# ESSAYS ON GLOBAL COMMODITIES MARKET

A THESIS SUBMITTED TO INDIAN INSTITUTE OF MANAGEMENT INDORE IN PARTIAFULFILLMENT OF THE REQUIREMENTS FOR THE FELLOW PROGRAMME IN MANAGEMENT


By

Prachi Jain

**FPM Student (Finance and Accounting)**


**THESIS ADVISORY COMMITTEE**

Prof. Debasish Maitra (Chairperson)

Prof. Saumya Ranjan Dash (Member)

Prof. Kousik Guhathakurta (Member)

सिद्धिमूलं प्रबन्धनम्

भा. प्र. सं. इन्दौर

IIM INDORE


**INDIAN INSTITUTE OF MANAGEMENT, INDORE**

**Prabandh Shikhar Rau-Pithampur Road, Indore 453556, Madhya Pradesh, Ind**

## Synopsis

Until the early 2000s, the commodity prices were primarily governed by the idiosyncratic forces of demand and supply. The precious metals were also sought as alternate investment vehicles, while the agricultural commodities were mostly demanded for consumption purposes. The supply was even more typical governed heavily by production and export policies for metals, and weather for agriculture. Consequently, the order of interaction amongst the commodities was limited and risk was predominantly associated with hampered growth and commodity. However, a major transition in the commodities sector was witnessed in response to the Global Financial Crises (2007-2009). Financial investors actively ventured into the commodities sector in pursuit of hedge. A staff report from the U.S. Commodity Futures Trading Commission (CFTC 2008), the total value of various commodity index–related instruments purchased by institutional investors increased from an estimated $15 billion in 2003 to at least $200 billion in mid-2008. Subsequently, the sector experienced a persistent rise in the strategic reliance on commodity assets as a medium of portfolio diversification. As a natural consequence, index investments and portfolio building induced higher comovements amongst commodities forming a deeply intertwined network. In this dissertation, we explore several facets of the commodities network and provide insights for investors, portfolio managers, market regulators and policymakers.

In our first essay, we propose a novel exogenous measure of uncertainty using news articles. The weekly uncertainty index is curated for every commodity from January 2000 to May 2021. Using a panel-ARDL model, we find that the uncertainty measure has a significant impact on the prices of commodities. Consequently, we analyse the uncertainty network among commodities and provide insights about portfolio diversification. We find that the uncertainty connectedness across commodities remains strong at approximately 49% for the entire sample period. Further, net pairwise interactions across commodities reveal that gold, silver, and copper are some of the prominent transmitters of uncertainty. Finally, uncertainty connectedness is found to rise during GFC, EZC, and for a very brief period during the COVID-19 crisis. The frequency decomposed network reveals high and turbulent connectedness at the higher frequency (1-4 weeks) and low and stable connectedness at lower frequencies. Interestingly, we find that uncertainty spillover precedes return and volatility spillovers in the commodities sector.

The second essay aims at quantifying the risk between oil and a broad sample of commodities by using copulae tools to model the dependence structures. Using daily returns of commodity futures from October 3, 2005 to January 21, 2022, we find that the oil has a symmetric dependence structure with most of the commodities. The conditional correlation between oil and commodities was found to strengthen during periods of crisis compared with periods of stability. Finally, in contrast with conventional wisdom, we find that a C-Vine outperforms D- and R-Vine in modelling the multivariate dependence structure between oil and commodities. We thereon compare the efficiency of copula based models against traditional models in forecasting the portfolio and systemic risk between oil and commodities. The findings suggest that copula-based models outperform traditional models in quantifying portfolio and systemic risk.

Finally, in essay III, we propose to measure the crash risk for commodity futures. We construct down-to-up volatility (DUVOL) using 1-minute data and a negative coefficient of skewness (NCSKEW) using daily data. We determine the drivers of crash risk for commodities and analyse the crash risk spillover across them at different quantiles. We further explore the impact of commodity-specific and macroeconomic factors in driving the transmission of crash risk from a commodity to the network. Findings indicate a significant impact of speculation, hedging pressure, basis, momentum, attention, and term structure on commodity crash risk. The crash risk spillovers are asymmetric, remaining low at 33% at the median and peaking at approximately 88% during extremities. Metals and agricultural commodities soyoil, soybeans, corn, and wheat are mostly the net transmitters of crash risk at all quantiles, while livestock and energy commodities are mostly net receivers. We find that speculation, hedging pressure, basis, momentum, attention, and term structure have heterogeneous impacts on different commodities, indicating their relative preferences in a portfolio given their characteristics.

*Keywords:* commodities, uncertainty, connectedness, vine copula, crash risk

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## 2. Commodity uncertainty impact and connectedness: Evidence using news-based indices and TVP-VAR


### Abstract

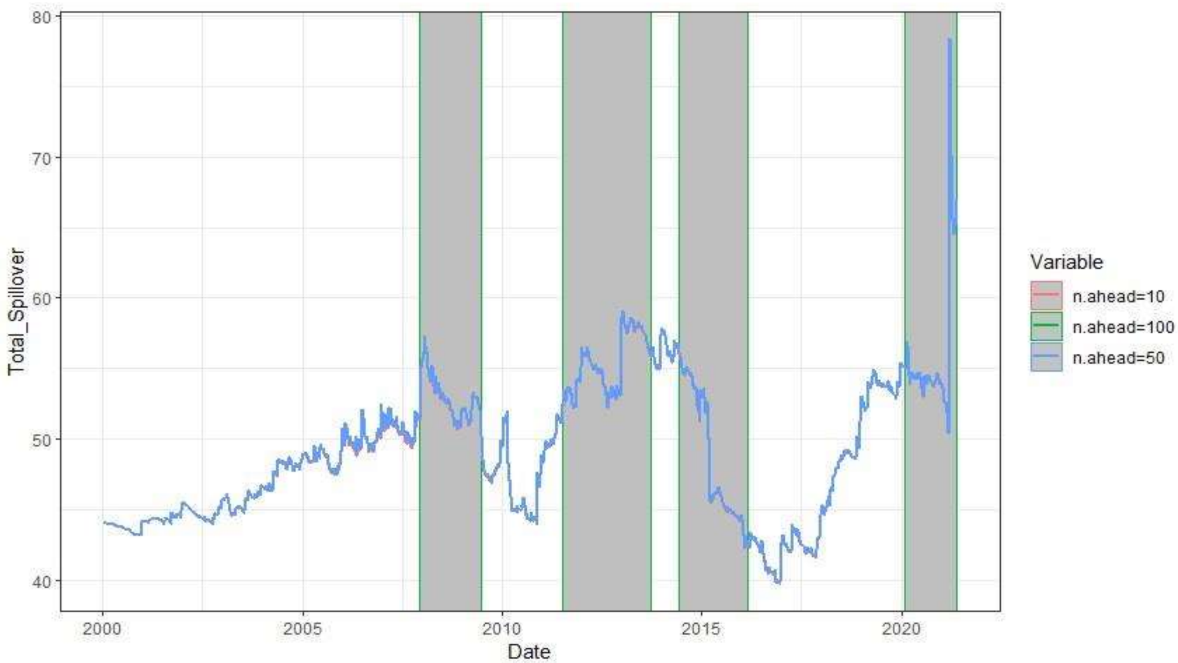
The study examines the uncertainty connectedness between oil and a bouquet of commodities. We construct a news-based index that measures commodity-specific uncertainty at a weekly frequency from January 2000 to May 2021. We find that news-based uncertainty index has a significant influence on the prices of commodity futures in the short run while oil specific uncertainty significantly drives the prices of commodities in both short run and long run. Thereon, we examine the uncertainty network between oil and commodities using the TVP-VAR and frequency-based approaches. We emphasize the need to identify uncertainty spillovers in a financial system by empirically verifying causality flow from uncertainty spillovers to conventional return and volatility spillovers. We find that the overall uncertainty connectedness between oil and commodities remains high (49%), which further increases during periods of crisis. Net pairwise interactions indicate a dominance of agricultural commodities during periods of global crisis including GFC, Shale oil revolution 2014-15 (oil supply shock) and COVID-19. Subsequently, gross pairwise connectedness indicates that most commodities paired with soyoil, platinum, and palladium rank the lowest across all sub-periods. Finally, the frequency decomposed network reveals high and turbulent connectedness at the higher frequency (1-4 weeks). The findings are instrumental for policymakers and investors with different horizons of investment.



*Keywords:* Uncertainty, oil, commodities, connectedness

*JEL: G*1*, G*11

**Fig. 2.12: Uncertainty spillover with different forecast horizons**




**Note:** This figure displays the time-varying movement of uncertainty spillover based on the forecast error variance decomposition forecast horizon of *J*=10 weeks, *J*=50 weeks, and *J*= 100 weeks with a lag length of 3(BIC). The shaded areas represent the period of the Global Financial Crisis(December, 2007 to June, 2009), Eurozone Debt Crisis (July, 2011 to September, 2013), Shale oil revolution (June 2014 to March 2015), and COVID crisis (February, 2020 to May, 2021) respectively.

## 2.8. Conclusion

The study proposes a novel exogenous measure of commodity-specific uncertainty where we construct a news-based commodity-specific uncertainty index by capturing the aggregate media attention garnered by a commodity for a given week by scrolling through a set of 6000 newspapers, publications, and journals available on the LexisNexis database. The indices are thereon found to be moving in close tandem with commodity-specific events across the world. The exogenous uncertainty indices capture the 'social' aspect of the market.

Using a CS-ARDL model, we find that the uncertainty indices significantly determine commodity futures prices in the short run; however, there is no long-run relationship between commodity uncertainties and prices. Subsequently, we examine the uncertainty network across the commodity assets in static and time-varying perspectives using a TVP-VAR-based framework. We find that the uncertainty connectedness across commodities remains strong at approximately 49% for the entire sample period. Further, net pairwise interactions across commodities reveal that gold, silver, and copper are some of the prominent transmitters of uncertainty. Finally, uncertainty connectedness is found to rise during GFC, EZC, and for a very brief period during the COVID-19 crisis.

