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From Decentralization to Emission: Assessing the Climate Impact of DeFi Operations

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ABSTRACT

Developments and changes in technology play a significant role in addressing climate change, one of which is decentralized finance, which is currently expanding, and it is still unclear whether it has a dynamic relationship with climate change. This study employs the TVP-VAR Connectedness model with the aim of analyzing the dynamic relationship between the decentralized finance operations and CO_2 emissions, the impact of shocks from DeFi operations (total value locked, volume, returns, fees, and revenues) dynamically increasing CO_2 emissions, as well as to assess the role of DeFi returns in strengthening the transmissions of DeFi activity to CO_2 emissions. The results show that DeFi operations have a dynamic relationship with CO_2 emissions at a moderate level through shocks transmitted by DeFi operational indicators. It was also found that TVL acts more as a net receiver than a net transmitter, unlike Volume, Fees and Revenues. Returns do not significantly transmit shocks to CO_2 emissions and are more exogenous in nature, while both TVL and Returns are predominantly influenced by internal idiosyncratic shocks. These findings emphasize the importance of integrating Green FinTech policies to ensure sustainable DeFi growth. The findings also provide important implications for regulators, industry practitioners and academics in their efforts to balance the advancement of DeFi with environmental sustainability.

Keywords: Blockchain, Climate Change, CO_2 Emissions, Decentralized Finance, Time-Varying Parameter Vector Autoregressive Connectedness
JEL Classifications: C32, O33, Q54

1. INTRODUCTION

The earth is already facing serious environmental challenges due to the use of fossil fuels and unsustainable human behavior that may cause significant global warming (Vergil et al., 2025). The acceleration of climate change can lead to extreme weather and serious risks to society (Zhang et al., 2023), thereby creating pressure to commit to keeping global warming below 2°C (Kurniadi et al., 2024). Jha (2024) stated that, to address these issues, sufficient financial resources are needed to achieve mitigation and adaptation goals. Therefore, it is crucial for individuals to understand the technology involved in assessing the impact of climate change, where technological changes and environmental improvements play an important role and can mitigate the impact of climate change (Aggarwal et al., 2019).

Technological innovations can bring new potential and impact to the surrounding environment, especially climate change (Zhang et al., 2023). One such innovation is decentralized finance (DeFi), which is built on blockchain technology (Lin et al., 2024). DeFi is currently evolving and holds the potential to be recognized as an alternative that is more secure, transparent, and effective than centralized finance, thereby enabling financing management to become much cheaper and efficient, without incurring additional fees, being constrained by banking hours, or requiring third-party involvement to verify transactions (Lin et al., 2024; Wronka, 2023). However, behind DeFi's reliance on blockchain (Bodo and

De Filippi, 2024), it holds the potential to indirectly consume large amounts of energy when transactions or network activities occur, driving computational load and energy consumption on blockchain networks that utilize consensus mechanisms, such as proof-of-work (PoW), thus underscoring the importance of this study.

In this context, high energy consumption especially in blockchain networks that use consensus mechanism such as PoW, can reduce transaction costs (Lasla et al., 2022; Nguyen and Nguyen, 2024), but it can also raise serious concern about its impact on the environment, especially its contribution to climate change (Zhang et al., 2023). Nevertheless, DeFi has potential in social impact sectors, including renewable energy finance, carbon credit trading, and climate focus lending (Shah et al., 2023; Shahed et al., 2023). This is also supported by Jain et al. (2023), who explain the consensus transition on the largest chain utilized by DeFi, namely Ethereum. They state that the primary objective of this transition was to reduce energy consumption, with evidence showing that Ethereum's shift from proof-of-work (PoW) to proof-of-stake (PoS) successfully reduced energy usage by up to 99.98%.

Although the literature on climate change, cryptocurrencies and DeFi is quite extensive, most research still focuses on the energy consumption of cryptocurrencies (Baur and Karlsen, 2024; Haq et al., 2025; Zhang et al., 2023), DeFi adoption (Nguyen and Nguyen, 2024), DeFi assets and conventional assets or portfolios (Ali and Manel, 2025; Younis et al., 2024; Yousaf et al., 2022; Yousaf and Yarovaya, 2022), as well as DeFi and NFTs (Ghosh et al., 2024; Karim et al., 2022; Maouchi et al., 2022). Moreover, DeFi is often viewed as merely part of the broader crypto ecosystem, but in fact DeFi has unique characteristics. As Bajpai (2022) stated, "as DeFi evolves, the carbon footprint and sustainability risks of cryptocurrencies have been widely debated," yet this debate has not been accompanied by focused scientific data.

We recognize that studies focusing on the dynamic relationship between DeFi operations and climate change remains limited. Therefore, to fill this empirical gap, this study offers novelty by incorporating different variables and context compared to previous studies, namely by examining DeFi in relation to climate change. Using the TVP-VAR approach, this study analyzes the dynamic relationship, shocks and transmission between DeFi and CO_2 emissions through indicators such as total value locked, volume, returns, fees, revenues and CO_2 emissions to obtain evidence and a deeper understanding.

To enhance a deeper understanding of the relationship between DeFi operations and climate change, this study has three key research objectives: (1) To analyze the dynamic relationship between decentralized finance operations and CO_2 emissions. (2) To analyze whether shocks from DeFi operations (total value locked, volume, returns, fees and revenues) dynamically increasing CO_2 emissions. (3) To assess the role of DeFi returns in strengthening the transmission of DeFi activity to CO_2 emissions.

This study makes several contributions. First, it enriches the literature and extends research on decentralized finance, particularly in the context of the dynamic relationship between DeFi and climate change, which remains limited. Second, it fosters a deeper understanding among DeFi users and opens opportunities for further research on DeFi operations and climate change. Third, it provides empirical evidence of the dynamic connectedness between DeFi and climate change through the TVP-VAR approach to offer new perspectives.

2. LITERATURE REVIEW

2.1. Theoretical and Conceptual Framework

2.1.1. Ecological modernization theory (EMT)

EMT has been developed by Huber (1982), that emphasized the role of technological innovation in environmental reform. Humans are closely connected to their natural surroundings, but environmental impact are sometimes caused by technological innovations, consumerist attitudes, or a lack of environmental awareness on the part of human themselves (Huber, 2008). This can be linked to DeFi activities (e.g., protocols) that operate on blockchain networks, which consume energy through the consensus mechanisms, such as PoW (Seven et al., 2022; Shah et al., 2023). PoW is known as an energy-intensive consensus mechanism (Nevil, 2025; Schinckus, 2021), with Bitcoin being one of the cryptocurrencies within DeFi that uses PoW for mining (Morey et al., 2024; Sharma, 2025). According to Morey et al. (2024), the estimated energy consumption of Bitcoin in 2023 reached 120 TWh/year, with a lower bound of 80 TWh/year and an upper bound of 390 TWh/year, which is almost equal to the total electricity consumption of Greece or Australia.

Miller (2024) said that although DeFi provides unlimited freedom, its impact on the climate is high, which could trigger a transparent and eco-friendly trading revolution. As stated by Lei et al. (2021), blockchain have the potential to increase electricity usage, especially if computation on blockchain becomes more widespread. This can be mitigated by shifting to more energy-efficient computing, such as transitioning from PoW to PoS consensus mechanism (Platt et al., 2021; Seven et al., 2022). This is in line with EMT which emphasized innovation between growth and environmental pressures, where system design and blockchain consensus choices are the primary determinants of energy demand and can impact all activities and applications running on the blockchain, such as DeFi.

2.1.2. Environmental Kuznets curve (EKC)

EKC is a theory that discusses economic growth and the environment proposed by Kuznets in 1955 and represented by an inverted U-shaped curve (Kuznets, 2019). As economic development in industries increases, the rate of resource use and exploitation begins to exceed the rate of resource regeneration, leading to rising waste generation and climate change, which pose serious challenges to ecosystem sustainability (Gyamfi et al., 2021). As stated by Zhang et al. (2023), who also used EKC, economic growth (in this study proxied by DeFi operational development) tends to increase environmental degradation (proxied by CO_2 emissions) before improving environmental quality through sustainable economic growth, such as adopting more energy-efficient innovations.

