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Dynamic DeFi-G7 stock markets interactions and their potential role in diversifying and hedging strategies

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Abstract

This study examines the link between stocks and decentralized finance (DeFi) in terms of returns and volatility. Major G7 exchange-traded funds (ETFs) and various highly traded DeFi assets are considered to ensure the robustness of the empirical experiment. Specifically, this study applies the vector autoregression generalized autoregressive conditional heteroskedasticity (VAR-GARCH) model to examine the information transmission of these two markets on a two-way basis and the dynamic conditional correlation (DCC)-GARCH model to assess the bivariate correlation structure between each DeFi and ETF pair. The volatility spillover analysis proves a contagion effect occurred between different geographic markets, and even between markets of different natures and typologies, during the most turbulent moments of the COVID-19 crisis and the war in the Ukraine. Our results also reveal a weak positive correlation between most DeFi and ETF pairs and positive hedge ratios that approach unity during turbulent times. In addition, DeFi assets, except for the Bazaar (BZR) Protocol, can offer diversification gains when included in financial investment portfolios. These results are particularly relevant for portfolio managers and policy-makers when designing investment strategies, especially during periods of financial crisis.

Keywords: Volatility spillovers, Dynamic correlations, DeFi, G7 ETF, Diversification strategies

JEL Classification: G11, G15, C13, C22, C41, C58

Introduction

In recent years, owing to financial liberalization, the opening up of economies, the severe crisis caused by the COVID-19 pandemic, the global turbulence resulting from the war in the Ukraine, the energy crisis, rising world prices and subsequent interest rate hikes by the monetary authorities in Europe and the United States, international markets have become increasingly volatile (Corbet et al. 2020a). This trend has triggered growing interest in the behavioral analysis of market volatility. Moreover, the rise of new security types, such as decentralized finance (DeFi) assets, and their increasing applicability in different market institutions are new factors to consider when examining price stability. Clearly, the COVID-19 crisis, the Russian invasion of the Ukraine, the energy crisis, and the digitalization of economies, among other factors, have boosted these assets, whose prices continue to break records as investment in DeFi becomes widespread (Corbet et al. 2020b; Caferra and Vidal-Tomás 2021). Similar to the cryptocurrency market, DeFi and non-fungible tokens (NFTs) were affected by the pandemic, but only in the early months (Sharif et al. 2020; Umar et al. 2022b; Díaz et al. 2023) and to a lesser extent than the broader cryptocurrency market and other conventional asset markets (Aharon et al. 2021; Umar et al. 2021a, 2022a; Wu et al. 2023; Yousaf et al. 2023).

Despite the pandemic, DeFi assets experienced remarkable growth, with 47% year-on-year growth in DeFi markets in 2022 (Cevik et al. 2022; Chowdhury et al. 2022). They play an important role in the recent growth of the cryptocurrency market (Yousaf and Yarovaya 2022a). Indeed, an increasing number of studies have confirmed that the cryptocurrency market's relevance continues to grow, particularly in the DeFi sector (Ghosh et al. 2023). As of July 31, 2022, the Coinbase's digital asset classification standard (DACS) outlines six sectors in the digital asset industry. Among these, the DeFi sector, ranks third, comprising 111 assets with a market share of 2.2% and a total capitalization of approximately $24 billion. Uniswap (UNI) leads the DeFi sector with over 25%, and the largest industry group within DeFi is exchanges, with 33 assets and a market capitalization of $12.1 billion.[1]

The extant literature shows that volatility transmissions and spillovers exist between different stock markets (Shahzad et al. 2017) and cross-market cryptocurrency prices (Gillaizeau et al. 2019). Cryptocurrencies exhibit long-memory properties in terms of volatility persistence (Abakah et al. 2020), and their prices are influenced by demand as a means of payment and speculation, which is highly volatile and uncertain (Yousaf et al. 2022b). There are interdependencies between cryptocurrencies and traditional financial assets with weak correlations, and cryptocurrency markets are prone to herding behavior (Gurdgiev and O'Loughlin 2020). DeFi assets influence cryptoasset prices; thus, understanding the volatility transmission and spillovers among DeFi assets and different market types is crucial (Corbet et al. 2021). Consequently, scholars have examined the efficiency of hedging strategies, such as generalized autoregressive conditional heteroskedasticity (GARCH) models and dynamic hedging, to minimize risk exposure (Díaz et al. 2023).

Within this framework, the present research seeks to provide empirical evidence of the theoretical benefits derived from DeFi–equities interaction by investors who are reluctant to diversify by asset class and who prefer to focus their investments exclusively on traditional assets (e.g., equities or new digital assets), which we may refer to as "equity and crypto investors." For this type of homogeneous investor, the asset class in which they invest is generally extremely complex in order to mitigate the specific risks to which their portfolios are exposed as they are composed of assets with very high positive correlations (Brauneis and Mestel 2019; Liu 2019). Moreover, both equity and cryptographic investors, but especially the latter, are affected by the traditionally high volatility of their respective markets (Karim et al. 2022). Therefore, it is clear that both investor types should be informed by studies such as the present one, which will demonstrate that

[1] https://www.coindesk.com/markets/2022/08/29/diving-deep-into-defi-to-navigate-the-new-wave-of-finance/.

combining investments in markets of very different natures will allow them to significantly reduce the overall market risk exposure of their investments (Yousaf et al. 2023).

This study analyzes the interaction between DeFi lending tokens and equity exchange-traded funds (ETFs) using the dynamic conditional correlation (DCC)-GARCH model to assess dynamic connectedness. Although more complex methods are available, the DCC-GARCH model remains the benchmark for computational efficiency. This study follows Esparcia et al. (2022) in advocating the bivariate DCC-GARCH model to estimate portfolio investment strategies. The vector autoregression (VAR)-GARCH model is used to estimate standardized innovations and analyze static volatility spillovers between DeFi assets and equity ETFs. Citing studies by Fisch and Momtaz (2020) and Qiao et al. (2020), this study explores the diversifying properties of cryptocurrencies in portfolios, The recent literature highlights the need to investigate the interaction between DeFi assets and conventional stocks, recognizing the relative novelty of DeFi as an asset class (Cevik et al. 2022; Umar et al. 2022; Yousaf et al. 2023).

Thus, this study contributes to the financial literature by exploring the joint evolution of continuous returns, time-varying correlations, and dynamic volatility spillovers between G7 stock markets and various highly capitalized DeFi lending tokens during the economic turbulence triggered by COVID-19, the Ukrainian War, and the energy crisis. Using the VAR-GARCH and DCC-GARCH models, this study provides insights into the volatility transmission, time-varying dynamics, and bidirectional effects of DeFi shocks on stock returns and vice versa. The study period extends to the end of 2022 and includes the aforementioned unstable periods, thus providing relevance for understanding volatility spillovers. Unlike previous work by Yousaf et al. (2023), this study uses a VAR-GARCH model, thereby enhancing robustness and going beyond connectedness and contagion to suggest efficient portfolio strategies. In addition, the use of ETFs as proxies for equity markets allows for direct applicability to portfolio management, distinguishing this study from Yousaf and Yarovaya (2022a).

The remainder of this paper is organized as follows. Sect. "Literature review" presents a recent literature review on volatility transmission and the interdependence among DeFi assets and different markets. Sect. "Data" describes the main data sources and the pertinent in-sample analyses. Sect. "Empirical methodology" introduces the VAR-GARCH and DCC-GARCH models implemented in the empirical assessment. Sect. "Empirical results" reports the relevant results and findings, including robustness checks of the constructed portfolios, and discusses implications for portfolio managers. Further discussion and the implications of the results are provided in Sect. "Discussion". Finally, Sect. "Concluding remarks" concludes the study by shedding light on the diversifying role of DeFi lending tokens.

Literature review

There is a vast body of recent literature dealing with the linkages and transmissions between diverse stock markets (Shahzad et al. 2017; Luo and Wang 2019; Zhang, Zhuang, Lu, et al. 2020). Shahzad et al. (2017) provide empirical evidence on the interactions between returns and volatility in Islamic and conventional stock markets. Luo and Wang (2019) implement the multivariate heterogeneous autoregressive (MHAR)-DCC model to analyze asymmetric volatility transmissions across major international stock markets (US, Japan, Hong Kong, and Singapore) under 5-min high frequency data and conclude that the relationship between the US and Singapore exhibits a normal leverage effect, whereas the transmissions between Japan and Hong Kong show the reverse leverage effect. Other studies, such as Zhang et al. (2020), examine the dependence relationship between G20 stock markets using a GARCH-Baba, Engle, Kraft and Kroner (BEKK) model and a quadratic assignment procedure (QAP) and provide strong evidence of the time-varying nature of volatility spillover effects and correlations among major markets.