Subsequently, we explore net pairwise interactions for the full period as well as periods of crises under scrutiny. For the full sample period, we find that gold, silver, and copper are some of the prominent transmitters of uncertainty; however, during periods of global crises GFC, EZC, and oil supply shock, we find an increased dominance of agricultural commodities, especially soyoil. However, during the regional crisis of EZC, oil garners a dominant role in uncertainty transmission in the network.

Third, we explore the aggregate pairwise connectedness between commodities and advise market players to invest in commodity pairs with the least PCI. Combinations of commodities with agricultural commodities- corn and wheat have high uncertainty synchronicity during GFC and COVID-19 crisis. Commodities paired with oil are included in the high-ranking set during the Shale oil supply shock. The pattern of pairs ranking during the EZC is similar to the ranking documented during the full period. Most commodity pairs with soyoil, palladium, and platinum maintain low uncertainty synchronicity across all sub-periods.

The network interactions across frequencies reveal that the uncertainty network dampens as the horizons widen. The network undergoes a drastic change in the order of pairwise interactions as one moves from 1 to 4 weeks band to a 5 to 12 weeks band and thereon to the lowest frequency of 12 weeks onwards. Moreover, the network also attains stability across medium and high frequencies. The network in the medium frequency experiences low uncertainty transmissions when compared with the high frequency. Finally, the network for lowest frequency (12 weeks onwards) closely resembles the network for medium frequency (5-12 weeks).

The findings are especially instrumental for investors seeking to diversify with commodities. The study provides a comprehensive yardstick by looking at network interactions across different dimensions. In addition, policymakers and regulators might be immensely benefited since commodities can be easily classified on the basis of their sensitivity to oil price shocks and their vulnerability to a market contagion. The direction of uncertainty transmission or spillovers between oil and other commodities and across commodities during the crises may also assist in better understanding of uncertainty networks and balancing the portfolio risk.

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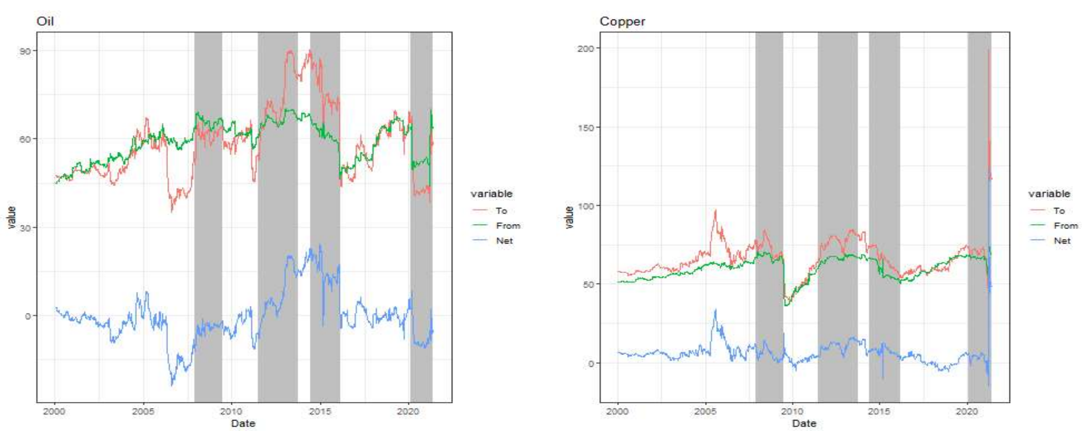
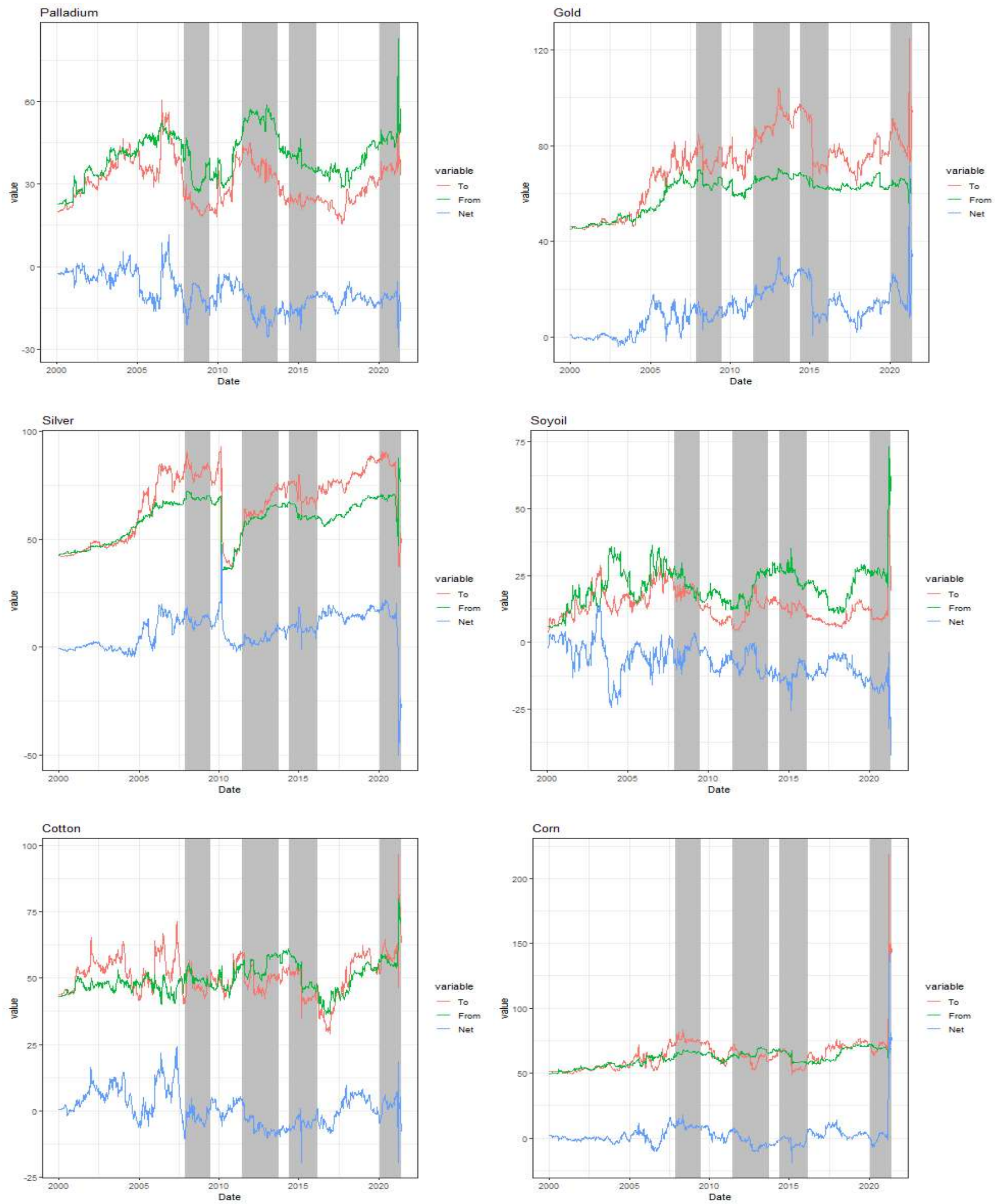
## Appendix

We plot the time varying shocks transmitted by the commodities to the network, the shocks received by commodities from the network and the net shocks transmitted to the network in Fig A1. In most cases, we find a synchronous movement between the ‘to’ and ‘from’ shocks causing slight variation in the ‘net’ shocks. The synchronous to and from movements are indicative of an external shock that raises the uncertainty for all commodities simultaneously such that the intensity of shock transmissions from one commodity resemble the intensity of shock transmitted by other commodities (also depicted as shocks received by the said commodity).

The asynchronous movements in the ‘to’ and ‘from’ shocks are especially evident for oil and gold where the shocks transmitted significantly exceed the shocks received from the network for most of the sample period. We also observe a noteworthy spike in the 'to' shocks of sugar in early 2015 and a simultaneous drop in 'from' shocks for sugar around the same time. This corresponds with an abnormal spike in sugar uncertainty in 2015. The period coincides with the declining supply of sugar from the world's two biggest producers, Brazil and India. An early departure of monsoons in India and a simultaneous ramping up of the production of ethanol in Brazil introduced severe uncertainty in the markets during this period (Chandran, 2015).

**Fig. A1:** To, from and net plots of uncertainty connectedness for all commodities

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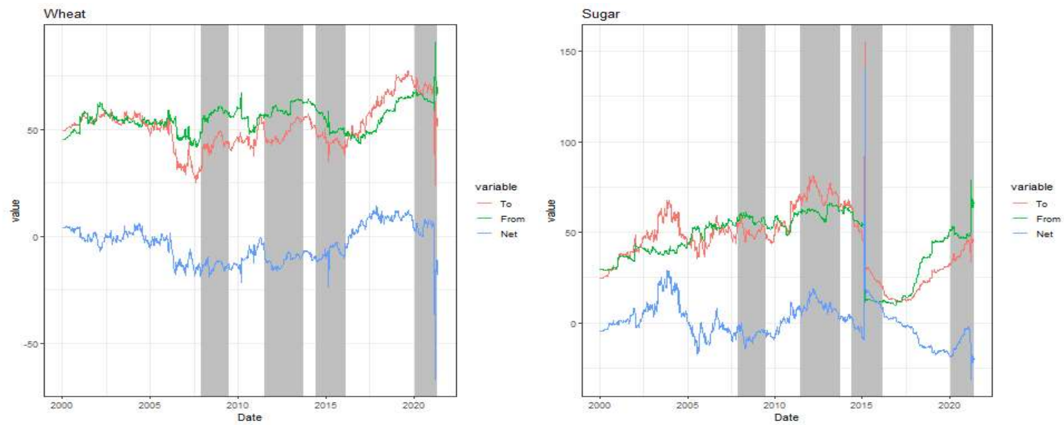


**Note:** The figures indicate the uncertainty shocks transmitted by a commodity to the network, the uncertainty shocks received by the commodity from the network and the net shocks transmitted by the commodity to the network.