The EKC consists of three main pathways: Scale effect, composition effect, and technique effect. In the context of this study, the scale effect illustrates that the expansion of operational activities in DeFi tends to increase energy consumption on blockchain network that relies on PoW, which aligns with the initial phase of the EKC where economic and technological growth exacerbate environmental pressures (Lei et al., 2021; Miller, 2024; Seven et al., 2022). The composition effect emerges as blockchains begin to shift their consensus mechanism from PoW to PoS, as exemplified by Ethereum's transition in 2022, which is reported to reduce energy consumption by approximately 99% while simultaneously improving scalability and transition processing efficiency (Lei et al., 2021; Nambiampurath, 2024). Meanwhile, the technique effect is reflected in technological innovations that enhance energy efficiency, such as Ethereum's reduction in energy use by nearly 99.95% after adopting PoS, providing strong evidence that staking is substantially more efficient than mining (Nambiampurath, 2024). Therefore, we adopt EKC as a supporting theory to explain the pattern of emission dynamic over the course of DeFi activities, as well as technological developments (decentralized finance).

2.1.3. Time-varying parameter vector autoregressive (TVP-VAR) connectedness

Before it was developed into the TVP-VAR model by Antonakakis and Gabauer (2017), Diebold and Yilmaz (2009) introduces a measure of volatility spillover based on forecast error variance decomposition from vector autoregressive (VAR). However, Antonakakis et al. (2020) noted that the VAR model developed by Diebold and Yilmaz still required improvements to achieve more accurate and detailed measurement. It is mentioned that these improvements are made in four ways: (i) no loss observation data, (ii) insensitivity to outliers, (iii) greater accuracy in detecting potential changes in parameter values, and (iv) no arbitrary setting of the rolling window-size (Antonakakis et al., 2019; Antonakakis and Gabauer, 2017).

TVP-VAR model can be used to examine dynamic connectedness at lower frequencies and utilizes time-series data to produce more accurate and reliable conclusions compared to the VAR model, which often arbitrarily selects a rolling-window-size and may eliminate observational data that could be valuable (Younis et al., 2024). Several studies have applied the model in DeFi. For example, Yousaf and Yarovaya (2022) used the TVP-VAR approach to analyze return and volatility transmission among NFTs, DeFi, and other assets. Using the same approach, Akkus and Dogan (2024) analyzed the dynamic connectedness relationship between DeFi, NFTs, and cryptocurrencies. In the context of climate change, Zhu et al. (2024) applied the TVP-VAR method to analyze the impact of extreme climate change on the connectivity among global gold markets. Therefore, this study adopts the TVP-VAR approach to analyze the dynamic relationship between DeFi and climate change.

2.1.4. Conceptual framework

DeFi closely related to smart contracts (Zhao et al., 2022), and smart contract are in turn closely tied to blockchain technology (Liu et al., 2021), meaning that without blockchain, smart contract cannot function. Likewise, without smart contract, transaction within DeFi cannot be executed. Therefore, DeFi heavily relies on blockchain technology to prevent the risk of third-party intervention (Bodo and De Filippi, 2024). This study focuses on DeFi in relation to climate change due to the significant computing power required for financial transactions within DeFi. This is because the validation and consensus processes on blockchain are carried out through PoW, which demands high energy consumption. Although some blockchain have shifted to PoS, which is considered more energy-efficient, PoS still not widely known (Escobar et al., 2022; Lasla et al., 2022; Platt et al., 2021). The high energy demand leads to increased fuel combustion to generate energy, resulting in rising carbon emissions that exacerbate climate change. Moreover, the global energy infrastructure still heavily depends on fossil fuels, which produce CO_2 and greenhouse gases that contribute to global warming (Pavel et al., 2024). Thus, this study highlights that although DeFi operations bring innovation to the financial sector, they also have the potential to generate positive or negative environmental impacts through energy consumption and carbon emissions.

To measure the network activity of DeFi variables, we use several indicators, namely total value locked (TVL), DeFi volume, DeFi returns, fees and revenues. These indicators are selected because they represent the amount of assets locked, tokens distributed, traded, fees and revenues obtained. Meanwhile, to measure energy consumption and CO_2 emissions as part of the climate change variable, the indicator used is World CO_2 emissions from the power sector. This indicator is chosen because it reflects energy usage and CO_2 emissions, with a specific focus on the power sector. The proposed conceptual framework is illustrated in Figure 1.

2.2. Hypothesis Development

2.2.1. Dynamic relationship between DeFi and CO_2 emissions

Concerns arise as many investors increasingly shift toward decentralized digital assets that remain heavily dependent on fossil fuels, which can further exacerbate existing environmental challenges (Gök, 2025). The blockchain networks that support DeFi operations have grown significantly and consume large amounts of energy, as exemplified by Bitcoin and Ethereum before the merge in 2022, with their energy usage often compared to that of entire countries (Morey et al., 2024).

According to the Crypto Carbon Ratings Institute (n.d.), which reports on electricity consumption and CO_2 emissions across various cryptocurrencies based on the type of consensus used, Ethereum serves as a key example. Prior to its transition to PoS, Ethereum's last recorded electricity consumption and CO_2 emissions under PoW on September 15, 2022, reached 19.45 TWh/day and 10.44 Mt CO_2. Following the transition to PoS, however, both figures dropped drastically to 0.0019 TWh/day and 0.0006 Mt CO_2 as of September 16, 2022. This can be linked to EMT, which states that technological innovation is a crucial component of ecological modernization and can have an impact on both humans and the environment (Huber, 2008). The aligns with the focus of this study, which explores

DeFi operations in the context of climate change, where DeFi activities can drive movements on blockchain networks that, in turn, lead to energy consumption. This is also supported by the EKC, where climate change will gradually increase and decrease, and inevitably when the EKC takes the shape of an inverted-U (Gyamfi et al., 2021). It is also in line with the three main pathways previously described: The scale effect, composition effect and technique effect. Therefore, this study proposes the following hypothesis:

H_{1a}: DeFi operations have a dynamic relationship with climate change.

2.2.2. Shock from DeFi operations on CO_2 emissions

Furthermore, regarding the shocks from DeFi operations that have the potential to increase CO_2 emissions. The explanation in this context is supported by empirical findings in the cryptocurrencies sector, where OECD (2022a) reports that consensus mechanisms such as PoW are a major driver of the carbon footprint in blockchain-based finance, including DeFi. In fact, they say that energy consumption such as Bitcoin, which uses PoW, generated annual emissions of around 65 Mt CO_2 in 2021, which has been proven to exceed the carbon footprint of many countries. In line with this, Corbet et al. (2021) and De Vries (2021) state that annual electricity consumption for cryptocurrency transactions has increased drastically along with the surge in demand and the number of new users driven by intensified mining activities resulting from rising digital asset prices, thereby sparking debates over energy usage and resulting carbon footprint. Similarity, Oğuz (2024) found that crypto trade volume has a positive and significant effect on carbon emissions. This means that an increase in transaction volume can be linked to an increase in carbon emissions. Likewise, Mustafa et al. (2024) found that Bitcoin trading volume has a significant negative impact on carbon emissions, meaning that a surge in Bitcoin trading volume leads to an increase in emissions. This illustrates that a surge in activity and participation in the crypto market, especially in the context of DeFi operations, has the potential to increase carbon emissions through increased computational load on the blockchain network. From an EMT perspective, technological advances and innovation can be used to reduce environmental impact without hindering economic growth (Weber and Weber, 2020). For example, Ethereum's transition from PoW to PoS, as mentioned earlier, proves that ecological modernization can change the relationship between economic activity (in this context, DeFi) and carbon emissions. This is supported by the OECD (2022a), which states that when Ethereum merged, DeFi reduced its dependence on high energy consumption such as PoW. However, high energy consumption is still necessary to secure some decentralized network, depending on the consensus mechanism used by the blockchain network (OECD, 2022b). Moving to the context of the EKC, which states that there is a relationship between economic development and environmental degradation in the form of an inverted U-curve (Wang et al., 2024). This is illustrated in the early stages of economic growth (in this context, DeFi), where emissions tend to increase along with economic activity until reaching a certain turning point (Shahbaz et al., 2019), where DeFi, as a digital financial innovation still in its early stages of growth, is likely to be in a growth phase followed by an increase in CO_2 emissions. Therefore, the following hypothesis is proposed:

H_{1b}: Shocks from DeFi operations can increase CO_2 emissions.

