Chapter 17
The Dynamics of Crypto Markets and the Fear of Risk Contagion

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Abstract Decentralized finance has gained significance in recent years, as have concerns about the financial system's stability. Exchange mechanisms, such as those utilized on cryptocurrency platforms, enhance volatility, and transmit risk contagion to other financial actors globally, which may increase financial calamity. We propose a Susceptible-Infected-Recovered model with a time delay to examine the mechanism of risk contagion in the cryptocurrency markets during the last decade. The governance token prices of the main cryptocurrency exchange platforms, as well as their spillover effects, crash risks and indicators of people's attention, are assessed, and the obtained parameters are used in the Susceptible-Infected-Recovered model to replicate the dynamics of risk contagion in the examined crypto markets. Findings suggest high interconnection among crypto markets in short-run and the fear spread among people play an important contribution to financial risks. Under the new decentralized finance paradigm, predictive modeling of the temporal distribution of risk among cryptocurrencies may provide useful insights for policy and financial system stability, as well as for contagion risk.

Keywords Financial contagion · Financial crises · Crises' transmission channels · Tokenization

Introduction

In some ways, fear of infection and viral transmission is inherent in human nature, as well as in the financial market. The financial markets' reaction to contagion has implications similar to those that happened to medical disease during COVID-19, albeit with distinct features whether investors or stock traders characterize what

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recently happened for Silicon Valley Bank, in the traditional banking system, but also for FTX, in the cryptocurrency sector.

We apply a Susceptible-Infected-Recovered (SIR) model to evaluate the effect of crashes on crypto platforms. To our best knowledge, this is the first attempt to apply this model to cryptocurrency platforms.

We suggest a structured approach that ensures readers can navigate through the details of our exploration seamlessly, gaining a holistic understanding of the nuanced interplay between SIR models, Granger Causality, Spillover effects, and the influence of fear on risk parameters in the dynamic realm of crypto platforms.

We show how risk contagion may evolve among Decentralized Finance (DeFi) exchanges using a dynamical method based on a SIR categorization. The SIR approach paradigm may be studied in the economic environment due to the parallels between financial systems and ecosystems.

While SIR models are not new, the application deserves to be highlighted due to the increased demand for financial services outside traditional schemes. We use the SIR approach to mimic risk contagion in the governance token market, which has recently been related to the most prominent cryptocurrency trading platforms. A governance token is a cryptocurrency token issued by a blockchain-based platform or protocol that allows its holders to participate in the governance of the platform. Holders of the governance token can vote on proposed protocol changes such as transaction fee changes or network infrastructure upgrades. In addition to voting, holders of governance tokens may have other benefits, such as earning a portion of the platform's revenue or suggesting changes themselves. Governance tokens are commonly utilized on DeFi platforms and protocols where the user community plays an important role in decision-making, according to Makridis et al. [1].

Given these token characteristics, which are analogous to equity instruments in certain ways, we evaluate governance price tokens and how they vary as a proxy for changing value for crypto platforms in our research. Furthermore, as a risk transmission channel method, we evaluate the information flow that we may capture in shifting price and risk for these governance tokens.

We investigate price movements for governance tokens in the context of market connectivity. In this regard, we conducted a causality analysis that revealed the presence of a link between the platform governance tokens in the data sample under consideration. We also make an original contribution by measuring the spillover effect and quantifying cross-platform contagion. The research on the spillover index computed from the price of the governance token shows how different platforms influence each other, which is known as interconnectivity. In this approach, risk contagion is related to information flow contained in the governance token.

The structure of the chapter can be outlined as follows: the second section extensively covers literature, the third section delves into data and methods, the fourth section presents findings and initiates discussion, and the final section addresses policy implications.

Literature Review

In the financial literature, contagion plays a key role in the so-called "systemic risk", in which both endogenous and exogenous events could determine a large cascade of crises (see [2]). According to the authors, starting from an outbreak with a domino effect, if a bank (or other financial intermediaries) moves toward a crisis or precrisis state, this could also cause a crisis or precrisis conditions for 50 other banks.

Financial network interdependencies, such as the interbank market, are one of the most important determinants of default propagation [3], and are considered a mechanism of contagion transmission. By using a probabilistic model, nodes, and Monte Carlo simulation, in Leonidova and Rumyantsev [4] the authors study the default contagion risk in the Russian interbank market. The use of network analysis in economic analysis has a long history, according to Callon [5], but it can also be used to explain financial crises.

For the banking sector, Babus [6] estimates the probability of systemic risk associated with a bank default in the interbank market, when it is at an equilibrium status. Financial networks are also analyzed, among other things, by Battiston and Caldarelli [7], who suggests that the interplay of network topology, capital requirements, and market liquidity are three important factors that could affect systemic risks. Under the liquidity risk perspective, Feinstein [8] outlines a model in which financial crisis propagation goes through illiquid assets and fire sales. Moreover, by accounting for the management effect, Caldarelli et al. [9] consider other networks: the board and director networks, price correlations, and stock ownership. A sort of spillover effect is used in Aït-Sahalia et al. [10], in which the authors propose a model to study the contagion jump process in different regions by studying the equity market and focusing their findings on the stock price propagation mechanism.

