Dynamic Spillovers and Portfolio Optimization in Tourism, Fintech, and Cryptocurrency

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Abstract

This paper investigates the spillover dynamics, hedging and portfolio optimisation strategies among tourism, cryptocurrency, and Fintech markets within a time-varying connectedness framework, accounting for spillovers from traditional financial markets. Using daily return indices, we document significant heterogeneity in spillovers over time, with the COVID-19 period exhibiting the highest levels of interconnectedness. Traditional financial markets emerge as the dominant net transmitters of spillovers, followed by the Fintech sector, while the tourism market is predominantly a net receiver. Cryptocurrency assets, despite offering the least expensive hedge, are ineffective hedging instruments, whereas tourism assets offer the most cost-effective and efficient hedge for cryptocurrencies, albeit at elevated risk levels. While sectoral hedges are generally costlier and less effective due to strong co-movements, cross-sectoral hedges between Fintech and traditional financial markets were also expensive and ineffective. Our analysis further reveals that dynamic bilateral portfolio weight strategies consistently outperform dynamic hedge ratio strategies, with cryptocurrency assets driving superior portfolio returns. The minimum connectedness portfolio strategy, grounded in our framework, outperforms traditional minimum variance and correlation portfolio strategies, underscoring its relevance for optimizing risk-adjusted returns in dynamic markets.

Keywords: Fintech, Cryptocurrency, Blockchain, Tourism, Bitcoin, Portfolio optimization
JEL: E42, G11, G15, G32, Z3.

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1. Introduction and background

In the past decade, the tourism, financial technology (Fintech), and cryptocurrency sectors have undergone transformative changes, redefining their roles in global economic systems. Tourism, once primarily viewed as a leisure-driven industry, has evolved into a multifaceted domain that drives cultural exchange, international relations, and regional economic development. The global tourism industry has expanded its economic footprint, creating employment opportunities and fostering economic resilience in both developed and developing economies. Similarly, Fintech innovations have disrupted traditional financial services, leveraging technological advancements to improve efficiency, accessibility, and inclusivity across banking, payments, and investment platforms. The rapid proliferation of digital payment systems, peer-to-peer lending platforms, and decentralized finance (DeFi) solutions underscores Fintech's transformative impact. However, perhaps no innovation has generated as much disruption and debate as cryptocurrencies. Introduced through Bitcoin and Ethereum, cryptocurrencies have emerged as both financial instruments and technological paradigms, challenging conventional currency systems and reshaping perceptions of value, trust, and financial governance. Cryptocurrencies operate on decentralized blockchain infrastructures, enabling transparent, immutable, and efficient transactions while raising critical questions about regulation, security, and economic implications.

Despite their distinct historical trajectories, tourism, Fintech, and cryptocurrencies are increasingly interconnected. The rationale for examining their convergence is rooted in three key factors. First, globalization and digitalization have significantly altered consumer preferences and behaviours across these sectors. Modern tourists demand seamless digital experiences, including the ability to book accommodations with cryptocurrencies or leverage blockchain technology for secure and transparent travel arrangements. Leading companies in the tourism industry, such as Norwegian Air, CheapAir, and Webjet, now accept payments in Bitcoin and Ethereum, reflecting a broader shift toward digital currencies as a medium of exchange (Reed, 2024). These developments highlight the role of cryptocurrencies as potential substitutes for traditional payment systems like VISA and Mastercard, which have historically dominated the market (Cross et al., 2021). Second, Fintech solutions are becoming increasingly integrated into tourism services, offering personalized financial management tools, dynamic pricing algorithms, and real-time payment systems that enhance the travel experience. These integrations illustrate how Fintech can drive innovation within the tourism ecosystem, bridging operational efficiency and consumer satisfaction.

Third, the financial landscape underpinning tourism has experienced a paradigm shift due to the adoption of cryptocurrencies. Beyond their utility as payment instruments, cryptocurrencies offer novel investment opportunities within the tourism industry. Tokenization, for instance, has enabled fractional ownership of hospitality assets, democratizing access to investment opportunities that were traditionally confined to institutional players. Companies such as Travala and Destinia have pioneered the use of tokens in loyalty programs, enabling customers to accumulate rewards that can be redeemed across a broad network of travel services. These developments underscore the potential of cryptocurrency to redefine financial relationships within the tourism industry, providing both consumers and businesses with flexible, secure, and innovative solutions.

The COVID-19 pandemic has further accelerated digital adoption across tourism and financial services, underscoring the relevance of examining these interconnected markets. During the pandemic, lockdown measures and social distancing protocols led to a dramatic surge in e-commerce, contactless payments, and decentralized financial solutions. Cryptocurrencies gained prominence during this period as resilient payment alternatives, enabling secure and borderless transactions in a time of economic uncertainty. Moreover, blockchain technology was explored for various pandemic-related applications, including vaccine distribution logistics and health record management. As economies transition into post-pandemic recovery, the synergies between tourism, Fintech, and cryptocurrencies are poised to play an even more significant role in shaping global commerce and leisure activities.

Our study makes three key contributions to this emerging discourse. First, we address a significant gap in the literature by exploring the connectedness between cryptocurrency growth and the tourism industry. While existing studies have largely focused on the broader applications of blockchain technology, there remains limited research examining the role of cryptocurrencies as financial instruments within tourism. Blockchain technology, often regarded as the underlying infrastructure of cryptocurrencies, has been widely studied for its potential to enhance transparency, efficiency, and trust in tourism transactions (Önder et al., 2018). However, the specific role of cryptocurrencies in payment facilitation, loyalty programs, and infrastructure investment remains underexplored. This study aims to bridge that gap by analyzing the connectedness between these markets and highlighting the implications for tourists, tourism companies, and investors.

Second, we employ a Time-Varying Parameter Vector Autoregression (TVP-VAR) model, as developed by Antonakakis et al. (2020a), to examine spillovers among these markets. The approach has two advantages. First, it captures dynamic relationships across normal and extreme market conditions, such as the COVID-19 pandemic, providing robust estimates of market connectedness. Second, unlike traditional techniques like Cholesky decomposition, the TVP-VAR model generates forecast-error variance decompositions that are invariant to variable ordering, ensuring greater methodological reliability. By applying this advanced econometric framework, we provide nuanced insights into the temporal heterogeneity of spillovers between tourism, Fintech, and cryptocurrency markets.

Third, we extend the analysis by conducting a portfolio evaluation of the assets examined in this study. This analysis provides actionable insights for investors and portfolio managers, enabling them to devise strategies that leverage the diversification and hedging properties of these interconnected markets. Notably, while previous studies, such as Manahov & Li (2024), have examined the spillover effects between mainstream cryptocurrencies and tourism-specific tokens, our study takes a broader perspective. By incorporating tourism exchange-traded funds (ETFs) alongside cryptocurrencies like Bitcoin and Ethereum, we offer a more comprehensive analysis of market connectedness.

Foreshadowing the main results, we find that cross-market spillovers are heterogeneous over time, with the highest spillover being observed during the COVID-19 pandemic. The results show that, compared to Fintech and cryptocurrency, the traditional financial market still plays a dominant role in spillover transmission to the tourism sector. Our analysis further reveals that dynamic bilateral portfolio weight strategies consistently outperform dynamic hedge ratio strategies, with cryptocurrency assets driving superior portfolio returns. The minimum connectedness portfolio strategy, grounded in our framework, outperforms traditional minimum variance and correlation portfolio strategies, underscoring its relevance for optimizing risk-adjusted returns in dynamic markets.

In summary, this paper seeks to advance the understanding of how tourism, Fintech, and cryptocurrencies interact within the broader context of global economic transformations. By integrating empirical analysis with theoretical insights, we aim to provide a foundation for future research and practical applications in these dynamic and interconnected markets.

The remaining structure of this paper is as follows: Section 2 provides a brief literature review of the interconnectedness between the markets. Section 3 shows a description of the data and specification of our empirical model. Section 4 provides the methods used in this study, Section 5 provides the empirical results, and Section 6 concludes.

2. Fintech, Blockchain and Tourism: A brief review

Given the limited studies on the interconnectedness between the Fintech, Crypto and Tourism sectors, the study will review the literature about Fintech and Tourism, Cryptocurrency and Fintech and Cryptocurrency Tourism. We will then summarise how the three sectors are interrelated and the gap we aim to fill in this paper. In this paper, we use connectedness and spillovers interchangeably (Diebold & Yılmaz, 2012).