2.2.3. Transmission from DeFi returns on CO_2 emissions

High returns can trigger increased activity and drive computational load on blockchain networks, which ultimately increases CO_2 emissions. This statement is supported by findings from cryptocurrencies such as Long et al. (2023), which state that Bitcoin returns have a significant impact on carbon emissions, energy prices, carbon prices and financial indicators. These findings are also supported by Zhang et al. (2023), who state that there is significant causality and predictability of Bitcoin returns on electricity consumption. This means that large returns can encourage mining, which increases computing power, resulting in a surge in energy consumption and carbon emissions (Zhang et al., 2023). Adam et al. (2025) also found the same thing, where Bitcoin returns and volume have a significant influence on increasing carbon emissions. In other words, large profit incentives tend to reinforce the environmental impact of crypto activities. In the context of DeFi, when the returns of a protocol increase, it can attract more users and capital to flow into the activity, thereby sharply increasing the energy consumed by the blockchain network. This is where EMT and EKC are considered relevant, with EKC arguing that increases in income or economic profits tend to be accompanied by increases in emissions before reaching a certain tipping point (Wang et al., 2024). This illustrates that high returns can trigger increased activity that drives greater computational load and energy resource exploitation. However, as stated by Wang et al. (2024), when a certain level is reached, this relationship can reverse from negative to positive due to environmental awareness. Furthermore, EMT argues that technology can have an impact on the environment (Huber, 2008). When linked, financial gains and technological advancement can either exacerbate or mitigate environmental issues, depending on how each technology or network is implemented. Mustafa et al. (2024) even propose efforts to undertake alternative energy projects by directing financial returns from cryptocurrencies to drive positive environmental impacts. Current conditions prove that returns can increase CO_2 emissions through network activities (in this context, DeFi activities). Therefore, based on these findings and statements, the following hypothesis is proposed:

H_{1c}: DeFi returns strengthen the transmission of DeFi activity to CO_2 emissions.

3. METHODOLOGY

This study is a quantitative study using secondary data. Population in this study includes total value locked (TVL), DeFi volume, DeFi returns, fees and revenues for the variable of operational DeFi. Meanwhile the emissions data used in this study is world CO_2 emissions from the power sector. All data will be collected from DefiLlama except for DeFi returns and CO_2 emissions, which will be collected via Coingecko and Carbon Monitor Website.

The sampling method used is the purposive sampling method, where the samples are selected based on specific characteristics (Ahmed, 2024). The selected DeFi dataset will be based on protocols with a TVL of over \$300 million, as listed in the "Protocol Rankings" section on DefiLlama as of August 4, 2025. Data will be collected from October 20, 2022, to July 31, 2025, on a daily frequency.

There are several reasons why the sample selection in this study is based on protocol rankings with TVL >\$300 million. First, TVL refers to the total value of assets or digital funds that are locked to support the operations of various DeFi protocols (Wronka, 2023). Second, the size of the DeFi is generally assessed by the amount of digital assets stored and locked within DeFi protocols, namely TVL (Born et al., 2022). Third, the sample is restricted to protocol with TVL >\$300 million to minimize bias or noise from smaller protocols that tend to be volatile and susceptible to manipulation, although no previous study has explicitly applied this threshold. The criteria applied to the DeFi dataset are reported in Table 1:

Based on the specified criteria, the DeFi protocols selected and used in this study were six protocols. These protocols include curve finance (CRV), PancakeSwap (CAKE), Raydium (RAY), Balancer (BAL), GMX (GMX), and Quickswap (QUICK).

It should be noted that the dataset contains variables with values ranging from decimals to millions or even higher, a logarithmic transformation was first applied to normalize the scale across variables (Huyen et al., 2023). Subsequently, the data were averaged before being tested in R. For DeFi returns, calculations were first to be conducted using price data, according to the formula used by Piñeiro-Chousa et al. (2022), as follows:

$$Rn_{it} = \frac{(Pt_{it} - Pt_{it-1})}{Pt_{it-1}} \tag{1}$$

Where Rn_{it} represent the return, Pt_{it} is the closing price of the token on that day and Pt_{it-1} is the closing price of the token on the previous day.

3.1. TVP-VAR Connectedness Model

The data will be analyzed using the dynamic connectedness approach based on the time-varying parameter vector autoregression (TVP-VAR) model, which estimation process was carried out using R. We chose TVP-VAR as the appropriate method to measure the relationship between decentralized finance and climate change because TVP-VAR can capture changes in the structure of relationship among variables over time. This allows for the depiction of variations in DeFi operational intensity over time, as well as in environmental indicators, which can also fluctuate.

The TVP-VAR method extended by Antonakakis and Gabauer (2017) from the connectedness approach proposed by Diebold and Yilmaz (2009; 2012; 2014). Antonakakis and Gabauer (2017), Antonakakis et al. (2020) and Kayani et al. (2024) said that the use of the TVP-VAR method has several advantages over the VAR method. First, TVP-VAR model can improve its resilience in handling data anomalies because TVP-VAR is not susceptible to outliers. Second, the results of rolling-window analysis and the use of the Kalman filter method to determine the variance and covariance matrices will not cause data observation loss in the calculation of dynamic connectivity measures. Third, TVP-VAR effectively controls flattened parameter estimation and eliminated the need to arbitrary window size selection. Lastly, TVP-VAR can analyze high-frequency data, including intraday and daily data. The TVP-VAR model can be expressed as:

$$W_t = \beta_t W_{t-1} + \varepsilon_t \text{ where } \varepsilon_t | F_{t-1} \sim N(0, P_t) \tag{2}$$

$$\beta_t = \beta_{t-1} + v_t \text{ where } v_t | F_{t-1} \sim N(0, Q_t) \tag{3}$$

From the equation mentioned above, W_t is a dimensional vector or conditional volatility vector $N \times 1$ where N is the number of sectors. W_{t-1} is the lag of the dependent variable/conditional vector ($Np \times 1$) and β_t is the dimensional time-varying coefficient matrix ($N \times Np$). ε_t and v_t are the dimensional error disturbance vector ($N \times 1$) with P_t, which is a time-varying variance-covariance matrix (N × N).

Sarma and Rajib (2025) state that there are difficulties in standardizing the interpretation of time-varying coefficients generated by TVP-VAR. Therefore, we use generalized impulse response function (GIRF) and generalized forecast error and variance decomposition (GFEVD) based on the World representation theorem by converting the TVP-VAR model into a TVP-VMA (vector moving average) model to calculate GIRF and GFEVD. The TVP-VAR to TVP-VMA model can be expressed as:

$$W_t = \beta_t W_{t-1} + \varepsilon_t \tag{4}$$

$$W_t = Z_t \varepsilon_t \tag{5}$$

$$Z_{0,t} = I \tag{6}$$

$$Z\_(i,t)=\beta\_(1,t)\ Z\_(i-1,t)+\cdots+\beta\_(p,t)\ Z\_(i-p,t) \tag{7}$$

Where $\beta_t = [\beta_{1,t}, \beta_{2,t}, \ldots, \beta_{p,t}]'$ and $Z_t = [Z_{1,t}, Z_{2,t}, \ldots, Z_{p,t}]'$ and therefore $\beta_{i,t}$ and $Z_{i,t}$ are N × N dimensional parameter matrix.

Next, because the model is non-structural, GIRF will be used to represent the response of all variables after a shock in variable *i* (Antonakakis et al., 2020). According to Antonakakis and Gabauer (2017), the computation of the difference between the K-step-ahead forecast, where variable is once shocked and once not shocked, can be calculated as follows:

$$GIR_t (K, \delta_{j,t}, F_{t-1}) = E(W_{t+K} \mid \varepsilon_{j,t} = \delta_{j,t}, F_{t-1}) - E(W_{t+K} \mid F_{t-1}) \tag{8}$$

$$\Psi^c_{j,t}(K) = \frac{Z_{K,t} P_t \varepsilon_{j,t}}{\sqrt{P_{jj,t}}} \frac{\delta_{j,t}}{\sqrt{P_{jj,t}}} \qquad \delta_{j,t} = \sqrt{P_{jj,t}} \tag{9}$$

$$\Psi^c_{j,t}(K) = P_{jj,t}^{-\frac{1}{2}} Z_{K,t} P_t \varepsilon_{j,t} \tag{10}$$

Where K is the forecast horizon, $\delta_{j,t}$ is a selection vector with a one on the *j*th position and zero in the other positions, and F_{t-1} is the set of information up to t–1.

