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Impact of Negative Tweets on Diverse Assets during Stressful Events: An Investigation through Time-Varying Connectedness

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Abstract: Tweets seem to impact diverse assets, especially during stressful periods. However, their interrelations during stressful events may change. Cryptos are apparently more sensitive to the sentiment spread by tweets. Therefore, a construct could be formed to study such complex interrelation during stressful events. This study found an interesting outcome while investigating three major asset classes (namely, Equity, Gold and Bond) alongside negative sentiment (derived from tweets of Elon Musk) and Dogecoin (an emerging asset class) from 1 June 2015 to 20 February 2022. Negative sentiment emerged as the significant risk transmitter, while Gold emerged as the significant net recipient of shocks (risk). Interestingly, Dogecoin was found to be less impacted and not impactful (not transmitting shock and receiving tiny shocks) at the same time. In fact, the interconnectedness between negative sentiment (percolated through Twitter) and Dogecoin prices was found to be rather feeble. Further, the study showed that the COVID-19 breakout and Brexit referendum in 2016 were less stressful events compared to the Greek debt crisis back in 2015.

Keywords: negative sentiments; textual analysis; financial catastrophe

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1. Introduction

When Elon Musk wanted to become a full-time influencer and expressed the same through Twitter on 10 December 2021, it became viral.[1] Elon Musk is one of the active users of Twitter, and many times, his messages have given a shock to the market (Jawad et al. 2022). Former US President Donald Trump, too, did not lag far behind. A recent paper proved the time-varying dependence of sentiments owing to Trump's untimely tweets (Huynh). Some cardinal research questions emerged during our study, leading toward a thematic literature review. Can tweets emit negativity? Intuitively, negative emotions often leave a lasting imprint. Negative messages through social media platforms such as tweets accelerates four times quicker than positive messages (Scott 2019). The negative news is typically long-lasting, and it produces stress (Park 2015). Negative emotions have more impact than positive emotions, and negative news influences the investors more than positive news (Deeney et al. 2018). Similar to negative word of mouth, negative tweets are given importance in decision making, and they are considered to be more reliable (Hennig-Thurau and Wiertz 2015). The negative information influences human feelings, emotions and decisions, and it also results in quick responses (Park et al. 2016). One daunting question looms large: does this negative sentiment percolate down to volatile asset classes such as crypto?

Previous studies have explored how Twitter can impact the cryptocurrency market (Kraaijeveld and De Smedt 2020; Naeem et al. 2021; Öztürk and Bilgiç 2021; Shen et al. 2019). Though Bitcoin and Ethereum are the major players in the crypto market, Dogecoin, introduced as a joke back in 2013, found an influential follower in Elon Musk (Ren and Lucey 2022). The value of meme-based Dogecoin shot up nearly 20% within an hour after Elon Musk's tweet.[2] Based on the recent trends and studies, Musk's tweets significantly impact the efficiency of the Dogecoin market (Jawad et al. 2022). The price explosiveness of Dogecoin is intensified based on Musk's crypto-related tweets. Positive tweets increase Dogecoin's trading volume and price. Further, they influence the volatility of Dogecoin compared with other cryptocurrencies. A significant price hike and more trading volume of Dogecoin during tweets shared on social media were found (Hamurcu 2022). Intuitively, tweets may not be the reasons for volatility, changes in price and trading volume. Some interesting hidden factors could have impacted Dogecoin. Elon Musk's posts on social media are always astonishingly influencing and have emitted outlandish shocks in financial markets. In fact, Scott Paul offered to sell his house through Dogecoin with a 10% discount in December 2021.[3] Interestingly, Dogecoin was one of the most volatile cryptocurrencies in the asset market, and after Musk's posts, it has got hasty growth from a joke to a force to reckon with in the crypto universe (Hamurcu 2022). It is currently the 11th most valuable token as per coinmarketcap.com and has a market capitalization of over USD 26 billion, according to CoinGecko.[4] However, investigations into the effect of Musk's tweets on Dogecoin have not been conducted. Despite being in highlight, serious research is yet to be conducted on some cardinal questions, such as: is there a time-varying relationship between a negative tweet and Dogecoin? Would Dogecoin move according to Twitter, or is there some other hidden pattern? Often, crypto is considered as a hedge against possible calamities.[5] Usually, Gold serves as a universal hedge. Typically, Gold is a tangible asset. It has been found to be a safe-haven asset for centuries due to transferability, durability and its physical characteristics (Wen et al. 2022). Gold is a safe investment for domestic and international investors, particularly when the share market falls down badly (Gözde and Ünalmış 2014). However, identifying the best possible safe asset becomes a challenge during the financial crisis period, and some studies doubt the reasons for the intensity in investing the Gold commodity market being extremely high during the global economic and financial crisis (Baur and Glover 2010; Klein 2017; Stelios et al. 2017). However, before and after global financial crisis, Gold lost its attraction and appeared riskier to invest in (Shahzad et al. 2019). Some studies have examined cryptocurrencies, Gold and crude oil to measure the safe haven and found that Gold had much more negative skewness than cryptocurrency. Thus, Gold received fewer gains and some extreme losses among the investors (Shahzad et al. 2019). However, investors in the developed nations prefer Gold as a safe asset, and emerging markets such as China consider Bitcoin as one of the best choices than Gold, leaving behind the curbs by the government of China. Therefore, Gold (tangible asset) is considered a safe investment traditionally. In the digital world, there is a possibility of alternative e-investments (cryptocurrencies) such as Dogecoin to occupy the investment trend. Another question that emerges from the existing literature is: which is the better hedge, Gold or Dogecoin? Traditionally, Gold is the eternal hedge against most financial catastrophes.

