negatively affected. Further, ref. [17] relate the strength of the correlation between financial market stress and commodity returns to the exposure of spot commodity prices and macroeconomic shocks, providing valuable insights into the underlying mechanisms of this relationship. Recently, ref. [7] found that an increase in financial market stress leads to persistent increases in the volatility of commodity indexes and individual prices. However, the destabilizing and persistent effects of a stress shock are conditional on the type of volatility regime.

Our work strongly complements the work of [18], who discuss the channels in which volatility may affect commodity prices, as well as the persistent impact of distress through these channels. Their work shows that hedgers' and financial traders' shocks induce opposite correlations between futures price changes and financial traders' position changes. Specifically, financial traders reduce their risk exposures in commodity futures markets during heightened market volatility, as reflected by the VIX, whereas hedgers reduce their net short positions in response to falling prices. These findings provide valuable insights into how shocks and market dynamics influence risk sharing and price movements in commodity markets, highlighting the complex interplay between different market participants. Our work also aligns with the recent study of [7], who examined the impact of financial market stress on commodity market price volatility. Notably, they found that an increase in stress leads to a sustained increase in both commodity index and individual commodity price volatility. In a similar spirit, we examine the impact of such stress in the financial markets on the returns to commodity indexes, often utilized by commodity index traders. Moreover, our work explores the directional causality of financial market distress. We employ a Markov-switching framework and time-varying Granger causality test, developed by [19], to examine these relationships. Our three main findings can be summarized as follows.

First, we find that higher levels of financial market stress tend to result in increased volatility of commodity returns. This applies both to the broad S&P GSCI commodity index and the sub-indices, indicating that stress affects a broad range of commodities. This finding is consistent with [7], who found a positive relationship between commodity price volatility and market stress. Second, financial market stress affects commodity returns negatively in low returns states (state 1) and positively in high returns states (state 2). The probability of a given commodity index remaining in either return state is, on average, quite high, with the notable exception of the Livestock sub-index. Third, and finally, dynamic Granger causality generally runs in both directions. While the conventional Granger causality results indicate causality only runs from financial market stress to the commodity markets, the time-varying Granger causality tests indicate Granger causality runs in both directions, from financial market stress to the commodity markets and vice versa. This latter result contrasts with [20], who studied time-varying Granger causality between crude oil and China's agricultural futures. Though the scope of their work is narrower, they found unidirectional Granger causality running from crude oil futures to agricultural product futures.

This paper contributes to the existing literature in three distinct ways. First, we conduct an in-depth analysis of the dynamic relationship between financial market stress and diverse baskets of commodity indices. While previous studies, including those of [21–23], have explored financial factors in relation to macroeconomic dynamics, our approach is notably distinct. Like [7], our study examines the effects of financial market stress on commodity volatility, but we diverge in both methodology and focus. Second, our research stands apart from [24,25], who investigate the connection between market stress and crude oil volatility, as the scope of our work is broader and encompasses a wider range of commodities for analysis. Moreover, we employ the time-varying Granger causality test. This innovative approach allows us to analyze the evolving relationship more accurately between financial market stress and commodity returns. Unlike the traditional static methods, this technique offers a more dynamic and comprehensive understanding of how stress impacts commodity markets over time. Third, our paper is the first to integrate the OFR FSI, a comprehensive gauge of global financial market stress, into a dynamic Markov-switching regression model. This innovative approach permits the exploration of varying dynamic relationships between financial market stress and commodity returns across hidden states through state-dependent parameters. This is particularly effective in addressing structural breaks or phenomena involving multiple states. Utilizing this framework, we evaluate the correlation between market stress and commodity returns under different state conditions.

We aim to provide a more granular look at risk and return behavior of commodities, allowing portfolio managers and policymakers to obtain unique insights that are not obvious at first glance. For instance, ref. [26] note that a cyclical relationship between stock and commodity markets can last for decades, but that during these cycles the relative strength of the relationship between the market's ebbs and flows. For instance, when the relative strength between the two markets is in an uptrend, stocks significantly outperform commodities; however, during a downtrend the inverse is true. In a similar spirit, while it is well-documented that increased financial market stress increases commodity price volatility, we demonstrate that such stress affects commodity returns distinctly in different return states. Furthermore, we highlight that causality can flow bidirectionally when you incorporate a dynamic framework. Such information can assist portfolio managers in optimizing asset allocation, especially in diversifying portfolios for different states and hedging against market volatility. For policymakers, they can leverage the causality findings of this study to better understand the broader economic implications of financial market stress, aiding in the development of more effective economic policies and regulations.

The remainder of the paper is organized as follows: Section 2 discusses the data, Section 3 outlines our methodology, Section 4 reviews the empirical results, and Section 5 provides concluding remarks.

2. Data

2.1. Commodity Data

We utilize weekly returns from the S&P GSCI and its corresponding sub-indices. The sub-indices represent five distinct areas of the commodity markets, namely, agriculture, energy, industrial metals, livestock, and precious metals. The data are retrieved from Barchart and span the period from January 2000 to July 2023.

2.2. Financial Stress Proxy

We use the OFR FSI as the proxy for financial market stress. The OFR FSI computes the levels of financial stress contributed by three regions: the United States, other advanced economies, and emerging markets. The OFR FSI serves as a daily market-based snapshot, capturing stress in the global financial markets. It is carefully constructed from 33 diverse financial market variables from five broad categories, including credit (measuring borrowing costs and default risk), equity valuation (reflecting investor confidence), funding (assessing ease of institutional funding), safe assets (indicating shifts to stable holdings in times of stress), and volatility (measuring market uncertainty). For a full list of 33 indicators used to construct the OFR FSI, please refer to the indicators table see [27]. The principal objective of the OFR FSI is to quantify systemic financial stress, pinpointing disruptions in the routine operations of financial markets. The value of the OFR FSI represents the weighted average level of its input variables as observed in the market, against its historical context. The index is normalized so that a zero value indicates that broad financial stress levels are within normal bounds. When the OFR FSI is positive, stress levels are considered above average. In contrast, when the index is negative, stress levels are below average; during normal economic periods, the index will typically register lower values. Importantly, the index is recalculated after the close of each U.S. trading day to ensure it reflects the most current market conditions.

2.3. Control Variables

When examining the association between financial market stress and returns, it is important to control for exogenous economic events that may impact commodity supply and demand. To this end, we create three dummy variables that capture recessionary periods, the COVID-19 pandemic, and the recent European war. The recession dummy variable is assigned a value of one during the three recession dates delineated by the National Bureau of Economic Research (NBER) during our sample period—specifically, 31 March 2001 to 1 December 2001; 31 December 2007 to 1 July 2009; and 2 February 2020 to 1 May 2020. During all other times, the variable takes a value of zero. The COVID-19 dummy variable denotes the period when most of the world's major economies were shuttered due to the rapid spread of the virus. Specifically, the variable takes a value of one from 15 March 2020 to 15 March 2021 and is zero otherwise. Finally, the European war dummy variable takes the value of one following Russia's invasion of Ukraine on 24 February 2022 and is zero otherwise.

3. Methodology

We use three econometric tools to examine the relationship between financial market stress and commodity returns. They include Markov-switching models, the static Vector Autoregressive (VAR) based Granger causality test, and the time-varying Granger causality test. Markov-switching models are particularly useful in examining the relationship between market stress and commodity prices due to their ability to capture the dynamic and non-linear nature of the relationship. Our dynamic model is specified in the following Equation (1):

$$y_t = \mu_{s_t} + \mathbf{x}_t\boldsymbol{\beta} + z_t\boldsymbol{\theta}_{s_t} + \epsilon_s \tag{1}$$

where, y_t is the index of commodity returns, μ_{s_t} is the state-dependent intercept, $\mathbf{x}_t$ is a vector of exogenous variables with state-invariant coefficients $\boldsymbol{\beta}$, $\boldsymbol{z_t}$ is a vector of exogenous variables with state-dependent coefficients $\boldsymbol{\theta}_{s_t}$, and ϵ_s is an independent and identically distributed (i.i.d.) normal error with mean zero and state-dependent variance σ^2. Based on both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), we fit a two-state dynamic model with state-dependent variances. We examine the fitted model for its adequacy by examining the estimated coefficients and residual series. We confirm that our residual series behaves much like white noise based on the QQ plot, ACF tests, and Ljun-Box statistics.

The Granger causality test necessitates that unit root and cointegration tests be carried out before applying the causality tests; therefore, we test each regression variable in Section 4.3 for the existence of a unit root in the level and first difference. We utilize three different tests, namely the augmented Dickey–Fuller, Phillips–Perron, and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) tests. We examine whether each variable is trend-stationary or difference-stationary. Commodity index returns and the first difference of the measure of financial market stress are confirmed stationary(for a detailed discussion of the unit root tests, see Appendix A and the results in Table A1). We perform Granger causality tests for each equation using the following bivariate VAR(m) model in Equation (2).

$$\boldsymbol{y}_t = \boldsymbol{\beta}\mathbf{x}_t + \epsilon_t \tag{2}$$

where, $\boldsymbol{y_t} = [r_t, fsi_t]$ represents a matrix of commodity index returns and financial market stress index, $\mathbf{x}_t$ represents the lag values of the commodity index returns and financial market stress index, $\boldsymbol{\beta}$ is a vector of estimated coefficients on the lag values of the independent variables, and ϵ_t is the serially uncorrelated error terms.