Antonakakis and Gabauer (2017) stated that GFEVD can be described as the variance shares of one variable in relation to another variable. These variance shares are then normalized, so that each row sums to one. This sum of one indicates that all variables together explain 100% of the forecast error variance of variable *i*. The calculation is as follows:

$$\phi_{ij,t}^{c}\left(K\right)=\frac{\sum_{t=1}^{K-1}\Psi_{ij,t}^{2,c}}{\sum_{j=1}^{N}\sum_{t=1}^{K-1}\Psi_{ij,t}^{2,c}} \tag{11}$$

With $\sum_{j=1}^{N}\phi_{ij,t}^{N}\left(K\right)=1$ and $\sum_{i,j=1}^{N}\phi_{ij,t}^{N}\left(K\right)=N$. By using GFEVD, we constructed a total connectedness index as follows:

$$Q_{t}^{c}\left(K\right)=\frac{\sum_{i,j=1,i\neq j}^{N}\phi_{ij,t}^{c}(K)}{\sum_{i,j=1}^{N}\phi_{ij,t}^{c}(K)}*100 \tag{12}$$

$$=\frac{\sum_{i,j=1,i\neq j}^{N}\phi_{ij,t}^{c}(K)}{N}*100 \tag{13}$$

This connectedness proves that how shocks in one variable affect other variables. We developed three different connectedness procedures. First, total directional connectedness to others (TO OTHERS) is used to see how variable *i* transmits its shocks to all other variable *j*. Second, total directional connectedness from others (FROM OTHERS), which is used to calculate the directional connectedness received by variable *i* from variable *j*. Third, net total directional connectedness (NET), which is used to describe the strength or power of variable *i* or its influence on the entire network of variables.

To others

$$Q_{i\rightarrow j,t}^{c}\left(K\right)=\frac{\sum_{j=1,i\neq j}^{N}\phi_{ji,t}^{c}(K)}{\sum_{j=1}^{N}\phi_{ji,t}^{c}(K)}*100 \tag{14}$$

From others

$$Q_{i\leftarrow j,t}^{c}\left(K\right)=\frac{\sum_{j=1,i\neq j}^{N}\phi_{ij,t}^{c}(K)}{\sum_{i=1}^{N}\phi_{ij,t}^{c}(K)}*100 \tag{15}$$

Net

$$Q_{i,t}^{c}(K)=Q_{i\rightarrow j,t}^{c}\left(K\right)-Q_{i\leftarrow j,t}^{c}(K) \tag{16}$$

If the result of the net total directional connectedness calculation for variable *i* is positive, it describes that variable *i* has a greater influence on the network. Conversely, if the result is negative, it means that variable *i* is driven or influenced by the network.

3.2. Robustness Test

This study conducted a robustness test on the data to verify the reliability of the results and conclusions obtained (Zhu et al., 2024). Robustness test have been widely used in previous studies, such as Zhang et al. (2023); Younis et al. (2024), and Zhu et al. (2024), who employed forecast horizons; Huyen et al. (2023), who used a new dataset; Zhang et al. (2023), who applied the Hurst exponent; and Aloui et al. (2024), Li et al. (2023), and Liu et al. (2024) who utilized Bayesian VAR (BVAR) to verify robustness. Therefore, to verify the reliability and resilience of the TVP-VAR model results, this study changed the forecast horizons from 10 days to 20 days, as applied by Younis et al. (2024).

4. RESULTS AND DISCUSSIONS

4.1. Stationary Test

Based on the results of the augmented dickey-fuller (ADF) test presented in Table 2, this evidence proves that the indicators of CO_2 emissions, TVL, Volume, Returns, Fees and Revenues are stationary, which can be used to estimate the TVP-VAR model, as they satisfy the stationarity assumption without requiring differencing transformation. Furthermore, the stationarity of all indicators shows that changes in DeFi operational activities and CO_2 emissions are temporary and will eventually return to their long-term equilibrium after experiencing shock. This finding is consistent with the assumption of the TVP-VAR model, that focuses on capturing the dynamic relationships between variables over time.

4.2. Descriptive Statistics and Correlation

As shown in Table 3, the mean CO_2 emissions from the power sector are recorded at relatively high level with fairly stable fluctuations (8.194), indicating that CO_2 emissions tend to be more stable compared to DeFi variables such as Returns (2950.446), which are highly volatile. This can reflects the volatile nature of the crypto market, as emphasized by Aloui et al. (2024) and Kayani et al. (2024). Further observation of the distribution shows that TVL has a positive skewness, meaning the data is skewed to the right with several large upward spikes, whereas Volume and Fees exhibit negative skewness, indicating the presence of several large downward spikes in certain periods. The results indicate that TVL does not always experience extreme spikes, but when major drivers

Table 1: DeFi data criteria

No.	Data criteria
1.	The DeFi protocols selected are based on those available through the DefiLlama API.
2.	The selected protocols are those with complete data on TVL, volume, returns (price), fees and revenues.
3.	The protocol data used is data that includes a combination of all protocols and has valid values.
4.	DeFi return data were taken from the price of native tokens in each selected protocol and available on Coingecko.
5.	The protocol taken is the protocol within the date range from October 20, 2022, to July 31, 2025.

Table 2: ADF test

Indicators	T-statistics	P-value
CO_2 emissions	−6.781	0.0000***
TVL	−24.052	0.0000***
Volume	−8.111	0.0000***
Returns	−31.933	0.0000***
Fees	−7.620	0.0000***
Revenues	−7.680	0.0000***

Significance at the ***1%, **5% and *10% levels emerge, such as large capital inflows or the entry of significant investors, extreme spikes may occur which lead to a right-tail.

As stated by Salsabila et al. (2024), if the result of the Jarque-Bera (JB) statistic yields a value greater than the Chi-Square or a $P < \alpha$, it indicates that the data are not normally distributed. The results of the normality test (JB) show that most variables are not normally distributed (P-value $< \alpha$). This finding strengthens the methodological justification for employing the TVP-VAR model, as this model can capture the time-varying dynamics or relationships among variables (Antonakakis et al., 2020; Antonakakis and Gabauer, 2017).

Furthermore, in Table 4, a Pearson correlation analysis was conducted to identify significant relationships between variables (Salsabila et al., 2024). The results show that Volume, Fees and Revenues have a significant positive correlation with CO_2 emissions, although the scale is not high. This indicates that energy-intensive transactions activities in DeFi are related to the increase in emissions. Moreover, not every DeFi transaction directly generates emissions, but in aggregate, increased use of the blockchain network when DeFi activity rises causes increased carbon emissions. Conversely, TVL and Returns do not have a significant correlation with CO_2 emissions, indicating that the amount of funds locked and financial returns reflect the economic aspects of DeFi rather than its contribution to energy consumption. Additionally, there is a very high correlation between DeFi variables, indicating potential multicollinearity when using the VAR approach. However, the TVP-VAR approach used in this study can accommodate this complexity because the relationship between variables can change according to surrounding conditions (e.g., market).

4.3. Main Results

Table 5 shows the dynamic connectedness analysis, where the noteworthy part is the cTCI/TCI of 48.82/40.69. This means that around 40.69% of the system variation comes from the dynamic connectivity between indicators, while the remaining 59.31% comes from the internal variation of each indicator. This finding addresses the hypothesis (H_{1a}), demonstrating a moderate level of interconnection between DeFi operations and CO_2 emissions, which may influence climate change. This was mentioned by Ghosh et al. (2024), that the increase in energy consumption resulting from DeFi mining is due to its reliance on blockchain technology, which faced extensive criticism regarding energy-related issues. Meanwhile, the cTCI value of 48.82% provides more robust evidence of time-varying relationships that may be concealed by the TCI (Diebold and Yılmaz, 2014), so that the connectedness reflected by cTCI is stronger than that captured in TCI.

It must be noted that the TO and FROM metrics are interpreted as measures of shocks transmitted to and received from indicators, thus describing the dynamics of a two-way relationship (Kayani et al., 2024). Table 5 also shows the interrelationships between indicators in the network, where the diagonal part of the table serves as a summary of the variation of an indicator determined by its own shocks (Huyen et al., 2023). To address the hypothesis (H_{1b}), it can be observed that Returns (97.90) and TVL (83.60) are highly dominated by their own shocks (idiosyncratic), whereas Volume (38.08), Fees (35.99), and Revenues (37.59) have lower diagonals values, meaning they are more open to shocks. This implies that changes in Returns and TVL are largely driven by internal factors, such as capital inflows and outflows, rather than direct influences from Volume, Fees, Revenue, or CO_2 emissions.