2.1. Fintech and Tourism

The interplay between financial technology (Fintech) and the tourism sector has garnered increasing academic attention in recent years. Several studies explored how technological advancements in financial services influence tourism dynamics.

Mombeuil & Uhde (2021) investigate the relative convenience, perceived security, and advantage of mobile payments in the tourism industry. Their findings reveal that tourists prefer mobile payment solutions for their convenience, leading to enhanced user satisfaction and loyalty. Ma & Ouyang (2023) also analyzes the spatiotemporal heterogeneity of digital inclusive finance on tourism economic development in China. Using panel data, the study finds that digital financial inclusion significantly boosts tourism revenue, especially in underdeveloped regions, by enhancing accessibility and reducing financial transaction costs. Lyu (2024) studies the impact of China's cross-border e-commerce pilot zones on urban residents' tourism consumption. The research highlights that the integration of e-commerce platforms with tourism services increases tourism spending, driven by improved digital payment mechanisms and service accessibility.

Xuan Luan et al. (2023) investigate cashless payments and access to credit for community-based tourism businesses in Vietnam. The study underscores the transformative impact of Fintech in enabling small tourism enterprises to expand their financial capabilities and operational efficiency. Kim et al. (2022) explore digital currency and payment innovations within the hospitality and tourism sectors. The study concludes that Fintech advancements facilitate seamless transactions, enhance customer satisfaction, and create opportunities for innovative service delivery. Shariffuddin et al. (2023) analyze the affordances of online travel sites in the tourism industry. Their findings suggest that digital payment systems and integrated Fintech solutions improve user experience and drive customer retention. Ratna et al. (2024) provide a comprehensive review of blockchain and Fintech applications in the tourism and hospitality industries. The study highlights the role of Fintech in fostering financial resilience, particularly during economic disruptions like the COVID-19 pandemic.

Critical analysis of these studies reveals a significant gap in the literature: while Fintech's role in facilitating payments and improving financial inclusion in tourism is well-documented, few studies explore its long-term implications for cross-sectoral connectedness, particularly for the interest of tourists, tourism companies and investors. This study fills this gap by empirically examining the interplay between Fintech, tourism, and cryptocurrency markets using measures that capture both the investment performance and spillovers among these sectors.

2.2. Blockchain's Role in Tourism and Fintech

Blockchain technology is widely recognised for its ability to transform operational processes in tourism and Fintech. The key features of blockchain, including transparency, security, efficiency, and smart contract functionality, have been extensively discussed in academic and industry contexts. In the tourism sector, blockchain enables the creation of decentralised platforms that eliminate intermediaries such as online travel agencies (OTAs).

For instance, blockchain-based platforms like Winding Tree, now defunct, allow travellers to book accommodations and services directly from providers, enhancing cost efficiency and trust. Blockchain also facilitates new business models, including developing immutable review systems, secure payment processing, and tokenised loyalty programs that enhance customer satisfaction. Gursoy et al. (2022) in a conceptual paper explores the application of non-fungible tokens (NFTs) in creating virtual goods and collectibles for the hospitality and tourism industry. Their study proposes a framework for enhancing customer experiences in the metaverse. However, it lacks empirical validation, particularly regarding the relationship between NFTs and customer experience in practical contexts. Treiblmaier (2021) also investigates the potential uses of digital tokens within the tourism industry, focusing on their role in enhancing customer value and interaction. The study identifies innovative applications of blockchain technology but remains largely theoretical. Empirical studies are needed to substantiate the claims and provide actionable insights for hotel managers. Boukis (2024) therefore examines the impact of tokenised rewards, enabled by blockchain technology, on the attractiveness and effectiveness of customer loyalty programs in the hospitality industry. The study found that tokenised rewards enhance perceived economic value, program attractiveness, and behavioural intentions, especially for luxury hotels and cryptocurrency-savvy customers, through the mediating roles of reward novelty and psychological ownership. The results suggest that tokenized rewards are more effective than traditional discounts, particularly for high-end brands aiming to differentiate their loyalty offerings.

While these studies focus on building new technologies for the tourism sector on blockchain infrastructure, our study focuses on examining empirically the spillovers of the widespread adoption of cryptocurrencies to the tourism industry. Therefore, we proceed to briefly review some empirical studies on how cryptocurrencies affect the tourism industry.

2.3. Cryptocurrency and Tourism

The integration of cryptocurrencies in the tourism industry has emerged as a significant development, reshaping traditional payment systems. Cryptocurrencies such as Bitcoin and Ethereum have facilitated new transaction mechanisms that reduce the dependence on traditional intermediaries, enabling faster and more cost-effective cross-border payments. This is particularly beneficial in the tourism sector, where travellers frequently face challenges related to currency exchange fees, credit card fraud, and fluctuating exchange rates. Researchers have explored various facets of this emerging trend.

Manahov & Li (2024) provide empirical evidence of the spillover effects between cryptocurrency markets and tourism tokens, indicating a statistically significant influence of cryptocurrency heists and market shocks on tourism-related digital assets. This interconnectedness suggests that developments in crypto directly affect investor sentiment and operational liquidity in tourism businesses. The use of stablecoins in tourism further mitigates volatility risks. Stablecoins pegged to stable assets such as fiat currencies or commodities, offer a reliable alternative for travel-related payments, reducing price fluctuations and enhancing transaction security.

Radic et al. (2022) investigate the adoption of cryptocurrency payments in South Korea and China's tourism sectors. The study finds that cryptocurrencies enable faster, more transparent transactions but also highlight regulatory and security challenges. Luo et al. (2024) examine consumer experiences with travel websites accepting cryptocurrency payments. They find that cryptocurrency integration enhances user satisfaction by offering alternative payment options, especially for international travelers. Kim et al. (2022) discuss the broader implications of digital currency adoption in tourism and hospitality. Their findings reveal that cryptocurrencies facilitate seamless cross-border transactions but require robust regulatory frameworks to ensure stability. Luo et al. (2024) touches on cryptocurrency's role in e-commerce-driven tourism consumption. The study emphasizes that blockchain-enabled payment solutions reduce transaction costs and increase consumer trust.

Meanwhile, in Fintech, blockchain drives innovation in digital payment systems by offering faster, more transparent, and secure transaction solutions. Yousaf & Goodell (2023) explores how cryptocurrency price and policy uncertainties affect digital payment stocks, revealing complex interdependencies between these markets. Their findings suggest that blockchain-based fintech solutions can hedge against uncertainties in cryptocurrency markets, while traditional digital payment giants like VISA and Mastercard remain relatively resilient. However, challenges such as regulatory uncertainty, security risks, and integration costs remain barriers to the widespread adoption of blockchain in both sectors.

2.4. COVID-19 and Sectoral Spillovers

The COVID-19 pandemic served as a stress test for global financial and tourism systems, revealing both vulnerabilities and opportunities for innovation. The pandemic caused a significant contraction in tourism and fintech sectors, with disruptions to travel demand, liquidity crises, and heightened market volatility. During this period, most governments implemented lockdown rules, which also caused a sharp decline in tourism around the world (Hampton et al., 2023; Ren et al., 2024). Due to these rules, economic activities were generally slow, causing central banks to implement aggressive monetary easing while governments pursued expansive fiscal policies to counter the economic effects of COVID-19. However, the pandemic also accelerated the adoption of digital payment systems and blockchain technologies as businesses adapted to new operational realities. Businesses sought secure, decentralised solutions to manage payments and loyalty programs in a contactless environment. Corbet et al. (2022) examine the role of government support programs in stabilising tourism markets during the pandemic. Their findings indicate that fiscal interventions, such as relief packages and loan facilities, alleviated investor fears and stabilised stock prices in the tourism sector.

In the fintech sector, the pandemic underscored the importance of resilience against systemic shocks. Yousaf & Goodell (2023) reveal that digital payment stocks acted as a hedge against uncertainties in cryptocurrency markets during the pandemic, highlighting the interconnectedness of these markets. The accelerated adoption of stablecoins in tourism further highlights the sector's response to pandemic-induced disruptions, offering secure, cost-effective alternatives to traditional payment systems.

Our literature review highlights the growing significance of Fintech and cryptocurrency in shaping tourism dynamics. Despite significant advancements, several critical gaps remain in the literature. First is the lack of empirical modeling of spillovers or connectedness among these sectors. While existing studies highlight the interconnectedness of Fintech with tourism or cryptocurrency with Fintech, there is a need for econometric models to quantify the joint inter-connectedness among these three sectors, particularly using ETF returns and crypto indices as proxies. Second, for risk management purposes, the inherent volatility of cryptocurrencies poses significant risks to both the tourism and Fintech sectors. Research is needed to develop frameworks for managing these risks and ensuring market stability through the empirical examinations of portfolio and hedging strategies. By addressing these gaps in the existing literature, this study provides a comprehensive understanding of the interconnectedness between these sectors, offering valuable insights for investors, policymakers, and stakeholders.

