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Speed of Adjustment in Digital Assets in a Decentralized Financial World

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ABSTRACT

This paper investigates the stability and co-movement of cryptocurrency assets in Decentralized Finance (DeFi), with a focus on the Speed of Adjustment (SA), the rate at which shocks dissipate, and prices revert to long-run equilibrium. SA provides a critical measure of market efficiency and portfolio allocation in a highly volatile DeFi environment. We extend conventional cointegration analysis by applying a Fractionally Cointegrated Vector Autoregressive framework, which captures slow error corrections. Rolling estimations generate a time-varying series of SA, allowing examination of its evolution and cross-asset spillovers. The results reveal multiple cointegrating relationships, heterogeneous adjustment speeds, and strong contagion effects among DeFi assets. For instance, RPL exhibits rapid yet volatile adjustment, while LDO, BAL, and SNX revert more slowly, reflecting distinct risk-return trade-offs. Spillover analysis highlights high systemic interconnectedness, underscoring challenges for diversification and contagion management. Overall, dynamic SA emerges as a valuable forward-looking indicator of stability in digital asset markets.

JEL Classification: C32, G12, G15

1 | Introduction

Lately, cryptocurrencies and blockchain technology have become one of the most disruptive innovations in the financial industry, with applications ranging from payments and trading to non-fungible tokens (NFTs) and decentralized financial services. A rapidly expanding segment of this ecosystem is Decentralized Finance (DeFi), which relies almost exclusively on crypto assets to fuel smart contracts, liquidity pools, and decentralized exchanges. Unlike major cryptocurrencies such as Bitcoin and Ethereum, which have been extensively studied in terms of return behavior, volatility, and market efficiency (Al-Amri et al. 2019; Alzahrani and Daim 2019; Grossman and Stiglitz 1980), DeFi assets remain underexplored despite their exponential growth—from less than USD 1 billion in 2019 to nearly USD 250 billion in 2022 (Chaudhuri and Wu 2003). Similarly, compared to emerging literature on NFTs and other crypto market segments (Spierdijk et al. 2012; Makarov and Schoar 2020), DeFi poses unique challenges because of its higher volatility, greater contagion risks, and structural reliance on token interdependence. This paper responds to this study gap by focusing specifically on DeFi assets.

We argue that the stability[1] of these assets is central to the sustainable development of DeFi networks. Excessive volatility discourages participation, undermines smart contract functionality, and deters institutional adoption. To evaluate stability, we employ the concept of the Speed of Adjustment (SA) – the rate at which shocks to asset prices dissipate and converge to a long-run equilibrium. Unlike most prior studies that examine volatility or return spillovers (Hillebrand 2003; Supra et al. 2016; Huang and Ritter 2009), we highlight SA as a more structural measure of market efficiency, investment horizon, and systemic resilience. Our contribution is twofold. First, we extend traditional cointegration analysis by applying a Fractionally Cointegrated Vector Autoregressive (FCVAR) framework, which better accounts for slow and persistent dissipation of shocks in crypto markets. Second, we examine spillover in SA, offering insights distinct from return and volatility spillovers documented in earlier research.

By focusing on DeFi, this study not only sheds light on an under-researched but economically significant market segment, but it also contributes to portfolio management and risk assessment by uncovering heterogeneous adjustment speeds and strong contagion effects across assets. These findings are of direct relevance to investors, asset managers, and policymakers seeking to navigate the evolving DeFi landscape.

Regarding stability, an important way to assess it is to provide a quantitative assessment of the way shocks in DeFi assets dissipate: the faster shocks disappear (or more technically, converge to zero, enabling the crypto assets to settle to a long-run stable mean value), the more profitable it becomes for asset managers and crypto investors. Econometricians exploit the mechanics of cointegration to assess how various components in a growing system form a long-term stable relationship. Accordingly, we employ a cointegration technique to understand the evolving pattern of co-movement of various crypto assets, but we expand the conventional cointegration mechanism to allow for 'slow' dissipation of shocks—one that is closer to reality. Indeed, shocks of any magnitude do not work in isolation in any growing system. Due to the intricacies of interactions, it becomes extremely difficult for stakeholders, such as managers, to dissociate the true effect of a shock from another, leading to either an under- or overestimation of the persistence of shocks and their predictive effects on a system. Adding to this problem, the markets under which crypto assets operate are not perfectly efficient (Grossman and Stiglitz 1980) because there is asymmetric and incomplete information and monopolistic control of crypto prices, thanks to the sentiment-driven demand-supply dynamics of crypto assets. Since markets cannot be perfectly efficient (Grossman and Stiglitz 1980), deviations from this relationship, which one can normally term in this context, mispricing, are to be expected. However, market participants taking advantage of temporary inefficiencies will help revert deviating assets to the long-run equilibrium.

A typical way to understand the efficiency of DeFi assets is to assess how fast shocks in these assets dissipate (or converge to zero). No asset manager would like to have an asset that displays non-converging shocks (i.e., ones that do not even react to policy interventions or are extremely slow to respond to policy). This is because only when assets are manageable by "transformative actions by policy intervention" (i.e., shocks can taper off to zero), they can predict a stable pattern of returns from an investment in these assets. We term this speed of convergence of shocks as the Speed of adjustment (SA). Statistically, it measures the speed of error correction in a growing system, such as a crypto asset. Only when errors disappear faster can the growth of crypto assets be mean-reverting; in other words, the fluctuation of prices (high and low) on the trajectory of growth of these assets, on average, the prices revert to their long-run mean value (a theoretical value that aligns with the expectation of the broad financial system). What we do not know yet is how this adjustment speed (asymptotic stability) can indicate overall productivity gains of the system.

Mean reversion has been documented for developed and emerging markets alike (Chaudhuri and Wu 2003). A study on mean reversion in various countries for more than a century has found that SA may vary considerably over time (Spierdijk et al. 2012), which makes it important to analyze the temporal evolution of this speed. We develop a dynamic version of SA since its characteristics over time can capture market volatility in a way that return volatility cannot, especially in the presence of large and recurring deviations in cryptocurrency prices (Makarov and Schoar 2020). SA is very useful for market participants since they will react to price movements based on their expectation of SA (Hillebrand 2003), and it is also a strong indicator of potential trade duration.

The concept of SA is not unique to cointegration. For example, it has been studied extensively in the capital structure literature (Supra et al. 2016). SA of firms to their target leverage tends to be moderate (Huang and Ritter 2009). However, not all firms consider leverage targeting highly important, and SA does vary across firms (Zhou et al. 2016). SA is quite high for nonfinancial firms in developed countries (Oino and Ukaegbu 2015). Over-levered and under-levered firms show very different SA, but only for short-term leverage. More importantly, transaction costs have a great impact on SA (Dufour et al. 2018) because higher transaction costs induce slower convergence of shocks: over time, as transaction costs become smaller, leaving a greater share of profit to investors, the system becomes stable, enabling asset managers and investors to make a stable prediction of their growth in the future. That way, the investors can control the negative externalities from the mispricing of crypto assets, restraining the proliferation of bubble-like tendencies in these assets. Similarly, debt covenants can moderate SA, especially for financially constrained and over-levered firms (Devos et al. 2017). Conversely, if a firm is further away from its target leverage, its incentive for capital structure rebalancing is stronger, leading to faster SA (Mukherjee and Wang 2013). SA is also higher for fast-growing firms and when the economic prospect is favorable, with a close relationship with the business cycle (Drobetz and Wanzenried 2006).