We employ the Sequential Likelihood Ratio Test in conjunction with several information criterions, including the AIC, BIC, and the Hannan-Quinn (HQ) Criterion, to determine the optimal order for our Vector Autoregression (VAR) model. To validate the adequacy of our fitted VAR model, we ensure most of the estimated parameters are statistically significant. Additionally, we verify that the residuals of the VAR exhibit neither cross-sectional nor serial correlations, contain no extreme outliers, and conform to the assumptions of multivariate normality. Our comprehensive testing, which includes a Parameter Stability Test, a Portmanteau Test for residual cross-correlation, and a Jarque-Bera Test, indicates that an order of four is most appropriate for the VAR model.

After fitting a VAR (4), we test whether one variable "Granger-causes" another using the Wald test. The financial market stress index is said to Granger-cause commodity index returns if, given the past values of commodity index returns, past values of the financial market stress index are useful for predicting returns. The Wald statistic tests the null hypothesis that the estimated coefficients on the lagged values of financial market stress are jointly zero. Failure to reject the null hypothesis is equivalent to failing to reject the hypothesis that market stress does not Granger-cause commodity returns. Similarly, we use the Wald statistic to test if past values of commodity index returns provide valuable information for predicting financial market stress. Failure to reject the null hypothesis implies that returns do not Granger-causes market stress.

For the time-varying Granger causality test, we use the test developed by [28,29]. The time-varying Granger causality test utilizes the Wald test statistic of bivariate VAR(m) as specified in Equation (2). Ref. [19] provide mathematical expressions for test statistics and methodology. It is based on recursive testing algorithms. Under the recursive testing algorithms, a sequence of test statistics of Granger causality—one for each period of interest—is computed. Three algorithms are utilized to produce a series of test statistics: the forward expanding (FE) window, the rolling (RO) window, and the recursive evolving (RE) window (see [19] for details). In the FE algorithm, the Wald test statistic is calculated using a minimum window length first. Subsequently, the sample size is incrementally expanded, adding one observation at a time. This process continues until the sample encompasses the entire dataset, at which point the final Wald test statistic is computed. This systematic expansion allows for a comprehensive analysis of the data, ensuring that the test statistic incorporates information from the entire sample. In the RO algorithm, a window of fixed size 'n' traverses the sample, progressing one observation at a time. At each position, a Wald test statistic is calculated for the data within the window. Finally, under the RE algorithm, a test regression is run for every possible subsample of size 'n' or larger, with the observation of interest providing the common endpoint of all subsamples. The procedure is iteratively applied, with each point in the sample considered as the observation of interest while adhering to the constraint of the minimum window size. Consequently, each observation in the sample, excluding the initial subsample that establishes the minimum window size, will be linked to a corresponding 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 found along the main diagonal of the matrix. Lastly, the maximum RE statistic is determined by identifying the largest value within the entire upper triangular portion of the matrix. The test of the null hypothesis is whether financial market stress (commodity index returns) does not Granger cause commodity index returns (financial market stress) at any time during the sample. The alternative hypothesis is that evidence of Granger causality exists at some time in the sample based on the empirical distribution of the test statistics computed under the null hypothesis by bootstrapping. If the test statistics are greater than the 95th or 99th percentiles, one would reject the null hypothesis of no Granger causality at the 5% or 1% levels, respectively.

4. Empirical Findings

4.1. Commodity Indices and Their Performance

The S&P GSCI commodity index and its sub-indices are production-weighted indices that evaluate the performance of the commodity market using futures contracts, with their design reflecting the importance of each constituent commodity to the global economy. They serve as benchmarks for commodity market performance, highlighting the economic value of the physical components. For a futures contract to qualify for inclusion in the S&P GSCI, it must be denominated in U.S. dollars and reference a physical underlying commodity. Additionally, the contract must be traded via a facility that is based in a country belonging to the Organization for Economic Cooperation and Development (for more information about the S&P GSCI indices and respective methodology, please refer to: https://www.spglobal.com/spdji/en/indices/commodities/sp-gsci/#overview (accessed on 9 August 2023).

The S&P GSCI is comprised of a total of 24 commodity futures contracts spanning five sectors. It is a weighted-average reflection of the overall performance of the commodity market. Table 1 displays the relevant sub-indices, their constituent commodities, and the reference percentage dollar weights included in the S&P GSCI. The S&P GSCI includes seven agricultural commodities, three livestock commodities, six energy commodities, five industrial metals commodities, and two precious metals commodities. As is common with commodity indexes, the S&P GSCI is heavily weighted towards the energy sector, accounting for 61.47% of its total weight. The balance of the index is composed as follows: agriculture, industrial metals, livestock, and precious metals sectors make up 17.97%, 10.57%, 5.86%, and 4.13%, respectively.

Table 1. Contracts and Contract Production Weights of S&P GSCI.

Sub−Index	Commodities	2023 Percentage Dollar Weights
Agriculture	Wheat	4.81
	Corn	5.66
	Soybeans	3.60
	Coffee	0.93
	Sugar	1.45
	Cocoa	0.25
	Cotton	1.27
Energy	WTI Crude Oil	21.83
	Heating Oil	4.62
	RBOB Gasoline	4.60
	Brent Crude	19.94
	Oil Gasoil	5.76
	Natural Gas	4.72
Industrial Metals	Aluminum	3.80
	Copper	4.35
	Nickel	0.98
	Lead	0.49
	Zinc	0.95
Livestock	Lean Hogs	1.83
	Live Cattle	2.98
	Feeder Cattle	1.05
Precious Metals	Gold	3.74
	Silver	0.39

This table shows the commodities included in the S&P GSCI and their contract production weights. Data is obtained from S&P Dow Jones Indices (https://www.spglobal.com/spdji/en/methodology/article/sp-gsci-methodology/ (accessed on 9 August 2023)).

We evaluate a variety of in-sample performance metrics for the S&P GSCI and its sub-indices, utilizing the S&P 500 equity index as a benchmark when appropriate. The value of analyzing each sub-index is that it provides a measure of specific sector performance within the overall commodity market. To compute weekly returns, we first calculate a daily return series, r_d, for each commodity index/sub-index by taking the natural log difference of daily prices on two consecutive trading days, $\mathrm{r_d} = \mathrm{Ln}(\mathrm{P_d}) - \mathrm{Ln}(\mathrm{P_{d-1}})$. Next, we compound the daily return into a cumulative weekly return, $R_{it} = \sum_{i=1}^{eow} r_{id}$, where "eow" refers to the end of the week, Friday to Friday. The descriptive statistics are presented in Table 2 (the mathematical formulas used for each measure can be found in [30]). The annualized arithmetic mean return for the S&P GSCI stands at 4.84%. Among the various sub-indices, precious metals have the highest arithmetic mean return of 7.98%, followed by energy at 5.04%. The precious metals sub-index also has the highest adjusted Sharpe ratio (34.27%) and cumulative returns (188.52%). In contrast, livestock has the lowest adjusted Sharpe ratio (10.86%) and cumulative returns (83.31%). In terms of volatility, measured by standard deviation, the energy sub-sector is the most volatile (35.59%), while livestock is the least (16.82%).

Table 2. Descriptive Statistics of S&P GSCI Commodity Index and Sub-Indices.

Statistic	S&P GSCI	Agriculture	Energy	Industrial Metals	Livestock	Precious Metals
Arithmetic Mean	4.84%	4.47%	5.04%	3.90%	3.53%	7.98%
Geometric Mean	1.83%	2.40%	−1.55%	1.89%	2.11%	6.41%
Std. Dev.	24.38%	20.31%	35.59%	20.00%	16.82%	17.72%
Skewness	−50.21%	−0.55%	−65.34%	−24.60%	−26.79%	−31.71%
Kurtosis	346.26%	160.34%	1204.30%	230.38%	231.24%	311.36%
Adj. Sharpe Ratio	12.74%	13.65%	9.28%	10.99%	10.86%	34.27%
Cumulative Returns	114.26%	105.48%	119.11%	92.12%	83.31%	188.52%
CAPM Alpha	1.31%	1.97%	1.16%	0.73%	3.17%	0.00%
CAPM Beta	44.25%	31.29%	48.68%	39.68%	4.42%	100.00%
M Square	4.09%	4.23%	3.44%	3.75%	3.72%	8.30%
Tracking Error	27.18%	25.93%	36.75%	23.22%	24.13%	25.25%
Sharpe % Change	−14.54%	−3.01%	−43.29%	−17.58%	−4.10%	35.28%

This table displays the annualized descriptive statistics of the S&P GSCI returns and its sectoral sub-indices over the sample period from January 2000 to July 2023. The S&P 500 returns are used to compute CAPM alpha, CAPM beta, M square, Tracking error, and Sharpe ratio percentage change. The GSCI index and sub-indices price data are obtained from Barchart (https://www.barchart.com/stocks/indices/commodity (accessed on 9 August 2023)).

For the calculation of CAPM alphas and betas, we use commodity index returns as the dependent variable and the S&P 500 equity index as the independent variable. Observing the beta values, the S&P 500 GSCI exhibits a strong correlation with the broad stock market. Furthermore, we assess the Sharpe ratio for each commodity index both independently and in conjunction with the S&P 500 equity market index. As shown in the "SR % Change" row, our analysis reveals a general decline in the Sharpe ratio of the commodity portfolios when the equity market index is incorporated into most of the commodity indices; the only sub-index that shows improvement is precious metals.

4.2. Commodity Indices and Financial Market Stress

We further explore the connection between commodity indices and financial market stress by simply plotting commodity index prices against aggregate levels of the OFR FSI. In Figure 1, the left y-axis denotes commodity index/sub-index prices, and the right y-axis represents the value of stress in the global financial markets. The x-axis represents the year of the sample period. It is readily apparent there is a negative relationship between commodity index/sub-index prices and market stress; performance of the commodity indices is generally low or negative when the stress level is high, indicating widening credit spreads, falling stock market values, difficulties for financial institutions in obtaining funding, high valuations for safe assets as investors seek to reduce risk, and increased market volatility. Despite the observable negative correlation between price performance and financial market stress across all groups, the magnitude of the relationship appears heterogeneous. For instance, during periods of high stress, the poor performance of the energy sub-index is considerably worse than, say, the precious metals sub-index.