3. Data Description and Sources

We obtain daily data from Refinitiv Datastream covering 10th November 2017 to 5th July 2024. The start of the period is chosen because all series have available data starting from that day. The data collected are prices of twelve Exchange-Traded Funds (ETFs) from 3 key sectors– Fintech, Tourism and the traditional financial sector – and prices of Bitcoin, Ethereum and Binance Coin (BNB). ETFs are investment vehicles that trade on stock exchanges, similar to individual stocks, but represent a basket of assets such as stocks, bonds, commodities, or other securities. They are structured to track the performance of specific indices, sectors, or asset classes. In this study, ETFs are relevant as they capture broad markets. These are described below with the variable names in brackets.

Fintech ETFs typically consist of companies that provide innovative financial services or develop financial technologies, such as digital payments and financial software. Examples include ETFs focusing on digital payment giants like Visa, PayPal, and Square. For Fintech ETFs, we use the following:

Global X Fintech ETF (GLOBALX_ETF): This ETF seeks to invest in companies on the leading edge of the emerging financial technology sector, which encompasses a range of innovations helping to transform established industries like insurance, investing, fundraising, and third-party lending through unique mobile and digital solutions.

Amplify Digital Payments ETF (AMPLIFY_ETF): The Index tracks the performance of common stocks (or corresponding American Depositary Receipts ("ADRs") or Global Depositary Receipts ("GDRs")) of Mobile Payments Companies.

Invesco KBW NASDAQ Fintech UCITS ETF (INVESCO_FINTECH_ETF): The Fund's investment objective is to replicate the net total return performance of the KBW NASDAQ Financial Technology Index (the "Reference Index"), adjusted for fees, expenses, and transaction costs. The Reference Index reflects the performance of financial technology companies listed on the NASDAQ Stock Market, the New York Stock Exchange, or NYSE MKT.

Tourism-focused ETFs invest in companies directly involved in travel, hospitality, and leisure industries, such as airlines, hotel chains, and online travel agencies. Examples include funds that track indices of tourism-related stocks or focus on geographically diverse travel companies. These include:

i) *US Global Jets ETF (US_GLOBALJETS_ETF)* provides investors access to the global airline industry, including airline operators and manufacturers worldwide. The Index consists of exchange-listed common stocks or depositary receipts of US and international companies involved in passenger airlines, aircraft manufacturing, airports, terminal services, and airline-related internet media and services, as identified by independent industry classifications (collectively referred to as "Airline Companies")

ii) *iShares DJSXX.600 Travel & Leisure (ISHARES_TRVL_ETF)*: This Fund seeks to track the performance of STOXX Europe 600 Travel & Leisure Index composed of companies from the European Travel & Leisure sector.

iii) *Invesco Leisure and Entertainment ETF (INVESCO_ETF)*: The Invesco Leisure and Entertainment ETF (Fund) is based on the Dynamic Leisure & Entertainment Intellidex Index (Index). The Index is comprised of common stocks of leisure and entertainment companies. These are companies that are principally engaged in the design, production or distribution of goods or services in the leisure and entertainment industries.

Given the dominant role of the traditional financial sector, we also include ETFs that track the traditional financial sector to control these companies' role in the interconnectedness between Fintech, Crypto and Tourism. We include the Top 3 [1]. Hence, we use ETFs that capture the financial sector, including banks, insurance companies, capital markets, and investment banks, among others, to capture the broader financial sector. These include:

i) *Financial Select Sector SPDR Fund (FINANCIAL_SELECT_FUND)*. This ETF aims to match the performance of the Financial Select Sector Index. This Index provides exposure to companies across multiple financial sectors, including financial services,

[1] Selection of the ETFs was influenced by these articles that identify some of the top performing ETFs in Fintech, Tourism and Financials https://www.nasdaq.com/articles/adventure-awaits:-ride-the-tourism-wave-with-these-etfs

insurance, banks, capital markets, mortgage real estate investment trusts, and consumer finance.

ii) II0 *iShares US Broker-Dealers & Securities Exchange ETF (ISHARES_US_ETF).* The ETF seeks to track the investment results of an index composed of US equities in the investment services sector with exposure to US investment banks, discount brokerages, and stock exchanges.

iii) *SPDR S&P Capital Markets ETF(SPDR_ETF)*: The ETF provides exposure to the capital markets segment of the S&P Total Market Index, including sub-industries such as Asset Management & Custody Banks, Diversified Capital Markets, Financial Exchanges & Data, and Investment Banking & Brokerage.

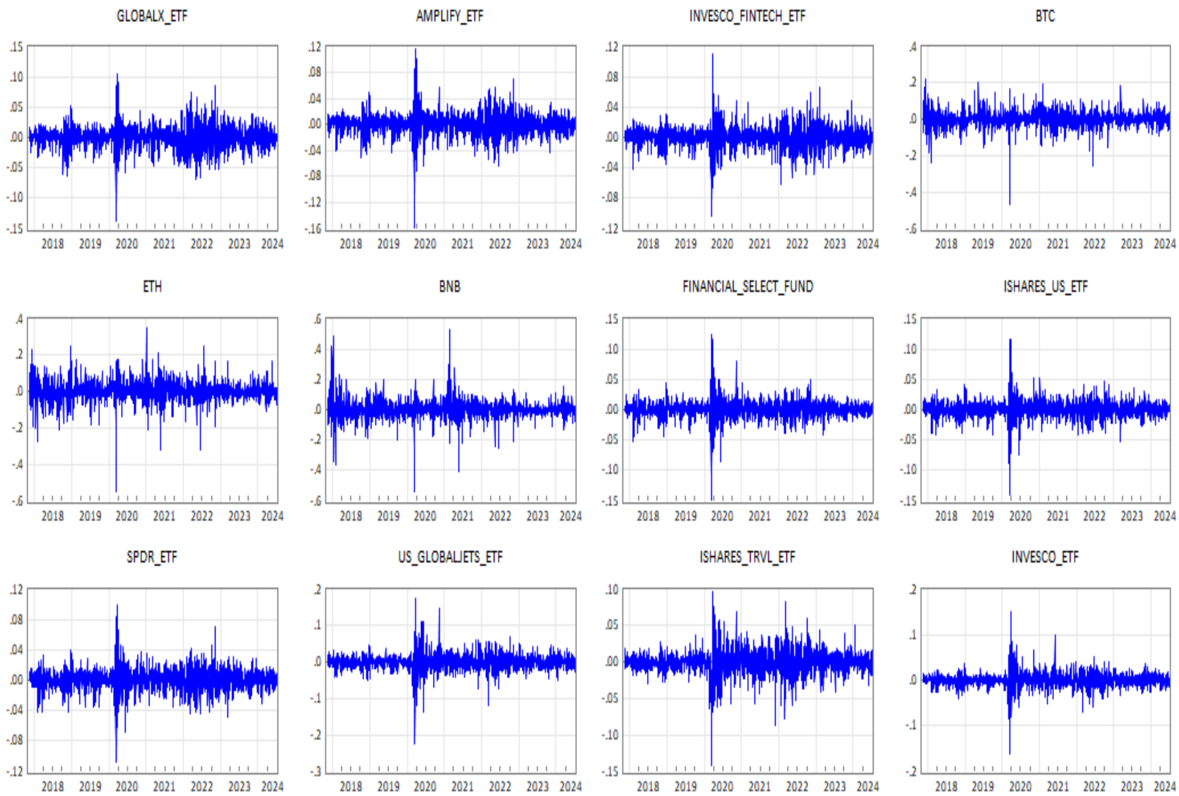
For data on cryptocurrency, we use Bitcoin, the world's largest cryptocurrency according to its market CAP. We also include two alternative coins, namely Ethereum, the second largest coin, and *BNB*, the native coin for Binance and the largest cryptocurrency trading exchange. While Bitcoin is designed as a decentralised digital currency and store of value, Ethereum functions as a platform for decentralised applications (DApps) and smart contracts. Binance Coin primarily facilitates transactions and services within the Binance exchange ecosystem, which is the largest crypto exchange in the world.