However, SA has received less attention within the context of co-movement (or cointegration) among financial assets, especially the novel crypto assets in DeFi. SA in this setting deserves more attention for two important reasons. First, given the increasing popularity of DeFi and blockchain technology, DeFi has become one of the most popular areas of interest in the crypto space recently (Arslanian 2022). The total value of virtual assets used in various DeFi applications increased exponentially, from less than $1 billion in 2019[2] to around $250 billion in 2022.[3] Similarly, blockchain is expected to be adopted extensively worldwide in the near future (Lu 2019). This development suggests greater reach and relevance of DeFi to many market participants. Secondly, SA is particularly important due to the high volatility of DeFi assets (Piñeiro-Chousa et al. 2022). DeFi is mostly powered by volatile crypto assets (Chen and Bellavitis 2020) and thus remains a risky environment for investors (Didenko 2022).

Regarding the determinants of SA, faster SA is observed in periods of greater uncertainty due to major economic and political events (e.g., war, energy crisis, recession, stock market crash) (Spierdijk et al. 2012). Similarly, substantially faster SA is observed when the market is in a large decline, which is robust to different markets, sampling periods, and investment horizons (Bali et al. 2008). SA is also generally higher in emerging markets than in developed markets (Ahmed et al. 2018). Moreover, the strength of cointegration may affect SA (e.g. strongly cointegrated assets may show fast adjustment).

Prior research has advanced understanding of digital assets by documenting stylized return and volatility properties of cryptocurrencies and NFTs (Ghosh et al. 2023), examining market efficiency during crises (Okorie et al. 2024), and exploring the hedging ability of gold-backed tokens against DeFi and NFTs (Belguith et al. 2024). While these studies enhance knowledge of short-term behavior, efficiency, and hedging performance, they do not address how assets structurally adjust to disequilibria. Our paper fills this gap by focusing on the SA, as noted earlier, the rate at which DeFi assets revert to long-run equilibrium following shocks. This perspective provides a deeper understanding of stability, systemic resilience, and productivity in DeFi markets. Methodologically, we employ an FCVAR model to capture the slow dissipation of shocks typical of crypto assets and introduce the novel concept of spillover in SA to evaluate contagion risk across tokens. These contributions offer new insights into the dynamic interdependence of DeFi assets with direct implications for trading, portfolio diversification, and risk management.

Our objective is to examine not only the SA of DeFi per se but also their spillover effects, motivated by not only the fast-growing significance but also strong empirical evidence in previous studies for a high level of interdependence and relationship among crypto assets (Mensi et al. 2021; Qureshi et al. 2020; Kim et al. 2021). This increased financial integration is associated with an increase in spillover effects, and an accurate analysis of spillover is essential for risk management and portfolio investment (Vo and Tran 2020). However, we investigate the spillover in SA, which is informative in a different way from the traditional return and volatility spillover in earlier research.

Our study is of immense interest to investment and portfolio managers who aim to utilize digital assets in the emerging area of DeFi based on the novel blockchain technology. We contribute to their practice in the following ways. First, we reveal the presence of cointegration and close relationships among the assets, which could potentially facilitate various lucrative trading strategies. Second, we uncover heterogeneous speed of adjustment among assets, which supports decisions about portfolio selection and risk management. Investment managers should select markets with a suitable speed for their risk appetite and pace their activities according to this speed. Third, we warn investors of a high level of contagion risk among the assets, as shown by their strong spillover effects. Investors need to be more cautious about holding a portfolio of these assets and adapt their strategies to how the spillover in market speed develops over time. Fourth, we highlight the most and least important assets in the spillover network, directing investors to the assets with the most diversification benefits. Finally, we alert investors to a potential bias to enhance their analysis and decision-making. Specifically, they should not assume that the larger assets always play the most important roles in spillover.

As noted earlier, we adopt the FCVAR model (Fractionally Cointegrated Vector Autoregressive) to estimate the SA for various crypto assets, following (Cheah et al. 2018). The 'fractional' nature of a time series refers to the speed at which shocks would dissipate. Fractional integration of crypto asset time series would mean that the shocks in these assets taper off very slowly—a realistic possibility. In a dynamically interdependent system such as the Vector Autoregression (VAR), shocks dissipate slowly, which inevitably makes interaction within the system very complex and highly nonlinear. It becomes increasingly difficult for an investor to derive a straightforward assessment of the nature of co-evolving patterns of assets without devoting attention to sophisticated modeling to disentangle shocks in a highly nonlinear environment. In this circumstance, researchers employ an FCVAR mechanic to model the effects of slow-converging shocks on the long-term stability of co-moving assets. Fractional cointegration is superior to traditional cointegration since it can measure various degrees of cointegration more accurately, thus reducing the chance of over- or underestimating the SA. Then we repeat the estimation on a rolling basis to obtain a time series of SA. To investigate the cross-market spillover of SA, we employ the (Diebold and Yilmaz 2012, 2014) method within a Fractionally Integrated Vector Autoregressive (FIVAR) model.

The rest of the paper is as follows. Section 2 provides a literature review on the issues to be examined in the subsequent analysis, namely, cointegration and spillover effects among crypto assets. Section 3 describes the research methodology, including data collection as well as the frameworks for analyzing fractional cointegration and spillover in SA. Section 4 presents and discusses our results. Finally, Section 5 concludes the paper and provides directions for future research.

2 | Literature Review

2.1 | Co-Movement

The phenomenon of co-movement, or more technically, cointegration among crypto assets, has been documented in several studies Keilbar and Zhang (2021) show that cryptocurrencies have multiple cointegrating relationships, and their error correction process became more nonlinear at the peak of the crypto bubble.[4] Cointegration has also been observed for crypto derivatives. Bitcoin spot and futures markets are fractionally cointegrated, and using the traditional full cointegration model may lead to estimation errors (Wu et al. 2021). Moreover, there is evidence that this cointegrating relationship is time-varying rather than fixed (Hu et al. 2020) and deviations from the long-run equilibrium can help predict spot returns (Kapar and Olmo 2019). Interestingly, cointegration has even been found among non-fungible tokens (NFTs), unique digital assets that have emerged on blockchains recently (Ante 2023).

Given the presence of cointegration, (Leung and Nguyen 2019) test and confirm the profitability of statistical arbitrage for cointegrated portfolios of several major cryptocurrencies. Similarly, (Tadi and Kortchemski 2021) find that a pairs trading strategy based on cointegration can outperform the buy-and-hold approach, with reasonably low drawdown. It is important to note that certain crypto assets have more arbitrage potential than others. However, despite excellent in-sample performance, out-of-sample results of arbitrage strategies suggest that they should be used with caution (Keilbar and Zhang 2021). A reason could be that disequilibria among cryptocurrency markets have been found to only adjust slowly in the long term (Cheah et al. 2018), which may be due to arbitrage frictions (Kroeger and Sarkar 2017). Since SA is a strong indicator of potential arbitrage duration, in this case, traders should be more patient and ready to be in the market for possibly a long time. There is also recent research (Ghosh et al. 2023), which studies return and volatility of NFTs and cryptocurrencies, capturing short-term price behavior rather than long-run stability mechanisms as we do in our work. In a related contribution, (Okorie et al. 2024) study market efficiency of NFTs under extreme events and offer evidence of crisis-driven inefficiencies in different asset classes, not the structural long-term dynamics like speed of mean-reversion. Some other research, such as (Belguith et al. 2024), explores hedging and safe-haven properties of gold-backed tokens against DeFi and NFTs and addresses the hedging performance rather than the internal systemic dynamics and spillovers within DeFi assets themselves. This paper fills the above gap in the existing literature and exploits the mean-reversion properties of DeFi.