At the operative and costumers' level, the investigation in Barja et al. [11] exploits quarterly client's data from BBVA (i.e., a Spanish Bank) to study customer–supplier chain transactions. The authors consider a Susceptible-Infected-Susceptible (SIS) model to evaluate the patterns that are similar to the ones used in a spreading epidemic. Starting from catastrophic events, Torri et al. [12] evaluate the effects on non-life insurance by using balance sheet analysis. Default contagion and default degree in the capital chain are studied with the Copula metric for listed Chinese companies by Han [13]. Among the measures that can be applied by policymakers to contain the contagion effect on financial markets for banks, there is the short-selling ban for stocks and other financial instruments [14]. In the end, financial crises are boosted by psychological factors (see [15]) not only in their buildings but also in their spread in markets, instruments, and among economic players. For example, during the COVID-19 period, virus diffusion raised fear and uncertainty in the market [16].

Generally, under more uncertain scenarios, the behaviors of financial players are characterized by: (i) actions more sensitive to investment losses than gains [17],(ii) players triggering risks, and emotional or sentimental behavior that drives decisions [18], and (iii) mostly damaging investment decisions [19]. The so-called spillover effects are measured not only on the financial market, when the correlation between indices and stocks is analyzed, but also between firms. Among other contributions, Filbeck et al. [20] exploits event study methodologies to understand the stock reactions to disruption in the automobile industry supply chain, and measuring the contagion effect of the reduction of stock prices. The financial distress of a company caused by customer-supply chain relations is analyzed by Lian [21] from 1980 to 2014. The author finds that financial distress transfers from major customer firms to supplier firms, and the interfirm effect is persistent for up to two years. In Agca et al. [22] a credit default swap is used to evaluate credit shocks in the supply chain. Spatial analysis of the proximity effects of both financial distress and failure is considered in Barro and Basso [23]. Local factors as determinants of the default of a company also emerge in Barreto and Artes [24], Calabrese et al. [25], Maté-Sánchez-Val et al. [26]. Starting from commonalities in banks' balance sheets, Shi et al. [27], analyses China's banking system by considering the vulnerability of each bank according to some channels of transmission and complex relations among financial players.

According to Egloff et al. [28] there is another contagion mechanism through credit deterioration channels, in which the credit deterioration of a company could also deteriorate credit in other counterparties. Hertzel et al. [29] consider intra-industry bankruptcy and evaluate the consequences of distress both for customers and suppliers. They capture financial wealth effects on stock price reactions to distress and failures. Furthermore, Escribano and Maggi [30] analyze the default dependencies in a multisectoral framework starting from 1996 and evaluating the dot-com bubble and the global financial crisis (until 2015). The authors argue that the contagion effect between sectors manifests in two ways: (i) the "infectivity", or the degree of transmission of default among sectors, and (ii) the "vulnerability" of each sector. Moreover, Xie et al. [31] examine a dual-channel financing model in supply chain finance characterized by loans from the bank and trade credit from the manufacturer. In this chapter, credit risk is considered as a contagion channel from the supply chain perspective for small and medium enterprises (SMEs). Then, Calabrese [32] studies the contagion effects of UK small business failures and finds that the geographical location and the industry group are significant. In addition, the model in Fanelli and Maddalena [33] considers analogies between medical disease and credit risk contagion. It describes a nonlinear dynamic in the SIR framework and accounts for the transitory immunity time lag before a bank becomes defaultable. From another perspective, the authors in Xu et al. [34] study a contagion mechanism of associated credit risk with corporate senior executives' alertness; they exploit the SIR approach to construct the interaction model between the corporate senior executive alertness and the associated credit risk contagion in the network.

Concerns have developed in recent years about financial service providers who operate outside standard schemes or without Centralized Finance (CeFi), particularly in connection with cryptocurrencies. In contrast to the old financial system, the so-called DeFi phenomenon and automated smart contracts on the blockchain have expanded internationally in the crypto financial system.

Under a complexity and machine learning framework perspective, Ciano [35] forecasts the closing price of Bitcoins from the 61st day using a training dataset constructed from closing prices from the previous 60 days, emphasizing the market's significant volatility. The study dives into the association between cryptocurrencies, improving the analysis and providing insights into anticipating prices in this complex financial landscape.

Many concerns, such as leverage and liquidity mismatches, might be managed by policymakers and financial regulators from the standpoint of financial stability, according to Aramonte et al. [36]. The lack of internal shock absorbers during stressful times can be visible in the traditional financial system, such as liquidity issues, but without banks and central banks, it might lead to crypto runs. There are also concerns about consumer safety, ranging from operational platform failures to cyber-attacks, from volatility difficulties to the use of leverage [37].

Collaterals offered in stable coin issuance reflect liabilities; additionally, if values decrease owing to a bearish market, the value of collateral for crypto keepers falls. As a result, even for a less hazardous cryptocurrency like a stable coin, this procyclical system defines a liquidity mismatch due to a stable coin's liability-driven character, according to McLeay et al. [38].

