4-28-2023

Do Automated Market Makers in DeFi Ecosystem Exhibit Time-Varying Connectedness during Stressed Events?

Bikramaditya Ghosh
Symbiosis Institute of Business Management

Hayfa Kazouz
University of Sousse

Zaghum Umar
Zayed University

Journal of
Risk and Financial Management

Article

Do Automated Market Makers in DeFi Ecosystem Exhibit Time-Varying Connectedness during Stressed Events?

Bikramaditya Ghosh [1,*], Hayfa Kazouz [2] and Zaghum Umar [3]

1 Symbiosis Institute of Business Management, Symbiosis International (Deemed University), Bangalore 560100, India
2 Faculty of Economic sciences and Management, University of Sousse, Sousse 4000, Tunisia
3 College of Business, Zayed University, Abu Dhabi P.O. Box 144534, United Arab Emirates; zaghum.umar@gmail.com
* Correspondence: b.ghosh@sibm.edu.in

Abstract: We investigate the connectedness of automated market makers (AMM) that play a pivotal role in liquidity and ease of operations in the decentralized exchange (DEX). By applying the TVP-VAR model, our findings show higher level of connectivity during periods of turmoil (such as Delta, Omicron variants of SARS-Covid, and the Russia Ukraine conflict). Furthermore, risk transmission/reception is found to be independent of the platform on which they typically run (Ethereum based AMMs were both emitters as well as receivers). Pancake (a Binance based AMM) and Perpetual Protocol (Ethereum based AMM) emerged as moderate to high receivers of risk transmission, whereas all of the other AMMs, including Ethereum, were found to be risk emitters at varying degrees. We argue that AMMs typically depend on the underlying smart contracts. If the contract is flexible, AMMs can vary (either receiver or emitter), otherwise AMMs behave in tandem.

Keywords: automated market makers (AMM); decentralized exchange (DEX); TVP-VAR; DeFi

Citation: Ghosh, Bikramaditya, Hayfa Kazouz, and Zaghum Umar. 2023. Do Automated Market Makers in DeFi Ecosystem Exhibit Time-Varying Connectedness during Stressed Events? *Journal of Risk and Financial Management* 16: 259. https://doi.org/10.3390/jrfm16050259

Academic Editor: Badar Nadeem Ashraf

Received: 20 March 2023
Revised: 22 April 2023
Accepted: 25 April 2023
Published: 28 April 2023

1. Introduction

DeFi is essentially a competitive online marketplace of financial dApps that function as exchanges. These dApps benefit from attracting increasing market shares from the traditional financial ecosystem due to their seamless nature. Blockchain remains the key to all DeFi. Blockchains are fundamentally software protocols which allow multiple parties to operate seamlessly and in a transparent manner. Usually the changes are packaged into "blocks" and are "chained" together cryptographically to allow a virtual audit of the historical transactions. A crucial ingredient of DeFi is smart contract platforms. Smart contracts automate the execution of a pre-determined agreement. Ethereum is a prime example of a smart contract platform. However, all of these would fail if substantial liquidity is not injected into the system. That is where AMMs or Automated Market Makers are crucial.

Automated market makers (AMMs) are perhaps the most integral part of the DeFi ecosystem. They create liquidity pools and allows the digital assets to be traded in an automated and permissionless way, unlike the traditional market consisting of buyers and sellers. Usually, AMM users constantly supply liquidity in the pools with tokens, whose prices are determined by a constant product construct. Typically, an Automated Market Maker (AMM) inside a decentralized exchange or DEX works on a mathematical equation to identify the price range for crypto assets. Therefore, AMM is an integral part of the DeFi ecosystem globally. There are many methods for the determination of AMMs. However, latest research proves constant circle cost functions are the best to build AMMs (Wang 2020). These make the AMMs seamless, automatic, low cost and permissionless at the same time. Instead of current peer-to-peer trading, they generate a pool of liquidity through peer-to-contract trade, as opposed to traditional exchanges. The fundamental of an

AMM remains the smart contracts underneath. Unlike a traditional marketplace (exchange) where buyer and seller quotes have to match for a transaction to take place (with plenty of fees), DEX provides plenty of peer to contract based prices already being available, making the transaction inexpensive and fast without affecting the market price. Therefore, liquidity holds the key in a DEX ecosystem (Aramonte et al. 2021), AMM provides the same. DEX faced liquidity problems before the advent and growth of AMM technology for good reasons. Additionally, AMM gave incentives to the assets-based liquidity sources. The traders pay a charge to the providers of liquidity. These days, they are also engaging in a practice known as "yield farming" to increase their yields (Mohan 2022).

One criticism of AMMs is that they work well for assets with low volatility (Pourpouneh et al. 2020). Typically, AMMs deal with volatile tokens; however, sometimes the volatility becomes too high, so an AMM could be replaced with Hybrid Function Market Makers (HFMM) (Mohan 2022). Trading is facilitated by liquidity, which also makes it quicker and more affordable. Liquidity pools generally consist of tokens whose prices may be changed through modifications to the underlying mathematical formula. This function supports optimization. Most of these infrastructure use Ethereum, where a select few uses Binance and Bitcoin. Almost all the AMMs use completely unique smart contracts (namely Uniswap uses v2 & v3; SushiSwap uses MasterChef, etc.). Therefore, they (AMMs) move in unique directions. AMMs are an integral part of the biggest and ever-growing online exchange (DEX) globally. Thus, their interconnectedness becomes crucial. Centralized crypto exchanges were beaten down both in size and usage by AMM giants such as Uniswap and Curve Dao; therefore, a better understanding about their architecture and connectedness of the smart contracts become critical (Bartoletti et al. 2021).