By using all these data series, we can capture the diverse markets of the Fintech, Crypto, Tourism as well as the traditional financial sectors. We calculate the log returns of all the series following: $Return = ln(R_t) - ln(R_{t-1})$. Figure 1 shows the time series plot of the returns. The Figure shows quite a similar trend over the period, with observable spikes during 2020 when COVID-19 was declared a pandemic.

The summary statistics of the series are shown in Table 1. From the table, *BNB* has the highest mean return of 0.3% but also has the highest variance. *BTC* and *ETH* have the same mean return of 0.1% even though *ETH* had a higher risk (variance) than *BTC*. The Fintech and traditional financial sector ETFs recorded mean returns ranging from 0.01% to 0.04%. However, all the traditional financial sector ETFs had similar risks, while the Fintech ETFs generally had higher risks. The tourism ETFs recorded the lowest mean returns/loss. This ranged from a mean loss of -0.006% to a mean return of 0.005%. Meanwhile, taking the first log-difference of the raw series results in a stationary series as shown by the Elliott et al. (1992) unit root test. However, the Jarque & Bera (1980) test rejects the null of normally distributed data. Hence, the use of the TVP-

VAR approach, which captures a dynamic (time-varying) variance-covariance structure, is suitable for the nature of the time series.

Figure 1: Time series trend of first log-difference of variables



4. Empirical Methods

4.1. Model Specification

4.2. Time-varying parameter vector autoregression

As we mentioned earlier, in this study, we use connectedness and spillovers interchangeably Diebold & Yılmaz (2012). To estimate spillovers among Fintech, cryptocurrency and tourism sectors, we use a TVP-VAR model with heteroscedastic variance-

Table 1: Summary statistics

Variable	Mean	Variance	Skewness	Kurtosis	JB	ERS
GLOBALX_ETF	0.0001	0.0005	-0.454***	4.975***	1849.601***	-17.995***
AMPLIFY_ETF	0.0002	0.0003	-0.668***	9.790***	7061.635***	-17.587***
INVESCO_FINTECH_ETF	0.0004	0.0002	-0.156***	6.126***	2721.859***	-18.356***
BTC	0.001	0.002	-0.786***	10.615***	8329.794***	-4.494***
ETH	0.001	0.003	-0.671***	9.357***	6463.045***	-5.827***
BNB	0.003	0.004	0.282***	13.712***	13623.009***	-4.502***
FINANCIAL_SELECT_FUND	0.0003	0.0002	-0.629***	15.461***	17404.479***	-16.314***
ISHARES_US_ETF	0.0004	0.0002	-0.759***	14.357***	15076.726***	-17.360***
SPDR_ETF	0.0004	0.0002	-0.556***	7.172***	3809.886***	-17.501***
US_GLOBALJETS_ETF	-0.0002	0.001	-0.542***	14.464***	15217.599***	-16.200***
ISHARES_TRVL_ETF	-0.00006	0.0003	-0.508***	7.902***	4590.763***	-17.569***
INVESCO_ETF	0.00005	0.0003	-0.913***	18.307***	24482.481***	-17.314***

Note: *** Significance at 1%. ** Significance at 5%, Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque & Bera (1980) normality test; ERS: Elliott et al. (1992) unit-root test. All other variables are as defined earlier.

covariances[2] as used by Antonakakis et al. (2020a) and Antonakakis et al. (2020b). This approach extends the works of Diebold & Yılmaz (2009, 2012, 2014) by applying a TVP-VAR with a time-varying covariance structure instead of the constant-parameter rolling-window VAR approach. In this approach, variances can vary over time via a Kalman Filter estimation, which relies on decay factors. Based upon the Bayesian information criterion (BIC) and the Hannan-Quinn information criterion (HQ), a TVP-VAR(1) model is selected which can be mathematically formulated as:

$$\boldsymbol{y}_t = \boldsymbol{B}_t \boldsymbol{y}_{t-1} + \boldsymbol{\epsilon}_t \qquad \boldsymbol{\epsilon}_t \sim N(\boldsymbol{0}, \boldsymbol{\Sigma}_t) \tag{1}$$

$$vec(\boldsymbol{B}_t) = vec(\boldsymbol{B}_{t-1}) + \boldsymbol{v}_t \qquad \boldsymbol{v}_t \sim N(\boldsymbol{0}, \boldsymbol{S}_t) \tag{2}$$

where $\boldsymbol{y}_t$, $\boldsymbol{y}_{t-1}$ and $\boldsymbol{\epsilon}_t$ are $K \times 1$ dimensional vector and $\boldsymbol{B}_t$ and $\boldsymbol{\Sigma}_t$ are $K \times K$ dimensional matrices. $vec(\boldsymbol{B}_t)$ and $\boldsymbol{v}_t$ are $K^2 \times 1$ dimensional vectors whereas $\boldsymbol{S}_t$ is a $K^2 \times K^2$ dimensional matrix. As the dynamic connectedness approach of Diebold & Yılmaz (2012, 2014) rests on the Generalised Forecast Error Variance Decomposition (GFEVD) of Koop et al. (1996) and Pesaran & Shin (1998), it is required to transform the TVP-VAR to its TVP-VMA representation by the Wold representation theorem:

[2]As the detailed algorithm is beyond the scope of this study interested readers are referred to Antonakakis et al. (2020b)

$\boldsymbol{y}_t = \sum_{h=0}^{\infty} \boldsymbol{A}_{h,t}\boldsymbol{\epsilon}_{t-i}$ where $\boldsymbol{A}_0 = \boldsymbol{I}_K$.

The H-step ahead GFEVD models the impact a shock in series j has on series i. This can be formulated as follows,

$$\phi_{ij,t}^{gen}(H) = \frac{\sum_{h=0}^{H-1}(\boldsymbol{e}_i'\boldsymbol{A}_{ht}\boldsymbol{\Sigma}_t\boldsymbol{e}_j)^2}{(\boldsymbol{e}_j'\boldsymbol{\Sigma}_t\boldsymbol{e}_j)\sum_{h=0}^{H-1}(\boldsymbol{e}_i'\boldsymbol{A}_{ht}\boldsymbol{\Sigma}_t\boldsymbol{A}_{ht}'\boldsymbol{e}_i)} \tag{3}$$

$$gSOT_{ij,t} = \frac{\phi_{ij,t}^{gen}(H)}{\sum_{k=1}^{K}\phi_{ik,t}^{gen}(H)} \tag{4}$$

where $\boldsymbol{e}_i$ is a $K \times 1$ dimensional zero vector with unity on its ith position. As the $\phi_{ij,t}^{gen}(H)$ stands for the unscaled GFEVD $(\sum_{j=1}^{K}\zeta_{ij,t}^{gen}(H) \neq 1)$, Diebold & Yılmaz (2009, 2012, 2014) suggested to normalize it by dividing $\phi_{ij,t}^{gen}(H)$ by the row sums to obtain the scaled GFEVD, $gSOT_{ij,t}$.

The scaled GFEVD is at the center of the connectedness approach facilitating the computation of the total directional connectedness *To (From)* all series *From (To)* series i. While the *To* total directional connectedness constitutes the effect series i has on all others, the *From* total directional connectedness illustrates the impact all series have on series i. These connectedness measures can be calculated by,

$$S_{i\to\bullet,t}^{gen,to} = \sum_{j=1,i\neq j}^{K} gSOT_{ji,t} \tag{5}$$

$$S_{i\leftarrow\bullet,t}^{gen,from} = \sum_{j=1,i\neq j}^{K} gSOT_{ij,t}. \tag{6}$$

Computing the difference between the *TO* and the *From* total directional connectedness results in the net total directional connectedness of series i:

$$S_{i,t}^{gen,net} = S_{i\to\bullet,t}^{gen,to} - S_{i\leftarrow\bullet,t}^{gen,from}. \tag{7}$$

If $S_{i,t}^{gen,net} > 0$ $(S_{i,t}^{gen,net} < 0)$, series i is influencing (influenced by) all others more than being influenced by (influencing) them and thus is considered to be a net transmitter (receiver) of shocks indicating that series i is driving (driven by) the network.

The connectedness approach also provides information on the bilateral level. The net pairwise directional connectedness shows the bilateral net transmission of shocks between series i and j,

$$S^{gen,net}_{ij,t} = gSOT_{ji,t} - gSOT_{ij,t}. \tag{8}$$

If $S^{gen,net}_{ij,t} > 0$ ($S^{gen,net}_{ij,t} < 0$), series i dominates (is dominated by) series j implying that series i influences (is influenced by) series j more than being influenced by (influencing) it.

