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Article

Is There Any Pattern Regarding the Vulnerability of Smart Contracts in the Food Supply Chain to a Stressed Event? A Quantile Connectedness Investigation

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Abstract: Blockchain can support the food supply chain in several aspects. Particularly, food traceability and trading across pre-existing contracts can make the supply chain fast, error-free, and support in detecting potential fraud. A proper algorithm, keeping in mind specific geographic, demographic, and additional essential parameters, would let the automated market maker (AMM) supply ample liquidity to pre-determined orders. AMMs are usually run by a set of sequential algorithms called a 'smart contract' (SM). Appropriate use of SM reduces food waste, contamination, extra or no delivery in due course, and, possibly most significantly, increases traceability. However, SM has definite vulnerabilities, making it less adaptable at times. We are investigating whether they are genuinely vulnerable during stressful periods or not. We considered seven SM platforms, namely, Fabric, Ethereum (ETH), Waves, NEM (XEM), Tezos (XTZ), Algorand (ALGO), and Stellar (XLM), as the proxies for food supply-chain-based smart contracts from 29 August 2021 to 5 October 2022. This period coincides with three stressed events: Delta (Covid II), Omicron (Covid III), and the Russian invasion of Ukraine. We found strong traces of risk transmission, comovement, and interdependence of SM return among the diversified SMs; however, the SMs focused on the food supply chain ended up as net receivers of shocks at both of the extreme tails. All these SMs share a stronger connection in both positive shocks (bullish) and negative shocks (bearish).

Keywords: traceability; smart contract; automated market maker; connectedness; spillover

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1. Introduction

Globalization and increased market competition have created a very complicated food supply chain industry. Food sourcing at the raw level to the processed level, shelf-life study, supply chain ineffectiveness, and other unexpected challenges make this issue a rather complicated one to be solved. Blockchain, in contrast, generates a detailed pool of contacts over digital ledgers and generates a pool of ready-made liquid contracts among different levels of participants engaged in this chain. Farmers, processors, and retailers can all gain from this effortlessly. It can assist in lowering low-quality food and fraud. When looking through a typical consumer's lens, we can obtain accurate and consistent information about the quality and source of the produce, shelf life, dietary details, and the whole transaction path. The current literature suggests that blockchain can deal with consumer concerns about these matters (Ge et al. 2017). Additionally, it could offer an opportunity for consumers to cooperate directly with producers. Therefore, they can comprehend the entire procedure thoroughly. Regulatory perspectives are also useful as Blockchain provides consistent and accurate information (Mao et al. 2018).

Likewise, the essential property of immutability makes blockchain even more reliable. For instance, the DNA of livestock animals or pesticide residue of grains is not possible to change. Examining such data by regulatory authorities becomes easy as all the samples will be noticeable in a distributed ledger technology system (DLT). Additionally, these checks are mutually cost-efficient and fast. This sort of transparency could certainly help in detecting incidents such as the horse meat scandal (2013) (Kamath 2018; Montecchi et al. 2019).

Recently, various resolutions aided by blockchain have been suggested to improve and enhance the traceability of farming produce. Radio frequency identification (RFID), a non-contact automatic identification, has been suggested by F. Tian (2016). RFID can trace products very efficiently. Caro recommended an additional pioneering blockchain-based traceability system associated with IOT in 2018 (Caro et al. 2018). This system is not only constrained to the academic world. Various organizations have employed such methods with good effects. Alibaba, Walmart, and JD.com apply food traceability projects and utilize blockchain technology. They tracing the entire procedure of production, processing, and sales. In October 2016, retail giant Walmart, Tsinghua University, and IBM employed the Hyperledger blockchain system to food supply chain management. This investigated the entire pork supply chain in China and the mango supply chain in the U.S. as a pilot. It was effective. In March 2017, Alibaba and Australia Post explored the 'paddock to plate' to good effect. This offered a supportive innovation concerning the detection of counterfeit food.

In 2017, the globe's top ten largest food giants, consisting of Walmart, Nestle, Dole, and Golden Food, collaborated with IBM to incorporate the blockchain into its supply chain. They desired the entire network (farmers to consumers) to be scanned frequently through a continuous blockchain interference to detect the causes behind foodborne illnesses at the earliest stage. Foodborne diseases often threaten public health, particularly in emerging countries. Contamination, heat exposure, and extending the perishables' shelf life without valid reasons make the situation even more complicated. The blockchain structure (with an open ledger of accounts and transactions) makes sure that every constituent of this chain shares its data entirely and safely. This exclusive technology can track a food's origin and helps build trust between producers and consumers. This, in sequence, would make a responsible and traceable system. Immediately after being reported, the data cannot be modified in a blockchain, guaranteeing no false reporting. Farm-to-fork can be observed completely and can be impeccably in real time. Many essential suppliers are ChainTrade, Farm2Kitchen, Arc-net, Owlchain, TE-Food, and IBM Food Trust. To enhance the system, ChainTrade is creating a decentralized trading platform for tokenized commodities, and Arc-net is creating a system for brand protection along with validation.

