


# “Connectedness between DeFi assets and TradFi sectors in emerging Asian markets”

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# CONNECTEDNESS BETWEEN DeFi ASSETS AND TradFi SECTORS IN EMERGING ASIAN MARKETS

## Abstract

The rise of decentralized finance (DeFi) presents new opportunities for accessing modern financial services. Despite their transformative architecture, most DeFi applications are currently unregulated, which exposes market participants to unforeseen risks. Therefore, understanding the level of connectedness between DeFi and traditional finance (TradFi) is crucial, particularly in emerging Asian markets where the level of cryptocurrency acceptance is high. Applying the time-varying parameter vector autoregressive model, this study examines the return connectedness between leading DeFi assets and traditional financial sectors in Indonesia, India, and Vietnam – the top three countries in Asia for cryptocurrency adoption. By analyzing TradFi at the industry level, this study captures sector-specific spillover dynamics that are essential to the monitoring of systemwide risk. The empirical results reveal low, time-varying return spillovers between DeFi and traditional financial sectors in the selected emerging Asian markets. The emerging financial sectors exhibit stronger linkages with broader traditional market indicators than with DeFi, in which assets interact primarily with each other. Emerging financial sectors and gold are the recipients of return spillovers, and DeFi assets act as the return transmitters. The current low degree of integration between DeFi and TradFi offers policymakers a window of opportunity to develop a robust financial regulatory framework that addresses issues of market stability and consumer protection while promoting the advancement of financial innovation.

## Keywords

DeFi, connectedness, return spillovers, emerging markets, TVP-VAR model

## JEL Classification

C32, G15, O33

## INTRODUCTION

Decentralized finance (DeFi) is an intricate ecosystem that represents a new era of financial innovation. As a branch of the cryptocurrency sector, DeFi uses blockchain technology, smart contracts, and decentralized applications to automate financial transactions in a permissionless, open, peer-to-peer fashion without the need for trusted intermediaries (Schär, 2021). Since the ultimate goal of the DeFi ecosystem is offering decentralized financial services that are more efficient, transparent, and accessible than those provided by traditional finance (TradFi), DeFi applications are particularly appealing to individuals in emerging regions with limited TradFi service availability.

Despite the growing attention that has been given to the DeFi ecosystem in recent years, research on the relationship between DeFi and TradFi is still limited (Ozili, 2022; Umar et al., 2022; Bennett et al., 2023; Billah et al., 2025). Therefore, several critical questions arise: (1) For countries with high levels of DeFi adoption, do DeFi and their TradFi systems exhibit a high degree of interconnectedness? (2) What implications does the current level of linkage have for market stability, risk transmission, investment opportunities, and regulatory frameworks?

This study addresses a gap in the literature by employing the time-varying parameter vector autoregressive (TVP-VAR) framework to investigate dynamic return spillovers between DeFi and TradFi sector indices in Indonesia, India, and Vietnam (hereinafter referred to as IIV). These underexplored emerging Asian markets not only exhibit a high level of cryptocurrency adoption but also favorable demographic factors for DeFi growth (OECD, 2024; Sergio & Wedemeier, 2025). By analyzing TradFi at the industry level, this study captures sector-specific spillovers that are often obscured in aggregate market-level analyses. The results of this study are of great interest to investors developing asset allocation strategies and policymakers establishing a data-driven regulatory framework that could enhance market stability and support financial innovation.

## 1. LITERATURE REVIEW

The emergence of DeFi has resulted in both unprecedented opportunities and challenges to TradFi and regulatory authorities. According to the World Bank (2025), 1.4 billion adults remained unbanked as of 2021, yet most of this unbanked population has mobile phones with internet access. In addition, a large population, a high level of network readiness, and a high level of financial instability are among the key drivers of high DeFi adoption rates at the country level (Nguyen & Nguyen, 2024). Therefore, DeFi's pursuit of efficiency and inclusion is attractive in regions where modern financial coverage has lagged. Importantly, however, the proliferation of DeFi applications does not indicate a diminishing role of TradFi. In fact, the introduction of the algorithm-based DeFi system has motivated TradFi to reimagine ways of leveraging modern information systems to better serve TradFi clients as technologies have advanced (Grassi et al., 2022; Asl & Jabeur, 2024). With the increased involvement of institutional investors in the DeFi ecosystem (OECD, 2022), understanding the degree of interconnectedness between DeFi and TradFi has become a critical area of scholarly research.