2.2 | Spillover Effects

Spillover effects can be considered a measure of contagion risk among crypto assets (Koutmos 2018). Kumar and Anandarao (2019) find a moderate level of volatility spillover, while (Katsiampa et al. 2019) confirms bidirectional pairwise volatility spillover for several major cryptocurrencies. The total spillover among many cryptocurrencies varies over time and has been on the rise since 2017 (Yi et al. 2018). Bitcoin is the main contributor to spillover (Koutmos 2018), and the bitcoin-USD market can help predict volatility shocks in other bitcoin markets (Gillaizeau et al. 2019). However, the role of Bitcoin has diminished since 2017 (Zięba et al. 2019). Surprisingly, some minor crypto assets with small market capitalization are more likely to transmit strong shocks to their larger counterparts (Yi et al. 2018; Huynh et al. 2020).

Regarding the drivers and determinants of spillover, previous studies have found several factors, such as market size, oil price, and important external events and news related to cryptocurrencies (Koutmos 2018; Kumar and Anandarao 2019; Yi et al. 2018; Moratis 2021; Katsiampa 2019). Moreover, this spillover effect has also been shown to strengthen in periods of high uncertainty and/or financial integration among markets (Gillaizeau et al. 2019; Moratis 2021). It is worth noting that the empirical results of spillover may depend on the measure of volatility used (Omane-Adjepong and Alagidede 2019). More importantly, due to the linkage among crypto assets, adding a less correlated asset, such as gold, can help diversify crypto portfolios (Huynh et al. 2020). However, diversification may be more efficient in the short and medium term (Omane-Adjepong and Alagidede 2019). Unlike earlier research on return and volatility spillover, we examine spillover in SA, which is uniquely informative given the importance of SA.

3 | Data and Methodology

3.1 | Data Collection

We use the Coin Market Cap database[5] to collect daily spot price data of the top DeFi assets, namely constituents of the DeFi Pulse Index (DPI),[6] which tracks the performance of the largest protocols in DeFi. The weighting scheme of DPI is based on the total value of each asset's current supply in circulation (i.e., market capitalization). The DPI aims to follow DeFi projects with substantial usage and commitment to development and maintenance on a regular basis. Table 1 shows the constituents of DPI, together with their relative contributions to the index and start dates (i.e., when they came into existence and their data records began).

TABLE 1 | DPI constituents.

Asset	Index contribution	Start date
Uniswap (UNI)	24.8%	September 17, 2020
Lido DAO (LDO)	20.7%	January 05, 2021
Synthetix Network Token (SNX)	14.6%	March 14, 2018
AAVE	13.7%	October 02, 2020
Maker (MKR)	12.5%	January 29, 2017
Rocket Pool (RPL)	5.2%	July 17, 2018
Compound (COMP)	3.6%	June 16, 2020
yearn. finance (YFI)	3.0%	July 18, 2020
Balancer (BAL)	1.8%	June 24, 2020
Wrapped Ether (WETH)	0.1%	August 08, 2022

We exclude Wrapped Ether (WETH) from our sample due to its much shorter period of available data (only from August 2022) compared to the other assets. WETH also contributes very little to the DPI (only 0.1%, the lowest weight among all the constituents). Out of the remaining nine assets, we use the introduction of the most recent one, namely Lido DAO (LDO, introduced in January 2021), as the beginning of our sampling period. Our data set ends in July 2025.

3.2 | Methodology

i. Fractional Cointegration

We estimate the fractionally cointegrated vector autoregressive model proposed by (Johansen 2008) to calculate the speed of adjustment (SA). The R package "FCVAR"[7] is used for the purpose. To briefly describe FCVAR, assume that for a time series X_t of order p, the error correction representation of the FCVAR model is given as

$$\Delta^d X_t = \alpha\beta'\Delta^{d-b}L_b X_t + \sum_{i=1}^{k}\Gamma_i\Delta^d L_b^i X_t + \varepsilon_t \quad (1)$$

where Δ^d is the operator for fractional difference, L_b is the operator for fractional lag ($L_b = 1 - \Delta^b$),[8] and ε_t is p-order i.i.d. $(0, \Omega)$. The most important parameters are α and β, which are $p \times r$ matrices where the cointegration rank r satisfies $0 \le r \le p$. β contains the vectors of cointegrating coefficients, so $\beta' X_t$ shows the long-run cointegrating relationships among the variables in the system. Meanwhile, α contains the SA of each variable toward the collective equilibrium. The parameter d denotes the order of fractional integration in the original time series, while b denotes the level of fractional cointegration (i.e., how much the fractional integration of X_t is reduced by the cointegrating combinations $\beta' X_t$).

The model is further augmented with the inclusion of autoregressive terms characterized by the parameters Γ_i. In terms of lag selection, we set the maximum lag length to 5 for parsimony and choose the optimal number of lags based on the Schwarz information criteria (SIC), which is stricter than the Akaike information criteria (AIC).

For the subsequent analysis of spillover effects, we develop a dynamic time-varying version of SA using a *rolling window* estimation approach. We set the window to be 6 months, which is a reasonable length given the available data (i.e. long enough for reliable estimations but still short enough to have many observations remaining for the spillover analysis). We apply Equation (1) to the first 6 months in the sample to derive the first value (point estimate) of SA, then we roll forward 1 day at a time until the end of the sample to obtain subsequent values. In the end, we have a time series of SA for each of the 9 DeFi assets.

ii. Spillover Analysis

To investigate the dynamic patterns of SA and its spillover effects across our 9 DeFi assets, we employ the approach of (Diebold and Yilmaz 2012, 2014) within the 9-dimensional Fractional Integrated VAR (FIVAR) model. The FIVAR specification is a general multivariate framework that allows flexibility in capturing long memory degrees of the SA time series. We estimate the 9-dimensional FIVAR model as follows:

$$\left(I_9 - \sum_{l=1}^{p} A_l L^l\right) B(L) X_t = v_t \quad (2)$$

where X_t is a column vector of the SA series. The error term, $v_t \sim i.i.d.\,(0, \mathrm{H})$, with $\mathrm{H} = \{h_{rc};\, r, c = 1, 2, ..., 9\}$ as its variance-covariance matrix. A_l denotes the (9×9) coefficient matrix associated with X_{t-l}, and I_9 is the (9×9) identity matrix. L represents the lag operator, and the lag order p is determined using the SIC. $B(L) = \mathrm{diag}\ \{(1-L)^{d_1}, ..., (1-L)^{d_9}\}$ where d_i denotes the memory degree of the ith SA. The memory degrees of the SA series are allowed to be different in our modeling framework. We follow (Do et al. 2014) and (Yip et al. 2017) to estimate Equation (2) using the two-step estimation method.

To construct the spillover index, we first obtain the generalized forecast error variance decomposition (FEV^g) matrix from Equation (2). We employ a rolling window of 200 days with a 10-day forecast horizon, which is a standard choice in the original papers (see Diebold and Yilmaz 2012). The (r, c) element of the FEV^g matrix can be calculated as

$$FEV^g_{r,c} = \frac{h_{cc}^{-1}\sum_{s=0}^{t-1}\left(e_r'\Lambda_s H e_c\right)^2}{\sum_{s=0}^{t-1}\left(e_r'\Lambda_s H \Lambda_s' e_c\right)} \quad (3)$$

Following (Do et al. 2014), we adapt the Diebold and Yilmaz approach in an FIVAR model by adjusting the moving average coefficient matrix $\Phi_s$with the long memory degree (d) to construct Λ_s as, $\Lambda_s = \sum_{l=0}^{s}\Xi_l^{(d)}\Phi_{s-l}$, where $\Xi_l^{(d)} = diag\left\{\frac{\Gamma(l+d_1)}{\Gamma(d_1)\Gamma(l+1)}, ..., \frac{\Gamma(l+d_9)}{\Gamma(d_9)\Gamma(l+1)}\right\}$ is a (9×9) diagonal matrix, and Φ_s can be obtained recursively from its previous lagged values Φ_{s-l} and the coefficient matrices A_l obtained from (2) as, $\Phi_s = \sum_{l=1}^{p}\Phi_{s-l}\mathrm{A}_l$. Note that both Φ_0 and Λ_0 are (9×9) identity matrices, and e_r is the identity vector with its r^{th} element being 1.