Overcollateralization and high leverage worsen this procyclicality and spread risk contagion to other global financial actors. As an example, Three Arrows Capital (3AC) collapsed in June 2022 because of the failure of the so-called margin calls, and a few weeks later, in July 2022, another crash happened for Voyager Digital, the cryptocurrency broker that sold the 3AC bankruptcy action. The interconnectedness of cryptocurrencies, operators, and FinTech firms [39], as well as the influence of significantly over collateralization phenomena on the relationship between primary brokers and hedge funds borrowing [40], are just a few of the factors that can enhance the traditional contagion scheme in the crypto-financial system.

We employed an index of internet search traffic associated with a set of terms to estimate people's sentiment, building on previous studies [41, 42]. Many researchers utilize Internet search activity as a proxy for investor mood, demonstrating a correlation between people's attentiveness and stock volatility during the epidemic [43], [44].

Building on the insights garnered from the preceding literature review analysis, we construct our chapter employing a comprehensive conceptual framework. Initially, we study the existence of interconnection between platforms facilitated by governance tokens, aiming to capture this phenomenon through the application of VAR (Vector Autoregression) and Spillover methods. This approach allows us to assess the immediate impact in the short run. Subsequently, we incorporate risk measures designed to understand crisis conditions. Lastly, we apply SIR methods, utilizing parameters derived from VAR, Spillover, and risk analyses. Additionally, we factor in considerations of people and investor attention to formulate a thorough understanding of the long-run equilibrium.

Data and Methods

We examine governance tokens that have recently been related to the most popular cryptocurrency trading platforms. Using the Yahoo Finance data source, we retrieved the daily unbalanced values of each currency from 2017 to 2023. Our database is a hand-curated compilation of publicly available data, beginning with Yahoo Finance, where token prices are expressed in US dollars, and we begin our simulation with these numbers. We study potential connections across platforms and estimate the factors that are included in the SIR model by measuring the spillover impact, identifying the risk, and people's attention to understand how risk may spread throughout the market. The risk dynamics are then projected into the future and focused on long-term contagion in a stable state.

However, while Bitcoin came into existence in 2009, the emergence of crypto platforms, along with their associated tokens, has occurred more recently, particularly within the past years. This growth aligns with the increasing prevalence of cryptocurrencies, whether in the form of coins (including stable coins) or as investment assets (excluding stable coins). Table 17.1 outlines the inception year of the initial token emissions linked to crypto platforms, with our selection based on their trading volume as of early 2023 (https://coinmarketcap.com).

Table 17.1 Sample of tokens by launch year

Token	Year
Binance	2017
OKB	2019
FTX	2019
KuCoin Token	2017
Huobi Token	2020
Uniswap	2020
AAVE	2020
Compound	2020
Decentraland	2017
0x	2017
Decred	2017
Avalanche	2020
Bounce	2021
Ampleforth	2021
AntiMatter	2021
UNION Protocol	2020
Terra Classic	2019
Curve DAO Token	2022

Source Authors' elaboration

Table 17.2 Descriptive statistics for governance tokens

	Mean	Standard deviation	Skewness	Kurtosis
Binance	0.004	0.060	1.915	22.238
OKB	0.004	0.061	2.380	26.572
FTX	0.003	0.062	-0.963	32.848
KuCoin Token	0.004	0.072	3.065	31.576
Huobi Token	0.002	0.054	1.188	16.351
Uniswap	0.002	0.070	0.900	5.895
AAVE	0.003	0.070	0.328	2.422
Compound	0.003	0.081	4.711	70.363
Decentraland	0.006	0.092	5.637	84.238
0x	0.002	0.072	1.168	9.025
Decred	0.002	0.062	2.552	44.062
Avalanche	0.004	0.078	1.488	12.340
Bounce	0.001	0.080	1.451	11.140
Ampleforth	-0.002	0.083	2.984	32.366
AntiMatter	0.000	0.100	1.014	11.763
UNION Protocol	-0.001	0.102	2.157	20.447
Terra Classic	0.006	0.144	10.971	277.346
Curve DAO	-0.002	0.069	0.145	2.467

Source Authors' elaboration

For a deeper understanding of the tokens under consideration, Table 17.2 provides descriptive statistics on the daily returns within the sample utilized in this chapter.

VAR and Spillover

To support the interconnectedness theory, we begin by examining Granger Causality and the spillover impact among cryptocurrency platform tokens. The Granger Causality approach cited by Diebold et al. [45–47] allows for determining information flow among platforms because it is an efficient tool for determining whether the predicted distribution of one set of time series variables (i.e., cause variables, CV) has changed over time (i.e., effect variables, EV). The test examines the effect of the EV forecast on the mean squared error. To accomplish this purpose, the variables involved in the analysis must have stationary time series, otherwise, the data must be differenced. In this regard, we begin with the data and use the VAR model fit approach as well as the Akaike information criterion (AIC) to examine the Granger Causality among return series. We recorded the AIC score after testing the VAR model with lags ranging from 1 to 4 day and chose the VAR lag with the lowest AIC