Yousaf and Yarovaya (2022) analyzed the static and dynamic connectedness among NFTs, DeFi, and other classes of assets. They reported that these innovative digital assets exhibit weak static returns and volatile interconnections with traditional assets such as gold, oil, and the S&P 500. Therefore, Yousaf and Yarovaya (2022) proposed that portfolio managers can consider NFTs and DeFi as potential assets for attaining diversification benefits. Ugolini et al. (2023) investigated the spillovers between four asset groups: DeFi, conventional cryptocurrencies, developed equity markets, and

safe-haven assets. The results indicate that these four groups of assets respond mainly to their own shocks and that digital assets exhibit greater spillovers in the system; safe-haven assets are the least connected to the rest of the asset groups. Abakah et al. (2023) investigated the dynamic price correlation and connectedness between blockchain-based assets and green assets. Their results demonstrate that the examined connectedness was initially low but became stronger during certain periods, which implies a growing integration of blockchain-based assets into the mainstream financial landscape over recent years. Ali et al. (2023) employed TVP-VAR models to investigate the interconnectedness between DeFi and precious metals and confirmed a weak association between them. Mensi et al. (2024) showed that DeFi assets act as net receivers of return spillovers, and that the dynamics between DeFi assets and conventional cryptocurrencies vary, with spillover effects being more pronounced in the long term than in the short- and medium- terms. Gunay et al. (2023) suggested that DeFi returns are partially driven by shocks originating in the FinTech sector. Gök (2025) adopted the quantile-on-quantile connectedness approach to analyze the return spillover between DeFi and natural resources and energy. They found an asymmetrical pattern in the return connectedness, which indicates the role of market conditions in influencing the connectedness dynamics. Furthermore, Gök (2025) revealed that clean energy markets are more strongly associated with conventional and DeFi assets than with dirty energy and carbon markets and that the carbon market exhibits the most substantial impact on DeFi.

Using the TVP-VAR model, Yousaf et al. (2023) investigated the dynamic connectedness between DeFi assets and equity markets in the U.S.

by sector. Their study reveals that DeFi and equity markets present a high level of total connectedness, specifically for sectors such as industrial, materials, and information technology. Nevertheless, Yousaf et al. (2023) noted the need to explore such interdependence within equity markets in Europe and Asia to obtain comprehensive insight into the role of DeFi in current market dynamics. Esparcia et al. (2024) assessed the volatility spillovers and portfolio hedging potential between DeFi and G7 ETFs. They revealed that while DeFi cannot act as a safe haven, it offers diversification benefits during market turbulence. Parrondo and Sala (2025) noted that while DeFi assets may offer diversification benefits with other cryptocurrencies and traditional equity markets during non-crisis periods, such advantages become less effective during a crisis.

With respect to the linkages between legacy finance and decentralized peers, Nekhili et al. (2024) suggested that both economic trends and the market climate impact the degree of interconnection between DeFi and centralized finance. While some DeFi assets act as shock transmitters and others act as shock receivers, DeFi assets and centralized finance indices exhibit significant associations with each other over the period investigated. Focusing on the tail interactions between DeFi lending tokens and banking stocks, Yousaf et al. (2022) demonstrated that the overall return spillovers between DeFi and bank stocks are positive but low, implying the potential that DeFi tokens hold in mitigating the risks in traditional financial sectors. However, such diversification benefits could shrink during extreme periods such as market booms and downturns. By applying TVP-VAR models, Younis et al. (2024) examined the connectedness among DeFi, G7 banking, and equity markets that occurred during crises such as the COVID-19 pandemic, the Russian-Ukrainian armed conflict, and the emergence of cryptocurrency bubbles. Their empirical results reveal substantial spillover effects from the G7 banking and equity markets to Japanese and DeFi assets, thereby indicating that TradFi and DeFi are interconnected to some degree and that policymakers should take a proactive approach to monitoring the emergent risks. Asl &

Jabeur (2024) analyzed the tail risk spillovers between centralized finance and DeFi. They reported that the level of connectedness intensifies during downturns, which highlights the risks of adopting DeFi as a diversifier during systemic stress. Billah et al. (2025) evaluated the level of tail risk connectedness between selected DeFi indices and the Islamic stock and bond markets. Their analysis reveals that the spillover effects are moderate and driven predominantly by short-term information. Therefore, Billah et al. (2025) suggested that DeFi continues to be a self-sufficient ecosystem with a weak connection to mainstream assets.

