QUALIFYING DECENTRALIZED FINANCE AS A FINANCIAL ASSET: A MULTIPLE FREQUENCY ANALYSIS

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Abstract

We examine the qualifying attributes of decentralized finance (DeFi) as a financial asset class. To achieve this objective, we perform analysis on the relationship (using both level and percentage-change data) between DeFi valuation and selected influencing variables, namely total value locked (TVL), Bitcoin (BTC) value, and market variables. A suite of long-panel data econometric methods is employed on a multi-frequency (daily, weekly, and monthly) panel dataset comprising 16 major DeFi protocols from January 2022 to December 2023. Our empirical design aims to be a comprehensive assessment and triangulation. There are several key findings. First, while there is evidence of cointegration suggesting a possible long-run relationship, this relationship is found to be inconsistent across different variables and time frequencies. However, the impulse response analysis suggests that shocks from the influencing variables do not have a permanent impact. Second, Bitcoin value is found to be the most important influencing factor (positive and highly significant), reflecting strong cryptocurrency market sentiment and aligning with previous research on spillover effects from major cryptocurrencies (Șoiman et al., 2022; Yousaf et al., 2022).

Keywords: Decentralized Finance, Financial Assets, Total Value Locked, Bitcoin, Market Variables, Panel Data Econometrics

Authors' individual contribution: Conceptualization — M.R.M.; Methodology — M.D.A.; Data Curation — M.R.M.; Writing — Original Draft — M.R.M.; Writing — Review & Editing — M.D.A.

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1. INTRODUCTION

The rising usage of decentralized finance (DeFi) has reshaped the financial landscape by providing decentralized, automated, and transparent alternatives to traditional financial systems. As a blockchain-based financial ecosystem, DeFi operates without intermediaries (Swan, 2015; Sobieraj, 2019; Saengchote, 2021; Almeida et al., 2022; Xu & Xu, 2022), enabling peer-to-peer transactions and financial services through smart contracts (Schär, 2021; Maouchi et al., 2022; Caldarelli & Ellul, 2021; Grassi et al., 2022). The emergence of DeFi as a distinct segment in the cryptocurrency market began with platforms like MakerDAO and Uniswap, which introduced decentralized stablecoins, flash loans (Qin et al., 2021; Chohan, 2021), and automated liquidity provision (Schär, 2021; Borisov, 2022), marking significant milestones in the development of the ecosystem.

In 2020, the "DeFi summer" phenomenon highlighted the explosive growth of total value locked (TVL) and trading activity, with the market capitalization of DeFi tokens surging from $1 billion to over $10 billion within months (Gudgeon et al., 2020; Allen, 2021). Since then, developers have continued expanding the ecosystem with innovations like Aave, which introduced flash loans; Compound, with governance token incentives; and

Synthetix, enabling synthetic asset trading (Chohan, 2021; Allen, 2021) and atomic swaps (Tefagh et al., 2020; Reiter, 2022).

Mechanisms like initial coin offerings (ICOs) further drove this growth, allowing developers to raise capital by issuing native tokens that grant governance rights, staking opportunities, or access to specific services (Zetzsche et al., 2020; Yousaf & Yarovaya, 2022). By late 2023, the number of DeFi wallet holders surpassed 6 million, while daily transaction volumes on major protocols exceeded $10 billion, reflecting the ecosystem's rapid adoption (Gudgeon et al., 2020). With such significant growth and innovation, the question arises: Can DeFi truly be classified as a financial asset class?

To be considered a financial asset class, DeFi must meet two essential criteria. First, it must possess inherent value, which in DeFi is represented by TVL — a metric measuring the total value of assets locked within protocols. Second, it must demonstrate significant correlations with other financial assets, indicating its integration with broader market dynamics. These two dimensions form the foundation of this study's investigation.

There are several variables that influence DeFi prices. Bitcoin (BTC) generally exhibits a significant influence on DeFi valuations, with most DeFi tokens showing a positive correlation due to BTC's liquidity and dominance in the cryptocurrency market (Șoiman et al., 2022). Macroeconomic indicators like the US dollar index (DXY) and volatility index (VIX) influence DeFi assets, reflecting their sensitivity to global risk sentiment, with periods of heightened risk aversion exerting negative pressure. The Federal Reserve's interest rates (FEDR) are also negatively correlated with DeFi valuations, as higher rates reduce investor appetite for riskier assets (Allen, 2021; Harwick & Caton, 2020). The S&P 500 index exhibits a limited connection with DeFi, suggesting partial integration with traditional financial markets (Yousaf et al., 2022).

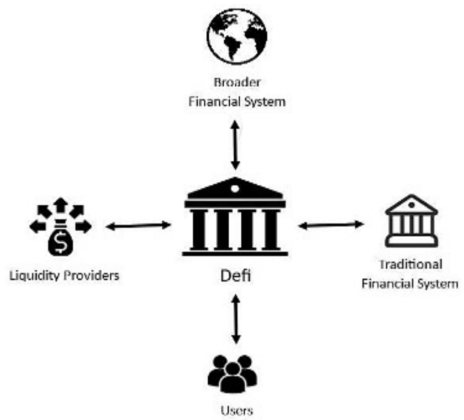
To analyze these interconnections, this study employs a robust methodological approach that examines two types of variables — level and percentage changes — across three frequencies: daily, weekly, and monthly. Using dynamic common correlated effects (DCCE) (Chudik & Pesaran, 2015) and panel vector autoregression (PVAR) (Abrigo & Love, 2016), the study captures both long-term equilibrium relationships and short-term dynamics. These methods provide a detailed and triangulated perspective on DeFi valuations, analyzing intrinsic value (TVL) and correlations with broader market variables. By employing this multifaceted approach, the study seeks to fill methodological gaps and offer a deeper understanding of DeFi's classification as a financial asset class.

The structure of this paper is as follows. Section 2 reviews the relevant literature on DeFi as a financial asset and develops the core hypotheses. Section 3 details the research methodology, including the data, sample selection, and the econometric models employed. Section 4 presents the empirical findings from our multi-frequency analysis. Section 5 discusses the research results. Section 6 concludes the paper by summarizing the key findings, discussing their implications, acknowledging the study's limitations, and suggesting avenues for future research.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Decentralized finance is now widely regarded as a new representation of financial assets, due to its ability to replicate various functions previously exclusive to traditional financial systems. The value within the DeFi ecosystem is derived from a combination of TVL, lending and borrowing activities, and revenue generated from transaction fees (Maouchi et al., 2022; Șoiman et al., 2022). TVL, as a key indicator of user trust and adoption, reflects the amount of assets users are willing to lock into a protocol, functioning similarly to deposits in the banking sector (Xu & Xu, 2022).

Figure 1. DeFi business model



However, DeFi's value does not end with TVL. DeFi tokens also exhibit high liquidity and can be traded globally 24/7 on decentralized exchanges, much like stocks and bonds on secondary markets (Chu et al., 2023; Schär, 2021). The high trading volume and continuous price discovery process indicate that these assets are actively traded and have deep markets.

Furthermore, DeFi tokens are often used as collateral in cross-protocol lending activities. Similar to how conventional assets such as stocks or real estate are pledged to secure loans, DeFi tokens are locked into smart contracts to access loans of other assets. Since DeFi systems do not rely on credit scoring, loans are over-collateralized as a form of risk management (Aramonte et al., 2021; Cornelli et al., 2024). This practice mirrors secured financing mechanisms in traditional finance.

Beyond liquidity and collateral functions, DeFi tokens offer passive income through staking, liquidity provision, and lending mechanisms. Much like bond interest or stock dividends, users earn returns on assets they "lock" into a protocol. Research by Schär (2021) shows that returns from staking and lending are often higher than those available in traditional financial channels, especially when market demand is high or real interest rates are low.