Firstly, decentralized exchange (DEX) is the marketplace where all Crypto trades take place. To run the marketplace efficiently, DEX employs a fundamental protocol for a smooth, well-timed, and frictionless movement of commodities, called the Automated Market Maker (AMM). Essentially, each AMM functions across a pre-determined set of sequential algorithms called a 'smart contract' (SM). Thus, SM is extremely crucial. As we delve deep into this blockchain ecosystem, we find SMs at the helm of affairs. SMs are usually algorithms that run the automated market maker and run the entire blockchain from the back. They generate a pool of liquidity of potential contracts among potential purchasers and suppliers. Usually, the effectiveness of a blockchain revolves around the pool of liquidity. Unlike a traditional exchange, they create a pool of liquidity through peer-to-contract trade rather than existing peer-to-peer trade. Liquidity makes trading more accessible, faster, and cheaper simultaneously. Pools of liquidity usually contain of tokens whose price can be altered by altering the mathematical equation. This feature assist in optimization. Thus, it allows for timely payments among stakeholders as well. In addition, AMM offers incentives to the liquidity suppliers (with assets). Liquidity providers gain a fee offered by the traders. Currently, they earn an additional yield called "yield farming" (Mohan 2022). However, SMs do not work well for lower liquidity instruments. Consequently, smallholder farmers and crop growers might find it challenging to apply, despite its affordability.

One more unresearched area is the adaptability of SMs. Whether they perform well under stressful events remains a question. Stressed periods have a chance of fake food emerging and of a disruption in supply. Moreover, food traceability takes a backseat in such conditions. The Russian invasion of Ukraine has severely threatened the global food supply chain, as 95% of its wheat production is exported between Asia and Africa. Further, Ukraine was the world's largest Sunflower Oil exporter as of December 2021. Therefore, anticipation and adaptation to this changing environment are essential. As per the latest work, poor development practices lead to vulnerabilities alongside incomplete design paradigms and undue simplicity (Hu et al. 2021). Therefore, SMs will not function well if those vulnerable areas are not addressed.

There has been a plethora of outstanding research on risk spillover/connectedness recently (Antonakakis et al. 2020; Bouri et al. 2020, 2021; Bouri and Harb 2022; Chatziantoniou et al. 2021a, 2021b; Chen et al. 2022; Ghosh et al. 2022, 2023; Iqbal Najaf et al. 2022; Pham and Nguyen 2021). These studies mostly found asymmetric spillover at extreme high and low quantiles across stocks, cryptos, carbon markets, oil and other commodities, etc. Furthermore, they found that the median quantile usually produces very low connectedness. These covered all possible asset classes; however, smart contracts, especially focused on food supply chain have not been researched till date.

Any supply chain usually faces challenges regarding storage, processing, distribution, consumption, and climate changes. The food supply chain is no exception. Furthermore, nowadays, it depends on DEX, and thus is run by automated sequential algorithms or SMs, which are not adaptable to the changing world. Finally, the food supply chain is additionally exposed to wide-ranging forms of challenges in the form of counterfeit, supply bottlenecks owing to war and terrorism, traceability, etc. A recent study in *Nature* encouraged an investigation on the propagation of shocks through food supply chains (Davis et al. 2021). We are precisely addressing that concern empirically.

Following this introduction and a literature review of the state-of-the-art topic, the next section provides details about the methods and data used. The next section shows the empirical findings of the analysis and Section 3 discusses the empirical findings, while Section 4 concludes with recommended policies.

2. Materials and Methods

2.1. Empirical Framework

Our methodology extends the connectedness framework by Diebold and Yilmaz (2012, 2014) and Ando et al. (2018). We used quantile vector autoregression (QVAR) to examine the connectedness across seven SM platform log returns (of prices) through the extreme lower, median, and extreme upper quantiles. This method assisted us in accommodating the extreme market movements throughout the Delta, Omicron, and Russian invasion of Ukraine events. The estimate of quantile vector autoregression, QVAR(p) is given as follows:

$$y_t(\tau) = \mu(\tau) + \sum_{j=1}^{p} \varphi_j(\tau) y_{t-j} + u_t(\tau) \tag{1}$$

Here, t indicates time and τ indicates the quantiles; y_t is a vector of n endogenous variables, including all of the seven SM platforms $\mu(\tau)$; $\varphi_j(\tau)$ denotes the coefficient matrices; and $u_t(\tau)$ depicts the error vector. The maximum lag length p is 4 (Blanchard and Perotti 2002; Linnemann and Winkler 2016). Deploying Wold's theorem, we convert QVAR(p) in Equation (1) to a quantile vector moving average representation, QVMA(∞): $Q_\tau(F_{t-1}) = \mu(\tau) + \sum_{i=0}^{\infty} A_i(\tau) u_{t-i}(\tau)$, with $A_i(\tau) = \Theta_1(\tau) A_{i-1}(\tau) + \Theta_2(\tau) A_{i-2}(\tau) + \ldots$ for $i = 1, 2, \ldots$; $A_0(\tau) = I_n$ and $A_i(\tau) = 0$ for $i < 0$. I_n is an $n \times n$ identity matrix. From the QVMA (∞) representation, we calibrated the H-step ahead generalized forecast error variance decomposition (GFEVD) as follows:

$$\psi^g_{i,j,\tau}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i^T A_h(\tau) \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i^T A_h(\tau) \Sigma A_h(\tau)^T e_i\right)} \tag{2}$$