The total connectedness index (TCI) or total spillover index (TSI) is another relevant metric highlighting the degree of network interconnectedness and, hence, market risk. Considering that the TCI can be calculated as the average total directional connectedness *To (From)* others, it is equal to the average amount of spillovers one series transmits (receives) from all others. Chatziantoniou & Gabauer (2021) and Gabauer (2021) have shown that as the own variance shares are by construction always larger or equal to all cross variance shares, the TCI is within $\left[0, \frac{K-1}{K}\right]$. To obtain a TCI which is within [0,1], we have to slightly adjust the TCI:

$$gSOI_t = \tfrac{1}{K-1} \sum_{i=1}^{K} S^{gen,from}_{i \leftarrow \bullet,t} = \tfrac{1}{K-1} \sum_{i=1}^{K} S^{gen,to}_{i \rightarrow \bullet,t}, \tag{9}$$

A high (low) value indicates high (low) market risk.

Finally, we calculate the pairwise connectedness index (PCI), which can be seen as the TCI on the bilateral level, illustrating the degree of interconnectedness between series i and j. This can be formulated as:

$$PCI_{ij,t} = 2\left(\frac{gSOT_{ij,t} + gSOT_{ji,t}}{gSOT_{ii,t} + gSOT_{ij,t} + gSOT_{ji,t} + gSOT_{jj,t}}\right), \qquad 0 \leq PCI_{ij,t} \leq 1. \tag{10}$$

4.3. Portfolio back-testing models

We use portfolio back-testing techniques to examine the investment performance of these assets while exploring any hedging advantages. To examine the investment performance of assets under examination, we use different measures of constructing portfolios that have been used traditionally, as well as a new approach based on the results from our connectedness technique. The underlying assumption of portfolio construction is that investors can buy assets directly and are willing to construct a portfolio considering these markets: cryptocurrency, Fintech, tourism, and traditional financial sectors. This underscores the key strength of the study as we present different assets from different markets, allowing investors to do an efficient portfolio allocation and diversification. Therefore, this assumption is plausible, given that all cryptocurrencies and ETFs are easily available for investors to purchase. Below, we provide a summary of the different techniques used.

4.3.1. Bilateral hedge ratios and portfolio weights

The dynamic hedge ratio of Kroner & Sultan (1993) can be formulated as follows,

$$\beta_{ij,t} = \mathbf{\Sigma}_{ij,t}/\mathbf{\Sigma}_{jj,t}, \tag{11}$$

where $\mathbf{\Sigma}_{ij,t}$ is the conditional covariance between series i and j at time t, and $\mathbf{\Sigma}_{jj,t}$ the conditional variance of series j at time t.

Kroner & Ng (1998) shows that the optimal bilateral portfolio weights between series i and j are calculated as,

$$w_{ij,t} = \frac{\mathbf{\Sigma}_{ii,t} - \mathbf{\Sigma}_{ij,t}}{\mathbf{\Sigma}_{ii,t} - 2\mathbf{\Sigma}_{ij,t} + \mathbf{\Sigma}_{jj,t}}, \tag{12}$$

with

$$w_{ij,t} = \begin{cases} 0, & \text{if } w_{ij,t} < 0 \\ w_{ij,t}, & \text{if } 0 \leq w_{ij,t} \leq 1 \\ 1, & \text{if } w_{ij,t} > 1 \end{cases} \tag{13}$$

where $w_{ij,t}$ is the weight of series i in a 1\$ portfolio between series i and j at time t. Thus, $1 - w_{ij,t}$ is the weight of series j at time t in the aforementioned portfolio.

4.3.2. Minimum Variance Portfolio (MVP)

A commonly used approach in portfolio analysis is the MVP method which attempts to create the portfolio with the least volatility founded on multiple assets as documented by Markovitz (1959). The portfolio weights are estimated using the following formula:

$$\boldsymbol{w}_{\mathbf{\Sigma}_t} = \frac{\mathbf{\Sigma}_t^{-1}\boldsymbol{I}}{\boldsymbol{I}\mathbf{\Sigma}_t^{-1}\boldsymbol{I}} \tag{14}$$

where $\boldsymbol{w}_{\boldsymbol{\Sigma}_t}$ denotes the $K \times 1$ dimensioanl portfolio weight vector, $\boldsymbol{I}$ represents the K-dimensional vector of ones and $\boldsymbol{\Sigma}_t$ depicts the $K \times K$ dimensional conditional variance-covariance matrix in period t.

4.3.3. Minimum Correlation Portfolio (MCP)

In recent times, another procedure in the construction of portfolios emerged, namely the *MCP* that has been introduced by Christoffersen et al. (2014). This approach is similar to the MVP; however, in this case, the portfolio weights are obtained by minimizing the conditional correlations and not the conditional covariances. This can be outlined as follows,

$$\boldsymbol{R}_t = diag(\boldsymbol{\Sigma}_t)^{-0.5}\boldsymbol{H}_t diag(\boldsymbol{\Sigma}_t)^{-0.5} \tag{15}$$

$$\boldsymbol{w}_{\boldsymbol{R}_t} = \frac{\boldsymbol{R}_t^{-1}\boldsymbol{I}}{\boldsymbol{I}\boldsymbol{R}_t^{-1}\boldsymbol{I}} \tag{16}$$

4.3.4. Minimum Connectedness Portfolio (MCoP)

Following the construction of the *MVP* and *MCP* portfolio techniques, we next generate MCoP by using the pairwise connectedness indices rather than the correlations or variances (Broadstock et al., 2020). The minimisation of bilateral interconnectedness offer a portfolio procedure that is not affected heavily by network shocks. Thus, assets that are not influencing others and are not influenced by others are allocated with a higher weight in the constructed portfolio. This is expressed as shown below:

$$\boldsymbol{w}_{C_t} = \frac{\boldsymbol{PCI}_t^{-1}\boldsymbol{I}}{\boldsymbol{I}\boldsymbol{PCI}_t^{-1}\boldsymbol{I}} \tag{17}$$

$\boldsymbol{PCI}_t$ denotes the pairwise connectedness index matrix while the identity matrix is represented by $\boldsymbol{I}$.

4.3.5. Portfolio evaluation

To ascertain the performance of the portfolios, we rely on two metrics, the Sharpe ratio (Sharpe, 1994) and the hedging effectiveness (Ederington, 1979).

On the one hand, the Sharpe ratio (SR), also called the reward-to-volatility ratio, is computed as follows:

$$SR = \frac{\bar{r}_p}{\sqrt{var(r_p)}} \tag{18}$$

Where r_p represents the portfolio returns assuming that the risk-free rate is equal to zero. As higher SR values connote higher returns relative to the level of risk in the portfolio, the SR allows us to compare various portfolios with each other as it informs us which portfolio has the highest return given the same volatility:

The second metric is Hedging Effectiveness (HE), which informs us about the risk percentage reduction of the portfolio over investing in a single asset i. We calculate the HE test statistics following Antonakakis et al. (2020a). The HE can be computed by following the equations below:

$$r_\beta = x_{it} - \beta_{jit} x_{jt}, \tag{19}$$

$$r_w = w_{ijt} x_{it} + (1 - w_{ijt})\, x_{jt}, \tag{20}$$

$$HE_i = 1 - \frac{\operatorname{Var}(r_{w,\beta})}{\operatorname{Var}(r_{unhedged})}, \tag{21}$$

where $\operatorname{Var}(r_{\text{unhedged}})$ denotes the variance of the unhedged position between variable i and j and $\operatorname{Var}(r_{w,\beta})$ is the hedged portfolio variance either from the optimal hedge ratio or the optimal portfolio weight strategy. Intuitively speaking, HE_i represents the percentage reduction in the variance of the unhedged position. The higher HE_i, the larger the risk reduction.

Following from Antonakakis et al. (2020a), we use the Brown & Forsythe (1974) test to estimate whether the variance reduction using either the hedge ratios or portfolio weights is successful or not. Thus, we test whether the HE test is statistically significant.