DeFi tokens also feature governance mechanisms resembling shareholder voting rights. Token holders can participate in decisions such as interest rate adjustments, protocol fees, and platform design changes (Metelski & Sobieraj, 2022). Liu et al. (2021) even note that some investors borrow tokens specifically to influence the outcomes of major votes. In this sense, tokens serve both as investment instruments and governance tools.

From an investment perspective, DeFi tokens exhibit risk-return profiles comparable to high-risk assets such as growth stocks or commodities. Piñeiro-Chousa et al. (2022) found that DeFi can act as a safe haven asset under certain conditions, although other studies show correlations with traditional market shocks, especially during periods of extreme volatility.

Overall, empirical evidence shows that DeFi tokens fulfill many of the essential roles of financial assets: they are tradable, can be used as collateral, generate yield, and offer governance rights — all within a decentralized blockchain-based framework.

Considering these dimensions, DeFi deserves to be positioned as a digital asset class functionally equivalent to stocks and bonds in the conventional financial system. However, previous studies often relied on static cross-sectional methods or lacked high-frequency validation, which limits their ability to capture dynamic shifts in DeFi valuation. Furthermore, few papers critically assess the role of TVL as a valuation anchor across different timeframes. This study seeks to address these gaps by employing a multi-frequency panel econometric approach to evaluate both short-term and long-term interactions between DeFi valuations and key financial indicators.

3. METHODOLOGY

This study focuses on 16 DeFi protocols that collectively represent approximately 65.66% of the total TVL, valued at $163 billion as of January 2022 (DefiLlama). The selected protocols reflect a diverse composition of the DeFi ecosystem, including large-scale protocols with TVL exceeding $1 billion, such as MakerDAO ($17.50 billion), TRON ($5.21 billion), Raydium ($1.55 billion), Lido ($11.93 billion), Compound ($14.94 billion), Uniswap ($8.37 billion), Aave ($27.30 billion), PancakeSwap ($7.89 billion), SushiSwap ($4.16 billion), Venus ($2.04 billion), Liquity ($1.81 billion), and JustCryptos ($1.43 billion). Additionally, medium-scale protocols with TVL between $200 million and $1 billion include RocketPool ($371.36 million), Osmosis ($854.20 million), and Beefy Finance ($981.27 million). Pendle, with a TVL of $33.83 million, is also included to capture the market dynamics of smaller protocols. Lastly, the selection of DeFi protocols is also aimed at the widest coverage possible (data availability). Variables employed in the study are described as follows.

Table 1. Variables measurement description

Category	*Variables*
At the level of data	*LOG_P* (log of DeFi price), *TVLMR* (TVL to market cap ratio), *L_BTC* (Bitcoin price), *L_SP500* (S&P 500 index), *L_DXY* (US dollar index), *L_VIX* (Volatility index), *FEDR* (Federal Reserve rate)
Return data	*R_Price* (return of DeFi price), *R_TVLMR* (return of *TVLMR*), *R_BTC* (return of Bitcoin price), *R_SP500* (return of S&P 500 index), *R_DXY* (return of *DXY*), *R_VIX* (return of *VIX*), *FEDR* (Federal Reserve rate)

We use *TVLMR* because this ratio normalizes TVL by market capitalization, serving as a proxy for the "book-to-market ratio" (Șoiman et al., 2022).

The period from January 2022 to December 2023 was selected as it captures critical phases in the DeFi ecosystem, including the bullish phase at the start of 2022, the significant downturn during the 2022 crypto winter, and the stable recovery throughout 2023. Notably, this timeframe also coincided with significant geopolitical turmoil, particularly the Russia-Ukraine war, which is known to have induced extreme volatility across global financial markets and impacted investor sentiment toward risk assets, including the cryptocurrency and DeFi sectors.

This timeframe ensures consistent and comprehensive data availability across 16 protocols, with a total of 11,680 daily observations, 1,664 weekly observations, and 384 monthly observations, enabling the analysis of short-term volatility and long-term equilibrium relationships within the DeFi market.

The preliminary analysis begins by summarizing the dataset's key characteristics using descriptive statistics, including measures such as mean, standard deviation, and range for both level and return variables. Pairwise correlation matrices are constructed to examine the initial relationships between variables. To further assess the properties of the data, we conduct stationarity tests to determine whether the variables exhibit unit roots. We perform a unit root test. For time series data, Bitcoin (*L_BTC*), *VIX* (*L_VIX*), *DXY* (*L_DXY*), and *FEDR*, we employ the Dickey-Fuller unit root test. For unit root testing, the maximum lag length was determined using the formula maximum *lag = floor T1 / 3*, where T is the number of time periods. For monthly data with *T = 24T = 24*, the calculation yielded.

$$Floor\left(2^{\frac{1}{3}}\right) = Floor(2.884) = 2 \tag{1}$$

Similarly, for weekly (*T = 104T = 104*) and daily (*T = 730T = 730*) data, the maximum lags were set to 4 and 8, respectively (Andrews & Lu, 2001).

For panel-type variables *LOG_P, TVLMR, L_SP500, R_Price, R_TVLMR, R_BTC, R_SP500, R_DXY,* and *R_VIX,* we employ Pesaran's cross-section dependence augmented Dickey-Fuller test. We employ cross-section dependence augmented Dickey-Fuller (Pesaran, 2007). Lastly, we check for the presence of cross-section dependence with the test developed by Pesaran (2004).

$$Defi_{it} = \beta_0 + \beta_1 TVMR_{it} + \beta_2\, BTC_t + \beta_3 VIX_t + \beta_4\, DXY_{it} + \beta_5\, SP500_{it} + \beta_6\, FEDR_t + \varepsilon_{it} \tag{2}$$

The above regression is implemented in level and percentage changes form for daily, weekly, and monthly frequency. For level regression, we implement the DCCE procedure, and for percentage changes, we employ the PVAR procedure. This results in six empirical schemes. For level regression, we perform the following procedure:

1) Slope heterogeneity (Pesaran & Yamagata, 2008; Blomquist & Westerlund, 2013);
2) Cointegration test (Westerlund, 2005);
3) Appropriate DCCE type regression based on the result of unit root, cross-section dependence, slope heterogeneity, and cointegration as explained above (Chudik & Pesaran, 2015).

For return regression, we perform the following procedure:

1) Lag determination (Andrews & Lu, 2001);
2) PVAR estimation (Abrigo & Love, 2016);
3) Stability test (Abrigo & Love, 2016).
4) Impulse response function (IFR) only for PVAR that met the stability test (Abrigo & Love, 2016).

To assess the data's properties, unit root tests are conducted to determine variable stationarity, followed by slope heterogeneity tests to evaluate variations across protocols, cross-section dependence tests to identify interdependencies among cross-sections, and pairwise correlation tests to measure variable associations. Cointegration tests further establish long-term equilibrium relationships between DeFi prices and other influential variables.

For a comprehensive analysis, the DCCE methodology (Chudik & Pesaran, 2015) is applied to level data in order to account for cross-sectional dependence and to capture potential long-term equilibrium relationships among variables. In contrast, PVAR (Abrigo & Love, 2016) is employed using return data to investigate short-term dynamic interactions within the DeFi ecosystem. Furthermore, IRF analysis (Abrigo & Love, 2016) is conducted to assess the temporal impact of shocks in key independent variables — such as *BTC, DXY*, and *TVLMR* — on DeFi returns. The stability of the PVAR model is evaluated using eigenvalue stability conditions, ensuring that the results are both robust and reliable.