Here, Σ is the variance matrix of the error term vector; σ_{jj} denotes the standard deviation of the error term of variable j. e_i is a $n \times 1$ vector, which takes the value 1 for element i and 0 otherwise. In addition, we computed the normalized generalized forecast error variance decomposition (GFEVD) (Koop et al. 1996; Pesaran and Shin 1998).

$$\psi_{ij,\tau}^{\smile g}(H) = \frac{\psi_{ij,\tau}^{g}(H)}{\sum_{j=1}^{k} \varphi_{ij,\tau}^{g}} \tag{3}$$

$\psi_{ij,\tau}^{\smile g}$(H) demonstrates the percent of forecast error variance in variable i that is clarified by variable j when variable i is in quantile τ. Then, we computed the subsequent spillover indexes to take the overall spillovers across the following variables:

$$FROM_{i,\tau}(H) = \frac{\sum_{j=1, j\neq i}^{n} \psi_{ij,\tau}^{\smile g}(H)}{n} \times 100 \tag{4}$$

$$TO_{i,\tau}(H) = \frac{\sum_{j=1, j\neq i}^{n} \psi_{ji,\tau}^{\smile g}(H)}{n} \times 100 \tag{5}$$

$$NET_{i,\tau}(H) = TO_{i,\tau}(H) - FROM_{i,\tau}(H) \tag{6}$$

$$TCI_{\tau}(H) = \frac{\sum_{i,j=1, j\neq i}^{n} \psi_{ji,\tau}^{\smile g}(H)}{n} \times 100 \tag{7}$$

Here, the *TO* connectedness/spillover index specifies the overall impact variable i has on all other variables j; on the other hand, the *FROM* connectedness/spillover index demonstrates the impact of the shock on all other variables j on variable i. The *NET* connectedness index shows the net spillovers from variable i to all other variables j, where a positive (negative) value indicates that variable i is a shock transmitter (receiver) in the system. Lastly, the total connectedness index (*TCI*) captures the overall spillover/connectedness among the variables under scrutiny in the system. Therefore, *TCI* is usually a proxy for market risk contagion.

During the empirical analysis, we focused on investigating the quantile connectedness at the extreme quantiles, namely 0.95, 0.5, and 0.05. These quantiles achieve connectedness among SM platforms at the extreme and median quantile movements. Further, regarding static connectedness, we examined the time-varying connectedness by calculating the rolling spillover indexes with a rolling window of 200 days.

2.2. Data

We selected seven SM platforms, namely, Fabric, Ethereum (ETH), Waves, NEM (XEM), Tezos (XTZ), Algorand (ALGO), and Stellar (XLM), as the proxies for food supply-chain-based SMs. Food supply chain is an automated process which is primarily driven a set of sequential instructions (smart contracts or SM) through codes. These seven contribute majorly to the global traceability, origin finding, tracking, and fraud detection of food supply chains[1]. Data have been procured from CoinDesk[2] and Coingecko[3] on a daily closing basis from 29 August 2021 and 5 October 2022. However, we used the daily log returns for our analysis. We started our investigation around end-August, as Delta wreaked havoc for global food supply chain around the same time[4]. This period coincides with three stressful events, Delta (Covid II), Omicron (Covid III), and the Russian invasion of Ukraine. These stressed events would have complicated the food supply chain mechanism. Therefore, it is prudent to check the risk spillover of these SM platforms during these stressful events. These SM platforms were chosen for the reason that of their practical use in the food supply chain market (Ge et al. 2017). As our objective is to capture the comovement of various SM platforms during Delta, Omicron, and the Russian Invasion of Ukraine, our sampling period ranged from 29 August 2021 and 5 October 2022.

Table 1 offers descriptive statistics. The average returns for all series are negative, in accordance with the decreasing prices throughout the observation period. Barring Fabric, all other SMs have low variances. This observation remains consistent with the fact that most SMs have a steady demand despite shocks due to stressful events. Kurtosis is higher than 3 for four variables, with the exception of XLM, XTZ, and ETH. As most kurtosis is distanced from mesokurtic distribution, most return series are not Gaussian, as illustrated by the JB test statistics. Importantly, the ERS unit root tests suggest that all returns are stationary. Figure 1 shows the development of the SM platform returns over time. The figure illustrates a sudden rise in volatility in XTZ around both Delta and Omicron and Fabric around the Russian invasion of Ukraine.