# 3. Risk implications of dependence in the commodities: A copula-based analysis

**Abstract**

The study aims to quantify the risk across a broad sample of commodities using copulae tools to model the dependence structures. Using daily returns of commodity futures from October 3, 2005, to January 21, 2022, we find that in contrast with conventional wisdom, a C-Vine outperforms D- and R-Vine in modeling the multivariate dependence structure among commodities. We then compare the efficiency of copula-based models against traditional models in forecasting the portfolio and systemic risk in the commodities sector. The findings suggest that copula-based models are more effective than traditional models in forecasting portfolio and systemic risk.

Keywords: commodity, copulae, portfolio, systemic risk

*JEL Classification:*

findings are especially useful for policymakers and market regulators who seek to gauge a system's fragility by monitoring the market's systemic risk.

## 3.6. Conclusion

The study provides a holistic perspective on the risk implications in the system of commodities. We use robust copula models to capture the asymmetry and non-linearity in the dependence between oil and commodities. We thereon quantify the portfolio risk and the systemic risk between oil and commodities using the bivariate and multivariate dependence structures previously unaddressed in literature. Using a robust framework, the study unifies the previously scattered and non-converging evidence in the literature. It serves as a comprehensive guide for investors and policymakers wary of portfolio and systemic risks, respectively.

A multivariate dependence modeling of commodity futures reveals that a dependence structure is most appropriately modeled using a C-Vine over D- and R-Vine. A C-Vine model shows that copper lies at the core of the commodities dependence model. The dependence between copper and oil is symmetric but weak, with a *tau* ($\tau$) value of 0.19. We find high within-sector dependence of copper with - zinc, aluminum, and nickel. Further, except for agricultural commodities (grains and soft commodities), the dependence of copper with all other commodities is mostly symmetric and modeled through a *t* copula. Moreover, the pair copula models are more effective than traditional GARCH-based models in forecasting portfolio risk. The number of violations upon pair copula modelling at a 95% level of confidence for the optimised portfolios are lower when compared with the number of violations while forecasting Value at Risk using a traditional GARCH-based model. The superiority of vine-based models over GARCH based models in the case of optimised portfolios has been validated by the Kupiec test and the Joint test. The same is not true for an equally weighted portfolio where the vine based models are rejected on backtesting by Kupiec and Joint test.

While using systemic risk using copula models, we find that the relationship between oil and most commodities is best modelled using a *student's t* copula, suggesting a symmetric tail dependence between the commodities. Finally, copula models, especially *Student's t* copula, are instrumental in modeling the systemic risk in the commodities market relative to the traditional models. The Multi-CoVaR estimate allows the most conservative approach to the systemic risk with the least number of violations (7), which is approximately 50 times lower than the number of exceedances observed while using the traditional ΔCoVaR models (345), followed by SCoVaR (58) and VCoVaR (158) Therefore, the findings reinforce the utility of copula models in quantifying risk in between oil and commodities over traditional linear models that are incapable of capturing asymmetric relationship.

## Appendix

Table A1. presents the results of an AR(1,1)-EGARCH-GED fit for all the sample commodities.

**Table A1: AR-EGARCH-GED fit of all commodities**

| Commodity | Parameters | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|---|
| **Crude oil** | Mu | 0.00 | 0.00 | 1.22 | 0.22 |
| | ar1 | -0.02 | 0.01 | -1.48 | 0.14 |
| | Omega | -0.09 | 0.02 | -4.54 | 0.00 |
| | alpha1 | -0.08 | 0.01 | -8.22 | 0.00 |
| | beta1 | 0.99 | 0.00 | 377.77 | 0.00 |
| | gamma1 | 0.12 | 0.05 | 2.43 | 0.02 |
| | Shape | 1.31 | 0.08 | 16.91 | 0.00 |
| **Natural gas** | Mu | 0.00 | 0.00 | -3.30 | 0.00 |
| | ar1 | -0.03 | 0.00 | -5.10 | 0.00 |
| | Omega | -0.09 | 0.00 | -34.10 | 0.00 |
| | alpha1 | 0.00 | 0.01 | 0.26 | 0.80 |
| | beta1 | 0.99 | 0.00 | 3753.93 | 0.00 |
| | gamma1 | 0.15 | 0.01 | 10.61 | 0.00 |
| | Shape | 1.33 | 0.05 | 25.78 | 0.00 |
| **Gasoline** | Mu | 0.00 | 0.00 | 4.81 | 0.00 |
| | ar1 | -0.02 | 0.00 | -3.46 | 0.00 |
| | omega | -0.15 | 0.01 | -17.92 | 0.00 |
| | alpha1 | -0.04 | 0.02 | -2.93 | 0.00 |
| | beta1 | 0.98 | 0.00 | 924.41 | 0.00 |
| | gamma1 | 0.17 | 0.03 | 6.36 | 0.00 |
| | shape | 1.15 | 0.04 | 25.98 | 0.00 |
| **Live cattle** | mu | 0.00 | 0.00 | 0.00 | 1.00 |
| | ar1 | 0.00 | 0.00 | -0.11 | 0.91 |
| | omega | -0.15 | 0.00 | -65.64 | 0.00 |
| | alpha1 | -0.03 | 0.01 | -2.89 | 0.00 |
| | beta1 | 0.98 | 0.00 | 4338.13 | 0.00 |
| | gamma1 | 0.09 | 0.00 | 25.30 | 0.00 |
| | shape | 0.95 | 0.04 | 24.54 | 0.00 |
| **Lean hog** | mu | 0.00 | 0.00 | 0.00 | 1.00 |
| | ar1 | 0.00 | 0.00 | 0.04 | 0.97 |
| | omega | -0.05 | 0.00 | -50.72 | 0.00 |
| | alpha1 | -0.03 | 0.01 | -4.29 | 0.00 |
| | beta1 | 0.99 | 0.00 | 32439.15 | 0.00 |
| | gamma1 | 0.05 | 0.00 | 16.78 | 0.00 |
| | shape | 0.69 | 0.02 | 27.95 | 0.00 |
| **Feeder cattle** | mu | 0.00 | 0.00 | 0.00 | 1.00 |
| | ar1 | 0.00 | 0.00 | 0.03 | 0.98 |
| | omega | -0.15 | 0.01 | -24.95 | 0.00 |
| | alpha1 | -0.05 | 0.01 | -5.17 | 0.00 |
| | beta1 | 0.98 | 0.00 | 1510.09 | 0.00 |
| | gamma1 | 0.10 | 0.01 | 6.45 | 0.00 |
| | shape | 0.86 | 0.04 | 24.44 | 0.00 |

| | | | | | |
|---|---|---|---|---|---|
| Wheat | mu | 0.00 | 0.00 | -0.60 | 0.55 |
| | ar1 | -0.01 | 0.01 | -0.92 | 0.36 |
| | omega | -0.09 | 0.00 | -48.07 | 0.00 |
| | alpha1 | 0.02 | 0.01 | 1.80 | 0.07 |
| | beta1 | 0.99 | 0.00 | 8283.51 | 0.00 |
| | gamma1 | 0.10 | 0.01 | 8.43 | 0.00 |
| | shape | 1.46 | 0.02 | 58.63 | 0.00 |
| Corn | mu | 0.00 | 0.00 | 0.56 | 0.58 |
| | ar1 | 0.00 | 0.00 | -2.39 | 0.02 |
| | omega | -0.09 | 0.00 | -18.43 | 0.00 |
| | alpha1 | 0.00 | 0.01 | -0.27 | 0.79 |
| | beta1 | 0.99 | 0.00 | 1615.19 | 0.00 |
| | gamma1 | 0.13 | 0.02 | 8.10 | 0.00 |
| | shape | 1.16 | 0.06 | 18.04 | 0.00 |
| Soybeans | mu | 0.00 | 0.00 | 3.61 | 0.00 |
| | ar1 | -0.01 | 0.00 | -3.15 | 0.00 |
| | omega | -0.09 | 0.00 | -24.90 | 0.00 |
| | alpha1 | 0.01 | 0.01 | 1.01 | 0.31 |
| | beta1 | 0.99 | 0.00 | 2416.87 | 0.00 |
| | gamma1 | 0.13 | 0.02 | 8.50 | 0.00 |
| | shape | 1.18 | 0.05 | 24.13 | 0.00 |
| Soybean oil | mu | 0.00 | 0.00 | -0.22 | 0.83 |
| | ar1 | 0.01 | 0.01 | 0.82 | 0.41 |
| | omega | -0.04 | 0.00 | -39.12 | 0.00 |
| | alpha1 | -0.01 | 0.01 | -0.89 | 0.37 |
| | beta1 | 1.00 | 0.00 | 20880.89 | 0.00 |
| | gamma1 | 0.08 | 0.01 | 7.82 | 0.00 |
| | shape | 1.54 | 0.05 | 31.58 | 0.00 |
| Aluminium | mu | 0.00 | 0.00 | 0.00 | 1.00 |
| | ar1 | 0.00 | 0.00 | 0.07 | 0.95 |
| | omega | -0.11 | 0.00 | -57.54 | 0.00 |
| | alpha1 | 0.01 | 0.01 | 1.08 | 0.28 |
| | beta1 | 0.99 | 0.00 | 2611.32 | 0.00 |
| | gamma1 | 0.12 | 0.03 | 3.57 | 0.00 |
| | shape | 0.83 | 0.11 | 7.69 | 0.00 |
| Copper | mu | 0.00 | 0.00 | 0.00 | 1.00 |
| | ar1 | 0.00 | 0.00 | 1.27 | 0.21 |
| | omega | -0.13 | 0.08 | -1.75 | 0.08 |
| | alpha1 | -0.06 | 0.14 | -0.40 | 0.69 |
| | beta1 | 0.96 | 0.01 | 127.60 | 0.00 |
| | gamma1 | 0.42 | 0.10 | 4.36 | 0.00 |
| | shape | 0.20 | 0.06 | 3.46 | 0.00 |
| Zinc | mu | 0.00 | 0.00 | 0.00 | 1.00 |
| | ar1 | 0.00 | 0.00 | -0.22 | 0.83 |
| | omega | -0.02 | 0.00 | -24.24 | 0.00 |
| | alpha1 | 0.00 | 0.01 | -0.38 | 0.71 |
| | beta1 | 1.00 | 0.00 | 26097.63 | 0.00 |
| | gamma1 | 0.06 | 0.00 | 17.00 | 0.00 |
| | shape | 0.95 | 0.07 | 13.64 | 0.00 |