By integrating both long-term and short-term econometric approaches across multiple frequencies (daily, weekly, and monthly), this study offers a comprehensive and nuanced perspective on the factors influencing DeFi valuations. Data for TVL, Bitcoin prices, DeFi prices, *SP500*, *VIX, DXY*, and *FEDR* were sourced from TradingView. The diverse range of TVL values, spanning from over $1 billion to tens of millions, captures varying dynamics across protocols and enriches the analysis.

These methodological procedures — ranging from unit root testing to PVAR stability diagnostics — serve not only as model construction tools but also as internal robustness checks. They ensure that the empirical results are statistically sound across different data structures and time frequencies. Although external robustness checks such as sub-sample analysis or alternative indicators were not conducted, the triangulation across daily, weekly, and monthly data frequencies helps reinforce the validity and generalizability of the findings.

While this study employs DCCE and PVAR models, several alternative methods would be suitable for conducting this research. For instance, to more rigorously address potential endogeneity and causality, methodologies such as the generalized method of moments (GMM) or an instrumental variables approach could be utilized.

4. RESULTS

4.1. Descriptive statistics

The first step involves calculating descriptive statistics to provide an overview of the collected data characteristics. For daily data, the average *LOG_P* is 1.37, with a standard deviation of 1.90, indicating significant volatility in DeFi price levels. Meanwhile, the average and standard deviation of *TVLMR* are 6.25 and 7.00, reflecting substantial variation. For weekly data, the average *LOG_P* is 3.13, with a standard deviation of 4.38, showing higher volatility than daily data, while *R_TVLMR* has a standard deviation of 116%, indicating significant variability. For monthly data, the average *LOG_P* is 1.37, with a standard deviation of 1.90, reflecting more moderate volatility, while *R_Price* has a standard deviation of 19%, lower than other frequencies.

The pairwise correlation analysis across daily, weekly, and monthly data frequencies reveals consistent and significant relationships between DeFi valuations and several key market indicators. In the daily level data, *TVLMR* and *LOG_P* exhibit the strongest positive correlation (0.4852, $p < 0.01$), suggesting that higher liquidity in DeFi protocols is closely associated with increased DeFi price levels. Conversely, *L_DXY* shows a strong negative correlation with Bitcoin (-0.7089, $p < 0.01$), indicating that DeFi assets are sensitive to global macroeconomic conditions.

For daily return data, *R_BTC* positively correlates with *R_Price* (0.2442, $p < 0.01$), confirming Bitcoin's influence on DeFi, while *R_TVLMR* negatively correlates (-0.232, $p < 0.01$), indicating liquidity does not always drive short-term gains. Weekly level data shows *L_BTC* strongly correlates with *L_SP500* (0.7819, $p < 0.01$), reinforcing crypto-traditional market ties, while *L_DXY* negatively correlates with *L_BTC* (-0.7086, $p < 0.01$), highlighting macroeconomic impact. Weekly return data also support *R_BTC's* positive link to *R_Price* (0.0794, $p < 0.01$), the unit root test statistic for *LOG_P* is -2.384 ($p < 0.01$), and for *TVLMR* is -2.497 ($p < 0.01$), confirming non-stationarity. In contrast, return variables such as *R_Price* have a value of -6.19 ($p < 0.01$), indicating strong stationarity. For weekly data, the value for *LOG_P* is -1.905 (not significant), while the value for *TVLMR* is -2.290 ($p < 0.01$), showing the presence of a unit root. However, return variables such as *R_Price* yield a value of -4.025 ($p < 0.01$), confirming stationarity. Similar results are observed for monthly data, where the value for *LOG_P* is -1.795 (not significant), while *TVLMR* has a value of -2.356 ($p < 0.01$), indicating non-stationary data. Return variables such as *R_Price* exhibit a value of -2.271 ($p < 0.01$), indicating stationarity.

Table 2. Slope heterogeneity test and cointegration test

Variable	*Daily slope*	*Weekly slope*	*Monthly slope*	*Daily cointegration*	*Weekly cointegration*	*Monthly cointegration*
Baseline	561.772***	75.46***	11.651***	-1.355*	-0.307***	-0.6464
L_BTC	190.22***	24.518***	4.085*	4.6396***	-0.111***	4.7594***
TVLMR	334.997***	44.081***	9.81*	0.8225	-0.8724	1.3058*
L_SP500	128.35***	15.784***	1.409	3.8862***	-0.0950***	4.8675***
L_VIX	333.601***	44.796***	6.988*	-1.5258*	-0.0925***	-0.4149
L_DXY	159.347***	20.662***	3.17*	2.2041**	-0.0924***	2.0662**
FEDR	553.088***	76.812***	15.838***	-3.3437***	-0.0977***	-3.2037***

*Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.*

The slope heterogeneity test shows significant variability in slope coefficients across cross-sectional units, particularly in daily and weekly data. For daily data, all variables are significant at the 1% level ($p < 0.01$) except *L_SP500*, which is not significant. Weekly data confirms consistent heterogeneity, with all variables significant at the 1% level. At the monthly frequency, most variables remain significant, but *L_SP500* becomes insignificant, indicating reduced heterogeneity at lower frequencies.

The cointegration test confirms long-term relationships for most variables. In daily data, *BTC*, *SP500*, and *FEDR* are significant at the 1% level, while *DXY* is significant at the 5% level and *VIX* is significant at the 10% level ($p < 0.10$). Analysis of weekly data shows that most variables are significant at the 1% level, indicating stable equilibrium adjustments. However, a key exception is *TVLMR*, which is found to be statistically insignificant with a test value of -0.8724. For monthly data, *BTC*, *SP500*, and *FEDR* remain highly significant at the 1% level, *DXY* is significant at the 5% level, and *TVLMR* is significant at the 10% ($p < 0.10$). Meanwhile, *VIX* becomes insignificant in the monthly analysis.

4.2. At level panel regression (DCCE)

From the result, we identified both long-term relationships and transient short-term dynamics. Key findings reveal that *BTC*, *SP500*, *DXY*, and *FEDR* significantly influence DeFi valuations *(LOG_P)* in the long term. While the DCCE results also show a statistically significant error correction mechanism (ECM) for *TVLMR*, its role as a consistent long-term anchor is challenged by other findings, such as its insignificance in the weekly cointegration test. Short-term analysis highlights Bitcoin's strong but temporary positive impact on DeFi returns, with macroeconomic shocks initially depressing prices before stabilization. Crucially, this combination of results suggests DeFi's price movements are dominated by speculative behavior rather than intrinsic value.

The results from DCCE reinforce these findings by capturing both short-term dynamics and long-term equilibrium adjustments. The error correction (EC) coefficients indicate that the monthly data exhibits the fastest corrections, with EC values ranging from -0.774 to -0.387, suggesting 1.3 months (= 1 / 0.774) to 2.6 months (= 1 / 0.387) of adjustment. Weekly data shows moderate correction speeds, with EC values between -0.307 and -0.092, suggesting 3.3 weeks (= 1 / 0.307) to 10.9 weeks (= 1 / 0.092) of adjustment, while daily data reflects the slowest adjustments, with EC coefficients between -0.0618 and -0.0199, suggesting 2.3 weeks (≈ 16.2 days) to 7.2 weeks (≈ 50.3 days) of adjustment. These differences highlight that DeFi market dynamics vary significantly across different time frequencies, where short-term fluctuations are more pronounced, but long-term equilibrium adjustments are stronger at the monthly level.