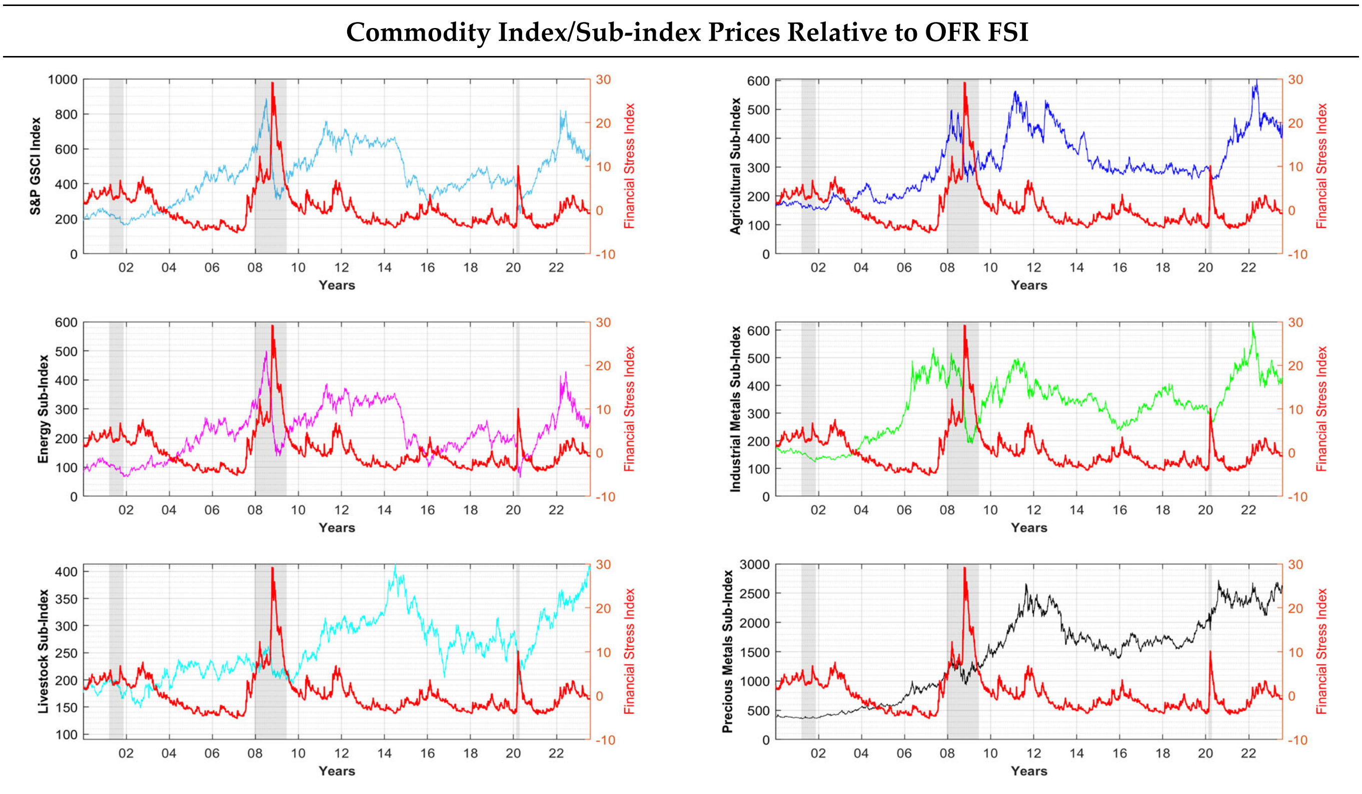

Figure 1. This figure shows the weekly prices of the S&P GSCI commodity index and its sectoral sub-indices plotted against the financial stress index. The sample period spans January 2000 to July 2023. Shaded bars represent recession periods in the United States. The red line represents the financial stress index, which is plotted against the right y-axis. The S&P GSCI index and sub-indices price data are plotted on the left y-axis. Commodity index data was obtained from Barchart, and the financial stress index data was retrieved from the Office of Financial Research (https://www.financialresearch.gov/financial-stress-index/ (accessed on 8 August 2023)).

Table 3 provides a detailed breakdown of in-sample return statistics for the S&P GSCI and its corresponding sub-indices during varying levels of financial market stress. The table is segmented into four quartiles based on aggregate financial stress index readings, with descriptive statistics compiled for each quartile accordingly. The first quartile summarizes index returns when the OFR FSI observations are in the bottom 25% of observations, thus corresponding to periods of low stress. In contrast, the fourth quartile summarizes index returns when the OFR FSI observations are in the top 25% of observations, correlating with periods of high stress. Consistent with the observations in Figure 1, the returns to the commodity index/sub-indices are, on average, higher in periods of low financial market stress (first quartile) and lower in periods of high financial market stress (fourth quartile). For instance, the S&P GSCI average weekly returns are 0.41% in the first quartile, whereas they drop to −0.32% in the fourth quartile. A similar trend is observable across all sub-indices. What is more, when compared to the first quartile, the fourth quartile displays substantially more variation in commodity returns, as evidenced by the higher standard deviation and more extensive range of weekly returns.

Table 3. Return Statistics in Different Quartiles of Financial Market Stress.

	Mean	Std. Dev.	Min.	Median	Max.
First Quartile					
S&P GSCI	0.41	2.44	−6.64	0.51	7.80
Agriculture	0.19	2.46	−7.77	0.29	8.34
Energy	0.49	3.35	−10.34	0.64	9.89
Industrial Metals	0.59	2.54	−10.47	0.65	11.87
Livestock	0.17	2.10	−5.59	0.05	7.45
Precious Metals	0.22	2.18	−9.44	0.36	5.89
Second Quartile					
S&P GSCI	−0.11	2.75	−12.17	0.06	7.26
Agriculture	−0.06	2.39	−7.45	0.00	10.31
Energy	−0.14	3.98	−15.96	0.16	11.7
Industrial Metals	−0.17	2.40	−11.03	−0.23	6.88
Livestock	0.10	2.26	−8.19	0.23	6.63
Precious Metals	−0.11	2.30	−13.83	0.13	5.59
Third Quartile					
S&P GSCI	0.39	3.45	−17.11	0.40	14.57
Agriculture	0.37	2.97	−12.14	0.30	11.19
Energy	0.45	4.92	−26.03	0.40	19.12
Industrial Metals	0.26	2.73	−10.72	0.52	8.80
Livestock	0.00	2.33	−11.90	0.17	6.13
Precious Metals	0.41	2.29	−7.61	0.50	5.83
Fourth Quartile					
S&P GSCI	−0.32	4.48	−19.92	0.16	17.47
Agriculture	−0.15	3.33	−12.59	−0.09	10.31
Energy	−0.43	6.77	−46.07	0.32	41.48
Industrial Metals	−0.38	3.25	−14.22	−0.45	12.72
Livestock	0.00	2.60	−10.64	−0.07	12.86
Precious Metals	0.10	2.96	−11.26	0.02	14.14

This table presents the weekly return statistics of the S&P GSCI and its sub-indices in different states of financial stress. The sample is divided into four quartiles based on the measure of the financial market stress index, and the return descriptive statistics are reported for each quartile. All figures are reported as percentages. The S&P GSCI and sub-indices data are obtained from Barchart (https://www.barchart.com/stocks/indices/commodity (accessed on 9 August 2023)). The measure of the financial stress index was retrieved from the Office of Financial Research (https://www.financialresearch.gov/ (accessed on 8 August 2023)).

The second quartile represents a scenario of relatively lower financial stress compared to the third quartile. However, the data shows that commodity returns in the third quartile outperform those of the second quartile, on average. For example, the S&P GSCI has an average weekly return of −0.11% in the second quartile, while in the third quartile, it registers a weekly average return of 0.39%. Similarly, the agriculture, energy, industrial metals, and precious metals sub-indices all post average weekly returns of 0.37%, 0.45%, 0.26%, and 0.41%, respectively, in the third quartile; yet, have average returns of −0.11%, −0.06%, −0.14%, −0.17%, and −0.11% in the second quartile, respectively. Consistent with expectations, overall volatility of the index/sub-indices is higher in the third quartile compared to the second quartile. For instance, the range of S&P GSCI returns is 19.43% in the second quartile, while in the third quartile, it expands to 31.68%.

4.3. Overall Descriptive Statistics

Table 4 provides descriptive statistics of the dependent and independent variables used in the regression analysis. The sample encompasses 1231 observations over the full period spanning from January 2000 to July 2023. On average, the S&P GSCI returns 0.09% weekly. The precious metals sub-index has the highest average weekly return of 0.15%, with the energy sector following closely behind at 0.10%. Volatility is highest in the energy sector index at 4.93%, while the livestock sub-index is the least volatile at 2.33%. Median returns are greatest for the energy sub-index at 0.41%, trailed closely by the S&P GSCI at 0.31%, and the precious metals sub-index at 0.24%.

Table 4. Descriptive Statistics of Regression Variables.