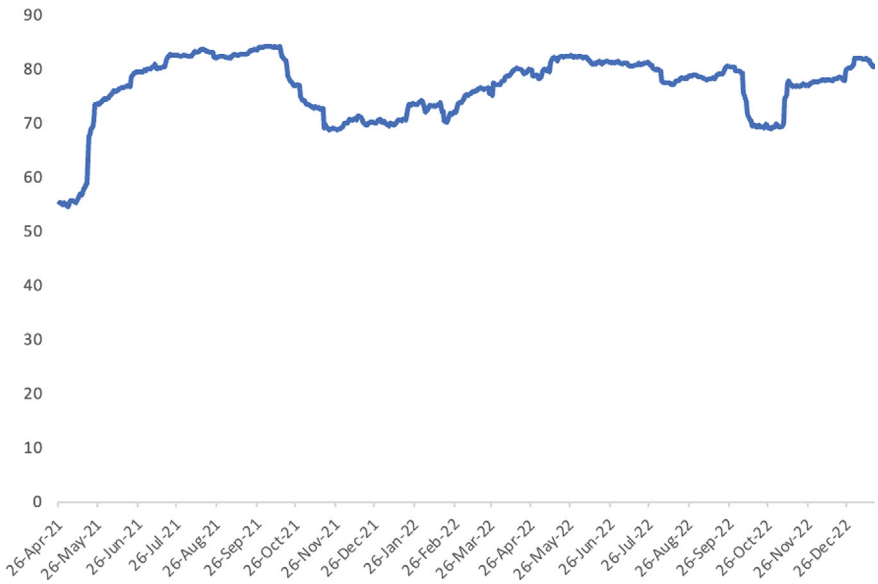

Fig. 17.1 Spillover Index

value. We ran a Granger Causality test on each variable and equation in the VAR system to see if one is the Granger causes of another. With the null hypothesis, we use Chi-Square to perform a leave-one-out Granger causality test.

We corroborate our initial interconnectedness intuition by conducting this causality analysis and conclude that there is a relevant interconnection in the platform governance tokens we account for. Then, considering the influence of spillover on risks and returns, we measure the extent of interconnection in platform governance tokens. In this regard, we create spillover indices using an extended decomposition of the forecast-error variance of the VAR model, as cited by Diebold et al. [45–47]. The net-spillover index (see also Fig. 17.1), as derived by the Diebold and Yilmaz technique, provides us with our answers. As a result, we may estimate the interconnection parameter involved in the prior SIR dynamics using this spillover analysis.

Risk Indicators

Daily prices are used to calculate risk indicators. Standard deviation, a well-known risk indicator for financial market analysis, serves as the initial measure. We also consider additional risk indicators, such as crash and idiosyncratic risks. After estimating token-specific daily returns, we compute risk indicators by taking into account the residual from regressing daily token returns in an enlarged index model, as proposed by Hutton et al. [48]:

$$r_{j,t} = \alpha_j + \beta_{a,j} r_{m,t-2} + \beta_{b,j} r_{m,t-1} + \beta_{c,j} r_{m,t} + \beta_{d,j} r_m + \beta_{e,j} r_{m,t+1} + \beta_{f,j} r_{m,t+2} + \varepsilon_{j,t} \tag{17.1}$$

where $r_{j,t}$ is the token return for daily t, and $r_{m,t}$ is the market index return for the same day (we use the S&P Cryptocurrency Broad Digital Market Index, as it has been recommended to utilize a worldwide index in the specific lack of a reference benchmark). We further insert forward and one- and two-day lagged market returns, per Hutton et al. [48]. We define $W_{j,t} = \ln(1 + \varepsilon_{j,t})$ to correct daily returns for the skewed residuals $\varepsilon_{j,t}$.

In our analysis of (1), we look at the next two risk metrics, which take idiosyncratic and crash risks into account.

The first one is a measure of crash risk that considers the negative conditional skewness of token-specific daily returns (cr1).

Cr1 measures token price up-movements [48] using an indicator of whether token-specific $W_{j,t}$ falls by more than 3.09 standard deviations above the average $W_{j,t}$ in that month:

$$cr1_{j,t} = \frac{\sum_{i=1}^{n} Risk_{j,i}}{n} \tag{17.2}$$

where, n in the number of observations and $Risk_{j,i}$ is:

$$Risk_{j,i} = \begin{cases} 1\ if\ \overline{W_{j,t}} * \sigma_w < -3.09 \\ 0\ otherwise \end{cases} \tag{17.3}$$

where $\overline{W_{j,t}}$ denotes the mean value of $W_{j,t}$, and σ_w denotes the standard deviation.