Various studies have addressed volatility transmission and spillovers in cross-market cryptocurrency prices (Gillaizeau et al. 2019; Abakah et al. 2020; Qureshi et al. 2020). Gillaizeau et al. (2019) analyze cross-market spillover in Bitcoin prices considering system dynamics and, interestingly, report on the net predictive power of Bitcoin–USD for volatility shocks in different markets and the role of Bitcoin–EUR as a volatility receiver. In a more recent study, Abakah et al. (2020) assess volatility persistence in a number of cryptocurrencies considering structural breaks and fractional integration methods and reveal that absolute and squared returns show long-memory properties, with orders of integration confirming the long-memory statement. Finally, Qureshi et al. (2020), using wavelet coherence analysis via continuous wavelet transform (CWT), find that the interdependence among major cryptocurrency markets fluctuates at high frequencies but remain stable at low frequencies.

However, the empirical literature presents mixed and even contradictory results on the factors affecting cryptoasset prices, which serve as collateral for DeFi digital assets (Yousaf et al. 2022), depending mainly on the variables included in each empirical valuation model or on data frequency (Maghyereh and Abdoh 2020). Overall, we can confirm that the price of a cryptocurrency is derived from its demand, both as a means of payment and as a speculative asset, and this demand fluctuates greatly and is uncertain. This, together with the rigidity in the supply of these assets, partly explains why cryptocurrency prices exhibit much higher volatility than those of currencies issued by governments with robust monetary and financial policies. Evidence also shows that these markets are highly susceptible to herding behavior and exuberant expectations or momentary social trends (Gurdgiev and O'Loughlin 2020).

In times of deep recession, such as the recent COVID-19 pandemic, the instability in prices is puzzling to researchers, academics, and portfolio managers. However, accurately estimating time-varying volatility as well as understanding and interpreting the volatility transmission and spillovers found among DeFi assets and markets of a very different nature are critical for both international investors and policy-makers (Corbet et al. 2021; Chowdhury et al. 2022; Karim et al. 2022; Piñeiro-Chousa et al. 2022; Yousaf and Yarovaya 2022a). Other key factors to consider in times of economic uncertainty are the main interdependent relationships that may exist between DeFi assets and other assets of financial provenance (Umar et al. 2022c; Yousaf et al. 2022a, b; Corbet et al. 2022; Yousaf and Yarovaya 2022b; Cevik et al. 2022; Qiao et al. 2023; Yousaf et al. 2023; Ugolini et al. 2023). It is important to consider these elements to have a clearer and more informed idea of the heights that the price of DeFi assets can reach, what stock market instruments affect them, and the possible reasons such instruments affect the price of DeFi assets. This information would aid governments, economic organizations, companies, and individuals seeking to invest or those who currently invest in the DeFi market to clarify which stock market instruments affect their prices. Prevention measures would be improved as a result, allowing policy-makers to develop appropriate tools, mechanisms, and policies to help regulate possible manipulations in the price of DeFi assets.

Other studies focus on volatility transmission, cointegration, and interdependence among cryptocurrencies and other financial assets, such as traditional currencies (Urquhart and Zhang 2019; Rognone et al. 2020; Umar and Gubareva 2020), commodities (Ji et al. 2019; Mensi et al. 2019; Okorie and Lin 2020), fixed income (Baur et al. 2018; Huynh et al. 2020; Le et al. 2021) and equities (Bouriet al. 2017; Kristjanpoller et al. 2020; James 2021), reporting different volatility patterns and evidence of a weak correlation for nearly all pairs. Focusing on the connectedness between cryptocurrency and stock markets, studies such as Kristjanpoller et al. (2020) suggest that investors should take advantage of asymmetric multifractality in the cross-correlation between cryptocurrency and stock markets. The particular linkages between crypto and stock markets are of key importance and highlight the need to consider the cointegration between equities and cryptoassets. Different financial studies have attempted to explain volatility spillovers and interdependencies by fitting various techniques related to copula models, wavelet analysis, and quantile regression methods (Boako et al. 2019; Fruehwirt et al. 2020; Nguyen et al. 2020). In this study, we focus on the strand of research based on the implementation of different variants of multivariate GARCH models with various degrees of complexity (Yi et al. 2018; Canh et al. 2019; Jiang et al. 2021).

In addition to portfolio construction, another strand of the literature deals with the minimum variance hedging analysis, whether constant or time-varying. Therefore, several optimal hedging strategies have been proposed. The fundamental strategies for constructing a constant minimum variance hedge ratio come from Johnson (1976) and Stein (1976), who attempt to minimize the overall variance of a spot-futures financial strategy by selecting an optimal futures position. Subsequently, Ederington (1979) developed an ordinary least squares (OLS) regression of spot returns on futures returns. However, the OLS method does not consider cointegration or conditional heteroscedasticity, leading to underhedged portfolios (Hill and Schneeweis 1981; Cecchetti et al. 1988). The theoretical assumptions of OLS contrast sharply with market behavior because, as new information is received, the risk exposure of each of the involved assets changes (Bollerslev 1986, 1987). Thus, Kroner and Sultan (1993) were among the first to implement an error correction model (ECM) and employ GARCH dynamics to provide more accurate hedging structures. This was a prelude to a boom in the application of GARCH models to assess hedge ratios. Recently, Qu et al. (2019) implemented a dynamic conditional correlation-generalized autoregressive conditional heteroscedasticity-error correction model (DCC-GARCH-ECM) scheme to assess the time-varying hedging performance of China's China Securities Index (CSI) 300 index futures, while others, such as Jin et al. (2020), compared different dynamic hedging strategies (i.e., the DCC-APGARCH, DCC-T-GARCH, and DCC-GJR-GARCH models) and the constant hedge ratio model (OLS model) in the context of green bonds. Specifically, in the context of cryptocurrencies and DeFi assets, new state-of-the-art methodologies are being developed to achieve increasingly efficient hedging, such as the extreme downside hedge (EDH) implemented by Ahelegbey et al. (2021). More recently, Díaz et al. (2023) implemented the generalized orthogonal (GO)-GARCH model to develop optimal portfolio strategies that include time-varying order moments in the context of traditional crypto portfolios and DeFi assets, such as stablecoins.

Data

We consider daily traded prices for the period July 2020–November 2022.[2] In this analysis, we use five DeFi assets (Maker, Celo, Compound, Kava, and the Bazaar (BZR) Protocol) and seven equity ETFs corresponding to each of the G7 economies (the USA, Japan, the UK, Canada, Italy, France, and Germany).

On the one hand, the choice of data period is related to the availability of DeFi assets. While the pandemic began in early 2020, it is important to note that we specifically downloaded data from mid-July 2020 onward for this study owing to the fact that several of the highest market cap DeFi lending tokens (e.g., Celo, Compound, and the BZR Protocol) did not start continuous trading until the second half of 2020. The BZR Protocol initiated trading in mid-July 2020, which served as the starting point for our comprehensive multivariate database and subsequent analysis. However, the choice of ETFs was based on the criterion of providing global exposure to each geographical area while maintaining a certain level of consistency in the tracking criteria across funds. By choosing ETFs from the same provider, iShares (a BlackRock brand), we help investors be confident in the uniformity of the methodology and criteria used to track the respective underlying funds. The selected ETFs are iShares Morgan Stanley Capital International (MSCI) Japan, France, UK, Germany, Canada, Italy, and USA.

Using DeFi assets instead of traditional digital assets (e.g., cryptocurrencies and equity ETFs from G7 countries) is an interesting approach for several reasons. First, DeFi assets offer a broader range of financial services than simple cryptocurrencies. While cryptocurrencies, such as Bitcoin and Ethereum, serve as digital currencies or value stores, DeFi assets provide decentralized platforms for lending, borrowing, stacking, and yield farming. These additional functions can enhance investment strategies, generate passive income, and diversify risk.

Second, DeFi assets operate on blockchain technology, enabling transparency, security, and automated execution of smart contracts. Unlike traditional financial systems, DeFi assets eliminate intermediaries, reduce transaction costs, and enhance efficiency. They also offer greater accessibility to global financial services, thereby empowering individuals who may not have access to traditional banking systems.

Third, DeFi assets provide opportunities for users to earn higher returns through various mechanisms, including yield farming and liquidity. By considering DeFi assets, investors can capitalize on the rapid growth of decentralized protocols and their associated tokens. However, DeFi assets also have higher risks, including smart contract vulnerability and market volatility.

Finally, equity ETFs offer several advantages over individual stock investments. ETFs provide instant diversification by holding a basket of securities across various sectors, which reduces the impact of individual stock price fluctuations. This diversification can mitigate risk and enhance portfolio stability. ETFs also provide liquidity through their

[2] The data were collected from Yahoo Finance and Coinmarketcap.