This study aims to add another dimension to the existing growth story of literature surrounding AMMs. Though there is fair bit of technical work available on AMMs, no study has delved into the behavior of smart contracts, without which AMMs cannot function. This study attempts to bridge that research gap. First, the connectedness pattern (alongside total connectedness) among the top smart contracts (through AMMs) were found. Second, there consistency and inconsistency were studied. Third, the optimum window size is identified for studying their group behavior. Finally, the volatility of the Ethereum based framework was compared to the Binance based framework.

Investors worldwide seems to chase decentralized financial services (Defi) as the "fear of missing out" (FOMO) is increasing with each passing trading day[1]. Moreover, the decentralized exchange (DEX) has doubled from 2019–2021 due to anonymity, privacy, and transparency[2]. According to various studies (Abdulhakeem and Hu 2021; Gubareva 2021; Johnstone 2020; Marecki and Wójcik-Czerniawska 2021; Xu and Vadgama 2021), Defi presents a different paradigm and calls for rebuilding the traditional services offered by financial institutions. These institutions have demonstrated negative instability and fragility during the challenging COVID-19 period. Defi is thereby becoming a new turning point in the technical development of finance on a worldwide scale (Chohan 2021; Katsiampa et al. 2021; Lin 2019; Zetzsche et al. 2020). In order to conduct transactions like using loans or paying interest on assets, "smart contracts" are used. Ethereum is the first platform for smart contracts (Chen et al. 2021; Negara et al. 2021; Schär 2021).

The self-running computational processes known as smart contracts, which operate on a blockchain, call for corrective, adaptive, perfective, and preventative maintenance (Vos 2021; Werner et al. 2021). DeFi's digital assets are an alternative to traditional financial assets exchanged by centralized financial institutions like banks, insurance companies, and stock exchanges, which is one of the creative characteristics of DeFi in the financial markets. Another crucial factor is DeFi's industrial development into emerging markets, with a strong focus on Asian countries such as China. In 2021's first half, the crypto currency market in China was the most active in Asia ($256 billion), while DeFi platforms accounted for 49% of the total.

DeFi asset classes might provide market players with a number of advantages, but there may also be unrecognized sources of risk. Given that crypto currencies are used as the collateral for DeFi digital assets, their extreme price volatility is one potential cause.

However, an investigation by Corbet et al. (2021) between the five largest DeFi products (Looping, Maker, Synthetix, Ren, and Lin) and the most traded cryptocurrencies revealed that DeFi assets have a high correlation to Bitcoin and are typically thought of as a separate asset class. The study measured spillovers based on Diebold and Yilmaz (2012) and causality based on the Wold test modified by Hacker and Abdulnasser (2006).

The results of the study find that the return and volatility transmissions between DeFi and traditional crypto-currencies are strongly influenced by the interactions between Bitcoin and Maker. Moreover, they discover a unidirectional causality running from Bitcoin to Maker and Link. Yousaf and Yarovaya (2021) use the Diebold and Yilmaz (2012, 2014) method to analyze the return and volatility spillovers between non-fungible tokens (NFTs), DeFi assets, and other asset classes (oil, gold, bitcoin, and S&P 500).

The COVID-19 pandemic advancement in the first third of 2020 and the 2021 cryptocurrency bubble are both confirmed to have significant returns and volatility. They have also demonstrated how diversity may be improved by include NFTs, DeFi, or both in a portfolio that already includes exposure to equities markets, gold, and oil.

Fundamentally, most studies concentrated on Crypto, s, and DeFi as a macro-system. However, these macro-systems are supported by micro-systems such as smart contracts. If the smart contracts do not function effectively, AMMs fail to provide liquidity and ease of operations. As a result, DEX would not function correctly. It would have an impact on the entire DeFi ecosystem. Consequently, in order to find hidden patterns, we have focused on the microsystem. The remainder of this attempt is structured as follows. In Section 2 we describe our proposed method, whereas in Section 3 we illustrate all our results and respective interpretations. In Section 4 we provide a conclusive statement.

2. Research Methodology

2.1. TVP-VAR

We used the TVP-VAR (time-varying parameter vector autoregressions) model in accordance with the Antonakakis et al. (2020) study while assessing the time-varying connectivity among the target variables (Antonakakis et al. 2018). This approach often extends the model for analyzing dynamic connectivity developed by Diebold and Yilmaz (2012, 2014). With the introduction of the TVP-VAR model, the issue of excessive subjectivity around a certain window size was never an issue again. This approach may manage additional, relatively lower sample sizes very well. The equations below describe the TVP-VAR model:

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

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

where the vectors Z_t, Z_{t-1} and the error term u_t have a dimension of k × 1 with size n × n, B_t and S_t are matrices with dimensions n × n; while $vec(B_t)$, is of size k2 × 1.

Here,p_{t-1} gives all of the information accessible till $t-1$. The second error term v_t has dimensions k2 × 1,whereas R_t has a dimension of k2 × k2. S_t and R_t are the time varing variance covariance matrices.

Following Koop, Pesaran, and others (Koop et al. 1996; Pesaran and Shin 1998), the next step was to construct scaled generalized forecast error variance decomposition (GFEVD). In contrast to the previous model, GFEVD is completely insensitive to changing ordering. To get GFEVD, TVP-VAR is translated to vector moving average representation (TVP-VMA) using the Wold theorem[3], as follows:

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

The unscaled GFEVD is represented by $\varphi^{g}_{ij,t}(H)$,which is then normalized to the scaled version.

This would guarantee that each row's summation is equal to one. Once more, this indicates the pairwise directional connectivity from variable j to variable i. The following procedure is used in order to calculate the terms above:

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

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

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

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

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

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

The network's total directional connectedness FROM j TO all others in the network is measured by Equation (5), while Equation (6) measures the total directional connectedness TO j FROM all others. Additionally, Equation (7) shows the net total direction of connectivity related to j and is derived from the difference between Equations (5) and (6). As an illustration, if $NET_{jt} > 0$, it is evident that j is a net driver involved in shock transmission. Equation (8) provides a proxy for the overall interconnectivity by measuring the total connection of all parties in aggregate. Typically, a greater TCI (total connectedness index) would show that the network has been affected by a shock in a particular variable. TCI often increases during stressful situations and decreases when the tension subsides.

