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Dynamic Connectedness between Energy and Agricultural Commodity Markets in China: Evidence from a Generalized VAR Framework

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Abstract: This study examines dynamic return-shock connectedness between China's energy and agricultural commodity markets using daily spot prices for WTI crude oil, thermal coal, liquefied natural gas (LNG), corn, cotton, soybean meal, and white sugar from 24 October 2013 to 12 January 2026. A VAR model with generalized forecast error variance decompositions (GFEVDs) is used to construct the Diebold–Yilmaz connectedness measures. The full-sample matrix shows asymmetric spillovers: thermal coal has the largest net spillover (1.03), followed by soybean meal (0.80), white sugar (0.59), WTI crude oil (0.57), and corn (0.26), while cotton (-2.61) and LNG (-0.65) are net receivers. The sum of off-diagonal shares is 38.38, which corresponds to a conventional normalized total connectedness index of 5.48%. Rolling connectedness rises materially around the 2016 corn reserve reform, the 2018 China–US trade frictions, COVID-19, the 2021 dual-control policy, and the Russia–Ukraine conflict. In particular, WTI-to-soybean meal spillovers are persistently positive after 2019, while coal-to-soybean meal spillovers are highly event-sensitive. The results identify coal and crude oil as important risk-transmission channels and soybean meal as a key intermediary within the domestic commodity system.

Keywords: China; Commodity Markets; Generalized Forecast Error Variance Decomposition; Connectedness; Energy–Agriculture Linkage; Diebold–Yilmaz

1. Introduction

Energy and agricultural commodities are linked through input costs, logistics, processing, storage, bioenergy demand, and common macroeconomic and policy shocks. For China, this linkage is particularly relevant because coal remains a foundational energy source, while corn and soybean meal are central to feed and food supply chains. Changes in energy prices can therefore alter agricultural production costs and price expectations, whereas agricultural-market shocks can feed back into energy demand through processing, transportation, and substitution channels.

Earlier studies document oil-to-food transmission, energy–biofuel linkages, and time-varying risk spillovers. Chinese evidence has considered international oil prices, food-price dynamics, and network-based cross-market contagion [1–5]. International research likewise finds that energy–agriculture connectedness is nonlinear, event-sensitive, and often stronger during stress episodes [6–14]. The Diebold–Yilmaz framework offers an order-invariant way to quantify total, directional, and pairwise connectedness through generalized variance decompositions [14–16].

Three gaps motivate this paper. First, relatively few studies jointly assess several energy commodities and agricultural spot markets that are directly relevant to China. Second, coal's role in China's energy structure is often underemphasized relative to crude oil. Third, the role of major shocks in reshaping transmission paths requires systematic dynamic analysis. Accordingly, this study addresses three questions: (i) how large is energy–agriculture connectedness; (ii) which markets are net transmitters or receivers; and (iii) how do these roles evolve around major policy, trade, and geopolitical shocks?

2. Literature and Analytical Expectations

Research generally identifies three mechanisms. The first is a cost channel: fuel, fertilizer, machinery, electricity, and transport costs transmit energy shocks to agricultural prices. The second is a demand/substitution channel, particularly for corn and other inputs with feed or bioenergy relevance. The third is a financial-information channel in which common uncertainty, trading behavior, and expectations synchronize price movements. Empirical evidence has used multivariate GARCH models, TVP-VAR models, copula-based risk measures, network methods, and the Diebold–Yilmaz index [1–16].

Based on this literature, energy markets are expected to be important transmitters to agricultural markets, with heterogeneity across energy products. WTI crude oil is expected to affect cost-intensive commodities such as soybean meal and cotton, whereas thermal coal should matter through electricity and industrial-input costs. Spillovers are also expected to intensify during major disruptions. These expectations are evaluated as empirical propositions rather than imposed as identifying assumptions.

3. Data and Methodology

3.1 Data

The dataset contains daily spot prices from the CSMAR database for 24 October 2013–12 January 2026. Energy variables are WTI crude oil (USD/barrel), Chinese thermal coal (CNY/ton), and Chinese LNG (CNY/ton). Agricultural variables are Chinese corn, CC Index 328 cotton, soybean meal, and Nanning white sugar spot prices (all CNY/ton). To accommodate different trading calendars, the series are aligned on common observations. As shown in Table 1, estimation uses first-differenced log prices (daily log returns).