Table 1 Descriptive statistics of DeFis and ETFs

DeFi returns	Maker	Celo	Compound	Kava	BZR-Protocol		
Mean (%)	0.061622	−0.1518	−0.1707	−0.082349	−0.2029		
Variance (%)	6.1476	7.4514	6.733	7.391	14.88		
Skewness	1.063	1.677	−0.2092	−0.61779	−2.8484		
Kurtosis	7.948	12.658	1.5037	3.8093	62.760		
Jarque–Bera	2397.8* (0.000)	6072.9* (0.000)	86.282* (0.000)	567.99* (0.000)	1.4065e05* (0.000)		
ARCH (Abakah et al. 2020; Aharon et al. 2021; Ahelegbey et al. 2021; Arouri et al. 2011; Baur et al. 2018) test	13.289* (0.000)	4.193* (0.0009)	10.836* (0.0007)	8.1266* (0.0000)	19.342* (0.000)		
ETF returns	USA	Japan	Italy	Canada	Germany	France	UK
Mean (%)	0.034229	−0.000436	0.01491	0.036111	0.023766	0.023356	−0.01113
Variance (%)	0.9409	0.8221	1.1769	0.9258	0.95808	1.0933	1.1423
Skewness	−0.04482	0.26426	−0.26022	−0.0738	−0.1148	0.41558	0.42649
Kurtosis	3.9459	3.855	4.8109	2.8053	4.517	5.0797	6.5075
Jarque–Bera	551.72* (0.000)	536.23* (0.000)	829.31* (0.000)	279.48* (0.000)	724.48* (0.000)	938.33* (0.000)	1525.6* (0.000)
ARCH (Abakah et al. 2020; Aharon et al. 2021; Ahelegbey et al. 2021; Arouri et al. 2011; Baur et al. 2018) test	3.3008* (0.0051)	3.0128** (0.0105)	15.785* (0.000)	4.7961* (0.0002)	5.2375* (0.001)	7.7988* (0.000)	8.2509* (0.000)

ARCH (Abakah et al. 2020; Aharon et al. 2021; Ahelegbey et al. 2021; Arouri et al. 2011; Baur et al. 2018) is the Engle (1982) test for conditional heteroscedasticity. Asymptotic p values of the LM test are given in parentheses

* Significant at: 1%; **significant at 5% and ***significant at 10%

tradability on exchanges, allowing investors to buy or sell shares throughout the trading day. This flexibility is beneficial for short-term trading strategies and risk management.

We use the log differences in prices to compute returns. Table 1 presents the descriptive statistics. Note that Maker has the highest average return while the average returns for all other DeFi assets are negative. The volatility of DeFi assets is also quite high compared with that of the equity indices. The skewness and kurtosis indicators and the Jarque–Bera (JB) statistic testify to the rejection of the null hypothesis of normality for all return series. In addition, the autoregressive conditional heteroskedasticity (ARCH) test shows the presence of conditional heteroscedasticity in the return volatility series, and hence, the need to fit autoregressive models.

Empirical methodology

This study analyzes the interrelationship between the volatility of DeFi assets and ETF returns. The intuition behind the choice of the VAR-GARCH and DCC-GARCH methodologies lies in their ability to capture conditional volatility spillovers and feedback effects between DeFi lending tokens and equity ETFs. By estimating the conditional variances and covariances, the model enables us to analyze the impact of shocks in one asset on the volatilities of the other, thus providing insights into the transmission mechanisms and connectedness between DeFi lending tokens and equity ETFs. Additionally, the DCC-GARCH model extends the VAR-GARCH framework by including the concept of dynamic conditional correlation. This modeling approach allows for a more nuanced understanding of the dynamics and interactions between these assets, which is essential for assessing their connectedness and potential risk implications.

We fit the VAR (1)-GARCH (1,1) model developed by Ling and McAleer (2003) and subsequently implemented by Chan et al. (2005), Hammoudeh et al. (2009) and Arouri et al. (2011) and Mensi et al. (2013). The conditional mean equation of the VAR(1)-GARCH(1,1) system is given by:

$$\begin{cases} Y_t = c + \phi Y_{t-1} + \varepsilon_t \\ \varepsilon_t = h_t^{1/2}\eta_t \end{cases} \tag{1}$$

where $Y_t = (\mathrm{R}_t^{\mathrm{DeFi}}, \mathrm{R}_t^{\mathrm{ETF}})$ and $\mathrm{R}_t^{\mathrm{DeFi}}$ and $\mathrm{R}_t^{\mathrm{ETF}}$ are the DeFi and ETF returns at time t, respectively. $\mathcal{E}_t = (\mathcal{E}_t^{\mathrm{DeFi}}, \mathcal{E}_t^{\mathrm{ETF}})$, where $\mathcal{E}_t^{\mathrm{DeFi}}$ and $\mathcal{E}_t^{\mathrm{ETF}}$ are the residuals of the mean equation for DeFi and ETF index returns, respectively. $\eta_t = \left(\eta_t^{DeFi}, \eta_t^{ETF}\right)$ refers to the innovation and is an i.i.d. random vector. $h_t^{1/2} = diag\left(\sqrt{h_t^{DeFi}}, \sqrt{h_t^{ETF}}\right)$, where h_t^{DeFi} and h_t^{ETF} are the conditional variances of $\mathrm{R}_t^{\mathrm{DeFi}}$ and $\mathrm{R}_t^{\mathrm{ETF}}$, respectively, given by

$$h_t^{DeFi} = C_{DeFi} + \alpha_{DeFi}(\mathcal{E}_{\mathrm{t-1}}^{\mathrm{DeFi}})^2 + \beta_{DeFi}h_{t-1}^{DeFi} + \alpha_{ETF}\left(\mathcal{E}_{\mathrm{t-1}}^{\mathrm{ETF}}\right)^2 + \beta_{ETF}h_{t-1}^{ETF} \tag{2}$$

$$h_t^{ETF} = C_{ETF} + \alpha_{ETF}\left(\mathcal{E}_{\mathrm{t-1}}^{\mathrm{ETF}}\right)^2 + \beta_{ETF}h_{t-1}^{ETF} + \alpha_{\mathrm{DeFi}}(\mathcal{E}_{\mathrm{t-1}}^{\mathrm{DeFi}})^2 + \beta_{\mathrm{DeFi}}h_{t-1}^{\mathrm{DeFi}} \tag{3}$$

Equations 2 and 3 show how volatility is transmitted over time across the ETF and DeFi markets. The cross value of the error terms $\left(\mathcal{E}_{\mathrm{t-1}}^{\mathrm{ETF}}\right)^2$ and $(\mathcal{E}_{\mathrm{t-1}}^{\mathrm{DeFi}})^2$ represents the return innovations in the stock ETF across the corresponding DeFi markets at time $(\mathrm{t}-1)$ and reflects the ARCH effect of past shocks, which captures the impact of the direct effects of shock transmission. The presence of h_{t-1}^{ETF} and h_{t-1}^{DeFi} captures volatility spillovers between the two markets.

Thus, the conditional covariance between each DeFi and ETF return is as follows:

$$h_t^{\mathrm{DeFi},ETF} = \rho_{\mathrm{DeFi},ETF}\sqrt{h_t^{\mathrm{DeFi}}h_t^{\mathrm{ETF}}} \tag{4}$$

Furthermore, we estimate the dynamic conditional correlations in each DeFi–ETF pair using Engle's (2002) seminal DCC-GARCH model. The relative dependence process for each DeFi–ETF pair is expressed as follows:

$$q_{\mathrm{DeFi,ETF},t+1} = \alpha\left(\eta_{\mathrm{DeFi},t}\eta_{ETF,t}\right) + \beta q_{\mathrm{DeFi,ETF},t} \tag{5}$$

with constraints:

$$\overline{\omega} = (1-\alpha-\beta)\rho_{\mathrm{DeFi,ETF}}\alpha > 0\beta > 0 \tag{6}$$

where $q_{\mathrm{DeFi,ETF},t}$ denotes instrumental variables that play the role of covariances at each moment in time t. $\eta_{\mathrm{DeFi},t}$ and $\eta_{ETF,t}$ are the standardized innovations of the chosen assets obtained via the VAR-GARCH (1,1) model.

Next, to extract the conditional correlations, $\rho_{\mathrm{DeFi,ETF},t}$, we standardize the prior instrumental variables, $q_{ij,t}$:

$$\rho_{\mathrm{DeFi,ETF},t+1} = \frac{q_{\mathrm{DeFi,ETF},t+1}}{\sqrt{q_{\mathrm{DeFi,DeFi},t+1}}\sqrt{q_{ETF,ETF,t+1}}} \tag{7}$$

After estimating the dynamic conditional correlation and conditional variance between stock markets and DeFi assets, we can use DeFi assets as diversifiers, especially during the COVID-19 pandemic and subsequent war in the Ukraine as investors aim to minimize portfolio risk in this context. Following Kroner and Ng (1998), the minimum variance portfolio weight of the holdings of cryptos/stock ETFs is given by

$$w_{\mathrm{DeFi},ETF,t} = \frac{h_{\mathrm{DeFi},ETF,t} - h_{\mathrm{DeFi},ETF,t}}{h_{ETF,t-}2h_{\mathrm{DeFi},ETF,t} + h_{DeFi,t}} \tag{8}$$

$$w_{\mathrm{DeFi},ETF,t} = \begin{cases} 0 if w_{\mathrm{DeFi},ETF,t} < 0 \\ w_{\mathrm{DeFi},ETF,t} if 0 \leq w_{\mathrm{DeFi},ETF,t} < 1 \\ 1 if w_{\mathrm{DeFi},ETF,t} > 1 \end{cases} \tag{9}$$

where $h_{ETF,t}$ and $h_{ETF,t}$ are the conditional variances for ETF and DeFi, respectively, and $h_{DeFi,ETF,t}$ is the conditional covariance between crypto and ETF returns at time t. Note that the weight of stock ETF in the one-dollar ETF/crypto portfolio at time t is equal to $(1 - W_{DeFi,ETF,t})$ following Chang et al. (2011), Wang and Wang (2010), Mensi et al. (2013), and Chkili (2016).