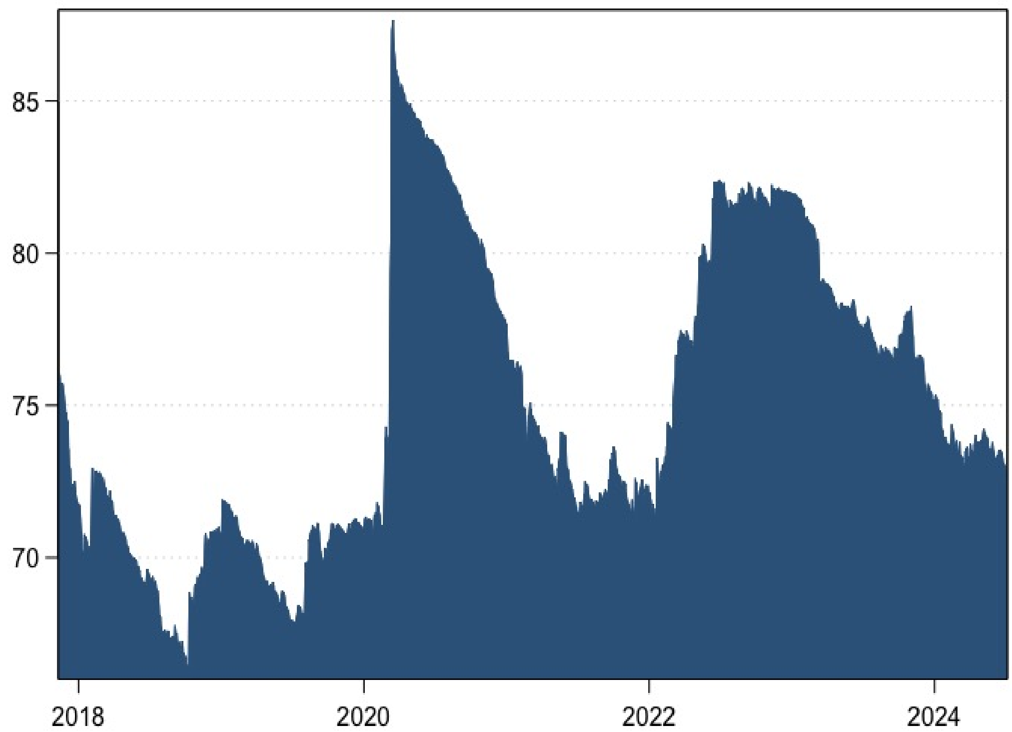
5. Results and Discussions

Here, we discuss the results of the spillover analysis and the portfolio back-testing models.

5.1. Dynamic total connectedness

The dynamic total connectedness results can be shown in Figure 2. We can see that the spillovers are heterogeneous over time. The highest TSI was observed in the first quarter of 2020 when COVID-19 was declared a pandemic. This was close to 90% even though the average TSI over the period is 75%, as shown in Table 2. Thus, it seems that during extreme periods, spillovers among Fintech, cryptocurrency, tourism, and the traditional financial sector rise sharply and possibly attain a new peak.

Figure 2: Dynamic total connectedness



Note: Results are based on a TVP-VAR model with a lag length of order 1 (BIC) and a 10-step-ahead forecast.

5.2. Average dynamic Connectedness

The average dynamic connectedness results, as presented in Tables 2 and 3, provide crucial insights into the interconnectedness among the fintech, cryptocurrency, tourism, and traditional financial markets. In these tables, the ij^{th} entry represents the contribution *To* the forecast error variance of market i from shocks originating in market j. The diagonal elements (in bold) capture the *Own*-variance shares of individual assets, while the off-diagonal column and row sums represent the *To Others* and *From Others* spillovers, respectively. The Total Connectedness Index (TCI), derived as the gross sum of *From* spillovers as a percentage of total variance (including *Own* variance), is reported as 75%, indicating a high level of interconnectedness and associated risk transmission among the markets under study.

Key findings emerge from these results. SPDR S&P Capital Markets ETF (*SPDR_ETF*), representing the traditional financial sector, is identified as the most prominent net transmitter of spillovers, with a net spillover of 18.95%. This underscores the critical role of the broader capital markets, encompassing commercial banks, investment banks, and asset management firms, in disseminating risk. Amplify Digital Payments ETF (*AMPLIFY_ETF*), a fintech-focused ETF tracking mobile payment companies, ranks as the second-highest transmitter. On the other hand, iShares DJSXX.600 Travel & Leisure ETF (*ISHARES_TRVL_ETF*), representing the tourism sector, emerges as the most significant net receiver of spillovers, with a spillback of 23.64%. These results highlight the vulnerability of the tourism sector to external shocks originating in other markets.

To provide a broader perspective, we aggregate spillovers across the four assets representing each market. Specifically, *GLOBALX_ETF*, *AMPLIFY_ETF*, and *INVESCO_FINTECH_ETF* form the fintech sector; *BTC*, *ETH*, and *BNB* represent the cryptocurrency sector; *FINANCIAL_SELECT_FUND*, *ISHARES_US_ETF*, and *SPDR_ETF* constitute the traditional financial market; and *US_GLOBALJETS_ETF*, *INVESCO_ETF* and *ISHARES_TRVL_ETF*, represent the tourism sector. Table 3 presents these aggregated spillover results, where diagonal values represent the sum of *Own* variance shares and off-diagonal values denote the sum of net spillover or spillback between markets. Notably, the traditional financial sector is the sole net transmitter to all other sectors, with the highest net spillover of 16.27% directed toward the tourism market. This emphasizes the dependence of the tourism sector on developments within traditional financial markets.

These findings are consistent with prior literature. For instance, Khanna & Sharma (2023) and Katircioglu et al. (2017) underscore the strong linkages between financial markets and the tourism industry, while De Vita & Kyaw (2016) highlight the pivotal role of financial development in the tourism-growth nexus. The ability of the financial sector to provide credit and liquidity for tourism businesses and individual travelers is well-documented (Xuan Luan et al., 2023). Our results reaffirm the dominance of the traditional financial sector in shaping tourism market dynamics. The potential for cryptocurrencies to disrupt this dominance through decentralized finance (DeFi) solutions remains an open question, particularly in the context of peer-to-peer lending and corporate financing.

Meanwhile, Fintech emerges as the second most significant transmitter of spillovers to the tourism sector, with a net spillover of 10.19%. This finding aligns with Yousaf & Goodell (2023), who emphasize the growing integration of fintech solutions in tourism services. Conversely, the cryptocurrency market is predominantly a net receiver of spillovers from all other markets, especially from the Fintech market, with an aggregate net spillback of 26%. This dependency on external market movements partially explains the high volatility observed in cryptocurrency returns (Abad et al., 2022). Table 3 further reveals that the tourism market, with a net spillback of 21.63%, remains highly vulnerable to spillovers, especially from the traditional financial sector, which dominates the four markets with a net spillover contribution of 35%.

In summary, the results underscore the asymmetric nature of spillover dynamics among the four markets. While the traditional financial sector remains the dominant transmitter of shocks, fintech plays an increasingly important role, particularly in its interactions with the cryptocurrency sector. The cryptocurrency market, despite its innovation, continues to exhibit susceptibility to shocks from more established markets. These findings provide critical insights for stakeholders seeking to understand cross-market risk transmission and its implications for portfolio management and policy interventions.

5.3. Dynamic net total directional spillovers

Here, we discuss the dynamic net connectedness of each asset as shown in Figure 3.

The key observation of the dynamic results is that it helps us to observe the net spillovers over time, giving particular insights into different times, especially during the COVID-19 pandemic. From Figure 3, values above the zero line indicate that the asset is

Table 2: Average dynamic connectedness between tourism, fintech and crypto markets