Table 1. Descriptive statistics of all the seven Smart Contract platforms.

	Fabric	XLM	XTZ	ALGO	XEM	Waves	ETH
Mean	−0.025	−0.003	−0.003	−0.003	−0.004	−0.005	−0.002
Variance	0.079	0.002	0.004	0.004	0.003	0.006	0.002
Skewness	−3.975 ***	−0.6 ***	0	0.503 ***	0.123	1.112 ***	−0.72 ***
Kurtosis	34.19 ***	1.95 ***	3.006 ***	7.184 ***	6.385 ***	10.886 ***	2.775 ***
JB	20,597 ***	87.4 ***	150.9 ***	879.2 ***	682.2 ***	2062.7 ***	163.5 ***
ERS	−3.182 ***	−4.3 ***	−3.34 ***	−9.46 ***	−6.47 ***	−4.835 ***	−9.13 ***
Q (10)	141.9 ***	11.8 **	12.28 **	16.2 ***	8.45	14.4 ***	4.024
Q^2(10)	141.47 ***	4.982	40.96 ***	43.98 ***	86.46 ***	5.522	8.901

Note: JB stands for the Jarque–Bera test statistics, ERS stands for the Elliott, Rothenberg, and Stock Unit Root test statistics. $Q(10)$ and $Q^2(10)$ stand for the Ljung–Box test statistics on returns and squared returns. ***, **, * indicate statistical significance at 1%, 5%, and 10% level. Other than XLM, XTZ, and ETH rest are having fat-tails (leptokurtic); all are mean-reverting (stationary) as per ERS; XLM, XTZ, and ETH are the weekly Gaussian.

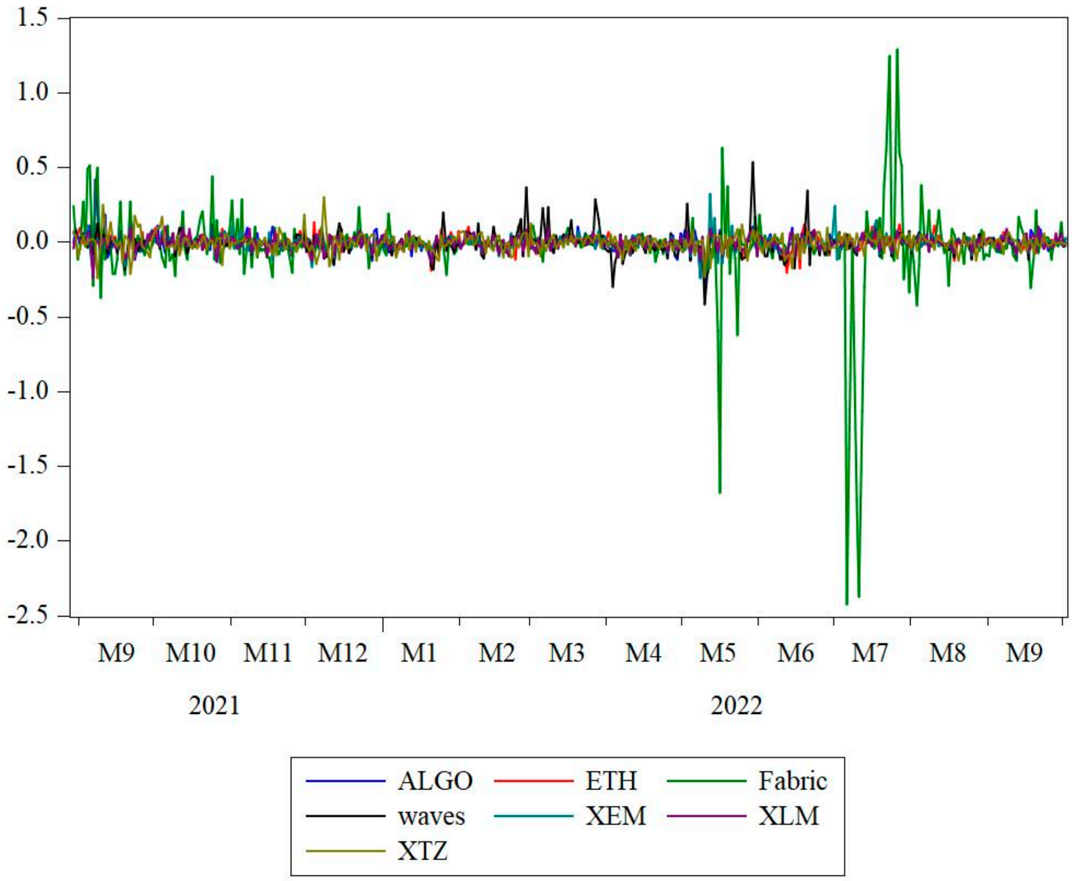
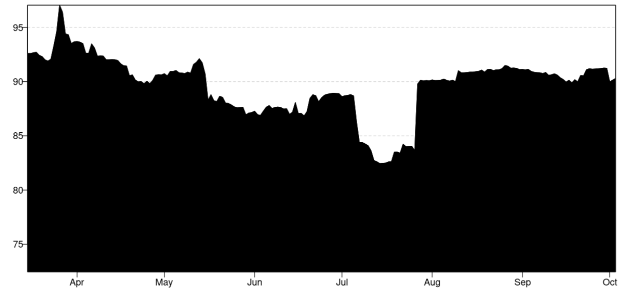
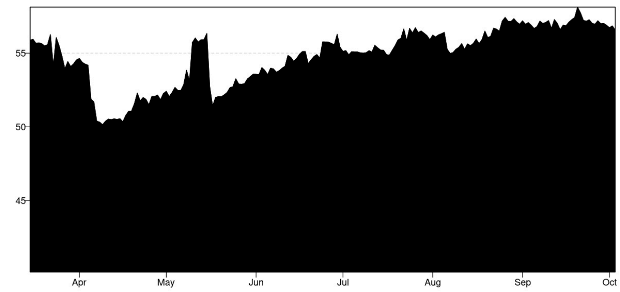