Following Kroner and Sultan (1993), to minimize the risk of a portfolio comprising two assets, a long position taken in stock ETF in a given G7 stock market should be hedged by a long position of $\$\beta_t^*$. The risk-minimizing hedge ratio is given as

$$\beta_t^* = \frac{h_{\mathrm{DeFi},ETF,t}}{h_{ETF,t}} \tag{10}$$

where β_t^* is the optimal hedge ratio at time t, $h_{ETF,t}$ is the conditional variance of stock ETF returns, and $h_{\mathrm{DeFi},ETF,t}$ is the conditional covariance between each DeFi asset and ETF.

Empirical results

From the G7 ETFs under investigation, we estimate five bivariate VAR (1)-GARCH (1,1) systems, each containing ETF and DeFi returns. Figure 1 shows the plots of DeFi asset and ETF volatilities during the study period. All the plots indicate that market volatilities peaked in 2022, or more precisely, in late February 2022, which corresponds to Ukraine's invasion by Russia launched on February 24, 2022 (Corbet et al. 2023).

Tables 2, 3, 4, 5 and 6 report the estimation results of the VAR (1)–GARCH (1, 1) model. The symbols h_t^{ETF} and h_t^{DeFi} denote the conditional variances of the ETFs and DeFi assets at time t, respectively. The error terms $\mathcal{E}_{t-1}^{ETF}$ and $\mathcal{E}_{t-1}^{DeFi}$ represent the effect of "news" (unexpected shocks) on ETFs and DeFi lending tokens, respectively. Tables 2, 3, 4, 5 and 6 show that the ARCH and GARCH coefficients are significant across all DeFi and G7 ETFs. Sensitivity to past conditional volatility (h_{t-1}^{DeFi}) appears to be significant for the DeFi assets studied. This finding suggests that the conditional volatility of these DeFi assets represents the recall memory. Alternatively, the current conditional volatility of the DeFi market depends on past shocks affecting return

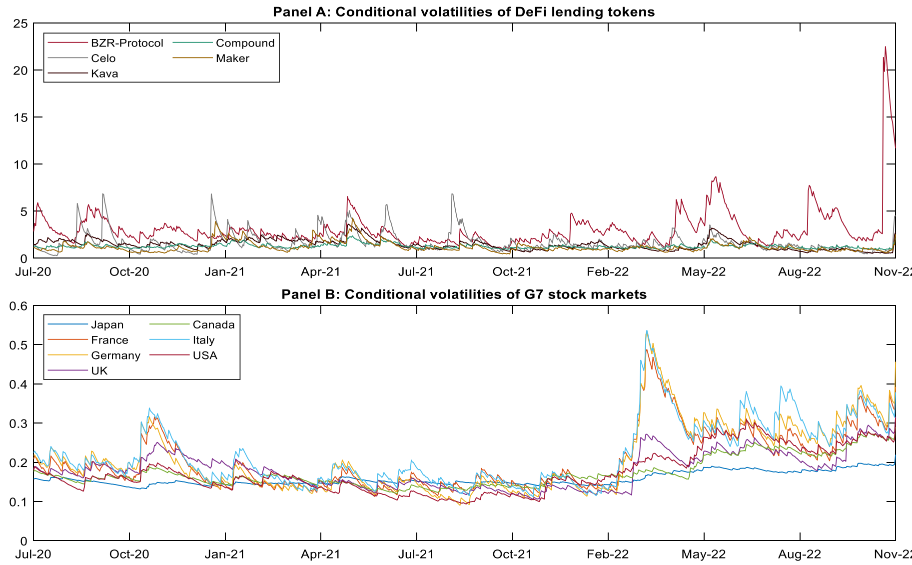

Fig. 1 Dynamic conditional volatilities for DeFi and G7 ETFs. Given the seminal definition of volatility, these graphs represent the annualized daily standard deviations provided by the VAR-GARCH model

dynamics because ($\mathcal{E}_{t-1}^{DeFi}$) is significant for all DeFi assets. For almost all DeFi lending tokens, $\mathcal{E}_{t-1}^{DeFi}$ is much smaller for each DeFi token than h_{t-1}^{DeFi}, the DeFi volatility, suggesting that the former volatilities of the DeFi market are more important than past shocks in predicting future volatility.

The results in Table 2, 3, 4, 5 and 6 also show that past G7 ETF shocks ($\mathcal{E}_{t-1}^{stock}$) have significant effects on the volatility of all DeFi assets. Consequently, past news of shocks in G7 ETFs positively affects the current conditional volatility of DeFi assets. The same applies in reverse; the results show that past DeFi market shocks ($\mathcal{E}_{t-1}^{DeFi}$) have significant effects on G7 ETF volatility. Moreover, past news about shocks in the DeFi market affects the current conditional volatility of G7 ETFs. The results of the GARCH estimation ($h_{t-1}^{\mathrm{DeFi},ETF,t}$ and h_{t-1}^{DeFi}) reveal evidence of volatility spillovers between the DeFi assets and the G7 ETFs. In other words, the current conditional volatility of the G7 ETFs depends not only on their past volatility but also on the past volatility of the DeFi market. Moreover, the current conditional volatility of the DeFi market depends not only on past volatility but also on the past volatility of the G7 ETFs.

As an illustration, in Table 2, we consider the volatility spillover effect between the Marker DeFi and the G7 ETFs, and the results show that past market shocks ($\mathcal{E}_{t-1}^{DeFi}$) significantly affect the volatility of G7 ETFs. Consequently, past news about shocks in Marker DeFi significantly affects the current conditional volatility of the G7 ETFs. However, the results show that past G7 ETF shocks ($\mathcal{E}_{t-1}^{ETF}$) significantly impact Marker volatility. Moreover, past news about shocks in G7 ETFs affects the current conditional volatility of the Marker DeFi. The estimation results of the GARCH (h_{t-1}^{ETF} and h_{t-1}^{DeFi}) parameters reveal evidence of volatility spillover between the Marker DeFi and the G7 ETFs. In other words, the current conditional volatility of Marker DeFi depends not only on its past volatility but also on the past volatility of G7 ETFs.

Table 2 Volatility spillover between Maker DeFi and ETFs

	Maker	Japan	Maker	France	Maker	UK	Maker	Germany	Maker	Canada	Maker	Italy	Maker	USA
Variance equation														
$'\varepsilon_{t-1}^{ETF})^2$	0.4048* (2.916)	0.0940* (3.842)	0.2193* (4.34)	0.2193* (4.512)	0.5082* (5.457)	0.5082* (5.456)	0.4272* (5.752)	0.20373* (4.626)	0.4238* (6.189)	0.1274* (7.020)	0.4366* (6.22)	0.2027* (3.412)	0.4174* (6.031)	0.1536* (6.458)
$'\varepsilon_{t-1}^{DeFi})^2$	0.41316* (5.69)	0.4137* (5.541)	0.4343* (6.184)	0.4342* (6.172)	0.4268* (6.164)	0.8720* (24.35)	0.4271* (5.755)	0.9765* (86.08)	0.4612* (6.620)	0.1295* (6.922)	0.4366* (6.217)	0.2027* (3.143)	0.4174* (6.002)	0.1536* (6.442)
h_{t-1}^{ETF}	− 0.275*** (− 1.648)	0.9933* (434.4)	0.9668* (53.16)	0.8571* (28.59)	0.2431 (1.511)	0.2431* (1.518)	0.8873* (39.70)	0.9765* (91.10)	0.8768* (24.79)	0.9903* (391.7)	0.8777* (24.04)	0.9723* (48.59)	0.8850* (25.17)	0.9865* (253.7)
h_{t-1}^{DeFi}	0.8778* (22.81)	0.8811* (22.28)	0.8784* (24.55)	0.8784* (24.53)	0.8721* (24.34)	0.8720* (24.35)	0.8849* (24.11)	0.8849* (24.10)	0.8570* (20.19)	0.9897* (358.8)	0.8777* (24.05)	0.9723* (43.95)	0.8850* (24.95)	0.9865* (252.6)
Log-likelihood	4154.328	4152.079	3978.52	3978.52	4038.03	4038.03	3969.307	3969.30	4081.97	4082.45	3912.16	3912.16	4112.69	4112.6

Significant at: *1, **5 and ***10 percent levels; t-values given in parentheses; the results of estimated mean equation and constants of each variance equation are not reported for the sake of brevity