Our measure of risk cr2 is built over Dumitrescu et al., [49] and Habib et al., [50] and it represents the Negative Conditional Skewness (NCSKEW) of token returns. We calculate by taking the negative of the third moment of token-specific daily returns for each year and normalizing it by the standard deviation of daily returns raised to the third power. Specifically, cr2 is calculated as:

$$cr2_{j,t} = \frac{-\left[n(n-1)^{3/2} \sum W^3{}_{j,t}\right]}{\left[(n-1)(n-2)(\sum W^2{}_{j,t})^{3/2}\right]} \tag{17.4}$$

The third measure of crash risk is the down-to-up volatility measure (DUVOL) of the crash likelihood. For each token j over a fiscal year period τ, token-specific daily returns are separated into two groups: “down” days when the returns are below the annual mean, and “up” days when the returns are above the monthly mean. The standard deviation of token specific daily returns is calculated separately for each of these two groups. DUVOL is the natural logarithm of the ratio of the standard deviation in the “down” days to the standard deviation in the “up” days:

$$cr3_{j,t} = log\left((n-1)\frac{\sum_{down} W_{j,t}^2}{ndown - 1} \sum_{up} W_{j,t}^2\right) \tag{17.5}$$

As the fourth measure, we define "idion" in the chapter as an idiosyncratic risk applying the logistic transformation of R2 obtained in (1). According to Ferreira and Laux [51], we obtain the following measure:

$$idion_{j,t} = \log\left(\frac{1 - r2}{r2}\right) \tag{17.6}$$

where r2 is the R-squared of model estimated in the Eq. (17.1). Jump measures token price up-movements [48] using an indicator of whether token-specific $W_{j,t}$ rises by more than 3.09 standard deviations above the average $W_{j,t}$ in that year (see cr1). According to previous scholars, investigating corporate governance and volatility risks [52] and financial return [49], we define Jump risk measures as one if a company or token record one or more $W_{j,t}$ 3.09 standard deviations above the mean value for that year, and zero otherwise:

$$Jump_{j,t} = \frac{\sum_{i=1}^{n} Risk_{j,i}}{n} \tag{17.7}$$

with $Risk_{j,i}$ defined as:

$$Risk_{j,i} = \begin{cases} 1\, if\ \overline{W_{j,t}} * \sigma_w > 3.09 \\ 0\, otherwise \end{cases} \tag{17.8}$$

where $\overline{W_{j,t}}$ denotes the mean value of $W_{j,t}$, and σ_w denotes the standard deviation.

On the one hand, we claim that "Susceptible" tokens are identified with platforms that have been quoted in the market; on the other hand, we need to develop a criterion for identifying "Infected" tokens and when they are "Recovered". In this regard, we assume that the infection will be evaluated in terms of crash risk (cr3). More particularly, we employ the risk assessment technique that estimates the Negative Conditional Skewness of the stock return variance, as cited in the literature [49, 50].

For the robustness check, we also consider other risk measures discussed in this paragraph, and the results do not change.

People and Investor Attention

We explore investor sentiment dynamics through a stock market-inspired lens, using internet research as a crucial tool. We argue that the Internet is a crucial avenue for gauging investor sentiment, especially during crisis periods when a significant portion of the population is confined to their homes, such as during the Covid-19 outbreak.

The Internet, acting as a primary information source, becomes instrumental for a diverse spectrum of investors, spanning institutional entities to individual households.

Our contribution aligns with the existing body of literature that delves into the intersection of online research activities and their intricate connection to risk considerations. Within this framework, we conceptualize online research as a manifestation of public interest, specifically geared toward concerns related to the crypto market—a surge in activity fueled by stakeholders (or token owners) seeking to stay abreast of patterns within the crypto landscape.

Drawing inspiration from the insights presented by Zhao et al. [53], our study posits that individuals engage in online research to evaluate endeavors and gauge public perceptions of performance behaviors. Mirroring the context of the stock market and beyond, stakeholders, including investors, leverage online research as a means of accessing information and asserting a form of regulatory oversight. This proactive engagement empowers stakeholders to exercise control, monitoring developments and staying well-informed about events and news that could potentially impact the companies and financial markets they are vested in.

To operationalize our approach, we draw on the foundations laid by previous literature [41, 42] and employ an internet search volume behavior index as a proxy for investor sentiment. This strategic choice allows us to establish a meaningful link between the attention parameter and token volatility, drawing upon insights from works such as Smales [43] and Tripathi and Pandey [44]. Our methodological approach enhances our understanding of the intricate interplay between online research, investor sentiment, and the dynamic landscape of the crypto market during unprecedented times.

We embark on the creation of a novel index, derived from the mean value of the Google Search Volume Index for key terms encompassing "crisis," "cryptocurrency," and "risk contagion." This innovative index serves as a foundational parameter in our exploration, enabling us to classify scenarios based on the level of contagion.

Our methodological approach involves the following steps. We aggregate the Google Search Volume Index for the specified keywords, calculating their mean value. This mean value, reflective of the collective online interest in crisis, cryptocurrency, and risk contagion, becomes a central parameter in our subsequent analysis. Moving forward, we employ this new index as a pivotal input for a SIR model. The SIR model, a widely used epidemiological framework, is adapted to our context, utilizing the derived index value as a crucial parameter. This strategic integration allows us to classify scenarios based on the influence of the aggregated online interest in crisis-related terms. By coupling the information gleaned from Google Search Volume with the SIR model, we establish a framework that discerns contagion scenarios in a nuanced manner. This innovative index not only reflects the collective attention on crisis, cryptocurrency, and risk contagion but also serves as a dynamic parameter guiding our classification of contagion intensity.