On this basis, the total generalized spillover index among the 9 DeFi assets is given as

$$TS = \frac{\sum_{r,c=1,\, r\neq c}^{9}\tilde{FEV}^g_{rc}}{9} \times 100 \quad (4)$$

where $\tilde{FEV}^g_{rc} = \frac{FEV^g_{r,c}}{\sum_{c=1}^{9}FEV^g_{r,c}}$ is the normalized generalized forecast error variance decomposition, which also represents the pairwise spillover from variable cth to variable rth in the system. The *net* pairwise spillover effect from the cth variable to the r variable is therefore, $NS_{rc} = \tilde{FEV}^g_{rc} - \tilde{FEV}^g_{cr}$.

4 | Results

In this section, we present and discuss results from FCVAR estimation, in particular, the Speed of Adjustment (SA). We begin by presenting some temporal properties of our data.

4.1 | Data Characteristics: Understanding Trend

Figure 1 demonstrates how the prices of the DeFi assets developed during the sampling period. For comparison purposes, we rescale the original prices such that the starting price of each asset is set to 1.

One can see that RPL, the third oldest constituent in the DPI (starting from July 2018), with a modest contribution of 5.2% (see Table 1), behaved differently from the rest. Except for RPL, all the assets show similar price changes over time, with higher volatility in the first half of the sample compared to the second half. Interestingly, the prices reached their highest levels around May 2021. At that time, traditional cryptocurrencies such as Bitcoin were suffering from a significant market crash (Bitcoin lost almost half of its value, plummeting from $65,000 to $35,000 in a very short time during April—June 2021), possibly due to the crackdown on mining in China and the announcement of Elon Musk that Tesla would no longer accept payments in bitcoin.[9] As a result, perhaps investors were looking for alternative crypto assets, and DeFi assets proved resilient to the crypto market crash.[10] We do not report the

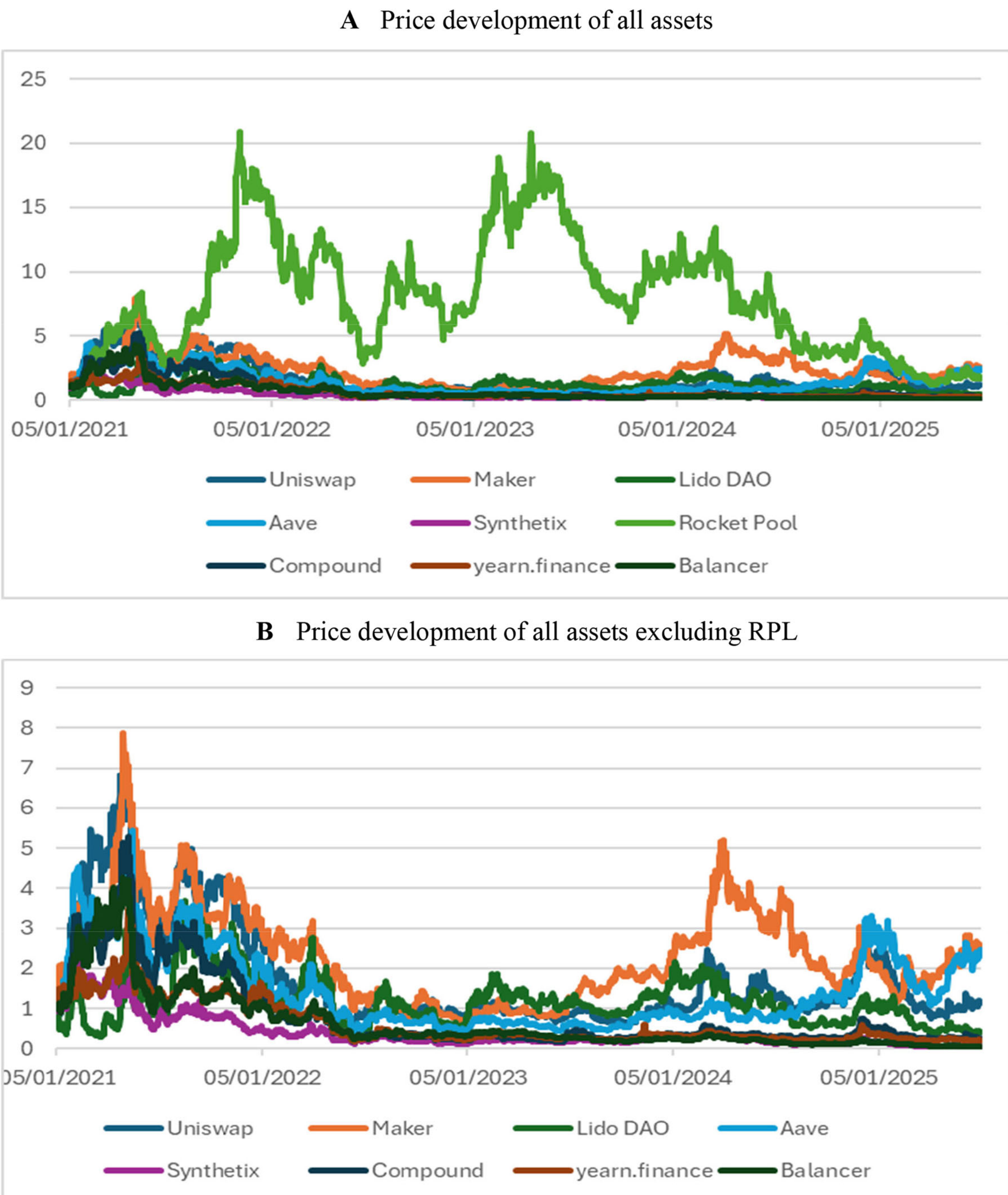

FIGURE 1 | Price development over time of the DeFi assets. For comparison purposes, the starting value of each asset has been set to 1, and the subsequent values adjusted accordingly. (A) Price development of all assets. (B) Price development of all assets excluding RPL. *Note:* The above figures present time series variations of assets. [Color figure can be viewed at wileyonlinelibrary.com]

descriptive statistics for returns of the assets since our cointegration analysis is based on prices. However, this information will be available upon request.

4.2 | Main Results

i. *Characterizing co-movement pattern: Evidence of Fractional Cointegration:*

Using our data, we have run long-run FCVAR and have recovered the fractional error correction component, which we broadly refer to as the Speed of Adjustment (SA). In Table 2, we have presented the descriptive statistics of the SA time series obtained from a rolling window estimation of fractional cointegration for the 9 DeFi assets. In our estimation, we find the three cointegration ranks, so there are three different cointegrating relationships among all variables in the system. This means that there are also three corresponding sets of SA series.[11]

For the first set of SA (SA1), the mean values are negative for 5 out of 9 assets, which suggests a general tendency of the DeFi assets to move toward the equilibrium and help correct disequilibrium errors. LDO shows the weakest response to disequilibria (lowest absolute value, 0.0001), whereas RPL shows the strongest response (highest absolute value, 0.2634), which is consistent with RPL being the most volatile asset (see Figure 1). The SA of RPL is also the most volatile, with the highest standard deviation and the largest range between minimum and maximum. Meanwhile, the SA of SNX is the most stable with the lowest standard deviation and the smallest range.

For the second set of SA (SA2), the mean values also show that 5 assets move toward equilibrium (i.e., UNI, MKR, AAVE, SNX, BAL) while others move away from it. On average, BAL and RPL show the weakest and strongest response to disequilibria, respectively. RPL still has the most volatile SA with the highest standard deviation and the largest range, while SNX still has the most stable SA with the lowest standard deviation and the smallest range.

