Master of Science in Corporate Finance

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Connectedness of DeFi tokens, Bitcoin and Ethereum

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Student: Ágúst Berg Arnarsson

Social Security Number: 030785-2589

Instructor: Ender Demir

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Declaration of Research Work Integrity

This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature of any degree. This thesis is the result of my own investigations, except where otherwise stated. Other sources are acknowledged by giving explicit references. A bibliography is appended.

By signing the present document, I confirm and agree that I have read RU's ethics code of conduct and fully understand the consequences of violating these rules in regards of my thesis.

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Abstract

In this paper, the transmission mechanism of 6 DeFi tokens, Bitcoin and Ethereum is examined using the TVP-VAR connectedness technique. To do so, we focus on six DeFi tokens in two DeFi categories, Bitcoin and Ethereum. The study period runs from October 3, 2020, to June 21, 2022, with dynamic variance ranging from 55% to 80% in total dynamic connectivity across the sample. High (low) price spikes are correlated with weak (strong) connectivity. I show how these results can be explained by the increased market concern associated with periods of extremely volatile prices. In addition, Ethereum is the main net receiving cryptocurrency and the fact that Bitcoin still has an impact on the cryptocurrency market as a net transmitting cryptocurrency. I also note that there is no significant difference between the different DeFi categories in terms of net receiving or net transmitting properties. Compound is the biggest transmitter of the other DeFi tokens to Bitcoin and Pancake Swap transmits most to itself of the DeFi tokens.

Keywords: Cryptocurrencies; Connectedness; DeFi; TVP-VAR.

1. Introduction

Cryptocurrencies have attracted a lot of attention in the international financial markets in recent years. Currently, the most widely used digital currency is Bitcoin, which was the first to be created using blockchain technology; however, others such as Ethereum are on the rise (Antonakakis et al., 2019). The growing interest in cryptocurrencies is mainly because many key areas of real economic activity could be affected by cryptocurrency applications in the future (Raskin & Yermack, 2018).

Decentralized finance, or DeFi, is the general term for various financial services that operate in a peer-to-peer fashion without a central authority. Spot and margin trading, interest income, derivatives, software wallets, market making, lending, and borrowing can all fall under this category. It is important to note that loans under the DeFi concept do not require physical collateral; instead, all assets are digital. As an illustration, one could use Bitcoin or Ethereum as collateral to borrow a specific stablecoin (the digital version of the dollar or euro, for example) and then use that stablecoin to buy more Bitcoin or Ethereum, thus taking a long position on those assets (Corbet et al., 2021). Users can also earn interest by lending cryptocurrency to other users without intervention from a centralized entity (Chen & Bellavitis, 2020; Schaer, 2021).

Over the past decade, decentralized finance has impacted all facets of financial systems and increased financial inclusion (Allen et al., 2022). The combined market capitalization of DeFi is growing exponentially and is approximately $170 billion in April 2022 CoinMarketCap, (n.d.) and the number of users has grown from approximately 150,000 in April 2020 to over 4,500,000 in April 2022 (*Total DeFi Users over Time*, n.d.).

Defi Llama *DefiLlama*, (n.d.) which is the largest Total Value Locked (TVL) aggregator for DeFi (Decentralized Finance) tracks over 800 DeFi protocols from over 80 different blockchains. DeFi Llama categorizes DeFi protocols into 26 categories and the two largest categories are decentralized exchanges or DEXs for short "protocols where you can exchange/trade cryptocurrency" and DeFi Lending "protocols that allow users to borrow and lend assets." Decentralized exchanges are in fact smart-contract-based limit order books operated without central authority, where the exchange of ownership occurs directly between counterparties' wallets and is recorded on a publicly accessible blockchain (Alexander et al., 2020). Wrapped tokens, as well as innovative cross-chain solutions, have enabled DEXs to overcome the limitation that they can only trade assets that are native to the chain on which they operate. Today, DEXs come in a variety of forms, including order book DEXs, batch settlement, and automated market makers, depending on the method of price discovery (Werner et al., 2021).

The emergence of protocols that facilitate programmatic lending and saving is a recent development within financial architecture based on decentralized ledgers or DeFi. These protocols represent a major advancement for DeFi due to the importance of borrowing and saving today (Gudgeon et al., 2020). However, because most DeFi protocols do not require customers to know their customers (Know Your Customer or KYC), borrowers are often required to fully collateralize or even overcollateralize their loans and run the risk of being liquidated. This is how the largest lending platforms such as Compound and AAVE do business (Qin, Zhou, Gamito, et al., 2021; Z. Wang et al., 2022). Token lending and borrowing are becoming the largest applications in decentralized finance, accounting for over 40% of the total value transacted in DeFi (Wang et al., 2022).

On-chain asset lending and borrowing is enabled by DeFi lending protocols, which create distributed ledger-based marketplaces for lending and borrowing crypto assets by aggregating deposited money into a smart contract (Werner et al., 2021). A market in the context of these protocols refers to the total amounts of a token provided and lent, and the liquidity of a market is composed of available deposits. If the market for the token is sufficiently liquid, an agent can borrow directly against the smart contract's reserves, with the cost of the loan determined by the market rate. Loans on these protocols often come in two varieties: over collateralized loans and flash loans (Werner et al., 2021). In an over collateralized loan, the borrower is required to post collateral or offer something of value as collateral to cover the amount of the debt if the value of the posted collateral exceeds the value of the debt. In this way, the collateral simultaneously gives the borrower an incentive to repay the loan and ensures that the lender (likely a smart contract) can recover the value borrowed. So-called liquidators can purchase the locked collateral at a discount and liquidate the borrower's debt position if the value of the locked collateral falls below a certain liquidation level. Flash loans are an alternative to loans with excessive collateral. These are short-term, unsecured loans that require the borrower to repay the full amount borrowed plus interest before the transaction expires. With several use cases, including decentralized exchange arbitrage and collateral swaps, flash loans leverage the atomicity of a blockchain ("i.e., the transaction fails if the loan is not returned in the same transaction") (Werner et al., 2021).

(Chohan, 2021), claims that flash loans and liquidity pools will most likely not be tolerated long by financial regulatory bodies. In 2021 there was a huge increase in loans, trades and other transactions in the DeFi space and total value locked or TVL was more than $150 million in May 2021 (Meister & Price, 2022). In their paper CeFi vs. DeFi (Qin et al., 2021) talk about three features that DeFi has and CeFi or traditional finance not. First, they mention transparency, secondly, they mention user control over their assets and last, they talk about accessibility. Law makers, regulators and legal scholar are critical of DeFi and point out that DeFi projects have the possibility to undermine traditional finance (Barbereau et al., 2022). Although most DeFi lending protocols pool assets there are alternatives like for example Smartcredit.io Peer-to-peer loans are being tokenized into Credit-Coins by SmartCredit.io (ccETH, ccDAI, etc.). Due to the loans' transferability, investors can create Personal Fixed Income Funds. Investors specify their investment criteria, and Personal Investment Funds then automatically invest in the loan requests of the borrowers. The loan is tokenized into loan tokens, and each investor (Personal Fixed Income Fund) is getting the loan tokens, allowing several investors to fulfill loan requests from one borrower at once. Loan tokens are a marketable asset for Personal Fixed Income Funds. Instead of constructing one pool (like Compound and AAVE do), SmartCredit.io creates many pools, one for each lender. This is an alternate, regulatory-secured strategy. These pools are always within the legal limit even if they can invest in the same loans. The whole legal and regulatory risk associated with asset and liquidity pooling is completely absent with SmartCredit.io (*DeFi Liquidity Pooling Regulatory Risks - SmartCredit.Io*, 2022).

A number of authors, including Urquhart and Zhang (2019), Bouri et al. (2017), and Dyhrberg (2016), claim that the Bitcoin might genuinely be used for hedging against various asset classes, including stock and currencies. Additionally, Guesmi et al. (2019) present evidence that using a sell order in the price of Bitcoin to effectively hedge risk initially expected in other capital markets and incorporating Bitcoin into portfolio diversification techniques considerably lowers total investment risk. Nevertheless, speculation in cryptocurrency markets can lead to periods of significant volatile market conditions (as shown, for instance, in recent fluctuations in the Bitcoin market), which may reduce the effectiveness of the appropriate portfolio diversification techniques (Cheah & Fry, 2015; Katsiampa, 2017). The primary focus of this study is to investigate the connectedness and spillover between Bitcoin, Ethereum and six DeFi tokens.

Although the cryptocurrency industry is much discussed in the financial literature, there is little DeFi research on cryptocurrencies. This is true regardless of the value of DeFi. DeFi could change the way money is organized and executed. As far as I know, there is no research on the correlations and return behavior of instruments focusing on different DeFi categories. This study seeks to examine financial transmission, return, and spillover effects in the area of decentralized finance.