| | | | | | |
|---|---|---|---|---|---|
| **Nickel** | mu | 0.00 | 0.00 | 0.00 | 1.00 |
| | ar1 | 0.00 | 0.00 | 0.01 | 0.99 |
| | omega | -0.05 | 0.01 | -7.02 | 0.00 |
| | alpha1 | 0.01 | 0.02 | 0.78 | 0.43 |
| | beta1 | 0.99 | 0.00 | 2941.34 | 0.00 |
| | gamma1 | 0.09 | 0.04 | 2.65 | 0.01 |
| | shape | 0.66 | 0.35 | 1.93 | 0.05 |
| **Gold** | mu | 0.00 | 0.00 | 3.58 | 0.00 |
| | ar1 | -0.03 | 0.01 | -4.34 | 0.00 |
| | omega | -0.06 | 0.01 | -7.38 | 0.00 |
| | alpha1 | 0.01 | 0.01 | 1.47 | 0.14 |
| | beta1 | 0.99 | 0.00 | 994.57 | 0.00 |
| | gamma1 | 0.09 | 0.03 | 2.88 | 0.00 |
| | shape | 1.06 | 0.04 | 25.83 | 0.00 |
| **Silver** | mu | 0.00 | 0.00 | 10.30 | 0.00 |
| | ar1 | -0.04 | 0.00 | -9.98 | 0.00 |
| | omega | -0.07 | 0.00 | -27.26 | 0.00 |
| | alpha1 | 0.02 | 0.01 | 1.39 | 0.16 |
| | beta1 | 0.99 | 0.00 | 3620.95 | 0.00 |
| | gamma1 | 0.11 | 0.02 | 5.65 | 0.00 |
| | shape | 1.00 | 0.03 | 30.42 | 0.00 |
| **Platinum** | mu | 0.00 | 0.00 | 0.00 | 1.00 |
| | ar1 | 0.00 | 0.00 | -1.26 | 0.21 |
| | omega | -0.28 | 0.03 | -8.70 | 0.00 |
| | alpha1 | -0.19 | 0.29 | -0.65 | 0.51 |
| | beta1 | 0.94 | 0.00 | 252.70 | 0.00 |
| | gamma1 | 1.15 | 0.54 | 2.14 | 0.03 |
| | shape | 0.15 | 0.04 | 3.49 | 0.00 |
| **Palladium** | mu | 0.00 | 0.00 | 0.06 | 0.95 |
| | ar1 | 0.00 | 0.00 | -0.23 | 0.82 |
| | omega | -0.28 | 0.01 | -50.27 | 0.00 |
| | alpha1 | -0.04 | 0.01 | -3.63 | 0.00 |
| | beta1 | 0.96 | 0.00 | 2361.35 | 0.00 |
| | gamma1 | 0.14 | 0.02 | 7.10 | 0.00 |
| | shape | 0.98 | 0.05 | 18.32 | 0.00 |
| **Sugar** | mu | 0.00 | 0.00 | -0.83 | 0.40 |
| | ar1 | -0.01 | 0.01 | -0.68 | 0.50 |
| | omega | -0.07 | 0.00 | -26.70 | 0.00 |
| | alpha1 | 0.00 | 0.01 | 0.07 | 0.94 |
| | beta1 | 0.99 | 0.00 | 3500.66 | 0.00 |
| | gamma1 | 0.09 | 0.01 | 15.89 | 0.00 |
| | shape | 1.19 | 0.04 | 29.71 | 0.00 |
| **Cotton** | mu | 0.00 | 0.00 | 0.52 | 0.60 |
| | ar1 | 0.00 | 0.00 | -0.08 | 0.94 |
| | omega | -0.11 | 0.01 | -8.93 | 0.00 |
| | alpha1 | -0.01 | 0.01 | -0.96 | 0.34 |
| | beta1 | 0.99 | 0.00 | 640.93 | 0.00 |
| | gamma1 | 0.11 | 0.03 | 3.95 | 0.00 |
| | shape | 1.13 | 0.06 | 19.85 | 0.00 |

| | | | | | |
|---|---|---|---|---|---|
| Coffee | mu | 0.00 | 0.00 | 0.77 | 0.44 |
| | ar1 | -0.03 | 0.01 | -2.00 | 0.04 |
| | omega | -0.15 | 0.00 | -97.88 | 0.00 |
| | alpha1 | 0.04 | 0.01 | 3.88 | 0.00 |
| | beta1 | 0.98 | 0.00 | 7241.51 | 0.00 |
| | gamma1 | 0.08 | 0.00 | 46.66 | 0.00 |
| | shape | 1.26 | 0.04 | 30.35 | 0.00 |
| Ethanol | mu | 0.00 | 0.00 | 0.00 | 1.00 |
| | ar1 | 0.00 | 0.00 | -0.36 | 0.72 |
| | omega | -0.15 | 0.18 | -0.80 | 0.42 |
| | alpha1 | 0.10 | 1.19 | 0.08 | 0.93 |
| | beta1 | 0.97 | 0.01 | 115.21 | 0.00 |
| | gamma1 | 0.50 | 0.57 | 0.89 | 0.37 |
| | shape | 0.25 | 0.27 | 0.92 | 0.36 |

**Note:** The table presents the AR-EGARCH-GED fit for all the commodities.

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# 4. Commodity price crash risk and crash risk contagion

**Abstract**

In this study, we measure the crash risk for commodity futures. We construct down-to-up volatility (DUVOL) using 1-minute data and a negative coefficient of skewness (NCSKEW) using daily data. We determine the drivers of crash risk and the subsequent crash risk spillovers for commodities at different quantiles. The findings indicate a significant impact of speculation, hedging pressure, basis, momentum, attention, and term structure on commodity crash risks. Crash risk spillovers are asymmetric, remaining low at 33% at the median and peaking at approximately 88% during the extremities. Metals and agricultural commodities, such as soybean oil, soybeans, corn, and wheat, are mostly net transmitters of crash risk in all quantiles, whereas livestock and energy commodities are mostly net receivers. We find that speculation, hedging pressure, basis, momentum, attention, and term structure have heterogeneous impacts on different commodities, indicating their relative preferences in a portfolio given their characteristics.

## 4.5. Conclusion

Crash risk has been extensively studied in the context of stock markets; however, this study explores crash risk for commodities for the first time. It proposes a novel perspective on commodity risk management. Given the apparent resemblance of the commodities market to stock markets post financialization, this study invokes stock price crash risk measures to estimate the crash risk for commodities. We measure crash risk for 17 commodities from four sectors using down-to-up volatility (DUVOL) and negative coefficients of skewness (NCSKEW). We estimated the crash risk at a weekly frequency using hourly data.

The crash risk is highest for wheat, sugar, and natural gas. We observe that the crash risk is more volatile for energy commodities. Simultaneously, the high synchronization between the DUVOL and BSADF bubble statistics for agricultural softs and livestock indicates that crash risk is frequently sentiment-driven. Spikes in the crash risk of commodities coincide with notable price-distorting events in the market. In line with the extant literature, we document that speculation, hedging pressure, basis, momentum, commodity attention, and the term structure of commodities are significant drivers of commodity crash risks. Overall, we observe that, in most cases, speculation and hedging pressure lead to an increase in crash risk, with the exception of crude oil. Subsequently, we find that this basis leads to a decline in crash risk for commodities. In most cases, momentum and term structure also lead to a decline in crash risk. Commodity attention, however, was found to increase the crash risk for corn, while decreasing it for crude oil in the given week.

Additionally, we find that the crash risk spillover across commodities is approximately 88% for the lower and upper quantiles and 33% for the median quantiles. The overall connectedness structure at all quantiles reveals the dominant role of metals and a few agricultural commodities, such as soybean oil, soybeans, corn, and wheat, in transmitting crash risks to other commodities.

Finally, we illustrate the influence of commodity-specific factors on crash risk spillovers at different quantiles, while controlling for macroeconomic and market factors. We document heterogeneity in commodities. A commodity-specific variable that raises crash risk spillover from one commodity may have no or adverse impact on crash risk spillover from other commodities. The nature and magnitude of the impact of commodity-specific variables on crash risk spillover are also contingent on the quantiles. We found that a variable is likely to have a significant impact on different sets of commodities across quantiles. However, in most cases, the direction of the impact remains the same across quantiles.

The study is limited in its scope of limiting the definition of crash risk index to a euphemistic implication of the conditional skewness of the return distribution, and does not extend to the forecasting of the expected negative returns. A natural extension of this study is to explore whether commodity crash risk explains the significant risk premium in commodity pricing. Moreover, in line with the recent findings of Chabi-Yo et al. (2022), one can extend the scope to analyse the financial asset's sensitivity to the extreme downside realisations of all risk factors in an asset pricing model.

We leave this analysis for future research. The findings are beneficial for portfolio managers and policymakers in the effective diversification of a commodity portfolio and reducing the crash risk in the market by identifying the locus of contagion.

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# Appendix

## A. Impact of control variables on crash risk

We report the impact of control variables including- log of volume of trade and volatility for every commodity, S&P500 returns, S&P GSCI returns, EPU, VIX, Federal bonds term spread, dollar index value, and CPI for USA and seasonal dummies on DUVOL (Table A1) and NCSKEW (Table A2).