Table 3. Dynamic common correlated effects

Variables	*Daily ECM*	*Weekly ECM*	*Monthly ECM*
Baseline	-0.0618***	-0.307***	-0.774***
TVLMR	-0.0258***	-0.125***	-0.482***
BTC	-0.0236***	-0.111***	-0.416***
SP500	-0.0204***	-0.0950***	-0.409***
VIX	-0.0207**	-0.0925***	-0.446***
DXY	-0.0199***	-0.0924***	-0.387***
FEDR	-0.0228**	-0.0977***	-0.450***

*Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.*

For the daily ECM, the results show that all variables, except *VIX* and *FEDR*, are significant at the 1% level, while *VIX* and *FEDR* are significant at the 5% level. In the weekly ECM, all variables, including *TVLMR*, *BTC*, *SP500*, *VIX*, *DXY*, and *FEDR*, are significant at the 1% level, indicating robust adjustment dynamics in the weekly data. Similarly, for the monthly ECM, all variables are significant at the 1% level, with the EC terms becoming more pronounced compared to the daily and weekly frequencies. The adjustment rates increase with lower data frequency, suggesting faster convergence to the long-term equilibrium in monthly data.

These findings challenge the conventional reliance on *TVLMR* as a valuation anchor, urging scholars to explore alternative metrics such as liquidity depth or protocol utility. Investors should approach DeFi with caution, limiting portfolio exposure due to its high volatility and prioritizing dynamic strategies to capitalize on short-term opportunities linked to Bitcoin's price movements. Regulators must enhance transparency frameworks for TVL reporting to mitigate risks of inflated metrics and closely monitor macroeconomic variables (e.g., *DXY*, *FEDR*) to anticipate systemic shocks. Future research should investigate investor behavior in balancing speculative trading with long-term DeFi holdings, particularly during market stress. Additionally, exploring alternative metrics like Total Value Redeemable (TVR) or protocol-specific utility scores could refine DeFi valuation models. Methodological extensions, such as machine learning applications to capture nonlinear interactions between DeFi and macroeconomic variables, and assessments of regulatory interventions on DeFi's risk-return profile, would further deepen our understanding of this evolving ecosystem.

4.3. At return panel regression (PVAR)

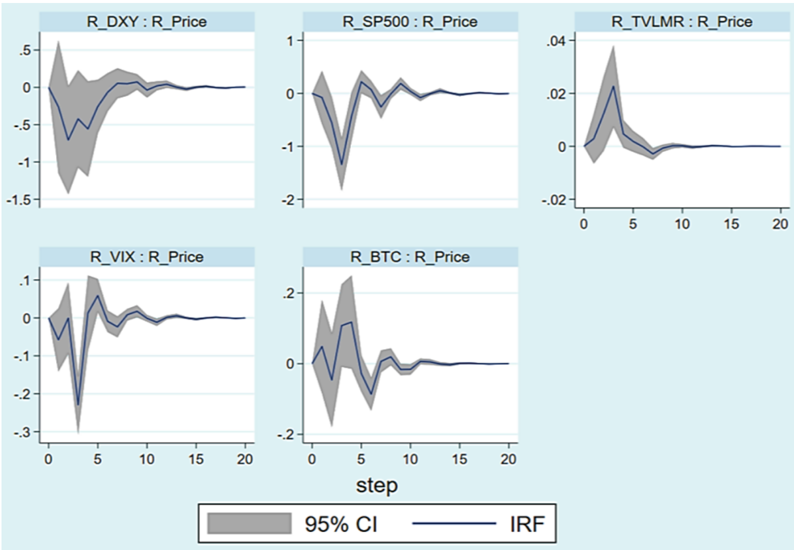
Impulse response function (IRF) analysis from PVAR results shows that DeFi returns (*R_Price*) react significantly to Bitcoin price shocks, with the effect peaking within the first few periods before dissipating. *SP500* and *DXY* also have a temporary influence on DeFi returns, with *SP500* showing contrasting effects across time horizons.

In the weekly analysis, *SP500* has a negative impact on DeFi returns, suggesting that short-term equity market gains may lead to capital outflows from DeFi. However, in the monthly analysis, the relationship turns positive, indicating that over longer periods, DeFi integrates more closely with traditional financial markets. *DXY* exhibits a strong negative impact on DeFi returns in both weekly and monthly analyses, suggesting that a stronger US dollar reduces investor interest in speculative assets like DeFi. *TVLMR's* influence on DeFi returns remains minimal across all time frequencies, further reinforcing its weak role as a valuation determinant. *VIX* shows an initial negative effect on DeFi returns, indicating that increased market volatility pressures

DeFi prices downward, but its influence diminishes over time. Bitcoin remains the most significant driver of DeFi price movements, with a strong but short-lived positive effect, reinforcing the idea that DeFi valuations are closely tied to broader cryptocurrency trends rather than intrinsic factors. The variance decomposition analysis confirms that Bitcoin is the primary driver of DeFi return fluctuations, followed by macroeconomic variables like *DXY* and *FEDR*. Additionally, the long-term relationships observed in the analysis appear to be spurious, as responses eventually revert to zero, suggesting that the impact of these variables does not persist over time.

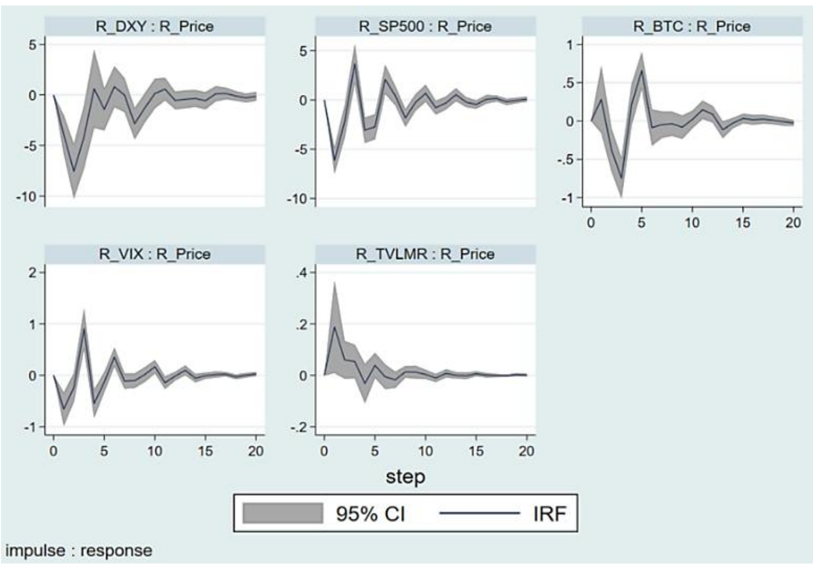
The PVAR analysis applied to stationary return data provides insights into how DeFi valuations respond to shocks in key variables, with model stability confirmed for both weekly and monthly data (stability test results are presented in Appendix B). The eigenvalue stability condition shows that the system is stable only for weekly data with the largest eigenvalue modulus at 0.753, and for monthly data at 0.832, both falling within the unit circle. This validation ensures that the IRF results accurately capture the dynamic relationships between *R_Price* and external/internal factors.

Figure 2. Weekly impulse response



For weekly data, shocks to *R_DXY* and *R_SP500* initially cause a significant negative impact on *R_Price*, stabilizing near zero between periods 10 to 20. This suggests that negative macroeconomic shocks, such as currency strength or the stock market. Volatility temporarily depresses DeFi asset values but does not lead to permanent declines. Conversely, a unit shock to *R_BTC* results in a strong but temporary positive effect, peaking at period 5 before returning to equilibrium. Shocks to *R_TVLMR* have a small yet significant impact, stabilizing more rapidly than other variables, while *R_VIX* shocks remain statistically insignificant with minimal fluctuations.

