Does the substitution effect lead to feedback effect linkage between Ethanol, Crude Oil, and Soft Agricultural Commodities?

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Abstract

Despite increased demand for cleaner fuel alternatives such as ethanol in recent decades, portfolio weight allocation has become challenging due to the complex interlinkage among crude, ethanol and soft agricultural commodities that form part of the value chain. As a result, portfolio returns face three trade-offs in terms of risk: dispersion across mean, risk arising due to market interconnectedness, and risk arising due to global shocks for assets sharing common macroeconomic fundamentals. This study proposes an optimal weight allocation portfolio strategy, encapsulating the three risk measures and returns, estimated using state-of-the-art multi-objective elitist Non-Dominated Sorting Algorithm II (NSGA-II). Our proposed strategy performs well for newly constituted objectives against the Markowitz Mean-Variance approach and Global Minimum Variance. A balanced diversification escapes the feedback spillover loop trap at the same time. Our results indicate that soybean oil, sugar, and rice offer a better reward to risk, aiding portfolio immunisation to extreme market movements. Furthermore, using GJR-GARCH volatility to capture the volatility asymmetry effect, the Generalized Forecast Variance Decomposition (GFVED) shows the existence of a strong triplet pair Crude-Ethanol-Soybean as a breeding ground for the feedback effect to occur. Moreover, replacing crude weight with ethanol depicts a fall in spillover risk up to a threshold of 30% Ethanol weight, after which the feedback effect kicks in.

Keywords: Crude Oil, Ethanol, Systemic Risk, COVOL, Feedback Effect

JEL Classification: O13, Q14, Q18, Q42.

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1. Introduction

Over the last two decades, the interaction of crude oil with its substitutes, such as ethanol, has evolved and become more complex (Natanelov et al., 2011). Apart from the petrodollar connection (Coudert and Mignon, 2016), technological advancement has resulted in using agricultural commodities in the production of biofuel substitutes, such as ethanol and biodiesel (Fernandez-Perez et al., 2016) that are part of the value chain (Zhang et al., 2009; Coudert and Mignon, 2016). Nevertheless, at the same time, commodities sharing macroeconomic fundamentals are vulnerable to extreme market movements due to global shocks exposing commodity investors to interconnectedness risks. Thus, this research aims to address the risk of complex market interlinkage between crude, ethanol, and soft agricultural commodities. We do this by segregating the three types of risks these commodities are exposed to (i) dispersion across the mean, (ii) risk arising due to market interconnectedness and (iii) risk associated with common global shock due to shared macroeconomic fundamentals.[1] The segregation of these three risk measures aids in addressing factors contributing to tail risk and further enables us to suggest an optimal portfolio balance to maximise reward to risk.

The inherent fundamental factors like carriage costs, stock of the commodity, and expected prices asserted by the rational expectation competitive storage theory primarily drive the agriculture commodity prices (Deaton, and Larowue, 1995; Rapsomanikis et al., 2003; Ahti, 2009). However, the use of ethanol (produced from corn or sugar) and biodiesel (produced from rapeseed oil and palm oil) as a cleaner alternative to crude has resulted in agricultural commodity price interconnection with crude prices (Chang et al., 2018). The substitution effect explains the interconnections among the fuel prices, i.e., crude and cleaner alternatives such as ethanol (Ji and Fan, 2012). In this regard, Natanelov et al. (2011) highlighted that the change in energy policy, which induced ethanol's market growth, impacted the co-movement of crude oil and agricultural commodities.

The increased interdependence between crude and agricultural commodities has raised concern for policymakers (Mensi et al., 2014) and investors. The economic interdependence between crude, ethanol, and soft agricultural commodities exposed to common macroeconomic shocks undermines the benefits of portfolio diversification. Moreover, events such as the Global financial crisis (GFC) (2008), Eurozone sovereign debt crisis (2010), and the Covid-19

[1] Noteworthy, empirical standard measures of the risk of the three types exist, i.e., variance for dispersion across the mean, Spillover Index by Diebold and Yilmaz (2012) to measure risk due to market interconnectedness, and COVOL measure by Engle and Campos-Martins (2022) to measure risk due to global shock exists.

pandemic (2019) have jolted the commodity market, wiping away investors' surplus accumulated over time. During such distress events, the feedback loops serve as sinkholes for systemic risk intensification, increasing extreme market movements. While deviation from the mean and interconnectedness are responsible for fatter tails owing to persistent spillover over time, a measure of sensitivity to common global shock can be attributed to the spike in tail due to a sudden market spurt.

Value at risk (VaR), Copula-based Approach, etc., the portfolio risk mitigation methods, primarily related to the tail risk, are responsive to assumptions on data distributions, which seldom deviate and hence are criticised. However, these methods use the historical occurrence of extreme events as given and therefore safeguard the portfolio position based on past experiences. On the other hand, incorporating systemic risk and COVOL measures aids investors in examining factors contributing to fatter tails on a pairwise and systemic basis. It is challenging to encapsulate the three risk measures, viz. dispersion across the mean, risk due to interconnectedness, and sensitivity to global shocks while retaining the essence of these measures. As a result, certain studies circumventing minimum spillover portfolio weight allocation are gaining popularity (Kumar and Singh, 2022; Do and Linh 2022; Jiang et al. 2019). Nevertheless, treating variance and spillover as separate risk measures needs improvisation.

In this manuscript, we aim to showcase the need for factoring the three risk measures separately in the portfolio construction along with the expected return. We further show the proposed portfolio's efficacy via cross-comparison with the Markowitz Mean-Variance approach (1952) and Global Minimum variance. Conceptually, the proposed portfolio strategy illustrates the evasion of feedback loops by minimal weight allocation to assets constituting the triplet pair for the loop to form. VAR based interconnectedness approach, as a proxy of systemic risk, are comprehensive and therefore have an advantage over traditional methods such as Johnson cointegration and DCC GARCH. Thus, we follow Diebold & Yilmaz (2012) to capture the systemic risk, an industry-standard spillover estimation measure based on interconnectedness. Importantly, volatility spillover quantified daily returns give equal weight to positive adverse shocks. However, during times of distress, the persistence of volatility spike is observed more frequently; thus, the conditional mean behaves differently to positive and negative shock (Glosten et al., 1993; Nelson, 1991; Engle and Ng, 1993). Thus, spillover-based measures must account for this asymmetry; the estimation may be understated, especially in times of distress, contributing adversely to the tail risk. Asymmetric volatility could be attributed to the volatility feedback effect driven by time-varying risk premium (French et al., 1987; Campbell and Hentschel, 1992). However, this assertion is based on the assumption that high volatility remains persistent. However, financial markets are exposed to large shocks triggering breakage of the consistency invariance, thus challenging the assumption of volatility persistence. Thus, the GARCH model chosen should account for the structural break (Hillebrand, 2008). We use the GJR-GARCH that incorporates asymmetricity by behaving differently for positive and negative shocks while managing the volatility persistence to account for the volatility feedback.

We estimate the COVOL as a risk measure for common global shocks after fitting a single index model with the real food price index as a factor explaining price volatility in crude, ethanol, and agri commodities. Since the research proposes a portfolio management approach encapsulating variance along with systemic risk and COVOL, we use standard estimation procedures.[2] As a result, there is no loss of generality with the application of this portfolio management strategy. Notably, substituting crude weight with ethanol changes the systemic risk dynamics and the portfolio's performance, as the other two risk measures are not invariant of the crude weight. Hence, the proposed portfolio strategy should bring the optimum balance amid the three risk measures. However, non-linear linkage dynamics increase the complexity to optimise the weights (Cheng and Cao, 2019). Thus, incorporating all three measures while framing portfolio objectives makes the portfolio management process more scientific.

For our study, the variables of interest are crude, soft agri-commodities, and ethanol (the cleaner alternatives of crude). Since the trading of biodiesel started only recently, i.e., in 2015 and due to insufficient data for a comparative study, we chose ethanol as the only substitute for crude for this study. Therefore, this study comparatively analyses the evolution of spillover dynamics post-induction of ethanol, i.e., July 2007. Our research factors in soft commodities such as corn, wheat, sugar, soybean, soy oil, palm, rapeseed, and rice that are gaining importance as raw material inputs for ethanol production. Thus, we contribute to the Crude-Ethanol-Commodity linkage study by identifying the feedback loops as the source for the intensification of systemic risk via triplet pairs. We provide insights into the impact on the dynamic linkage of Crude-Ethanol-Soft Agri Commodities due to the substitution of Crude weight with ethanol in investor's portfolio. Finally, we propose a portfolio management

[2] However, we acknowledge that improvisations with other spillover estimation measures can be used to reflect systemic risk better. Likewise, COVOL, as a measure of common global shock, being a market-based measure, can be replaced with other measures of common global shocks.

strategy with encapsulation of three risk measures viz. dispersion across mean, systemic risk arising due to market interconnectedness, and risk associated with common global shock due to shared macro-economic fundamentals.

The remainder of the paper is outlined as follows: Section 2 reviews the contemporary literature concerning our topic. Section 3 deals with the research design, followed by the discussion of results in Section 4. In the last section, we provide conclusions with suggestions to policymakers and investors.

2. Literature Review

In the last two decades, many studies have been conducted to determine fossil fuel's substitution effect, which leads to its linkage with biofuel and soft commodities. However, studies exploring the substitution effect of fossil fuel leading to the cross-asset linkage of crude, biofuel, and soft commodities and the feedback effect of the same are rare. These studies can be classified by time as pre and post-renewable fuel policy implementations. Few of the studies have focused on finding the short & long-term co-movement between these indices, and few others focused on directional causalities & volatility spillover amongst them (Busse et al., 2011; Liu, 2014; Serra et al., 2011; Trujillo-Barrera et al., 2012; Nazlioglu et al., 2013).