Figure 1. Log Returns of the smart contract platforms (SMs). Note: Log returns (natural) is depicted in the figure above for all the variables used in this study.

The figure below (Figure 2) shows the time-varying total connectedness indexes across the quantiles, estimated using a rolling-window analysis of the quantile connectedness model. The size of the rolling window is 200 days, corresponding to a trading year. The black area captures the adjusted total connectedness index, which is taken by replacing the denominator n in Equation (7) with $n - 1$. Here, $n = 7$ is the number of variables. The greater the value of TCI, the more the risk spillover/connectedness.



(0.95)



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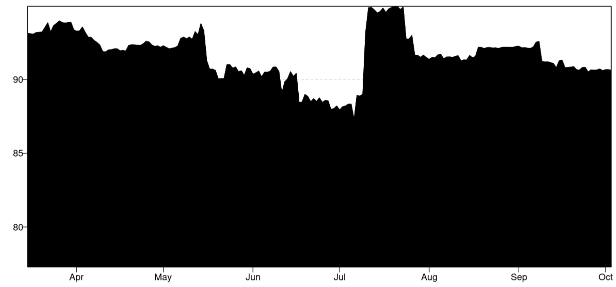
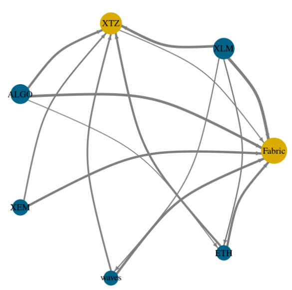


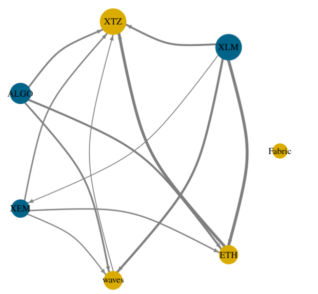
(0.05)

Figure 2. Total connectedness/spillover index at three quantiles (0.95, 0.50, and 0.05).

The figure below (Figure 3) represents a network plot for the connectedness across the smart contract market across quantiles. Blue (yellow) nodes indicate net shock transmitters (receivers) and the size of the nodes corresponds to the absolute values of the NET connectedness index. The direction of the arrows denotes the direction of spillovers between two variables and the thickness of the arrows indicates the strength of these spillovers. Fabric is Hyperledger Fabric, ETH is Ethereum, Waves is Waves, XTZ is Tezos, ALGO is Algorand, XLM is Stellar, and XEM is NEM.



(0.95)



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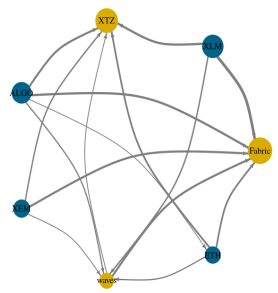

(0.05)

Figure 3. Network plot at three quantiles (0.95, 0.5, and 0.05).

Figure 4 presents the total connectedness index across the quantiles. Risk spillover/connectedness is the lowest around normal circumstances ($Q = 0.5$) and sharply increases in the stressed periods (represented by $Q = 0.05$ and 0.95).

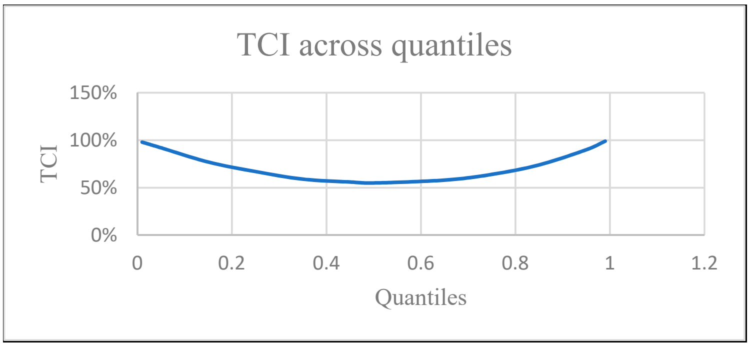

Figure 4. Varying TCI values across quantiles.