Figure 3. Monthly impulse response



For monthly data, the responses are more pronounced, with some notable differences compared to weekly results. A unit shock to *R_DXY* results in a strong negative impact on *R_Price* during months 1 to 2, stabilizing after month 5. Similarly, shocks to *R_SP500* initially exert a negative influence but gradually stabilize, with a small positive effect emerging after month 5. However, unlike in weekly data, the longer-term influence of *SP500* becomes positive, suggesting a growing integration of DeFi with traditional financial markets over extended periods. In contrast, shocks to *R_BTC* lead to a substantial positive impact, peaking in month 2 before returning to zero by month 10, emphasizing Bitcoin's role as a key driver of DeFi prices. *R_TVLMR* continues to exhibit a minor but significant effect, stabilizing by month 3, while *R_VIX* remains weak and statistically insignificant throughout the analysis.

5. DISCUSSION

The results of the DCCE analysis indicate the presence of a statistically significant long-term relationship between DeFi prices (*LOG_P*) and several key variables, though the consistency of these relationships varies across different time frequencies. While variables like *BTC*, the *SP500*, and *FEDR* show fairly consistent significance, there are notable exceptions. For instance, *TVLMR* lacks a significant long-term relationship in the weekly data, and *VIX* becomes insignificant at the monthly frequency. Despite these inconsistencies, the estimated EC rates, particularly at the monthly frequency, suggest a strong adjustment mechanism toward long-term equilibrium for the significant variables, potentially reflecting an underlying structural stability within the DeFi ecosystem.

However, the findings from the PVAR model reveal that this perceived long-term relationship may be superficial: short-term responses are highly volatile and mean-reverting, eventually converging to zero. Notably, Bitcoin exerts a significant positive influence on DeFi returns in the short run — a result consistent with the findings of Șoiman et al. (2022) and Yousaf et al. (2022), both of whom emphasize the dominant spillover effects from major cryptocurrencies. However, this effect dissipates rapidly, suggesting that the impact is speculative rather than grounded in fundamental value.

In contrast, *TVLMR*, often regarded as a key fundamental in DeFi valuation (Stepanova & Eriņš, 2021), exhibits a negative short-term impact in this study. This finding, compounded by the lack of a consistent long-term cointegrating relationship — as evidenced by its statistical insignificance in the weekly data — challenges earlier assertions that TVL functions as a stable valuation anchor for DeFi protocols (Maouchi et al., 2022).

These results highlight the dominance of short-term fluctuations over meaningful long-term stability, consistent with research that underscores the speculative nature of DeFi and broader crypto markets (Corbet et al., 2021; Grassi et al., 2022). Macroeconomic shocks — such as movements in the *SP500* or *DXY* — exert only transient effects, which aligns with the findings of Baur and McDermott (2013) and Yousaf et al. (2022), who report that crypto assets respond rapidly to global risk sentiment but lack persistent linkages with traditional financial markets.

Although the cointegration analysis through the DCCE method suggests the presence of long-term relationships for many of the selected market variables, the short-term analysis using PVAR reveals that these relationships are temporary and quickly dissipate. This apparent contradiction does not necessarily imply a fundamental inconsistency; rather, it highlights that while DeFi valuations may theoretically align with certain market fundamentals in the long run, short-term DeFi markets are predominantly influenced by speculative sentiment, leading to high volatility and temporary effects. Future studies should explicitly address issues of endogeneity and causality more rigorously by employing methodologies such as instrumental variables or the GMM approach to clarify these fundamental relationships.

As a result, DeFi continues to operate as a high-risk environment, prompting many investors to restrict their exposure to a small share of their portfolios. In light of these dynamics, future studies may benefit from deeper exploration of investor behavior, particularly in terms of position management and exit strategies under varying levels of market volatility (Harwick & Caton, 2020).

6. CONCLUSION

DeFi exhibits characteristics of a financial asset by analyzing its relationship with key market indicators (*TVLMR, BTC, SP500, DXY, VIX*, and *FEDR)*. Utilizing DCCE (Chudik & Pesaran, 2015) and PVAR (Abrigo & Love, 2016) across daily, weekly, and monthly frequencies (January 2022 to December 2023), the results indicate that *BTC* has a significant but short-lived influence on DeFi valuations (*LOG_P*), reinforcing the view that DeFi prices are primarily driven by speculative activity rather than intrinsic fundamentals. Meanwhile, the role of *TVLMR* as a core valuation metric is challenged by mixed evidence; while it exhibits a statistically significant long-term correction mechanism in the DCCE model, it lacks a persistent association in the weekly cointegration test, questioning its reliability in determining DeFi's market value.

The DCCE analysis confirms the presence of strong cross-sectional dependence and reveals varying speeds of price correction across time frequencies. Monthly data demonstrates the most rapid correction rates, with EC coefficients ranging from -0.774 to -0.387, suggesting robust long-term equilibrium adjustments. Weekly data shows moderate correction dynamics (EC values between -0.307 and -0.092), whereas daily data exhibits the weakest adjustment speeds (EC coefficients between -0.0618 and -0.0199). This implies that while long-term DeFi price adjustments for most variables appear efficient, the inconsistent findings for *TVLMR* suggest that short-term movements remain highly volatile and speculation-driven, further undermining its role as a stable price anchor.

The results from PVAR and IRF analyses further validate these conclusions. Bitcoin emerges as the dominant short-term driver, with effects that peak within the first few lags and then quickly dissipate — indicating temporary speculative reactions rather than fundamental value creation (Șoiman et al., 2022; Yousaf et al., 2022). Both *SP500* and *DXY* show transitory effects on DeFi returns, with *SP500* having contradictory time-based impacts — negative in the weekly model, but positive in the monthly model. This duality suggests that DeFi may act as a substitute for equities in short-term rallies but evolves into a complementary asset class amid long-term institutional integration (Yousaf et al., 2022). Meanwhile, *DXY* exerts a consistently negative influence on DeFi returns across weekly and monthly scales, reinforcing the notion that a strong US dollar suppresses appetite for speculative assets. *TVLMR*, across all time frequencies, remains largely insignificant. The *VIX* initially shows a negative impact but quickly loses significance, suggesting that general market volatility plays only a limited role in DeFi price behavior.

This study has several limitations, primarily related to the methodological approaches employed. Specifically, the DCCE and PVAR models demonstrated limited capability in effectively capturing daily-level dynamics due to excessive noise and volatility inherent in high-frequency DeFi data. Consequently, the daily-level analysis may contain biases or less reliable estimations compared to weekly and monthly frequencies. The inconsistent role of *TVLMR* — found to be insignificant in certain long-term contexts (e.g., weekly cointegration) and largely insignificant in short-term dynamics — might be attributable to market manipulation, measurement errors, or fundamental differences between nominal TVL and actual liquidity conditions. Future research is advised to apply alternative econometric or statistical methods specifically designed to mitigate noise and volatility, such as wavelet analysis, frequency-domain approaches, or advanced filtering techniques. Moreover, future studies may explore the use of alternative liquidity proxies — such as liquidity-adjusted TVL or TVR — to better reflect true market conditions and enhance valuation accuracy.