Natanelov et al. (2011) studied the co-movement of crude oil futures with agricultural commodities for mature markets. In the context of biofuel, they found that when crude price exceeds a certain threshold, biofuel policy has buffered the co-movement of agri-commodities such as corn and soybean with crude. Additionally, they stressed the importance of understanding the dynamics of crude and agri-commodities to aid policymaking. Some researchers worked on using biofuels in tandem with crude and Agri commodity prices. For example, Du et al. (2011) find strong evidence of volatility spillover amongst the wheat, corn, and crude post-2006. The spillover linkage was attributed to the usage of corn and wheat for ethanol production instead of rising crude prices. Thus, the intense price shocks have triggered volatility in wheat and corn. Chang and Su (2010) deployed a bivariate EGARCH model to explore the usage of biofuels such as ethanol as a substitute for crude in times of high and low oil prices. The study finds the substitution effect during higher oil prices. The effect resulted from price spillover from crude to commodities such as corn and soybean futures amid rising crude prices.

Antonakakis et al. (2018), Broadstock et al. (2022), Khalfaoui et al. (2019) propose measures to mitigate systemic risk exposure of investors in asset-cross linkages. The systemic risk minimisation approach concentrates on the tail risk, a shift in how risk minimisation happens for fat tails. This proactive approach targets the factors contributing to tail risk (as against responsive approaches). At the same time, systemic risk measures are intensifying due to risk transgression via market interconnectedness due to exposure to the common global shock "COVOL" Engle and Campos-Martins (2022). Though different sensitivity measures of common global shocks exist, Baker et al. (2016) and Caldara and Iacoviello (2022) use macroeconomic news announcements to quantify the risk arising from common global shocks. Nevertheless, market practitioners appreciate market-based measures. Building on the idiosyncratic correlated volatilities, Herskovic et al. (2016) and Engle and Campos-Martins (2022) propose COVOL, exploiting the correlation existing in the error residuals to be attributed to the risk associated with common global shocks. Notably, the existence of feedback loops leads to the intensification of systemic risk in the system (Singh et al., 2019). Since only a proportion of risk arising due to COVOL is reflected in estimated systemic risk, ignorance of COVOL while framing a portfolio management strategy could be problematic.

The current study gives a new dimension to the work of Chiu et al. (2016) and Paris (2018) from an investor's perspective while constituting a portfolio with the existence of a multi-directional feedback effect amongst fossil fuel and agricultural commodities. Furthermore, spillover intensification has been studied in light of risk arising due to common global shock by proposing a portfolio management strategy for better reward to risk. Thus, the research via crude, ethanol and commodity linkage dynamics intends for a paradigm shift in defining the risk a portfolio is exposed to while framing a portfolio management strategy. It treats the three risk exposures: dispersion across the mean, risk arising due to interconnectedness, and risk arising due to global shocks.

3. Research Design

As part of the empirical strategy, we employ three methodologies, viz. Sensitivity to global shocks, estimation of systemic risk, and portfolio weight allocation to minimise variance, systemic risk, and risk arising due to common global shocks.

3.1 Sensitivity to Global Shocks

The estimation involves fitting a single index model for each commodity, with the Real Food Price Index as the explanatory variable. We source the data from the Food and

Agricultural Organization of the United Nations. Additionally, we undertake an autoregressive process to account for historical information in return for discovery. For the analysis, we include crude oil, soft commodities (wheat, corn, rice), and oil seeds (soybean, rapeseed, sugar, crude palm oil, and soybean oil). The commodities data is obtained from the Bloomberg database. The Bloomberg codes used are CL1 Comdty for WTI Crude Oil, ETHNCHIC index for Ethanol, C 1 Comdty for Corn, KO1 Comdty for Crude Palm Oil, IJ1 Comdty for Rapeseed, RR1 Comdty for Rice, BO1 Comdty for Soybean oil, S 1 Comdty for Soybean, QW1 Comdty for Sugar LIFFE, W 1 Comdty for Wheat. The ethanol trading data obtained from the Chicago Exchange Argo Ethanol data starts from February 2007 as the trading began only in late February 2007. The monthly periodic sample spans several significant financial and commodity market high volatile episodes.

Figure 1 displays the time series plot of prices and the return of crude oil and soft commodities. We observe that in the post-2008 crisis, prices of all commodities remained highly volatile. The WTI crude oil price rose significantly in 2006-07 and the first half of 2008 to almost USD 143 per barrel. Contemporaneously price rise is observed amongst soft commodities, such as corn, wheat, and rice; prices rose sharply between 2007 and 2008. However, after peaking in 2008, prices fell sharply in the late-2009 due to the global recession. The prices rose again in 2011 and 2012 post-recession. Over the following years until 2016, prices fell again, reaching low levels similar to 2008. The contemporaneous price movement of crude, ethanol and soft commodities observed in the Figure 1 time-series plot indicates their dependence structure.

Table 1 depicts the preliminary statistics of the variables considered for the study for the entire sample. Compared to crude oil and ethanol, soft commodities generally show higher average monthly returns but with a lower standard deviation than crude oil. For investors, it looks plausible to bag the commodities with a higher average monthly return per unit of risk estimated from variance. However, bagging the commodities sharing a significant Pearson correlation coefficient Table 2, of less than one would serve the Markowitz portfolio selection approach. However, this ignores the risk associated with the spillover effect amongst the commodities (Tiwari et al, 2022) and the risk associated with global events, be they political, economic, or related to the pandemic or climate (Nam, 2021). Hence, considering only variance would underestimate the importance of systemic and global risks.

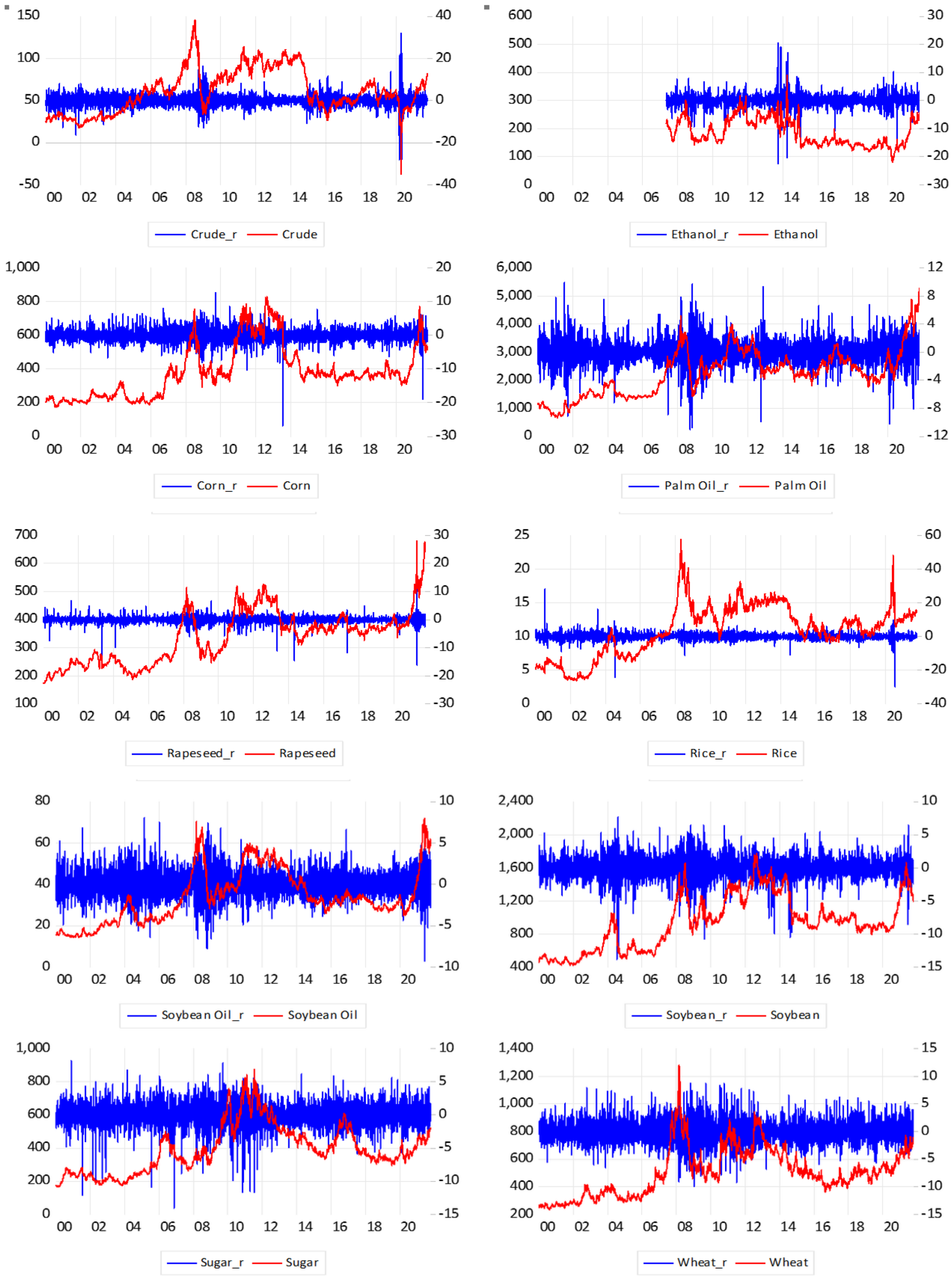

Figure 1: Time Series Plot of Price and Return of Crude, Biofuel, and Soft Commodities

Note: The left axis represents daily price levels. The right axis represents return levels.