2. More on Bitcoin, Ethereum and DeFi

Nakamoto (2008) is credited with inventing Bitcoin, which he introduced to the public in his white paper. Both blockchain technology and digital money were not invented by Nakamoto (2008); rather, many of the basic technological aspects of Bitcoin were already well established in the computer science literature (Narayanan & Clark, 2017). Indeed, the fact that Bitcoin is a solution to an economic problem and not just a technological advance is its most important contribution. The problem of double spending is the problem that Bitcoin addresses in the economy. Any payment system can have the problem of double spending. Double spending is when a user uses the same amount of money twice, as the term implies. This is concerning because a single expenditure should transfer ownership of the money, which precludes further spending by the original owner of the currency. In a centralized system, this problem is easily solved because all spending except the first is rejected. The double spending problem has been solved by Bitcoin without the use of a centralized entity, making it significant in a situation where the same problem would otherwise be trivial. This was achieved by introducing a brand-new method for reaching consensus in a decentralized environment (John et al., 2021). While there are debates about the identity of Nakamoto, one thing is certain: he has offered the world something innovative, and it is up to users to decide what to do with it. Some will use this opportunity to develop applications to solve social problems, while others will invest in it or trade the ups and downs of cryptocurrency prices (Vujičić et al., 2018).

Vitalik Buterin's paper Buterin & others, (n.d.) introduced Ethereum to overcome Bitcoin's scripting limitations. Ethereum supports all forms of computation, including loops, and is Turing-complete. Ethereum supports transaction state and other blockchain features. Ethereum has a Turing-complete programming language built in. It provides an abstract layer for creating ownership, transaction, and state transition rules. It uses smart contracts, a set of cryptographic principles (Buterin & others, n.d.). Ethereum consensus uses a modified GHOST protocol (Sompolinsky & Zohar, 2015). It deals with stale network blocks. Stale blocks can occur when one group of miners in a mining pool has more computational power than the rest, leading to centralization. GHOST considers stale blocks in the longest chain estimates. The centralization problem is solved by giving stale blocks a reward: 87.5% for the stale block and 12.5% for its nephew. Miners are compensated even if their block does not make it to the main blockchain - these blocks are called uncles. Ethereum uses a modified GHOST system with seven generations of uncles (Buterin & others, n.d.). In Ethereum, fees are essential. A price is charged for each Ethereum transaction. This price is paid in "gas." Gas measures the computation fees. "gwei" measures how much Ether you are willing to spend per unit of gas. 1018 gwei is equal to 1 ether. One gwei is equal to 1,000,000 Wei. The sender sets the gas limit and price for each transaction. Gas price plus gas limit equals the most wei a sender is willing to spend on a transaction (Kasireddy, 2017).

Both Bitcoin and Ethereum currently use proof-of-work; the Ethereum network is moving to a proof-of-stake consensus mechanism with the Ethereum 2.0 upgrade expected in the coming months (Arslanian, 2022).

In proof-of-work, or PoW, each node must solve a cryptographic puzzle to create the next block. The first to solve this challenge becomes the leader responsible for sealing and delivering the block. Therefore, the faster you solve the problem, the more chances you have to create the next block. These people are called miners and they perform the mining process (Ouyang et al., 2021). The function of miners is twofold. First, new coins are created when the computers solve the problem, and second, miners ensure the reliability and security of payments in the network by validating the transaction details. As a result of his work to create the block, the leader is rewarded (Ouyang et al., 2021). The network uses this incentive to maintain the loyalty of the nodes. Most of the power of CPU is in the hands of honest nodes if they are motivated to solve the challenge. This maintains the security of the system. Therefore, increasing the number of prospectors reduces the probability that malicious nodes control 51% of CPU power, making network fraud virtually impossible (Ouyang et al., 2021).

The main limitations of proof-of-work are centralization and energy consumption. The incentive that the blockchain provides to keep nodes in line is a payoff each time a node creates the next block. From that point, miners begin to improve their chances of getting a payout by developing what are known as mining pools. The concept is that multiple miners pool their computing resources and share the profit from the block they mine together. Everything that is claimed about the decentralization of the blockchain would be false if one of these mining pools were to usurp most of the total CPU power (Ouyang et al., 2021). Therefore, it is advisable to avoid this type of centralization. The mining process also consumes a significant amount of energy. Krause & Tolaymat, (2018) claim that the entire process is CPU -intensive and consumes a lot of energy, like how gold miners use resources. The nodes trying to crack the code are now referred to as miners. For example, it is estimated that the annual energy consumption of the Bitcoin network is comparable to that of Ireland or Hong Kong. According to the study by Krause & Tolaymat, (2018), it costs three times as much to mine a Bitcoin as it does to mine an ounce of gold. In addition, the high energy consumption has a negative impact on the environment and could change the way people view this technology in the future.

Because of these limitations in PoW, blockchain developers have developed a new consensus method called Proof-of-Stake (PoS) (Ouyang et al., 2021). The term "stake" emphasizes how many tokens a user stakes to participate in the validation process. Peercoin King & Nadal, (2012), who first introduced this idea in 2012, later inspired numerous other blockchains to build their systems on it. The technique is quite simple: each node participates in the consensus process (by creating or validating the next block) according to its deployment. The more you deploy, the more control you have over the validity of the next block. The process is more effective and consumes less energy because nodes do not have to compete with each other to solve a mathematical challenge (Ouyang et al., 2021). The reward for passing the block goes to the leader to keep the nodes in line. According to (Buterin & Griffith, 2017), there are two forms of PoS design:

• Proof-of-Stake based on chains. A leader is periodically chosen in a semi-random manner, and they provide the next block to be added to the chain. As a result, a global clock is needed to record the time.

• Byzantine fault tolerance (BFT) protocol consensus inside the consortium. A voting process is used to determine the consensus when a node is elected in a semi-random manner. Every node participates in the voting process in proportion to the stake it wagers. In contrast to chain based PoS, asynchronous networks need Byzantine fault tolerance.

There are two different types of nodes. A node has two choices: It can simply have an account and spend money, or it can participate in the consensus, cast votes, and eventually propose a block. Note that additional blocks are proposed only by the leader. In a two-stage process, a node takes the leadership position. (1) In the first stage, the amount of money a user contributes to the system is considered. (2) This method gains a little unpredictability in the second stage (Buterin & Griffith, 2017).

A random selection method is used to prevent wealthy nodes from getting richer by giving them the advantage of sending erroneous transactions. However, each blockchain implements its own approach or a combination of them, which only exacerbates the problems. Some blockchains combine the lowest hash value and the largest stake, while others select coins based on their age, rewarding long-term investors with higher returns. Unfortunately, this last approach also has a drawback. Due to money stagnation issues, nodes are motivated to store tokens for a long period of time rather than use them (Deuber et al., 2018). This contradicts the concept of a smart blockchain builder (Ouyang et al., 2021). Yermack (2018) argues that while Bitcoin is widely used as a substitute for fiat currencies, it is also vulnerable to speculation, and that blockchain technology could impact corporate governance and central banking. Central banks around the world are already exploring the possibility of issuing central bank digital currencies (CBDCs). According to a survey conducted by the Bank for International Settlements (BIS) in Switzerland, 68 central banks have investigated CBSCs. These banks cover about 80% of the world's population (Allen et al., 2022). In addition, scholars such as Fern'andez-Villaverde and Sanches (2016), Bordo and Levin (2017), Schilling and Uhlig (2018), and others have examined monetary policy issues and consequences considering the emergence of cryptocurrency markets.

It would be helpful to point out that Ethereum should not be considered a direct competitor to Bitcoin due to significant differences. It should be emphasized that Ethereum is more focused on smart contracts and transaction automations Antonakakis et al, (2019) and does not necessarily require a central server, although a thorough examination of the exact differences between these cryptocurrencies is beyond the scope of this study. There are also a lot of technical similarities and differences between the various currencies. For example, unlike Bitcoin, Ethereum has an unlimited supply of tokens, as reported by Ciaian et al. (2018).

According to Werner et al., (2021) DeFi demonstrates four characteristics in its perfect state.

1. Non-custodial: Participants are always in complete control of their money.

2. Permissionless: Everyone can use financial services without a third-party censoring or blocking them.

3. Openly auditable: Everyone can evaluate the system's condition, for example, to make sure it's in good shape.

4. Composable: New financial goods and services can be formed by arbitrary composition of its financial services

Like Bitcoin, DeFi protocols require a decentralized peer-to-peer array data log of transactions, a blockchain (Corbet et al., 2021). The difference between Bitcoin and DeFi protocols is that DeFi uses smart contracts, which are computer programs that exist on the blockchain, these smart contracts can be used with the underlying ledger. They can interact with each other via message invocations while operating in the same execution context. They also support atomicity, which ensures that no execution can result in an invalid state because a transaction either completely succeeds (updating the state) or completely fails (the state remains unchanged). These properties enable compositional capability, which allows the construction of complicated financial architectures by connecting smart contracts (Werner et al., 2021). Another important factor in DeFi is the process of integrating off-chain data into the blockchain so that smart contracts can read it. These processes are called price oracles. They contain information needed for validating the results of prediction markets as well as for pricing assets off the blockchain, such as ETH /USD. Most DeFi protocols rely on Oracles (Werner et al., 2021).