Table 1. Descriptive Statistics of Price Series

Market	Mean	Max.	Min.	S.D.	Median	Skew.	Kurt.	JB
Corn	2213.00	2901.43	1527.33	391.79	2252.00	0.143	-1.212	0.128***
Cotton	15687.75	22963.00	11091.00	2396.14	15543.00	1.024	1.431	0.144***
Soybean meal	3389.43	5660.00	2434.00	609.00	3217.57	1.107	0.917	0.116***
White sugar	5848.11	7566.00	4412.00	644.72	5755.00	0.273	-0.193	0.092***
WTI crude oil	65.39	123.70	11.57	19.17	63.51	0.367	-0.220	0.045***
Thermal coal	714.30	2587.50	371.00	246.87	631.00	1.729	7.461	0.133***
LNG	4227.94	8477.78	2350.00	1126.85	4083.33	1.016	0.848	0.108***

*Notes: *** denotes significance at the 1% level. Prices are reported in their original units; WTI is in USD/barrel and all other prices are in CNY/ton.*

3.2 Generalized VAR Connectedness Framework

Let x_t be the 7×1 vector of daily returns. A VAR(p) model is specified as $x_t=c+A_1x_{t-1}+\cdots+A_px_{t-p}+\varepsilon_t$, where ε_t has covariance matrix Σ. Following Koop et al. and Pesaran and Shin, generalized forecast error variance decompositions (GFEVDs) are used so that results do not depend on the ordering of variables. The normalized h -step share $\tilde{\theta}_{ij}(H)$ measures the contribution of shocks in market j to the H-step forecast-error variance of market i. Total connectedness is the average off-diagonal GFEVD share; directional connectedness measures what a market receives from others (From) and transmits to others (To); net connectedness equals To minus From. Pairwise net connectedness is defined as $\tilde{\theta}_{ji}(H)-\tilde{\theta}_{ij}(H)$.

ADF, PP, and KPSS tests are used to assess stationarity. AIC, BIC, and HQ information criteria are compared over lags 1–10. Because BIC selects two lags and favors a parsimonious specification in a large sample, the baseline VAR uses p=2.

Table 2. Unit-Root Tests

Market	Level ADF	Level PP	Level KPSS	Δ ADF	Δ PP	Δ KPSS
Corn	-1.50 (0.79)	-0.98 (0.94)	10.69*** (0.01)	-9.89*** (0.01)	-37.35*** (0.01)	0.41 (0.07)
Cotton	-2.74 (0.26)	-2.15 (0.52)	2.39*** (0.01)	-9.83*** (0.01)	-51.70*** (0.01)	0.22 (0.10)
Soybean meal	-3.23 (0.08)	-2.73 (0.27)	5.79*** (0.01)	-12.20*** (0.01)	-45.76*** (0.01)	0.10 (0.10)
White sugar	-1.42 (0.82)	-0.59 (0.98)	8.86*** (0.01)	-10.02*** (0.01)	-47.36*** (0.01)	0.31 (0.10)
WTI crude oil	-2.42 (0.40)	-2.55 (0.34)	4.07*** (0.01)	-13.91*** (0.01)	-57.77*** (0.01)	0.12 (0.10)
Thermal coal	-4.12*** (0.01)	-4.18*** (0.01)	16.21*** (0.01)	-13.65*** (0.01)	-30.47*** (0.01)	0.02 (0.10)
LNG	-4.37*** (0.01)	-4.24*** (0.01)	3.46*** (0.01)	-14.50*** (0.01)	-37.89*** (0.01)	0.02 (0.10)

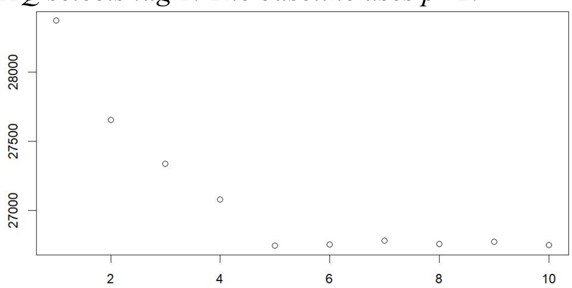
*Notes: p-values are reported in parentheses. *** denotes significance at the 1% level. The evidence supports using first-differenced log prices in the VAR.*

As shown in table 2, prior to estimating the VAR, stationarity of the seven price series is examined using ADF, PP, and KPSS tests. The results, reported in Table 2, show that the level series of corn, cotton, soybean meal, white sugar, and crude oil have ADF and PP p-values greater than 0.05, while the KPSS statistic rejects stationarity for all variables at the 1% level, indicating non-stationarity. Although the ADF and PP tests for coal and LNG reject the unit-root null, their KPSS values also strongly reject stationarity, suggesting possible structural breaks. After first-differencing, all series become stationary: both ADF and PP reject the unit-root null at the 1% level, and KPSS fails to reject stationarity ($p > 0.10$). We therefore use log-returns in the VAR connectedness analysis.