Table 1: Descriptive Statistics of Crude Oil, Soft Commodities and Ethanol

	mean	sd	min	max	skew	kurtosis	ADF-Test
Crude	0.00135	0.12186	-0.78187	0.63327	-0.96122	11.64173	-7.74287
Ethanol	0.00063	0.1301	-0.57108	0.55057	-0.28729	4.73659	-9.46799
Corn	0.00249	0.09277	-0.30838	0.27115	-0.3705	0.7755	-7.34414
Palm Oil	0.00135	0.09671	-0.31295	0.28122	-0.24996	0.49714	-6.43777
Rapeseed	0.00293	0.07022	-0.18911	0.20853	-0.13985	0.59195	-6.60824
Rice	0.00277	0.0748	-0.26491	0.20074	-0.45788	1.38764	-7.52932
Soybean Oil	0.00412	0.07614	-0.28052	0.25747	-0.14125	2.01119	-6.84074
Soybean	0.00304	0.07435	-0.24266	0.17747	-0.5415	0.60803	-7.9072
Sugar	0.00247	0.06881	-0.28455	0.18154	-0.15835	0.95052	-8.60775
Wheat	0.00355	0.09671	-0.29099	0.35301	0.0823	0.77038	-8.68671

Table 2: Unconditional Correlation Statistics of Crude Oil and Soft Commodities (Full Sample)

	Crude	Ethanol	Corn	Palm Oil	Rapeseed	Rice	Soybean Oil	Soybean	Sugar	Wheat
Crude	-									
Ethanol	0.259^{***}									
Corn	0.233^{**}	0.366^{***}								
Palm Oil	0.289^{***}	0.074	0.322^{***}							
Rapeseed	0.349^{***}	0.180^{*}	0.482^{***}	0.481^{***}						
Rice	0.046	0.254^{***}	0.377^{***}	0.115	0.168^{*}					
Soybean Oil	0.422^{***}	0.199^{**}	0.529^{***}	0.711^{***}	0.640^{***}	0.185^{*}				
Soybean	0.275^{***}	0.240^{***}	0.633^{***}	0.480^{***}	0.563^{***}	0.275^{***}	0.701^{***}			
Sugar	0.204^{**}	0.163^{*}	0.263^{***}	0.204^{**}	0.260^{***}	0.088	0.276^{***}	0.285^{***}		
Wheat	0.09	0.265^{***}	0.603^{***}	0.326^{***}	0.513^{***}	0.327^{***}	0.418^{***}	0.515^{***}	0.186^{*}	-

Computed correlation used Pearson-method with listwise-deletion.
Note: All correlation coefficients are significant at 5%

Table 2 shows a significant correlation coefficient between crude and soft commodities. Ethanol, too, shows a significant correlation with crude and soft commodities. The univariate linear dependence ascertains further multivariate exploration of crude, soft commodity, and ethanol. For tracking the trending behaviours of commodities, the time series (level and log return) is checked for (no) stationarity using the unit root test Augmented Dickey-Fuller test (ADF). The ADF test rejects the null hypothesis at 1%, thus implying the time series to be I(0). The correlation matrix does not provide information on how these commodity indices interact in a system.

3.1.1 Methodology to Capture Sensitivity as an indicator of Common Global Shock

Here the approach is based on the COVOL measure proposed by Engle and Campos-Martins (2022). The approach attributes to factor analysis of the unexplained variance after fitting a single index model. For our analysis, we have taken the Real Food Price index (RFP) as an explanatory variable for the single index model, as shown in equation (1).

Step 1: $\Delta \ln C_i = \Delta \ln RFP + \varepsilon_i$ (1)

Where C_i represents the commodities considered for the study. Next, we check the existence of the ARCH effect in the residuals of the conditional mean model. For this, we first estimate an autoregressive process on the residuals of the Single Index model and then check for the ARCH effect. Affirmative volatility persistence leads to fitting a suitable GARCH model. For homogeneity, GARCH (1,1) model has been fit. The leftover erroneous terms after GARCH estimation are attributed to common global shocks, provided the correlation of the squared residuals differs significantly from zero. It is to be noted here that the correlation amongst the squared residuals is attributed to the shocks arising from a common global event impacting the commodity.

Mathematical deduction:

Step 2: GARCH(1,1) estimation

$$\varepsilon_{it} = e_{it}\,\boldsymbol{\sigma}_{it} \tag{2.a}$$

$$\sigma_{it}^2 = \boldsymbol{\omega}_i + \boldsymbol{\alpha}_{i1}\,\varepsilon_{it-1}^2 + \boldsymbol{\beta}_{it}\,\sigma_{it-1}^2 \tag{2.b}$$

Step 3: COVOL estimation

The error term after the GARCH(1,1) fit is assumed to follow the equation (3.a)

$$e_{it} = \sqrt{g(s_i x_t)}\ \boldsymbol{\xi}_{it}\ ;\ g = s_i x_t + 1 - s_i \tag{3.a}$$

After that, we deduct the covariance estimator of the residuals from the following specifications:

$$\boldsymbol{\Psi}_t = \frac{1}{T}\left[\, E\ \sum_{t=1}^{T} e_t^2 e_t^{2\prime}\ \right] \Rightarrow \frac{1}{T}\sum_{t=1}^{T} \Psi_t\ = ss`\boldsymbol{v} + D \tag{3.b}$$

$$D = \text{diag}\{2s_i^2 + 2\} \tag{3.c}$$

Where "*s*" reflects the factor loadings after the Principal Component Analysis (PCA) estimation performed on the residuals of the GARCH(1,1) estimation. Further, we also perform a z-test to check the correlation amid the residuals of GARCH fit differs significantly from zero.

3.2 Estimation of Systemic Risk

We use the standard Diebold and Yilmaz (2008) connectedness-based Spillover index to estimate the systemic risk between the commodities. We compute the Spillover index on the GJR-GARCH volatility.

3.2.2 Estimation of GJR-GARCH Volatility Parameters

The initial step involves estimating GJR-GARCH volatility, followed by Spillover estimation. The GJR-GARCH volatility of Glosten et al. (1993) has been used on each time series under consideration to capture the asymmetric volatility. The mathematical formulation for the GJR-GARCH (1,1) is as follows.

$$\sigma_t{}^2 = \boldsymbol{\omega} + \alpha_1\ \eta_{t-1}{}^2 + \alpha_2\ I_{t-1}\ \eta_{t-1}{}^2 + \beta\ \sigma_{t-1}{}^2 \tag{4}$$

Where, σ_t is the forecasted conditional standard deviation, $\boldsymbol{\omega}$ is the intercept for the equation, $\alpha_1\ \eta_{t-1}{}^2$ is the previous residuals, $\alpha_2\ I_{t-1}$ is the dummy variable to account for negative shocks. GJR-GARCH volatility helps capture the leverage effect by setting different equations based on past residual behaviour (Asgharian, 2016). Thus, negative shocks induce a much higher variance captured by GJR-GARCH. A high magnitude of negative persistence shock will aid in better capturing spillover during distress. Moreover, the persistence of negative shocks aids in observing the volatility feedback effect (Bollerslev et al., 2006).

3.2.3 Connectedness using Standard Diebold & Yilmaz (2012) Spillover Index (D&Y)

One of the VAR model characteristics is variance error decomposition, which distributes the share of variance amongst the variables fitted in the VAR model. Generalised

Forecast Error Variance Decompositions (GFEVD) are invariant of the ordering of the variable. The GFEVD-based connectedness approach is computationally feasible with a closed-form solution; hence system-wide connectedness assessment is feasible without the curse of dimensionality. Moreover, since the logarithmic returns are I(0), it satisfies the VAR model assumptions of the stationary data series.

Using the GFEVD, Diebold and Yilmaz (2012) derived a set of connectedness measures and deployed them to different levels of granularity from pairwise to system-wide. In Diebold and Yilmaz (2012), the pairwise connectedness values, i.e., off-diagonal elements, demonstrate how much average shock variance each system entity contributes to all the other entities. Further, the summation of all H-step ahead forecast error variance terms of the pairwise sets is computed as per the equations (5.a-5.d) below to showcase "From," "TO," "NET," and "TOTAL" connectedness values (for details, please see Diebold and Yilmaz, 2012)

$$C_{FROM(i \leftarrow \blacksquare)}(H) = \frac{\sum_{j=1}^{N}{}_{i \neq j} \tilde{\vartheta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\vartheta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{j=1}^{N}{}_{i \neq j} \tilde{\vartheta}_{ij}^{g}(H)}{N} \times 100 \tag{5.a}$$

$$C_{TO\,(\blacksquare \leftarrow i)}(H) = \frac{\sum_{j=1}^{N}{}_{i \neq j} \tilde{\vartheta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\vartheta}_{ji}^{g}(H)} \times 100 = \frac{\sum_{j=1}^{N}{}_{i \neq j} \tilde{\vartheta}_{ji}^{g}(H)}{N} \times 100 \tag{5.b}$$

$$C_{i\,(NET)}(H) = C_{\blacksquare \leftarrow i}(H) - C_{i \leftarrow \blacksquare}(H) \tag{5.c}$$

$$C_{TOTAL}(H) = \frac{\sum_{i,j=1}^{N}{}_{i \neq j} \tilde{\vartheta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\vartheta}_{ij}^{g}(H)} = \frac{\sum_{i,j=1}^{N}{}_{i \neq j} \tilde{\vartheta}_{ij}^{g}(H)}{N} \tag{5.d}$$

The connectedness concept is built from pieces of rolling variance decompositions to track the directional connectedness in real-time. The connectedness measure based on the standard D&Y Spillover index suffers shortcomings with data insufficiency. This is especially true when dealing with macroeconomic data, which are limited in their periodicity. Time-varying parameter VAR (TVP-VAR) (Antonakakis and Gabauer, 2017) is an extension to the GFEVD by Diebold & Yilmaz (2012) to help resolve this issue. We use Minnesota prior to capturing time-varying error decomposition parameters serving as spillover estimation on a pairwise basis.

4. Results

We systematically present our empirical analysis. The first subsection presents the "COVOL" analyses as an indicator of risk to common global shocks. Next, we present the analyses of the systemic risk utilising network diagrams. The third section explores the dynamic linkage of crude-ethanol and soft agri commodities by substituting crude with ethanol and vice versa. We follow this with the section where we propose a strategy for portfolio weight allocation incorporating measures related to risk, viz. standard deviation, COVOL, and systemic risk from historical information. Finally, we conclude the empirical analysis with a cross-comparison of the proposed portfolio weight allocation strategy with the Markowitz Mean-Variance approach and Global Minimum Variance Portfolio.