Table 3 Volatility spillover between Celo DeFi and ETFs

	Celo	Japan	Celo	France	Celo	UK	Celo	Germany	Celo	Canada	Celo	Italy	Celo	USA
Variance equation														
$'\varepsilon_{t-1}^{ETF})^2$	0.4048* (2.916)	0.1143* (3.886)	0.2193* (4.34)	0.2193* (4.512)	0.6667* (4.98)	0.1817* (1.549)	0.6817* (4.694)	0.2632* (3.92)	0.6272* (4.828)	0.1364* (5.60)	0.6874* (4.574)	0.2459* (4.336)	0.6240* (4.655)	0.1642* (5.401)
$'\varepsilon_{t-1}^{DeFi})^2$	0.6398* (4.758)	0.1143* (3.88)	0.6713* (4.514)	0.2516* (4.767)	0.6667* (4.965)	0.1816 (0.885)	0.6817* (4.699)	0.2632* (3.809)	0.6271* (4.828)	0.1364* (5.597)	0.6872* (4.583)	0.2457* (4.27)	0.6259* (4.644)	0.1644* (5.408)
h_{t-1}^{ETF}	0.6987* (10.51)	0.9903* (226.2)	0.9668* (53.16)	0.8571* (28.59)	0.6705* (8.959)	0.9786* (25.14)	0.6688* (8.69)	0.9614* (44.7)	0.7005* (11.89)	0.9888* (232.2)	0.6707* (8.34)	0.9614* (45.39)	0.7112* (10.88)	0.9846* (177.7)
h_{t-1}^{DeFi}	0.6987* (10.50)	0.99036* (226.2)	0.6729* (8.43)	0.9583* (49.10)	0.6706* (9.006)	0.9786* (14.11)	0.6689* (8.712)	0.9614* (43.11)	0.7005* (11.89)	0.9888* (232.1)	0.6705* (8.345)	0.9615* (44.58)	0.7115* (10.93)	0.9845* (177.4)
Log-likelihood	3976.26	3975.24	3795.38	3795.38	3870.10	3870.10	3794.48	3794.47	3905.81	3905.81	3730.40	3730.40	3923.01	3923.01

Significant at: *1, **5 and ***10 percent levels; t-values given in parentheses; the results of estimated mean equation and constants of each variance equation are not reported for the sake of brevity

Table 4 Volatility spillover between Compound DeFi and ETFs

	Compound	Japan	Compound	France	Compound	UK	Compound	Germany	Compound	Canada	Compound	Italy	Compound	USA
Variance equation														
$'\varepsilon_{t-1}^{ETF})^2$	0.2677 * (5.848)	0.0871 * (4.21)	0.2850 * (5.253)	0.2509 * (4.607)	0.2749 * (3.455)	0.2312 * (0.638)	0.2857* (5.553)	0.2352* (3.805)	0.2801* (7.314)	0.1260* (6.561)	0.3020* (5.47)	0.2515* (3.95)	0.2676* (6.46)	0.1523* (4.038)
$'\varepsilon_{t-1}^{DeFi})^2$	0.2678 * (5.794)	0.0871 * (4.212)	0.2850 * (5.255)	0.2509 * (4.598)	0.2759 * (6.998)	0.5992 (6.521)	0.2845 * (5.64)	0.2360 * (3.751)	0.2801* (7.296)	0.1260* (6.558)	0.2986* (6.56)	0.5294* (6.13)	0.2595* (7.95)	0.6601* (7.248)
h_{t-1}^{ETF}	0.9457 * (41.22)	0.9956 * (604.8)	0.9302 * (25.74)	0.9579 * (47.57)	0.9326 * (19.75)	0.9573 * (5.32)	0.9291* (26.68)	0.9693* (55.49)	0.9317* (40.50)	0.9918* (428.1)	0.9194* (22.68)	0.9589* (39.47)	0.9433* (44.08)	0.9875* (127.7)
h_{t-1}^{DeFi}	0.9456* (40.62)	0.9956 * (603.8)	0.9301 * (25.75)	0.9579 * (47.40)	0.9374 * (37.20)	0.2975 (1.569)	0.9302 * (28.10)	0.9691* (54.08)	0.9317* (40.35)	0.9918* (427.7)	0.9278* (30.08)	0.2256 (0.926)	0.9406* (78.03)	0.2108* (2.20)
Log-likelihood	4036.32	4036.32	3858.11	3858.11	3870.10	3870.10	3852.48	3794.47	3967.86	3967.86	3766.45	3796.73	3967.81	3991.03

Significant at: *1, **5 and ***10 percent levels; t-values given in parentheses; the results of estimated mean equation and constants of each variance equation are not reported for the sake of brevity

Table 5 Volatility spillover between Kava DeFi and ETFs

	Kava	Japan	Kava	France	Kava	UK	Kava	Germany	Kava	Canada	Kava	Italy	Kava	USA
Variance equation														
$'\varepsilon_{t-1}^{ETF})^2$	0.3049 * (5.38)	0.0915 * (4.264)	0.3131 * (5.15)	0.2304 * (4.497)	0.2957 * (5.17)	0.1626 * (2.63)	0.3065 * (5.28)	0.2223 * (4.78)	0.3026 * (5.42)	0.1244 * (6.23)	0.3169 * (5.08)	0.2173 * (3.70)	0.2908 * (5.649)	0.1526 * (4.91)
$'\varepsilon_{t-1}^{DeFi})^2$	0.3059 * (5.43)	0.0914 * (4.41)	0.3130 * (5.15)	0.2305 * (4.45)	0.2763 * (5.85)	0.5751* (5.88)	0.3064 * (5.29)	0.2223 * (4.76)	0.2644 * (6.107)	0.5396 * (5.755)	0.3169 * (5.088)	0.2173 * (3.667)	0.2594 * (7.004)	0.6787 * (6.906)
h_{t-1}^{ETF}	0.9444 * (49.75)	0.9952 * (516.1)	0.9412 * (45.49)	0.9674 * (57.08)	0.9454 * (49.02)	0.9840 * (59.31)	0.9433 * (48.32)	0.9737 * (82.66)	0.9422 * (47.70)	0.9922 * (398.5)	0.9397 * (43.28)	0.9717 * (52.65)	0.9485 * (59.94)	0.9878 * (164.6)
h_{t-1}^{DeFi}	0.9442 * (49.97)	0.9952 * (526.9)	0.9413 * (45.51)	0.9673 * (56.24)	0.9491 * (56.37)	0.3455 * (2.010)	0.9433 * (48.56)	0.9737 * (81.93)	0.9500 * (70.91)	0.2063 (1.30)	0.9397 * (43.26)	0.9716 * (51.96)	0.9528 * (88.33)	0.2438 * (3.028)
Log-likelihood	3976.53	3976.56	3798.72	3798.72	3869.25	3875.76	3790.32	3790.32	3889.82	3907.56	3732.37	3732.37	3899.81	3926.02

Significant at: *1, **5 and ***10 percent levels; t-values given in parentheses; the results of estimated mean equation and constants of each variance equation are not reported for the sake of brevity

Table 6 Volatility spillover between BZR-Protocol DeFi and ETFs

	BZR-Protocol	Japan	BZR-Protocol	France	BZR-Protocol	UK	BZR-Protocol	Germany	BZR-Protocol	Canada	BZR-Protocol	Italy	BZR-Protocol	USA
Variance equation														
$'\varepsilon_{t-1}^{ETF})^2$	0.0920***	0.3692*	0.3547*	0.2439*	0.3577*	0.1772**	0.3604*	0.2382*	0.3754*	0.1357*	0.3581*	0.2389*	0.3571*	0.1628*
	(1.791)	(4.371)	(4.93)	(3.65)	(4.765)	(2.015)	(4.78)	(3.724)	(3.96)	(5.81)	(4.84)	(3.69)	(4.604)	(4.21)
$'\varepsilon_{t-1}^{DeFi})^2$	0.3707*	0.0916*	0.3146*	0.6467*	0.3270*	0.6262*	0.3604*	0.2382*	0.3754*	0.1356*	0.3580*	0.2389*	0.3573*	0.1628*
	(4.41)	(3.007)	(4.983)	(5.876)	(4.319)	(5.929)	(4.78)	(3.66)	(3.96)	(5.83)	(4.85)	(3.68)	(4.62)	(4.66)
h_{t-1}^{ETF}	0.8917*	0.9957*	0.8904*	0.9648*	0.8917*	0.9814*	0.8911*	0.9705*	0.8984*	0.9907*	0.8879*	0.9670*	0.8944*	0.9866*
	(62.46)	(116.6)	(58.02)	(42.7)	(56.98)	(38.62)	(62.89)	(55.72)	(85.39)	(321.3)	(54.66)	(46.05)	(72.27)	(124.5)
h_{t-1}^{DeFi}	0.8915*	0.9957*	0.8987*	− 0.2108	0.9018*	0.3399***	0.8911*	0.9705*	0.8984*	0.9907*	0.8879*	0.9670*	0.8943*	0.9866*
	(63.03)	(350.7)	(68.67)	(− 1.23)	(73.76)	(1.768)	(62.82)	(54.42)	(85.23)	(322.5)	(54.58)	(45.70)	(71.88)	(153.3)
Log-likelihood	3365.30	3365.30	3147.5	3187.40	3258.86	3875.76	3181.98	3181.98	3302.98	3302.98	3123.95	3123.95	3316.9	3316.9