For the third set of SA (SA3), the mean values are all positive except LDO, which suggests that most of the assets generally move away from the equilibrium and thus do not contribute to the error correction process. The average response of SNX is the weakest and that of RPL is still the strongest. Finally, like SA1 and SA2, RPL and SNX have the most and least volatile SA, respectively, as shown by the standard deviation as well as the range from minimum to maximum.

Overall, some results are consistent across the three sets of SA. First, there is always at least 1 asset that tends to move toward the equilibrium (i.e. negative mean SA). Second, RPL always responds most strongly to disequilibrium errors, with the highest absolute value of mean SA. Third, RPL and SNX have the most and least volatile SA, respectively, in all cases.

ii. *Results of Spillover Analysis:*

Table 3 shows the fractional degrees estimated from the FIVAR model for the SA time series of the 9 DeFi assets. All estimates are consistently between 0 and 1, and statistically significant at 1% level. These results show strong evidence of the long-memory characteristics in the SA series, which supports our use of the FIVAR model.

Table 4 shows the overall spillover effects in SA among the assets. Again, there are three sets of results for the three sets of

TABLE 2 | Descriptive statistics of SA.

	UNI	MKR	LDO	AAVE	SNX	RPL	COMP	YFI	BAL
Panel A: SA1									
Mean	−0.0645	0.0122	0.0001	0.0056	−0.0008	−0.2634	0.0121	−0.0009	−0.0020
Std. Deviation	0.1185	0.1453	0.1136	0.1025	0.0257	1.4965	0.0527	0.0330	0.0579
Minimum	−0.3816	−0.3087	−0.4736	−0.2418	−0.0744	−7.3541	−0.1676	−0.1060	−0.1796
Maximum	0.2230	0.4903	0.2759	0.4513	0.0858	1.5246	0.2346	0.1357	0.2323
Panel B: SA2									
Mean	−0.0050	−0.0356	0.0036	−0.0105	−0.0065	0.0775	0.0016	0.0069	−0.0005
Std. Deviation	0.0559	0.0565	0.0460	0.0484	0.0180	0.3851	0.0272	0.0210	0.0223
Minimum	−0.1333	−0.2309	−0.1409	−0.1924	−0.0751	−1.1438	−0.0979	−0.0606	−0.0801
Maximum	0.3673	0.1257	0.1731	0.2268	0.0761	1.7217	0.2414	0.1688	0.1316
Panel C: SA3									
Mean	0.0488	0.0204	−0.0524	0.0149	0.0067	0.1335	0.0104	0.0139	0.0077
Std. Deviation	0.1029	0.1011	0.0899	0.0695	0.0135	0.6318	0.0281	0.0229	0.0193
Minimum	−0.2253	−0.4406	−0.4086	−0.3896	−0.0642	−2.0818	−0.0973	−0.0598	−0.1021
Maximum	0.5994	0.2399	0.1250	0.3080	0.0588	1.6600	0.1054	0.1215	0.0716
N	1465	1465	1465	1465	1465	1465	1465	1465	1465

Note: This table presents descriptive statistics for the time series of the speed of adjustment for three sets of SA series selected based on their cointegrating rank (of order 3).

TABLE 3 | Fractional degrees of the SA time series from the FI-VAR model.

	SA1	SA2	SA3
UNI	0.80	0.80	0.88
MKR	0.87	0.79	0.95
LDO	0.73	0.72	0.83
AAVE	0.81	0.88	0.76
SNX	0.83	0.90	0.84
RPL	0.77	0.75	0.80
COMP	0.82	0.85	0.88
YFI	0.70	0.76	0.90
BAL	0.82	0.77	0.76

Note: This table presents estimates of the fractional order of integration (d) for the Speed of Adjustment time series for three sets of SA. The values are less than 1, which implies that the series has long memory but can be mean-reverting in the long run (in the absence of intervention of any other stochastic shocks in the system).

SA time series. The empirical findings reveal a high degree of interconnectedness among the SAs of the considered DeFi assets. The total spillover index, which quantifies the contribution of shocks from SAs of other assets to the forecast error variance of a given asset on average, is substantial across all three sets of SA time series. As presented in Table 4, the total spillover is calculated at 74.39% for SA1, 74.88% for SA2, and 65.58% for SA3. These figures indicate that a significant majority of the volatility in any SA of a single asset is attributable to shocks originating from elsewhere in the network, underscoring the systemic nature of risk in this market. This can be considered solid evidence of the close connectedness among these DeFi assets.

A detailed analysis of directional spillovers identifies specific assets that are key transmitters and receivers of SA's shocks. The primary sources of spillover vary across the different sets of SAs, as shown in Table 4. BAL emerges as the largest shock transmitter in SA1 (110.34), a role assumed by AAVE in SA2 (110.28) and COMP in SA3 (109.27). In contrast, RPL is consistently one of the weakest transmitters of SA's shocks (34.21 in SA1 and 19.82 in SA2), with LDO occupying this position in SA3 (29.26). On the receiving side, the impact of spillovers is more diffuse, with no single asset consistently absorbing the most risk. The largest shock recipients are SNX in SA1 (79.73), YFI in SA2 (84.44), and BAL in SA3 (75.46). Conversely, RPL and LDO are consistently the weakest receivers of systemic shocks.

Based on the results in Table 4, Figure 2 provides a visual representation of these complex interdependencies. The size of the nodes, which corresponds to the magnitude of transmitted spillovers, visually confirms the shifting dominance of BAL, AAVE, and COMP as the central players in the network across the three sets of the SA time series. Other assets, such as UNI and SNX, are also shown to be consistently significant within the network structure. In stark contrast, RPL and LDO are consistently depicted as peripheral players, reflecting their minimal role in the transmission of spillovers throughout the system.

Figure 3 shows the time-varying total spillover in SA among the assets. These indices follow a similar pattern in all three sets of results until early 2024. More specifically, the index exhibits a decline to a low point of approximately 60%–65% in the third quarter of 2022 before recovering to and maintaining a heightened level of around 80% until early 2024. The indices dropped quickly to between 50% and 60% within the first quarter of 2024 before bouncing back. This pattern suggests a period of decreased systemic risk followed by a rapid return to a state of high market integration.

4.3 | Discussion of Findings

In our research, we show that DeFi assets, though resilient during major crypto crashes, exhibit strong interconnectedness with important implications for trading and risk management. We find multiple cointegrating relationships among leading tokens, creating opportunities for arbitrage and directional strategies, but the speed of adjustment (SA) determines how long such opportunities last. Assets differ widely: fast adjusters like RPL are volatile and suit risk-tolerant, short-horizon traders, while slow adjusters such as LDO, BAL, and SNX are more stable and appeal to conservative investors. Spillover analysis reveals high contagion risk, with about 75% of SA variations driven by cross-asset transmissions. Key transmitters (BAL, AAVE, COMP) reduce diversification potential, while marginal players (RPL, LDO) offer valuable hedging opportunities. Crucially, asset size does not equal systemic influence—smaller tokens can drive major spillovers, while some larger ones play minor roles. Investors and regulators must recognize these dynamics to design resilient portfolios and policies.

Our findings have important implications for investment and portfolio managers interested in the emerging assets in DeFi, possibly as an attractive alternative to traditional crypto assets such as Bitcoin. DeFi assets have proved resilient to crypto market crashes on several occasions, such as March 2020 and May 2021.[12] Our cointegration analysis reveals multiple cointegrating relationships among the leading DeFi assets in the DPI index, which is consistent with the study of (Keilbar and Zhang 2021) for cryptocurrencies. The presence of cointegration offers excellent trading opportunities. For example, (Leung and Nguyen 2019) confirm the profitability of statistical arbitrage for cointegrated portfolios of several major cryptocurrencies. Similarly, (Tadi and Kortchemski 2021) find that a pairs trading strategy based on cointegration can outperform the buy-and-hold approach, with reasonably low drawdown. However, arbitrage strategies should be used with caution (Keilbar and Zhang 2021) due to arbitrage frictions (Kroeger and Sarkar 2017) and hence the possibility of the assets only adjusting slowly (Cheah et al. 2018). Since SA is a strong indicator of potential arbitrage duration, in this case, traders should be more patient and ready to be in the market for possibly a long time.