In summary, the literature on DeFi connectedness reveals several mixed findings regarding the roles that DeFi plays within broader markets. As DeFi is an immature sector, the evolution of the understanding of market connectedness is expected to continue, making regular investigations of this topic essential.

This study aims to provide a timely analysis of the rapidly expanding DeFi sector, focusing on emerging countries such as IIV, where DeFi services may exert a transformative impact on financial systems.

## 2. METHODS AND DATA

To analyze the time-varying return connectedness between DeFi and TradFi in emerging Asian markets, we employed the TVP-VAR structure proposed by Antonakakis et al. (2020), which is itself an extension of Diebold and Yilmaz's (2014) framework. The model of Antonakakis et al. (2020) presents several advantages. First, permitting the adjustment of the variance-covariance matrix via a Kalman filter technique advances the literature by overcoming the need to subjectively set the rolling window size. Second, this revised framework prevents the loss of observations in the calculation, making it especially useful for empirical studies with low frequency and a limited data span, such as the current study. The TVP-VAR ( $p$ ) model can be written as follows:

$$y_t = C_t x_{t-1} + \omega_t, \quad \omega_t | \rho_{t-1} \sim N(0, \Phi_t), \quad (1)$$

where

$$\begin{aligned} \text{vec}(C_t) &= \text{vec}(C_{t-1}) + v_t, \\ v_t | \rho_{t-1} &\sim N(0, \Psi_t), \\ x_{t-1} &= \begin{pmatrix} y_{t-1} \\ \vdots \\ y_{t-p} \end{pmatrix}, C_t' = \begin{pmatrix} C_{1t} \\ \vdots \\ C_{pt} \end{pmatrix}, \rho_{t-1} \end{aligned}$$

represents the information up to  $(t-1)$  and  $y_t$  and  $x_{t-1}$  are the  $(k \cdot 1)$  and  $(kp \cdot 1)$  vectors, respectively.  $\omega_t$  and  $v_t$  are the error terms with  $(k \cdot 1)$  vectors and  $(k^2 p \cdot 1)$  dimensional vectors, respectively. The time-varying variance-covariance matrices,  $\Phi_t$  and  $\Psi_t$ , are the  $(k \cdot k)$  and  $(k^2 p \cdot k^2 p)$  matrices, respectively. In accordance with Koop et al. (1996), Pesaran and Shin (1998), and Diebold and Yilmaz (2014), Antonakakis et al. (2020) calculated generalized impulse response functions and generalized forecast error variance decompositions,  $\tilde{\phi}_{ij,t}(H)$ , to derive a series of connectedness indices. In this study, the number of forecast horizons,  $H$ , was set at 20, and the order of lag,  $p$ , was set to one per the Bayesian information criterion (BIC).

The total connectedness index (TCI),  $L_t(H)$ , can be presented as

$$L_t(H) = \frac{\sum_{i,j=1, i \neq j}^k \tilde{\phi}_{ij,t}(H)}{k} \cdot 100. \quad (2)$$

The total impact that asset  $i$  passes on to all other assets,  $j$ , is defined as

$$L_{i \rightarrow j,t}(H) = \frac{\sum_{j=1, i \neq j}^k \tilde{\phi}_{ji,t}(H)}{\sum_{j=1}^k \tilde{\phi}_{ji,t}(H)} \cdot 100. \quad (3)$$

and the total impact that asset  $i$  receives from all other assets,  $j$ , is specified as

$$L_{i \leftarrow j,t}(H) = \frac{\sum_{j=1, i \neq j}^k \tilde{\phi}_{ij,t}(H)}{\sum_{i=1}^k \tilde{\phi}_{ij,t}(H)} \cdot 100. \quad (4)$$

Therefore, the net total directional connectedness index (NDCI) can be calculated as the difference between Equations (3) and (4). When the NDCI is positive, asset  $i$  exerts a greater impact on the

network than it receives. Hence, asset  $i$  acts as a transmitter of spillovers. Alternatively, if the NDCI is negative, asset  $i$  is characterized as a receiver. Furthermore, the net pairwise directional connectedness (NPDC) can be presented as

$$\left[ \tilde{\phi}_{ji,t}(H) - \tilde{\phi}_{ij,t}(H) \right] \cdot 100. \quad (5)$$

Together, the TCI, NDCI, and NPDC were used to identify the interconnectedness among the assets in the system. The Rpackage “ConnectednessApproach” developed by Gabauer (2022) was used to execute the empirical calculations.