Significant at: *1, **5 and ***10 percent levels; t-values given in parentheses; the results of estimated mean equation and constants of each variance equation are not reported for the sake of brevity

Table 7 DCC GARCH estimated parameters between DeFis and equity ETFs

	Japan	France	UK	Germany	Canada	Italy	USA
Maker/ETFs							
α	0.00013** (2.455)	0.00477* (3.046)	0.00991* (2.982)	0.02562** (2.587)	0.0934** (2.142)	0.0920* (4.256)	0.0107* (3.561)
β	0.8749* (6.503)	0.9886* (126.5)	0.7806* (3.187)	0.84564* (4.62)	0.8323* (3.591)	0.8362* (2.922)	0.932* (7.90)
LL	4157.5	3986.7	4058.94	3983.6	4090.8	3925.29	4120.5
Celo/ETFs							
α	0.0132** (2.303)	0.00804* (2.448)	0.0904* (4.174)	0.0841** (2.457)	0.00355** (2.253)	0.00794** (2.004)	0.0119* (3.607)
β	0.9832* (113.2)	0.9886* (126.5)	0.8365* (3.97)	0.5640* (3.247)	0.8853* (10.99)	0.9884* (122.4)	0.9826* (64.93)
LL	3982.7	3802.67	3874.2	3795.4	3911.2	3736.8	3933.5
Compound/ETFs							
α	0.0076** (2.278)	0.0403* (4.218)	0.0768* (3.478)	0.05542** (2.248)	0.00865* (2.606)	0.0755*** (1.775)	0.1547* (2.772)
β	0.9892* (261.1)	0.7681* (3.77)	0.7738** (2.253)	0.3640** (1.997)	0.8930* (14.76)	0.1977* (4.859)	0.8832* (8.23)
LL	4041.14	3863.4	3937.2	3859.74	3971.35	3803.4	3933.5
Kava/ETFs							
α	0.0119** (2.279)	0.00893* (3.84)	0.0387* (2.882)	0.0069** (2.012)	0.01305* (3.607)	0.0616* (4.42)	0.0235* (4.345)
β	0.9837* (141.3)	0.9858* (154.1)	0.4947* (2.82)	0.9846* (81.9)	0.6005** (2.49)	0.7021** (2.197)	0.8539* (3.16)
LL	3981.4	3805.4	3882.01	3798.6	3912.8	3740.5	3933.7
BZR-Protocol/ETFs							
α	0.0921** (2.44)	0.0401* (3.444)	0.0109* (4.501)	0.0394* (2.931)	0.0330** (2.08)	0.0220* (3.664)	0.0336* (5.46)
β	0.8597* (7.61)	0.7368* (6.49)	0.8745* (9.58)	0.7594* (2.699)	0.9277* (56.9)	0.7261* (2.657)	0.9277* (31.9)
LL	3366.9	3189.8	3266.08	3183.2	3301.8	3126.8	3316.5

Significant at: *1, **5 and ***10 percent levels; t-values given in parentheses. LL refers to the Log-Likelihood estimator

Moreover, the current conditional volatility of G7 ETFs depends on both their past volatility and the past volatility of Marker DeFi. Tables 3, 4, 5, and 6 show the same results, which, in line with recent studies, such as Yousaf et al. (2023), indicate a bidirectional volatility spillover between DeFi lending tokens and G7 ETFs during the study period.

From the standardized innovations resulting from previous VAR-GARCH models, we separately estimate a bivariate DCC-GARCH (1,1) model for each DeFi–ETF pair to design an efficient portfolio management strategy. The DCC-GARCH model is estimated using Eqs. 5–7. From Table 7, we find that all parameters have a significant influence on the fitted bivariate dependence processes; thus, the DCC-GARCH (1,1) model seems to be relevant and necessary in the DeFi–stock market context. Moreover, the magnitude of the α and β coefficients suggests that, overall, new information shocks have a weak impact on the DeFi–ETF dependence relationships but are highly persistent across the time horizon.

Figure 2A shows that the correlation between Marker DeFi and G7 ETFs is positive and hovers at approximately 0.3. This interdependence becomes more intense in early 2022 with the Russian invasion of Ukraine; thus, the Marker DeFi cannot be considered

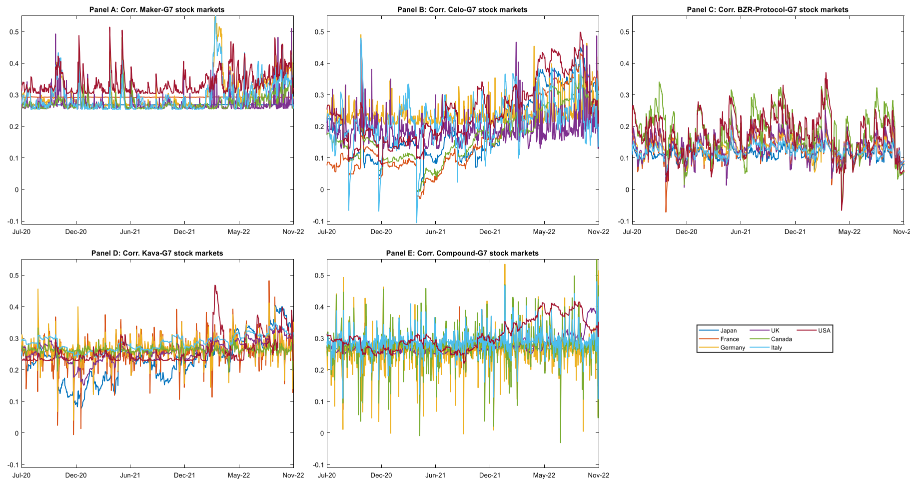

Fig. 2 Dynamic conditional correlation between each DeFi and G7 ETFs provided by the bivariate DCC GARCH schemes

a safe haven. This finding is confirmed for other DeFi assets by the visualizations in Fig. 2B–E. This result contradicts that of Piñeiro-Chousa et al. (2022), who reported the effectiveness of DeFi as a safe haven. In fact, in the present study, the dynamic correlation coefficients are, in most cases, positive and rarely negative or zero. Moreover, the Ukrainian War contributed to the amplification of these coefficients, and the interdependence between the DeFi and G7 ETFs became stronger. Our results suggest that DeFi assets may generate diversification gains for G7 investors due to their positive but low conditional correlation with G7 equity ETFs (Corbet et al. 2021; Alawadhi and Alshamali 2022; Yousaf and Yarovaya 2022a). Further analyses will allow us to answer this question.

Tables 8 (A–E) show the estimation results of Eqs. 8–10, which illustrate how VAR-GARCH models coupled with DCC-GARCH schemes can be implemented by market makers and portfolio managers to design optimal allocation strategies. The left sides of these tables display the average dynamic optimal allocation weights for the study period, $W_{DeFi,ETF,t}$. More precisely, this variable can be defined as the weight of DeFi in the dollar value of the two assets (DeFi, ETF) at time t. For example, the data show that the average weight of the Marker DeFi in Marker/US ETFs is − 0.03, which indicates that for a portfolio of \$1, one should sell approximately 3 cents' worth of Marker DeFi and purchase US ETFs for \$1.03. Moreover, for the Marker DeFi, all average weights in the minimum variance portfolios are negative. Otherwise, the optimal minimum variance portfolio for G7 investors is to sell the Marker DeFi and invest the result (initial wealth plus sale proceeds) into G7 ETFs.