Any stressful situation (such as a financial crisis or pandemic) emits shocks. It has an impact and fluctuation in the traditional assets (Gold, Equity and Bonds), real estate or cryptocurrencies. In the case of developed nations' stock markets, Gold is exhibited as a weak and safe-haven asset because extreme downturn stocks in developed nations are not correlated with the best returns in Gold in the upcoming periods (Shahzad et al. 2019). Similarly, evidence showed that Bitcoin or traditional assets are not weak/strong safe-haven assets. However, in the emerging economies, traditional assets acted as weak safe haven, and Bitcoin was not in the picture. Therefore, for any such stressful events, Bitcoin received shocks in the global scenario. However, in the cryptocurrency market, especially the Dogecoin context, this type of textual analysis is from the perspective of network connectedness. Financial markets, like any other, are a complex network of agents with multiple agendas. Therefore, the risk is transmitted in a unique fashion through this network. Further, it has been observed that the total connectedness index or TCI (representing the summation of net shocks) shoots up rapidly (Bouri et al. 2021b) during microstructure disturbance caused owing to stressful situations (read as a financial crisis as well as a pandemic).

Financial investments such as Gold and Equity are interdependent by nature. Market participants could ideally differentiate between various asset classes as per EMH (Fama 1970). However, it is far from reality, where the interconnected dynamics between asset classes are extremely difficult to decipher (Shahzad et al. 2019). The connectedness among these investment options is apparent and complex to understand in any market in a developing economy during a financial crisis (Baur and Glover 2010; Klein 2017; Stelios et al. 2017). These investment options are highly interconnected with one another; if any investment receives the shock from any other external source, it impacts other connected investments (Ando 2019). Whether traditional asset classes are connected to cryptocurrency remains a puzzle to be solved. The cryptocurrency market has recently emerged as an attractive investment avenue for individual and institutional investors (Bouri et al. 2021b). The addition of cryptocurrency to the existing connectedness nexus has made it even more complex (Kraaijeveld and De Smedt 2020). Connectedness exists during calmer periods; however, it would be curious to examine whether network connectedness surged during extreme events such as COVID-19 outbreak. Lastly, the movement of TCI in an asset mix during extreme circumstances needs to be carefully studied. Questions regarding the same emerged as well from the review so far. Network connectedness in extreme circumstances, does it really surge? Typically, connectedness (TCI) surges rapidly during extreme events.

2. Literature Review

We further delved deep into three specific themes, namely Twitter and sentiments, crypto (especially Dogecoin) and connectedness, and impact on other assets. The first theme is to investigate the embedded sentiments of Musk's tweets on different investment options. The second theme revolves around the impact of Twitter on the cryptocurrency market. The third is to understand the interconnectedness of different assets and how they impact each other during stressful events.

2.1. Twitter and Sentiments

Elon Musk's negative tweets could be the most influential on Dogecoin and other interconnected assets, as he has more than 81 million tweet followers.[6] Elon Musk is known for his active participation in Twitter. His tweets on cryptocurrencies are emitting shocks among the investors; subsequently, investors register positive and negative responses to various cryptocurrency options. Elon Musk's followers and investors highly consider his tweets, and they have shocked the investment market, including cryptocurrency. Empirical findings unearth that people undergo negative emotions as a result of negative news from Twitter (Park 2015).