The emerging financial sectors that we analyzed are those of Indonesia (FININDO), India (FININDI), and Vietnam (FINVIET). These emerging markets were selected because of their high degree of cryptocurrency adoption and similar sociodemographic features, as presented in Table 1. For IIV, over 60% of the population has access to internet services, and a large proportion of the population falls within the 15–44 age range. While India has a high reported bank account penetration rate, studies have found that more than one-third of bank accounts are inactive (Waghmare, 2025). Due to the lack of sufficient infrastructure for providing modern financial services, a high level of internet penetration enables DeFi applications to serve as a viable, efficient alternative to TradFi, particularly since the interest rates offered by DeFi platforms tend to be more competitive than those offered by TradFi peers (Mensi et al., 2024).

To ensure robustness of the analysis, DeFi tokens were analyzed with at least four years of trading activity, focusing on those ranked highest by market capitalization as of October 2024 and belonging to the lending and decentralized exchange sectors – the two most active segments in the DeFi ecosystem. Consequently, Aave (AAVE), Maker (MKR), Uniswap (UNI), and PancakeSwap (CAKE) were selected. Macroeconomic variables such as gold (GOLD), the equity market volatility index (VIX), and the global financial sector, as proxied by the MSCI World Financial Index (WFI), were included to assess the influences of global markets. Since most DeFi applications emerged in 2020 and continue to develop, our sample period was contingent on data availability. In this study, the daily sample period ranged from November 1st, 2020, to October

**Table 1.** Key indicators of IIV

Country	Overall Crypto Adoption Index Ranking	Retail DeFi Value Received Ranking	Population in Million	Young Population (15 - 44 years) as % of Total Population	GDP (per capita) in Thousand USD	Internet Penetration (% of population) in Percent	Mobile Internet Penetration (% of population) in Percent	Bank Account Penetration (% of adults) in Percent	Savings Rate (% of GDP) in Percent
<b>IIV</b>									
India	1	2	1,450.9	49.1	2.7	65.8	48.6	85.6	32.5
Indonesia	3	1	283.5	45.8	4.9	74.9	61.0	64.5	29.4
Vietnam	5	5	100.9	44.8	4.6	87.5	84.9	48.0	35.2
<b>Reference Countries</b>									
Nigeria	2	3	232.7	44.8	0.9	36.5	22.1	58.3	24.2
United States	4	4	345.4	40.3	84.4	93.8	89.7	99.9	17.9

Notes: All key indicators are based on the values reported for 2024, as cited in Statista (2025) and Chainalysis (2024).

31st, 2024. The data sources include Investing.com, CoinMarketCap, MSCI Inc., and S&P Capital IQ. The return of an asset,  $R_p$ , was calculated as the logarithmic difference of its prices. That is,

$$R_t = \ln(P_t) - \ln(P_{t-1}), \quad (6)$$

where  $P_t$  and  $P_{t-1}$  refer to the prices at time  $t$  and  $(t-1)$ , respectively. Table 2 reports the descriptive statistics of the returns, and Figure 1 shows the return series.

The descriptive statistics indicate that DeFi assets exhibit greater volatility than all financial sector indices do, which demonstrates their high

risk and speculative nature. Among the three emerging financial sectors, the financial industry of Vietnam appears to be the most volatile. Consistent with the stylized facts of empirical finance, all returns are leptokurtic, and the results of the Jarque-Bera test suggest that the assets are not normally distributed. According to the ERS tests, all returns are stationary. Except for gold, the Ljung-Box Q statistics for the residuals,  $Q(20)$ , and squared residuals,  $Q^2(20)$ , indicate autocorrelation and ARCH effects across assets, suggesting that the dependencies in the return data are not constant. Therefore, these empirical observations offer justifications for the adoption of a TVP-VAR framework.