In essence, our approach amalgamates insights from online search behaviors with a robust epidemiological model, presenting a comprehensive strategy for classifying contagion scenarios. This innovative index stands as a testament to our commitment to leveraging diverse data sources and methodologies to enhance our understanding of contagion dynamics in the context of cryptocurrency and financial risk.

We employ this index, as elucidated in the subsequent paragraph, to moderate high and low risk levels and to delineate the designation of "Infected" within the SIR model.

SIR Model

We aim to model the spreading of financial risk among DeFi exchanges by employing a dynamical compartmental approach based on SIR classification. This mathematical tool was developed in the context of epidemiological models to analyze how an infectious illness spreads from its initial outbreak [54, 55]. Since it is possible to draw comparisons between financial systems and ecosystems, the SIR paradigm can be reviewed in the perspective of economics. To model crisis contagion, for example, the method is used to the banking network [33, 56], global financial crises across different nations [57], and credit risk contagion of peer-to-peer lending platforms on the Internet [58].

In our case, SIR approach is applied for modelling the contagion in terms of crash risk with low and high levels in a crypto market. The underlying concept is that platforms with higher risk are referred to as "Infected" because they have the potential to infect those with lower risk, which are referred to as "Susceptible". To refine our approach, we introduce a corrective measure for risk, incorporating the investor/people attention index. This correction factor is applied to distinguish between high and low risk for Infected tokens through the index established on GVSI (as detailed in Sect. 3.4). By doing so, we align high or low risk assessments with the prevailing perception among people, thereby calibrating our risk evaluations in accordance with public sentiment.

A portion of infected platforms become able to control and sustain a minimal degree of risk, making them no longer contagious. Consequently, these platforms are "Recovered" after healing and get a temporary financial immunity for a period of length $\tau > 0$. Under a mathematical viewpoint, this parameter τ represents a time delay involved in the dynamics. Over the time period τ, immunity ends, and some cryptocurrency platforms that have recovered may revert to come back susceptible compartment.

In this framework, risk contagion is described by modelling the dynamics of densities $S(t), I(t)$ and $R(t)$ related to the susceptible, infected and recovered compartments, respectively, at each time $t \geq 0$. Moreover, by assuming that $0 < \delta < 1$ and $0 < \gamma < 1$, we account for the recovery rate δ from the high risk to the low risk and suppose that a portion of cryptocurrency platforms exits the market at any time according to the mortality rate γ. Under the previously stated reasoning, recovered cryptocurrency platform density evolves according to

$$\frac{dR}{dt} = \delta \cdot I(t) - \gamma \cdot R(t) - e^{-\gamma\tau}\delta \cdot I(t-\tau), \tag{17.9}$$

where the term $\delta \cdot I(t)$ corresponds to the portion of infected cryptocurrency platforms which is recovered, $\gamma \cdot R(t)$ is related to the cryptocurrency platforms which leave the market, while the portion $e^{-\gamma\tau}\delta \cdot I(t-\tau)$ reverts to susceptible compartment again. The previous equation can be integrated and density $R(t)$ can be evaluated once $I(t)$ is known. Therefore, we focus on the dynamics of the infected class which is closely related to the one of the susceptible compartments. In this respect, the strong analogy between any financial market and an ecosystem can be exploited to model the contagion among cryptocurrency platforms by employing Holling's response functions, which represent a common tool for studying population dynamics (for instance see [59, 60], [61], [62]. The extremely quick interconnectedness in cryptocurrency markets allows us to disregard the incubation period needed by a high-risk platform to process a susceptible one through infection. Therefore, we employ the type I response and model risk spread by the bilinear incidence term $a \cdot S(t) \cdot I(t)$, where $a > 0$ measures the interconnections among the exchanges and represents the removal rate due to contagion. Assuming further that new susceptible platforms enter the market at a given growth rate $b > 0$, the dynamics of the susceptible and the infected are described by the delay differential system.

$$\begin{aligned}\frac{dS}{dt} &= b - \gamma \cdot S(t) - a \cdot S(t) \cdot I(t) + e^{-\gamma\tau}\delta \cdot I(t-\tau),\\ \frac{dI}{dt} &= a \cdot S(t) \cdot I(t) - (\delta + \gamma) \cdot I(t),\end{aligned} \tag{17.10}$$

which is completed by the following initial conditions:

$$\begin{gathered} S(0) = S_0, \\ I(s) = I_0(s) \geq 0 \, for\, all\; s \in [-\tau, 0], \; with\, I_0(0) > 0. \end{gathered} \tag{17.11}$$

We assume that $I_0(\cdot)$ is a continuous function in the whole-time lag interval $[-\tau, 0]$ and determines the history of infected class before the initial time $t = 0$. Under this assumption, the fundamental theory of functional differential equations (see for instance [63] assures that the previous differential model admits a unique solution satisfying the initial conditions. It is not so difficult to prove that any solution gets positive values at any time.