In addition to market-neutral strategies such as statistical arbitrage/pairs trading, directional strategies could also be highly lucrative. We find that RPL always responds most strongly to disequilibrium errors with the fastest adjustment, whereas LDO, BAL, and SNX have the weakest response and slowest adjustment. Effective strategies can be designed to

TABLE 4 | Overall spillover (%) in SA among the 9 DeFi assets.

	UNI	MKR	LDO	AAVE	SNX	RPL	COMP	YFI	BAL	To others
Panel A: SA1										
UNI	**28.51**	13.91	12.24	17.24	12.42	13.94	12.97	9.69	13.44	105.85
MKR	8.95	**29.23**	6.20	7.87	8.64	5.13	6.89	5.46	8.03	57.16
LDO	6.05	4.72	**26.36**	5.23	5.48	13.71	5.26	4.21	5.37	50.04
AAVE	13.52	10.23	8.27	**26.40**	10.87	6.99	11.36	9.98	9.80	81.01
SNX	11.19	12.06	10.00	11.00	**23.93**	8.05	12.52	11.72	12.72	89.28
RPL	5.28	2.80	10.62	3.17	3.52	**26.68**	2.22	2.61	3.99	34.21
COMP	10.88	10.10	7.99	12.40	14.07	4.52	**27.53**	15.56	14.43	89.95
YFI	5.74	5.05	4.42	7.71	8.41	3.90	9.05	**27.08**	7.41	51.69
BAL	14.26	13.45	10.99	12.64	16.33	11.50	16.84	14.33	**30.15**	110.34
From others	75.86	72.32	70.73	77.27	79.73	67.74	77.11	73.57	75.19	**Total**
Net spillover	29.99	−15.16	−20.69	3.74	9.54	−33.53	12.84	−21.88	35.15	**74.39**
Panel B: SA2										
UNI	**27.86**	7.78	10.72	14.80	12.80	10.61	10.76	13.34	10.94	91.74
MKR	4.49	**35.35**	6.58	6.74	6.79	5.60	8.42	4.26	9.03	51.91
LDO	5.62	4.35	**26.19**	3.97	4.11	11.58	3.93	5.15	3.79	42.50
AAVE	17.15	11.13	9.58	**26.58**	17.24	7.31	16.92	16.25	14.70	110.28
SNX	14.09	9.20	9.79	14.31	**22.67**	6.03	15.43	14.71	12.22	95.78
RPL	2.86	2.09	6.98	1.76	1.70	**31.62**	1.12	1.13	2.17	19.82
COMP	11.15	12.92	9.23	14.95	15.10	4.31	**24.23**	15.88	14.16	97.70
YFI	9.99	3.06	7.12	8.85	9.86	2.88	9.12	**19.36**	6.30	57.19
BAL	11.69	16.30	9.68	14.84	15.67	8.62	16.46	13.73	**34.36**	106.99
From others	77.04	66.84	69.68	80.22	83.27	56.95	82.15	84.44	73.33	**Total**
Net spillover	14.70	−14.93	−27.18	30.07	12.51	−37.13	15.55	−27.26	33.67	**74.88**
Panel C: SA3										
UNI	**35.12**	10.95	5.83	13.40	9.49	5.92	9.07	9.73	8.90	73.28
MKR	8.89	**40.57**	4.34	4.63	5.95	4.30	7.64	5.65	5.68	47.07
LDO	2.71	2.81	**40.22**	2.94	1.76	14.00	1.61	1.43	2.00	29.26
AAVE	13.32	6.01	5.87	**38.04**	9.67	3.99	11.61	9.62	7.89	67.98
SNX	9.78	10.28	4.97	11.12	**29.87**	7.02	15.79	14.47	16.64	90.07
RPL	3.32	2.79	18.15	2.25	3.27	**42.71**	2.38	2.04	3.66	37.87
COMP	12.45	14.14	5.88	15.67	18.11	6.35	**33.62**	18.62	18.04	109.27
YFI	9.04	6.33	2.09	8.69	13.47	2.91	13.00	**31.40**	12.65	68.18
BAL	8.24	6.10	3.94	7.04	13.11	6.65	11.40	10.73	**27.53**	67.21
From others	67.76	59.41	51.06	65.74	74.83	51.14	72.49	72.29	75.46	**Total**
Net spillover	5.52	−12.34	−21.80	2.24	15.24	−13.26	36.78	−4.12	−8.25	**65.58**

Note: The above table presents estimates of spillover using the Diebold and Yilmaz method. "To others" shows the total spillover from each asset to all the others. "From others" shows the total spillover to each asset from all the others. "Net spillover" is the difference between "To others" and "From others." "Total" shows the total spillover in the whole system of all nine assets. The remaining values show the spillover for each pair of assets. The principal diagonal elements (in bold face) indicates spillover to itself, for instance, UNI to UNI (28.51), and BAL to BAL (30.15).

exploit the difference in SA between these assets, since this difference is particularly suitable and offers a fertile ground for certain types of strategies. For instance, traders can wait for a signal from the fast markets (e.g., RPL) and then use a lead-lag algorithm to trade the slow markets (e.g. LDO, BAL, SNX) in the same or opposite direction of the fast markets (perhaps depending on their correlations) before the slow markets make their moves. Meanwhile, contrarian trading strategies based on mean reversion outperform not only buy-and-hold but also other contrarian strategies in many markets (Balvers et al. 2000), and the error correction process in cointegration is a type of mean-reverting behavior. Moreover, deviations from