**Table 2.** Descriptive statistics of the data

	AAVE	MKR	CAKE	UNI	WFI	GOLD	VIX	FININDI	FINVIET	FININDO
Mean	0.0018	0.0010	0.0019	0.0014	0.0008	0.0004	-0.0005	0.0008	0.0008	0.0003
Std. Dev.	0.0764	0.0678	0.0833	0.0729	0.0099	0.0757	0.0114	0.0125	0.0202	0.0099
Skewness	-0.331*** (0.000)	0.361*** (0.000)	0.717*** (0.000)	-0.061 (0.457)	-0.091 (0.266)	-0.508*** (0.000)	1.142*** (0.000)	-0.380*** (0.000)	-0.432*** (0.000)	0.112 (0.170)
Ex. Kurtosis	6.142*** (0.000)	6.627*** (0.000)	11.473*** (0.000)	5.810*** (0.000)	2.884*** (0.000)	2.230*** (0.000)	6.142*** (0.000)	5.414*** (0.000)	2.728*** (0.000)	1.593*** (0.000)
Jarque-Bera	1413.411*** (0.000)	1646.017*** (0.000)	4951.745*** (0.000)	1251.020*** (0.000)	309.214*** (0.000)	222.455*** (0.000)	1590.547*** (0.000)	1107.324*** (0.000)	303.238*** (0.000)	95.864*** (0.000)
ERS	-7.011 (0.000)	-13.27 (0.000)	-3.446 (0.001)	-6.643 (0.000)	-2.252 (0.025)	-5.491 (0.000)	-8.24 (0.000)	-2.055 (0.040)	-4.996 (0.000)	-6.838 (0.000)
Q(20)	16.186* (0.079)	22.816*** (0.005)	38.935*** (0.000)	15.736* (0.094)	16.166* (0.080)	10.918 (0.409)	16.894* (0.061)	25.745*** (0.001)	25.945*** (0.001)	15.539* (0.100)
Q <sup>2</sup> (20)	43.061*** (0.000)	42.569*** (0.000)	204.146*** (0.000)	20.725** (0.013)	46.751*** (0.000)	12.038 (0.306)	83.988*** (0.000)	57.639*** (0.000)	277.217*** (0.000)	53.630*** (0.000)

Notes: \*\*\*, \*\*, and \* refer to significance at the 1%, 5%, and 10% levels, respectively. Jarque-Bera is the normality test, and ERS is the unit root test. Q(20) and Q<sup>2</sup>(20) are the Ljung-Box Q-statistics.