Furthermore, the DeFi weights in the minimum variance portfolios are almost negative and close to zero. On average, Celo is the DeFi asset most used by G7 investors to build minimum variance portfolios, whereas Compound is the least used (most short-sold) DeFi asset to reduce risk. In general, it seems that G7 investors do not use DeFi to construct their minimum variance portfolios and consequently reduce their risk exposures. The static analysis shows, a priori, that DeFi cannot provide diversification benefits to G7 equity investors. The results presented thus far report the average interconnections between DeFi markets and G7 ETFs. However, these results do not reveal important

Table 8 Average DeFi-ETFs weights and betas

	Weights	Betas		Weights	Betas
Panel A: maker/ETFs			*Panel B: Celo/ETFs*		
Maker/USA	−0.0259	2.0602	Celo/USA	−0.0103	2.3254
Maker/UK	−0.0117	1.9520	Celo UK	0.0019	1.7483
Maker/France	−0.0072	1.9688	Celo/France	0.0066	1.1324
Maker/Italy	−0.0088	1.7625	Celo/Italy	0.0068	1.7469
Maker/Germany	−0.0122	1.9940	Celo/Germany	0.0029	2.2538
Maker/Canada	−0.0135	2.0388	Celo/Canada	0.0008	1.4086
Maker/Japan	−0.0154	2.5852	Celo/Japan	−0.0067	1.8604
Panel C: Compound/ETFs			*Panel D: Kava/ETFs*		
Compound/USA	−0.0161	2.3811	Kava/USA	−0.0108	2.2850
Compound/UK	−0.0161	2.0118	Kava/UK	−0.0104	2.1747
Compound/France	−0.0109	1.8961	Kava/France	−0.0003	2.0722
Compound/Italy	−0.0147	1.8710	Kava/Italy	−0.0024	2.1263
Compound/Germany	−0.0101	1.807	Kava/Germany	0.0026	2.1744
Compound/Canada	−0.0163	2.1163	Kava/Canada	−0.0099	2.3246
Compound/Japan	−0.0147	2.1610	Kava/Japan	−0.0125	2.0654
Panel E: BZR-Protocol/ETFs					
BZR/USA	−0.0064	3.0805			
BZR/UK	−0.0036	2.3361			
BZR/France	−0.0014	1.9582			
BZR/Italy	−0.0003	1.7968			
BZR/Germany	−0.0016	2.0520			
BZR/Canada	−0.0072	3.1775			
BZR/Japan	−0.0024	2.0707			

This table provides the average time-varying weights and betas for the period that spans from early July 2020 to end November 2022

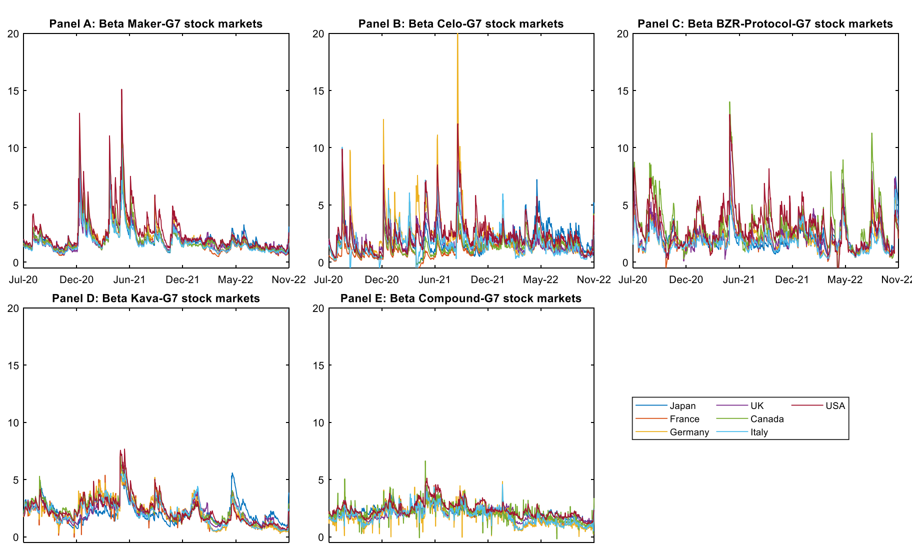

Fig. 3 Time-varying betas between each DeFi and G7 ETFs

relationships between these markets, especially during crisis periods; therefore, we cannot be confident about the diversification potential of DeFi. Therefore, a dynamic study covering the entire study period is required. This study enabled us to deepen our analysis. From Fig. 3A–E, we note that almost all $W_{DeFi,ETF,t}$ weights increased considerably during the war in Ukraine for all DeFi assets and for all G7 investors. Otherwise, these investors devoted a larger portion of their wealth to DeFi to build their minimum variance portfolios during the Ukraine War. Thus, G7 investors use DeFi to reduce their risk of exposure during turbulent periods. From this study, we can conclude that DeFi offers investors diversification opportunities during times of crisis (Corbet et al. 2021; Ko et al. 2022; Corbet et al. 2022).

Furthermore, Fig. 3 and Table 8 report on the minimum variance hedge ratios or betas, β_t^*. As a measure of systematic risk, the beta coefficient shows the sensitivity of portfolio returns to changes in market index returns. The Celo/French ETF presents the lowest systematic risk among all the portfolio pairs under analysis, with a statistically significant beta coefficient of approximately 1.13, which implies that in market moments when the French ETF increases its quoted value, this portfolio will increase by approximately 113% of the proportion of the index's upward movement. This beta is notably lower than that associated with other portfolio pairs, such as Marker/US ETFs (2.58), whose movements are more closely linked to the market. In this case, an upward trend in US ETF returns is followed by an upward trend in Marker returns with a smaller proportion of approximately 258%.

Among the betas that return, lower values are more often calculated for the G7 Celo–ETFs. The average beta for the pair Celo–ETFs G7 is 1.78. The DeFi BZR Protocol's betas showed positive and high values in a greater proportion of opportunities. Indeed, the BZR Protocol/Canadian ETFs pair had the highest overall beta (3.16), and the BZR Protocol/G7 ETF pairs had the highest average beta (2.35). This finding suggests that DeFi does not have as much of a diversifying influence on the analyzed markets.

The static analysis of the average betas seems too crude to draw conclusions about the hedging or diversification properties of DeFi. Therefore, we analyze the temporal evolution of the betas of different DeFi assets for different G7 countries. Figure 4A–E shows that the betas (except for the BZR Protocol) became increasingly weaker during the Ukrainian War. During this period, these betas approached the unit and sometimes fell below one. Otherwise, DeFi assets (except the BZR Protocol) become defensive stocks and can be added to ETFs in all G7 countries to reduce risk. The introduction of DeFi (except the BZR Protocol) into an all-equity portfolio has diversification benefits for G7 investors during the study period, characterized by the health crisis and the war in the Ukraine.

Discussion

Markowitz (1952) introduced the seminal concept of diversification, which is the foundation of modern portfolio theory. Markowitz's groundbreaking work fundamentally transformed the field of finance by emphasizing the importance of spreading investment capital across a range of assets to reduce risk and optimize returns. His theory posits that by carefully selecting a mix of assets with varying levels of

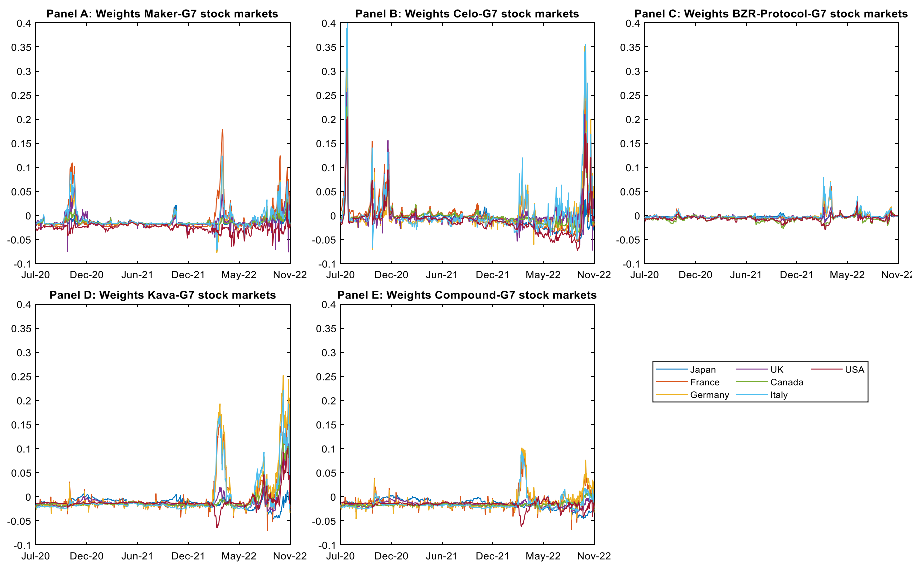

Fig. 4 Time-varying weights between each DeFi and G7 ETFs

correlation, investors can construct portfolios that offer higher expected returns for a given level of risk or, conversely, lower risk for a targeted level of returns.

Markowitz's approach was instrumental in shifting the focus of investment analysis from individual assets to the broader context of portfolio management, subsequently fostering a paradigm shift that continues to shape contemporary investment strategies and asset-allocation methodologies. His concept of diversification has become an indispensable tool for investors and financial professionals seeking to navigate the complexities of financial markets and make informed decisions to achieve investment objectives.

Based on the more recent seminal research conducted by Baur and Lucey (2010), which was further expanded by Baur and McDermott (2010), a diversifying asset can be aptly characterized as a financial instrument that demonstrates a positive correlation, albeit a relatively weak one, with another security, on average. In contrast, a strong hedging asset assumes a contrasting role, exhibiting a negative correlation with another asset on average. This negative correlation serves as a shield against potential losses and provides a valuable safeguard for investment portfolios. An asset considered weakly correlated or uncorrelated is deemed a weak hedge, providing a more limited level of protection against market fluctuations. Expanding on these concepts, we encounter the notion of a safe haven, which shares a striking resemblance with the concept of a hedge asset. However, the key distinction between the two lies in the temporal context in which the safe haven asset operates. Specifically, a safe haven asset acts similar to a hedge during periods of market instability or turbulence, shielding investors from potential downturns and offering stability in uncertain times. This unique attribute further solidifies its status as a reliable port in a storm, enabling investors to weather volatility with a greater sense of confidence. By delving into the nuances of diversifying assets, strong and weak hedge instruments, and safe havens, investors can gain a comprehensive understanding of the intricate dynamics that shape the financial landscape. Armed with this knowledge, they can strategically construct and manage their portfolios, optimize risk–risk–reward trade-offs, and navigate the ever-changing currents of the market with a heightened level of fluency.