Figure 5 illustrates the difference between the TCI at the 95th quantile and 5th quantile, computed based on the dynamic quantile connectedness with a rolling window of 200 days. Positive RTD values imply a stronger connectedness during bullish conditions, whereas negative values indicate stronger connectedness during bearish conditions.

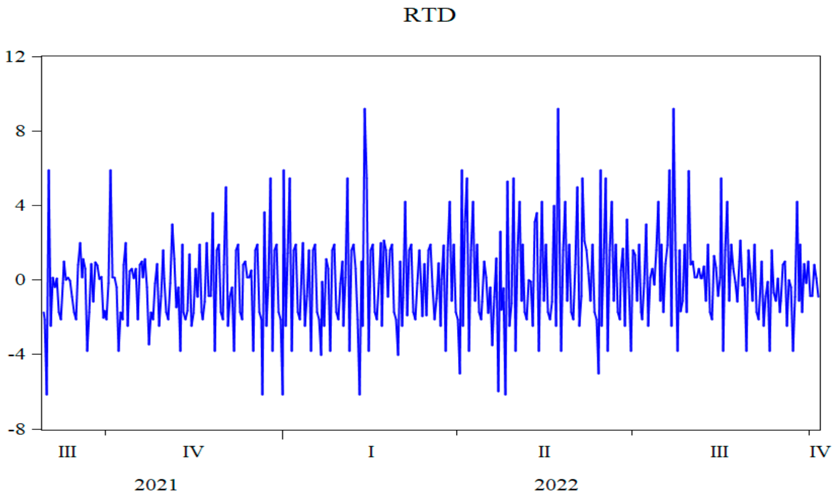

Figure 5. Relative tail dependence (RTD).

GFEVD (See Figure 6) indicates the robustness of the calibration. All of our calibrations are in perfect accordance with the typical shape of GFEVD curve and the value range specified (0.00–1.00), depicting that the errors were well within control. Our results are consistent with the existing literature on this error plotting (Lanne and Nyberg 2016).

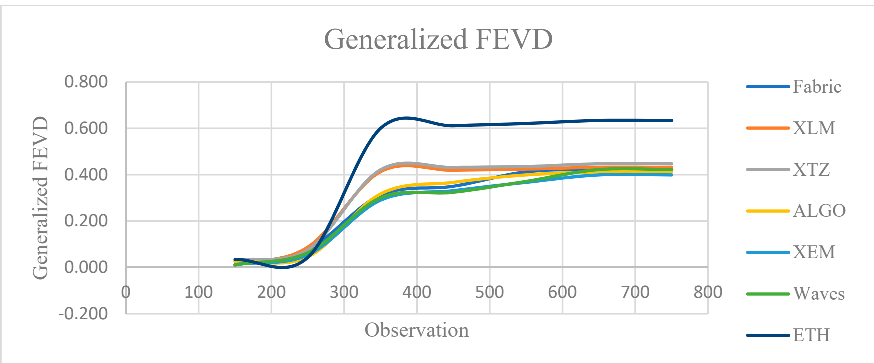

Figure 6. Generalized forecast error variance decomposition (GFEVD) for the smart contracts through QVAR.

3. Results and Discussion

Firstly, the total connectedness index (TCI) clocked 90–92% around the extreme quantiles (See Figure 2), indicating risk transmission. This is logical as our study period overlapped two pandemic levels (Delta and Omicron) and the Russian invasion of Ukraine (leading to severe food supply chain problems).

Second, we found that the XTZ and Fabric returns are mostly independent, whereas the others are relatively well diversified (See Table 2a–c). For example, Ethereum (ETH) accounted for 14–15% of returns in XLM, ALGO, XEM, and Waves during the extreme high quantile (See Table 2c). Similarly, ALGO accounted for 16–17% of returns in XLM, XEM, Wave, and ETH during the extreme low quantile (See Table 2a). Previous studies have proven that the median quantile is not a suitable parameter compared with extreme quantiles (Saeed et al. 2021). Therefore, we concentrated our findings on these extreme quantiles (0.95 and 0.05).

Third, we found a unique but logical phenomenon. Ethereum offers its SM (ERC-20) in a user-friendly and relatively known domain; however, its network is often overloaded due to diversified usage across domains. Critics often report that SM codes of Ethereum are prone to hacking far more quickly. However, due to the diversified pattern of its SM, it transmits risk/shock rather than receiving it (see Figure 3, 0.95 and 0.05, i.e., extreme quantiles). Next, we have Hyperledger Fabric or simply Fabric. It is ably supported by IBM and mostly used for the food supply chain domain, and it is open to shocks. Therefore, intuitively and empirically, it receives shocks for having a concentrated portfolio around the food supply chain. Tezos or XTZ uses a less energy-intensive 'proof of stake' mining process.