Variable	Obs.	Mean	Std. Dev.	25th Perc.	Median	75th Perc.
S&P GSCI	1231	0.09	3.38	−1.74	0.31	2.18
Agriculture	1231	0.09	2.82	−1.69	0.11	1.65
Energy	1231	0.10	4.93	−2.50	0.41	2.91
Industrial Metals	1231	0.08	2.77	−1.46	0.10	1.78
Livestock	1231	0.07	2.33	−1.28	0.11	1.54
Precious Metals	1231	0.15	2.46	−1.26	0.24	1.60
OFR FSI	1231	0.19	4.29	−2.88	−0.78	2.14

This table shows the weekly descriptive statistics of commodity index/sub-index returns and the global financial market stress index over the full sample period of January 2000 to July 2023. All figures, except observations, are reported as percentages. The S&P GSCI and sub-indices data are obtained from Barchart (https://www.barchart.com/stocks/indices/commodity (accessed on 9 August 2023)). The measure of the financial market stress index was retrieved from the Office of Financial Research (https://www.financialresearch.gov/ (accessed on 8 August 2023)).

Table 5 displays the pair-wise correlations of the data. The correlation matrix reveals a very strong positive relationship between the S&P GSCI and the energy sub-index; this is not too surprising given the substantial weight of the sub-index in the S&P GSCI. There is also a substantial positive correlation of 0.46 between the weekly returns of the S&P GSCI and the agriculture sub-index. Finally, the correlation between the financial market stress index (OFR FSI) and all commodity indices is negative and statistically significant, apart from precious metals.

Table 5. Pairwise Correlations.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) S&P GSCI	1.00						
(2) Agriculture	0.46 ***	1.00					
(3) Energy	0.97 ***	0.32 ***	1.00				
(4) Industrial Metals	0.47 ***	0.32 ***	0.36 ***	1.00			
(5) Livestock	0.17 ***	0.08 ***	0.11 ***	0.09 ***	1.00		
(6) Precious Metals	0.32 ***	0.27 ***	0.24 ***	0.35 ***	0.05 *	1.00	
(7) OFR FSI	−0.12 ***	−0.06 **	−0.10 ***	−0.15 ***	−0.05*	0.00	1.00

This table shows the pair-wise correlation between commodity returns and the financial stress index. The asterisks ***, **, and * represent significance levels at 1%, 5%, and 10% respectively. The S&P GSCI and sub-indices data are obtained from Barchart (https://www.barchart.com/stocks/indices/commodity (accessed on 9 August 2023)). The measure of the financial market stress index was retrieved from the Office of Financial Research (https://www.financialresearch.gov/ (accessed on 8 August 2023)).

4.4. Regression Analysis

We investigate the presence of regime-switching behavior in commodity returns and the financial market stress index. 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), Likelihood Ratio Test, AIC, and HQ Criterion. Results indicate that a model accommodative of two regimes with varying variances is most suitable.

Table 6 presents the results derived from the Markov-switching dynamic models as specified in Equation (1). The dependent variable utilized in each equation is the commodity index/sub-index returns, while the independent variables include the OFR FSI and three dummy variables discussed in Section 2.3. Results for each state-dependent mean and the constant error variance are reported. Estimates reported in the table show that all three dummy variables are statistically insignificant, except for COVID-19 for the energy sub-index. This result is likely because the OFR FSI variable is capturing the financial market stress resulting from these turbulent periods.

Table 6. Markov−switching Regression Results.

	S&P GSCI	Agriculture	Energy	Industrial Metals	Livestock	Precious Metals
Main						
Recession	−0.6555	−0.2746	−1.1878	0.3139	−0.1013	−0.3491
	(0.11)	(0.43)	(0.05)	(0.34)	(0.68)	(0.20)
COVID-19	0.7865	0.6773	1.1252	0.5587	0.8990 **	−0.0553
	(0.07)	(0.07)	(0.09)	(0.14)	(0.01)	(0.87)
European War	−0.1687	−0.0819	−0.2751	−0.2117	0.0924	−0.1414
	(0.66)	(0.80)	(0.64)	(0.51)	(0.73)	(0.61)
State 1						
OFR FSI	−0.2967 ***	−0.2020 ***	−0.3587 ***	−0.3380 ***	−0.7071 ***	−0.1236 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	−0.9429 ***	−0.4707 *	−1.1378 **	−0.3500	−5.8408 ***	0.0477
	(0.00)	(0.03)	(0.01)	(0.22)	(0.00)	(0.74)
State 2						
OFR FSI	0.2629 ***	0.2356 ***	0.3277 ***	0.0566	−0.0125	0.3359 ***
	(0.00)	(0.00)	(0.00)	(0.27)	(0.53)	(0.00)
Constant	1.1471 ***	0.8123 **	1.3380 ***	0.2885	0.1546	0.5484 *
	(0.00)	(0.00)	(0.00)	(0.11)	(0.05)	(0.03)
Volatility	2.9421	2.5677	4.5009	2.5815	2.1544	2.2646
	[2.7991–3.0924]	[2.4505–2.6903]	[4.2968–4.7146]	[2.4725–2.6952]	[2.0588–2.2544]	[2.1681–2.3654]
P11	0.4767	0.6088	0.50141	0.51860	0.1666	0.5799
P21	0.4412	0.4635703	0.3806	0.28404	0.0166	0.8574

This table reports the estimates from Markov-switching models in Equation (1). The dependent variable in each equation is commodity returns. The independent variables are the financial stress index and three additional dummy variables representing a financial recession, the COVID period, and global war. All coefficients are reported as percentages. The *p*-values are reported in parentheses. P11 provides the probability of staying in State 1, and P21 represents the probability of staying in State 2. The asterisks ***, **, and * represent significance levels at 1%, 5%, and 10% respectively. For volatility, 95% confidence intervals are given in the brackets. The S&P GSCI and sub-indices data are obtained from Barchart (https://www.barchart.com/stocks/indices/commodity (accessed on 9 August 2023)). The measure of the financial market stress index was retrieved from the Office of Financial Research (https://www.financialresearch.gov/ (accessed on 8 August 2023)).

Except for the industrial metals and livestock sub-indices in "State 2", the financial market stress variable has a statistically significant coefficient, irrespective of state. In "State 1", which is characterized by low average commodity index returns (−0.9429%), the stress variable (OFR FSI) has a negative impact on the commodity index returns. The negative coefficient on the stress variable suggests that increases in market stress result in a decrease in average commodity index returns. The coefficients on the stress variable switch to positive for all index/sub-indices in State 2, which is characterized by high average commodity index returns (1.1471%).

The transition probabilities, given by P11 and P21 in Table 6, represent the probability of staying in State 1 and State 2, respectively. Values closer to one indicate a more persistent process, whereas values closer to zero indicate a less persistent process. Given the estimated values of transition probabilities are close to 0.5 or higher, except for the livestock sub-index, return processes are equally likely to remain in State 1 and State 2. However, in the case of precious metals, the probability of staying in State 2 is quite low (1 − 0.86 = 0.14).

4.5. Granger Causality Test Results

The findings from the Granger causality tests, derived from the bivariate VAR(4) model, are presented in Table 7. The commodity index/sub-indices utilized in the VAR are presented in the first column of the table. The second column indicates the causality direction being examined, as denoted by the arrow (→). For instance, OFR FSI → Returns indicates that changes in financial market stress Granger-cause changes in commodity index returns. The Chi-Square statistics, employed to assess the null hypothesis that variable x does not Granger-cause variable y, are presented in the third column of the table. The associated *p*-values are recorded in the last table column.

Table 7. Granger Causality Tests.

Index/Sub-Index	Direction of Causality	Test Statistic (Chi-Square)	*p*-Value
S&P GSCI	OFR FSI → Returns	22.52 ***	0.0002
	Returns → OFR FSI	6.59	0.1595
Agriculture	OFR FSI → Returns	10.26 **	0.0363
	Returns → OFR FSI	2.04	0.7279
Energy	OFR FSI → Returns	18.80 ***	0.0009
	Returns → OFR FSI	5.90	0.2064
Industrial Metals	OFR FSI → Returns	35.22 ***	0.0000
	Returns→ OFR FSI	14.67 ***	0.0054
Livestock	OFR FSI → Returns	10.70 **	0.0302
	Returns → OFR FSI	0.81	0.9365
Precious Metals	OFR FSI → Returns	26.37 ***	0.0000
	Returns → OFR FSI	6.96	0.1383

This table shows the bivariate VAR(4) based Granger causality test statistics and associated *p*-values. The first column shows the S&P GSCI and its sub-indices. The second column shows the direction of causality. The third and fourth columns report Chi-square statistics and *p*-values, respectively. The asterisks ***, and ** represent significance levels at 1%, and 5% respectively. The S&P GSCI and sub-indices data are obtained from Barchart (https://www.barchart.com/stocks/indices/commodity (accessed on 9 August 2023)). The measure of the financial market stress index was retrieved from the Office of Financial Research (https://www.financialresearch.gov/ (accessed on 8 August 2023)).

Results suggest that past values of market stress contain useful information in predicting commodity index returns. Specifically, for all indices, Chi-Square test statistics are significant when testing the null hypothesis that changes in financial market stress do not Granger-cause changes in commodity returns, implying a rejection of the null hypothesis. In contrast, we fail to reject the null hypothesis that commodity index returns do not Granger-cause changes in financial market stress, with the notable exception of the industrial metals sub-index. In general, test results indicate unidirectional causality from financial market stress to commodity index returns.

Table 8 presents the results of the time-varying Granger causality tests using a VAR model, with $p = 4$ lags and $d = 1$ lag for the lag-augmented component. The first column of the table specifies the index/sub-index used in the VAR model. The second column indicates the direction of causality using the arrow (→). The last three columns present the FE, RO, and RE statistics, which are calculated through the application of the forward expanding window, rolling window, and recursive evolving window algorithms, respectively. We utilize a minimum window size of 72 observations. Bootstrap test statistics are depicted with the 95th and 99th percentiles enclosed in parentheses and brackets, respectively. These statistics are derived from 499 replications over a one-year period to maintain control size, and the Wald tests are robust to heteroskedasticity.