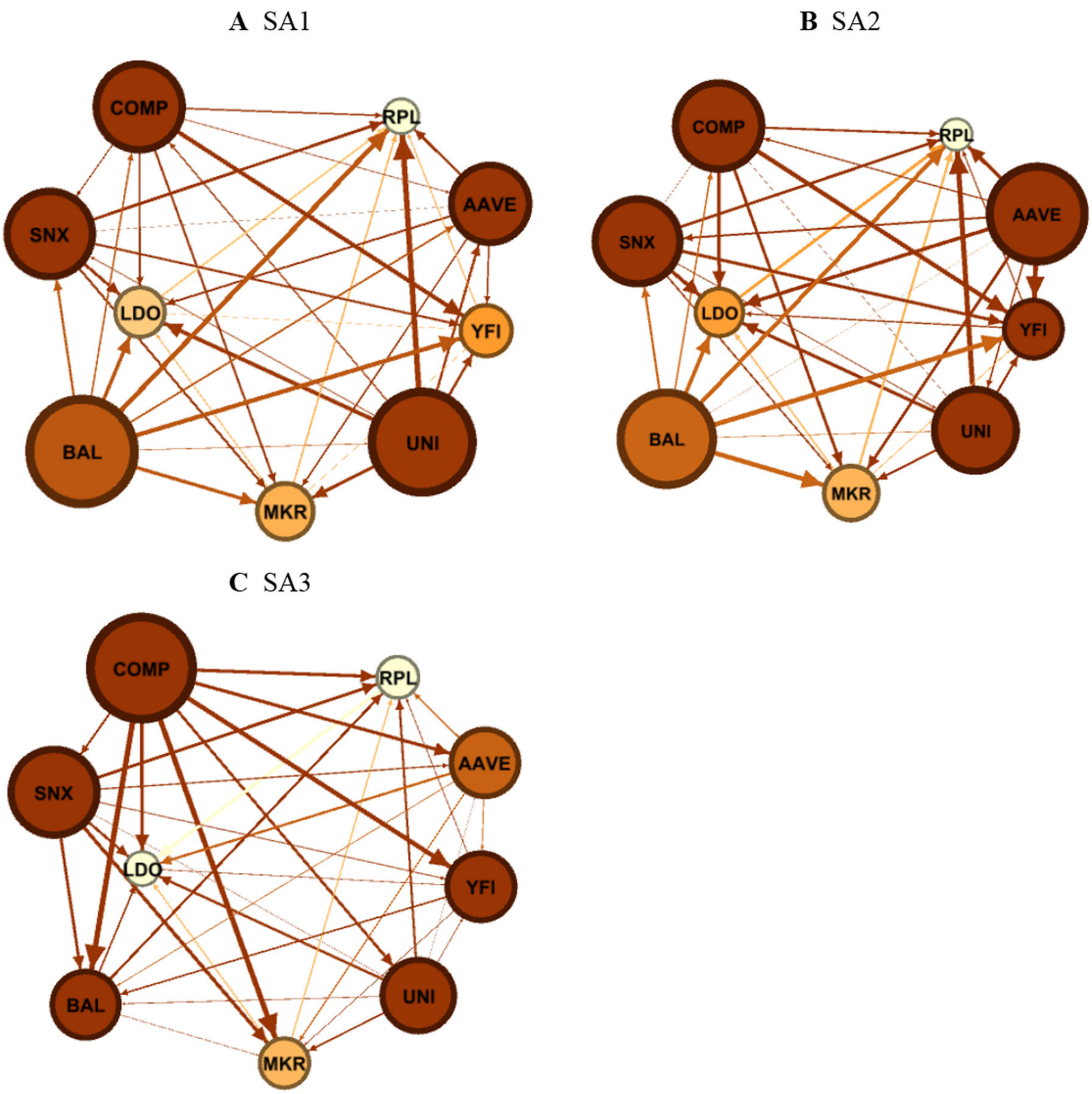

FIGURE 2 | Network of pairwise spillover in SA. The node size (smaller to bigger) indicates the strength (weaker to stronger) of total spillover from that asset to all other assets. The node color (from lighter to darker) shows the strength (weaker to stronger) of total spillover to that asset from all other assets. The arrows indicate the direction of net pairwise spillover, and their thickness shows the strength of this net pairwise spillover. [Color figure can be viewed at wileyonlinelibrary.com]

the long-run equilibrium can help predict returns of crypto assets (Kapar and Olmo 2019).

On one hand, traders with a higher level of risk tolerance may be more interested in and comfortable with fast and volatile periods/markets, which offer ample opportunities to capture quick profits. On the other hand, risk-averse and conservative participants may choose to trade in less volatile periods/markets, which also decreases their risk of missing out on opportunities. The risk aversion aptitude differs measurably across investors' life cycle: a young investor (in their 30s, for instance) will be more inclined to take higher risks than one who is in their 50s or close to retirement. For the latter type, the investors would like greater security with their savings (pension funds) that are less susceptible to volatility contagion. Therefore, for those classes of investors, there is a high degree of substitutability between riskier (viz., crypto assets) and less risky (e.g., pension savings or fixed investment).[13]

Regarding market timing, SA is a strong indicator of how fast investors should act since they need to react to price movements based on their expectation of SA (Hillebrand 2003). If they participate in fast markets with high expected SA (e.g., RPL), they must respond faster and adjust their pace accordingly to keep up. Conversely, slow markets with low expected SA (e.g. LDO, BAL, SNX) should give participants more time to act. Moreover, since markets cannot be perfectly efficient (Grossman and Stiglitz 1980), temporary inefficiencies, such as over- or under-reaction, will happen. SA can directly measure the current extent of this over- or under-reaction in markets (Theobald and Yallup 2004) and help investors make more informed decisions about whether/how to take advantage of this phenomenon. SA is particularly relevant for crypto assets since (Borgards and Czudaj 2020) find that over-reaction is common in this market.

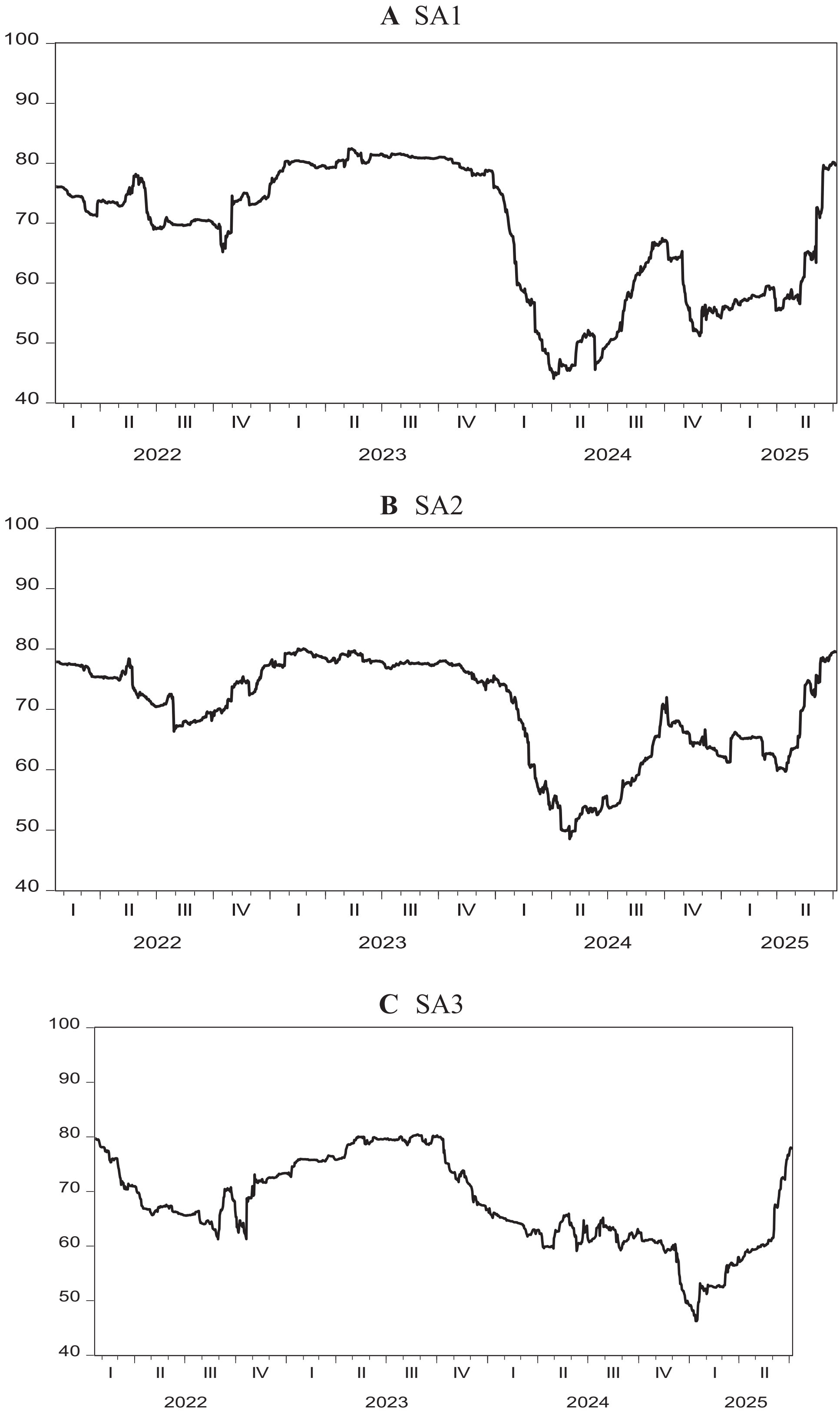

FIGURE 3 | Dynamic total spillover in SA over time among the 9 DeFi assets. *Note:* The set of figures presents temporal variations of the dynamic total spillover of the speed of adjustment for 9 DeFi assets, each demonstrating a sharp fall in the second quarter of 2024.