A couple of studies of late have found the predicting capacity of Twitter-based sentiments, making it an interesting proposition as a predictor variable. The number of tweets has been a proven proxy for investor attention (sentiment); it further determines both volume and volatility for crypto (Shen et al. 2019). In addition, Twitter-based sentiment is found to be quite a strong predictor for various crypto returns (Kraaijeveld and De Smedt 2020). Therefore, Twitter-based sentiments (especially negative) can be used as a justified proxy for understanding the market microstructure through connectedness during stressful events.

2.2. Crypto (Especially Dogecoin)

A recent study (Ante 2022) provides empirical evidence that Elon Musk's referral content on social media (i.e., Twitter) could affect the crypto market. Another study (Huynh 2022) examined rigorously and identified that tone of his content drives the Bitcoin market. Recent studies confirmed that social networking sites influences cryptocurrency in the market and found that (Urquhart 2016) it is possible to predict the Bitcoin price, volatility and trading volumes based on using the number of hashtags on the Twitter platform. Elon Musk tweeted in early February 2021 that Tesla had spent USD 1.5 billion to purchase Bitcoin.[7]

Noticeably, the value of cryptocurrencies surged, especially Bitcoin, after the tweet. Bitcoin holds the top position among the cryptocurrencies (Yuan and Wang 2018). Recently (Huynh 2022), the link between Elon Musk's tweet content and Bitcoin market was investigated. Investors may or may not perceive the messages as investment advice; however, they blindly followed Musk's tweets to gain an advantage from the information in crypto trading (Huynh 2022). Musk intends to create positive statements on social media, but sometimes, his posts emit negative sentiments as well (Kraaijeveld and De Smedt 2020). The market observes shocks whenever tweets emit negativity at the receiver's hand (Al Guindy 2021).

Our focus on this paper rests solely on Dogecoin, principally because of the patronage of Elon Musk, SpaceX and Tesla chief. On the advent of winter way back in 2013, a meme surfaced and was considered a joke. A meteoric spike of 800% in January 2021, followed by another strong upsurge of 400% in three months' time, took it to the limelight. Critiques still questioned its apparently weak fundamentals. As per recent studies, tweets have impacted the value of Dogecoin transactions (Lansiaux 2022). However, its phenomenal growth has been strongly attributed to Twitter-driven sentiments, especially from Musk (Tjahyana 2021). Noticeably, the price of Dogecoin witnessed a steady decline whenever Musk's perception was negative (Cary 2021).

2.3. Connectedness and Impact on Other Assets

To understand the complexity of the context, the study adopted VAR models at upper and lower percentiles through quantile regression, which allows it to capture the network connectedness associated with extreme negative shocks. This remains the same even during the economic crisis because the changes in the market interdependencies and return had significant connectedness during extreme events (Mensi et al. 2016). The interesting pivotal factor is uncovering the connectedness of shocks in a predetermined network through the approach of connectedness (Shahzad et al. 2019). The COVID-19 shock led to a large disruption in the global financial markets (Corbet et al. 2020). Recent studies proved that the COVID-19 outburst had a considerable effect on financial markets, including the cryptocurrency market; the total connectedness index (TCI) has been observed to spike rapidly around the declaration of the COVID-19 outbreak in early 2020 (Bouri et al. 2021a; Naeem et al. 2021). Further, extreme circumstances such as COVID-19 add more complexity to the network connectedness among the variables. The financial system is typically an interconnection of various assets consisting of Gold, Bonds, Equity, cryptocurrencies and sentiment, which often cannot be explained by EMH but can be explained by both AMH and FMH (Fama 1970; Lo 2004; Peters 1994). The remaining of the paper goes as follows: Section 3 presents the data and methodology, Section 4 depicts results and illustrates the interpretations, Section 5 includes the conclusive remarks and, finally, Section 6 is about limitations and scope for future studies.