REFERENCES

Abrigo, M. R. M., & Love, I. (2016). Estimation of panel vector autoregression in Stata. *The Stata Journal: Promoting Communications on Statistics and Stata, 16*(3), 778–804. https://doi.org/10.1177/1536867X1601600314

Allen, D. E. (2021). *Cryptocurrencies, diversification and the COVID-19 pandemic* (MPRA Paper No. 111735). Munich Personal RePEc Archive (MPRA). https://mpra.ub.uni-muenchen.de/111735/1/MPRA_paper_111735.pdf

Almeida, J., & Gonçalves, T. C. (2022). A systematic literature review of volatility and risk management on cryptocurrency investment: A methodological point of view. *Risks, 10*(5), Article 107. https://doi.org/10.3390/risks10050107

Andrews, D. W. K., & Lu, B. (2001). Consistent model and moment selection criteria for GMM estimation with application to dynamic panel data models. *Journal of Econometrics, 101*(1), 123–164. https://doi.org/10.1016/S0304-4076(00)00077-4

Aramonte, S., Huang, W., & Schrimpf, A. (2021). DeFi risks and the decentralization illusion. *BIS Quarterly Review*, 21–36. https://www.bis.org/publ/qtrpdf/r_qt2112b.pdf

Baur, D. G., & McDermott, T. K. J. (2013). *Financial turmoil and safe haven assets*. https://doi.org/10.2139/ssrn.2004796

Blomquist, J., & Westerlund, J. (2013). Testing slope homogeneity in large panels with serial correlation. *Economics Letters, 121*(3), 374–378. https://doi.org/10.1016/j.econlet.2013.09.012

Borisov, S. (2022). DeFi — Potential, advantages and challenges. *Economic Studies, 31*(4), 33–54. https://www.researchgate.net/publication/361890666_DeFi-Potential_Advantages_and_Challenges

Caldarelli, G., & Ellul, J. (2021). The blockchain oracle problem in decentralized finance — A multivocal approach. *Applied Sciences, 11*(16), Article 7572 https://doi.org/10.3390/app11167572

Chohan, U. W. (2021). *Decentralized finance (DeFi): An emergent alternative financial architecture*. https://doi.org/10.2139/ssrn.3791921

Chu, J., Chan, S., & Zhang, Y. (2023). An analysis of the return-volume relationship in decentralised finance (DeFi). *International Review of Economics & Finance, 85*, 236–254. https://doi.org/10.1016/j.iref.2023.01.006

Chudik, A., & Pesaran, M. H. (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of Econometrics, 188*(2), 393–420. https://doi.org/10.1016/j.jeconom.2015.03.007

Corbet, S., Goodell, J. W., Gunay, S., & Kaskaloglu, K. (2021). *Are DeFi tokens a separate asset class from conventional cryptocurrencies?* https://doi.org/10.2139/SSRN.3810599

Cornelli, G., Gambacorta, L., Garratt, R., & Reghezza, A. (2024, November 15). *Decoding DeFi lending: Motivations, risks, and investor behaviours*. Centre for Economic Policy Research (CEPR). https://cepr.org/voxeu/columns/decoding-defi-lending-motivations-risks-and-investor-behaviours

Grassi, L., Lanfranchi, D., Faes, A., & Renga, F. M. (2022). Do we still need financial intermediation? The case of decentralized finance — DeFi. *Qualitative Research in Accounting & Management, 19*(3), 323–347. https://doi.org/10.1108/QRAM-03-2021-0051

Gudgeon, L., Perez, D., Harz, D., Livshits, B., & Gervais, A. (2020). The decentralized financial crisis. In *2020 Crypto Valley Conference on Blockchain Technology* (pp. 1–15). Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1109/CVCBT50464.2020.00005

Harwick, C., & Caton, J. (2020). What's holding back blockchain finance? On the possibility of decentralized autonomous finance. *The Quarterly Review of Economics and Finance, 84*, 420–429. https://doi.org/10.1016/J.QREF.2020.09.006

Liu, Y., Lu, Q., Zhu, L., Paik, H. Y., & Staples, M. (2021). *A systematic literature review on blockchain governance*. arXiv. https://doi.org/10.48550/arxiv.2105.05460

Maouchi, Y., Charfeddine, L., & El Montasser, G. (2022). Understanding digital bubbles amidst the COVID-19 pandemic: Evidence from DeFi and NFTs. *Finance Research Letters, 47*(Part A), Article 102584. https://doi.org/10.1016/J.FRL.2021.102584

Metelski, E., & Sobieraj, J. (2022). Decentralized finance (DeFi) projects: A study of key performance indicators in terms of DeFi protocols' valuations. *International Journal of Financial Studies, 10*(4), Article 108. https://doi.org/10.3390/ijfs10040108

Pesaran, M. H. (2004). *General diagnostic tests for cross section dependence in panels* (Discussion Paper No. 1240). Institute of Labor Economics (IZA). https://doi.org/10.2139/ssrn.572504

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics, 22*(2, special issue), 265–312. https://doi.org/10.1002/jae.951

Pesaran, M. H., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics, 142*(1), 50–93. https://doi.org/10.1016/j.jeconom.2007.05.010

Piñeiro-Chousa, J., López-Cabarcos, M. A., Sevic, A., & González-López, I. (2022). A preliminary assessment of the performance of DeFi cryptocurrencies in relation to other financial assets, volatility, and user-generated content. *Technological Forecasting and Social Change, 181*, Article 121740. https://doi.org/10.1016/j.techfore.2022.121740

Qin, K., Zhou, L., Livshits, B., & Gervais, A. (2021). Attacking the DeFi ecosystem with flash loans for fun and profit. In N. Borisov & C. Diaz. (Eds.), *Financial cryptography and data security* (pp. 3–32). Springer. https://doi.org/10.1007/978-3-662-64322-8_1

Reiter, J. (2022). *Atomic swaps as options: A derivative finance approach*. https://doi.org/10.2139/ssrn.4127846

Saengchote, K. (2021). *Where do DeFi stablecoins go? A closer look at what DeFi composability really means*. https://doi.org/10.2139/ssrn.3893487

Schär, F. (2021). Decentralized finance: On blockchain- and smart contract-based financial markets. *Federal Reserve Bank of St. Louis Review, 103*(2), 153–174. https://doi.org/10.20955/r.103.153-74

Sobieraj, J. (2019). *The fourth industrial revolution*. Aurum Universitas.

Șoiman, F., Dumas, G., & Jimenez-Garces, S. (2022). *The return of (I)DeFiX*. arXiv. https://doi.org/10.48550/arXiv.2204.00251

Stepanova, V., & Eriņš, I. (2021). Review of decentralized finance applications and their total value locked. *TEM Journal, 10*(1), 327-333. https://doi.org/10.18421/TEM101-41

Swan, M. (2015). *Blockchain: Blueprint for a new economy*. O'Reilly Media.

Tefagh, M., Bagheri, F., Khajehpour, A., & Abdi, M. (2020). Atomic bonded cross-chain debt. In *Proceedings of the 2020 3rd International Conference on Blockchain Technology and Applications* (pp. 50–54). Association for Computing Machinery (ACM). https://doi.org/10.1145/3446983.3446987

Westerlund, J. (2005). New simple tests for panel cointegration. *Econometric Reviews, 24*(3), 297–316. https://doi.org/10.1080/07474930500243019

Xu, T. A., & Xu, J. (2022). A short survey on business models of decentralized finance (DeFi) protocols. In S. Matsuo, L. Gudgeon, A. Klages-Mundt, D. Perez Hernandez, S. Werner, T. Haines, A. Essex, A. Bracciali, & M. Sala (Eds.), *Financial cryptography and data security. FC 2022 international workshops* (pp. 197–206). Springer. https://doi.org/10.1007/978-3-031-32415-4_13

Yousaf, I., & Yarovaya, L. (2022). Static and dynamic connectedness between NFTs, DeFi and other assets: Portfolio implication. *Global Finance Journal, 53,* Article 100719. https://doi.org/10.1016/j.gfj.2022.100719