Table 3: Descriptive statistics

Indicators	CO_2 emissions	TVL	Volume	Returns	Fees	Revenues
Mean	38.448***	14.237***	7.904***	7.448***	5.135***	4.525***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Variance	8.194	0.234	0.093	2950.446	0.073	0.066
Skewness	−0.012	0.332***	−0.254***	25.376***	−0.245***	−0.067
	(0.879)	(0.000)	(0.001)	(0.000)	(0.002)	(0.382)
Ex. Kurtosis	−0.752***	−0.217	−0.554***	732.158***	−0.557***	−0.232
	(0.000)	(0.137)	(0.000)	(0.000)	(0.000)	(0.107)
JB	23.959***	20.665***	23.853***	22779595.390***	23.282***	3.037
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.219)
ERS	−1.944**	−5.317***	−2.415**	−14.003***	−2.515**	−2.618***
	(0.052)	(0.000)	(0.016)	(0.000)	(0.012)	(0.009)
Q (20)	5392.891***	621.736***	6207.520***	0.393	6499.780***	6155.818***
	(0.000)	(0.000)	(0.000)	(1.000)	(0.000)	(0.000)
Q^2 (20)	5361.230***	617.263***	6196.841***	0.019	6493.662***	6141.708***
	(0.000)	(0.000)	(0.000)	(1.000)	(0.000)	(0.000)

Significance at the ***1%, **5%, and *10% levels

Table 4: Correlation matrix

Indicators	CO_2 emissions	TVL	Volume	Returns	Fees	Revenues
CO_2 emissions	1.000***					
TVL	0.018	1.000***				
Volume	0.157***	0.360***	1.000***			
Returns	0.037	−0.045	−0.013	1.000***		
Fees	0.145***	0.325***	0.926***	−0.012	1.000***	
Revenues	0.128***	0.291***	0.896***	−0.003	0.969***	1.000***

Significance at the ***1%, **5%, and *10% levels

Table 5: Dynamic connectedness analysis

Indicators	CO_2 emissions	TVL	Volume	Returns	Fees	Revenues	From
CO_2 emissions	62.72	1.48	13.78	0.45	11.49	10.08	37.28
TVL	1.94	83.60	6.70	0.75	4.08	2.92	16.40
Volume	5.34	3.31	38.08	0.48	27.30	25.49	61.92
Returns	0.55	0.80	0.33	97.90	0.23	0.20	2.10
Fees	3.56	2.20	24.66	0.52	35.99	33.07	64.01
Revenues	3.28	1.61	23.18	0.43	33.91	37.59	62.41
TO	14.67	9.39	68.65	2.63	77.01	71.76	-
Inc.Own	77.40	93.00	106.73	100.52	113.01	109.35	cTCI/TCI
NET	−22.60	−7.00	6.73	0.52	13.01	9.35	48.82/40.69
NPT	2.00	1.00	2.00	3.00	4.00	3.00	

This is also in line with the negative NET TVL (receiving more shocks than giving shocks). Volume, Fees, and Revenues are the most interconnected DeFi operational metrics, where their variations are largely explained by cross-indicators shocks and at the same time they are also the main net transmitters to CO_2 emissions, which can be seen from the high TO and positive NET in Table 5.

The CO_2 emissions value of 62.72% indicates that there is a large component native to the global power sector (energy structure, electricity demand, policy). However, since 37.28% originated from other variables, CO_2 emissions remain relatively open to transmissions from DeFi operational metrics. This reflects that in the negative NET value of CO_2 emissions and the thickness of the incoming and outgoing arrows in the network plot shown in Figure 2, where approximately one-third of its variation is explained by shocks from DeFi operational metrics. It must be noted that, in addition to the thickness of the incoming and outgoing arrows, there are differences in the size and color of the nodes in Figure 2 that need to be understood. The size of each node serves as a metric indicating how interconnected a particular indicator is with the overall system, while the color difference of each node indicates its role, blue represents net transmitters, whereas gold represents net receivers. These findings is in line with EMT, which posits a dual role between environmental improvement and degradation (Mol and Sonnenfeld, 2014). The results indicate that DeFi operations have not yet demonstrated a strong green transformation effect, but they also do not entirely worsen environmental conditions, as the relationship remains at a moderate level and not all operational indicators of DeFi fully contribute to the impact on CO_2 emissions. This means that when DeFi operations experience large-scale growth and volatility, they can still transmit an influence on CO_2 emissions. From the perspective of the EKC, the results show that nearly half of the dynamics in CO_2 emissions are still influenced by DeFi operations. Viewed through the inverted U-shaped curve, DeFi is in the middle stage of the curve, where its activities have developed sufficiently to begin generating digital efficiency, yet have not reached the ecological turning point, one example of this is Ethereum's transition from PoW to PoS (Kaneko, 2025).

Figure 3 shows a moderate connectedness between DeFi operations and CO_2 emissions, which around 45-55% throughout the 2023-2025 period, with some increases at the beginning and end of 2023 and 2025, and a decline around mid-2024. This value illustrates that activities within the DeFi ecosystem have a significant influence on global carbon emissions dynamics but are not entirely dominant. This means that about half of the variation in the system comes from cross-indicator transmission, while the other half comes from internal shocks to each indicator. This pattern is consistent with the results in Table 5, where when TCI increases, the transmission from Volume, Fees and

Figure 1: Conceptual framework

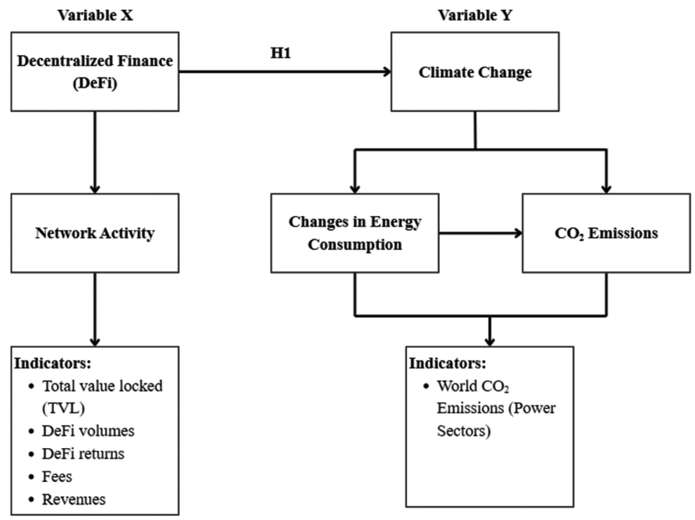
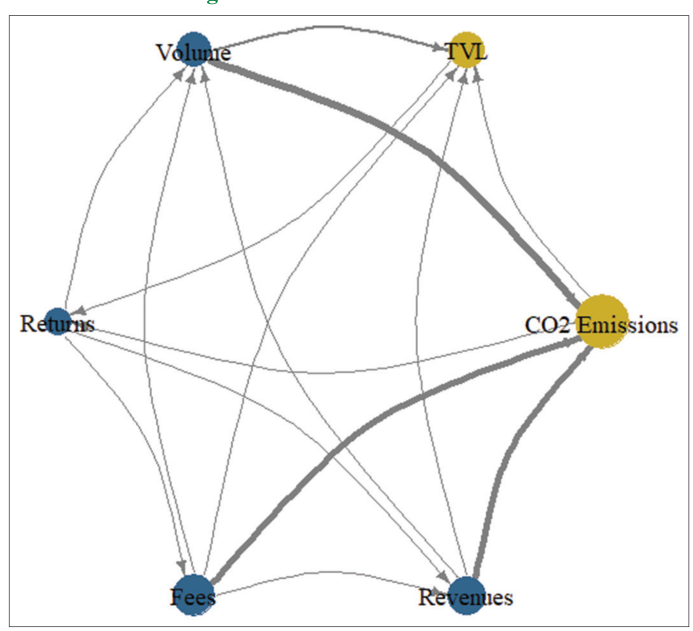


Figure 2: Network connectedness

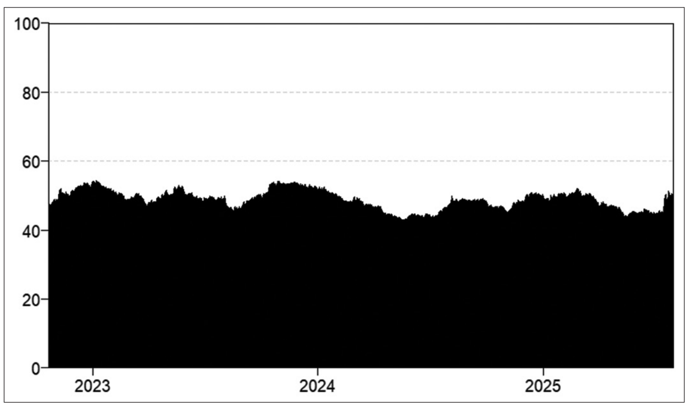


Revenues to CO_2 emissions strengthens, making CO_2 emissions a more dominant net receiver. However, when TCI decreases, the movement of indicators is more determined by internal shocks. This is also in line with the idiosyncratic nature of TVL and Returns, which tend to absorb shocks.