3. Research Methodology

3.1. TVP-VAR

We have followed Antonakakis and Gabauer's research work while deploying the TVP-VAR model to measure the time-varying connectedness amongst the target variables (Antonakakis et al. 2018). This methodology is typically an extension of the model proposed and perfected by Diebold and Yilmaz for analyzing dynamic connectedness (Diebold and Yilmaz 2012, 2014). The undue subjectivity around a certain window size was never a problem again with the advent of TVP-VAR. Further, relatively smaller sample sizes could well be accommodated by this method. The equations below describe the TVP-VAR model:

$$Z_t = B_t Z_{t-1} + u_t u_t \sim N(0, S_t) \quad (1)$$

$$vec(B_t) = vec(B_{t-1}) + v_t v_t \sim N(0, R_t) \quad (2)$$

where Z_t, Z_{t-1} and the error term u_t are vectors having dimension k $\times$ 1, B_t and S_t are matrices having dimensions n $\times$ n; $vec(B_t)$, is of dimension k2 $\times$ 1. Here, all information that is available until $t-1$ is given by p_{t-1}. The other error term v_t has dimensions k2 $\times$ 1 while R_t has a dimension k2 $\times$ k2. St and R_t represents the variance–covariance matrices, which vary with time.

Scaled generalized forecast error variance decomposition (GFEVD) was calculated as the next step following Koop, Pesaran, etc. (Koop et al. 1996; Pesaran and Shin 1998). Unlike the pre-existing model, GFEVD is entirely invariant to the ordering of variables. Further, to obtain GFEVD, TVP-VAR is transformed to vector moving average representation or TVP-VMA using the Wold theorem by the following transformation:

$$Z_t = \sum_{i=1}^{p} B_{it} Z_{t-i} + u_t \tag{3}$$

$\varphi^{g}_{ij,t}(H)$, is the unscaled GFEVD, which is further normalized to the scaled version. This would ensure that the summation in each row is unity. Again, this implies the pairwise directional connectedness from variable j to variable i. To compute the above terms, the following step is conducted:

$$\widetilde{\varphi}^{g}_{ij,t}(H) = \varphi^{g}_{ij,t}(H) / \sum_{j=1}^{k} \varphi^{g}_{ij,t}(H) \tag{4}$$

In addition, the connectedness measures are derived as suggested by Diebold and Yilmaz (2012, 2014).

$$TO_{jt} = \sum_{i=1, i\neq j}^{k} \widetilde{\varphi}^{g}_{ij,t}(H) \tag{5}$$

$$FROM_{jt} = \sum_{i=1, i\neq j}^{k} \widetilde{\varphi}^{g}_{ji,t}(H) \tag{6}$$

$$NET_{jt} = TO_{jt} - FROM_{jt} \tag{7}$$

$$TCI_t \equiv k^{-1} \sum_{j=1}^{k} FROM_{jt} \tag{8}$$

We find Equation (5) as a measure of total directional connectedness from j *TO* all others in the network, whereas Equation (6) is a measure of total directional connectedness to j *FROM* all others. Moreover, Equation (7) is obtained as the difference between (5) and (6) and indicates the net total direction of connectedness associated with j. For instance, if $NET_{jt} > 0$, shows j is a net driver who is involved in transmitting shocks. Equation (8) is an aggregate measure of the total connectedness amongst all and serves as a proxy to the overall interconnectedness. Typically, a higher *TCI* would indicate a shock in a particular variable affecting the network. Usually, *TCI* is in a higher range during extreme events and subsequently reduces as the stress gets relieved.

3.2. Textual Analysis

We collected all 14,206 tweets posted to Elon Musk's account (@elonmusk) from 1 June 2015 to 20 February 2022. We selected specific negative words (see Table 1), adopting Loughran and McDonald (2011) since it specifies sentiment words used by Tetlock (2007) for financial context analysis (Tetlock 2007; Loughran and McDonald 2011). We carefully went through the context of using those words. Therefore, we followed existing research to create a proxy for the negative sentiment (Huynh 2021).

$$\rho = \frac{n}{N} \times 100 \tag{9}$$

where ρ represents Ngsnt or negative sentiment, n is the number of negative words and N is the total number of words.

Table 1. Showcasing the negative words which are taken into consideration.

S. No	Negative Words	Occurrences
1	Boring	158
2	Problem	130
3	Down	100
4	Stop	82
5	Death	43
6	Challenge	25
7	Counter	22
8	Die	21
9	Sad	20
10	Hate	19
11	Abort	18
12	Bore	17
13	Fake	16
14	Lose	16
15	Mad	15
16	Trouble	15
17	Loss	14
18	Sick	8
19	Lie	7
20	Disable	5
21	Paranoid	4
22	Disadvantage	3
23	Losses	3
24	Suicide	3
25	Punish	2
26	Adverse	1

Context was paid attention to while identifying the negative words, following Loughran and McDonald (2011).