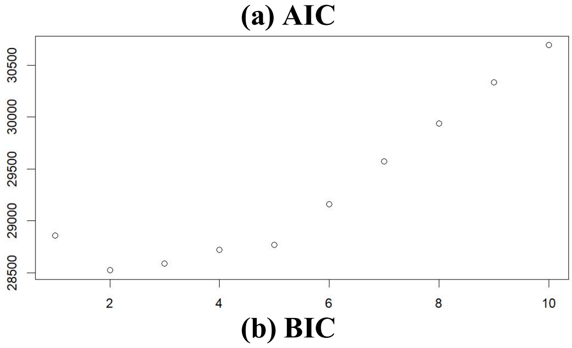
Table 3. VAR Lag-Order Selection

Lag	AIC	BIC	HQ
1	28375.21	28856.99	-28213.21
2	27656.62	28523.77	-27364.62
3	27338.21	28590.70	-26916.21
4	27080.59	28718.37	-26528.59
5	26744.15	28767.18	-26062.15
6	26754.71	29162.95	-25942.71
7	26778.97	29572.37	-25836.97
8	26758.41	29936.94	-25686.41
9	26774.56	30338.17	-25572.56
10	26747.78	30696.43	-25415.78

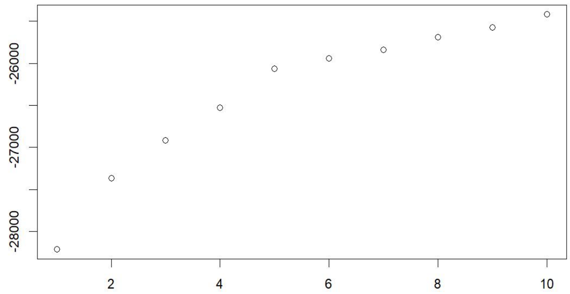
Notes: AIC selects lag 5, BIC selects lag 2, and HQ selects lag 1. The baseline uses p=2.



(a) AIC



(b) BIC



(c) HQ

Figure 1. Information-Criterion Profiles for VAR Lag Selection (AIC, BIC, and HQ).

As shown in Table 3, figure 1 shows that the information criteria do not point to a single common lag order: AIC reaches its minimum at five lags, HQ at one lag, and BIC at two lags. The baseline specification therefore adopts VAR(2), following BIC. This choice prioritizes parsimony while retaining short-run transmission channels across the seven commodity returns. In a seven-variable system, a substantially higher lag order would quickly increase parameterization and reduce estimation efficiency.

The lag-selection evidence is used as a specification decision rather than as an additional empirical claim. It does not alter the reported connectedness values; instead, it documents that the chosen model is anchored in a transparent and reproducible selection rule. The interpretation of all subsequent results should therefore be read conditional on the VAR(2) representation and the generalized, order-invariant variance decomposition.

4. Empirical Results

4.1 Full-Sample Connectedness

As shown in table 4, own-market innovations dominate the forecast-error variance of every series (92.18%–95.77%), but the cross-market pattern is nonetheless asymmetric. Thermal coal is the strongest net transmitter (1.03), followed by soybean meal (0.80), white sugar (0.59), WTI crude oil (0.57), and corn (0.26). Cotton is the clearest net receiver (−2.61), and LNG is also a net receiver (−0.65). The largest receipt is observed for cotton (From=7.82), whereas soybean meal has the strongest outbound connectedness among agricultural commodities (To=6.84).

Several bilateral relationships are economically intuitive. WTI has its largest links with soybean meal and cotton, consistent with energy-cost channels through agricultural inputs, processing, and transport. Coal's role is also prominent: it transmits to LNG and soybean meal and has the highest net value in the system. Soybean meal appears to intermediate energy-related shocks within agriculture, while cotton persistently absorbs shocks from the rest of the network.