Regarding the roles of individual DeFi assets in the spillover effects, our findings are as follows. First, BAL, AAVE, and COMP are the system's key players in the transmission of the spillovers. Second, UNI and SNX are also important contributors to the network's dynamics. Third, RPL and LDO consistently feature as the least minor players, characterized by their smaller node sizes across all three considered cases. Finally, RPL is both the weakest transmitter and the weakest receiver of spillover. For portfolio management purposes, markets with a low level of integration can offer diversification benefits and vice versa (Patel et al. 2022). Hence, investors should consider the smallest players with the least connections in the spillover network (i.e., RPL and LDO) in their portfolio selection. RPL is particularly interesting since it is the weakest asset in terms of both transmission and receipt of spillover, which suggests that it is quite detached from the rest of the system. This may help explain the different price behaviors of RPL compared to the others, and it may indeed be the best option for those who want some exposure to DeFi assets while also avoiding their contagion risk via the SA spillover mechanism. Meanwhile, investors may want to exclude certain assets (e.g., BAL, COMP, and AAVE) from their portfolios since they are closely connected to other assets, so they may offer little diversification benefit.

Our spillover analysis shows that the total spillover in SA among all 9 DeFi assets is quite strong, around 75% over the whole sample period. This finding is different from (Kumar and Anandarao 2019), who only report a moderate level of spillover among cryptocurrencies. Since spillover effects can be considered a measure of contagion risk among crypto assets (Koutmos 2018), there is a high contagion risk among the assets in our sample. We also find that the total spillover varies over time, which is consistent with the study of (Yi et al. 2018) for many cryptocurrencies. Therefore, portfolio managers must pay attention to this temporal development of spillover in SA and act accordingly.

Several studies have found that some minor crypto assets with small market capitalization are more likely to transmit strong shocks to their larger counterparts (Yi et al. 2018; Huynh et al. 2020). Similarly, we find that AAVE, which contributes only 13.7% to the DPI index (not even in the top 3 constituents), is one of the strongest transmitters of spillover. COMP is another important player in the network despite its small index weight of only 3.6%. Meanwhile, LDO plays a very minor role despite being the second-largest index constituent with a contribution of more than 20%. UNI and SNX are two notable exceptions since their sizes do correlate with their roles in the spillover effects. They are the largest and third largest assets (with around 25% and 15% index weight, respectively), and they play important roles in the system. These observations imply that investment managers need to be aware of and avoid their own potential bias where they assume that the largest assets are also the most dominant in terms of spillover, which may not always be the case. To ensure financial stability, regulators should also be aware of the quantitative importance of the likelihood of the large assets being more/less contagious. The financial stability policy should be nonlinearly proportional (such as the inverted *U*-shaped) to the weight of volatility spillovers of those assets.

5 | Conclusions

To conclude, we contribute to the under-researched strand of existing finance literature on the time-varying co-movement and spillover among emerging DeFi asset classes based on the novel blockchain technology and argue as well as demonstrate that greater adjustment speed is an important marker of greater productivity of the interdependent system. Given the strong significance and profound implications of SA, it is high time for investment and portfolio managers to learn about its dynamics, especially in the emerging area of DeFi. The time-varying nature of SA makes it even more important to keep a close eye on its temporal evolution. In our work, we find multiple cointegrating relationships among the assets, which should pave the way for various lucrative trading strategies. We also confirm cross-sectional heterogeneity in SA. More specifically, RPL always responds most strongly to disequilibrium errors with the fastest adjustment, whereas LDO, BAL, and SNX have the weakest response and slowest adjustment. In addition, RPL and SNX have the most and least volatile SA. These findings help investors make more informed decisions about asset selection and risk management. Adventurous investors may prefer fast and volatile markets, whereas their conservative peers may prefer slow and stable markets. Regarding market timing, investors need to pace their activities in line with the speed of their chosen markets.

We confirm a high level of contagion risk among the assets, as shown by their strong spillover effects (around 75% over the whole sample period). Thus, investment managers need to be more cautious about holding a portfolio of these assets. They must also pay attention to the development of spillover in SA over time and act accordingly. For diversification purposes, investors should consider the smallest players with the least connections in the spillover network (i.e., LDO and especially RPL) in their portfolio selection. Meanwhile, they should exclude certain assets (e.g. AAVE, COMP, and BAL) since they may offer little diversification benefit. Also importantly, investors should not make decisions or act based on the assumption that the large assets are always the dominant ones in spillover. Finally, we conclude our study by suggesting several promising directions for future research.

Future research should examine empirically the performance and profitability of these strategies, and potentially many others, for the emerging DeFi assets. Another promising research direction is to explore determinants/drivers of SA and its spillover among crypto assets. Regarding SA, previous studies have found several determinants in the context of stock markets, such as economic and political uncertainty or market conditions (Spierdijk et al. 2012; Bali et al. 2008). In terms of spillover among crypto assets, many drivers have been reported, such as (i) market size, (ii) oil price, (iii) important external events and news related to cryptocurrencies, (iv) uncertainty, and/or (v) financial integration among markets (Koutmos 2018; Kumar and Anandarao 2019; Yi et al. 2018; Gillaizeau et al. 2019; Moratis 2021; Katsiampa 2019). However, the spillover examined previously was in return and volatility rather than SA. Future studies can investigate the role of all the factors above, among others, in the unique setting of SA and its spillover among crypto assets.

Author Contributions

Jeremy Eng-Tuck Cheah: conceptualization, coordination, writing. **Thong Dao:** data collection and curation, conceptualization, estimation, writing. **Hung Do:** data collection and curation, estimation, writing. **Tapas Mishra:** model design, estimation, drafting.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data used for the empirical analysis in this paper are available from the authors upon request.

Endnotes

[1] We will shortly present our proposed mechanism, the FCVAR, to model stability.

[2] https://wifpr.wharton.upenn.edu/wp-content/uploads/2021/05/DeFi-Beyond-the-Hype.pdf.

[3] https://medium.com/momentum6/the-new-wolf-of-wall-street-defi-2021-overview-and-2022-outlook-70cb053442c5.

[4] Cryptocurrency bubbles have occurred several times since February 2011, when the price of Bitcoin rose to US $1.06, then fell to US $0.67 that April. Likewise, the prices experienced large fluctuations in 2013 (boom) and 2014–2015 (crash). Bitcoin once again experienced a boom in 2017 and a crash in 2018 and a pattern that occurred in 2021, 2022, and 2024.

[5] https://coinmarketcap.com/.

[6] https://indexcoop.com/products/defi-pulse-index.

[7] https://cran.r-project.org/web/packages/FCVAR/index.html.

[8] Both operators are defined based on their binomial expansion in L, the lag operator. There is no term in L^0 for the expansion of L_b, so Equation (1) contains only lagged disequilibria.

[9] https://time.com/6175370/why-bitcoin-crashing/.

[10] https://cointelegraph.com/news/defi-proved-resilient-during-the-march-2020-and-may-2021-market-crises.

[11] Given the various sets of results, we only report the most important and relevant statistics for our discussion to avoid potential confusion and unnecessary information. However, other statistics (e.g. skewness, kurtosis) will be available upon request.

[12] https://cointelegraph.com/news/defi-proved-resilient-during-the-march-2020-and-may-2021-market-crises.

[13] Many thanks to an anonymous referee for suggesting this argument.

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