Table 2. Average quantile connectedness depicting the shock emitters and receivers (refer to the note below).

(a)

Q 0.95	Fabric	XLM	XTZ	ALGO	XEM	Waves	ETH	FROM
Fabric	31.13	12.22	10	11.53	12.45	11.43	11.23	68.87
XLM	7.58	20.7	9.13	17.19	16.32	14.5	14.58	79.3
XTZ	8.34	13.22	26.22	13.59	11.35	13.36	13.92	73.78
ALGO	7.38	17.56	9.97	20.35	15.64	14.6	14.51	79.65
XEM	8.72	17.06	8.85	16.73	21.28	13.17	14.19	78.72
Waves	7.64	16.38	10.56	15.68	13.55	21.75	14.45	78.25
ETH	7.59	16.77	10.51	15.97	14.5	14.06	20.6	79.4
TO	47.26	93.21	59.02	90.68	83.81	81.11	82.88	537.97
Inc.Own	78.39	113.91	85.24	111.02	105.1	102.86	103.48	TCI = 90%
NET	−21.61	13.91	−14.76	11.02	5.1	2.86	3.48	89.66
NPT	0	6	1	5	4	2	3	

(b)

Q 0.50	Fabric	XLM	XTZ	ALGO	XEM	Waves	ETH	FROM
Fabric	91.97	1.49	0.54	1.48	2.16	0.97	1.39	8.03
XLM	1.12	34.82	0.63	20.61	20.06	11.53	11.23	65.18
XTZ	0.8	4.66	77.86	3.94	3.38	2.37	6.99	22.14
ALGO	0.93	22.1	0.34	37.05	16.89	11.46	11.24	62.95
XEM	1.25	21.87	0.4	17.31	38.6	8.81	11.76	61.4
Waves	0.64	16.35	0.52	15.14	11.27	48.82	7.26	51.18
ETH	0.92	17.42	1.01	15.51	14.63	8.47	42.03	57.97
TO	5.67	83.89	3.44	74	68.38	43.61	49.87	328.86
Inc.Own	97.64	118.71	81.3	111.05	106.99	92.42	91.9	TCI = 55%
NET	−2.36	18.71	−18.7	11.05	6.99	−7.58	−8.1	54.81
NPT	1	6	0	5	4	3	2	

Table 2. *Cont.*

(c)

Q 0.05	Fabric	XLM	XTZ	ALGO	XEM	Waves	ETH	FROM
Fabric	28.47	13.33	10.25	12.25	12.59	11.11	12.01	71.53
XLM	9.13	18.91	10.32	16.77	16.22	13.63	15.03	81.09
XTZ	10.97	13.56	24.21	13.09	12.08	11.77	14.33	75.79
ALGO	9	17.16	10.02	19.57	15.68	13.74	14.84	80.43
XEM	9.5	16.99	9.93	16.3	18.92	13.2	15.16	81.08
Waves	8.02	15.85	10.41	15.65	14.55	21.22	14.3	78.78
ETH	9.32	16.05	11.59	16.08	15.61	12.46	18.9	81.1
TO	55.95	92.93	62.51	90.13	86.72	75.91	85.66	549.8
Inc.Own	84.42	111.84	86.72	109.7	105.65	97.12	104.56	TCI = 92%
NET	−15.58	11.84	−13.28	9.7	5.65	−2.88	4.56	91.63
NPT	1	6	0	5	4	2	3	

Fabric is Hyperledger Fabric, ETH is Ethereum, Waves is Waves, XTZ is Tezos, ALGO is Algorand, XLM is Stellar, and XEM is NEM. Each cell symbolizes the intensity of spillovers from the market listed in the column to the market listed in the row (See Table 2). The column 'FROM others' captures the spillovers from all other variables to each row variable. The row 'TO others' captures the spillovers from each column variable to all other variables. The row 'Inc.own' captures the spillovers from each column variable to all variables, as well as itself. The row 'NET' captures the net connectedness, where a positive (negative) value indicates a shock transmitter (receiver).

Moreover, these are pretty flexible as far as Web3 is concerned. However, their focus is mainly on the food supply chain. Therefore, they, too, are receivers of shocks (see Figure 3, 0.95 and 0.05, i.e., extreme quantiles). Considering Stellar, or XLM, they are a decentralized protocol in a genuinely diversified manner, where the food supply chain remains a small part. They were found to be emitting shocks. Algorand or ALGO, uses a less energy-intensive 'proof of stake' mining process, but unlike Tezos, they are well diversified across domains. New Economy Movement or NEM (XEM) is a SM platform that use 'Proof of Importance'. They have a truly diversified portfolio where they even assist governments (Ukraine, Malaysia, etc.) in developing the prevention of hoarding the tokens and e-voting platforms. Waves, on the other hand, is well-diversified with ICO issuances and crowd-sales. ALGO, XEM, and Waves were all found to be emitting shocks (see Figure 3, 0.95 and 0.05, i.e., extreme quantiles). Essentially, we understand that diversification in working portfolios can make the SM platform emit shocks; otherwise (in the case of concentrated portfolios), they are receiving shocks.