**Table A1:** Determinants of DUVOL

| Variables | CL | NG | CC | KC | SB | CT | ZC | SB | BO | W | LC | LH | G | SI | PA | PL | CU |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2.month | -0.0278 | -0.0909* | -0.0185 | -0.0116 | 0.0255 | 0.0286 | 0.0175 | -0.0639 | -0.0204 | 0.00104 | -0.158** | 0.0483 | 0.0269 | 0.0102 | -0.0300 | 0.0193 | -0.00451 |
| 3.month | -0.0211 | -0.0931** | 0.0535 | 0.0190 | 0.0388 | 0.0432 | 0.0190 | 0.0744 | 0.0555 | 0.00619 | 0.0136 | 0.00940 | 0.0176 | 0.0344 | -0.0291 | 0.0227 | 0.0327 |
| 4.month | -0.0889* | -0.164*** | 0.0372 | 0.0211 | 1.70e-05 | 0.0549 | 0.0263 | -0.00140 | 0.116** | -0.0270 | -0.0856 | -0.00813 | 0.0108 | 0.0597 | 0.0531 | 0.00676 | -0.0321 |
| 5.month | -0.0575 | -0.0963** | 0.0736 | 0.00783 | -0.0243 | 0.0684 | 0.0813 | 0.0745 | -0.00710 | -0.0492 | -0.104* | -0.00847 | 0.0454 | 0.0261 | -0.0243 | 0.0102 | 0.0433 |
| 6.month | -0.0537 | -0.0651 | -0.0509 | 0.0624* | 0.00151 | 0.00413 | 0.0768 | -0.00447 | 0.0237 | 0.0285 | -0.111 | 0.00550 | 0.0336 | 0.0639* | 0.0434 | 0.138*** | 0.00136 |
| 7.month | -0.00819 | -0.0382 | 0.0375 | -0.0241 | -0.120** | 0.0364 | 0.0133 | 0.0588 | -0.0162 | -0.0705 | 0.00963 | -0.00697 | 0.0260 | 0.0671* | -0.0284 | 0.0469 | 0.0624 |
| 8.month | 0.0302 | -0.145*** | 0.0462 | -0.0166 | -0.00857 | 0.0613 | -0.00237 | 0.00163 | 0.0444 | -0.0532 | -0.0546 | -0.0498 | 0.0411 | 0.0690* | -0.0600 | 0.0713 | 0.00168 |
| 9.month | -0.0592 | -0.130** | 0.0684 | -0.0444 | -0.0687 | 0.0506 | -0.000995 | -0.0349 | 0.0532 | -0.0391 | -0.00631 | -0.0524 | 0.0456 | 0.0474 | 0.00372 | 0.136*** | 0.00554 |
| 10.month | -0.0134 | -0.175*** | 0.0168 | -0.0831*7* | 0.0756 | 0.0225 | -0.0950** | -0.0382 | -0.0509 | -0.0300 | -0.113 | -0.00701 | 0.0228 | 0.0458 | -0.0573 | 0.0387 | 0.0387 |
| 11.month | 0.0151 | -0.0964** | -0.00559 | -0.0584 | 0.0130 | 0.00672 | -0.00814 | -0.00456 | -0.00264 | -0.0378 | -0.0985* | -0.0375 | 0.0870*** | 0.0902*** | -0.0274 | 0.0544 | 0.0340 |
| 12.month | -0.119*** | -0.0371 | 0.0272 | -0.0596 | -0.0564 | -0.0346 | -0.00819 | -0.0459 | -0.0238 | -0.0103 | -0.170** | 0.0688 | 0.0198 | 0.0167 | -0.00528 | 0.000482 | -0.0515 |
| ln_volume | -0.0353 | -0.141** | -0.144*** | -0.0458 | 0.00483 | -0.0126 | -0.0484 | -0.0311 | -0.0467 | -0.0753* | 0.102 | 0.000752 | 0.0339 | 0.0641* | 0.0201 | -0.0237 | -0.00200 |
| L.ln_volume | -0.0766 | 0.107 | 0.0600 | | | | | | 0.0148 | | 0.0483 | | | | | | -0.0453 |

| | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| L2.ln_volume | -0.0611 | 0.0137 | 0.171** | | | | | | -0.000740 | | 0.0842 | | | | | | 0.0123 |
| L3.ln_volume | -0.0367 | 0.00662 | -0.0867* | | | | | | 0.0634 | | 0.0364 | | | | | | 0.00470 |
| L4.ln_volume | 0.104* | -0.0222 | | | | | | | 0.00200 | | 0.183** | | | | | | 0.0753* |
| L5.ln_volume | | -0.0323 | | | | | | | 0.0708 | | -0.0296 | | | | | | 0.0324 |
| L6.ln_volume | | -0.0676 | | | | | | | 0.0412 | | 0.0257 | | | | | | 0.0402 |
| L7.ln_volume | | -0.0630 | | | | | | | -0.0462 | | 0.0536 | | | | | | -0.0636* |
| L8.ln_volume | | 0.197*** | | | | | | | -0.0734 | | -0.187** | | | | | | |
| volatility | 0.0804** | 0.0305 | 0.0406 | -0.00375 | -0.0520 | 0.0104 | -0.0514 | 0.0195 | 0.0198 | -0.0236 | -0.0718 | -0.0259 | 0.0400 | -0.0271 | 0.0210 | 0.00399 | 0.00581 |
| L.volatility | | -0.0809** | 0.00941 | | | 0.00378 | | | | | | | | | | 0.180*** | |
| L2.volatility | | | 0.0551* | | | -0.0378 | | | | | | | | | | | |
| L3.volatility | | | | | | -0.0813** | | | | | | | | | | | |
| sp500 | 0.0814** | 0.0340 | -0.0976*** | -0.0205 | 0.0258 | -0.0262 | 0.0348 | 0.0454 | 0.0269 | 0.0297 | -0.0411 | -0.00305 | -0.00429 | 0.0223 | -0.0353 | -0.00618 | -0.0117 |
| L.sp500 | | | | | | | | | | | | | | | | 0.0691* | |
| gsci_ret | -0.484*** | -0.0816** | -0.0281 | -0.0486 | -0.128*** | -0.0573 | -0.132*** | -0.0700* | -0.0894** | -0.00333 | -0.0465 | -0.0586 | 0.0262 | 0.0391 | 0.0328 | -0.0770* | 0.00777 |
| L.gsci_ret | -0.102*** | | | | | | | | | -0.0655** | | | | | | | |
| vix | -0.0544 | 0.0469 | 0.0195 | 0.0197 | -0.0123 | -0.00416 | -0.0285 | 0.199 | 0.187* | 0.0295 | 0.0809* | 0.0753* | 0.00160 | 0.0214 | 0.0377 | -0.0921* | -0.00200 |
| L.vix | | | | | | | | -0.214* | -0.181* | | | | | | | | |
| gepu_ppp | -0.0340 | 0.0256 | 0.131*** | 0.0200 | -0.0100 | -0.0229 | 0.00669 | 0.00893 | 0.0485 | -0.0216 | -0.0267 | -0.0269 | 0.0278 | -0.296* | -0.113 | 0.136** | -0.0734 |
| L.gepu_ppp | | | | | | | | | | | | | | 0.305* | | | |
| usa_cpi | -0.158*** | 0.145* | 0.0536* | -0.0572 | 0.0293 | -0.116*** | -0.0275 | -0.0273 | -0.0517 | -0.0164 | 0.0512 | 0.130* | 0.0118 | 0.0226 | -0.210* | 0.0578 | 0.00775 |
| L.usa_cpi | 0.206*** | -0.136* | | 0.109* | | | | | 0.0866 | | | -0.153** | | | 0.255** | | |
| dollarindex | -0.00444 | 0.0137 | 0.105*** | -0.0217 | 0.00557 | 0.0832** | 0.0903*** | 0.0757** | 0.0831*** | 0.0782** | 0.0710* | 0.0424 | 0.0395 | 0.0443 | 0.0963** | 0.166*** | 0.0857*** |
| L.dollarindex | -0.0822*** | | 0.0717** | 0.0595** | | | | 0.0620** | | | | | | | 0.105** | | |
| termspread | -0.0247 | -0.0353 | -0.0105 | -0.0262 | 0.0169 | 0.0833** | -0.0197 | -0.0122 | -0.00933 | -0.0154 | -0.00729 | -0.0873** | 0.102*** | 0.0315 | -0.0604 | 0.0115 | 0.0214 |

| | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| L.termspread | | | | | 0.0771** | | | | -0.0536* | | | | | | | | |
| | | | | | | | | | | | | | | | | | |
| Observations | 768 | 763 | 746 | 782 | 773 | 772 | 789 | 777 | 774 | 783 | 782 | 784 | 772 | 775 | 436 | 526 | 768 |
| Adjusted R-squared | 0.297 | 0.224 | 0.311 | 0.379 | 0.268 | 0.137 | 0.165 | 0.221 | 0.342 | 0.298 | 0.048 | 0.055 | 0.434 | 0.412 | 0.210 | 0.213 | 0.312 |

**Note:** The table reports the results from the regression equation (10). Crash risk is measured as DUVOL using one minute data at weekly frequency. Controls include the log of volume of trade and volatility for every commodity, S&P500 returns, S&P GSCI returns, EPU, VIX, Federal bonds term spread, dollar index value, and CPI for USA and seasonal dummies. The lags have been manually selected where the benchmark model for initial regression was motivated from BIC lag selection for Vector Autoregression. Lags that were insignificant for all commodities have been omitted for brevity. Standardised betas are reported. Abbreviations: CL- crude oil, NG – natural gas, CC-cocoa, KC-coffee, SU-sugar, CT-cotton, ZC-corn, SB- soybeans, BO- soybean oil, W-wheat, LC-live cattle, LH- lean hogs, G-gold, SI- silver, PA- palladium, PL- platinum, CU- copper.