3. Literature review

3.1 Spillover, connectedness and TVP-VAR method

The volatility of financial markets, which rises in times of crisis and spreads across markets. Clearly, it would be desirable to be able to quantify and track such spillover effects, both to provide early warning structures for emerging crises and to track the evolution of existing crises (Diebold & Yilmaz, 2012a). Most of the time, financial crises are unpredictable. Yet there are certain parallels in the way such crises transmit shocks (Reinhart & Rogoff, 2008). There are two categories of traditional ideas that focus on the context or spillover effects of volatility and the associated information transmission mechanisms. The first category speaks of the visible transmission mechanism and asserts that asset values change in lockstep with macroeconomic factors and the global distribution of capital (Adler & Dumas, 1983; McQueen & Roley, 1993). The other category is invisible transmission mechanisms, which include investor behavior, psychological expectations, and market inefficiencies. Proponents of this mechanism believe that investors seek investment or hedging opportunities in a particular market by evaluating the performance of other markets, thus generating transmission through a linked information channel (Forbes & Rigobon, 2002). Some studies use various methods such as conditional correlation (Dua & Tuteja, 2016), Granger causality (Billio et al., 2012; Zhang & Broadstock, 2020), copulas (Q. Ji et al., 2018; Philippas & Siriopoulos, 2013), or conditional value-at-risk to examine transmission across assets (L. Ji et al., 2018).

Diebold and Yilmaz (2009) propose a volatility spillover measure based on variance decompositions of forecast errors from vector autoregressions (VARs) motivated by these concerns. It can be used to calculate return spillovers or return volatility (or any other return characteristic of interest) across individual assets. Much attention has already been paid to this VAR -based interdependence technique in the economics literature, with studies on topics such as interdependencies between bond returns and equity markets, business cycle spillovers, and volatility spillovers (Antonakakis et al., 2020). In addition, other initiatives have been taken to extend and improve the above linkage measures, including the asymmetric extension by Baruník et al. (2016). Further progress is needed to address some of the shortcomings of the connectivity measures (Antonakakis et al., 2020). They used a vector autoregression with time-varying parameters (TVP-VAR) instead of the generally recommended rolling-window VAR, to extend and improve existing studies of connectivity. This significantly improves the technique offered by Diebold and Ylmaz (2012) because (1) the size of the rolling window does not need to be randomized, (2) there is no loss of data, and (3) it is not prone to outliers.

3.2 Connectedness and spillover in finance literature

There are several studies that deal specifically with connections and spillovers. Publications such as Liow and Newell (Liow & Newell, 2012) use the paradigm developed by Diebold and Ylmaz (Diebold & Yilmaz, 2009, 2012a; Diebold & Yılmaz, 2014b). They use an asymmetric BEKK-GARCH model to construct a volatility spillover index Diebold & Yilmaz, (2009) which they use to analyze volatility interdependence between China, Hong Kong and Taiwan and the United States in both crisis and non-crisis periods. The Asian Financial Crisis and the Global Financial Crisis are the two crisis events that make up the entire study period, which spans from January 1995 to December 2009. In this case, the volatility spillover index combines the effects of the individual spillovers of the four countries, each assessed by the variance component of the forecast error for each country, resulting from shocks to other countries in the system. They find that volatility spillovers peaked during the 2009 global financial crisis and that, as predicted, the United States alone was the source of virtually all volatility shocks communicated during that period (Lesame et al., 2021). The second highest spillover effects were in Hong Kong, which has a fairly mature REIT industry. (The coefficients of the BEKK-GARCH model for return spillovers reflect these effects, and the results show that there are bidirectional return spillover effects between the U.S. and Hong Kong. China experiences less spillover effects from the U.S.). According to (Lesame et al., 2021), Liow & Newell, (2012) were the first to capture the transmission of volatility shocks to global REITs using the volatility spillover index (Diebold & Yilmaz, 2009). Nguyen et al. (2021) examined the time co-movement of green bonds and stocks and concluded that there are negative correlations between the two. According to Wang et al. (2020), green bonds have a favorable impact on stock returns. Gao et al. (2021) use a multidimensional DCC-GJRGARCH model to investigate the impact of green bonds on the stock market. They find that there are unidirectional risk spillovers from industrial stock markets to green bond markets. However, Reboredo (2018) shows that green bonds move slowly with equity markets. According to Reboredo and Ugolini (2020), green bonds have a weak relationship with equity markets. Wang and Chueh (2013) focus on the links between gold, oil, interest rates, and the currency market. Many of the market pairs studied show evidence of a price transmission link, and there is also evidence of a feedback effect in the relationship between interest rates and major commodities such as gold and crude oil. Kang et al. (2017), while focusing on price transmission, also consider agricultural commodities, crude oil, and precious metals. They provide evidence of larger return spillovers during the GFC, which can affect a portfolio and hedging. The high volatility of the MSCI World Stock Price Index contributes to the fluctuation of the WilderHill Clean Energy Price Index, according to Elsayed et al. (2020) in their analysis of volatility spillovers between the stock price index and the clean energy price index using Diebold and Yilmaz time-domain connectedness measures. Razmi et al. (2020) establish the positive relationship between stock prices and the renewable energy market using an autoregressive distributive lag (ARDL) model. The relationship between the global stock market and the renewable energy sector is examined by Urom et al. in (2021). They conclude that increasing global stock market turbulence may cause the value of clean energy stocks in the United States, Europe, and Asia to decline.

Recent literature has unquestionably focused on the current crisis created by the COVID-19 epidemic (Umar et al., 2021). Ali et al. (2020) examines the reactions, in terms of uncertainty, of capital markets as COVID-19 spread from China to Europe and the United States. They find that global markets went into a freefall in March 2020, and even safer commodities were affected by the pandemic's arrival in the United States. Corbet et al. (2020) examine the possible impacts of the COVID-19 pandemic on gold and cryptocurrencies, speculating that cryptocurrencies may play a comparable function to precious metals during economic crises. Gharib et al. (2021) investigate how the economic impact of COVID-19 has affected the relationship across oil and gold spot prices and discover a bilateral contagion effect on oil and gold markets during the pandemic crisis. Bakas and Triantafyllou (2020) examine the impact of the COVID-19 pandemic crisis on the volatility of commodities prices. Rizwan et al. (2020) investigates the impact of COVID-19 on the financial sector of the eight nations' most severely hit by SARS-CoV-2. Sharif et al. (2020) examines the relationship between the spread of COVID-19, the stock market, oil price volatility shocks, geopolitical risk, and economic policy uncertainty in the United States and conclude that COVID-19 has a significant impact on geopolitical risk.

3.3 Connectedness and spillover in cryptocurrency market

The underlying technology and market environment of cryptocurrencies are different from those of traditional financial assets (such as currencies, futures, stocks, and bonds); therefore, such practices could be different in the evolving cryptocurrency market. Therefore, it is critical for market participants to examine how volatility shocks are transmitted from one cryptocurrency to another. Cryptocurrencies are specifically used by certain investors as a hedge against equities or speculative investments (Yi et al., 2018). Information about volatility spillovers among cryptocurrencies would help them select an appropriate coin to change their investment portfolio according to their risk preferences when facing macroeconomic uncertainty. If the price of cryptocurrencies decreases, fewer miners will be willing to participate in the mining process due to high hardware costs and energy consumption. If miners, especially small miners, are aware of the volatility correlations or spillovers between different cryptocurrencies, they can select and mine a portion of the less correlated cryptocurrencies to reduce the risks associated with the markets (Yi et al., 2018). In recent years, studies on volatility spillovers in cryptocurrency markets have increased. Understanding potential spillover effects between cryptocurrencies can help inform investment and hedging decisions. For example, investors can optimize their diversification or hedging options by using the evidence of insufficient linkages between cryptocurrencies (Ji et al., 2019). To improve and expand our knowledge of the dynamics by which these relatively young products operate, further studies on the price volatility behavior of cryptocurrencies and the links between price volatility and liquidity changes are important (Katsiampa et al., 2019b). Corbet et al.'s (2018) research on the links between cryptocurrencies and other assets suggests the benefits of diversification. Similarly, Kurka (2019) examines the transmission of shocks to determine whether or not cryptocurrencies and traditional assets affect each other. Trabelsi (2018) asks a similar question from the perspective of volatility spillover effects. Balcilar et al. (2017) use trading volume data to forecast bitcoin returns and volatility. They argue that while transaction volume can sometimes help investors predict returns, it does not provide information about volatility. Katsiampa (2017) applies many GARCH models to bitcoin volatility and learns the value of combining the long-run and short-run components of the conditional variance. Bitcoin can be used as a hedge against commodity indices and uncertainty indicators, claim Bouri et al. (2017). Bouri et al.'s (2018) research, using a VARGARCH-in-mean smooth transition model, suggests that the timing and market environment in which the asset classes studied were used have an impact on the spillovers between Bitcoin and these classes. Bitcoin is more closely related to other assets via returns than via volatility.