4.1 Analysis of COVOL

The estimation initially requires fitting a Single Index model, with RFP Index as an explanatory variable. Table 3 provides the output of the OLS estimates for the model. As observed, the RFP Index is a highly significant explanatory variable for all commodities, which is in line with the studies related to food price volatility owing to speculation in the commodity market (Gilbert and Morgan, 2010). In the same study, Gilbet and Morgan (2010) find rice to be less associated with food grains such as wheat along with soybean. As a result, the RFP Index gets shaped by the aggregation of agricultural commodities and has less influence on rice than other commodities. On the other hand, the influence on crude is supported by the import/export angle giving rise to the petrodollar connection. Increased volatility in food prices will transmit to crude price fluctuations via dollar movement.

Though the RFP Index explains a portion of the volatility in commodity prices, some information remains encapsulated in historical data that can be exploited for price discovery. Thus, we aim to explore the volatility persistence in the residuals after fitting the factor model for the presence of the ARCH effect. As a result, after fitting the conditional mean equation with an AR(1) process, we perform the ARCH – LM test on the residuals. Appendix Table A2, displays the choice of lag 1 for the AR process based on Akaike Information criteria. Noteworthy, though, for certain commodities, different lags have the lowest AIC; however, to maintain homogeneity, the lag order with the maximum frequency of the lowest AIC is chosen. Post-fitting the AR process on each commodity, we check for the ARCH effect by Lagrange Multiplier test up to lag order 4. As we can observe from appendix Table A2 that all the commodities residual after fitting the conditional mean equation show the ARCH effect.

Table 3: Factor Model Regression Output

	Crude	Ethanol	Corn	Palm Oil	Rapeseed	Rice	Soybean Oil	Soybean	Sugar	Wheat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
RFP Index	1.342***	1.069***	1.011***	1.109***	0.972***	0.293*	0.913***	0.873***	0.674***	0.882***
	-0.266	-0.293	-0.203	-0.21	-0.147	-0.173	-0.164	-0.161	-0.153	-0.216
Number of observations	187	187	187	187	187	187	187	187	187	187
R^2	0.12	0.067	0.118	0.13	0.19	0.015	0.142	0.137	0.095	0.082
Adjusted R^2	0.115	0.062	0.113	0.126	0.185	0.01	0.137	0.132	0.09	0.077
Residual Std. Error (df =186)	0.114	0.126	0.087	0.09	0.063	0.074	0.071	0.069	0.066	0.093
F Statistic (df = 1; 186)	25.411***	13.340***	24.776***	27.900***	43.539***	2.878*	30.801***	29.407***	19.544***	16.708***

****Significant at the 1% level, **Significant at the 5% level, *Significant at the 10% level*

Thus, we proceed with fitting a GARCH(1,1) model. It is also to be noted that student – t distribution has been chosen for fitting individual GARCH processes as the residuals of the Single Index model lack normality appendix Table A2. Attributing the significant correlation amongst the standardised square residuals post-fitting GARCH process appendix Table A1, to common global shocks, we opt to fit the COVOL model proposed by Engle and Campos-Martins (2022). Notably, crude shares a highly significant correlation with ethanol, which indicates synchronisation of sensitivity to global shocks. Thus, we observe that apart from sharing a significant correlation with ethanol in the return series Table 2, it also shares an interrelationship while responding to global shocks appendix table A1.

Fig. 2 shows the temporal movement of combined sensitivity to global shocks of the commodities. By construction, the sensitivity to global shocks for commodities is in sync after extracting the return explained by the RFP index. As we can observe, the pandemic era 2019-21 marks the time frame with the highest sensitivity owing to the complete lockdown and disruption of the financial markets. The sensitivity during the covid era surpasses episodes of economic downturns such as the GFC 2008, the Eurozone sovereign debt crisis 2010-11, Chinese Slowdown 2014-15 by a large margin. Notably, spikes are only observed for the time frames for which an economic/political/pandemic event happens with a global outreach to impact financial markets. However, the commodity faced much more backlash during Covid-19 than any financial downturn, as evident from Fig. 2. The recent Russian aggression on Ukraine, yet another event with global repercussions, has resulted in a rise in combined sensitivity mid-2022.

Fig. 3 depicts a synchronisation of the rise and fall in COVOL across the time frame. Though the sensitivities of some of the commodities differ, they tend to rise and fall together with the occurrence of global events. Since COVOL is not commodity specific and somewhat tied to the severity of the global event to affect financial markets, the behavioural trend rightly reflects the temporal movement of commodities to be in sync. However, investors need to be wary of sensitivity to global shocks while allocating weights during distress years.

Fig. 4 shows the asymmetry amongst commodities regarding the two risk measures estimated so far. The basic measure is based on variance, i.e., standard deviation and risk associated with global events estimated via COVOL. Rapeseed, corn, soybean, etc., offer much lower standard deviation than crude, yet their sensitivity to global shock supersedes that of crude. Hence, the trade-off between the two risk measures has to be factored in to mitigate the exposure to global shocks and market risk. An important observation is that the sensitivity of crude to global shocks is comparatively lower than the soft commodities in general. Barring sugar, all the commodities, including ethanol, surpass crude in terms of COVOL loadings. Corn, followed by ethanol, shows extreme sensitivity to global shocks. Previous studies have explored the causal linkage amongst the commodities; however, research on the impact of general macroeconomic conditions shaping commodities return is limited (Serra and Gil, 2013; Bouri et al. 2020).

Apart from the risk associated with global events and market co-movement, the contagion effect is also prominent amongst the commodities. Past research has found significant spillovers among them. For instance, see Gomez-Gonzalez et al. (2022), Ameur et al. (2021), and Just et al. (2022). Though these studies differ in methodological perspective, the research rests on the need for policymakers and portfolio managers to account for systemic risk while portfolio formation. Moreover, the researchers have found spillover intensification amid years of distress. During the same time frames, the sensitivity to global shocks has intensified. Thus, bagging assets in the portfolio and weight allocation involves consideration of these risks viz. "variance risk," "COVOL risk," and "spillover risk." The following section explores the systemic risk estimation based on the connectedness measure.