**Table A2:** Determinants of NCSKEW

| | Energy | | Agriculture | | | | | | | | Livestock | | Metals | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variables** | **CL** | **NG** | **CC** | **KC** | **SB** | **CT** | **ZC** | **SB** | **BO** | **W** | **LC** | **LH** | **G** | **SI** | **PA** | **PL** | **CU** |
| 2.month | -0.0508 | 0.0224 | 0.0457 | 0.0568 | 0.0187 | 0.108** | 0.0630 | 0.0758 | 0.0601 | -0.0309 | -0.0235 | -0.0872* | 0.00290 | 0.0179 | 0.0302 | 0.135** | 0.00721 |
| 3.month | -0.0338 | -0.0936* | 0.0323 | 0.0337 | 0.104** | 0.0389 | 0.0257 | 0.0769 | 0.0360 | -0.0764 | 0.0218 | -0.0188 | 0.00285 | 0.0294 | 0.218** | 0.133** | 0.00569 |
| 4.month | -0.0120 | -0.133*** | 0.0524 | 0.0205 | 0.0497 | 0.0983** | 0.0583 | -0.00255 | 0.104* | -0.0292 | -0.0289 | -0.0680 | -0.0238 | 0.0274 | 0.0875 | 0.0431 | 0.00854 |
| 5.month | -0.0485 | -0.0853* | 0.0444 | -0.0241 | -0.0612 | 0.0813 | 0.0450 | 0.0450 | 0.0358 | -0.0659 | -0.0229 | -0.0405 | 0.0494 | 0.0627 | 0.144** | 0.100* | -0.0377 |
| 6.month | -0.0372 | -0.113** | 0.00748 | 0.0196 | -0.0602 | 0.0519 | 0.0407 | 0.0300 | 0.0671 | 0.00129 | -0.0493 | -0.0315 | -0.000301 | 0.0806* | 0.225** | 0.0420 | -0.0201 |
| 7.month | -0.000162 | -0.0382 | -0.0298 | -0.0197 | -0.0955* | 0.0335 | 0.0504 | 0.0964* | 0.0833* | -0.0999 | -0.0556 | 0.135** | 0.0476 | 0.0245 | 0.0385 | 0.0755 | -0.0597 |
| 8.month | -0.00837 | -0.0693 | 0.0490 | -0.0679 | -0.0236 | 0.0328 | -0.00207 | 0.0228 | 0.0644 | -0.0663 | 0.00278 | 0.100* | 0.0314 | 0.0181 | 0.129* | 0.120** | 0.0263 |
| 9.month | 0.0125 | -0.228*** | 0.0657 | -0.0889* | -0.0170 | 0.0159 | -0.0588 | 0.0137 | 0.0810* | -0.121* | -0.106** | -0.0135 | 0.0443 | -0.00719 | 0.134 | 0.184*** | -0.0511 |
| 10.month | 0.0306 | -0.166*** | 0.0871* | -0.0407 | 0.0177 | 0.0441 | -0.0417 | 0.0703 | -0.0291 | -0.0929** | -0.0347 | 0.0115 | 0.0718 | 0.0387 | 0.0324 | 0.139** | -0.00943 |
| 11.month | 0.0143 | -0.172*** | 0.153*** | -0.0439 | -0.0523 | 0.0809* | 0.00520 | 0.00218 | 0.0128 | -0.105* | -0.0960* | -0.0252 | 0.0613 | 0.0663 | 0.0674 | 0.136*** | 0.0551 |
| 12.month | -0.0188 | 0.0373 | 0.0583 | -0.0717 | -0.0555 | 0.0510 | -0.0409 | 0.0274 | 0.0149 | -0.0810 | -0.0166 | -0.0643 | 0.0873 | 0.0813 | 0.123 | 0.0941* | -0.0357 |
| ln_volume | 0.00218 | -0.0787* | -0.0459 | -0.0868* | -0.0400 | -0.0636 | -0.0559 | -0.0155 | -0.0825 | -0.193*** | 0.190* | -0.0306 | 0.0828* | 0.00607 | -0.0493 | 0.102** | 0.0531 |
| L.ln_volume | 0.0519 | | | | | | | | 0.0737 | 0.189*** | -0.0178 | | 0.0124 | | | | |
| L2.ln_volume | 0.0627 | | | | | | | | -0.129** | -0.0940 | 0.0366 | | 0.0183 | | | | |
| L3.ln_volume | 0.00515 | | | | | | | | | 0.108* | 0.0208 | | 0.0379 | | | | |
| L4.ln_volume | -0.0834 | | | | | | | | | -0.108** | 0.145** | | -0.00398 | | | | |

| | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| L5.ln_volume | 0.116 | | | | | | | | | 0.158*** | | | -0.0431 | | | | |
| L6.ln_volume | -0.00741 | | | | | | | | | | | | 0.106** | | | | |
| L7.ln_volume | -0.194** | | | | | | | | | | | | | | | | |
| L8.ln_volume | 0.0766 | | | | | | | | | | | | | | | | |
| L9.ln_volume | 0.0794 | | | | | | | | | | | | | | | | |
| L10.ln_volume | -0.133* | | | | | | | | | | | | | | | | |
| L11.ln_volume | 0.221*** | | | | | | | | | | | | | | | | |
| Volatility | 0.151*** | -0.0295 | 0.0365 | -0.0140 | -0.0449 | 0.0362 | 0.0660 | 0.105** | 0.0371 | -0.0835** | -0.0404 | -0.111*** | -0.0250 | -0.0384 | 0.0987 | -0.0440 | -0.0208 |
| L.volatility | | | | | | | | | 0.0770* | | | | | 0.0309 | | | |
| L2.volatility | | | | | | | | | | | | | | 0.0787** | | | |
| sp500 | -0.0429 | 0.0109 | 0.000511 | -0.00594 | -0.115*** | -0.0839* | -0.00975 | 0.0956* | -0.0270 | -0.0221 | -0.0248 | -0.00941 | -0.0234 | -0.0512 | -0.0421 | -0.0411 | -0.118** |
| L.sp500 | | | | -0.0613* | | | | | | | | | | | | -0.100** | |
| gsci_ret | 0.00798 | 0.0824** | 0.109*** | 0.0382 | 0.105*** | 0.159*** | 0.136*** | 0.0783** | 0.150*** | 0.162*** | 0.0267 | 0.00809 | 0.138*** | 0.220*** | 0.0751 | 0.138*** | 0.111*** |
| L.gsci_ret | | | | | 0.0861** | | | | 0.127*** | | | | 0.110*** | 0.210*** | | 0.131** | 0.133*** |
| Vix | -0.0393 | 0.0427 | -0.0398 | -0.0412 | -0.107** | 0.00288 | -0.120*** | 0.202 | -0.0747 | 0.0581 | 0.0868* | -0.0503 | -0.00592 | -0.0183 | -0.0307 | -0.0279 | -0.0445 |
| L.vix | | | | | | | | -0.284** | | | | | | | | | |
| gepu_ppp | -0.103 | 0.0419 | 0.0368 | -0.0347 | 0.0443 | -0.0363 | 0.0238 | 0.0791** | 0.0845* | -0.0337 | 0.00383 | 0.0212 | 0.0110 | 0.0120 | -0.0625 | 0.476** | -0.0763* |
| L.gepu_ppp | | | | | | | | | | | | | | | | -0.459** | |
| usa_cpi | 0.0204 | 0.0693* | -0.00403 | 0.0468 | 0.136** | 0.0104 | 0.00683 | 0.0248 | 0.0404 | 0.00941 | 0.0383 | -0.0250 | -0.0362 | -0.00382 | 0.107* | -0.0360 | 0.00652 |
| L.usa_cpi | | | | | -0.169*** | | | | | | | | | | | | |
| Dollarindex | -0.0770* | -0.00434 | 0.0125 | -0.0508 | -0.00901 | 0.00873 | -0.0154 | 0.00370 | -0.0514 | -0.0154 | 0.0195 | 0.0194 | -0.0563 | -0.0404 | 0.0280 | 0.0280 | -0.00612 |
| L.dollarindex | | | 0.0979*** | | | | | | | 0.0842** | | | | | | | |
| Termspread | -7.89e-05 | -0.0467 | -0.0103 | 0.0643** | 0.000109 | 0.0648* | -0.0255 | 0.0188 | 0.0739** | -0.0224 | 0.0341 | 0.0562* | 0.0498 | 0.0481 | -0.0412 | 0.0770* | 0.0243 |
| L.termspread | | | | | | | | | | | | -0.0661** | | | | | |
| Constant | | | | * | * | | | | | | *** | | | | | | |
| Observations | 675 | 678 | 687 | 688 | 682 | 706 | 687 | 708 | 686 | 708 | 687 | 705 | 672 | 682 | 378 | 474 | 672 |
| Adjusted R-squared | 0.044 | 0.212 | 0.308 | 0.345 | 0.316 | 0.186 | 0.196 | 0.235 | 0.234 | 0.254 | 0.202 | 0.257 | 0.375 | 0.340 | 0.185 | 0.237 | 0.200 |

**Note**: The table reports the results from the regression equation (10). Crash risk is measured as NCSKEW using one minute data at weekly frequency. Controls include the log of volume of trade and volatility for every commodity, S&P500 returns, S&P GSCI returns, EPU, VIX, Federal bonds term spread, dollar index value, and CPI for USA and seasonal dummies. The lags have been manually selected where the benchmark model for initial regression was motivated from BIC lag selection for Vector Autoregression. Lags that were insignificant for all commodities have been omitted for brevity. Standardised betas are reported. Abbreviations: CL- crude oil, NG – natural gas, CC-cocoa, KC-coffee, SU-sugar, CT-cotton, ZC-corn, SB- soybeans, BO- soybean oil, W-wheat, LC-live cattle, LH- lean hogs, G-gold, SI- silver, PA- palladium, PL- platinum, CU- copper.