The interaction between variables increases with stress resulting in higher TCI. Frequency and amplitude of the interaction comes down with lowering of stress causing a decline in TCI (Benlagha and Omari 2022).

We have followed Antonakakis et al. (2020) and, therefore, did not follow the rolling window method. They showed that TVP-VAR outcomes adjust rather quickly to sudden stress events, whereas the rolling-window-based estimates typically overreact or underreact (Antonakakis et al. 2020). This method is better than an arbitrary rolling window-based on selection process. Furthermore, the original TCI is not within 0 and 1 it is rather between 0 and $(k - 1)/k$ when k is the number of variables (k is 7 in this study). The adjusted TCI is within 0 and 1 when the forecast horizon converges to infinity.

2.2. Data Details

Data for this research was taken from CoinGecko.[4] Daily prices of the top six (volume wise) automated market makers (AMM) are considered, namely, Uniswap (Uni), Pancake Swap (Cake), Curve Dao Token (CRV), Sushi Swap, Bancor Network Token (BNT), Perpetual Protocol (PERP) were considered from 17 September 2020 to 25 April 2022. Additionally, we have considered Ethereum's daily closing for the same specified time period, since most AMMs are based on the Ethereum network. The newness of this segment and limited availability of the data hindered obtaining a longer time period for all the AMMs. It must be noted that barring Pancake Swap (Cake), the rest all are on the Ethereum platform in some way or the other; Cake is operative on Binance platform. Returns were calculated and all of the calibrations were conducted on the daily returns indicating volatility (refer

Figure 1). Therefore, all of the connectedness calculated in this study are in relation with volatility-based connectedness.

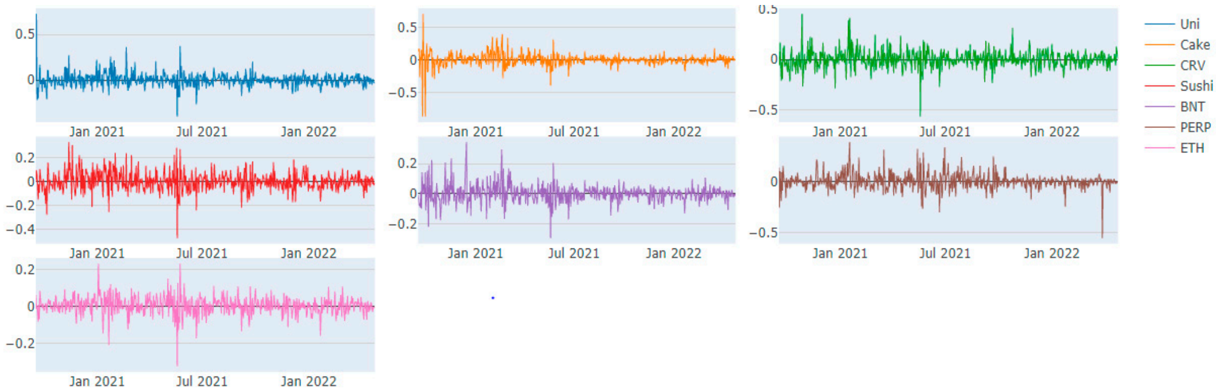

Figure 1. Transformed Data (all variables return series).

Most AMMs (Table 1) are currently running on the Ethereum platform; smart contracts are a mathematical formula which can be used as a software protocol to create a deal. Some smart contracts are flexible (such as ERC20) whereas some are rigid (such as V2). Each smart contract is unique. V2 implements a relatively straight forward bonding curve in achieving a low gas fee, V3 allows for concentrated liquidity provision for improving capital efficiency and ERC20 is suitable for swapping assets having the same peg (Xu et al. 2021). Traits are shown below in Table 2.

Table 1. Automated Market Maker Details.

AMM Name	AMM Code	Smart Contract	Running on
Uniswap	Uni	V3	Ethereum
Pancake	Cake	V2	Binance
Perpetual protocol	PERP	V2	Ethereum
Curve Dao	CRV	ERC20	Ethereum
Bancor Network	BNT	ERC20	Ethereum
SushiSwap	Sushi	MasterChef	Ethereum

Table 2. Descriptive Statistics of the seven variables (return series).

	Uni	Cake	CRV	Sushi	BNT	PERP	ETH
Mean	0.001	0.004	0.001	0.001	0.001	0.001	0.004
Variance	0.006	0.011	0.008	0.007	0.004	0.007	0.003
Skewness	1.527 ***	−1.262 ***	0.052	0.037	0.519 ***	0.039	−0.441 ***
	0	0	−0.604	−0.708	0	−0.694	0
Kurtosis	14.676 ***	20.980 ***	4.282 ***	2.616 ***	4.644 ***	5.736 ***	4.657 ***
	0	0	0	0	0	0	0
JB	5486.7 ***	10903.1 ***	448.02 ***	167.2 ***	552.8 ***	803.4 ***	548.4 ***
	0	0	0	0	0	0	0
ERS	−11.714 ***	−2.947 ***	−8.740 ***	−11.19 ***	−9.718 ***	−3.101 ***	−4.094 ***
	0	−0.003	0	0	0	−0.002	0
Q (10)	15.168 ***	16.932 ***	2.442	21.216 ***	6.538	6.452	11.630 **
	−0.005	−0.002	−0.892	0	−0.302	−0.311	−0.032
Q2(10)	9.307 *	136.731 ***	21.691 ***	60.940 ***	47.469 ***	9.837 *	46.381 ***
	−0.096	0	0	0	0	−0.075	0

As usual, *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

3. Results and Interpretation

We employed the TVP-VAR model to quantify the connectedness of the various AMMs described in the previous section.