Fourth, TCI across quantiles is symmetric (See Figure 4). This further proves that return spillovers/connectedness are more robust in the tails or extreme quantiles compared with the median. The symmetry observed in Figure 4 indicates that SM platforms cannot differentiate between large and small shocks. Therefore, new features to identify the nature of shocks would be imperative. However, we investigated further to identify if any asymmetry was present. Therefore, we describe the relative tail dependence (RTD) in Figure 5. This time we found embedded asymmetry. Figure 5 has been calculated by taking differences in the TCI for 0.95 and 0.05. RTD is mostly non-zero, highlighting the asymmetry in connectedness/ spillover across quantiles. Positive RTD values indicate stronger connectedness during bullish conditions, whereas negative values show stronger connectedness during bearish conditions. The robustness of our calibration is proven by GFEVD estimation (See Figure 6) to be within specified limits.

One observation is common in this study. Smart contracts (SM) are vulnerable and less-adaptable to stressed events, especially in extreme quantiles. SMs are the cornerstone for the food supply chain, and it assure timely delivery, less wastage, counterfeit checks, and most importantly food traceability. Therefore, if they cannot adjust automatically against stressed events such as pandemic and war-like situations, it would certainly cause shortages of key components and higher raw material and energy costs in practically no time. Sudden congestion and a shortage of container shipping capacity owing to stressed events cannot be avoided. Therefore, technological research around the smart contracts (SM) are required to make them less vulnerable to such situations. Perhaps, a back-propagation of error (Back propagating Neural Network) would assist it to cut down the prediction error (Cheng et al. 2007).

4. Conclusions

This study is focused on certain points such as: (a) whether the smart contracts in the food supply chain crumble under pressure (pandemic/war), (b) if they succumb, what is the pattern, and (c) do the diversified smart contracts have the same characteristics compared to the concentrated smart contracts (only caters to the food supply chain).

This study finds high-risk spillover/connectedness among the smart contracts across extreme quantiles (both upper and lower extremes). That translates to risk spillover during stressed periods. A good deal of delay and shortages in the U.S. food supply chain was caused by the Delta variant of COVID-19[5]. Production, processing, storage, and logistics of food supply chain was severely affected, especially in Europe and Africa (risk spillover), owing to the Ukraine and Russia conflict (extreme quantile), as proved by a recent study (Jagtap et al. 2022). Therefore, our study is in sync with the outcome of other studies from different standpoints.

Furthermore, this found that diversified smart contracts are mostly shock transmitters/emitters, whereas concentrated smart contracts are mostly shock receivers. Diversified smart contract platforms are arguably risk averse (such as Ethereum or ETH)[6]. Therefore, our outcome is plausible. Moreover, diversified smart contracts show prominent interdependence, whereas concentrated smart contracts show prominent self-dependence.

Relative tail dependence showed that all smart contracts share a more substantial connection during both positive and negative shocks. Ideally, this would emerge as a weakness of the existing smart contracts. Smart contracts are viewed as solid and immutable, although they are not legal contracts (Routledge and Zetlin-Jones 2022). In fact, smart contract vulnerability against various malicious virus attacks have been researched (Qian et al. 2022; Sun and Gu 2021); however, no research has been conducted on the adaptability of smart contracts. Risk spillover problem can be solved only if the adaptability of the smart contract is addressed properly. This will make the underlying food supply chain indifferent to the various shocks such as pandemic or war. They can truly become proper antifragile systems (Taleb 2012). Problems regarding food traceability, fake food detection, maintaining control, and seamless checking to find an alternate path during stressed time could be kept at bay.

Policymakers can recommend the smart contracts to have an additional feature in the form of 'demand prediction'. This would reduce risk transmission to a large extent. Further, their deployment costs and transaction fees can be controlled as well. Another aspect that should be examined is that if the smart contract is coded improperly there is the risk that it will fail to consider a change in circumstances. Thus, while smart contracts have been used widely, there is no formal evaluation made by legal authorities such as the Uniform Law Commission or the American Law Institute, leaving open the opportunity for clearer guardrails in the future regarding whether a smart contract amounts to a legal contract.

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Notes

1 https://www.cronj.com/blog/smart-contracts-platforms/ (accessed on 28 October 2022).
2 https://www.coindesk.com/ (accessed on 28 October 2022).
3 https://www.coingecko.com/ (accessed on 28 October 2022).
4 https://www.japantimes.co.jp/news/2021/08/26/business/worsening-supply-chain-crunch/ (accessed on 28 October 2022).
5 https://www.npr.org/2021/10/28/1049923883/how-the-delta-variant-and-supply-chain-problems-smothered-the-economys-sparkle (accessed on 28 October 2022).
6 https://www.fool.com/investing/2022/11/12/these-are-my-top-risk-averse-cryptocurrencies/ (accessed on 28 October 2022).

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