Table 4. Full-Sample Generalized Variance-Decomposition Matrix

Receiving market	Corn	Cotton	Soybean meal	White sugar	WTI	Coal	LNG	From
Corn	95.39	0.75	1.02	0.65	0.71	0.76	0.72	4.61
Cotton	0.87	92.18	1.86	1.77	2.18	0.59	0.56	7.82
Soybean meal	1.00	1.00	93.97	1.11	1.41	1.01	0.50	6.03
White sugar	1.05	1.26	0.87	94.44	0.93	0.84	0.62	5.56
WTI	0.85	1.03	1.76	0.65	94.30	0.96	0.45	5.70
Coal	0.59	0.71	0.77	0.75	0.49	95.77	0.94	4.23
LNG	0.52	0.45	0.56	1.23	0.56	1.11	95.57	4.43
To	4.87	5.21	6.84	6.16	6.27	5.26	3.78	38.38
Net	0.26	-2.61	0.80	0.59	0.57	1.03	-0.65	5.48

Notes: Diagonal values are own-market shares. “From” is received connectedness; “To” is transmitted connectedness; “Net” = To − From. The off-diagonal sum is 38.38; divided by seven markets, the conventional total connectedness index is 5.48%.

4.2 Time Variation and Major Events

The rolling total connectedness measure is time-varying. Its central range is approximately 4.5%–6.5%, with a trough near 2.8% in late 2017 and an estimated peak near 8.8% in mid-2018. The 2018 peak coincides with China–US trade frictions, when tariff uncertainty affected soybean, cotton, and LNG-related trade flows. Connectedness subsequently rose after the COVID-19 shock and remained high during the 2021 energy-consumption dual-control episode, reaching approximately 8.2%. A further increase occurred around the Russia–Ukraine conflict, with a secondary peak around 6.6% during 2022–2023.

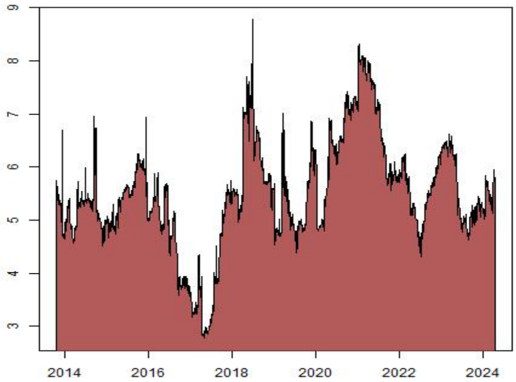


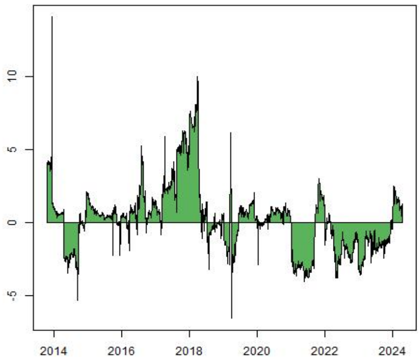
Figure 2. Rolling total Connectedness Across Energy and Agricultural Commodity Markets.

Figure 2 makes two points clear. First, the system is not persistently highly integrated: most return innovations remain market-specific, and rolling total connectedness generally fluctuates within a moderate band. Second, cross-market dependence rises sharply when an event simultaneously changes production costs, trade conditions, and expectations. The mid-2018 surge is particularly notable because trade-policy uncertainty directly affected soy-related imports, cotton, and energy-related trade flows.

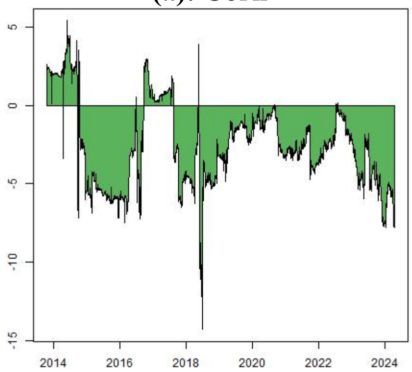
The later high-connectivity regime is consistent with a succession of overlapping shocks rather than a single isolated disturbance. COVID-19 disrupted logistics and demand patterns; the 2021 energy-consumption controls coincided with sharp coal-price pressure; and the Russia-Ukraine conflict intensified global energy and food-supply uncertainty. These event associations are descriptive, not causal identification results. They nevertheless motivate an event-sensitive interpretation of the time-varying connectedness measure.