3.1. Average Connectedness

We start our analysis by discussing the average connectedness over the entire sample period reported in Table 3. The total connectedness of the various AMMs employed in this study (denoted by TCI, right corner) of Table 3 is sizable with a value of 77%. Thus, underscoring the interconnectedness of the AMMs. In order to identify he transmitters and receivers of spillover, we study the penultimate row of Table 3. We notice that ETH is the biggest transmitter of spillover (9.1%), whereas PERP is the largest recipient of spillover (−15.32%). Other transmitters include Uni, Sushi, and BNT, whereas other recipients include Cake and CRV.

Table 3. Average Dynamic Connectedness Table.

	Uni	Cake	CRV	Sushi	BNT	PERP	ETH	FROM
Uni	33.5	7.71	11.76	16.64	11.63	6.05	12.71	66.5
Cake	9.95	50.92	7.66	8.33	9.05	4.57	9.53	49.08
CRV	12.56	6.32	36.51	15.09	12.19	5.81	11.51	63.49
Sushi	16.4	6.42	13.73	32.87	11.55	6.27	12.75	67.13
BNT	11.63	7.18	11.21	11.74	34.32	6	17.92	65.68
PERP	8.6	5.43	7.74	9.5	8.92	48.01	11.8	51.99
ETH	12.16	7.01	10.13	12.56	17.3	7.97	32.87	67.13
TO	71.3	40.06	62.23	73.86	70.65	36.67	76.23	430.99
Inc. Own	104.8	90.97	98.74	106.73	104.98	84.68	109.1	TCI = 77%
NET	4.8	−9.03	−1.26	6.73	4.98	−15.32	9.1	

In order to identify the pairwise, net transmitter, and net receiver of spillover, we employ a network diagram, presented in Figure 2. The source of the arrow identifies a net transmitter, whereas the edge of the arrow identifies a net receiver of spillover. On a pairwise basis, we notice that PERP is the recipient of pairwise spillover from all other AMMs, followed by Cake, which is a recipient from all other AMMs except PERP, for which it is a transmitter of spillover. ETH, followed by Sushi, are the biggest transmitters of pairwise spillover to all other AMMs.

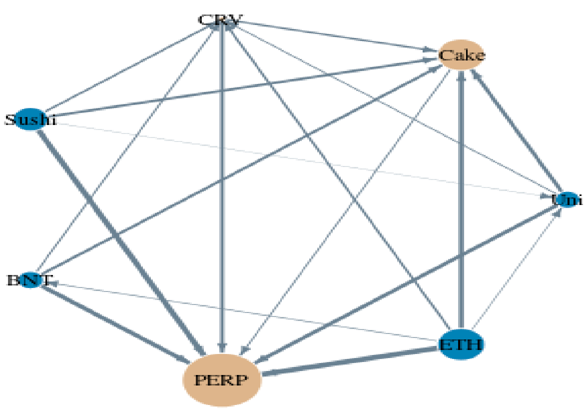

Figure 2. Network Connectedness, depicting volatility connectedness calculated using TVP-VAR (Yellow is the net receiver and Blue is the net emitter).

3.2. Time-Varying Connectedness

We extend our analysis and report the time-varying connectedness in this section. The time-varying analysis allows us to study the evolution of connectedness over the sample period and the effects of various events on the connectedness dynamics.

Figure 3 depicts the total connectedness of all seven AMMs over the sample period. The connectedness exhibits sizable variation with minimum value of approximately 45% and maximum value of approximately 84%. We report the main stress triggering dates in Table 4. Interestingly, the connectedness surges exponentially after May 2021, which coincides with the declaration of Delta variant, to 78% and reaches a peak of 84% with the onset of the Russia-Ukraine conflict. This pattern of heightened interconnectedness and contagion during periods of uncertainty are consistent with the existing literature (Allen and Gale 2000). We attribute this spike in TCI to the transmission of volatility shocks through markets in times of financial stress (Fuentes and Herrera 2020). The period coinciding with the initial relaxation of restrictions post COVID-19 lockdown from September 2020 to November 2020 depicts a sizeable reduction in the connectedness. Subsequently, we notice that from October 2020 and May 2021, the connectedness stays at relatively lower levels, until the declaration of the Delta variant mentioned above, that led to a new period of financials stress and hence heightened connectedness. This phenomenon of reduction (increase) in connectedness during period of low (high) financial stress is in line with the existing literature (Bouri et al. 2021; Karim et al. 2022; Umar et al. 2020). Our findings support and extend this literature to the AMM market.

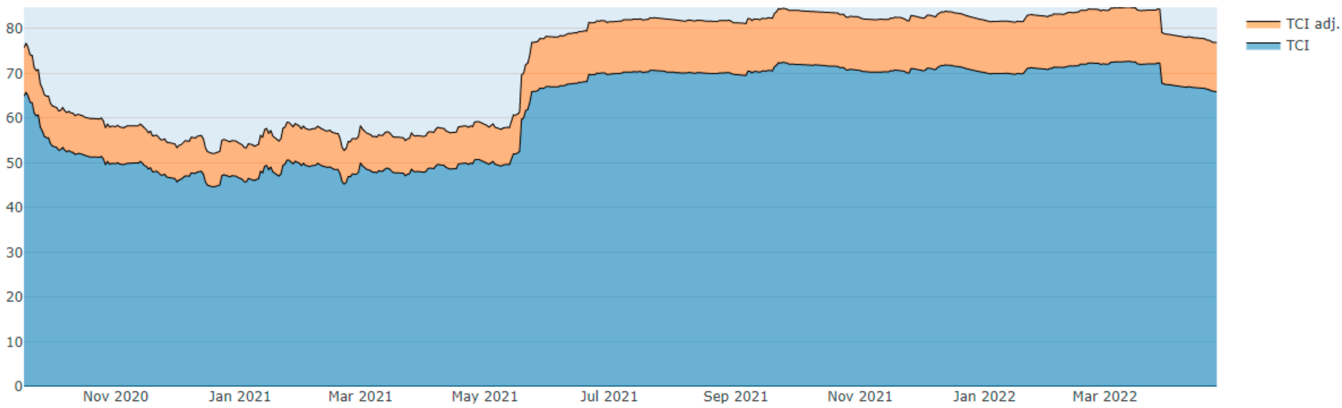

Figure 3. Time-varying total connectedness. Notes: This figure shows the TCI calculated for the specific network of seven variables using TVP-VAR.