When viewing from the perspective of EMT, the emergence of financial innovations such as DeFi has the potential to bring economic benefits, but on the other hand, it poses environmental risks if not balanced with a transition to clean energy. Meanwhile, according to the EKC, the relationship between DeFi and CO_2 emissions may reflect an inverted U-shaped curve, where the early stages, DeFi growth may increase emissions due to high energy intensity, but in the long term, the adoption of energy-efficient blockchain technologies such as PoS has the potential to reduce emission intensity. Therefore, a fairy stable TCI at a moderate level shows that the relationship between DeFi and CO_2 emissions is not static but rather changes in line with market dynamics and technological developments.

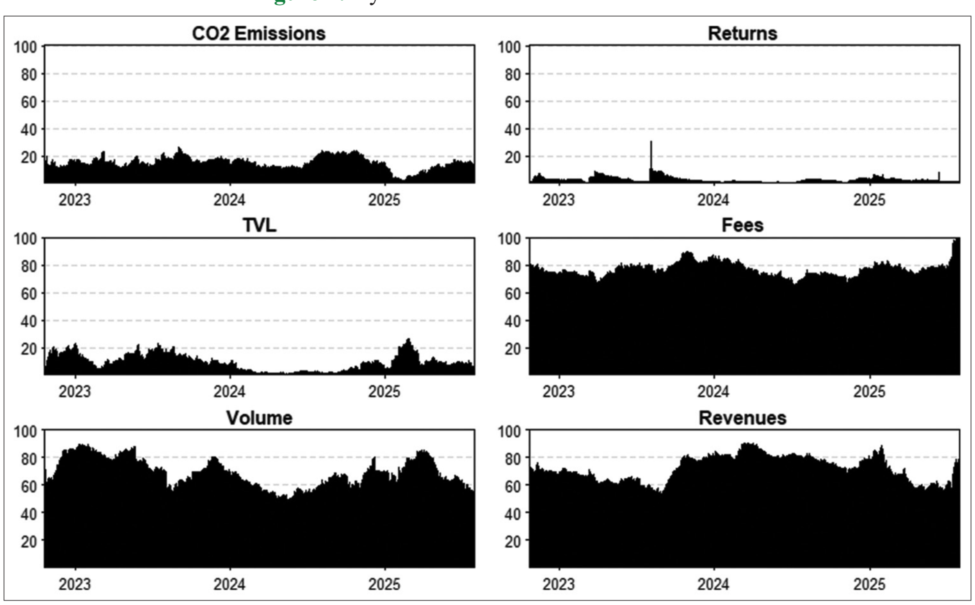
As shown clearly in Figure 4, Volume, Fees and Revenues act as the main transmitters of the system's connectedness. Volume, with values ranging between 50 and 90, indicates that an increase in DeFi transaction activity has a significant impact on other indicators. This aligns with the findings of Sedlmeir et al. (2020), who stated that high on-chain volume can increase the computational energy load of blockchain networks. Furthermore, Fees and Revenue also show relatively high values, ranging from 60 to 80, with Fees even approaching 100 toward mid-2025. This suggests that Fees serve as one of the primary channels for shock transmission within the system. The higher the Fees, the more intensive the network activity becomes, which in turn leads to higher energy consumption and emissions. According to the literature, the imposition of Fees tends to occur when transaction involve blockchains where CO_2 per transaction is considered, including the execution of smart contracts (Truby, 2018). Revenues, which act as a strong transmitter, demonstrate a close relationship with Volume and Fees. This is reasonable since revenues are a function of transaction activity, the more transactions occur, the higher the protocol's revenues. In contrast, TVL shows fluctuations at the beginning of 2023 and 2025, where TVL impacts the system but not as strongly as Volume, Fees, or Revenues. This condition indicates that TVL occasionally acts as a source of shocks, as it reflects the level of investor trust in the protocol rather than direct energy-related activity (Grande and Borondo, 2025).

Figure 3: Dynamic total connectedness



Note that Returns are almost always low, indicating that Returns do not transmit significant shocks to the system. This suggests that Returns are more closely related to financial risk than to energy interconnectedness. Attention should also be given to CO_2 emissions, which remain relatively low and stable, with an average below 30. This means that CO_2 emissions act more as a net receiver than a transmitter. This finding is consistent with the results in Table 5, showing that CO_2 receives shocks from DeFi operational activities rather than transmitting them. Sedlmeir et al. (2020) and Truby (2018) also stated that, the blockchain utilized by DeFi serves as an energy consumer, whereas emissions and climate impact are

Figure 4: Dynamic total connectedness to others



the consequences. These results are reinforced by the EMT, which suggest that without sufficient technological modernization, digital economic activities (such as DeFi operations) can continue to exert pressure on the environment. Empirical evidence from the Trend Report - Ethereum Merge (2023) also indicates that design innovations like PoS can reduce energy consumption by up to 99.98%, opening the possibility of achieving a decoupling between technology and environmental impact. In contrast, networks that continue to use PoW mechanisms may exacerbate climate change due to the CO_2 emissions they produce (Sedlmeir et al., 2020). These findings are further supported by the EKC, as the dominance of DeFi operational indicators as transmitters underscores the scale effect in the early phase, followed by a transition toward a declining phase that requires composition and technological effects, particularly through the adoption of energy-efficient systems, leading to a gradual reduction in emissions.

Figure 5 discusses the shock reception of each indicator from other indicators. In addition to being shock senders, Volume, Fees and Revenues are also high shock receivers. This supports that fees will increase when transaction volume is high, and revenues on the protocol will increase as the number of transactions rises, which will ultimately transmit and drive CO_2 emissions through the blockchain network. This shows the characteristics of indicators that are two-way interconnected with other components in the system.

Figure 5 also shows that the FROM Others value for CO_2 emissions is quite high end fluctuate throughout the period, indicating that CO_2 emissions are greatly influenced by DeFi dynamics, especially from Volume, Fees and Revenues. These results are also consistent with previous results, where CO_2 emissions act as a net receiver and have a dynamic relationship with DeFi operations. Returns remain in a condition similar to Figure 4 where there are not many spikes. This clearly emphasizes that Returns are more exogenous and are not greatly influenced by other indicators. It can also be seen that TVL occasionally fluctuates or is influenced by other indicators, but it is not the center of shock reception. Therefore, TVL reflects the funds locked in the protocol to support DeFi operations (Wronka, 2023), so TVL responds more slowly to changes in daily transaction than other indicators.

These findings are supported by EMT, as the high FROM value of CO_2 emissions indicates that technological innovation still has an impact on the environment. This means that emissions still respond to shocks from DeFi operations. Meanwhile, EKC provides further support that a high value reflect the dominance of the scale effect, while the subsequent declining trend of FROM following technological innovations and energy composition changes indicates a shift toward the turning point. Note that market fluctuations such as prices can lead to variations in energy consumption and CO_2 emissions. For instance, due to the adoption of energy-efficient technologies, the FROM value may decline, forming an inverted U-shaped pattern, but a surge in activity can raise it again, resulting in an N-shaped pattern. Qin et al. (2023) prove that Bitcoin prices can influence carbon emissions, emphasizing that price setting and the pursuit of carbon neutrality are key to ensuring aa sustainable decline in CO_2 emissions in the future.