Market roles also shift during stress. Cotton's net connectedness fell to roughly −15 during the 2018 trade-friction episode, confirming its sensitivity to external shocks. Coal reached a net connectedness value of roughly 18 in 2018 and rose again to about 7 in 2021–2022. WTI shifted from a net receiver in 2013–2017 to a transmitter after 2018, approaching 9 by late 2023/early 2024. These changes show that connectedness is not fixed: policy interventions, trade disruptions, public-health shocks, and geopolitical tensions reconfigure both the magnitude and direction of shock transmission.

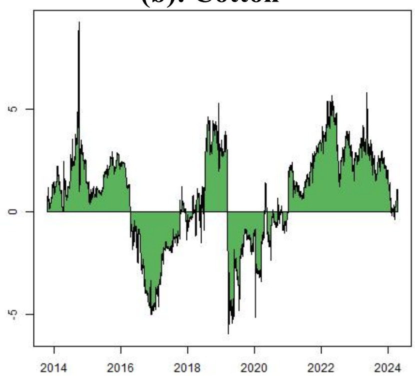
Figure 3 shows that net positions are not fixed. Cotton remains predominantly below zero, particularly around the 2018 trade-friction episode, and thus behaves as the most persistent net recipient in the system. By contrast, coal exhibits repeated positive episodes and reaches the strongest positive values among the energy commodities, supporting the full-sample finding that coal is an important domestic transmitter. WTI shifts from a largely negative position in the earlier sample to a clear positive position in the later period, especially after the energy and geopolitical shocks of 2021–2024.



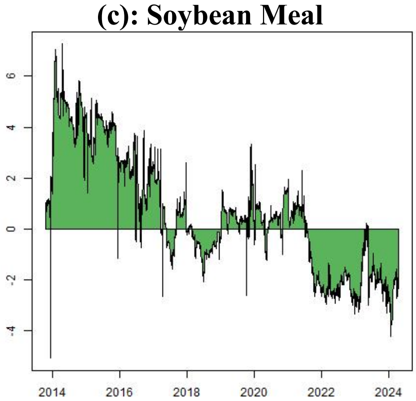
(a): Corn



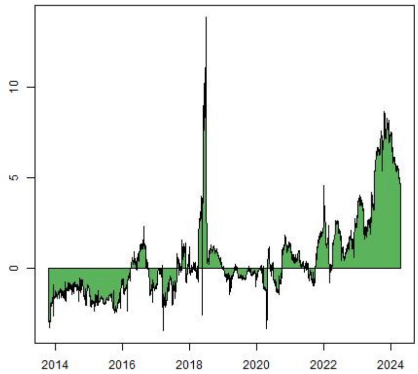
(b): Cotton



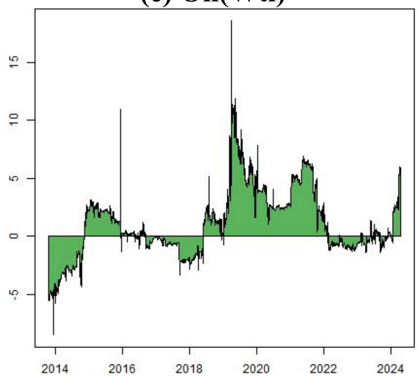
(c): Soybean Meal



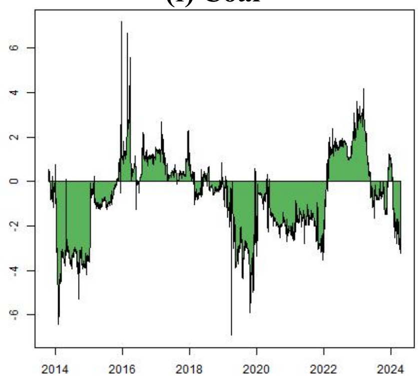
(d) White Sugar



(e) Oil(Wti)



(f) Coal



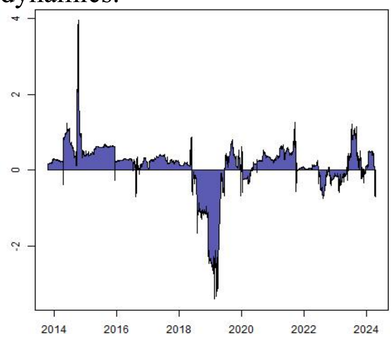
(g) Natural Gas

Figure 3. Rolling Net Connectedness for Corn, Cotton, and Natural Gas. Positive Values Indicate Net Transmission; Negative Values Indicate Net Reception.