Table 4. Stressed events induced higher connectedness across AMMs and Ethereum.

Date	TCI	Events
31 May 2021	78%	Delta variant was declared
22 November 2021	82%	Delta variant reached over 180 countries
24 November 2021	83%	Omicron variant was declared
24 February 2022	84%	Russian aggression on Ukraine

Note: Data was considered from 17 September 2020 to 25 April 2022. TCI was rangebound between 55–60% during October 2020 and May 2021 before surging to substantially higher levels.

The above analysis discussed the total connectedness over the sample period of all the AMM employed in this study. However, it is important to identify the role of each variable in connectedness. Therefore, we extend our analysis and report the spillover to all other AMM transmitted by each AMM in Figure 4. We notice that the spillover exhibits significant variation for all of the AMMs. However, certain patterns are distinctively noticeable. The most distinctive pattern is exhibited by Cake, which has a very low spillover compared with other AMM in the early part of 2021 but exhibits a sudden spike after July 2021 and reached a very high level of spillover. A similar pattern is exhibited by PERP, but the magnitude is relatively less. Among other AMMs, ETH and Sushi exhibit the highest spillover to all other AMMs. Next, we discuss the spillover received by each AMM from all other AMMs, depicted in Figure 5. We notice that the magnitude of spillover is lower relative to the one reported in Figure 4, however, qualitatively we see similar patterns.

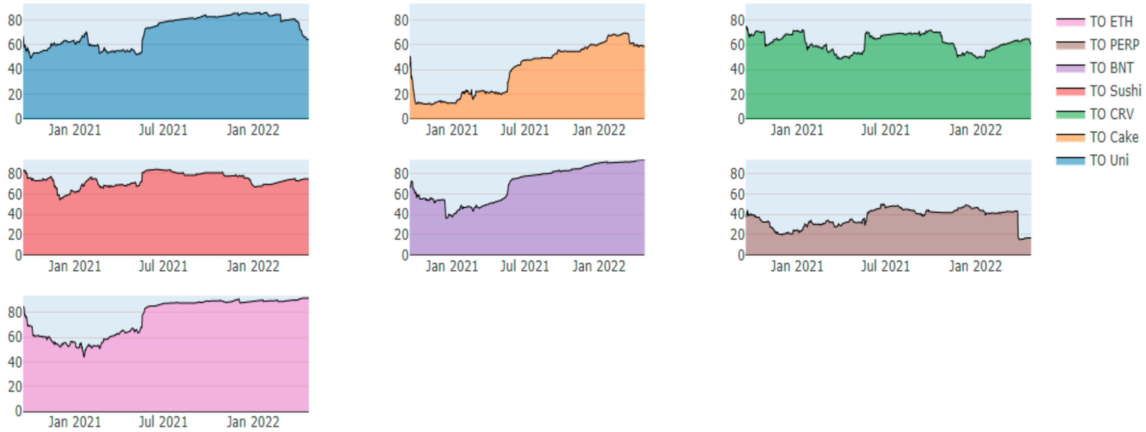

Figure 4. Risk transmission TO others. Notes: This figure shows the spillover that each AMM listed transmits to all the other AMM.

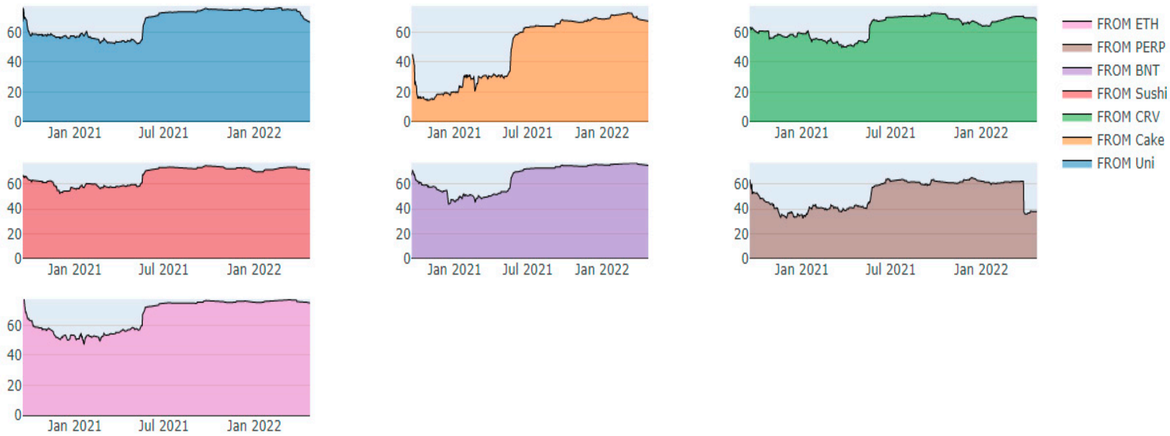

Figure 5. Risk transmission FROM others. Notes: This figure shows the spillover that each AMM listed receives from all the other AMM.

One of the main objectives of our analysis is to identify the net transmitter and receivers of spillover. We report this important result in Figure 6. We notice that PERP and Cake are persistent receivers of spillover whereas all of the other AMM exhibit alternating patterns with partial periods of net transmitters and partial periods of net receivers. However, ETH is predominantly a net transmitter with a very short period where it acts as a net receiver. Interestingly, BNT and CRV depict opposite patterns, with BNT a receiver (transmitter) in the early (later) part of sample period and CRV a transmitter (receiver) in the early (later) part of the sample period.