To assess the null hypothesis that there is no time-varying Granger causality, the test statistics are compared against the bootstrapped critical values at 5% and 1% significance levels. If a test statistic is greater than the 95th percentile of the bootstrapped empirical distribution, the null hypothesis is rejected in favor of the alternative hypothesis at the 5% significance level. Similarly, if a test statistic is greater than the 99th percentile of the empirical distribution from bootstrapping, we reject the null hypothesis of no causality and accept the alternative hypothesis. In contrast, should the test statistics fall below these critical values, one would fail to reject the null hypothesis.

Table 8. Wald Tests of Time−Varying Granger Causality.

Index/Sub-Index	Direction of Causality	Max Wald FE	Max Wald RO	Max Wald RE
S&P GSCI	OFR FSI → Returns	25.646	29.661	31.779
		(17.267)	(17.23)	(17.81)
		[23.008]	[22.622]	[23.258]
	Returns → OFR FSI	29.823	47.057	47.057
		(7.505)	(8.433)	(8.943)
		[11.25]	[12.043]	[13.416]
Agriculture	OFR FSI → Returns	8.933	22.199	24.934
		(9.819)	(10.667)	(11.554)
		[14.985]	[15.126]	[16.042]
	Returns → OFR FSI	20.016	31.696	32.319
		(7.811)	(8.483)	(8.909)
		[12.577]	[12.082]	[12.986]
Energy	OFR FSI → Returns	22.414	31.392	32.988
		(13.854)	(13.848)	(14.45)
		[19.817]	[19.718]	[21.992]
	Returns → OFR FSI	25.958	46.45	46.45
		(7.816)	(7.874)	(8.268)
		[12.327]	[12.049]	[13.078]
Industrial Metals	OFR FSI → Returns	12.733	33.088	33.672
		(19.814)	(19.667)	(21.038)
		[27.489]	[25.662]	[27.531]
	Returns → OFR FSI	22.17	42.617	46.545
		(12.234)	(12.151)	(13.22)
		[16.782]	[17.669]	[17.758]
Livestock	OFR FSI → Returns	5.567	23.423	28.107
		(9.619)	(9.879)	(10.966)
		[15.35]	[15.884]	[16.163]
	Returns → OFR FSI	20.664	86.581	88.726
		(7.641)	(8.051)	(8.531)
		[10.749]	[12.21]	[12.234]
Precious Metals	OFR FSI → Returns	17.77	22.492	25.406
		(8.072)	(8.482)	(9.335)
		[10.849]	[11.932]	[12.093]
	Returns → OFR FSI	27.808	64.684	72.907
		(8.408)	(8.565)	(9.086)
		[13.043]	[12.255]	[13.043]

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 window, the rolling window, and the 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 size. The S&P GSCI and sub-indices data are obtained from Barchart (https://www.barchart.com/stocks/indices/commodity (accessed on 9 August 2023)). The measure of the financial market stress index was retrieved from the Office of Financial Research (https://www.financialresearch.gov/ (accessed on 8 August 2023)).

The results for the full sample show that we fail to reject the null hypothesis of no Granger causality from financial stress to commodity index returns and vice versa. Specifically, the test statistic values for FE, RO, and RE, which test the null hypothesis that financial market stress does not Granger-cause S&P GSCI returns, are 25.65, 29.66, and 31.78, respectively. In contrast, the 99th percentile values for these statistics are 23.00, 22.62, and 23.25, respectively. Since the computed test statistics exceed these critical values, we reject the null hypothesis of no Granger causality and conclude that changes in market stress do, in fact, Granger cause changes in the S&P GSCI returns. Similarly, the FE, RO, and RE test statistic values for examining the null hypothesis that S&P GSCI index returns do not Granger-cause financial market stress are 29.82, 47.06, and 47.05, respectively. These values are significantly larger than their corresponding 99th percentile critical values of 11.25, 12.04, and 13.42, respectively, leading to a rejection of the null hypothesis. In contrast to Table 7, we find bi-directional causation between market stress and the S&P GSCI returns.

In general, the bi-directional nature of the relationship between stress and commodity index returns holds across all index/sub-indices, implying that changes in commodity index returns can affect various aspects of the real economy and financial markets, including asset values, inflation rates, interest rates, exchange rates, and liquidity; thus, contributing to financial market stress.

To better understand the nature of the time-varying relationship between financial stress and commodity returns, we also provide plots of time-varying Granger causality test statistics in Figure A1, located in Appendix A. The three sequences of test statistics presented in the figure (denoted by Forward, Rolling, and Recursive) are computed using the forward expanding window, rolling window, and recursive evolving window algorithms. These plots all support the conclusion that Granger-causal relationships change dramatically over any given sample period. Moreover, the observed causal patterns are influenced by the specific recursive algorithm applied.

5. Concluding Remarks

We examine the relationship between financial market stress and commodity returns using weekly data from the S&P GSCI and its five sub-indices, spanning the period from January 2000 to July 2023. Our results indicate that higher levels of stress are linked to increased volatility in commodity returns. This is evident not only in a general commodity index (S&P GSCI) but also across the various sub-indices, suggesting a widespread impact across different types of commodities. The influence of financial market stress on commodity index returns varies depending on the state of the market. In State 1, characterized by lower average returns, financial stress has a negative effect; in contrast, in State 2, characterized by higher average returns, the effect of market stress is positive.

We also examine the causality relationships between commodity index/sub-indices returns and financial market stress using both conventional and time-varying Granger causality tests. The conventional tests indicate, on average, unidirectional causality running from stress to the commodity markets. However, the time-varying tests reveal a more complex interaction, with causality running in both directions—from financial market stress to the commodity markets and vice versa. This suggests a dynamic and interdependent relationship between market stress and commodity index returns, where each can influence the other over time. Such results underscore a much more nuanced relationship between financial market stress and commodity markets—highlighting the time-varying bidirectional nature of commodity markets. These findings have implications for investors, policymakers, and analysts in predicting and responding to market changes.

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Appendix A

For augmented Dickey–Fuller and Phillips–Perron tests, the null hypothesis is that the variable is non-stationary, and the alternative hypothesis is that the variable is stationary.

We test the null hypothesis of $\beta = 1$ against the alternative hypothesis $\beta < 1$ using the following equation:

$$\Delta y_t = \alpha + \delta t + \beta y_{t-1} + \sum_{i=1}^{p} \Delta y_{t-1} + \varepsilon_t \text{ or } \Delta y_t = \alpha + \beta y_{t-1} + \sum_{i=1}^{p} \Delta y_{t-1} + \varepsilon_t$$

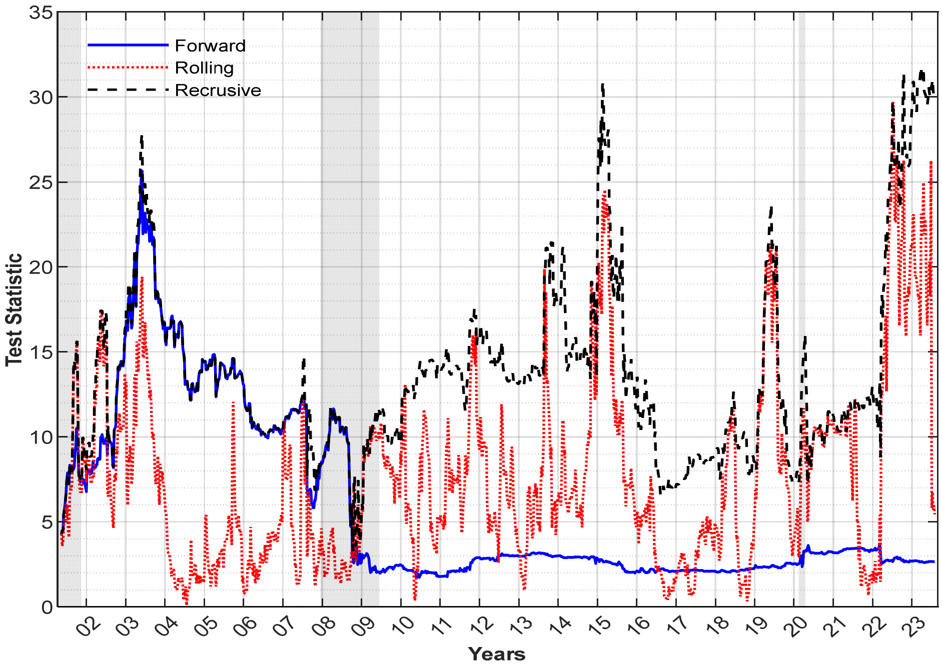
We use the following equation for the KPSS test:

$$y_t = \alpha + \delta t + z_t + \varepsilon_t \text{ or } y_t = \alpha + z_t + \varepsilon_t$$

where, the z_t is given by $z_t = z_t + u_t,\ u_t \sim iid\ N\left(0, \sigma_u^2\right)$. The KPSS hypothesis reverses the null and alternative hypotheses of the augmented Dickey–Fuller and Phillips–Perron tests. The null hypothesis is stationarity, or I(0), as $H_0 :\ \sigma_u^2 = 0$. The alternative hypothesis is $H_1 :\ \sigma_u^2 > 0$. The lag length for each test is determined by AIC/BIC.

The unit root test results are summarized in Table A1. Panel A reports the results from trend stationary applied to each variable, while Panel B reports the results from difference-stationary applied to the first difference of each variable. The findings in Panel A show that the p-values for both the augmented Dickey–Fuller and Phillips–Perron tests exceed 5% across all variables. This suggests that the null hypothesis of a unit root cannot be rejected. This inference is further corroborated by the results of the KPSS test. In contrast, Panel B reveals that the p-values for the augmented Dickey–Fuller and Phillips–Perron tests are below 5%, signifying that the variables are difference-stationary. The KPSS test results align with this conclusion, reinforcing the notion of difference stationarity in the variables. The unit root test results suggest all series are I(1) and candidates for cointegration. The tests of bivariate cointegration reveal no stable long-run relationship. Therefore, Granger causality tests and regression estimates use the index returns series.