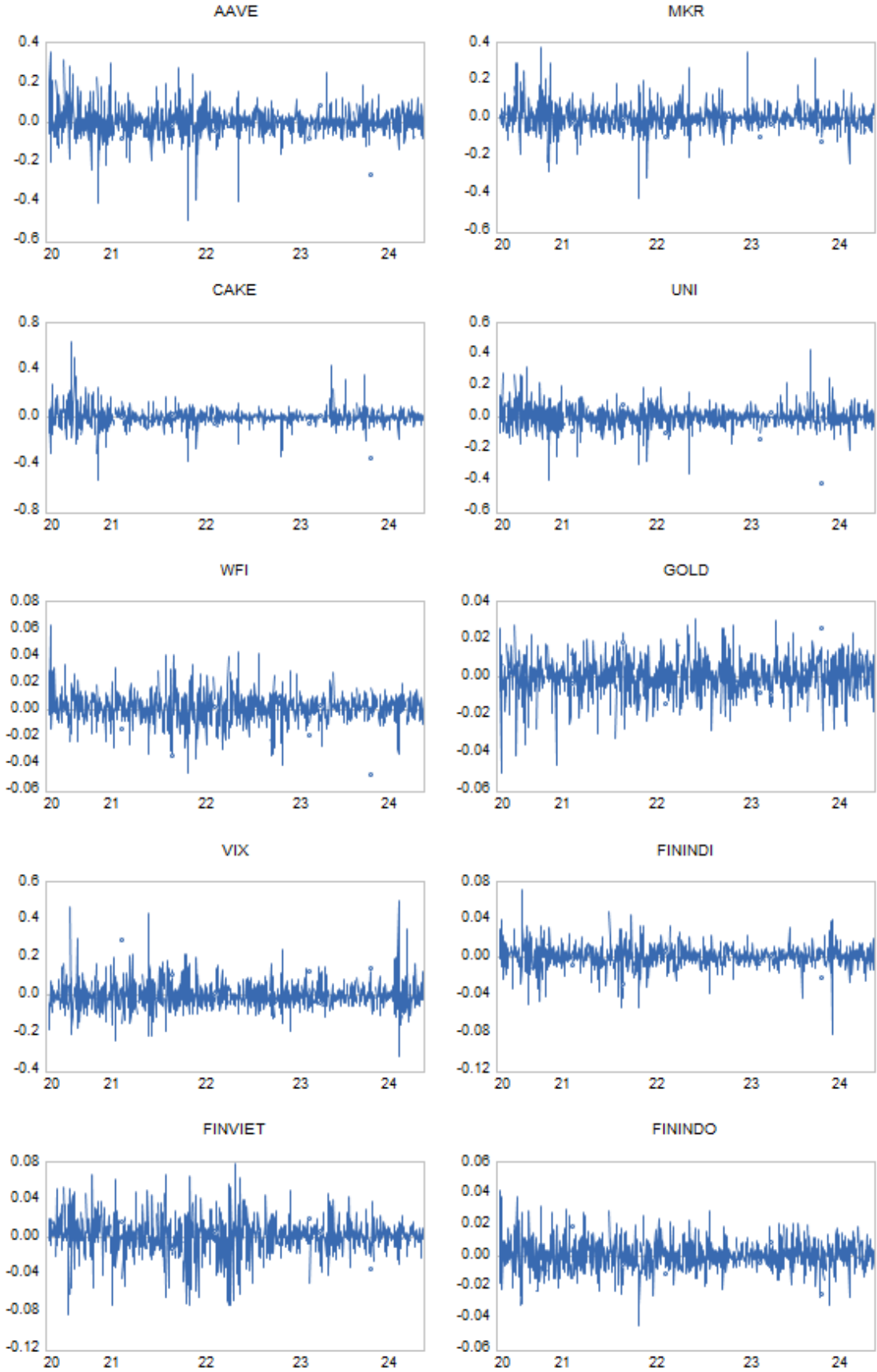


Figure 1. Daily returns of DeFi assets and the traditional financial sector

### 3. RESULTS AND DISCUSSION

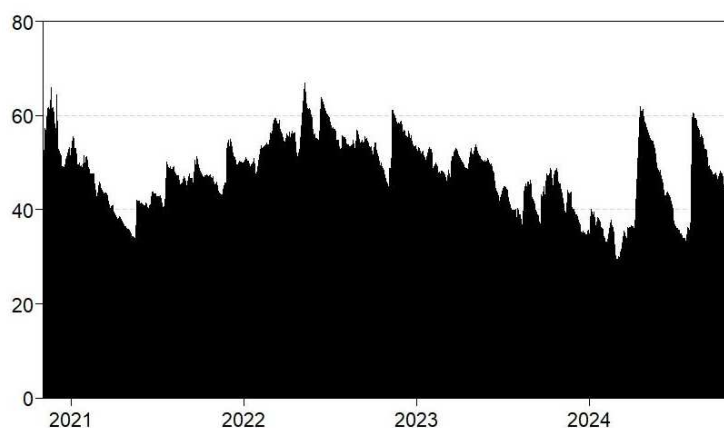
Table 3 presents the averaged dynamic return connectedness among selected emerging Asian financial markets and DeFi. The results reveal that the total connectedness index (TCI) is 47.56%, which indicates moderate return spillovers within the system over time. In this system, the largest recipient of the return spillover is the financial sector in India (-16.65%), followed by that in Indonesia (-12.02%), that in Vietnam (-7.48%), and gold (-7.02%). On the other hand, WFI, VIX, and all DeFi assets act as return transmitters, among which AAVE (13.39%) is the largest, followed by WFI (9.42%), UNI (9.06%), and CAKE (5.37%). As shown in Figure 2, the dynamic total connectedness index fluctuates over time, with some notable periods of heightened connectedness occurring in 2022 and 2024, which coincides with times of market uncertainty, such as the geopolitical armed conflicts between Russia and Ukraine and inflation concerns. During periods of market stress, investors seek alternative assets to hedge, thus resulting in higher return transmissions.

Figure 3 and Figure 4 present the system's NDCI and NPDC, which offer further insights into the roles played by assets in the system. They also show that while financial sectors in IIV interact with DeFi assets, the bilateral spillovers that occur between DeFi assets and these emerging Asian financial sectors are low, indicating that these emerging markets are not yet closely integrated with DeFi assets. All the DeFi assets appear to be self-contained, transmitting only limited spillovers to the financial sectors of emerging markets.