Koutmos (2018) measures return and volatility spillovers for 18 major conventional cryptocurrencies and concluded that Bitcoin is the main source of return and volatility spillovers. They note that the magnitude of spillover effects also increases as cryptocurrency-related news events and cryptocurrency interactions increase during the 2017 bull market. According to Symitsi & Chalvatzis (2018), Bitcoin has long-term volatility spillovers from fossil fuel and renewable energy stocks, as well as return spillovers from energy and technology stock indices to Bitcoin, and short-term volatility spillovers from technology companies to Bitcoin. According to Yi et al. (2018), eight out of 52 cryptocurrencies have overall linkages that change over time, with the degree of inbound or outbound linkages partially correlated with market capitalization. They find that Bitcoin is not necessarily dominant despite its significant importance as a net sender of linkages. Katsiampa (2019) focuses on the interactions between Bitcoin, Ethereum, and Litecoin and discovers mainly favorable time-varying conditional correlations. Bouri et al. (2018) focus on the impact of spillovers between Bitcoin and other assets during bull and bear markets. By studying conditional cross effects and volatility spillovers, Guesmi (2019) examines the legitimacy of Bitcoin in financial markets and concludes that hedging strategies with gold, oil, equities, and Bitcoin significantly reduce risk compared to a portfolio without Bitcoin. Hudson and Urquhart (2021), building on the work of

Bistarelli et al. (2019) and work based on technical trading rules, note the presence of a Bitcoin market bubble over several different time periods in recent work that extends the market-specific features of cryptocurrency research. Other market dynamics in bitcoin pricing have also been studied, including herd and feedback training, price forecasting, and price discovery effects using correlation networks (Giudici & Polinesi, 2021).

Jareño et al. (2020) examines the potential interdependence between Bitcoin price returns and gold price returns and discover a positive and statistically important connection. González et al. (2021) analyze the dependence between Bitcoin and the returns of ten different altcoins and discover positive interdependences. Demir et al. (2021) identify disparity in the long- and short-term effects of Bitcoin on altcoins. Song et al. (2019) investigates the market structure for cryptocurrencies and highlight the dominance of Bitcoin and Ethereum. Shi et al. (2020) identify correlations amongst six cryptocurrencies and assert that knowledge of them is crucial for implementing trading strategies. Canh et al. (2019) examine the potential of key cryptocurrencies to diversify against changes in oil and gold prices, interest rates, the US dollar's strength, and stock market volatility. Selmi et al. (2018) find evidence that cryptocurrencies are a haven during times of crisis.

Much has been written about the categorization or performance of cryptocurrencies. However, most research focuses exclusively on Bitcoin and pays little attention to the linkages or spillover effects between different cryptocurrencies, especially in terms of volatility (Yi et al., 2018a). With few exceptions, such as Antonakakis et al. (2019) and other work on NFTs (Aharon & Demir, 2021).

3.4 Connectedness and spillover in the DeFi market

DeFi ideas are new and have not been thoroughly tested. DeFi is fraught with risk. For example, flash loans, a DeFi-specific business, have been the target of many cyberattacks, as explained in (Gudgeon et al., 2020; Qin, Zhou, Gamito, et al., 2021). In the emerging literature on DeFi, Gudgeon et al. (2020) evaluates the methods used to determine interest rates on some of the major DeFi platforms for lending and borrowing. The potential of DeFi to destabilize established economic markets is highlighted by (Zetzsche et al., 2020). In contrast, typical cryptocurrency bubbles have received more attention. For example, Kyriazsis et al. (2020) claim that there has been a bubble phase for Bitcoin and several other major cryptocurrencies since the summer of 2015. In their study (2017), Phillips & Gorse examined how cryptocurrency price bubbles can be predicted using social media data and pandemic modeling. Fry & Cheah, (2016) analyze the speculative and volatile nature of Bitcoin and cryptocurrency markets and show examples of spillovers from Ripple to Bitcoin by using econophysics models to observe spikes and collapses in the crypto market. Fry (2018) focuses on building rational bubble models for cryptocurrencies and finds that empirical research on Bitcoin and Ethereum does not always lead to bubble patterns in cryptos. The results of (Yousaf et al., 2022) show that return spillovers in the context of DeFi assets and traditional currencies lead to time-varying transmission/reception patterns for the markets under consideration, with the most significant variation occurring between the pre-pandemic and pandemic subsamples. The results of a study on DeFi by (Corbet et al., 2021) show that DeFi is largely a separate asset class from other cryptocurrencies.

While some researchers have looked specifically at the DeFi market and others have looked at bubbles and spillover effects in cryptocurrencies, there has generally been a lack of studies on spillover effects from and to the DeFi market, specifically from and to traditional cryptocurrencies and the DeFi market. This research aims to fill this gap.

4. Data and methodology

4.1 Data

Eight tokens traded on Binance between October 3, 2020, and June 21, 2022, are used in the study. These cryptocurrencies include the three largest decentralized exchange tokens categorized by DeFi Llama by Total Value Locked (TVL): Curve (CRV), Uniswap (UNI), and Pancake Swap (CAKE). The three largest decentralized credit protocols categorized by DeFi Llama by Total Value Locked (TVL): AAVE (AAVE), Just Lend (JST), and Compound (COMP). And then Bitcoin (BTC) and Ethereum (ETH). Price information is from coinmarketcap.com, which includes the closing price for each cryptocurrency. AAVE was chosen as the start date for the sample because trading began on October 3, 2020. I chose the end date for the sample because the most recent ranking date I could obtain was June 21, 2022. These eight coins were chosen for two reasons. First, cryptocurrencies are constantly appearing and disappearing, and my eight selected currencies have all been publicly traded for almost two years in a row or more. Second, while Bitcoin and Ethereum are considered decentralized (Gencer et al., 2018; Lin et al., 2021). This means that they are neither produced nor controlled by governments, banks, or other financial organizations. Instead, they depend on machines running replicas of their networks, called nodes, to ensure that every network user is on the same page (Zwitter & Hazenberg, 2020). They are not categorized under DeFi tokens on DeFi Llama and Coinmarketcap.com like the other six tokens in this study. So, the sample of eight cryptocurrencies includes four types of cryptocurrencies. Bitcoin and Ethereum, the top two cryptocurrencies in terms of both popularity and market capitalization (*Coinmarketcap*, n.d.). The three biggest decentralized exchanges and three biggest decentralized lending protocols by TVL (*DefiLlama*, n.d.). This could give researchers insight into connectedness of the DeFi market.

4.2 Methodology

The TVP-VAR framework proposed by Antonakakis & Gabauer, (2017) is used in this thesis, which extends the connectedness work of (Diebold & Yilmaz, 2012) approach to examine the time-varying return transmission mechanism between the selected DeFi tokens, Bitcoin and Ethereum. The TVP-VAR method avoids the drawbacks of using an arbitrary rolling-window size, which can result in unpredictable or flattened parameters, as well as the loss of valuable data (Antonakakis et al., 2018; Antonakakis & Gabauer, 2017; Diebold & Yılmaz, 2014; Gabauer & Gupta, 2018). In accordance with BIC lag criteria2, I use a TVP-VAR (1), which may be written as.

$$\mathrm{Y_t} = \beta_{\mathrm{t}} Z_{t-1} + \varepsilon_{\mathrm{t}}, \varepsilon_{\mathrm{t}} | \Omega_{t-1} \sim \mathrm{N}(0, \Sigma_{\mathrm{t}}), \tag{1}$$

$$\beta_{\mathrm{t}} = \beta_{t-1} + \vartheta_{\mathrm{t}}, \vartheta_{\mathrm{t}} | \Omega_{t-1} \sim \mathrm{N}(0, \mathrm{R_t}). \tag{2}$$

Based on the Wold representation theorem, the model provided in Eq. (1) may be translated to its moving average (VMA) representation as follows:

$$\mathrm{Y_t} = \sum_{j=0}^{\infty} \Theta_{jt} \varepsilon_{t-j}, \tag{3}$$

where Θ_{jt} is an N × N dimensional matrix.