Time-varying Granger Causality Test Statistics



(**a**)

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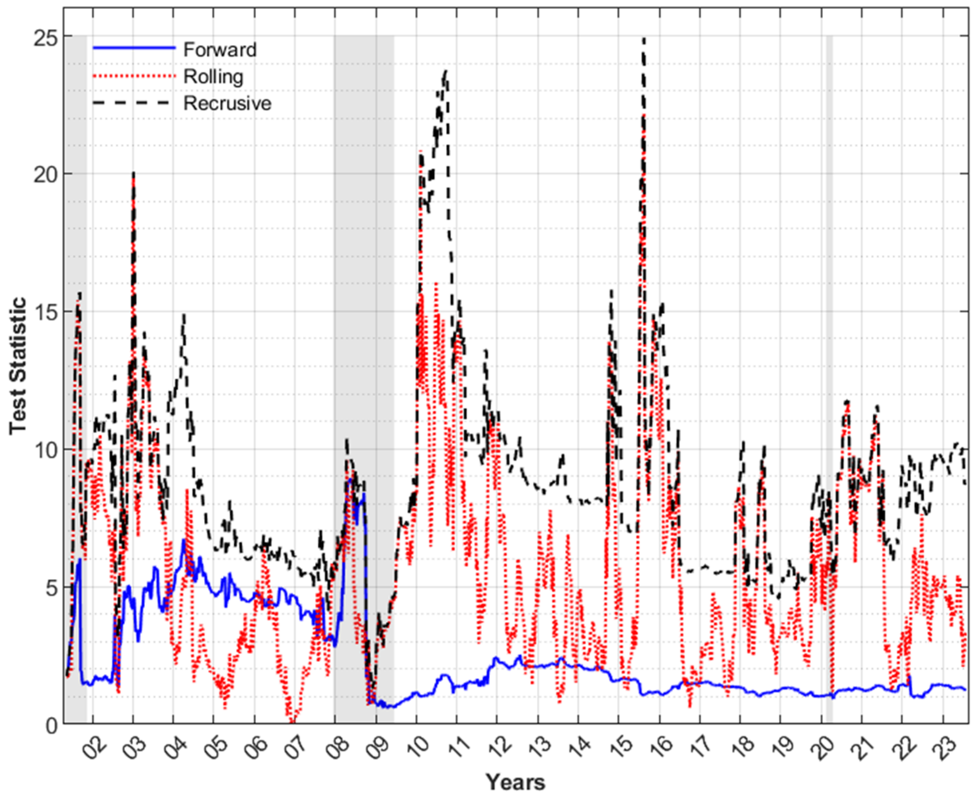

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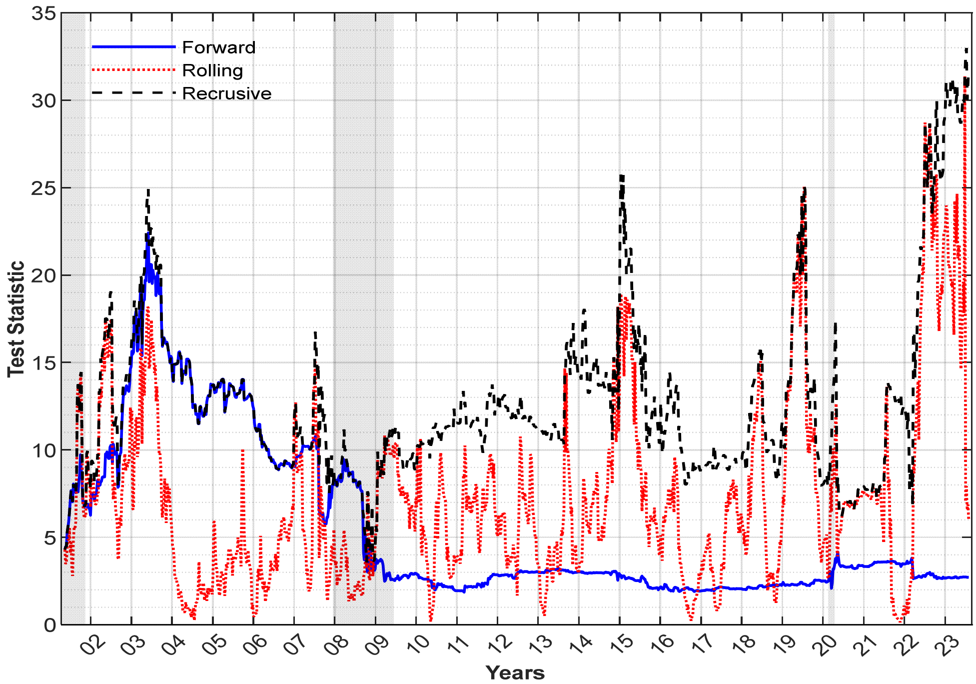

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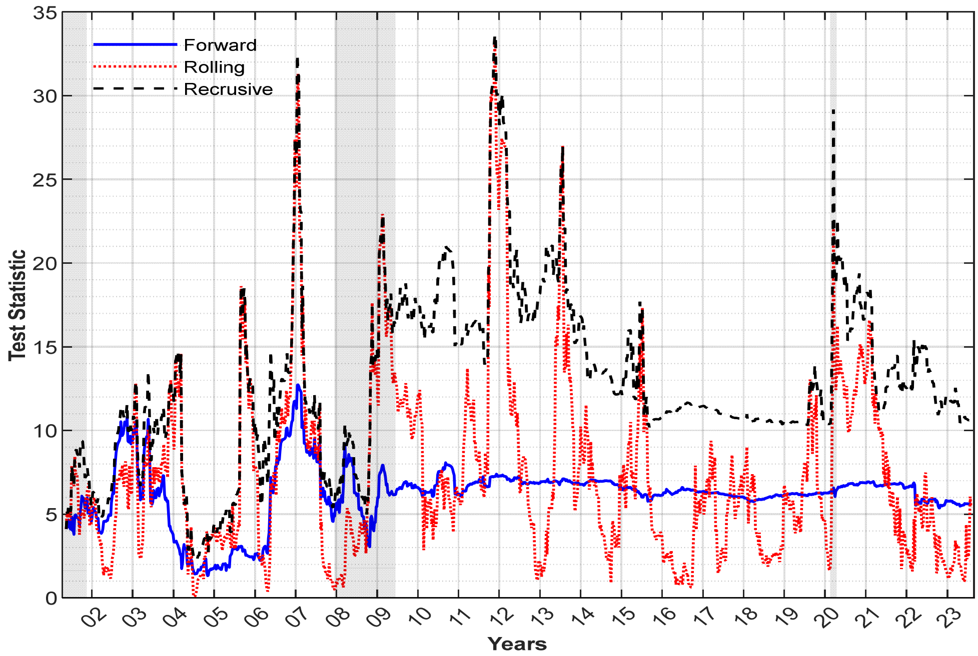

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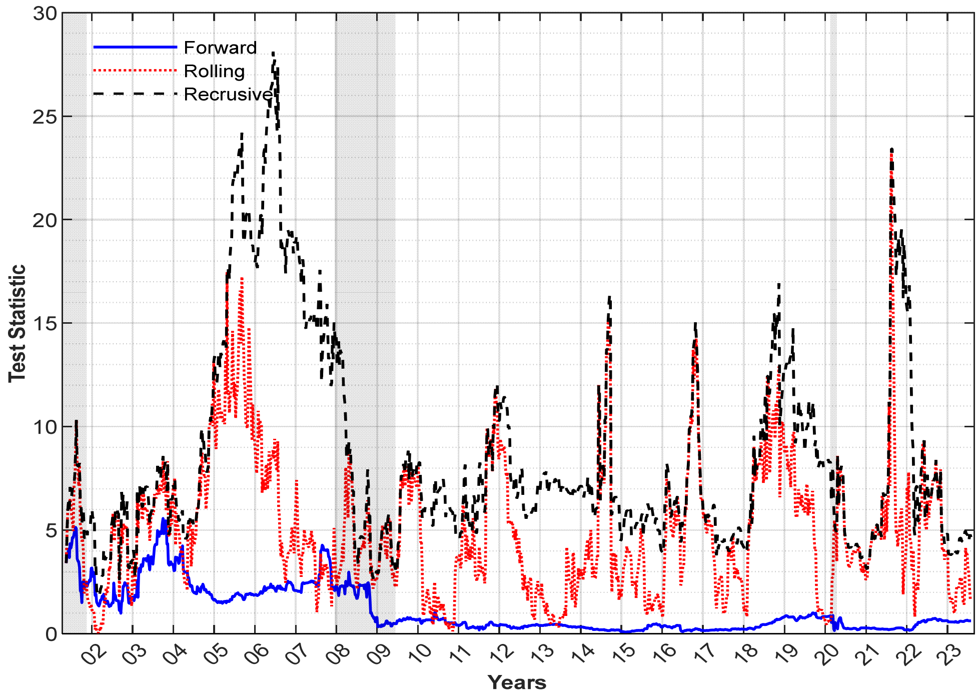