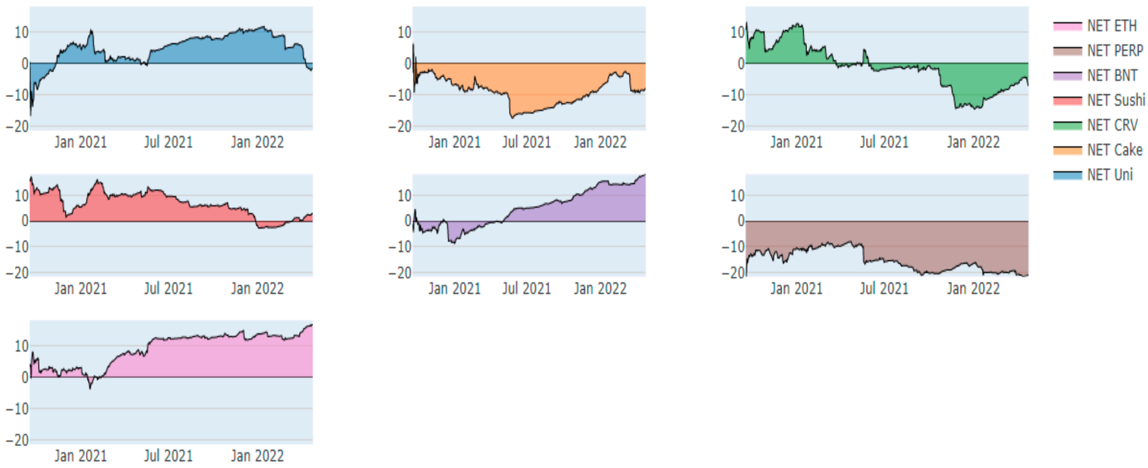

Figure 6. Net directional connectedness. Notes: This figure shows the net directional connectedness of each AMM to identify the role of each AMM as a transmitter and receiver of spillover.

4. Discussion

Our results are consistent with broader studies conducted on DeFi recently (Karim et al. 2022). Ethereum is an undisputed ecosystem provider for the DeFi ecosystem. However, DeFi applications using Ethereum are around 70%, as reported on mid-January 2022[5]. Our results show the prominence of the Binance ecosystem in the network connectedness of AMM. We attribute this to the phenomenal growth of the Binance ecosystem which is outpacing Ethereum[6]. This may be attributable to following reasons. Firstly, the Binance platform is substantially inexpensive in comparison to the actual coin. Therefore, the volume surges in no time (e.g., ETH in Ethereum infrastructure is $20 whereas representation of ETH in Binance is about $0.75)[7]. Secondly, ERC20 fees are more compared to V2 due to Ethereum gas fees[8]. Ethereum block sizes vary entirely on the amount of gas spent per block. Usually, the competitors pay a priority fee induced by the network congestion (in Ethereum network) to push their transactions ahead, causing the surge in the gas fee (Liu et al. 2022).

Platforms such as Ethereum and Binance typically work as a digital marketplace, where pre-established computerized protocols (smart contracts) are executed. These ecosystems store dApp's or decentralized applications. Ethereum currently holds most dApp's than any other blockchain ecosystem. Some even support two Blockchain (Ethereum and Avalanche are supported by Solidity code). Therefore, the common thread must be the underlying smart contract, most importantly, the conditions of that contract. In our study, the common thread between PERP and Cake is a strict binary smart contract with rigid fee named V2.

Another salient outcome of our analysis is that the risk emitters as well as receivers were found to be independent of the operating platform in this study. As mentioned above both Ethereum and Binance are the predominant transmitters of spillover. On the contrary, Perpetual Protocol or PERP is the largest receiver (works on Ethereum platform) alongside Pancake Swap or Cake (works on Binance platform) and both are the biggest receivers of spillover. Therefore, the operating platform is not as important compared with the underlying protocol or smart contract.

Smart contracts (written by coding languages like Solidity, Vyper, Rust, Haskell, etc.) are typically used for settlements by the AMMs. Existing literature documents that Uniswap, the largest AMM, is using smart contract V2 (now they have migrated to V3), was stable under various circumstances (Angeris et al. 2020). Therefore, V2 as a smart contract has proved to be quite stable as well, though some may argue that this stability is due to its rigidity of fee. Both Cake and PERP are on smart contract V2 (despite being in different platforms, namely Binance & Ethereum). We found both Cake and PERP are moderate to high-risk transmission receivers. It is pertinent to mention here that V2 is a smart program based on a constant product formula and saved inside the blockchain and is a binary contract with a rigid fee structure unlike most other smart contracts. V2 being a smart contract, is immutable or cannot be altered again. The output of the contract is validated as well. We attribute the similarity in patterns exhibited by PERP and Cake to this phenomenon.

5. Conclusions

DeFi has emerged as a significant technological phenomenon in the financial industry during the last few years and has attracted attention of investors, policy makers, and academics. Automated market makers (AMM) are essential for any DeFi ecosystem as they are responsible for liquidity and ease of operations in the DEX. Their main distinguishing feature compared with any traditional marketplace is since the contracts are all pre-made and readily available with a fairly strong pool of funds to back them up. This leads to an increase in liquidity on one hand and a reduction in the transaction friction on the other hand, thus making them very desirable.

The purpose of this study is to analyze the connectedness of various AMMs and identify the net transmitters and receivers of spillover among the major seven AMMs. We employ a TVP-VAR connectedness framework to document a high level of connectedness between AMMs during periods of market uncertainty such as Delta and Omicron variants of SARS-Covid and the Russia Ukraine conflict. Our results also show that AMMs tend to be independent of their operating ecosystem (platform). For instance, Ethereum based AMMs were both emitters as well as receivers of spillover. Cake or Pancake (operative on Binance) and PERP or Perpetual Protocol (operative on Ethereum) emerged as moderate to high receivers of risk transmission, whereas all of the other AMMs, and even Ethereum, were found to be risk transmission emitters at varying degrees. Therefore, the investors of DeFi through DEX can de-risk their portfolio by using PERP and Cake as a hedge against Uniswap, Bancor and Sushi swap.