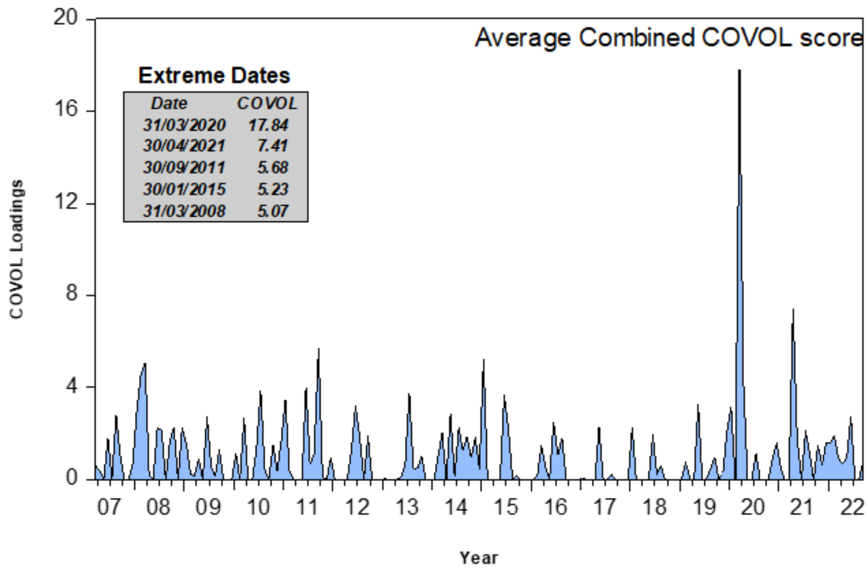

Figure 2: Average combined Sensitivity to global shock across the time frame

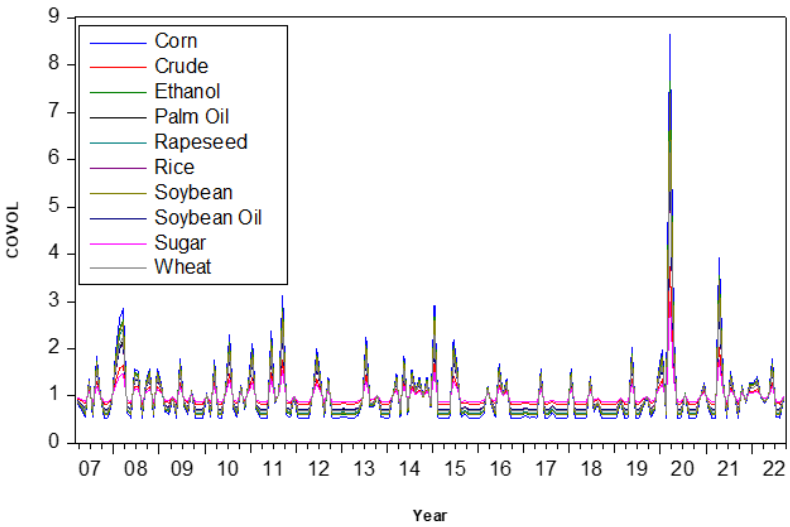

Figure 3: COVOL - Commodity wise across the time frame

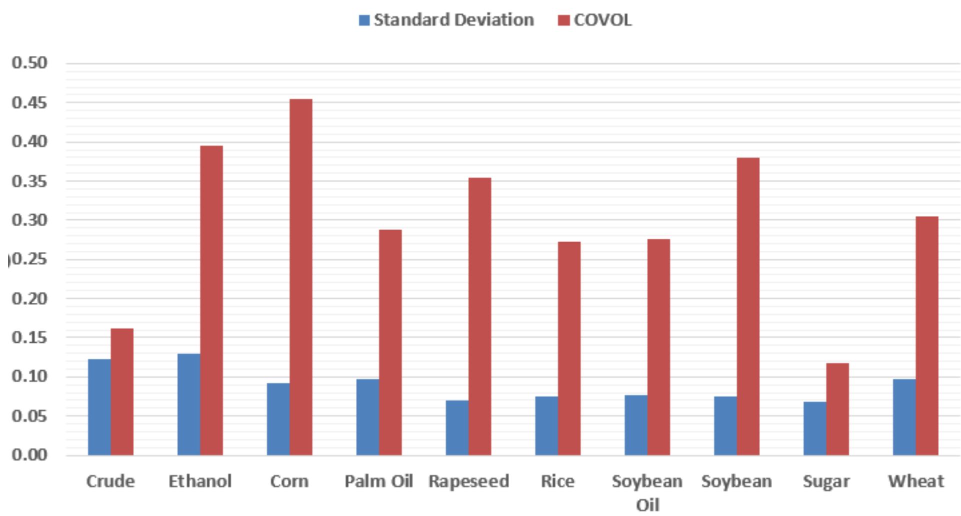

Figure 4: Average COVOL and Standard Deviation for the full sample

4.2 Analysis of Systemic Risk

The analysis estimates average connectedness as a measure of systemic risk using the standard Diebold & Yilmaz Spillover Index (2012). Noteworthy, the spillover estimation has been done on the estimated GJR-GARCH volatility for each time series. Table 4 provides the average connectedness among the crude, ethanol, and soft commodities. The diagonal elements of the matrix depict the variance in volatility explained by the self. In contrast, the off-diagonal elements compute the variance contributed by others and displays the pairwise directional connectedness. The difference between two directional connectedness for a pair thus computes the net directional connectedness and decides the direction of connectedness. For each variable, the second last row computes the net spillover sent by the variable in the system, coined as "TO" connectedness. At the same time, the last column of the matrix computes the net spillover received by the variable from all others, coined as “FROM” connectedness. The last row calculates the difference between the “TO” and “FROM” connectedness value for each variable to determine whether it is a net transmitter of shock in the system or a net receiver. The last row’s last column value, an average of all the “FROM” or “TO” connectedness, computes the “TOTAL” connectedness of the system.

As we can observe from Table 4, on average, the total connectedness amongst the crude, ethanol and soft commodities is strong enough to reflect the intensity of system-wide systemic risk. The “Total” connectedness measure stands close to 60%. It implies the importance of systemic risk to be factored in when constituting a portfolio comprising crude, ethanol, and soft agri commodities. Nevertheless, at the same time, each commodity’s contribution to systemic risk varies system-wide and pairwise, as we can observe that soft commodities viz. soybean oil, rapeseed, and palm oil, are net transmitters of shock in the system. Crude and ethanol are net receptors, with ethanol being the primary receptor.

Though crude offers moderate COVOL and spillover reception, the variance stays high as shown in Fig. 4. Thus, a trade-off emerges between the estimated risk measures, viz. variance, COVOL, and spillover. Compared to COVOL, the systemic risk measure is somewhat complex and shares the same structure as the covariance matrix, where the off-diagonal elements reflect the spillover. Hence, pairwise analysis deems necessary to explore the spillover interaction. To address the multidimensional pairwise structure, we utilise network diagrams shown in Fig. 5. For segregation of the strength of the pairwise net directional relationship, edges have been imparted thickness, weighted on the pairwise directional connectedness amongst the variables based on quantiles. The color codes have been incorporated with “red,” showing spillover of the highest intensity followed by “blue” and “green .” Within the same color code, segregation has been done based on the thickness of the edge, which is based on the value of directional spillover connectedness. The color code has been based on the quartile division of the net pairwise directional connectedness values. Red color depicts values greater than the third quartile, blue between the second to the third quartile, and green for less than the second quartile. Nodes on the same lines have been segregated as net transmitter and net receptor based on net spillover as $\{TO - FROM\}$, see Table 4. However, size allocation is based on absolute net spillover with the third quartile as base 100. The transmitter and receiver have two further segregations for colour: moderate and strong transmitter/receptor.

Table 4: Static Connectedness Matrix of Crude, Ethanol, and Soft Commodities

	Crude	Ethanol	Corn	Palm Oil	Rapeseed	Rice	Soybean Oil	Soybean	Sugar	Wheat	FROM
Crude	55.82	4.51	2.29	9.73	8.28	0.53	10.75	4.6	1.69	1.79	44.18
Ethanol	7.32	33.74	7.12	8.53	14.13	2.95	15.72	5.12	3.02	2.36	66.26
Corn	0.3	3.91	43.44	1.18	6.5	2.92	9.95	16.28	3.64	11.88	56.56
Palm Oil	4.17	0.41	3.32	43.46	16.26	0.37	19.72	7.1	1.48	3.72	56.54
Rapeseed	4.03	1.29	5.47	20.6	33.46	0.69	16.46	7.78	1.13	9.08	66.54
Rice	2.21	4	9.43	2.6	4.13	59.53	2.98	5.95	1.4	7.78	40.47
Soybean Oil	4.91	1.07	7.93	19.72	18.53	0.6	28.72	12.24	1.7	4.57	71.28
Soybean	1.85	2.12	12.69	11.11	12.7	2.81	15.7	30.42	2.15	8.45	69.58
Sugar	1.62	1.3	5.6	9	5.21	1.16	8.43	6.82	58.93	1.94	41.07
Wheat	1.6	1.99	10.76	9.24	16.21	4.37	10.04	10.23	1.09	34.49	65.51
TO	28.01	20.6	64.6	91.71	101.94	16.4	109.75	76.1	17.31	51.56	**Total**
NET	**-16.17**	**-45.66**	**8.04**	**35.17**	**35.41**	**-24.1**	**38.47**	**6.52**	**-23.8**	**-13.95**	**57.8**

The spillover relationship observed amongst agricultural commodities apart from cross-asset investment bears an economic linkage too. One linkage arises due to soft commodities being close substitutes, such as wheat and corn, while some form part of the value chain, such as soy oil extracted from the soybean. On the other hand, the spillover relationship with crude traces its routes to the petrodollar connection, as the trade of commodities is primarily settled in US dollars. Thus, the demand for a particular soft commodity shapes the price dynamics of the commodity itself and is also reflected in the crude prices (Singh et al., 2019; Dahl et al., 2020). In contrast, the relationship of soft agricultural commodities with ethanol is attributed to two reasons. The first is that it forms part of the value chain with corn. Notably, raw input for ethanol production involves feedstocks, where corn is the leading crop to serve as feedstock for ethanol production. From Fig. 5, we can observe a spillover from corn to ethanol. Significantly, starch and sugar-based feedstocks aid large-scale ethanol production economically. Brazil’s ethanol production is led by sugarcane molasses (Wheals et al, 1999). Lately, wheat and soybean have served as feedstock for ethanol production. On the other hand, the second reason is that rapeseed oil provides excellent blending material in ethanol production (Mazanov et al., 2016). Thus we can observe that ethanol’s economic linkage with soft commodities relates to the latter being a part of the value chain in ethanol production. The connectedness value quantifies that economic linkage is reflected in the market in the form of price. Demand for ethanol shapes its price, and the price of raw feedstocks is part of its value chain and vice versa.

The plausible economic relationship between ethanol with crude primarily derives from two fundamental reasons for our study. The first is the direct relationship arising due to the substitution effect, where the demand for a cleaner alternative to crude, i.e., ethanol, would ultimately lead to a fall in demand for crude. The second is related to increased volatility in crude due to geopolitical events leading to ethanol being a choice by investors to bag yet another energy commodity in their portfolio. Besides endogenous linkage, global economic circumstances also shape the price and volatility of agricultural commodities. Economic events such as GFC, Eurozone sovereign debt crisis, the Chinese Slowdown, and the pandemic Covid 19 are part of this time frame, where the spillover relationship intensifies quite obviously. Thus the intensified spillover relationship could be either due to endogenous or global factors, as we can observe from Fig. 5 that the net directional spillover is from Crude -> Ethanol.

Importantly the incorporation of commodities in the spillover system makes the interlinkage complex, yet at the same instance, interesting features are observed. Heavy directional spillover is observed from commodity -> crude. The same pattern is observed for ethanol too. Due to the emergence of indirect economic linkage amid {crude – ethanol – commodity}, a significant feedback effect of shock originating at crude can be observed to transgress across ethanol to commodity and back to crude. Thus, a multichannel shock propagation involving crude-ethanol-commodity is feasible apart from a bi-directional feedback reciprocation amid crude – ethanol. Thus, a spillover triplet emerges amongst crude – ethanol–commodity with economic underpinnings and empirically showcasing the feedback effect. Nevertheless, identifying such triplet pairs utilising the static connectedness table would be messy and will not aid in rapid decision-making by an investor or policymaker. Hence, the network diagram comes into use. As we can observe, {Crude-Ethanol-Soybean}, {Crude-Ethanol-Rapeseed} and {Crude-Ethanol-Palm Oil} are major triplets with strong directional transmissions, thus providing breeding grounds for a feedback mechanism to happen.

Furthermore, pairwise analysis of the triplet pair gives two inferences: First, which soft commodity pair is more connected with the crude-ethanol pair? Second, the level of connectedness among the triplet pair showcases an intense feedback spillover effect. The importance of feedback spillover routes from rerouting idiosyncratic shocks endogenous to an asset via market interconnectedness is noteworthy. As a result, not only the macroeconomic factors endogenous to an asset are essential for a fundamental analysis while investing, but also the market connectedness has to be considered. In the case of increased market connectedness, the underlying risk of fallout is underestimated if the feedback spillover arising due to connectedness is not factored in. To counter the feedback mechanism, an alternative could be replacing crude share with ethanol in a portfolio constituting crude, ethanol, and soft commodities. However, the strategy would mitigate the feedback propulsion provided the average linkage dynamics of ethanol with soft commodities subdues or remains statistically insignificant. Apart from that, the other two risk factors, viz. COVOL and variance come into play, thus making the weight allocation a complex exercise.