The previous model has been proposed in the literature by Kyrychko and Blyuss, [64], for describing a disease transmission and an epidemic behavior. Here we apply this approach in the different framework of risk transmission through a cryptocurrency market.

The question of whether risk continues to exist in the cryptocurrency market over time requires careful consideration. In this respect, it is worthwhile to discuss the existence of different steady states. An important role is played by the basic reproduction number defined as

$$\rho_0 = \frac{ba}{\gamma(\gamma + \delta)}. \tag{17.12}$$

The model admits the risk-free steady state $E_0^* = (b/\gamma, 0)$ and another non-trivial equilibrium $E_\tau^* = (S_\tau^*, I_\tau^*)$ with

$$S_\tau^* = \frac{\gamma + \delta}{a}, I_\tau^* = \frac{\gamma(\gamma + \delta)}{a(\gamma + \delta - \delta e^{-\gamma\tau})}(\rho_0 - 1). \tag{17.13}$$

We notice that E_τ^* corresponds to an endemic or not-free-risk equilibrium. Moreover, understanding long-term risk contagion requires a thorough analysis of steady state stability. According to the results provided in Kyrychko and Blyuss [64], the basic reproduction number ρ_0 has a cutoff value of 1 which marks the boundary between two distinct regions of stability. The first region corresponds to the case when $\rho_0 < 1$: the risk-free equilibrium E_0^* is locally asymptotically stable and no other equilibrium is feasible. In this stability region, risk contagion tends to vanish at the long run as the trajectories of the SIR system converge towards a risk-free situation corresponding to E_0^*. On the other hand, the second region corresponds to the opposite case when $\rho_0 > 1$: E_0^* is unstable, while the not-free-risk equilibrium E_τ^* becomes feasible. Without going into details, we state that condition $\rho_0 > 1$ can be enforced in order to guarantee the not-free-risk equilibrium point's stability both locally and globally.

Results

In this section, we endeavor to separate the results based on their short and long-term effects. The focus is on disentangling the outcomes derived from VAR analysis and spillover effects, which predominantly address short-term dynamics and their immediate impact on the behaviors of price tokens. Concurrently, the SIR results delve into the medium to long-term effects, providing insights into the overall structural dynamics of the token market. This dual perspective, examining both short-term volatility and the enduring impact on the broader market structure, aims to enhance the readability and comprehensive understanding of the results. By juxtaposing these two distinct aspects, we aim to offer a holistic view of the intricate dynamics shaping the cryptocurrency token landscape.

Short-Term Interconnection and Spillover Effect

In Fig. 17.1, the Spillover index is plotted for the last two years of a sample. We consider these two years according to Table 17.2 evaluating more tokens. Since the range goes from 0 to 100, the figure value shifts from 54 in April 2021 to 82 in October 2021. After this period, the Spillover index range is still high. The ascending phase of the Spillover index aligns with an upward trajectory in the valuation of cryptocurrencies, specifically referencing the S&P Cryptocurrency Broad Digital Market Index (USD). However, diverging from the latter, despite a substantial decline in cryptocurrency values commencing in November 2021 (with the pinnacle reached on November 10, 2021), the spillover index demonstrates a propensity to sustain elevated levels even in the latter period. This observation implies that the impact and interconnectedness across diverse platforms, notably heightened during the cryptocurrency boom, have endured beyond the reduction in cryptocurrency values. Consequently, in the short term, the interconnectivity between platforms has markedly surged, exhibiting a robust correlation with the people's attention metrics employed.

Simulated Dynamics Under the SIR Approach

Our numerical simulations illustrate the importance of time delay in establishing a long-term equilibrium for crypto platforms. Indeed, the results reveal that the shorter the financial immunity delay time, the sooner equilibrium is reached, and it is characterized by a low level of infection.

As a crucial observation, it's important to note that the time delay is not explicitly quantified in the available data. Nevertheless, we take a nuanced approach by considering various values for the time delay parameter (τ) to simulate diverse risk dynamics, accommodating different assumptions regarding the duration of financial immunity. Although precise measurements of the time delay are unavailable, we explore various values for τ to capture a spectrum of risk scenarios. Upon examining the data, we find that the minimum period between successive incidents of the same platform crashing spans three years throughout the sample. Consequently, we contend that τ does not surpass the threshold of 3. Given the recent surge in crypto platform crashes, it is reasonable to assume that, in the absence of policy and regulatory intervention, the immunity period is relatively short in comparison to this threshold. In this context, considering the swift pace facilitated by technology in market transactions, it becomes meaningful to compare the dynamics of very brief periods of immunity with longer intervals. To explore this, we delineate three distinct scenarios. Firstly, we assume a very brief temporary immunity, setting $\tau = 0.5$; subsequently, we consider a longer time delay, opting for $\tau = 2$. Finally, the third scenario involves a significantly extended financial immunity, setting $\tau = 3$. Numerical simulations of risk contagion are conducted, and the corresponding dynamics