## B. Regression robustness check

We present the Cumby and Huizinga (1992) serial correlation test results in Table B1. The null hypothesis indicates that the errors are serially uncorrelated. The results indicate that there is no serial correlation for both dependent variables.

Table B2 reports the mean VIF for all the regression equations. We find that the VIF is lower than 10 in all cases.

**Table B1:** Cumby and Huizinga (1992) serial correlation test

| Commodities | p-value | |
|---|---|---|
| | DUVOL | NCSKEW |
| **Crude oil** | 0.904 | 0.25 |
| **Natural gas** | 0.964 | 0.602 |
| **Cocoa** | 0.505 | 0.151 |
| **Coffee** | 0.804 | 0.75 |
| **Cotton** | 0.595 | 0.141 |
| **Sugar** | 0.181 | 0.361 |
| **Corn** | 0.303 | 0.473 |
| **Soybeans** | 0.129 | 0.845 |
| **Soybean oil** | 0.675 | 0.671 |
| **Wheat** | 0.786 | 0.101 |
| **Cattle** | 0.939 | 0.339 |
| **Hogs** | 0.416 | 0.356 |
| **Gold** | 0.14 | 0.848 |
| **Silver** | 0.402 | 0.876 |
| **Palladium** | 0.91 | 0.135 |
| **Platinum** | 0.191 | 0.131 |
| **Copper** | 0.721 | 0.858 |

**Note**: The p-values indicate that the null hypothesis cannot be rejected. The test has been run for the final equation using one lag.

**Table B2:** Mean VIF for regression models

| VIF | Commodity | DUVOL | NCSKEW |
|---|---|---|---|
| **Energy** | **CL** | 7.93 | 9.75 |
| | **NG** | 5.45 | 5.2 |
| **Agriculture** | **CC** | 5.18 | 3.94 |
| | **KC** | 4.59 | 3.81 |
| | **SB** | 3.33 | 5.72 |
| | **CT** | 7.14 | 3.75 |
| | **ZC** | 2.19 | 4.77 |
| | **SB** | 4.58 | 4.42 |
| | **BO** | 4.49 | 3.14 |

| | | | |
|---|---|---|---|
| | **W** | 2.65 | 3.59 |
| **Livestock** | **LC** | 3.86 | 7.61 |
| | **LH** | 9.16 | 7.31 |
| **Metals** | **G** | 2.89 | 3.59 |
| | **SI** | 3.62 | 3.18 |
| | **PA** | 2.37 | 3.77 |
| | **PL** | 2.54 | 3.67 |
| | **CU** | 3.42 | 5.93 |

## C. Quantile on Quantile plots for commodities' crash risk

In this section, we advocate the need for undertaking a Quantile VAR connectedness analysis for commodities' crash risk. We present the quartile distribution for DUVOL in tbale C1, followed by Q-Q plots in Fig. C1. We find that DUVOL mostly ranges from -3 to 3 for all the commodities with substantial variation in the first and the fourth quantiles.

Subsequently, the Q-Q plots indicate that the distribution of commodity crash risk for all the commodities is fat tailed with high kurtosis. This implies that the tails do not behave like the mean and hence warrants a cautious analysis in the tails as well.

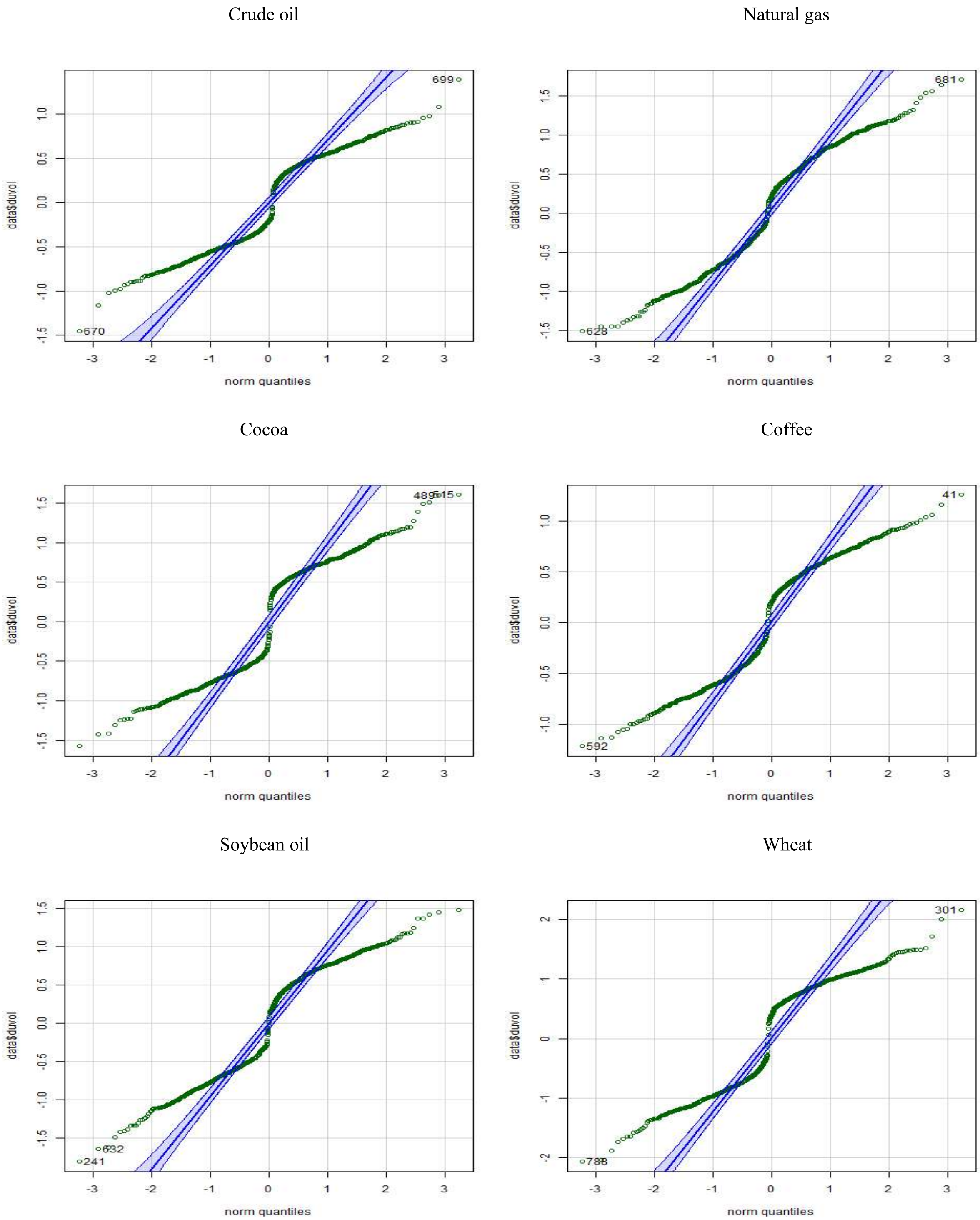
**Table C1: Detailed summary statistics for DUVOL**

| Commodities | Min. | 1st Qu. | Median | 3rd Qu. | Max. |
|---|---|---|---|---|---|
| **Crude oil** | -1.45 | -0.48 | -0.21 | 0.48 | 1.39 |
| **Natural gas** | -1.51 | -0.57 | 0.22 | 0.70 | 1.71 |
| **Cocoa** | -1.58 | -0.67 | -0.19 | 0.67 | 1.60 |
| **Coffee** | -1.22 | -0.51 | 0.20 | 0.54 | 1.26 |
| **Sugar** | -1.81 | -0.76 | 0.45 | 0.84 | 1.71 |
| **Cotton** | -2.50 | -0.46 | -0.13 | 0.41 | 2.57 |
| **Corn** | -2.47 | -1.00 | -0.51 | 0.95 | 2.53 |
| **Soybeans** | -2.15 | -0.77 | -0.43 | 0.73 | 2.29 |
| **Soybean oil** | -1.81 | -0.63 | -0.01 | 0.65 | 1.48 |
| **Wheat** | -2.07 | -0.81 | 0.40 | 0.85 | 2.15 |
| **Cattle** | -1.67 | -0.59 | -0.14 | 0.56 | 2.42 |
| **Hogs** | -1.74 | -0.55 | 0.16 | 0.58 | 2.00 |
| **Gold** | -1.29 | -0.47 | -0.21 | 0.46 | 1.27 |

| | | | | | |
|---|---|---|---|---|---|
| **Silver** | -1.41 | -0.66 | -0.19 | 0.64 | 1.66 |
| **Palladium** | -0.92 | -0.29 | -0.10 | 0.27 | 1.06 |
| **Platinum** | -0.89 | -0.32 | -0.09 | 0.30 | 0.78 |
| **Copper** | -1.26 | -0.53 | -0.25 | 0.46 | 1.28 |

**Note:** The table highlights the distribution of DUVOL for sample commodities across quartiles.

**Fig.C1:** Quantile on Quantile plots of DUVOL

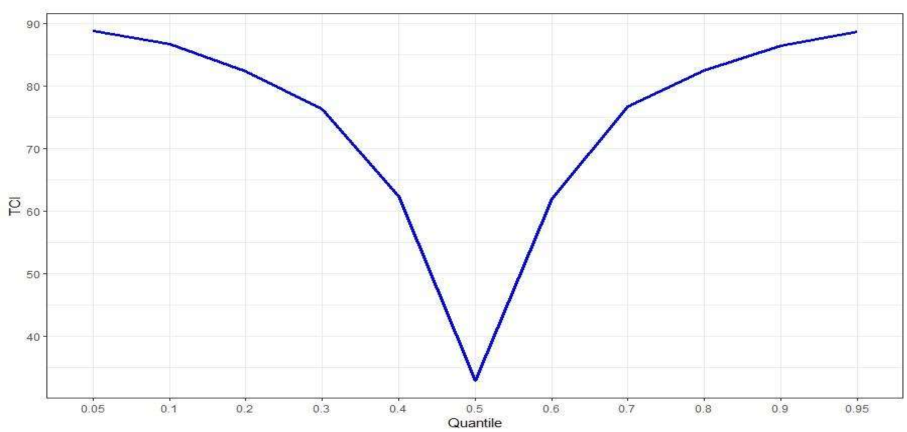


## D. Quantile on Quantile plots for commodities' crash risk

We present the plot of the total average network connectedness of crash risk across commodities at different quantiles in Fig. D1. We observe a -V shaped curve indicating that while the connectedness is much higher at the extremes, it reaches a minimum at the median quantile. A similar hike in connectedness at the extremes has been documented by Tiwari et al. (2022) who find a higher connectedness between energy and agricultural commodities at the tails than at the median quantile.