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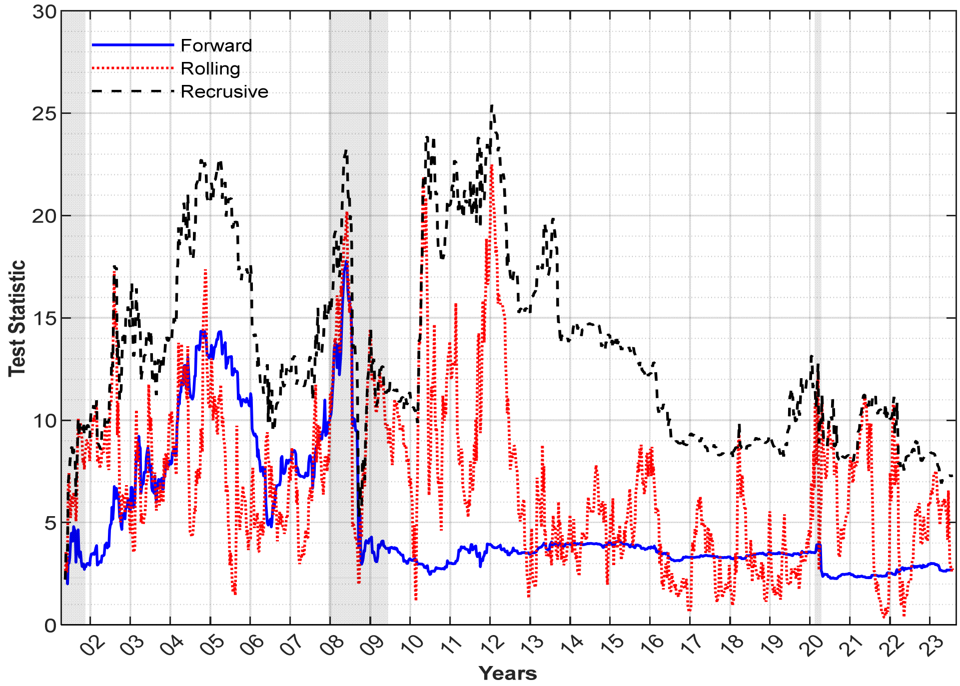

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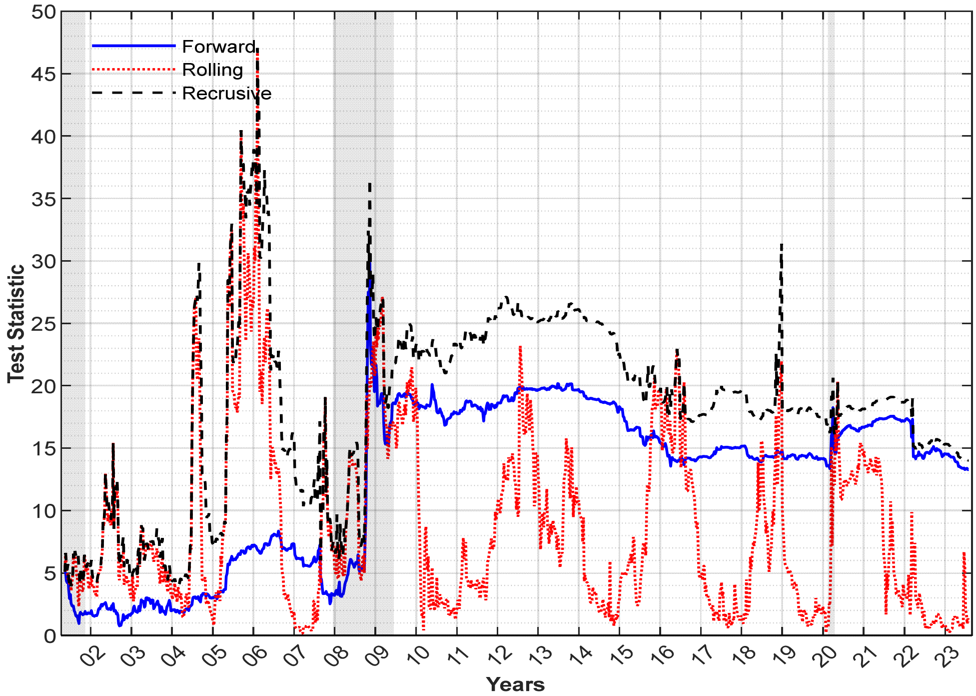

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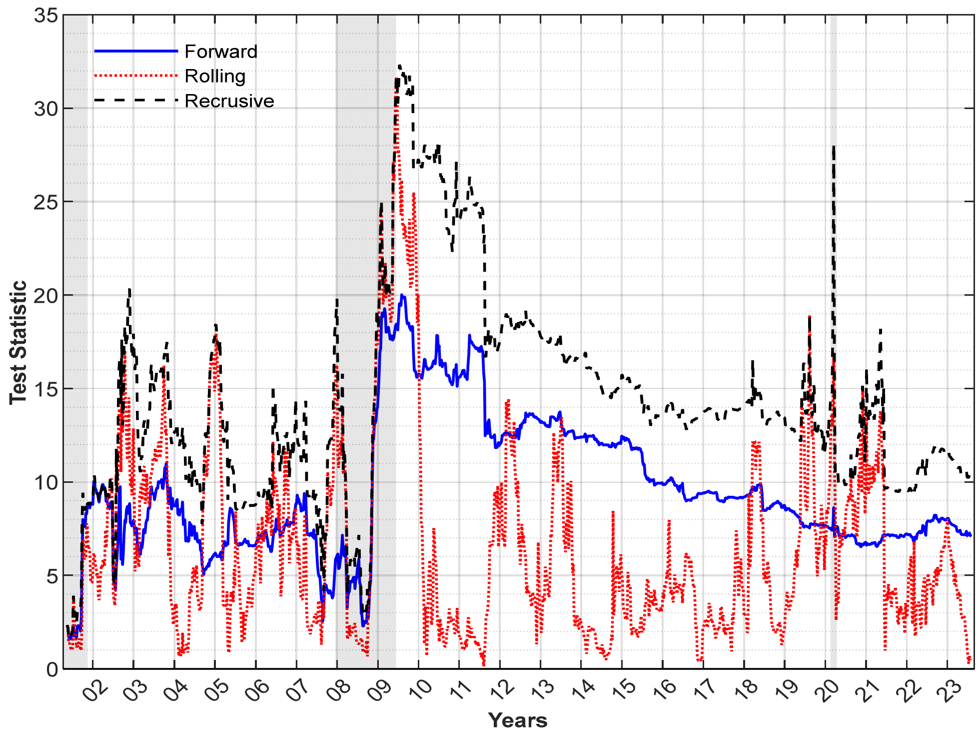

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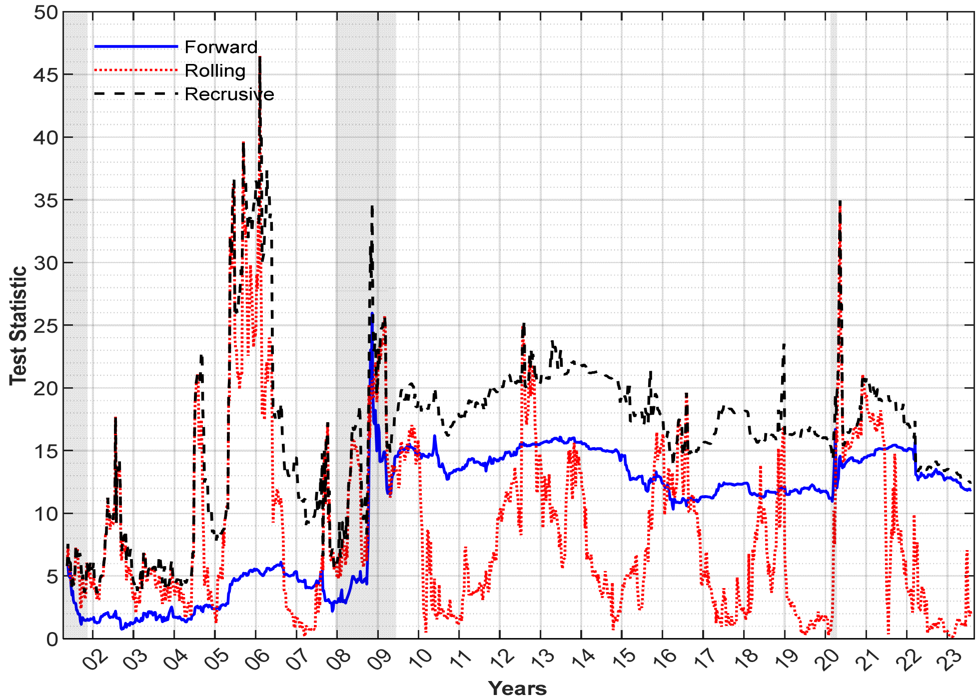

(**i**)

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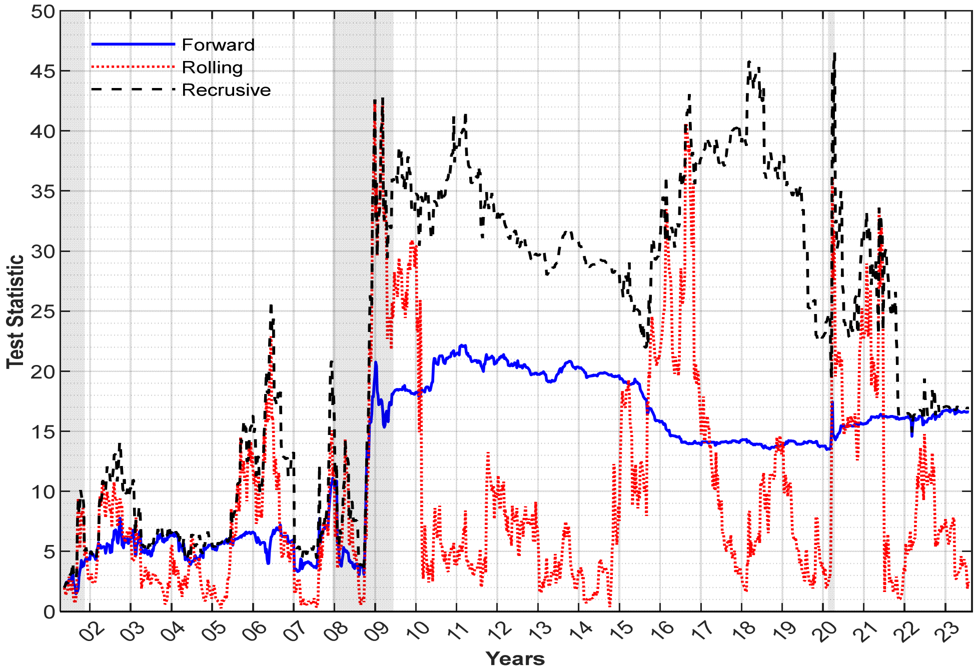