We attribute the connectedness to the nature of smart contracts. The theoretical premise of most AMMs is found to be homogeneous. This can certainly be attributed to the underlying smart contracts being similar (most use either V2 or ERC20) (Jensen et al. 2021). If they are replicated exactly (such as V2) then they seem to produce similar results, otherwise, the movement of AMMs are strictly due to the movements of their unique smart contracts. Though this is rather complex to comprehend, there is a causal relationship. In simple words, we can say that DeFi depends on DEX, DEX depends on AMM, and AMM depends on smart contracts. Our findings have important implications for researchers, policy makers, and investors. For instance, investors can devise cross hedging and risk management strategies in light of the net emitters and net receivers AMM documented in this study. Similarly, policy makers can gain insight from the interrelation of DEX, AMMs, and smart contract nexus documents in this study.

6. Limitations and Scope for Future Studies

The stability of automated AMM markets depends on the stability of cryptocurrencies, therefore, in the future, we may explore how to maximize the stability of cryptocurrency portfolios (Ethereum, Bitcoin, etc.), reducing the risk that is transmitted to AMMs and DEX in the process. Moreover, to determine asymmetric relationships using the DCC MEGARCH model.

Author Contributions: B.G.: 1st author has contributed in idea development, original draft of the manuscript, data curation, methodology implementation, interpretation and conclusion. H.K.: 2nd author has contributed in modifications, redrafting the manuscript, contributing in idea, data curation. Z.U.: 3rd author has contributed in modification, redrafting the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data is available upon request.

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

Notes

1. https://medium.datadriveninvestor.com/dex-in-the-fast-lane-binance-and-okex-with-defi-fomo-524e260ba56b, accessed on 1 May 2022.
2. https://www.globenewswire.com/news-release/2022/03/02/2394967/0/en/FAMEEX-Set-to-Develop-Its-DEX-Applications.html#:~:text=Blockchain%20data%20platform%20Chainanalysis%20published,only%20risen%2020%25%20to%20120, accessed on 1 May 2022.
3. The stationary time series may be divided into two components using the wold theorem. The first component is deterministic and can be represented by a linear combination of deterministic functions such as polynomials, trigonometric functions, and so on. The second component is stochastic, and it is represented as a weighted sum of innovations, which are i.i.d random variables with finite variance.
4. https://www.coingecko.com/en/coins/, accessed on 1 May 2022.
5. https://www.economist.com/finance-and-economics/the-race-to-power-the-defi-ecosystem-is-on/21807229, accessed on 1 May 2022.
6. https://finance.yahoo.com/news/ethereum-binance-smart-chain-blockchain-defi-crypto-074504608.html, accessed on 1 May 2022.
7. https://www.binance.com/en/fee/cryptoFee, accessed on 1 May 2022.
8. https://coinremitter.com/fees, accessed on 1 May 2022.

References

Abdulhakeem, Saif Ahmed, and Qiuling Hu. 2021. Powered by Blockchain technology, DeFi (decentralized finance) strives to increase financial inclusion of the unbanked by reshaping the world financial system. *Modern Economy* 12: 1–16. [CrossRef]

Allen, Franklin, and Douglas Gale. 2000. Financial Contagion. *Journal of Political Economy* 108: 1–33. [CrossRef]

Angeris, Guillermo, Hsien-Tang Kao, Rei Chiang, Charlie Noyes, and Tarun Chitra. 2020. An Analysis of Uniswap markets. *Cryptoeconomic Systems* 1: 1–30. [CrossRef]

Antonakakis, Nikolaos, David Gabauer, Rangan Gupta, and Vasilios Plakandaras. 2018. Dynamic connectedness of uncertainty across developed economies: A time-varying approach. *Economics Letters* 166: 63–75. [CrossRef]

Antonakakis, Nikolaos, Ioannis Chatziantoniou, and David Gabauer. 2020. Refined Measures of Dynamic Connectedness based on Time-Varying Parameter Vector Autoregressions. *Journal of Risk and Financial Management* 13: 84. [CrossRef]

Aramonte, Sirio, Wenqian Huang, and Andreas Schrimpf. 2021. Trading in the DeFi Era: Automated Market-Maker. BIS Quarterly Review. Available online: https://www.bis.org/publ/qtrpdf/r_qt2112v.htm (accessed on 1 May 2022).

Bartoletti, Massimo, James Hsin-Yu Chiang, and Alberto Lluch-Lafuente. 2021. *A Theory of Automated Market Makers in DeFi*. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). Cham: Springer, vol. 12717, pp. 168–87. [CrossRef]

Benlagha, Noureddine, and Salaheddine El Omari. 2022. Connectedness of stock markets with gold and oil: New evidence from COVID-19 pandemic. *Finance Research Letters* 46: 102373. [CrossRef]

Bouri, Elie, Saeed Tareq, Xuan Vinh Vo, and David Roubaud. 2021. Quantile connectedness in the cryptocurrency market. *Journal of International Financial Markets, Institutions and Money* 71: 101302. [CrossRef]

Chen, Jiachi, Xin Xia, David Lo, John Grundy, and Xiaohu Yang. 2021. Maintenance-related concerns for post-deployed Ethereum smart contract development: Issues, techniques, and future challenges. *Empirical Software Engineering* 6. Available online: https://www.springerprofessional.de/en/maintenance-related-concerns-for-post-deployed-ethereum-smart-co/19599936 (accessed on 1 May 2022). [CrossRef]

Chohan, Usman. 2021. Decentralized Finance (DeFi): An Emergent Alternative Financial Architecture. Critical Blockchain Research Initiative (CBRI) Working Papers. Available online: https://ssrn.com/abstract=3791921 (accessed on 1 May 2022). [CrossRef]