Yousaf, I., Nekhili, R., & Gubareva, M. (2022). Linkages between DeFi assets and conventional currencies: Evidence from the COVID-19 pandemic. *International Review of Financial Analysis, 81*, Article 102082. https://doi.org/10.1016/j.irfa.2022.102082

Zetzsche, D. A., Arner, D. W., & Buckley, R. P. (2020). Decentralized finance. *Journal of Financial Regulation, 6*(2), 172–203. https://doi.org/10.1093/jfr/fjaa010

APPENDIX A

Table A.1. Descriptive statistics at the daily level (logarithmic)

Statistic	*LOG_P*	*TVLMR*	*L_BTC*	*L_VIX*	*L_DXY*	*L_SP500*	*FEDR*
Mean	1.360059	6.191329	4.437233	1.309025	2.015478	3.62151	3.359986
P50	0.8023532	4.870836	4.436142	1.313551	2.015485	3.618909	4.215
Std. dev.	1.902739	6.811352	0.1261017	0.1190197	0.0161942	0.029064	1.953428
Min	-1.462143	0.232729	4.197072	1.082087	1.976763	3.553524	0.08
Max	5.938927	72.72492	4.679574	1.561578	2.057308	3.680931	5.33
P1	-1.294573	0.373412	4.215954	1.081667	1.979544	3.554953	0.08
P5	-1.175172	0.4620499	4.228634	1.115278	1.982466	3.574351	0.08
P95	5.403893	15.12383	4.639826	1.496238	2.045127	3.666863	5.33
P99	5.643809	29.89178	4.667744	1.523616	2.053816	3.678502	5.33
N	11680	11680	11680	11680	11680	11680	11680
Unit root test	-2.384***	-2.497	-1.342	-1.912	-2.215	-1.837	-1.796
Result unit root	Stationary	Not stationary	Not stationary	Not stationary	Not stationary	Not stationary	Not stationary
CD test	146.28***	9.47***					

*Note: The significance levels of 0.01, 0.05, and 0.1 are denoted by ***, **, and *, respectively.*

Table A.2. Descriptive statistics of daily return

Statistic	*R_Price*	*R_TVLMR*	*R_BTC*	*R_VIX*	*R_DXY*	*R_SP500*	*FEDR*
Mean	0%	0%	0%	0%	0%	0%	25%
P50	0%	0%	0%	0%	0%	0%	21%
Std. dev.	12%	9%	3%	5%	1%	5%	19%
Min	19%	-91%	-16%	-14%	-100%	-14%	-1%
Max	1181%	808%	14%	38%	2%	38%	70%
P1	-14%	-15%	-9%	-11%	-1%	-11%	-1%
P5	-8%	-7%	-4%	-7%	-1%	-7%	-1%
P95	8%	7%	5%	11%	1%	11%	65%
P99	18%	13%	9%	19%	1%	19%	70%
N	11680	11680	11680	11680	11680	11680	11680
Unit root test	-6.19***	-6.19***	-8.582***	-9.015***	-8.025***	-9.015***	-2.483
Result unit root	Stationary	Stationary	Stationary	Stationary	Stationary	Stationary	Not stationary
CD test	100.1***	32.35***					

*Note: The significance levels of 0.01, 0.05, and 0.1 are denoted by ***, **, and *, respectively.*

Table A.3. Descriptive statistics at weekly level (logarithmic)

Statistic	*LOG_P*	*TVLMR*	*L_BTC*	*L_VIX*	*L_DXY*	*L_SP500*	*FEDR*
Mean	3.135773	6.164962	10.21512	3.022125	4.641073	8.338668	3.349731
P50	1.858349	4.869054	10.22051	3.019674	4.640885	8.331671	4.215
Std. dev.	4.382859	6.750711	0.2878417	0.2789715	0.0371972	0.0671113	1.954571
Min	-3.361534	0.232729	9.69917	2.531313	4.555612	8.192127	0.08
Max	13.61369	71.37192	10.76611	3.595667	4.737102	8.475657	5.33
P1	-2.980863	0.3728022	9.701637	2.536866	4.558068	8.203865	0.08
P5	-2.703647	0.4670611	9.731642	2.571649	4.566565	8.229415	0.08
P95	12.425	15.04739	10.66977	3.473518	4.714267	8.438676	5.33
P99	13.03181	30.31018	10.75182	3.547604	4.728662	8.468876	5.33
N	1664	1664	1664	1664	1664	1664	1664
Unit root test	-1.905	-2.290***	-1.299	-1.254	-2.349	-1.721	-2.292
Result unit root	Not stationary	Stationary	Not stationary	Not stationary	Not stationary	Not stationary	Not stationary
CD test	55.51***	3.69***					

*Note: The significance levels of 0.01, 0.05, and 0.1 are denoted by ***, **, and *, respectively.*

Table A.4. Descriptive statistics of weekly return

Statistic	*R_Price*	*R_TVLMR*	*R_BTC*	*R_VIX*	*R_DXY*	*R_SP500*	*FEDR*
Mean	4%	5%	0%	1%	0%	0%	26%
P50	0%	0%	0%	-2%	0%	0%	21%
Std. dev.	162%	116%	8%	14%	1%	3%	19%
Min	-63%	-92%	-23%	-26%	-5%	-9%	-1%
Max	6601%	4321%	28%	56%	4%	7%	70%
P1	-33%	-40%	-22%	-25%	-3%	-6%	-1%
P5	-21%	-17%	-11%	-17%	-2%	-4%	-1%
P95	23%	18%	12%	25%	2%	4%	65%
P99	55%	36%	22%	42%	3%	6%	70%
N	1664	1664	1664	1664	1664	1664	1664
Unit root test	-4.025***	-4.463***	-4.099***	-6.027***	-3.376***	-4.374***	-2.207
Result unit root	Stationary	Stationary	Stationary	Stationary	Stationary	Stationary	Not stationary
CD test	42.06***	3.38***					

*Note: The significance levels of 0.01, 0.05, and 0.1 are denoted by ***, **, and *, respectively.*

Table A.5. Descriptive statistics at the monthly level (logarithmic)

Statistic	*LOG_P*	*TVLMR*	*L_BTC*	*L_VIX*	*L_DXY*	*L_SP500*	*FEDR*
Mean	1.370954	6.257463	10.23142	2.999734	4.639044	8.342239	3.35375
P50	0.8141295	4.781292	10.23545	2.981873	4.638556	8.336233	4.215
Std. dev.	1.907771	7.009703	0.2982118	0.282102	0.0390088	0.0684958	1.959563
Min	-1.405353	0.3308948	9.713579	2.535283	4.560152	8.184884	0.08
Max	5.923723	71.06794	10.74332	3.508256	4.719543	8.469302	5.33
P1	-1.28735	0.3725616	9.713579	2.535283	4.560152	8.184884	0.08
P5	-1.17073	0.4950845	9.75188	2.571084	4.568351	8.249397	0.08
P95	5.408781	15.22197	10.72609	3.506158	4.713854	8.432846	5.33
P99	5.682839	35.34176	10.74332	3.508256	4.719543	8.469302	5.33
N	384	384	384	384	384	384	384
Unit root test	-1.795	-2.356***	-1.868	-0.524	-2.831**	-1.175	-2.865**
Result unit root	Not stationary	Not stationary	Not stationary	Not stationary	Stationary	Not stationary	Stationary
CD test	-27.78***	1.1					

*Note: The significance levels of 0.01, 0.05, and 0.1 are denoted by ***, **, and *, respectively.*