3.3. Data Details

We considered daily observations from 1 June 2015 to 20 February 2022. We had a total of five variables, namely Gold (GC.CMX), Bond (pimco), Equity (GSPC), Dogecoin (Doge) and Negative sentiment or Ngsnt (calculation is shared in the previous section). The first four variable information were gathered from BLOOMBERG, whereas Ngsnt was calculated based on the Twitter feed (see representation in Figures 1 and 2).

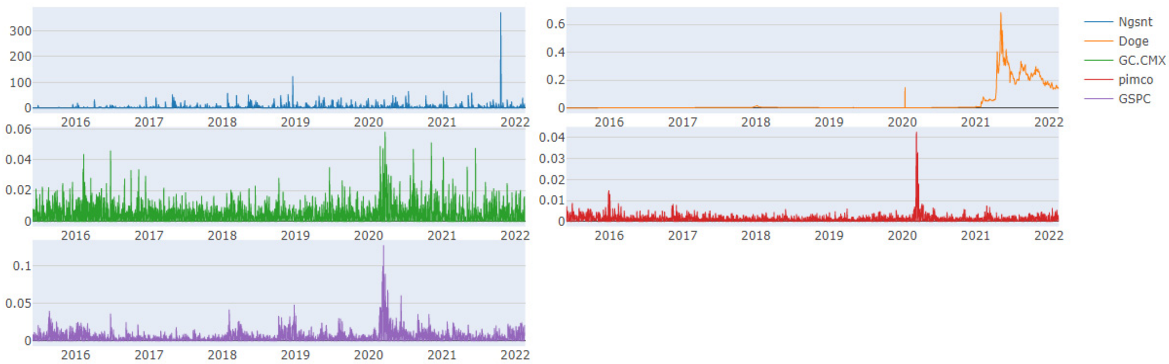

Figure 1. Raw data representing all the five variables.

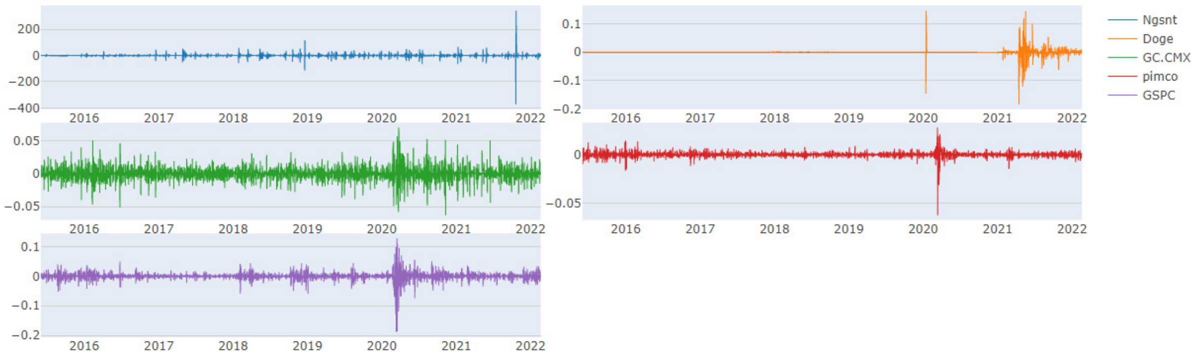

Figure 2. Transformed data representing all the five variables.

4. Results and Interpretation

This section exhibits all the outcomes and tries to explain the reason underneath. Interpretation and implication also extend to the next section.

We found a leptokurtic (heavy-tailed distribution) trail in all out variables, however, with varying degrees. The negative sentiment (Ngsnt) was significantly leptokurtic compared to others (see Table 2). This seems rather logical, though. Bond is second in the list (referring to Kurtosis), having a substantially higher skewed nature over the rest. The presence of fat-tails or heavy tails in all the variables under consideration proves significant deviation from EMH due to behavioral traces (represented by Ngsnt). The stationarity of the variables has been proved by ERS test (Elliot et al. 1996).

Table 2. Descriptive statistics of all five variables.