Figure 6 clearly shows the differences in the roles of each indicator in the operational variables of DeFi and CO_2 emissions. Indicators such as Volume, Fees, and Revenues are consistently in the positive area, indicating that these three indicators are the main net transmitters of shocks in the system. This means that transaction activity in DeFi operations is the main source of dynamic relationships that transmit their influence to other variables such as CO_2 emissions. Conversely, CO_2 emissions tend to be in the negative area, indicating their role as net receivers, supporting the changes in emissions are more influenced by the intensity of DeFi operations rather than exerting an influence back on DeFi operations. This finding also reinforces that CO_2 emissions are indeed influenced by DeFi operations running on the blockchain network, which is in line with the finding of

Figure 5: Dynamic total connectedness from others

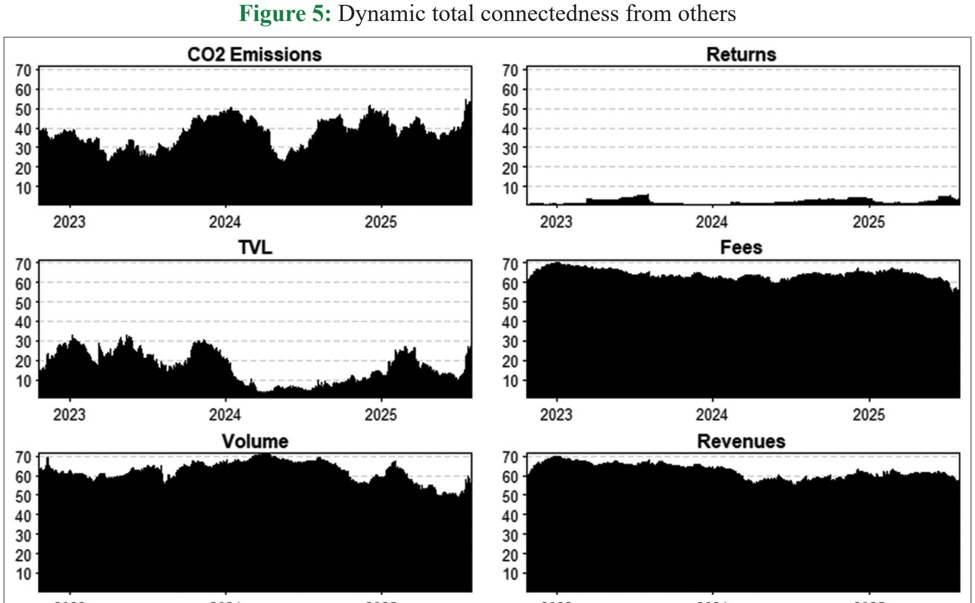
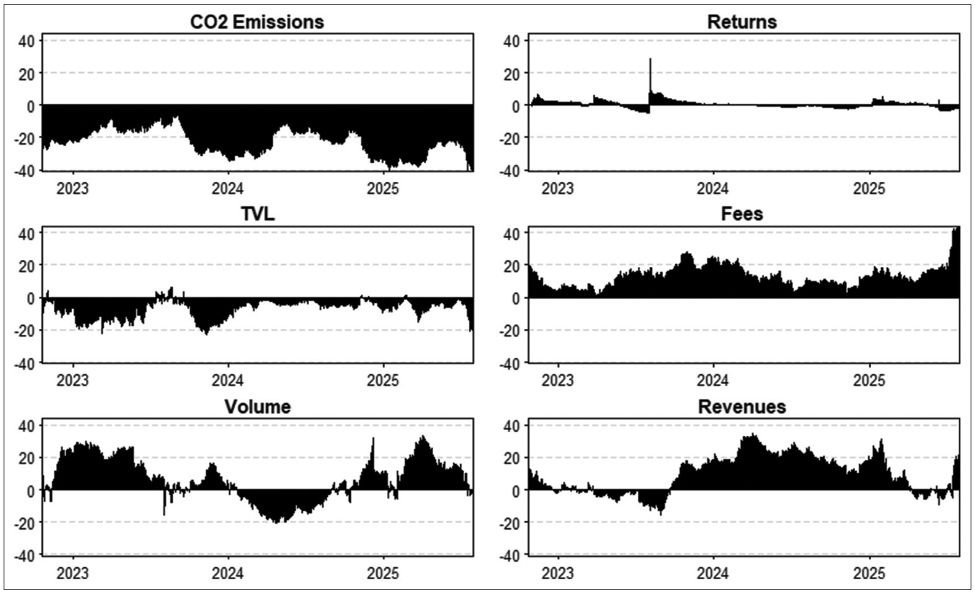


Figure 6: Net total directional connectedness



Zhang et al. (2023), Sedlmeir et al. (2020), Stoll et al. (2019), and Truby (2018), who state that energy consumption through the PoW consensus mechanism by blockchain has a direct link to CO_2 emissions, where the energy used by blockchain networks can impact climate change. This is in line with EMT and EKC, which essentially state that technological innovation is inherently linked to energy consumption that can place pressure on the environment when energy efficiency principles are not fully implemented. This issue becomes critical when energy use and CO_2 emissions rise solely due to digital activities that could otherwise be shifted toward low-energy alternatives. Such optimization would allow energy to be allocated to more essential sectors and extend supply resilience, rather than being rapidly consumed by energy-intensive computational processes, such as those seen in Bitcoin which is widely recognized for its high energy consumption.

Furthermore, TVL also largely acts as a net receiver, while Returns remain nearly neutral, with only a minimal impact as either a net transmitter and net receiver. This shows that indicators such as TVL and returns in DeFi play a limited role in dynamic connectedness with CO_2 emissions. Therefore, the patterns provided by each indicator confirm that the intensity of DeFi network usage is the main channel for transmitting environmental impacts, rather than asset values or speculative gains.

Turning to Figure 7, which shows the plot between indicators, where the consistent negative relationship pattern between CO_2 emissions - Volume, CO_2 emissions - Fees, and CO_2 emissions - Revenues indicates that CO_2 emissions predominantly receive shocks from DeFi operational activities. In other words, the increase in DeFi activity through the blockchain network is the main source of global energy emission fluctuations. In addition, the strong positive relationship between Volume - Fees, Volume - Revenues, and Fees - Revenues shows that they transmit shocks to each other, indicating the existence of a feedback loop within the DeFi operational system. This means that any increase in transaction Volume on DeFi can drive an increase in Fees, which in turn increases protocol Revenues. The cycle can intensify energy usage due to increased computational load on the blockchain network. Meanwhile, TVL and Returns show a relatively weak and fluctuating connectedness, indicating that the value of locked assets and investment returns do not have a direct contribution to CO_2 emissions. Thus, the explanation above, particularly regarding Returns, address the hypothesis (H_{1c}). These findings are further supported by EMT, which demonstrates that every shock generated by each indicator of DeFi operations is still perceived as a trigger for emissions. The dominant influence of Volume, Fees and Revenues on CO_2 emissions indicates that the digital financial modernization driven by DeFi has not yet fully achieved the stage of green modernization, where blockchain innovations through DeFi development enhance economic activity but have not yet substantially reduced energy intensity and carbon emissions. Although several protocols have transitioned to PoS mechanisms, the NPDC results showing a positive relationship between DeFi and CO_2 emissions suggest that energy efficiency improvements remain insufficient to offset ecological impacts. From the EKC perspective, DeFi appears to be in the early to middle stages of the curve, where the growth of the digital economy remain causing environmental impacts. There are no strong signs of a turning point yet, although slight shifts toward reduced energy usage can be observed through transition to energy-efficient system such as PoS mechanisms.

4.4. Robustness Test

The results of the robustness test are shown in Table 6, where there is a slight increase in cTCI/TCI from 48.82/40.69 to 50.10/41.75. This indicates a stronger connection between DeFi operations and CO_2 emissions. Note that CO_2 emissions and TVL remain net receivers after the change in forecasting horizons, and the largest net transmitters are still the Volume, Fees and Revenues indicators. Meanwhile, returns still provide weak results for both net transmitters and net receivers of CO_2 emissions. This sufficiently proves that the main results remain valid after adjustments to the forecasting horizons.