Building on the seminal definitions put forth by Baur and Lucey (2010) and Baur and McDermott (2010), recent studies, such as Ugolini et al. (2023) and Yousaf et al. (2023), have contributed to the growing body of research that characterizes DeFi assets as diversifying assets. Their studies provide empirical evidence of relatively weak average correlations between DeFi assets and traditional equities, particularly during periods of market volatility. This alignment with established definitions further strengthens the argument that DeFi assets possess the requisite attributes to be classified as diversifying assets in investment portfolios. By highlighting the correlations and connections between DeFi assets and equity markets, these studies underscore DeFi assets' potential to enhance portfolio diversification strategies, thereby providing investors with opportunities to manage risk and achieve more stable returns.

By exploring DeFi assets and their correlation dynamics with equities, we establish a connection between our results and previously defined concepts. Similar to other diversifying assets, DeFi assets have a positive but weak average correlation with equity investments. However, their potential as strong hedging assets or safe havens is yet to be fully established as sustained periods of negative correlation are required to classify them.

The remainder of this study provides compelling evidence for characterizing DeFi assets as diversifying assets. DeFi assets exhibit hedge-like properties, as evidenced by their hedge ratios approaching unity under volatile market conditions. Additionally, their price behavior demonstrates resilience and often outperforms or remains on par with that of equity ETFs during turbulent periods. The observed increase in the DeFi weights (see Fig. 4) during crisis periods highlights their perceived value as assets that can enhance portfolio stability and risk management. These insights shed light on the evolving landscape of investment opportunities as DeFi assets emerge as a potential avenue for diversification of equity portfolios. Investors seeking to optimize risk management and navigate the complexities of the market can explore DeFi assets as a means to enhance their portfolio resilience and potentially benefit from unique correlations during periods of market instability. As the field of DeFi assets continues to develop, it will be fascinating to observe their role in diversification strategies and whether they can provide the desired characteristics of hedges or safe havens over extended periods.

Certain features set our research apart from the prior literature examining the interplay between DeFis and equities. First, in contrast to Yousaf et al. (2023), we enhance robustness by employing a VAR-GARCH model that transcends the realms of connectivity and contagion, thereby providing valuable insights into the formulation of efficient portfolio strategies. Second, our use of ETFs as proxies for equity markets establishes a direct link with portfolio management, setting our approach apart from that of Yousaf and Yarovaya (2022). Third, our initial analysis of the correlations suggests that DeFi should not be regarded as a secure haven for inclusion in hedging strategies, in line with the findings of Conlon et al. (2020), Umar et al. (2021a), and Goodell and Goutte (2021), who assert that traditional cryptocurrencies do not act as safe havens for equities during crises such as the pandemic. The present study contributes to the existing literature by exploring this phenomenon in the context of novel tokens with distinct attributes. Finally, our study enriches the seminal literature by presenting the temporal evolution of betas, thereby confirming preceding correlation results. This underscores the notion that DeFi assets may not serve as safe havens but can offer diversification benefits to G7 investors when integrated with their equity ETFs, as corroborated by Corbet et al. (2021), Ko et al. (2022), Corbet et al. (2022), Yousaf and Yarovaya (2022a), and Yousaf et al. (2022).

Concluding remarks

The confusion surrounding the fallout of volatility is a matter of great concern for financial participants, and further in-depth research is needed, especially in the financial and DeFi lending token markets, whose investors are eager for relevant information in times of market instability. Thus, our research comprehensively analyzed the potential interdependent and connected relationships between the G7 ETFs and DeFi markets during the COVID-19 pandemic and the Ukrainian War. Trading data for the major ETFs in each of the G7 countries were used as proxies for each of these markets (the USA, Japan, the UK, Canada, Italy, France, and Germany). For DeFi, a number of high-impact, high-volume trading stocks were selected from global markets during the pandemic period and the Ukraine War, including Maker, Celo, Compound, Kava, and the BZR Protocol. The daily returns from July 2020 to November 2022 for the different DeFi assets and ETFs were analyzed using the VAR-GARCH and DCC-GARCH models.

This study draws two interesting conclusions. On the one hand, the two-way volatility spillovers between the DeFi equity markets and some of the correlation pairs analyzed are sufficiently convincing to prove that a contagion effect occurred between different geographical markets, even those of different nature and typology, during the most turbulent moments of the COVID-19 crisis and the war in the Ukraine, which was arguably triggered by the resulting global economic collapse.

On the other hand, there is significant evidence of a weak positive correlation between most DeFi and ETF pairs throughout the analyzed period, confirming that most DeFi assets cannot be considered safe havens during periods of market turbulence or instability. Nevertheless, DeFi assets can be used to reduce portfolio risk and generate diversification benefits. This last result was tested by constructing investment portfolios consisting of DeFi–ETF pairs for each market and the different DeFi–loan tokens analyzed. As an additional robustness test, the hedging properties of these assets in portfolio construction were checked using a beta or minimum variance hedging analysis. The results of these analyses clearly demonstrate the diversification benefits that DeFi assets (excluding the BZR Protocol) could have provided if they had been included in active investment strategies during the most volatile periods of the pandemic or the subsequent war in the Ukraine. The beta analysis also shows that while DeFi assets (except for the BZR Protocol) are far from being a safe haven, adding these products to a portfolio of equity ETFs can mitigate against risk in times of crisis.

Our results and comprehensive analysis of the volatility and correlations between exchanges and DeFi currency markets provide crucial and useful insights for investors, traders, and policy-makers dealing with DeFi lending tokens and ETFs, especially in terms of designing diversification and hedging strategies to partially mitigate inherent market risk. Further research can explore the potential impact of DeFi in terms of volatility propagation and interdependence of other asset types (e.g., currencies, commodities, fixed income, financial derivatives) on the above underlying factors. In addition, two classic measures of risk and return—Jensen's alpha and Treynor's ratio—can be calculated from the estimated beta or minimum variance coverage ratios to assess the overperformance or underperformance of an investment strategy.

The empirical results of this study have important implications for various financial actors and researchers, especially in times of crisis (e.g., the Russian invasion of Ukraine in 2022, the COVID-19 pandemic, or any other systemic risk event) when financial markets are characterized by downturns and high volatility. Indeed, based on these empirical results, we show that investing in DeFi assets in addition to equity ETFs allows G7 investors to reduce portfolio risk. Accordingly, we recommend that G7 investors and portfolio managers develop hedging strategies that consider the diversification benefits of adding DeFi assets. Our results may also motivate researchers to investigate the dynamic interdependencies between DeFi and other asset classes, as well as in other geographical areas and country groups.

As with any research, this study suffers from several limitations that can be addressed in future studies and can be seen as avenues for extension. The first is the length of the study period. Therefore, the first avenue is to extend the analysis period to better explore the impact of the war between Russia and the Ukraine on the shock transmission mechanisms between different asset classes. A second line of research extension centers of considering investor sentiment/attention, media coverage indicators, and the "fake news" index to better understand the dynamic interdependencies between the DeFi and G7 stock markets. Another weakness of this study is its use of a linear model (VAR-GARCH) to specify the interdependent relationships between financial markets that are logically non-linear. Therefore, another approach is to extend the measures used to a non-linear framework/VAR to capture the non-linear aspects of interdependencies. In addition, the dependence structure using the DCC-GARCH model can be seen as a shortcoming of this study. Future research can employ other models that incorporate asymmetry in the correlation matrix, such as symmetric dynamic conditional correlation (ADCC)-GARCH.

Abbreviations

ADCC-GARCH	Asymmetric Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity
CSI	China Securities Index
DACS	Digital Asset Classification Standard
DCC-APGARCH	Dynamic Conditional Correlation-Asymmetric Power GARCH
DCC-GARCH	Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity
DCC-GARCH-ECM	Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroscedasticity-Error Correction Model
DCC-GJR-GARCH	Dynamic Conditional Correlation-Glosten, Jagannathan, and Runkle-GARCH
DCC-T-GARCH	Dynamic Conditional Correlation-Threshold GARCH
DeFi	Decentralized Finance
EDH	Extreme Downside Hedge
ETFs	Exchange-Traded Funds
G7	Group of Seven
GO-GARCH	Generalized Orthogonal-GARCH
MSCI	Morgan Stanley Capital International
OLS	Ordinary Least Squares
SP500	Standard & Poor's 500 Index
TVP-VAR	Time-Varying Parameter Vector Autoregressive

UNI	Uniswap
VAR-GARCH	Vector Autoregressive-Generalized Autoregressive Conditional Heteroscedasticity

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Availability of data and materials
Data and codes could be provided upon author request.

Competing interests
The authors declare no competing interests.

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