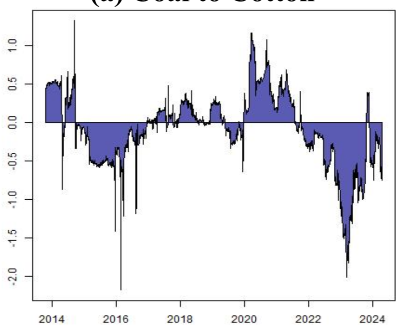
The agricultural markets display more mixed roles. Corn and soybean meal alternate between transmission and reception, reflecting their exposure to feed-demand conditions, procurement policies, and substitution within livestock and crop-production chains. Soybean meal is especially informative because it can receive cost shocks from WTI while redistributing them to other agricultural markets. White sugar also moves from earlier positive net positions toward negative values in the later sample, suggesting that its role is more sensitive to changes in production costs and agricultural supply conditions.

4.3 Pairwise Transmission Channels

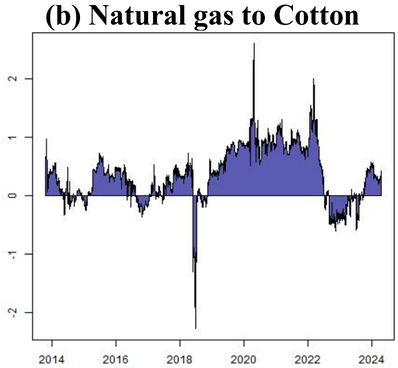
As shown in Figure 4, four pairwise patterns are especially informative. First, coal-to-cotton connectedness changes sign across the sample: coal is a transmitter in early 2014 and again after 2020, but cotton becomes a transmitter during 2018–2019. Second, LNG-to-cotton connectedness is mostly negative, except for a short positive episode around the onset of COVID-19. Third, WTI-to-soybean meal connectedness becomes persistently positive after 2019, reaching about 2.5 in 2020 and remaining above zero through 2022. Fourth, coal-to-soybean meal connectedness is the most volatile: it reaches around 2.2 in 2018–2019, falls to approximately −5 in 2019–2020, and rises again to around 1.8 in 2022. Together, these results support the view that both cost transmission and agricultural substitution/demand mechanisms shape cross-market dynamics.



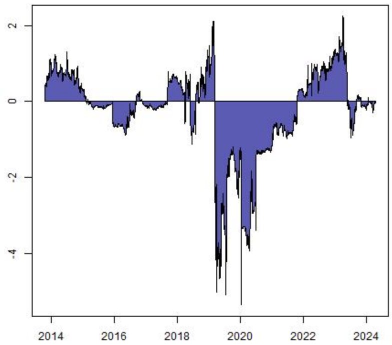
(a) Coal to Cotton



(b) Natural gas to Cotton



(c) Oil(wti) to Soybean meal



(d) Coal to Soybean meal

Figure 4. Rolling Pairwise Net Connectedness for Selected Energy–Agriculture Market Pairs

The selected pairwise series refine the aggregate results. Coal-to-cotton connectedness changes sign over the sample, indicating that relative market leadership is event-dependent rather than mechanically determined by sector membership. Natural gas is generally a net recipient relative to cotton, apart from short-lived reversals around the onset of COVID-19. This is consistent with the comparatively limited and indirect role of LNG in the domestic agricultural input structure. WTI-to-soybean-meal connectedness is the most consistently positive of the four selected relationships in the later sample. The pattern is compatible with energy-cost transmission through transport, processing, and agricultural inputs, though the generalized variance decomposition does not separately identify each physical channel. Coal-to-soybean-meal connectedness is more volatile and reverses several times, underscoring the interaction of coal-based power and input costs with feed-demand cycles, trade-policy uncertainty, and domestic market adjustment.

5. Discussion and Implications

The evidence indicates that energy–agriculture connectedness in China is best understood as a dynamic network rather than a unidirectional cost pass-through process. Coal's systemic role reflects its continuing importance in China's energy mix, while WTI provides an internationally priced channel into domestic agricultural costs. Soybean meal connects energy shocks to other agricultural markets, plausibly through feed-chain and substitution relationships. Cotton's receiver role is consistent with its exposure to energy-intensive production and downstream textile demand.