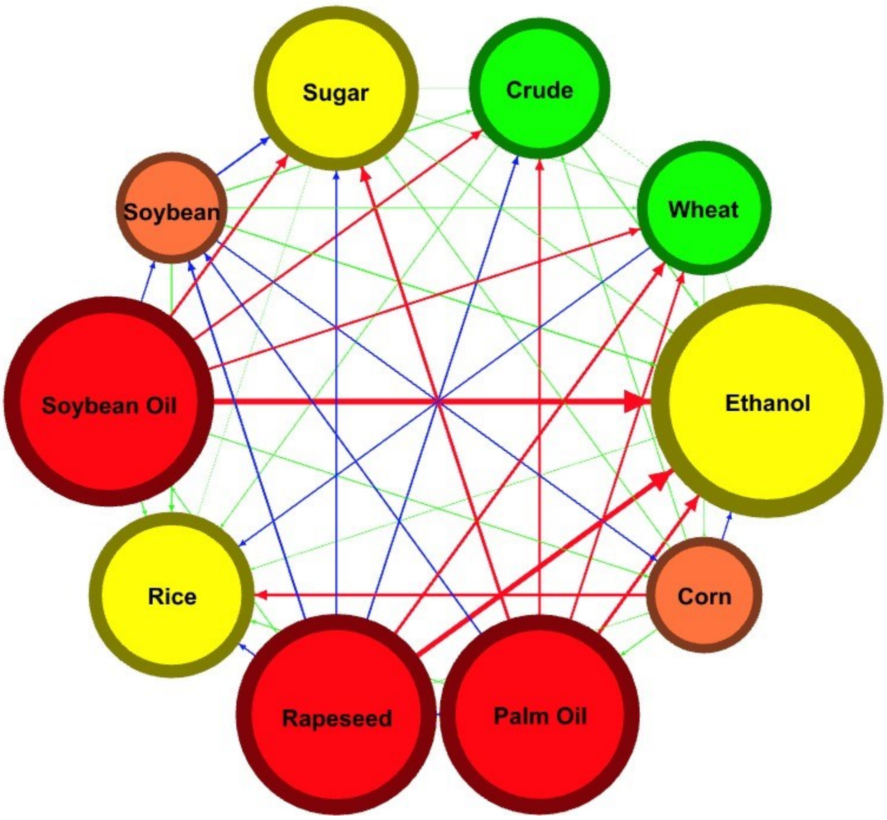

Figure 5: Network diagram based on Pairwise Net Directional Connectedness

Note: Node size based on quartile division of Absolute Net Spillover; color transmitters {Net Spillover > 10 (Red) else Orange} receptors {Net Spillover > -20 (Yellow) else Green} ; Edge color based on Net pairwise directional connectedness (NPDC) {NPDC > 75% "Red", 50% < NPDC < 75% "Blue", NPDC < 50% "Green}

4.3 Linkage Dynamics of Crude, Ethanol and Soft commodity with substitution

To investigate the change in linkage dynamics of the soft commodities along with crude and ethanol, we perform sensitivity analysis with varying weights of crude and ethanol. After that, we randomly allocate weights to the soft commodities while maintaining the summation of weights for the portfolio to be unity. The portfolio weights for soft commodities are simulated one million times, with a spillover of the portfolio estimated for each trial. We then average the estimated spillovers for each ethanol-crude weight combination. Table 5 displays the linkage dynamics of spillover amid crude-ethanol and soft commodities. As we can observe from Table 5, with ethanol weight fixed, a reduction in the weight of crude leads to a fall in average spillover linkage with soft commodities. The pattern holds true for each fixed weight of ethanol. At the same time, asymmetry is observed when crude weight is fixed while ethanol weight varies across the scale. Thus, with fixed ethanol weight in the portfolio, crude weight allocation has to be low to reduce systemic risk. However, the same only holds when the weight of crude is static. While limiting weight allocation to ethanol would reduce the exposure to COVOL Fig. 4, weight allocation to crude can also be scaled to limit exposure to systemic risk.

Based on an investor's risk appetite, COVOL and spillover risk can be calibrated well. Notably, crude and ethanol offer a low reward to risk (Table 1), and ethanol showing high sensitivity (Fig. 4) would be a low priority for investors. An investor, who may speculate a spurt in prices of these two commodities, can calibrate the weight allocation to mitigate the risk exposure to COVOL along with systemic risk. Notably, a low weight allocation to crude and ethanol already addresses the variance; hence calibration would also monitor the portfolio exposure to systemic risk and COVOL.

The diagonal values of Table 5 matrix represent the weight variation for both crude and ethanol. Along the diagonal from left to right, a fall is observed in the spillover linkage with the substitution of crude by ethanol till a threshold limit of 30% ethanol weight in the portfolio. Hence, an upper threshold value for ethanol exists while substituting for crude, as the exposure to systemic risk reduction happens to a limited extent. Nevertheless, at the same time, more weight allocation exposes the portfolio more to COVOL (Fig. 4). Importantly, due to trio linkage, a possibility of feedback effect intensifying the spillover always exists. Hence, the substitution of crude with ethanol would reduce system spillover to an extent, after which a spurt in systemic risk will be observed owing to the feedback effect. Thus, on one side, static ethanol weight offers calibration of crude weight to limit spillover risk based on the investor's risk preference and appetite. On the other hand, substituting crude with ethanol reduces spillover risk to a certain threshold before the feedback effect kicks in. Hence, the challenge lies for an investor to choose the optimal level of weight allocation in order to mitigate the three risk measures. Moreover, while constituting a portfolio, the return has to be weighed to the risk undertaken, thus adding complexity to weight allocation.

Table 5: Spillover Linkage with Varying weights of Crude - Ethanol

		Ethanol							
	Weights	**0.05**	**0.1**	**0.15**	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**
Crude	**0.4**	18.24	18.06	18.107	18.38	18.878	19.603	20.554	21.731
	0.35	16.549	16.305	16.287	16.495	16.929	17.589	18.475	19.588
	0.3	15.228	14.919	14.836	14.98	15.349	15.945	16.766	17.814
	0.25	14.276	13.903	13.756	13.834	14.139	14.67	15.427	16.41
	0.2	13.694	13.256	13.044	13.059	13.299	13.765	14.457	15.376
	0.15	13.482	12.979	12.703	12.652	12.828	13.229	13.857	14.711
	0.1	13.639	13.072	12.731	12.616	12.726	13.063	13.627	14.416
	0.05	14.166	13.534	13.128	12.948	12.995	13.267	13.766	14.49

4.4 Implications for Investors

On account of the existence of the three risks, viz. market co-movement (covariance), the risk to global shocks (COVOL), and systemic risk (Spillover), weight allocation to portfolio constituting soft commodities, crude, and ethanol is complex. Factoring the three risk measures and returns forms a multi-objective function, which can be either addressed by scalarisation or pareto optimality of the multi-objective function. Notably, the allocation of weights to different objectives would be arbitrary and depend solely on the decision-maker. One strategy would be the maximisation of return and the minimisation of the three objectives. A multi-objective approach should involve the trade-off among each objective to pursue optimality conditions. We allocate random weights to a portfolio constituting crude, ethanol, and soft agri commodities to explore the same. We fetch portfolios constituting maximum return and minimum of the three risk measures using one million trials. Thereafter, return and the three risk measures are scaled for each portfolio. Fig. 6 Panel A showcases that maximising return increases all three risk measures considered in the study. However, at the same instance, the minima of the three risk measures are not in congruence, implying that a reduction of any risk measure does not result in the reduction of the rest. As a result, the first challenge is to frame objectives that have to be maximised or minimised. The behavior of the three risk measures with return maximisation is in sync, and henceforth we consider framing objectives as reward to risk.

This is followed by the formulation of three objectives to reflect the reward per unit of risk, viz. [R/V := Portfolio Return / Portfolio Variance] , [R/Sp := Portfolio Return/Portfolio Spillover], [R/C := Portfolio Return/Portfolio COVOL]. Importantly, the challenge to address the multi-objective function can be catered to using state-of-the-art multi-objective algorithms such as NSGA-II (Deb et al., 2002). Nevertheless, the possibility of numerous pareto optimal solutions remains. Further, the trade-off between the three risk measures has to be ascertained before proceeding with multi-objective optimisation. The convexity should bring forward the plausible weights to the soft commodities along with crude and ethanol. Importantly, the three objective measures are on different scales; hence for trade-off comparison, min-max scaling is performed. Fig. 6 Panel B displays the heatmap for the three framed objectives and vis-à-vis maximisation of reward to risk for the three objectives. The maximisation of one objective bears a negative relationship with the other two, implying the existence of a trade-off. Henceforth, we proceed with finding the optimal balance between the three trade-offs.

The approach to finding the optimal solution requires optimisation of multi-objective function viz. R/V, R/Sp, R/C. All three objectives need to be maximised. For the same, we opt for elitist Non-dominated Sorting Genetic Algorithm II (NSGA-II), (Deb et al., 2002). Fig. 6 Panel C tunes the number of crossovers for a population size of 200, for which the number of pareto optimal solutions stabilises. We proceed with 100 crossovers to find the pareto optimal solution for the three objectives. Importantly, though all the solutions are non-dominated, hence equally likely, nevertheless, an investor has to take a call to choose the best among the available pareto optimal solutions. An alternative would be a subjective call by an investor to weigh any one of the objectives more than the other and, after that, choose weights. However, if the decision maker opts to rank the pareto optimal solution, he will be constrained by the different scales for each objective Appendix Table A3 (min-max) values. Hence, a simple merger would be a fallacy.

As a result transformation of the pareto solutions to scores deems necessary. Nevertheless, opting out of a strategy to transform must suffice the two primary conditions; first, the scales should be the same, and second, it should rightly reflect the position of the solution of where it stands. To address the same, we opt for normalisation of each objective by min-max scaling so that each solution ranges from [0,1]. Notably, a higher value on the scale reflects a higher objective. Fig. 6 Panel D plots the scatter diagram of all the non-dominated solutions on an ellipsoidal plane, reflecting them as equally probable solutions. After that, we summarise the transformed three objectives for a unified pareto solution. The next issue of reflecting the position of the output is catered via fitting the empirical CDF on the unified scale, subtracting it from unity { 1 - eCDF (x) }. The lower the value of { 1 – eCDF(x) }, the closer the unified objective to 1, signifying a better solution. After sorting the fitted empirical CDF on the unified scale of the pareto optimal solution, we can order the pareto efficient solutions and thus choose the best among them.