The time-varying parameters is employed and variance-covariance matrices of the TVP-VAR model in Diebold and Yilmaz's measure of connectedness to derive dynamic connectedness measures between the various variables. As a consequence, the dynamic H-step generalized variance decomposition matrix's components $D_t^{gH} = [d_{ij,t}^{gH}]$ can be defined as:

$$d_{ij,t}^{gH} = \frac{\sigma_{jj,t}^{-1} \sum_{h=0}^{H-1} (e_i' \Theta_{h,t} \Sigma_t e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Theta_{h,t} \Sigma_t \Theta_{h,t}' e_j)},$$

Where $\sigma_{jj,t}^{-1}$ is the j[th] diagonal element of Σ_t. The normalized terms $\tilde{d}_{ij,t}^{gH} = \frac{d_{ij,t}^{gH}}{\sum_{j=1}^{N} d_{ij,t}^{gH}}$ are used to determine the dynamic total directional connectedness, net total directional connectedness, and total connectedness as follows. The total connectedness index (TCI) measures the interconnectedness of the various variables and is computed as:

$$C_t^{gH} = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{d}_{ij,t}^{gH}}{\sum_{j=1}^{N} \tilde{d}_{ij,t}^{gH}} \times 100. \tag{4}$$

The directional spillover received by variable i from all other variables j, is measured as:

$$C_{i\leftarrow j}^{gH} = \frac{\sum_{j=1,i\neq j}^{N} \tilde{d}_{ij,t}^{gH}}{\sum_{i=1}^{N} \tilde{d}_{ij,t}^{gH}} \times 100. \tag{5}$$

The spillovers received by variable j from all other variables i are computed in the same way:

$$C_{i\rightarrow j}^{gH} = \frac{\sum_{j=1,i\neq j}^{N} \tilde{d}_{ij,t}^{gH}}{\sum_{j=1}^{N} \tilde{d}_{ij,t}^{gH}} \times 100. \tag{6}$$

Then total directional connectedness to others is subtracted from total directional connectedness from others to get the net pairwise directional connectedness. This may be thought of as the influencing variable i has on the network under investigation. That is,

$$C_{ij,t}^{gH} = C_{j\leftarrow i,t}^{gH} - C_{i\leftarrow j,t}^{gH}. \tag{7}$$

Finally, net pairwise directional connectedness is defined as:

$\mathrm{NPDC}_{ij}^{gH} = (\tilde{d}_{ji,t}^{gH} - \tilde{d}_{ij,t}^{gH}) \times 100$. Variable i dominates variable j if the value is larger than zero; otherwise, the latter dominates the former.

The empirical analyses are based on daily returns, calculated as the difference in the log of prices.

5. Empirical Results and Discussion

In this section, the focus is exclusively on the key findings to achieve the precise objectives of the study. These include determining the degree of interconnectedness among cryptocurrencies and identifying the senders and receivers of shocks over time. To implement Gabauer's (2020) approach, we use the Connectednessapproach package in RStudio (Gabauer, 2022).

Particular attention is paid to the pairwise interconnectedness between cryptocurrencies, the total net interconnectedness for each cryptocurrency, and the change in TCI over time. In Figure 1, we see the historical evolution of the eight cryptocurrencies over the indicated time period.

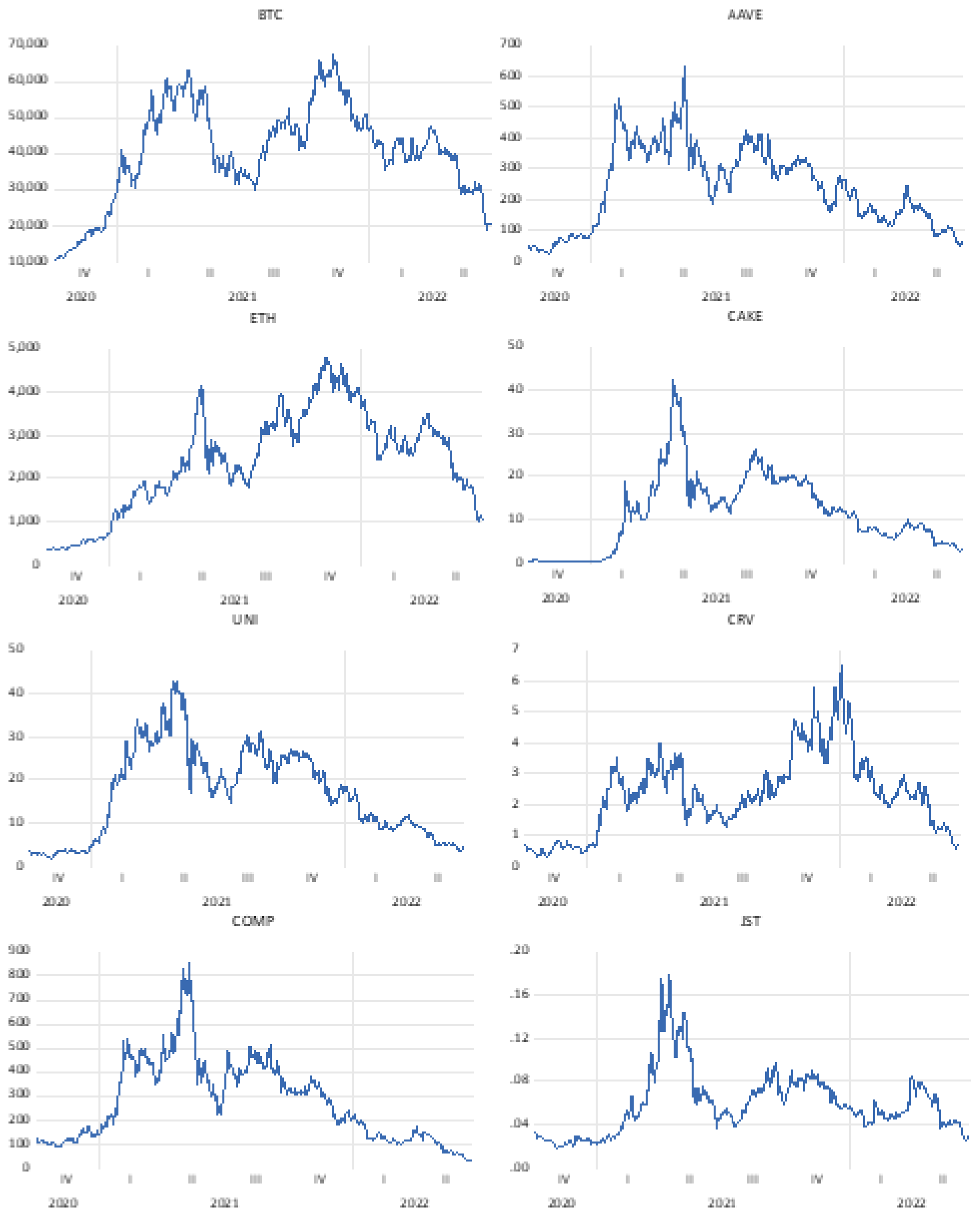


Figure 1. Historical trend of cryptocurrency prices

Figure 1 demonstrates that the eight cryptocurrencies' price patterns all roughly follow the same course, with significant price increases occurring largely in the beginning of 2021 and again late 2021. Notably, the price of Bitcoin, Ethereum and CRV peaked in late 2021, but the price of AAVE, CAKE, UNI, CRV, and COMP peaked in early 2021.

Table 1. Summary statistics for returns of cryptocurrencies

	BTC	ETH	UNI	AAVE	CAKE	CRV	COMP	JST
Mean	0.001	0.002	0.000	0.000	0.002	0.000	-0.002	0.000
	(0.521)	(0.390)	(0.879)	(0.933)	(0.481)	(0.969)	(0.523)	(0.923)
Var	0.002***	0.003***	0.005***	0.006***	0.007***	0.008***	0.005***	0.005***
Skew	-0.205**	-0.450***	0.308***	-0.118	0.052	-0.022	-0.236**	-0.080
	(0.036)	(0.000)	(0.002)	(0.225)	(0.591)	(0.821)	(0.016)	(0.409)
Ex. Kurt	2.059***	3.802***	4.249***	2.382***	5.270***	4.114***	1.486***	5.325***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	115.185***	398.876***	481.647***	149.733***	725.714***	442.109***	63.548***	741.535***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-8.890***	-11.062***	-7.982***	-11.143***	-2.140**	-4.449***	-10.199***	-10.013***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.033)	(0.000)	(0.000)	(0.000)
Q (20)	10.437	16.678*	24.705***	17.311*	29.101***	8.036	9.670	17.010*
	(0.459)	(0.066)	(0.002)	(0.052)	(0.000)	(0.721)	(0.541)	(0.058)
Q^2(20)	14.380	65.044***	58.298***	71.549***	177.081***	25.378***	65.100***	23.378***
	(0.150)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.004)
			Unconditional Correlation					
	BTC	**ETH**	**UNI**	**AAVE**	**CAKE**	**CRV**	**COMP**	**JST**
BTC	1.000***							
ETH	0.030	1.000***						
UNI	0.589***	0.042	1.000***					
AAVE	0.577***	0.069	0.757***	1.000***				
CAKE	0.541***	-0.028	0.529***	0.547***	1.000***			
CRV	0.544***	0.034	0.641***	0.662***	0.495***	1.000***		
COMP	0.631***	0.032	0.709***	0.754***	0.577***	0.641***	1.000***	
JST	0.628***	0.058	0.559***	0.549***	0.519***	0.563***	0.593***	1.000***

Notes: ***, **, * denote significance at 1%, 5% and 10% significance level; Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Stock et al. (1996) unit-root test; LB (20) and LiMak (20): Fisher and Gallagher (2012) weighted portmanteau test.