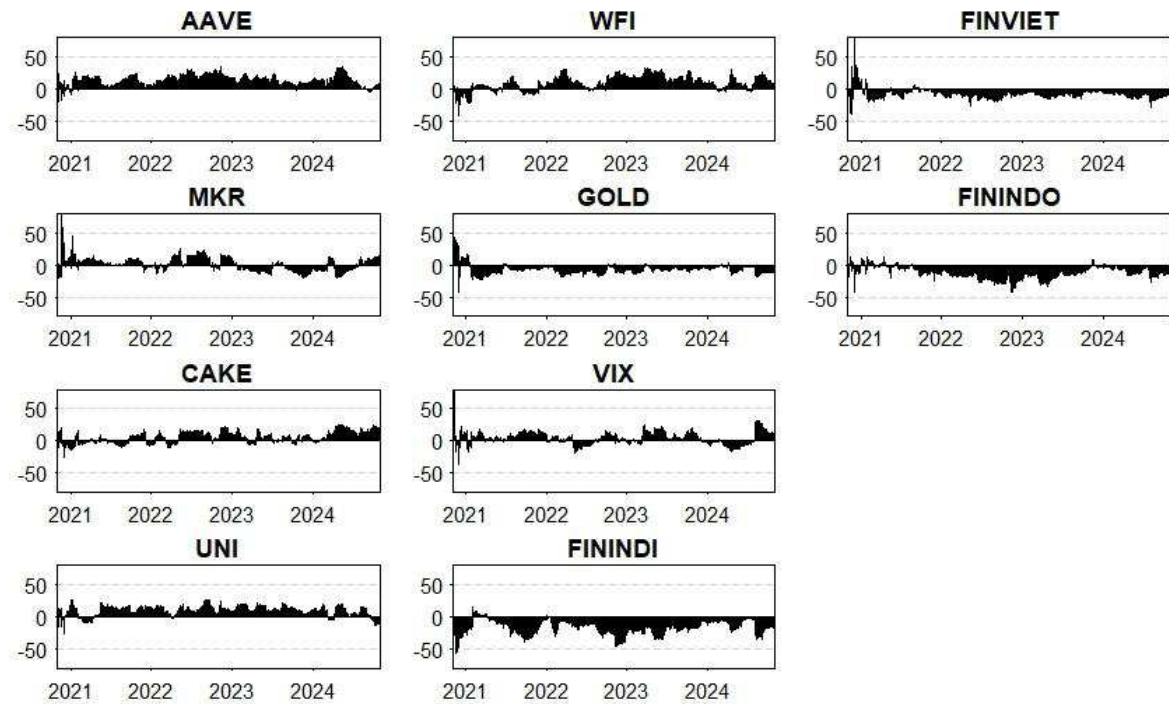
In contrast, broader traditional market indicators, such as WFI and VIX, strongly influence these emerging financial sectors.

In retrospect, our results indicate that while the total connectedness index for the entire system is moderate, there is a low, time-varying connectedness between DeFi and the financial sectors in IIV. Therefore, there is a limited but material return propagation between DeFi and TradFi. One possible explanation for the observed low connectedness is that these prices are driven by distinct variables. For TradFi sectors, share prices are driven by both macroeconomic fundamentals and the profitability of their operations. For DeFi assets, on the other hand, prices are determined by their protocol-specific metrics, such as liquidity provisions, arbitrage opportunities, and smart contract risks and designs, all of which are factored through predefined mathematical functions (Harvey et al., 2021). Therefore, returns of DeFi assets are idiosyncratic and isolated from the movements of conventional financial markets, such as the selected emerging markets.

From a market stability perspective, these findings have several important policy implications. Emerging Asian economies are known for their high engagement in digital payments, with DeFi users projected to rise to 16.49 million (Statista, 2025). A low level of connectedness allows policymakers to support the progressive development of the DeFi ecosystem as a complementary financial channel to the existing TradFi, potentially enhancing the degree of financial inclusion without triggering the immediate concern of causing a sys-



**Figure 2.** Dynamic total connectedness



**Figure 3.** Net total directional connectedness

temwide contagion with TradFi. This is especially critical for Vietnam, where bank account penetration is only 48%, but the mobile internet penetration rate is close to that of a developed country, as indicated in Table 1. Therefore, DeFi platforms present some niche features that could contribute to greater financial inclusion and access to credit, thereby ultimately promoting economic growth in the region.