Corbet, Shaen, John W. Goodell, John W. Goodell, and Kerem Kaskaloglu. 2021. Are DeFi Tokens a Separate Asset Class from Conventional Cryptocurrencies? *Annals of Operations Research* 322: 609–30. Available online: https://ssrn.com/abstract=3810599 (accessed on 1 May 2022). [CrossRef]

Diebold, Francis X., and Kamil Yilmaz. 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting* 28: 57–66. [CrossRef]

Diebold, Francis X., and Kamil Yilmaz. 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics* 182: 119–34. [CrossRef]

Fuentes, Fernanda, and Rodrigo Herrera. 2020. Dynamics of connectedness in clean energy stocks. *Energies* 13: 3705. [CrossRef]

Gubareva, Mariya. 2021. Lower reversal limit of the European Central Bank deposit rate and sustainability of traditional banking business model. *Journal of Financial Economic Policy* 13: 686–97. [CrossRef]

Hacker, R. Scott, and Hatemi-J. Abdulnasser. 2006. Tests for causality between integrated variables using asymptotic and bootstrap distributions: Theory and application. *Applied Economics* 38: 1489–500. [CrossRef]

Jensen, Johannes Rude, Mohsen Pourpouneh, Kurt Nielsen, and Omri Ross. 2021. The Homogeneous Properties of Automated Market Makers. *SSRN Electronic Journal* 131: 1–17. [CrossRef]

Johnstone, Syren. 2020. Secondary markets in digital assets: Rethinking regulatory policy in centralized and decentralized environments. *Stanford Journal of Blockchain Law & Policy* 3: 146–88. Available online: https://stanford-jblp.pubpub.org/pub/secondary-markets-digital-assets/release/2 (accessed on 1 May 2022).

Karim, Sitara, Brian M. Lucey, Muhammad Abubakr Naeem, and Gazi Salah Uddin. 2022. Examining the Interrelatedness of NFTs, DeFi Tokens and Cryptocurrencies. *Finance Research Letters* 47: 102696. [CrossRef]

Katsiampa, Paraskevi, Larisa Yarovaya, and Damian Zięba. 2021. High-Frequency Connectedness between Bitcoin and Other Top-Traded Crypto Assets during the COVID-19 Crisis. *Journal of International Financial Markets, Institutions and Money* 79: 101578. [CrossRef]

Koop, Gary, M. Hashem Pesaran, and Simon M. Potter. 1996. Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics* 74: 119–47. [CrossRef]

Lin, Lindsay X. 2019. Deconstructing decentralized exchanges. *Stanford Journal of Blockchain Law & Policy* 2: 58–77. Available online: https://stanford-jblp.pubpub.org/pub/deconstructing-dex/release/1 (accessed on 1 May 2022).

Liu, Yulin, Yuxuan Lu, Kartik Nayak, Fan Zhang, Luyao Zhang, and Yinhong Zhao. 2022. Empirical Analysis of EIP-1559: Transaction Fees, Waiting Time, and Consensus Security. *arXiv* arXiv:2201.0557.

Marecki, Krzysztof, and Agnieszka Wójcik-Czerniawska. 2021. Defi (decentralized finance) will Lead to a revolution in the world of financial services. *Economy & Business Journal* 15: 284–90.

Mohan, Vijay. 2022. Automated market makers and decentralized exchanges: A DeFi primer. *Financial Innovation* 8: 1–48. [CrossRef]

Negara, Edi Surya, Achmad Nizar Hidayanto, Ria Andryani, and Rezki Syaputra. 2021. Survey of smart contract framework and its application. *Information* 12: 257. [CrossRef]

Pesaran, H. Hashem, and Yongcheol Shin. 1998. Generalized impulse response analysis in linear multivariate models. *Economics Letters* 58: 17–29. [CrossRef]

Pourpouneh, Mohsen, Kurt Nielsen, and O. Ross. 2020. Available online: www.econstor.eu (accessed on 1 August 2020).

Schär, Fabian. 2021. Decentralized finance: On Blockchain- and smart contract-based financial markets. *Federal Reserve Bank of St. Louis Review* 103: 153–74. [CrossRef]

Umar, Zaghum, Dimitris Kenourgios, and Sypros Papathanasiou. 2020. The static and dynamic connectedness of environmental, social, and governance investments: International evidence. *Economic Modelling* 93: 112–24. [CrossRef] [PubMed]

Vos, M. A. 2021. Decentralization and Disintermediation in Blockchain-Based Marketplaces. Ph.D. thesis, Delft University of Technology, Delft, The Netherlands. [CrossRef]

Wang, Yongge. 2020. Automated Market Makers for Decentralized Finance (DeFi). *arXiv* arXiv:2009.0167.

Werner, Sam, Daniel Perez, Lewis Gudgeon, Ariah Klages-Mundt, Dominik Harz, and William J. Knottenbelt. 2021. SoK: Decentralized Finance (DeFi). Available online: https://arxiv.org/pdf/2101.08778.pdf (accessed on 1 May 2022).

Xu, Jiahua, and Nikhil Vadgama. 2021. From banks to DeFi: The evolution of the lending market. *arXiv* arXiv:2104.00970.

Xu, Jiahua, Krzysztof Paruc, Simon Cousaer, and Yebo Feng. 2021. SoK: Decentralized Exchanges (DEX) with Automated Market Maker (AMM) Protocols. *arXiv* arXiv:2103.12732. [CrossRef]

Yousaf, Imran, and Larisa Yarovaya. 2021. Static and Dynamic Connectedness between NFTs, Defi and other Assets: Portfolio Implication. Available online: https://ssrn.com/abstract=3946611 (accessed on 1 May 2022).

Zetzsche, Dirk A., Douglas W. Arner, and Ross P. Buckley. 2020. Decentralised finance. *Journal of Financial Regulation* 6: 172–203. [CrossRef]