Table 1 contains the summary data for the returns of all eight cryptocurrencies. The results show that Curve Finance, AAVE, and Just Lend each have the highest mean returns. In terms of variance, Curve has the highest variance, followed by Pancake Swap and AAVE. It is interesting to see that Bitcoin and Ethereum have the lowest standard deviation and mean. This finding is hardly unexpected considering that despite Bitcoin's price increase of around 640 percent in 2021 and Ethereum's price increase of 1400 percent in 2021, each of the other six cryptocurrencies considered, with the exception of Just Lend, experienced a price increase of at least around 2000 percent. All cryptocurrencies, but especially Pancake Swap and Just Lend, have excessively high kurtosis values. This is interesting because Pancake Swap runs on the

Binance Smart Chain and Just Lend runs on the Tron blockchain, while all the others run on Ethereum, except Bitcoin of course. The only two cryptocurrencies with positive skew are Uniswap and Pancake Swap, both of which are decentralized exchanges.

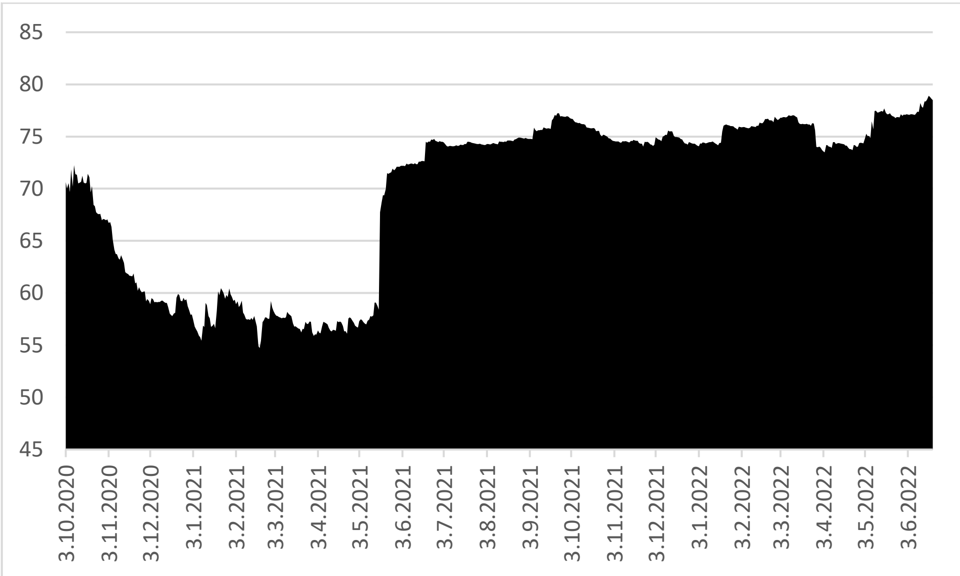
Table 1 also shows the Pearson correlation matrix between the returns of the eight cryptocurrencies. Overall, the returns of the eight cryptocurrencies exhibit moderate to high positive relationships, with the exception of Ethereum. Specifically, the Uniswap/AAVE (0.757) and Compound/AAVE (0.754) pairs have the highest correlation coefficients, while Ethereum/Bitcoin and Ethereum/Compound have the lowest correlation values (0.030 and 0.032, respectively) and Ethereum/Pancake Swap appears to be negatively correlated (-0.028). These results show that Ethereum is not correlated with the other seven cryptocurrencies. This could also be due to the fact that most DeFi apps are developed on Ethereum, the first smart contract platform. Ethereum is the operating system for these decentralized apps, so they are all interconnected. If the price and market capitalization of these DeFi tokens change significantly, it will directly affect Ethereum, as Ethereum's market capitalization will also decrease/increase. All six DeFi tokens Uniswap (UNI), AAVE (AAVE), Pancake Swap (CAKE), Curve Finance (CRV), Compound (COMP), and Just Lend (JST) appear to be highly correlated across DeFi categories, meaning there is little hedging across categories. It is also interesting to note that these eight cryptocurrencies.

Uniswap and Pancake Swap are right skewed, while the other six cryptocurrencies are left skewed. Ethereum, Uniswap, Pancake Swap, Curve, and Just Lend have kurtosis statistics that are greater than 3, indicating that the distribution of these series has a peak and a thick tail. The Jarque-Bera test showed that the null hypothesis of normality was rejected for all series at the 1% level. I used the Elliot-Rothenberg-Stock test (ERS), which can be used to test the null hypothesis of a unit root versus the alternative that there is no unit root in the yield series, to determine whether there is a unit root in the yield series (Youssef et al., 2021). The results of Table 1 show that the null hypothesis was rejected at the 1% level for all series and consequently I (0) of order zero is integrated. The Ljung-Box Q-statistics show that the serial correlation exists for all cryptocurrencies except Bitcoin.

5.1 Dynamic total connectedness

Figure 2 shows dynamic TCI data for the entire data sample, starting with the overall dynamic linkage. The value of the index changes over time and fluctuates in a wide range, roughly between 55% and 80%. This essentially means that the interconnectedness between these eight cryptocurrencies can range from moderately strong to very strong. The fact that the TCI is extremely sensitive to numerous events related to the relevant markets could be an explanation for the high dynamic variability of this index. Berentsen et al. (2018) reiterates an earlier point: because cryptocurrencies are decentralized and have a relatively finite volume, they are susceptible to significant short-term changes.

Figure 2. Dynamic Total Connectedness



Notes: Results are based on a TVP-VAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

The analysis time can be divided into two separate periods of decrease and increase. In particular, I observe that the link begins to decline in late 2020 and reaches a minimum of about 55% in early 2021. This is followed by a period of fluctuations around 60% until the summer of 2021, after which the curve clearly rises until it reaches its peak of nearly 80% in mid-June 2022. Short-term fluctuations are another feature of each of these periods, most likely related to certain economic changes. Although there may be a variety of factors that influence cryptocurrency returns (Cheah et al., 2018; Corbet et al., 2018), to put my findings in context, one must look at the cryptocurrency market as a whole. In this sense, we experienced a bull market in the cryptocurrency market Lehtonen (2022) in late 2020 and early 2021, and Bitcoin, for example, rose from about $10,500 in October 2020 to over $63,000 in April 2021, exceeding $1 trillion in market capitalization for the first time. The so-called "DeFi Summer," in which TVL surpassed $10 billion in late September 2020, served as a catalyst for that figure's explosive growth the next year. By November 2021, the TVL figure exceeded USD 100 billion for Ethereum alone (Cousaert et al., 2022).

These changes in the cryptocurrency market and the resulting implications for investors and economic actors are closely related to the declining trend in connections shown in Figure 1 for the period ending May 2021. Similarly, Gajardo et al. (2018) report that there was an upward trend in the Bitcoin price that began in mid-2015 and continued through August 2017; however, this trend was supported by comparatively moderate returns compared to the high returns from late 2020 through summer 2021. Given Bitcoin's dominance in the cryptocurrency market at the time, it follows that reasonable Bitcoin returns did not lead economic actors to believe that there was speculation in the cryptocurrency market. This allowed traders and/or investors to focus more on the many features that make up this cryptocurrency ecosystem, which led to a decoupling of the corresponding returns. Between 2015-2017, the interdependence between cryptocurrencies loosened during this relatively quiet period for the cryptocurrency market. On the contrary, my results show that interdependence decreased in the period from late 2020 to May 2021 during a very volatile bull market.

Looking at the second interval, which spans from the end of May 2021 to the end of our sample period, we see that connectivity rises sharply at the end of May and then gradually increases for the rest of the period, with few exceptions. The potential for greater connectivity between cryptocurrencies is further reinforced by authors such as Bech and Garratt (2017), who demonstrate that the release and expansion of coins has steadily increased in recent years (note that in 2017, the market capitalization of all other currencies matched that of Bitcoin). Moreover, according to Gandal et al. (2018), Bitcoin's market capitalization increased by 300 percent in mid-May 2017, while that of other cryptocurrencies increased even further. Such significant increases appear to have heightened market skepticism and uncertainty similar to what is occurring now. Consistent with the rationale above, the increased connectivity seen during this period is a result of significant price volatility and uncertainty in the cryptocurrency market, driven primarily by Bitcoin. Particularly during this somewhat difficult period, concerns about the Bitcoin industry increased as a global inflationary surge began in early 2021.