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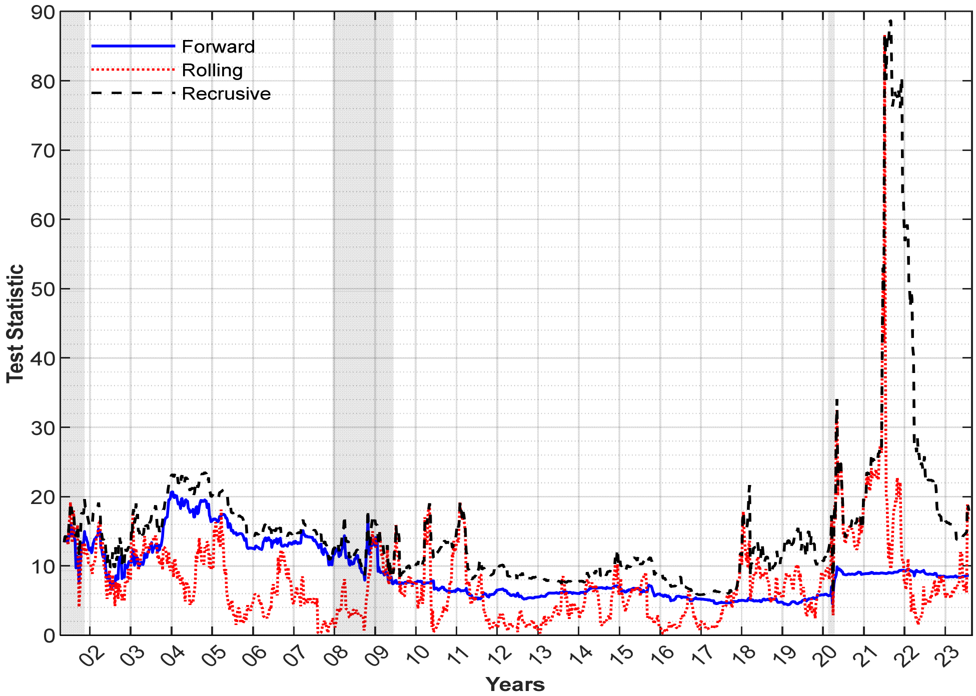

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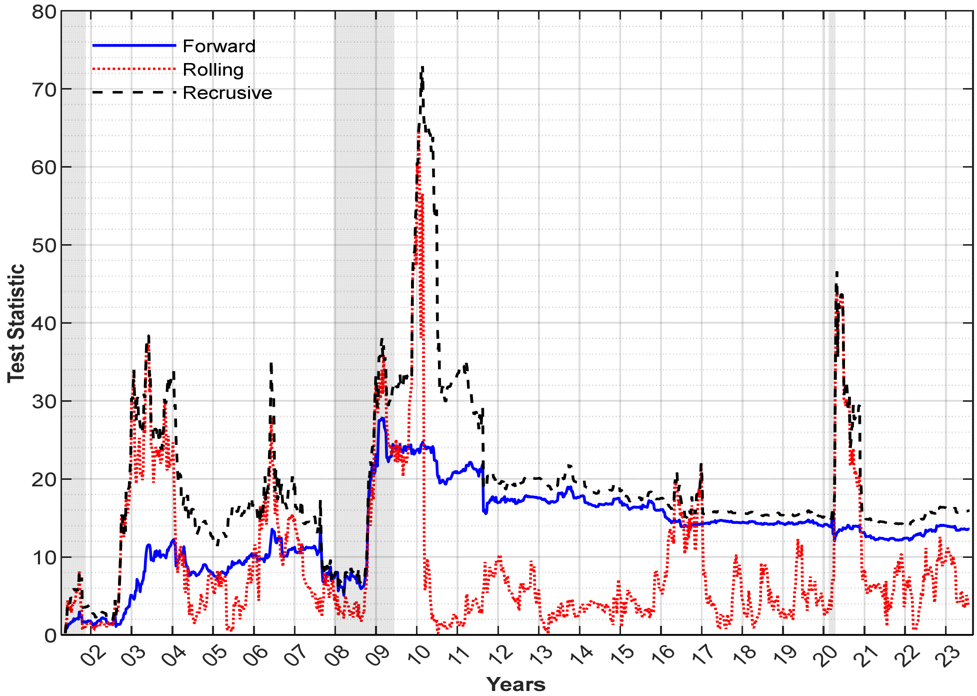

(**l**)

Figure A1. The gray area in each figure represents the US recession period. (**a**) The chart shows three (forward, rolling, and recursive) time-varying Granger causality test statistics over time. The direction of causality being tested runs from OFR FSI to S&P GSCI; (**b**) The chart shows three (forward, rolling, and recursive) time-varying Granger causality test statistics over time. The direction of causality being tested runs from OFR FSI to Agriculture; (**c**) The chart shows three (forward, rolling, and recursive) time-varying Granger causality test statistics over time. The direction of causality being tested runs from OFR FSI to Energy; (**d**) The chart shows three (forward, rolling, and recursive) time-varying Granger causality test statistics over time. The direction of causality being tested runs from OFR FSI to Industrial Metals; (**e**) The chart shows three (forward, rolling, and recursive) time-varying Granger causality test statistics over time. The direction of causality being tested runs from OFR FSI to Livestock; (**f**) The chart shows three (forward, rolling, and recursive) time-varying Granger causality test statistics over time. The direction of causality being tested runs from OFR FSI to Precious Metals; (**g**) The chart shows three (forward, rolling, and recursive) time-varying Granger causality test statistics over time. The direction of causality being tested runs from S&P GSCI to OFR FSI; (**h**) The chart shows three (forward, rolling, and recursive) time-varying Granger causality test statistics over time. The direction of causality being tested runs from Agriculture to OFR FSI; (**i**) The chart shows three (forward, rolling, and recursive) time-varying Granger causality test statistics over time. The direction of causality being tested runs from Energy to OFR FSI; (**j**) The chart shows three (forward, rolling, and recursive) time-varying Granger causality test statistics over time. The direction of causality being tested runs from Industrial Metals to OFR FSI; (**k**) The chart shows three (forward, rolling, and recursive) time-varying Granger causality test statistics over time. The direction of causality being tested runs from Livestock to OFR FSI; (**l**) The chart shows three (forward, rolling, and recursive) time-varying Granger causality test statistics over time. The direction of causality being tested runs from Precious Metals to OFR FSI.

Table A1. Unit Root Test Results.

	ADF Statistic	ADF *p*-Value	PP Statistic	PP *p*-Value	KPSS Statistic	KPSS *p*-Value
Panel A						
GSCI Index	−2.031	0.57	−2.048	0.56	7.588 ***	0.01
Agricultural	−3.120 *	0.1	−3.124 *	0.10	7.694 ***	0.01
Industrial Metals	−2.443	0.37	−2.419	0.38	5.081 ***	0.01
Livestock	−3.282 *	0.06	−3.496 **	0.04	1.698 ***	0.01
Energy	−2.309	0.43	−2.300	0.44	7.999 ***	0.01
Precious Metals	−2.652	0.27	−2.657	0.26	5.747 ***	0.01
OFR FSI	−3.753 *	0.08	−3.316 *	0.06	0.592 ***	0.01
Panel B						
D(GSCI Index)	−24.566 ***	0.00	−34.651 ***	0.00	0.127 *	0.10
D(Agricultural)	−26.040 ***	0.00	−34.695 ***	0.00	0.073 *	0.10
D(Industrial Metals)	−22.858 ***	0.00	−34.174 ***	0.00	0.065 *	0.10
D(Livestock)	−26.005 ***	0.00	−37.624 ***	0.00	0.049 *	0.10
D(Energy)	−24.478 ***	0.00	−33.569 ***	0.00	0.078 *	0.10
D(Precious Metals)	−24.878 ***	0.00	−34.147 ***	0.00	0.100 *	0.10
D(OFR FSI)	−20.674 ***	0.00	−31.890 ***	0.00	0.030 *	0.10

This table shows the test statistics, and associated *p*-values, for the unit root tests. ADF refers to the augmented Dicky-Fuller test, PP refers to the Phillips–Perron test, and KPSS refers to the Kwiatkowski, Phillips, Schmidt, and Shin test. Panel A performs unit root tests on the variables with trend. Panel B perform units root rests on the variables in first difference. The asterisks ***, **, and * represent significance levels at 1%, 5%, and 10% respectively. The S&P GSCI and sub-indices data are obtained from Barchart (https://www.barchart.com/stocks/indices/commodity (accessed on 9 August 2023)). The measure of the financial market stress index was retrieved from the Office of Financial Research (https://www.financialresearch.gov/ (accessed on 8 August 2023)).

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