Figure 7: Net pairwise directional connectedness (NPDC)

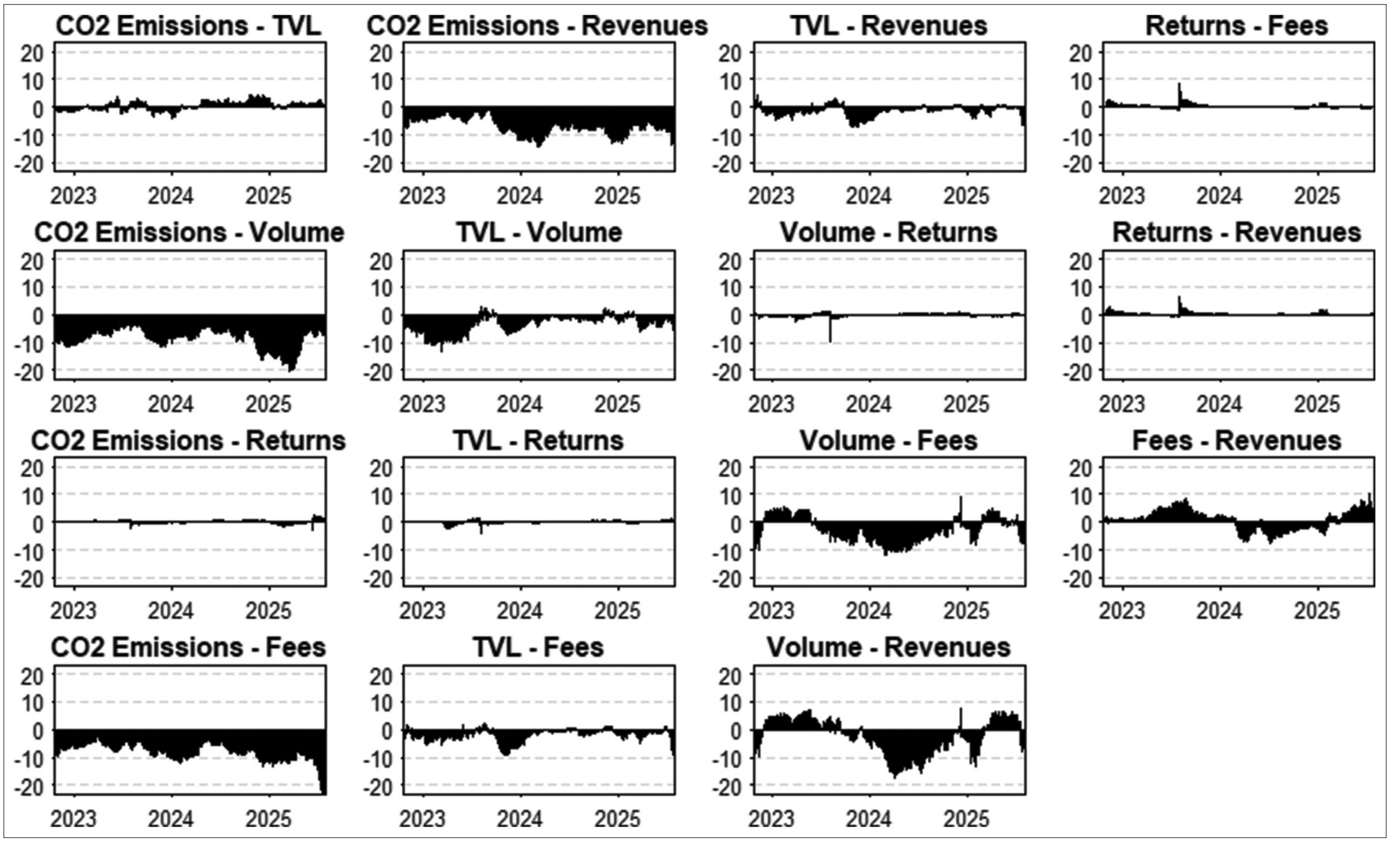


Table 6: Robustness test using 20-days ahead forecasting horizons

Indicators	CO_2 emissions	TVL	Volume	Returns	Fees	Revenues	From
CO_2 emissions	62.59	1.51	13.53	0.52	11.64	10.20	37.41
TVL	2.14	80.46	7.94	0.83	5.02	3.61	19.54
Volume	5.27	3.67	36.75	0.65	27.74	25.92	63.25
Returns	0.59	0.80	0.34	97.84	0.23	0.21	2.16
Fees	3.98	2.59	24.94	0.67	35.23	32.60	64.77
Revenues	3.92	1.96	23.51	0.57	33.40	36.64	63.36
TO	15.89	10.53	70.26	3.24	78.04	72.54	-
Inc.Own	78.48	90.99	107.00	101.08	113.27	109.18	cTCI/TCI
NET	−21.52	−9.01	7.00	1.08	13.27	9.18	50.10/41.75
NPT	2.00	0.00	2.00	4.00	4.00	3.00	

The model's residuals passed autocorrelation and normality checks, and the forecasting horizons for the system, confirming the robustness of fit.

5. CONCLUSION

This study focuses on DeFi operational activities in relation to climate change through CO_2 emissions with three research objectives that have been achieved. First, to analyze the dynamic relationship between decentralized finance operations and CO_2 emissions. Second, to analyze whether shocks from DeFi operations (TVL, volume, returns, fees and revenues) dynamically increase CO_2 emissions. Third, to assess the role of DeFi returns in strengthening the transmission of DeFi activities on CO_2 emissions. the testing was conducted using the TVP-VAR approach developed by Antonakakis and Gabauer (2017) based on daily data from October 20, 2022, to July 31, 2025. DeFi operational variables are represented by TVL, volume, returns, fees and revenues indicators. Meanwhile, climate change variables are represented by World CO_2 emissions from the power sector.

The analysis results have proven the research hypotheses by providing several insights that support and validate them. The first insight is that DeFi operations do have a dynamic relationship with climate change through CO_2 emissions, although only at a moderate level. This dynamic relationship is illustrated by the opened to shocks from CO_2 emissions themselves and the interconnection of several aspects of DeFi operations in general, namely Volume, Fees and Revenues. Second, from several indicators in DeFi operations, it proves Volume, Fees, and Revenues provide shocks (net transmitters) to CO_2 emissions, while TVL plays more of a role as a shock receiver (net receiver) similar to CO_2 emissions, and Returns do not provide much response to either net transmitters or net receivers. Note that Volume, Fees and Revenues also act as high shock receivers, while TVL and Returns are actually more dominated by internal idiosyncratic shocks. Third, the analysis results prove that Returns do not transmit many shocks/ transmissions to CO_2 emissions (almost neutral) and are more exogenous in nature. This demonstrates that Returns are more related to financial risk than to energy connectivity, so Returns in DeFi have a limited role in net transmitters and net receivers of CO_2 emissions.

This finding also reinforces EMT, which states that technological innovation can be both a source of solutions and a source of pressure on the surrounding environment, depending on the system used. This can be illustrated in DeFi operational activities, particularly the indicators of Volume, Fees and Revenues, which act as net transmitters of CO_2 emissions fluctuations. Showing that blockchain-based financial innovations such as DeFi are not yet completely free from environmental impacts. In addition, the results are also in line with the EKC, where in the early stages of DeFi development, an increase in activity or digital transaction volume tends to increase CO_2 emissions, before a decline occurs due to improved energy efficiency through the transition from PoW to PoS in the blockchain network. Note that DeFi is currently still in the early to middle stages of the EKC curve, where environmental impacts continue to increase. A turning point has not yet been reached, although there has been a slight shift toward reduced energy consumption, such as the energy transition from PoW to PoS by Ethereum. These results confirm the hypotheses of the EMT and EKC, whereby economic activity driven by DeFi initially increases emissions, but later declines as greener consensus mechanisms are adopted.

This study also has significant implications for regulators, industry practitioners and academics in balancing the advancement of DeFi with environmental sustainability. For regulators, the finding highlight the need to develop a Green FinTech Disclosure Framework to report the carbon footprint of DeFi activities, including emissions generated by consensus mechanisms and energy usage. Such a policy would enhance transparency and accountability in the digital finance sector while supporting the achievement of national emissions targets. For the industry, the results encourage DeFi operators to transition from energy-intensive PoW mechanisms to the more efficient PoS, or at least implement carbon offset schemes to compensate for emissions produced by DeFi operations through blockchain network. Finally, for academics, this research opens opportunities to develop cross-country DeFi models with climate analysis that can be more comprehensively assess the environmental impacts of DeFi activities across different contexts.

This study has several limitations. First, the data is limited and only covers DeFi operations within protocols with a TVL above $300 million. Second, the CO_2 emissions indicator data used only covers the world power sector. Third, this study uses the TVP-VAR approach, which only captures dynamic relationships without considering quantile levels. Therefore, with these limitations, future research is recommended to: (1) use another variable or indicators that more comprehensively cover DeFi operations or extend the scope, (2) use a different scope of CO_2 emissions other than the power sector or specific to a country, (3) use another approaches such as Quantile-in-Quantile Connectedness (QQC) or Granger Causality to gain broader new insights.

6. ACKNOWLEDGEMENT

Author Contribution

Sendy Sendy: Conceptualization, Data Collection, Data Analysis, Writing. Kevin Deniswara: Conceptualization, Review, Editing, Interpretation.

Data Availability

Dataset is available from the Mendeley Data, DOI: 10.17632/ g8cjc96cs2.1

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