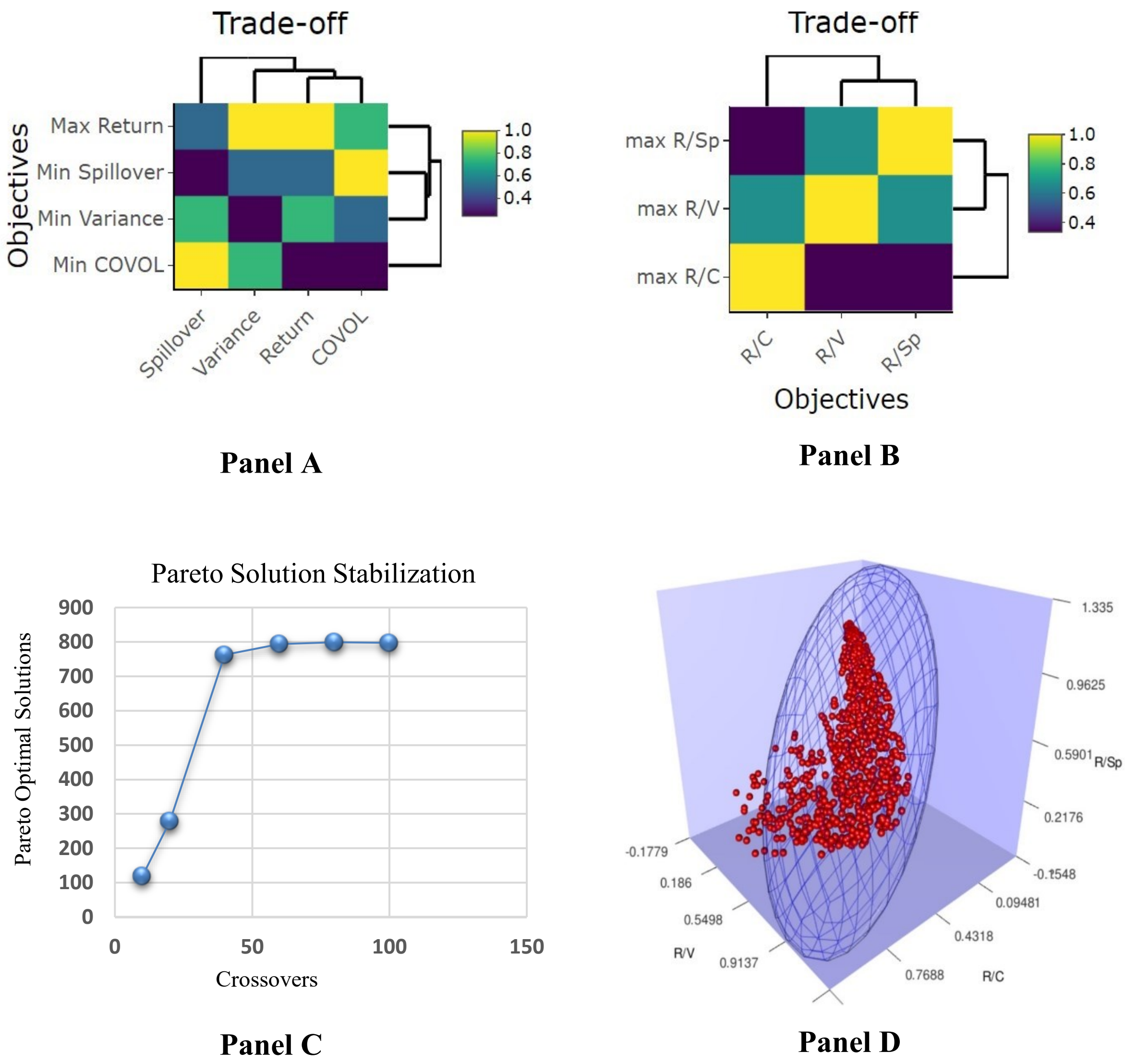

Figure 6: Pareto Optimal Portfolio

4.4.1 Portfolio Cross-Comparison

For the same portfolio universe, the Global Minimum Variance Portfolio and Markowitz Mean-Variance Portfolio approach is taken for weight allocation. After that, reward to risk for the three Portfolio strategies viz. Global Minimum Variance Portfolio, Markowitz, and Multi-objective approach are cross-compared. Since the three objectives are on different scales, min-max scaling is performed, proceeded by the unification of the score and estimation of empirical cdf. Based on the empirical CDF of the unified score of the three objectives, viz. {R/V, R/Sp, R/C}, the results for three portfolio strategies are sorted. We can observe that the three objectives attain unified maxima under the multi-objective optimisation approach, followed by the Markowitz approach. While Global minimum Variance minimises the variance to extremum, it fails to maximise reward to risk for all the three risk measures considered.

Table 6: Portfolio strategies Cross-Comparison

Models	R/V scaled	R/Sp scaled	R/C scaled	ecdf
MO	1.000	0.856	1.000	0.000
MMV	0.384	1.000	0.993	0.333
GMV	0.000	0.000	0.000	0.667

Note: *MO = Multi-objective Portfolio strategy; MMV = Markowitz Portfolio; GMV = Global Minimum Variance Portfolio*

Table 7: Weight allocation under different Portfolio Strategies.

	Crude	Ethanol	Corn	Palm Oil	Rapeseed	Rice	Soybean Oil	Soybean	Sugar	Wheat
MO	0.004	0.000	0.000	0.000	0.016	0.251	0.342	0.002	0.296	0.090
MMV	0.000	0.000	0.000	0.000	0.000	0.250	0.481	0.000	0.201	0.068
GMV	0.032	0.018	0.000	0.048	0.212	0.297	0.006	0.059	0.328	0.000

Note: *MO = Multi-objective Portfolio strategy; MMV = Markowitz Portfolio; GMV = Global Minimum Variance Portfolio*

Table 7 provides the weight allocated under different portfolio strategies. We can observe that portfolio constructed using a multi-objective approach is more diversified than Markowitz's. As Markowitz's diversification strategy suffers from portfolio concentrated to certain weights, the multi-objective optimisation strategy offers a better solution in terms of diversification. Though the Global Minimum Variance Portfolio strategy diversifies by allocating weights across all the commodities, it lags behind Reward to Risk to multi-objective and Markowitz. Notable, Soybean Oil, Sugar, and Rice rank high in weight allocation for multi-objective and Markowitz owing to better reward to risk. The reward Risk approach factoring the three risk measures diversifies the portfolio better and maximises the Reward to Risk. Significantly, GMV allocates significant weights to Crude and Ethanol, whereas MO allocates much less weight 4% to crude, while there is no allocation to ethanol. The trend is in line with what is observed in sensitivity study Section 4.3, where a reduction in systemic risk is observed for a fixed Ethanol weight, and Crude weight allocation is calibrated to minima. Notably, the fall in systemic risk observed with crude replaced by ethanol is accompanied by a fall in return along with a spike in COVOL, thereby reducing reward to risk. Hence, for a risk-averse investor, bagging in ethanol could be safe, yet reward has to be considered for a higher risk appetite. Another stark observation is the prominent triplet pairs for feedback effect loop transgression Fig. 5 weigh low in the Multi-objective Portfolio Strategy. Whereas the Global Minimum Variance Portfolio strategy allocates significant weight to the assets forming the triplets, viz. { Crude, Ethanol, Soybean, Rapeseed, Palm Oil}. Thus, a balance has emerged in terms of diversification benefits reaped to maximise Reward to Risk. MO provides more diversification than Markowitz, yet at the same time, checks the level of diversification in comparison to GMV to maximise Reward to Risk. Notably, feedback loops associated with Triplet pair have macroeconomic fundamentals as the soft Agri commodities form part of the value chain. Hence, portfolio weights concentrated for the triplet pairs are more exposed to spillover risk due to the intensification of feedback loops arising due to the substitution of Crude for Ethanol.

4.5 Temporal movement of COVOL and Spillover and Investor's limitation

As we can observe that the overall rolling total connectedness estimated on a window of 90 periods is more pronounced for GFC and Eurozone, followed by covid and the crude oil crisis, respectively (see Fig. 7). Despite the endogenous shock to crude being higher for the oil crisis and the COVOL peak for covid era, the volatility feedback effect plausibility is more pronounced during GFC and Eurozone sovereign debt crisis. If translated from an economic viewpoint, the observation stresses triplet linkage arising due to substitution from crude to ethanol for a cleaner fuel alternative rather than an economic incentive in light of high volatility in crude prices. If this had not been the case, the volatility spillover would have been more pronounced during the oil crisis, i.e., 2014-15. Nevertheless, at the same instance, global events engulf all the assets contemporaneously; hence the feedback becomes more pronounced due to the contribution of shocks at every node that forms part of the economic connection amid erude-ethanol-commodities. Thus, the spillover-based study opens the dual channel of exploration. First, the upswing in spillover was observed during crisis times, and second intense volatility feedback shocks were observed during times of distress. Both observations add misery to portfolio managers, as systemic risk works as a double-edged sword. One is the upswing in volatility observed due to endogenous economic factors, and the second is due to market interconnectedness. Importantly, if the price fluctuations in crude remained the sole driver of ethanol used as an alternative, then the motive for cleaner fuels would be despair.