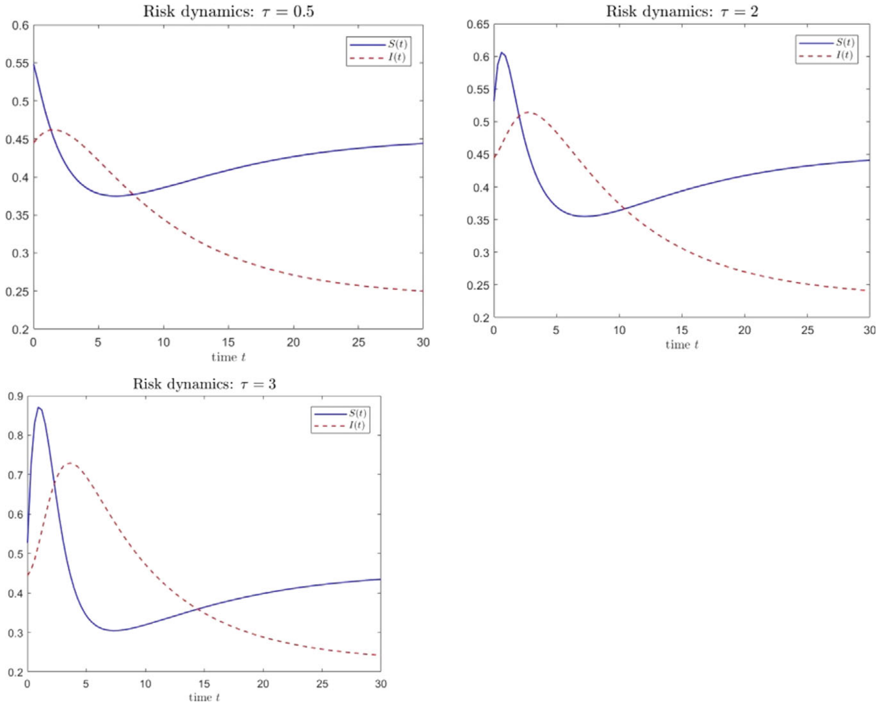

Fig. 17.2 SIR dynamics in terms of Susceptible and Infected densities

are illustrated in Fig. 17.2. The results for $\tau = 0.5$, $\tau = 2$, and $\tau = 3$ are displayed. This comprehensive exploration allows us to assess and compare the implications of different time delay scenarios on the simulated dynamics of risk contagion.

The not-free-risk equilibrium endemically attracts the trajectories of SIR solution in each case connected to the varied time delays under study. From a financial standpoint, this means that risk infection will stay prevalent in the market among crypto platforms in the long term. However, it is reassuring that at steady state, the number of vulnerable platforms surpasses the level of infected platforms by roughly 30%. Additionally, it is possible to note that as time delay τ lengthens, then the level of infected cryptocurrency platforms is lower at the steady state.

Conclusions and Policy Implications

In summary, our study highlights the growing concerns regarding contagion risk and the performance of interconnected assets, especially within cryptocurrency platforms. The significance of these findings is underscored by the implication of a potentially endemic condition, suggesting a scenario with low or virtually no risk. Turning our attention to the global landscape, the policy implications aimed at reducing the period of financial vulnerability present a formidable challenge. While the role of over-indebtedness and collateral assets is evident in platform failures and contagion spread, the ultimate challenge lies in the implementation of effective global policies. It is crucial to maintain awareness of the contrast between cryptocurrencies viewed as a form of investment and those regarded strictly as money, especially when interpreting the outcomes of risk contagion simulations. The stark difference in interpretation requirements for these two aspects of cryptocurrencies highlights the necessity for a currency, whether considered an investment or medium of exchange, to possess a maximum level of confidence to achieve a risk-free equilibrium, irrespective of trading circuit failures.

The lack of boundaries within the crypto asset ecosystem limits the effectiveness of national regulatory efforts (see to [65] and emphasizes the importance of international collaboration. The lack of boundaries within the crypto asset ecosystem hampers the effectiveness of national regulatory efforts and underscores the need for international collaboration. For instance, the European Union's Market-in-Crypto-Asset (MiCA) regulatory framework aims to address this issue by promoting legislative uniformity across member states. A worldwide framework could increase collaboration across platforms and users, therefore encouraging the adoption of risk-prevention and risk-containment strategies. Adhering to the constraints and control mechanisms stated in international laws may encourage cryptocurrency platforms to embrace better ethical standards, particularly when it comes to client relations. The success of these rules is dependent on collective collaboration and conformity to the global framework.

Our analysis marks an initial effort to address and mitigate risk within a specific crypto market. While the dynamics proposed by the SIR model are a valuable aspect of future research, it is essential to acknowledge the limitations of our study. Overlooking factors such as the high degree of interconnectedness among platforms and the rapid spread of effects through technology, our analysis lays the groundwork for further exploration and a more comprehensive understanding of risk dynamics in the cryptocurrency landscape. Future work should also take into account the selection of governance tokens, the types of trade assets, and the rights associated with each contract. On the other hand, this work serves as the foundation for an analysis that can be strengthened by incorporating cooperative activities to reduce opportunistic behavior and control risk contagion.

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