The COVID -19 pandemic, the Russian invasion of Ukraine, and supply shortages (especially chip and energy shortages) were blamed along with high consumer demand. Because of this, several countries have experienced the highest inflation in many years, and their central banks have responded by drastically raising interest rates (Bloomberg n.d 2022). With China once again banning cryptocurrencies and lawmakers focusing on regulation (Locke, n.d), the drop in prices and increase in interconnectedness could also be seen as an expected reaction from economic actors, considering how new and undeveloped the Bitcoin market is. In their paper, Peng et al. (2018) emphasize the need to develop a deeper understanding of the potential role of cryptocurrencies in today's financial world.

Table 2. Dynamic Connectedness Table

Lower connectedness period									
	BTC	**ETH**	**UNI**	**AAVE**	**CAKE**	**CRV**	**COMP**	**JST**	**FROM**
BTC	55,64	0,63	6,24	4,67	4,61	5,90	10,67	11,66	44,36
ETH	22,43	18,00	9,64	10,74	4,90	7,26	15,43	11,60	82,00
UNI	5,15	0,99	42,74	16,99	3,18	12,21	13,44	5,30	57,26
AAVE	5,15	0,86	17,56	42,37	3,67	11,25	13,95	5,19	57,63
CAKE	7,07	1,61	3,56	4,93	64,54	5,04	7,66	560	35,46
CRV	5,78	0,96	12,39	11,11	3,73	43,90	14,87	726	56,10
COMP	8,06	0,67	12,67	13,11	4,94	11,53	42,05	6,97	57,95
JST	11,62	0,82	6,28	6,27	4,55	8,64	8,20	53,62	46,38
TO	65,26	6,53	68,34	67,81	29,57	61,82	84,21	5360	437,14
Inc. Own	120,89	24,53	111,08	110,19	94,11	105,72	126,26	107,22	cTCI/TCI
NET	20,89	-75,4	11,08	10,19	-5,89	5,72	26,26	7,22	62,45/54,64
Higher connectedness period									
	BTC	**ETH**	**UNI**	**AAVE**	**CAKE**	**CRV**	**COMP**	**JST**	**FROM**
BTC	24,83	0,87	13,80	12,51	12,52	10,74	11,49	13,24	75,17
ETH	14,69	6,30	15,36	14,42	13,37	10,97	12,84	12,04	93,70
UNI	11,80	0,96	21,47	15,52	14,01	11,09	13,88	11,27	78,53
AAVE	10,75	1,04	14,97	21,93	13,28	12,14	16,32	9,57	78,07
CAKE	11,13	0,83	14,63	14,47	22,29	11,52	13,17	11,96	77,71
CRV	10,67	0,89	12,59	14,56	12,32	24,95	13,49	10,53	75,05
COMP	10,38	1,07	14,00	16,75	12,88	11,58	22,44	10,91	77,56
JST	13,07	0,72	13,14	11,47	12,91	10,90	12,15	25,64	74,36
TO	82,48	6,37	98,48	99,70	91,29	78,94	93,34	79,52	630,14
Inc. Own	107,32	12,67	119,96	121,63	113,58	103,89	115,78	105,16	cTCI/TCI
NET	7,32	-87,3	19,96	21,63	13,58	3,89	15,78	5,16	90,02/78,77

Notes: Values reported are variance decompositions based on a 20-step-ahead forecasts. In both periods, a TVP-VAR lag length of order 1 is selected by the BIC.

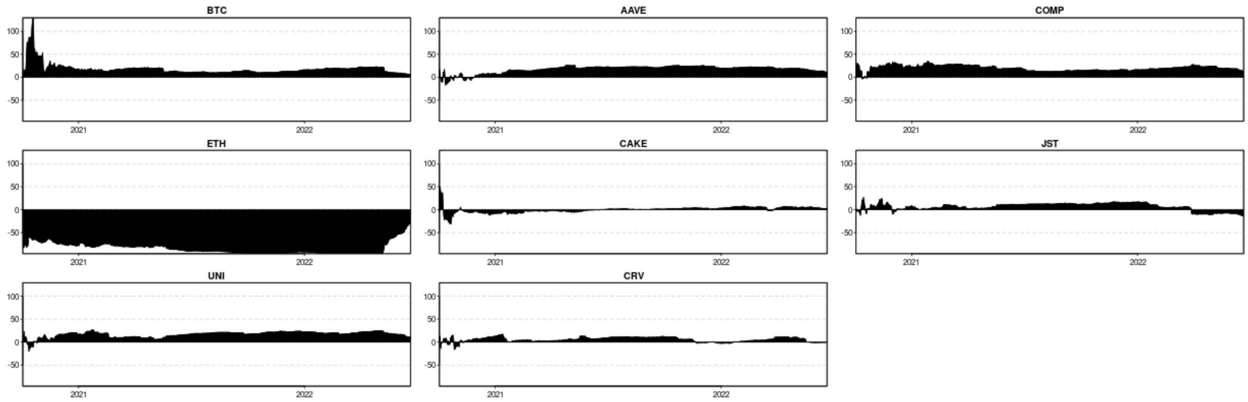
In a similar fashion to Antonakakis et al., (2019) and Yousaf et al., (2022), we proceed with the strategy as shown in Table 2 to fully analyze the split evident in the connectivity data shown in Figure 1. The study period is divided into the period before and after May 17, 2021, as the cryptocurrency market has become more interconnected since then, as evidenced by a rapid increase in interconnectivity. Interconnectivity has increased significantly, as shown in Table 2. Given that the market is a net transmitter for 8 other assets in both periods, we can also see that the market is driving all cryptocurrencies. In the pre-regime, Compound, Bitcoin, Uniswap, and AAVE are the strongest transmitters, with Ethereum acting as a shock absorber. After the TCI break, the pattern changes a bit. AAVE as the strongest transmitter is now followed by Uniswap, Compound, Pancake Swap and Bitcoin according to the post-period regime. Ethereum is still a shock recipient. This study is interesting because it shows that although Ethereum still has a significant impact, it is a shock absorber for all other cryptocurrencies in this sample.

Bitcoin transmits the most to Ethereum (22.43) in the lower connectedness period but is less of a transmitter in the higher connectedness period (14.69). Compound transmits the most to Bitcoin (10.67) in the lower connectedness period, but it is Uniswap that transmits the most to Bitcoin (13.8) in the higher connectedness period. Bitcoin and Pancake Swap transmit the most to themselves (55.64) and (64.54) in the lower connectivity period, but in the higher connectivity period, Bitcoin, Curve, and Just Lend transmit the most to themselves (24.83), (24.95), and (25.64).

5.2 Dynamic Connectedness network analysis

In order to understand net transmitters and net receivers in the cryptocurrency market, the net connectivity statistics is provided for all currencies across the analysis period. Indicated by Figure 3. Be aware that positive numbers represent net shock transmitters, whereas negative values represent net shock receivers.

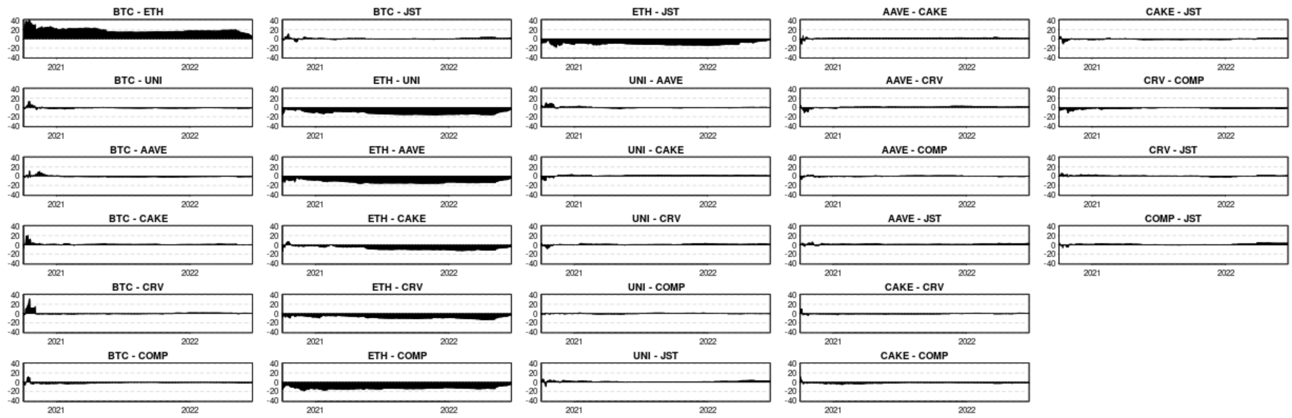
Figure 3. Net Directional Connectedness



Positive (negative) values indicate that the cryptocurrency is a net transmitter (receiver) of spillover effects.