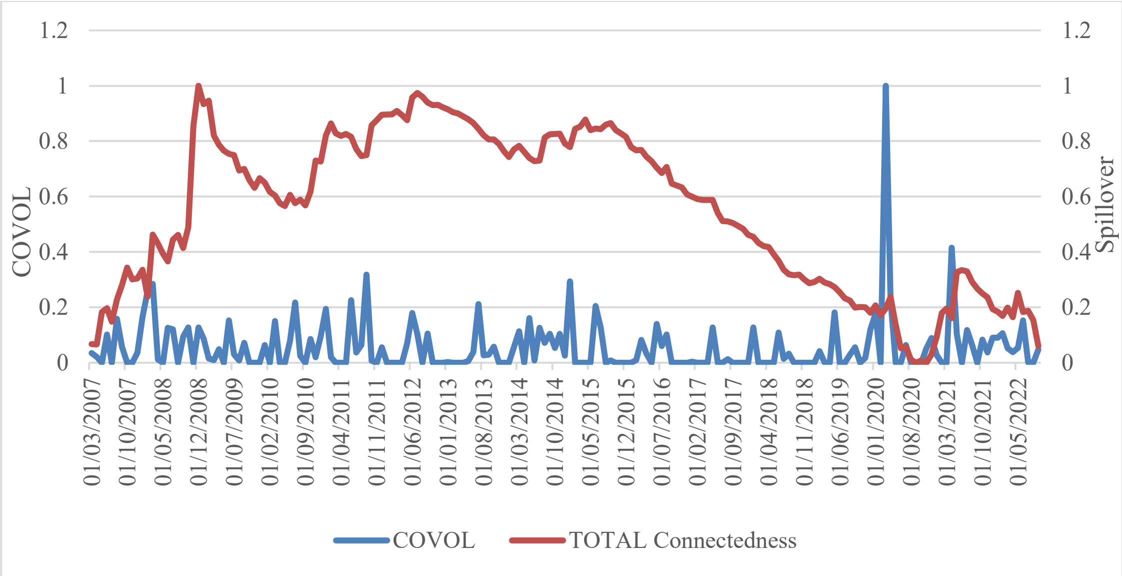

Figure 7: Temporal Movement of Spillover and COVOL

5. Conclusion & Policy Implications

The complex price interlinkage of crude, along with its substitute ethanol, engulfs the agricultural commodities that form part of the value chain in Ethanol production. The desire for cleaner alternatives and volatility in crude prices has made the dynamics amongst the crude-ethanol and soft agri commodities rather complex. An investor is a struct to strike an optimum balance of weight allocation while constituting a portfolio. Despite the abundance of historical information on return movement, a strategy to empirically translate the risks contributing to fat tail along with spikes during global shocks still needs to be developed. To address the same, risk measures have been segregated. Apart from risk captured via variance due to market co-movements, risk transmission arising due to market interconnectedness Diebold & Yilmaz (2012) and risk captured due to common global shock Engle and Campos-Martins(2022) COVOL has been estimated. Thereafter, portfolio weight allocation has been done by framing three objectives reflecting Reward to Risk, viz. [R/V := Portfolio Return / Portfolio Variance] ,[R/Sp := Portfolio Return/Portfolio Spillover], [R/C := Portfolio Return/Portfolio COVOL]. Notable, for COVOL estimation, first, the commodities co-movement with the Real Food Price Index is harnessed to fit a single index model, followed by fitting AR(1) and GARCH(1,1) models. After that, extracted loadings in the first component of the correlating residuals are attributed as COVOL, which remains in sync as per the construction and reflects risk owing to common global shocks. The average combined COVOL loadings show that the Covid-19 pandemic period surpassed the GFC(2008) and Eurozone Sovereign Debt Crisis(2010) by mammoth terms. Recently, a rise in combined sensitivity to global shocks has been observed owing to Russian aggression on Ukraine. To measure the risk associated with market interconnectedness, we adopt the measure proposed by Diebold and Yilmaz spillover estimation as a proxy for systemic risk. Importantly, spillover estimation has been done on estimated GJR-GARCH volatility characterised by incorporating asymmetry in response to positive and negative shocks while managing volatility persistence to account for volatility feedback. Since substituting Crude with Ethanol is a vital component of the research, volatility feedback must be captured well. The findings suggest the average systemic risk to be significant, implying market interconnectedness to be considered while framing Portfolio strategies. Pairwise directional spillover analysis aided by Network diagrams showcases the emergence of triplet pair for feedback effect to transgress, to be more prominent for {Crude-Ethanol-Soybean}, {Crude-Ethanol-Rapeseed}, {Crude-Ethanol-Rapeseed}. In the case of substituting Crude with Ethanol, either driven by price volatility in oil or a desire for cleaner alternatives, intensifying systemic risk can be observed with these Feedback loops serving as sinkholes. Sensitivity analysis to capture the substitution effect of Crude with Ethanol shows a reduction in systemic risk of the portfolio up to a threshold of 30% Ethanol weight, post which the Feedback effect kicks in. However, freezing Ethanol weight provides calibration of Crude weight to monitor systemic risk.

Post ascertaining the trade-off existing amid the three framed objectives viz. {R/V; R/Sp; R/C}, multi-objective optimisation algorithm NSGA-II is applied to generate equally possible Pareto solutions. After that, Pareto optimal solutions are ranked based on the subtraction from the unity of the empirical cumulative distribution function. Notably, empirical CDF is calculated on each objective's unified min-max scaled score. The proposed Portfolio Management strategy outshines the Markowitz Mean-Variance approach and Global Minimum Variance approach in terms of Reward to Risk and providing ample diversification. Compared to Markowitz, weight allocation is not concentrated on a selected few commodities but instead diversified across groups of assets. Apart from outperformance on empirical grounds, the proposed strategy allocates low weight to the triplet pair {(Crude-Ethanol-Soybean), (Crude-Ethanol-Rapeseed), (Crude-Ethanol-Palm Oil)} thus escaping the trap of Feedback loops of systemic risk. The proposed Portfolio strategy, to be the first of its type, proves to be more holistic as it encapsulates the three risk measures, Variance, Spillover, and COVOL, in Portfolio weight allocation while maintaining their essence by treating them separately. Soybean Oil, Sugar, and Rice are the most favored soft Agri commodities regarding Reward to Risk, with Crude weighing pretty low in portfolio. We observe how allocating weights at an optimum level to mitigate the three risk exposures over the whole sample resolves the investor's dilemma. Nevertheless, portfolio rebalancing remains challenging, especially in the presence of temporal movement of Spillover and COVOL with time. As we can witness, systemic risk and COVOL have different episodes of high and low with few in-sync episodes when both show a spurt Fig. 7. Henceforth, metaheuristics application could be challenging in case of frequent rebalancing owing to time complexity. Though constraint by the periodicity of data for spillover estimation has way out to perform Bayesian-based VAR estimation; however, the choice of a prior would be subjective, thus introducing uncertainty in output owing to the decision maker's perception. Nevertheless, the need to factor the two risks, viz. systemic and COVOL, provides a better return and aids in the immunisation of portfolio to global shocks. Further, it makes the portfolio robust to external shocks, provided portfolio rebalancing occurs before the distress period kicks in. Apart from macroeconomic fundamentals, the temporal movement of systemic risk and COVOL can be utilised to generate early warning signals, thus adjusting the portfolio weights accordingly.

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Appendix

Table A1: Pearson Correlation on standardised square residuals of the AR(1) GARCH(1,1) process

	Crude	Ethanol	Corn	Palm Oil	Rapeseed	Rice	Soybean Oil	Soybean	Sugar	Wheat
Crude										
Ethanol	0.416***									
Corn	-0.042	0.124								
Palm Oil	-0.033	-0.009	0.074							
Rapeseed	-0.048	-0.011	0.207**	0.161*						
Rice	-0.007	-0.051	0.019	-0.008	0.174*					
Soybean Oil	-0.017	0.014	0.308***	0.308***	0.342***	0.018				
Soybean	-0.025	0.001	0.264***	0.139	0.122	-0.052	0.323***			
Sugar	0.043	0.032	-0.011	-0.043	0.078	0.043	0.056	0.082		
Wheat	0.007	0.017	0.281***	0.113	0.306***	-0.011	0.092	0.157*	0.007	

Computed correlation used Pearson-method with listwise-deletion.

Table A2: Akaike Information Criterion for different lags and ARCH – LM test for Commodities

Akaike Information Criteria for different AR lag length																			
Crude		**Ethanol**		**Corn**		**Palm Oil**		**Rapeseed**		**Rice**		**Soybean Oil**		**Soybean**		**Sugar**		**Wheat**	
p	**AIC**	**p**	**AIC**	**p**	**AIC**	**p**	**AIC**	**p**	**AIC**	**p**	**AIC**	**p**	**AIC**	**p**	**AIC**	**p**	**AIC**	**p**	**AIC**
1	-279.12	1	-249.75	1	-389.59	1	-369.51	1	-507.97	1	-441.81	1	-471.33	1	-468.97	1	-485.84	1	-365.26
2	-283.11	2	-267.64	2	-388.6	2	-367.59	2	-506.62	2	-439.99	2	-469.75	2	-466.99	2	-484.94	2	-371.62
3	-281.4	3	-265.93	3	-386.6	3	-366.82	3	-504.63	3	-438.19	3	-467.83	3	-471.04	3	-485.53	3	-370.15
4	-283.79	4	-264.45	4	-385.35	4	-365.16	4	-503.21	4	-437.2	4	-467.2	4	-469.47	4	-483.54	4	-368.74

Lagrange Multiplier Test up to lag 4																			
LM	**p.value**	**LM**	**p.value**	**LM**	**p.value**	**LM**	**p.value**	**LM**	**p.value**	**LM**	**p.value**	**LM**	**p.value**	**LM**	**p.value**	**LM**	**p.value**	**LM**	**p.value**
99.237	0	83.579	0	66.14	0	37.781	0	55.736	0	66.787	0	78.395	0	57.966	0	65.692	0	73.54	0

Shapiro Wilk Test																			
SP	**p.value**	**SP**	**p.value**	**SP**	**p.value**	**SP**	**p.value**	**SP**	**p.value**	**SP**	**p.value**	**SP**	**p.value**	**SP**	**p.value**	**SP**	**p.value**	**SP**	**p.value**
0.862	0	0.914	0	0.984	0.027	0.992	0.393	0.979	0.006	0.976	0.002	0.973	0.001	0.977	0.004	0.986	0.057	0.993	0.571

Table 3: Preliminary Statistics of Pareto Optimal Solutions

	Return/Variance	Return/Spillover	Return/COVOL
Mean	1.131	0.004	0.022
Std. Deviation	0.116	0.001	0.004
Median	1.138	0.004	0.022
Minimum	0.885	0.001	0.014
Maximum	1.332	0.005	0.032
Range	0.447	0.004	0.018
Skewness	-0.204	-0.064	0.13
Kurtosis	-0.983	-1.241	-0.972