Variable	GLOBALX_ETF	AMPLIFY_ETF	INVESCO_FINTECH_ETF	BTC	ETH	BNB	FINANCIAL_SELECT_FUND	ISHARES_US_ETF	SPDR_ETF	US_GLOBALJETS_ETF	ISHARES_TRVL_ETF	INVESCO_ETF	FROM others
GLOBALX_ETF	**19.44**	16.69	8.97	2.19	2.19	1.78	7.86	9.03	11.15	6.54	4.28	9.88	80.56
AMPLIFY_ETF	15.22	**17.63**	8.82	1.7	1.73	1.44	9.56	9.98	11.36	7.41	4.72	10.42	82.37
INVESCO_FINTECH_ETF	11.87	12.42	**20.32**	1.65	1.78	1.41	8.24	9.11	10.71	6.27	7.41	8.81	79.68
BTC	3.72	3.21	2.1	**37.72**	23.39	16.39	2.05	2.59	3.07	1.75	1.61	2.4	62.28
ETH	3.71	3.22	2.23	23.23	**37.33**	17.15	2.02	2.46	3	1.61	1.6	2.45	62.67
BNB	3.42	3.05	2.27	18.2	19.15	**41.97**	1.78	2.14	2.67	1.46	1.74	2.14	58.03
FINANCIAL_SELECT_FUND	7.76	10.17	6.3	1.17	1.24	0.95	**18.88**	15.87	14.89	8.77	4.18	9.83	81.12
ISHARES_US_ETF	8.64	10.3	6.85	1.37	1.42	1.07	15.32	**18.23**	15.51	7.75	3.93	9.6	81.77
SPDR_ETF	9.91	10.98	7.45	1.56	1.59	1.24	13.45	14.5	**16.99**	8.03	4.21	10.07	83.01
US_GLOBALJETS_ETF	7.71	9.39	5.87	1.24	1.2	0.93	10.34	9.44	10.49	**22.31**	7.02	14.07	77.69
ISHARES_TRVL_ETF	6.87	8.18	10.35	1.48	1.58	1.44	6.64	6.66	7.82	9.49	**29.8**	9.7	70.2
INVESCO_ETF	9.87	11.3	6.39	1.43	1.48	1.15	9.96	10.02	11.27	11.94	5.85	**19.34**	80.66
Spillovers TO Others	88.7	98.9	67.6	55.21	56.75	44.94	87.23	91.8	101.96	71.03	46.56	89.37	900.05
Spillovers Inc. Own	108.13	116.53	87.92	92.93	94.08	86.91	106.11	110.03	118.95	93.34	76.36	108.71	**TCI/TSI = 75%**
Net Spillovers/Spillback	8.13	16.53	-12.08	-7.07	-5.92	-13.09	6.11	10.03	18.95	-6.66	-23.64	8.71	

Table 3: Summary of average aggregate net spillovers: market-to-market

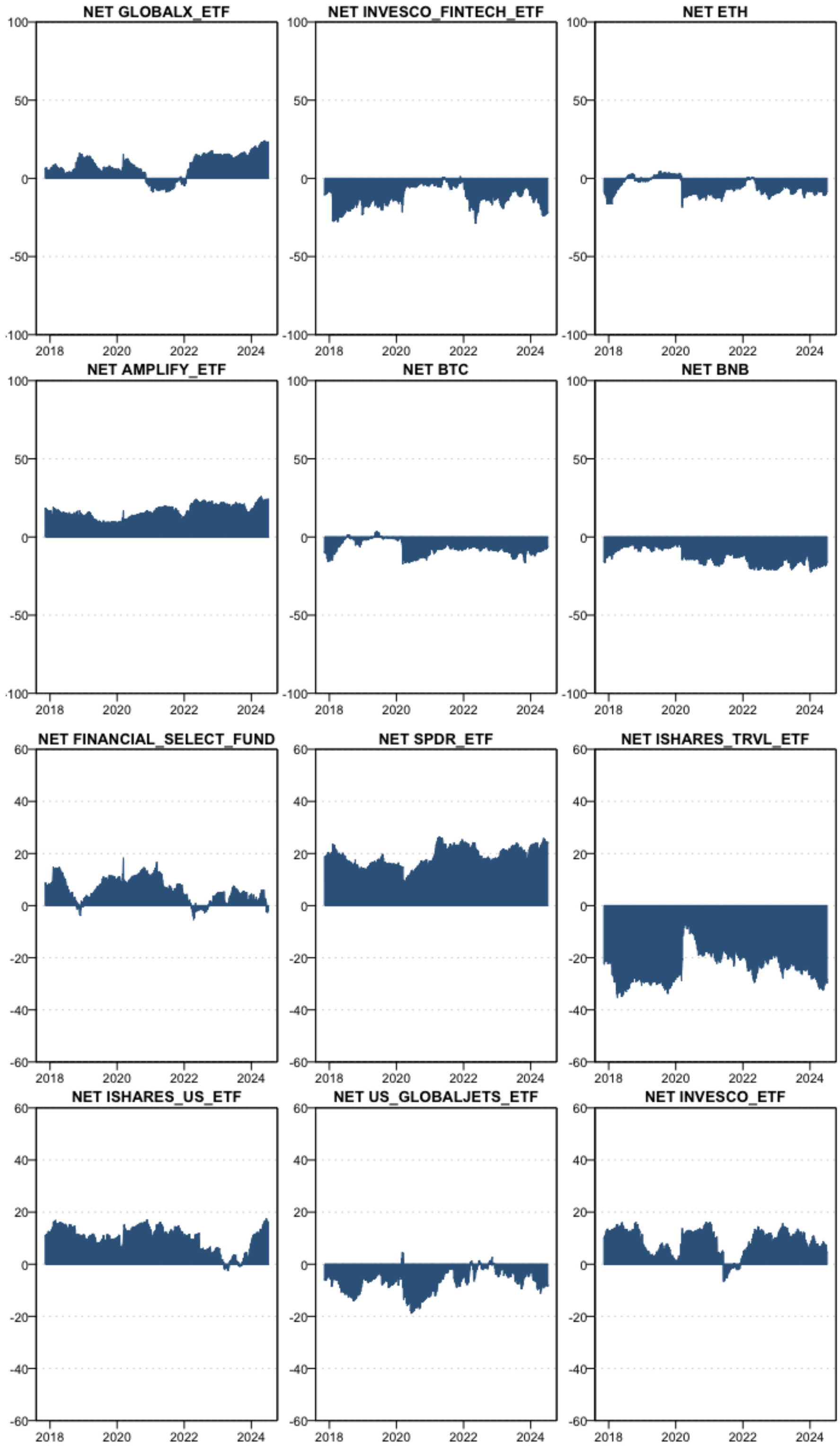
Variable	Traditional financial market	Fintech	Tourism	Cryptocurrency
Traditional financial market	**54.1**	-8.64	-16.27	-10.17
Fintech	8.64	**57.39**	-10.19	-11.06
Tourism	16.27	10.19	**71.45**	-4.83
Cryptocurrency	10.17	11.06	4.83	**117.02**
Net Aggregate Market spillover/spillback	35.08	12.61	-21.63	-26.06

a net transmitter of shocks, while values below show the asset is a net receiver of shocks or spillovers. The results are generally consistent with the average net connectedness results discussed earlier – the spillovers are heterogeneous over time. All the assets belonging to the traditional financial market are generally net transmitters of spillovers over the study period, with minimal observed net spillbacks. Among the Fintech assets, *INVESCO_FINTECH_ETF* receives the most spillbacks over time, contributing significantly to the aggregate net spillback of the sector, as discussed earlier. Among the tourism assets, apart from *IVESCO_ETF*, the remaining assets are all net receivers of spillovers over time. Also, all the cryptocurrency assets are net receivers of spillovers over time with ETH showing some positive net contribution of spillovers in late 2019.