	Ngsnt	Doge	GC.CMX	Pimco	GSPC
Mean	2.443	0.035	0.004	0.001	0.005
Variance	107.482	0.008	0.000	0.000	0.000
Skewness	20.47 ***	2.99 ***	2.76 ***	7.79 ***	4.94 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Kurtosis	671.57 ***	9.6 ***	11.82 ***	120.8 ***	43.94 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	46,325,450 ***	132,289 ***	17,365 ***	1,518,545 ***	207,602 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	−18.609 ***	−2.795 ***	−12.080 ***	−10.884 ***	−10.853 ***
	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)
Q (10)	14.7 ***	12,817.7 ***	105.3 ***	701.31 ***	934.93 ***
	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)
Q2(10)	0.077	10,720.5 ***	89.8 ***	620.8 ***	1216.2 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

*** indicate statistical significance at 1% level.

The negative sentiment (Ngsnt) was found to be 3.3 times stronger net emitter over GSPC (S&P 500) (see Table 3). Results remain consistent with the fundamental intuitive understanding. Tweets (negative) of Elon Musk emitted the shocks toward all other asset classes. This disapproves EMH and establishes the fundamental premise of behavioral finance. Moreover, it is substantially stronger than that of shocks generated from Equity markets (S&P 500 or GSPC). Further, Ngsnt impact (risk emission) on Gold, Bond and Equity are almost identical (namely, 0.41, 0.43 and 0.47). Therefore, we can infer that negative sentiment percolated by Twitter messages impacts similarly to the traditional asset classes.

Table 3. Depicting average dynamic connectedness.

	Ngsnt	Doge	GC CMX	Pimco	GSPC	From
Ngsnt	98.45	0.25	0.41	0.43	0.47	1.55
Doge	0.7	97.44	0.43	0.68	0.75	2.56
GC.CMX	1.13	0.32	76.27	11.23	11.05	23.73
pimco	3.25	0.27	9.86	72.14	14.48	27.86
GSPC	2.13	0.52	9.35	13.04	74.97	25.03
TO	7.2	1.35	20.04	25.38	26.75	80.72
NET	5.64	−1.21	−3.68	−2.47	1.72	16.14

Average dynamic connectedness is depicted in this table for all the variables using TVP-VAR model.

Gold has received a shockwave three times over that of Dogecoin (see Table 3). We observed that both Gold (represented by GC.CMX) and Bond (represented by pimco) received shocks; however, their quantum varied. While Gold received the bulk of it, Bonds received at a moderate level. Interestingly, Dogecoin received low levels of shocks, which can be explained by the unexplored nature of cryptocurrencies barring Bitcoin and perhaps Ethereum. Gold and Bond being traditional and age-old asset classes, typically find significantly higher traction.

Another interesting observation (see Figures 3 and 4) exhibits that dynamic PCI between Equity (GSPC) and Bond (pimco) surged sharply to 75% (from 25%) around the COVID-19 outbreak.

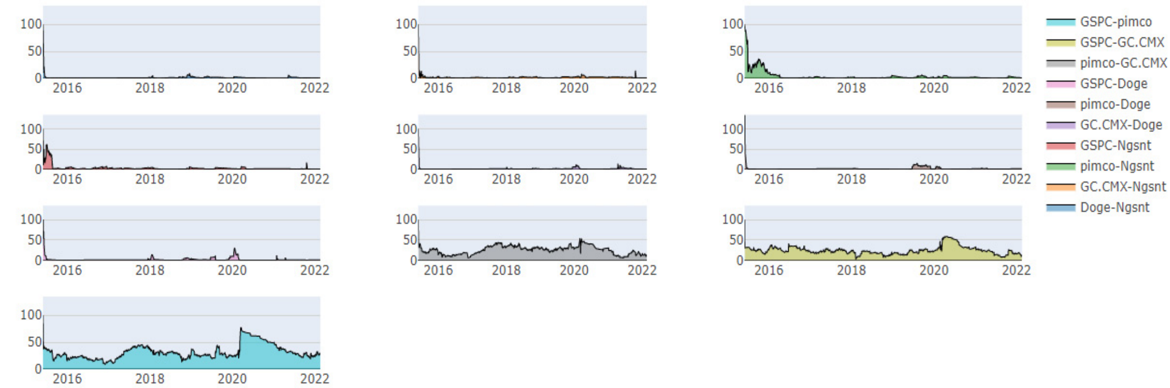

Figure 3. Dynamic pairwise connectedness index (PCI).