However, from a regulatory standpoint, the complexity of DeFi platforms, the lack of proper regulatory supervision over these new blockchain-based services, and the fact that cryptocurrency

adoption in the IIV region is not currently driven by genuine use cases but rather by speculative behaviors, such as yield chasing and a fear of missing out (Cornelli et al., 2024), have posed unforeseen risks to retail DeFi users. The collapse of the Terra-Luna ecosystem in 2022 serves as an example of how a fragile, unregulated DeFi ecosystem could fall apart and cause a significant financial impact on investors. Therefore, the establishment of adequate regulations is imperative if DeFi is to reach its full potential (Zetsche et al., 2020). Since stablecoins are the primary channel through which capital flows are facilitated between DeFi and TradFi (OECD, 2024), they have become an ideal

**Table 3.** Averaged dynamic return connectedness

	AAVE	MKR	CAKE	UNI	WFI	GOLD	VIX	FININDI	FINVIET	FININDO	FROM
AAVE	37.79	12.67	14.89	20.43	4.24	1.29	4.14	1.78	1.17	1.61	62.21
MKR	14.72	45.85	11.88	13.42	4.42	1.16	3.85	1.9	1.4	1.4	54.15
CAKE	15.78	10.79	41.03	17.86	4.32	1.38	3.68	2.05	1.27	1.84	58.97
UNI	20.69	11.6	16.58	38.16	3.59	1.41	3.82	1.44	1.12	1.59	61.84
WFI	5.59	5.65	5.06	4.45	44.24	4.7	18	5.17	2.79	4.35	55.76
GOLD	2.66	2.15	2.11	2.28	6.64	72.9	3.95	2.12	1.85	3.37	27.1
VIX	5.36	4.59	4.76	4.75	18.94	3.11	49.09	3.98	2.35	3.08	50.91
FININDI	4.37	3.38	3.64	2.95	10.49	2.26	8.62	57.88	1.6	4.81	42.12
FINVIET	1.85	2.16	1.95	1.74	4.9	2.15	3.94	2.15	75.35	3.81	24.65
FININDO	4.58	2.53	3.48	3.01	7.65	2.62	5.48	4.89	3.63	62.13	37.87
TO	75.6	55.52	64.34	70.89	65.19	20.08	55.49	25.47	17.16	25.84	TCI
NET	13.39	1.37	5.37	9.06	9.42	-7.02	4.57	-16.65	-7.48	-12.02	47.56



starting point for establishing an adaptive regulatory framework in an attempt to mitigate the hidden risk exposure of DeFi. One potential solution for regulating complex cryptocurrency assets is the implementation of embedded regulation (Auer, 2022), which advocates building regulatory oversight directly into blockchain protocols. Currently, regulatory initiatives around the globe are still in their pilot stages. In addition, designing an early warning system, such as the one proposed by Bertomeu et al. (2024), to monitor a protocol's liquidation and insolvency risks could help to provide initial risk assessments of DeFi projects.

Another key dimension to address is the enhancement of DeFi consumer protection in emerging markets through the promotion of financial literacy in digital asset ecosystems. Cryptocurrencies

are known for their high volatility, and studies have shown that technical analysis plays a significant role in the projection of DeFi prices (Grobys et al., 2020; Ghosh et al., 2023). As such, investors' trend-chasing behaviors could lead to price bubbles, which will eventually burst. While some studies argue that DeFi can be used as a diversifier in investment portfolios, this type of investment strategy needs to be executed cautiously and may not be universally suitable for retail investors, who typically lack sophisticated resources. Owing to the unique institutional and socioeconomic factors of IIV markets, building trust through financial literacy and supportive digital asset policies is essential to sustaining the growth of cryptocurrency adoption and achieving the benefits resulting from innovations (Nguyen et al. 2025).

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## CONCLUSION

Understanding the dynamics between different assets is a critical task in finance, particularly for those that are unregulated and in the early stages of development. This study employs a TVP-VAR model to examine the return interconnectedness between leading DeFi assets and TradFi sectors in selected emerging Asian markets. The results indicate that the interactions between the emerging Asian financial sectors and DeFi assets are limited and exhibit fluctuations over time. The selected emerging financial sectors act as the receivers of return spillovers, whereas DeFi assets act as the return transmitters. In addition, emerging financial sectors respond more closely to movements from conventional financial markets than to those from DeFi. Since DeFi assets remain relatively decoupled from TradFi, the contagion risk between the two sectors appears low, allowing policymakers to establish effective oversight frameworks. However, as the public's acceptance of cryptocurrency continues to increase, the role of DeFi within the broader financial system may evolve. Future research could investigate the determinants and evolution of DeFi connectedness across different market conditions.

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