Ethereum is largely a net shock recipient, as can be seen in the data shown in Figure 3. In addition, it can be seen that most other currencies are net senders throughout the interest period, with brief moments when some of these currencies appear to receive. Pairwise net connectivity is also considered to further evaluate these results. Figure 4 illustrates this.

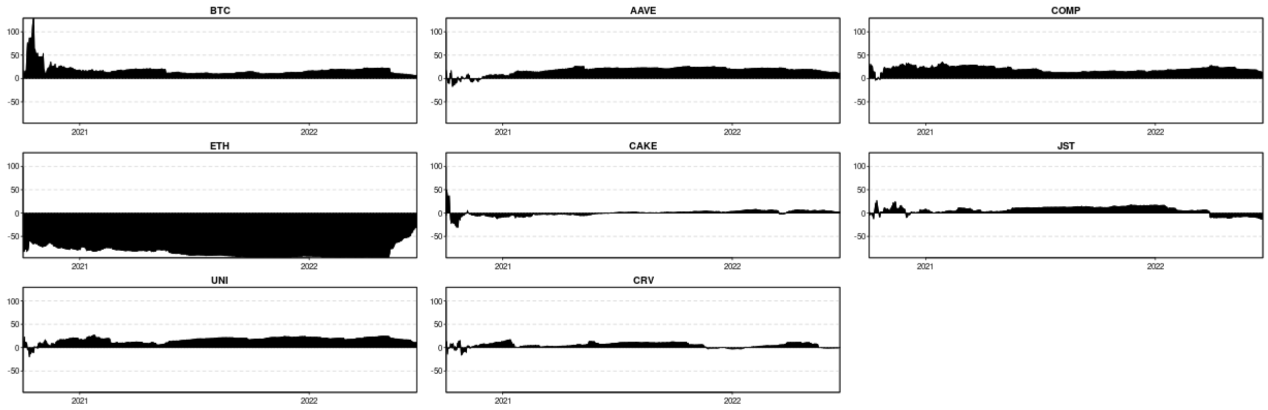
Figure 4. Net Pairwise Directional Connectedness



Positive (negative) values indicate that the cryptocurrency is a net transmitter (receiver) of spillover effects.

Relevant facts point to the importance of Bitcoin (BTC). It is obvious that Bitcoin transmits shocks to all other currencies on a net basis. In the same time frame, Ethereum also receives shocks from Uniswap (UNI), but also from AAVE, Pancake Swap (CAKE), Curve (CRV), Compound (COMP), and Just Lend (JST). Overall, these results point to the beginning of a phase in the cryptocurrency market where interconnectedness between cryptocurrencies is increasing and at the same time becoming more complex. To better understand the corresponding expression of connectivity. It would be quite instructive, in the context of the current study, which seems to indicate that I Bitcoin remains the most influential cryptocurrency, to make a first attempt to identify possible factors that make these specific cryptocurrencies important to the overall market. On the other hand, digital currencies such as AAVE, Uniswap (UNI), Pancake Swap (CAKE), Curve (CRV), Compound (COMP) and Just Lend (JST) influence Ethereum returns. Starting with Ethereum, I argue that the recent surge in popularity of DeFi on the Ethereum blockchain and all the Ethereum contained in these protocols has amplified Ethereum's apparent shock role in the cryptocurrency market. The findings show that while Bitcoin is still the cryptocurrency that dominates the overall cryptocurrency market, the unique features of blockchain technology associated with some digital currencies such as Ethereum, Uniswap, Pancake Swap, AAVE, and Compound have led to a more complex and interconnected market. This study also shows that there are still unanswered concerns, including how DeFi will affect Ethereum. However, this is to be expected, considering that there is undoubtedly still much to be discovered in the cryptocurrency industry. It follows that greater openness that explains or/and improves processes and transactions is crucial. Although examining the legal environment surrounding transactions in the cryptocurrency market is beyond the scope of this study, it would be instructive to point out that greater transparency could allow for a better understanding of the fundamental differences between cryptocurrencies, which (as the results of our study suggest) would not only increase confidence in the market, but also open up new opportunities for portfolio diversification. Similar to Antonakakis et al. (2019), it should go without saying that the growth of the cryptocurrency market requires the creation of an appropriate legal framework for flash lending and asset pooling, for example, to create the atmosphere necessary to deter financial crime and other criminal activity.

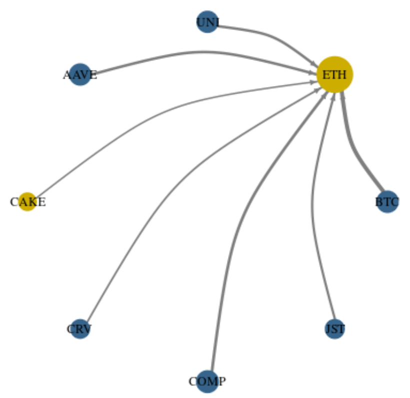
Figure 5. Net Total Directional Connectedness



Positive (negative) values indicate that the cryptocurrency is a net transmitter (receiver) of spillover effects.

Figure 4 shows the time-varying directional net return spillovers from each cryptocurrency to every other cryptocurrency. Most of the time, the net spillovers are in positive territory, with the exception of Ethereum, although AAVE, Pancake Swap, Uniswap, Curve, and Just Lend switch between negative and positive territory during the period of lower connectivity between October 2020 and mid-May 2021, suggesting that each cryptocurrency can occasionally act as either a net sender or a net receiver. Bitcoin behaves more like a net sender during this period of lower connectivity, while Ethereum takes on the obvious role of a net receiver.

Figure 6. Network Plot



Blue (yellow) nodes represent the shock's net transmitter (receiver). Measures of averaged net pairwise directional connectedness are used to weight vertices. The size of nodes represents the weighted mean net total directionality.

Figure 6 shows the Network Plot and further strengthens the analysis mentioned above by showing that Bitcoin is the strongest net transmitter and Ethereum is the net receiver of shock from all the other cryptocurrencies in this sample. The small arrows pointing to Ethereum show that Ethereum is a net receiver and the thickest line from Bitcoin shows that Bitcoin is the main transmitter to Ethereum. The blue color shows the net transmitters and the yellow net receiver and the lowest transmitter.

6. Conclusion

This study is likely to be relevant given the current interest in whether DeFi cryptocurrencies are safe havens or diversifiers for other cryptocurrency asset classes (Antonakakis et al., 2019; Conlon et al., 2020; Goodell & Goutte, 2021). To maximize diversity, the operational function of portfolio development must consider DeFi cryptocurrencies. It is critical to look at how different cryptocurrencies interact with each other to better understand the wide range of potential uses of recently unveiled blockchain technology that could impact things like risk assessment, governance practices, and financial regulation. This study focuses on interconnectivity issues and seeks to identify potential influencers that could be active in the DeFi market. The main objectives of the study are to identify net senders and net receivers among the 6 DeFi cryptocurrencies, Bitcoin and Ethereum, ranked by market capitalization and total value locked, and to observe spillovers. The time frame of the study is between October 3, 2020, and June 21, 2022, and the method used is a TVP-VAR method introduced by Antonakakis et al. (2020), an improved version of the connectivity strategy first proposed by Diebold and Yilmaz (2014). Discovering the contagion dynamics between cryptocurrencies can therefore open the door for research into risk hedging techniques. Understanding the interconnectedness of the cryptocurrency market would allow risk managers to better understand the risk associated with specific cryptocurrencies, which in turn could form a significant part of an investment portfolio (Antonakakis et al., 2019). What is also certain is that uncertainty is magnified by the fact that little is known about the Bitcoin market and its potential impact on the financial industry.

In terms of pairwise networking results, we see that the complexity of the DeFi market has increased significantly over the last two years. This can be seen in the network transfer function that certain cryptocurrencies such as AAVE and Compound have taken on. In contrast, Bitcoin is still the cryptocurrency that causes the biggest market shocks. From these results, although studies such as Corbet et al. (2021) show that DeFi is largely a separate asset class from other cryptocurrencies, the different categories within DeFi offer little diversity and are closely related. Because different cryptocurrencies have different technologies and features that provide users with different options, certain results suggest that the connectedness method captures the complex nature of the cryptocurrency industry. The risk management implications of the many features and services that distinguish each cryptocurrency should also be the subject of research. Given Bitcoin's influence on Ethereum and the rapid rise of cryptocurrencies that followed Bitcoin, it would be fascinating to see if other cryptocurrencies show different connectedness and if other DeFi categories would show different results. Overall, I strongly believe that this is a promising area of research with a variety of applications that affect modern finance and that there is much potential for further study.

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