Table A.6. Descriptive statistics of monthly return

Statistic	*R_Price*	*R_TVLMR*	*R_BTC*	*R_VIX*	*R_DXY*	*R_SP500*	*FEDR*
Mean	2%	17%	1%	0%	0%	0%	25%
P50	-3%	1%	-1%	-4%	0%	1%	21%
Std. dev.	42%	178%	17%	24%	3%	6%	19%
Min	-65%	-91%	-38%	-41%	-7%	-9%	-1%
Max	385%	3062%	40%	62%	5%	10%	70%
P1	-63%	-80%	-38%	-41%	-7%	-9%	-1%
P5	-40%	-36%	-20%	-30%	-6%	-9%	-1%
P95	71%	42%	29%	36%	4%	8%	65%
P99	131%	525%	40%	62%	5%	10%	70%
N	384	384	384	384	384	384	384

Table A.7. Monthly unit root test results

Panel A: Data level							
Variable	*LOG_P*	*TVLMR*	*L_BTC*	*L_VIX*	*L_DXY*	*L_SP500*	*FEDR*
Test value	-1.795	-2.356***	-1.868	-0.524	-2.331***	-1.175	-2.865**
Panel B: Data return							
Variable	*R_Price*	*R_TVLMR*	*R_BTC*	*R_VIX*	*R_DXY*	*R_SP500*	*FEDR*
Test value	-2.271***	-2.288***	-1.915	-4.291***	-2.912**	-3.024**	-1.641

*Note: The significance levels of 0.01, 0.05, and 0.1 are denoted by ***, **, and *, respectively.*

Table A.8. Pairwise correlation at the daily level

Variable	*TVLMR*	*LOG_P*	*L_BTC*	*L_SP500*	*L_DXY*	*L_VIX*	*FEDR*
TVLMR	1						
LOG_P	0.4852***	1					
L_BTC	0.0996**	0.0715*	1				
L_SP500	0.0554	0.0453	0.7881***	1			
L_DXY	-0.1299***	-0.0614**	-0.7089***	-0.6481***	1		
L_VIX	0.0778*	0.0164	-0.2443***	-0.6567***	0.1686***	1	
FEDR	-0.1347***	-0.0595**	-0.2723***	0.0764*	0.3360***	-0.7209***	1

*Note: The significance levels of 0.01, 0.05, and 0.1 are denoted by ***, **, and *, respectively.*

Table A.9. Pairwise correlation of daily return

Variable	*R_TVLMR*	*R_Price*	*R_BTC*	*R_SP500*	*R_DXY*	*R_VIX*	*FEDR*
R_TVLMR	1						
R_Price	-0.232***	1					
R_BTC	-0.1137**	0.2442***	1				
R_SP500	0.0129	-0.0044	0.0219	1			
R_DXY	-0.0049	0.0062	0.0261	0.0225	1		
R_VIX	0.0129	-0.0044	0.0219	0.0225	0.0225	1	
FEDR	-0.0007	0.0294	0.0655	-0.0553	-0.0422	-0.0553	1

*Note: The significance levels of 0.01, 0.05, and 0.1 are denoted by ***, **, and *, respectively.*

Table A.10. Pairwise correlation at the weekly level

Variable	*TVLMR*	*LOG_P*	*L_BTC*	*L_SP500*	*L_DXY*	*L_VIX*	*FEDR*
TVLMR	1						
LOG_P	0.4886***	1					
L_BTC	0.1001**	0.0718*	1				
L_SP500	0.0587	0.0451	0.7819***	1			
L_DXY	-0.1373***	-0.0611**	-0.7086***	-0.6398***	1		
L_VIX	0.0774*	0.0152	-0.2528***	-0.6657***	0.1694***	1	
FEDR	-0.1429***	-0.0599**	-0.2814***	0.0774*	0.3398***	-0.7161***	1

*Note: The significance levels of 0.01, 0.05, and 0.1 are denoted by ***, **, and *, respectively.*

Table A.11. Pairwise correlation of weekly return

Variable	*R_TVLMR*	*R_Price*	*R_BTC*	*R_SP500*	*R_DXY*	*R_VIX*	*FEDR*
R_TVLMR	1						
R_Price	0.0424	1					
R_BTC	0.0438*	0.0794***	1				
R_SP500	-0.0187	0.0243	0.3369***	1			
R_DXY	-0.1527***	-0.1111***	-0.1285***	-0.4398***	1		
R_VIX	0.1118***	0.0338	-0.2823***	-0.7008***	0.2123***	1	
FEDR	-0.0609**	-0.0285	0.1952***	0.1653***	-0.1329***	-0.1559***	1

*Note: The significance levels of 0.01, 0.05, and 0.1 are denoted by ***, **, and *, respectively.*

Table A.12. Pairwise correlation at the monthly level

Variable	*TVLMR*	*LOG_P*	*L_BTC*	*L_SP500*	*L_DXY*	*L_VIX*	*FEDR*
TVLMR	1						
LOG_P	0.4775***	1					
L_BTC	0.1148**	0.0788	1				
L_SP500	0.0713	0.0517	0.7766***	1			
L_DXY	-0.1389***	-0.0672	-0.7090***	-0.7099***	1		
L_VIX	0.0818	0.019	-0.1550***	-0.6102***	0.1787***	1	
FEDR	-0.1574***	-0.0712	-0.4183***	-0.0955*	0.4618***	-0.6597***	1

*Note: The significance levels of 0.01, 0.05, and 0.1 are denoted by ***, **, and *, respectively.*

Table A.13. Pairwise correlation of monthly return

Variable	*R_TVLMR*	*R_Price*	*R_BTC*	*R_SP500*	*R_DXY*	*R_VIX*	*FEDR*
R_TVLMR	1						
R_Price	-0.0772	1					
R_BTC	0.0864	0.4629***	1				
R_SP500	0.0349	0.3537***	0.5448***	1			
R_DXY	-0.2105***	-0.1557***	-0.4152***	-0.6751***	1		
R_VIX	0.1512**	-0.1826***	-0.2371***	-0.7493***	0.3748***	1	
FEDR	-0.1513**	0.1149**	0.2372***	0.2422***	-0.0773	-0.3466***	1

*Note: The significance levels of 0.01, 0.05, and 0.1 are denoted by ***, **, and *, respectively.*

APPENDIX B

Figure B.1. PVAR stable daily

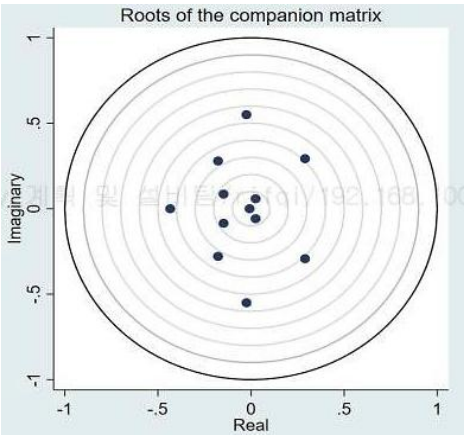


Figure B.2. PVAR stable weekly

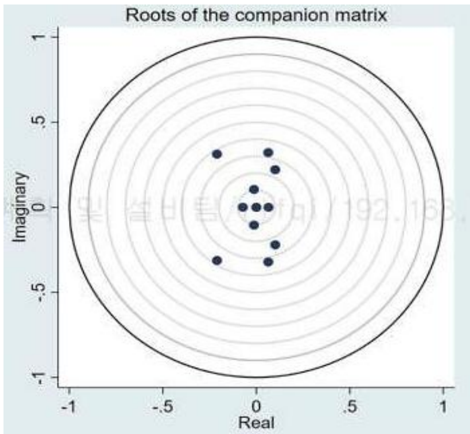


Figure B.3. PVAR stable monthly