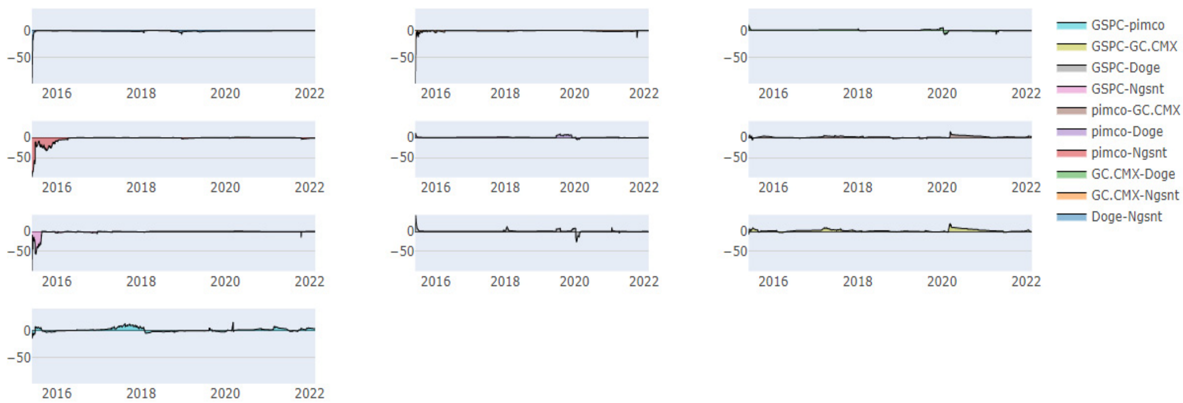

Figure 4. Net pairwise directional connectedness (NPDCI).

Typically, stressful events increase connectedness (TCI). We found that TCI was more than 70% during 2015–16 (see Figure 5) and nosedived during 2017–19. TCI was stable until the COVID-19 breakout (around 20%). Spike was observed at 38% (see Figure 5 and Table 4) as COVID-19 surfaced globally (early 2020). Perhaps the most interesting observation was yet to come. We found COVID-19 breakout was surprisingly less impactful (see Table 4) when compared to the Greek debt crisis back in 2015 (half of it). TCI during the Greek debt crisis was around double the mark than in the COVID-19 outbreak.

Typically, TCI is supposed to surge when stress increases in its underlying assets. Further, TCI decreases as stress reduces. Therefore, excess TCI indicates a stressful situation. Figure 5 identifies two zones (see Table 4) with higher levels of TCI values.

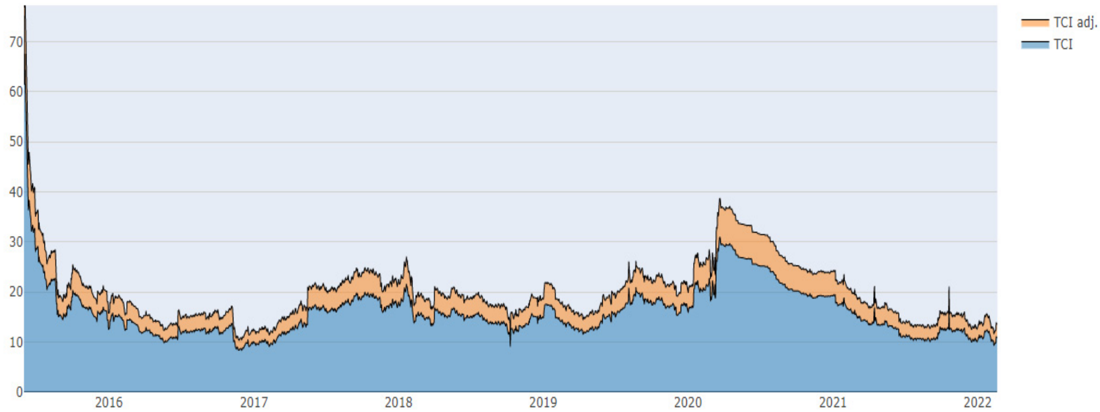

Figure 5. TCI over the years (from June 2015 to February 2022).

Table 4. Events linked with relatively higher TCI values.