For market participants, coal and crude-oil conditions should be treated as cross-market risk indicators, particularly when hedging soybean meal and cotton exposures. For policymakers, the results support coordinated monitoring across energy, agriculture, logistics, and commodity-reserve systems. Stress protocols should be strengthened during trade disruptions, energy-policy changes, and geopolitical crises because these events amplify connectedness and may reverse transmitter–receiver roles.

Three limitations should guide future work. First, the analysis uses a seven-market system and does not include financial, carbon, or international benchmark markets beyond WTI. Second, the results describe return-shock connectedness; a dedicated analysis of volatility spillovers would require realized-volatility proxies or conditional-variance estimates. Third, the economic channels are inferred from market structure rather than directly identified using firm-level cost, inventory, or trade-flow data. Future work could use time–frequency measures, richer market systems, and explicit policy-uncertainty indicators to test these mechanisms.

5.1 Interpretation Boundaries

The connectedness results should be interpreted as a summary of predictive variance shares within the estimated system, not as structural causal effects. A positive net value indicates that innovations in one market explain more of the other markets' forecast-error variance than they receive over the selected horizon. It does not, by itself, establish that a particular physical cost channel, policy intervention, or international shock is the sole source of transmission. This distinction matters in commodity markets, where common shocks and expectations can move several prices simultaneously.

The empirical design also deliberately focuses on a parsimonious seven-market domestic system with WTI included as an internationally priced energy benchmark. The analysis does not include futures positions, exchange-rate changes, fertilizer prices, carbon prices, weather variables, or explicit external-shock regressors. These omissions are not innocuous: they delimit the interpretation of the network and point to a clear next step for future work. A richer conditional framework could test whether the coal, WTI, and soybean-meal roles documented here remain after controlling for these additional channels.

5.2 Practical Implications

The evidence has immediate implications for cross-market risk monitoring. A monitoring system focused only on individual commodity price levels would miss the fact that system-wide connectedness can rise before or during disruptions to trade, energy supply, and production. Regulators and commodity-market institutions should therefore track both market-specific stress and network indicators such as total connectedness, directional transmission, and large changes in net positions. Such indicators cannot replace structural diagnosis, but they can support earlier detection of periods when shocks are likely to spread across energy and agricultural supply chains.

For agricultural and food-sector firms, the results point to differentiated rather than uniform hedging priorities. Exposure to coal-price conditions is especially relevant for businesses whose costs are sensitive to electricity, logistics, or energy-intensive inputs. Exposure to WTI is particularly relevant for soybean-meal users and processors because the WTI-to-soybean-meal relationship becomes persistently positive in the later sample. Cotton-oriented businesses should instead be treated as vulnerable receivers of external disturbances, which calls for contingency planning that combines input-cost management with procurement and inventory flexibility.

For policymakers, the persistent role of coal suggests that energy-security measures and agricultural-stability measures should not be designed in isolation. Policies affecting coal availability, power costs, transport capacity, or energy-consumption constraints can propagate through agricultural production and processing even when the initial policy target lies outside agriculture. Coordinated communication is also important: policy uncertainty may itself reinforce connectedness by changing expectations simultaneously in several commodity markets. A practical response is to align energy, agricultural, and trade-policy risk assessments during episodes of acute market stress.

Finally, the changing position of soybean meal illustrates why sectoral labels can be misleading. It is neither simply an agricultural endpoint nor merely a recipient of energy shocks. Instead, it functions as a potential bridge across input costs, feed substitution, livestock demand, and trade exposure. This type of intermediary role should be considered when selecting commodities for stress testing, strategic reserves, or information disclosure. In short, the policy-relevant unit is not a single market but an interconnected production and price system.

6. Conclusion

Using daily data from 2013 to 2026 and a generalized VAR connectedness framework, this study documents asymmetric and time-varying spillovers across China's energy and agricultural commodity markets. The full-sample off-diagonal share is 38.38, equivalent to a normalized total connectedness index of 5.48%. Coal and WTI are key energy-side transmitters, soybean meal is an important agricultural intermediary, and cotton is the principal receiver. Connectedness intensifies during the 2016 corn reserve reform, 2018 trade frictions, COVID-19, the 2021 dual-control policy, and the Russia–Ukraine conflict. The findings underscore the value of integrated energy–food risk monitoring and event-contingent policy responses.

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06
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