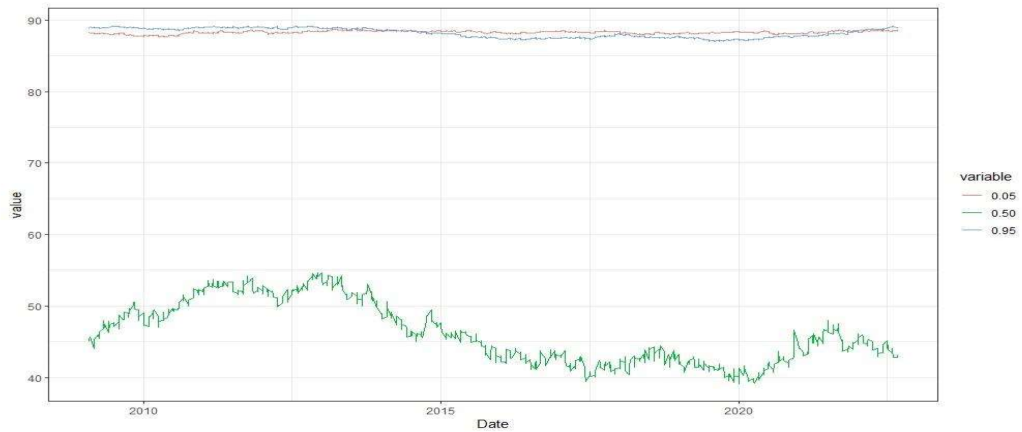
Subsequently, we also plot the time varying TCI of the upper (0.95), median (0.5) and lower quantile (0.05) in Fig. 2b. We find that the connectedness at extreme quantiles is very high and mostly symmetric whereas connectedness remains low at the median quantile and keeps declining over time.

**Fig. D1:** The total crash risk connectedness at different quantiles




**Note:** The figure presents the Total connectedness of crash risk across commodities at different quantiles.

**Fig. D2: Total connectedness at different quantiles**




**Note:** The figure presents the total connectedness index for extreme upper, extreme lower and median quantile over the sample period.

# 5. Summary and Conclusion

## 5.1. Summary of findings

In this thesis, we focus on exploring and anlaysing the interlinkages in the global commodities market from multiple dimensions. In essay I, we indicate that analysing uncertainty contagion is relatively more important than exploring return and volatility spillovers, since uncertainty is the precursor to return and volatility. We construct a novel news-based measure of uncertainty for a set of highly liquid commodities in the market and subsequently explore the spillover of uncertainty across commodities in periods of stability, crises, and across different frequency horizons. Using a panel-ARDL model, we discover that commodity uncertainty has a significant impact on commodity futures prices. Additionally, we find that the overall uncertainty spillover across commodities remains high at 49%, indicating at the high cross-asset linkages in the commodities sector. The study finds a rise in uncertainty connectedness during the GFC 2007–2009, the Eurozone Debt crisis 2011–2013 (EZC, hereafter), the Shale oil supply shock 2014–2015 (oil supply shock), and the COVID-19 crisis 2020. It's interesting to note that during the GFC, Shale oil supply shock, and COVID-19, agricultural commodities, especially soyoil, become more dominant in the network, while crude oil continues to be a marginal shock recipient. Given that food security is a top priority for economies during global crises, the findings seem logical. The pairwise connectivity indices point to higher uncertainty synchrony between oil and commodities like corn, wheat, and sugar. The lowest uncertainty synchronisation across all sub-periods is found in oil combined with soyoil, platinum, and palladium. We see that for the high frequency of 1–4 weeks, the connectedness of uncertainty is greater and more turbulent; however, at medium (5–12 weeks) and low frequencies (12 weeks and beyond), the connectedness is not only sparse but also stable.

In our second essay, we move beyond the conventionally popular measures of modelling commodity interlinkages. Based on recent research indicating the presence the non linear and asymmetric connectedness across commodities, we advocate the utility of copula models in adequately capturing the commodity interdependence. We find that C-Vine performs better than the R-Vine and D-Vine in modelling commodity interdependence, in contradiction to earlier research where copper is the central node in the vine structure. Consequently, we discover that while vine copula models significantly outperform the conventional EGARCH-based models in forecasting the Value-at-Risk (VaR, hereafter) for optimised (tangency and minimum variance) portfolios, even though they are unable to accurately predict the VaR for an equally weighted portfolio. The Kupiec test and the Joint test have both been used to corroborate the same finding. In addition, copula-based models are more effective at capturing the systemic risk associated with the commodities than conventional marginal models. When systemic risk is assessed using Multi-CoVaR, System-CoVaR, and finally Vulnerability-CoVaR, the occurrences of Value at Risk (VaR) breaches are at their lowest. When systemic risk is assessed using the conventional Delta CoVaR technique, the number of violations is at its maximum.

The third essay highlights the importance of assessing the risk of crash in commodities sector and the consequent bubble. We find that the proposed crash risk measures closely follows all the critical incidents of crash in the commodities prices. Additionally, agricultural commodities like wheat, sugar, and the energy commodity natural gas are more vulnerable to crashes. The risk of a commodity crash is consequently significantly influenced by commodity-specific characteristics such as speculation, hedging pressure, basis, momentum, commodity attention, and term structure. We find that the total spillover is substantial (about 88%) during extremities and low (33%) at the median quantile, showing an asymmetry in crash risk contagion. Additionally, depending on the status of the market, the commodity-specific characteristics have a variety of effects on the crash risk spillover.

## 5.2. Contributions of the study

The study aims to extend the existing body of knowledge by yielding constructive insights for market makers, regulators, policy makers, investors, and portfolio managers. In the given light, Essay I makes multifaceted contributions to the literature. The proposed measure of news based uncertainty not only has a significant impact on the futures prices, but also overcomes the problem of endogeneity associated with a price-deconstructed measure of uncertainty used in literature. Moreover, the study is perhaps the first to highlight the antecedence of uncertainty spillovers over return and volatility spillovers, emphasising the need to analyse uncertainty spillovers over the conventionally popular commodity networks. Further, the study supplements the extant literature by using robust method of measuring spillover that is independent of the size of the rolling window. Finally, the study also highlights the diversification benefits expected from a commodity pair in different periods by estimating the pairwise . We assert that such sorting is imminent for portfolio managers seeking commodity pairs with the least uncertainty connectedness for a given period.

At the same time, essay II attempts to enrich the literature with robust empirical evidence of the performance of multiuvariate copula models in the context of commodities. First the study delineates the relative efficiency of C-Vine and D-Vine modeling in comparison with R-Vine while quantifying portfolio risk in contrast with limited prior evidence that has focussed on an R-Vine in isolation. Second, the study is the first to our knowledge to compare the relative efficiency of copula and GARCH based models in quantifying systemic risk beyond portfolio risk in the commodities sector. Moreover, we ensure the comprehensiveness and robustness of results by examining an ambitious dimension of 22 commodities and relying on the Schwarz Information criterion to find the optimal GARCH model and return distribution for commodities.

In our third essay, we first use intraday commodities data to construct a Down to Up volatility measure that measures the weekly crash risk for every commodity. To our knowledge, on a few studies have looked at risk measures in the commodities sector. Subsequently, we contribute to the literature by undertaking an exploratory analysis of the determinants of crash risk and crash risk spillover. The study is the pioneer in determining the relative impact of commodity-specific and other macro-economic factors on crash risk and crash risk spillover. Last, we also evaluae the heterogeneity in the crash risk spillover networks at different quantiles.

## 5.3. Scope for future research

The dissertation explores multiple dimensions of global commodity linkages. In this section, we discuss the avenues for further research in this direction.

In our first essay, we have proposed a new measure of uncertainty and subsequently analysed the network linkages of commodity specific uncertainty using time varying parameter-based estimations. The findings of the study can be extended by analysing the impact of news-based commodity uncertainty on other markets such as equity, cryptocurrency, bonds and others. The findings would provide insights about how uncertainty pertaining to commodities have an impact on other financial markets. Given the rising connectedness across financial markets, an understanding of how commodity uncertainty traverses to other markets will yield useful insights for effective portfolio diversification.

In our second essay, we have empirically tested the relative efficiency of copula-based models over the traditional models in quantifying systemic and portfolio risk in the commodities sector. Extant studies, including ours have explored the modelling of portfolio returns using vine copula models, however, it may be interesting to identify the locus of contagion for other integral variables such as commodity risk and volatility. One may also explore a copula-based portfolio optimisation technique where the weights of the commodities are identified while incorporating the vine modelled inter-commodity dependence. The existing optimisation techniques do not account for the past price comovements across the assets. Hence, it will be interesting to check if vine-based portfolio optimisation techniques are able to yield better risk return trade-off than the conventional mean variance optimisation techniques.

Our third essay provides a novel variable to measure the crash risk for commodities. We find that DUVOL detects the historical price crashes in commodities. Thereon we explore the crash risk spillover across commodities for different quantiles. We have also explored the antecedents to the crash risk and the subsequent contagion. In an extension to the study, we find it intriguing to explore if there is a recurring pattern or seasonal variation in the occurrence of price crashes for different commodities such that price crash could be forecasted using a time series model. It will further be interesting if the proposed crash risk is priced in the commodities market using asset pricing models.

We aim to take up these research questions in our further research endeavours and make significant contributions to the stream of literature.