TCI	Date Range	Event	Interpretations
75%	June–July 2015	Greek debt crisis	Stressful events pushed the TCI to an extreme limit
17%	June–July 2016	Brexit referendum	Stressful events pushed the TCI to a relatively smaller limit
38%	March–April 2020	COVID-19 breakout	Stressful events pushed the TCI to a relatively higher limit

This table depicts the intensity of TCI during two stressful events (namely Greek debt crisis and COVID-19).

5. Conclusive Remarks

We found four research queries during our extensive literature review (which is written all across this paper). First, we wanted to empirically confirm whether Twitter emits negative sentiment. Interestingly, it was found that the Twitter induced negative sentiment (Ngsnt) was found to be three times stronger net emitter over Equity, which is represented by GSPC (or S&P 500) (see Tables 3 and 5). Second, our query was regarding the negative tweet (Ngsnt) and Dogecoin prices interconnectedness. Their interconnectedness was found to be quite feeble in comparison to other asset classes (see Table 3). The relative newness of Dogecoin over Bitcoin and Ethereum could justify this outcome. Third, we checked whether Gold as a traditional hedge wins over Dogecoin or not. It was found that Gold has received three times (3.68 vs. 1.21) shockwave over that of Dogecoin (see Tables 3 and 5). This proves that Gold remains a better hedge over Dogecoin by a margin. Last, we have empirically checked the ‘stylized fact’ of connectedness (TCI) shooting up during extreme events. We found that it does; however, the COVID-19 breakout was surprisingly less impactful (see Table 4) when compared to the Greek debt crisis back in 2015 (in fact, half of it). Shockingly, Brexit (23 June 2016) did not seem to have much impact on TCI, as it stayed around 17% levels. This further proves that all stressful events do not have a similar impact on time-varying connectedness. Therefore, many useful findings emerged during this humble attempt, which are perfectly in sync with the latest studies around the same domain (Ante 2022; Huynh 2021, 2022). In addition to that, these outcomes can be of some use to the policymakers and portfolio managers alike.

Table 5. Network connectedness table (showcasing net emitters/receivers).

Node	Size	Asset/Sentiment	Interpretation
Blue	Large	Ngsnt	Significant net transmitter of shocks; high weighted average net total directional connectedness (see Figure 6)
	Small	GSPC	Low net transmitter of shocks; low weighted average net total directional connectedness (see Figure 6)
Yellow	Large	GC CMX	Significant net receiver of shocks; high weighted average net total directional connectedness (see Figure 6)
	Medium	pimco	Moderate net receiver of shocks; moderate weighted average net total directional connectedness (see Figure 6)
	Small	Doge	Low net receiver of shocks; low weighted average net total directional connectedness (see Figure 6)

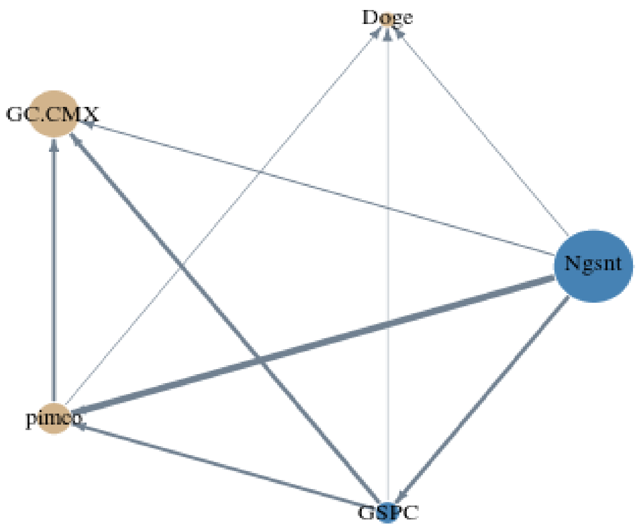

Figure 6. Network plot analysis depicting the net emitter of shocks (blue) and the net receiver of shocks (yellow).

6. Limitations and Scope for Future Studies

Twitter was purchased just after this paper was sent for publication. Therefore, new research can be carried forward in a different direction altogether. Instead of Dogecoin, other coins can be investigated as well. In addition to that, other methods such as DCC-GARCH can be used to check the connectedness.

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Conflicts of Interest: The authors declare no conflict of interest.

Notes

1 https://economictimes.indiatimes.com/tech/technology/elon-musk-polls-followers-on-converting-twitter-hq-to-homeless-shelter-jeff-bezos-likes-idea/articleshow/90771702.cms (accessed on 14 April 2022).

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