5.4. Network analysis of spillovers

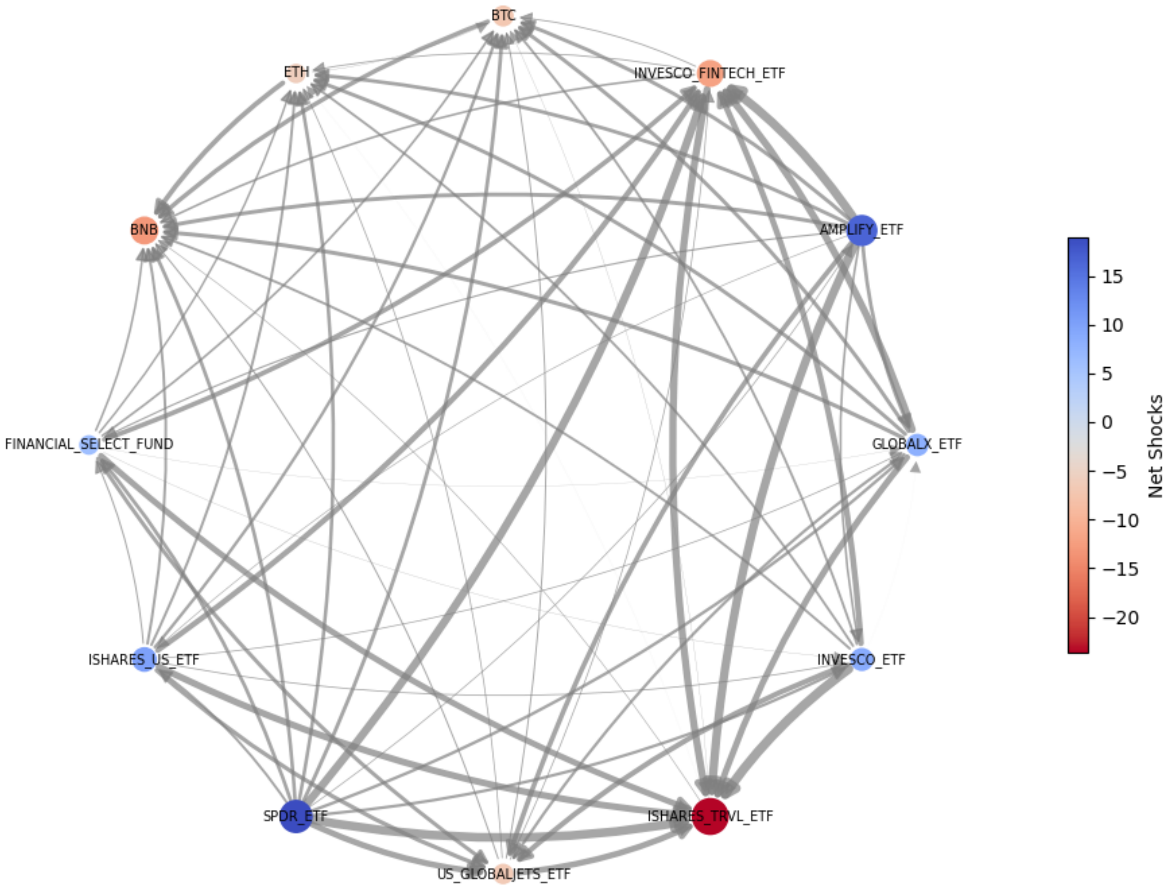
To further discuss the average pairwise spillovers between the variables, we present a network plot in Figure 4. The network plot shows the net directional spillovers between the pair of variables and the intensity of the net directional spillovers. From the figure, the node's size and color represent that particular variable's net spillover/spillback to all other variables; these represent the values on the last row of Table 2. The color scale ranges from the highest net receiver (red) to the highest net transmitter (blue) of spillovers or shocks. Again, the direction of the arrows shows which of the pairs of the variables is the net contributor or receiver of spillovers, while the size of the line shows the intensity or degree of the net pairwise spillover. As noted earlier, we can see that *ISHARES_TRVL_ETF* is the highest net receiver of spillover with the biggest node and deepest red, while *SPDR_ETF* is the highest net contributor of spillover in the system,m underscoring the critical role of the broader capital markets, encompassing commercial banks, investment banks, and asset management firms, in disseminating risk.

Figure 3: Dynamic net total directional connectedness



Note: Results are based on a TVP-VAR model with lag length of order 1 (BIC) and a 10-step-ahead forecast.

Figure 4: Network spillover plot



Note: Results are based on a TVP-VAR model with lag length of order 1 (BIC) and a 10-step-ahead forecast.

5.5. *Dynamic net pairwise directional spillovers*

Due to the large net pairwise connectedness among all 12 assets, the results are presented in the Appendix. We highlight some key observations from these results. The net pairwise spillovers, as depicted in Figure **??**, provide valuable insights into the interconnectedness among the individual assets from the Fintech, cryptocurrency, tourism, and traditional financial markets. Each chart represents the directional spillovers from one asset to another, highlighting the temporal dynamics of risk transmission across these sectors. The results are consistent with our earlier findings. First, the traditional financial sector emerges as the primary transmitter of spillovers, underscoring its role in shaping risk transmission across sectors. Second, the cryptocurrency market predominantly receives spillovers, reflecting its sensitivity to external shocks and its high return volatility. The tourism sector remains highly susceptible to spillovers, particularly from the traditional financial sector, emphasizing its reliance on external financial conditions.

These findings underscore the asymmetric spillover dynamics among fintech, cryptocurrency, tourism, and traditional financial markets. The dominance of traditional financial markets in risk transmission, coupled with the vulnerability of the tourism sector, highlights the need for strategic portfolio diversification and policy interventions. Moreover, the interdependencies between the Fintech and cryptocurrency sectors reveal opportunities for innovation and market integration. We, therefore, proceed to discuss the results from the portfolio back-testing.

5.6. *Hedging and portfolio Analysis*

5.6.1. *Bilateral hedge ratios and portfolio weights*

We proceed to discuss the results of our portfolio analysis. We first provide a discussion of the summary statistics of the bilateral hedge ratios and the hedging effectiveness (*HE*). The bilateral hedge ratios reported in Table **??** Appendix A provide critical insights into the effectiveness of hedging strategies across different asset pairs. The hedge ratios' mean values reflect the average relationship between the returns of the hedged and hedging instruments. From the table, a $1 long position in the first asset can be hedged with the average value of the hedge ratio of a short position in the second asset. For instance, asset pairs such as *GLOBALX_ETF* – *AMPLIFY_ETF* with a mean hedge ratio of \$1.061 exhibit strong positive co-movement. This means that every \$1 long position in *GLOBALX_ETF* can be hedged for \$1.061 investment in *AMPLIFY_ETF*. This would be an expensive hedge and is not surprising given that both asset classes are in the Fintech sector; hence, it may not be a good hedge. Hence, from the table, the cheapest hedge for *GLOBALX_ETF* is the cryptocurrency assets ranging from \$0.120 for *BNB* to \$0.155 for *BTC*. This is consistent for all the other Fintech and other asset classes, with crypto assets providing the cheapest hedge for all other assets. *BNB* broadly provided the cheapest hedge for these assets, followed by *ETH*.

We also observe that it is expensive to use asset classes within the same sector as a hedge for the other. This highlights the importance of asset-specific characteristics and their relationships when selecting hedging instruments. Moreover, we do see that it is expensive to hedge Fintech assets with assets in the traditional financial sector. For instance, hedging a \$1 long position in *LOBALX_ETF* will require at least \$0.754 from the traditional financial sector. This shows the high positive co-movement between the two sectors. Meanwhile, we can observe that the cheapest source of hedge for the cryptocurrency market is the Tourism sector, while the Fintech and traditional financial sectors provide an expensive hedge. For instance, hedging a \$1 long position in *BTC* will require at least \$0.526 (*GLOBALX_ETF*) and \$0.463 from the Fintech and traditional financial sectors, respectively. Meanwhile, a minimum of \$0.296 (*US_GLOBALJETS_ETF*) from the tourism sector can be used to hedge the BTC. These results are similar for all crypto assets.

The standard deviations also provide additional insights into the variability of hedge ratios. Pairs with higher standard deviations, such as *BNB* – *INVESCO_ETF* (0.986), suggest greater uncertainty in the stability of their hedging relationships, potentially complicating consistent risk management. In contrast, pairs using cryptocurrencies as a hedge generally show low standard deviations. For instance, the pair of *INVESCO_FINTECH_ETF* – *BNB* exhibit the lowest variability of 0.063, indicating stable and reliable hedging relationships. These values indicate that hedge ratios are not constant over time. This is confirmed by the results in Figure 5, which shows the time-varying nature of the optimal hedge ratios. From the figure, we see observable peaks in the hedge ratios during the COVID-19 pandemic. Investors should, therefore, be mindful to adjust their portfolios with time.

Alternatively, the optimal portfolio weights can be used as a diversification strategy. These results are summarized in Table ??. The results show the dynamic optimal portfolio weights for two-asset portfolios. The mean weight reflects the dollar cents that need to be invested in the first asset in any $1 portfolio. The results are generally consistent with the conclusions from the dynamic hedge ratios. Here also, we see that all the cryptocurrency assets, especially *ETH*, in the bilateral portfolios have higher mean weights with associated good stability or low risk (standard deviation). For instance, in the *SPDR_ETF–ETH* portfolio, $0.03 needs to be invested in *SPDR_ETF* while $0.97 needs to be invested in *ETH*, also given by the mean of *ETH–SPDR_ETF*. This asset pair also has the most stable portfolio weights (standard deviation = 0.032). The portfolio weights of crypto and other asset pairs generally exhibit the lowest risk, with lower standard deviations.

Also, the results generally show that between Fintech and traditional financial sector portfolios, higher weights should be given to Fintech assets. Similarly, higher weight should be given to tourism assets in tourism–traditional financial sector portfolios. Meanwhile, for tourism-fintech portfolios, the asset shares are heterogeneous, with some pairs assuming higher weight for tourism while others assume higher weight for Fintech. Generally, the most unstable portfolio weights are between assets of the same sector, especially between assets of the traditional financial sector. Similar to the dynamic hedge ratios, these results suggest the dynamic nature of portfolio weight over time, as shown in Figure 8. From the figure, We also see observable peaks during the COVID-19 pandemic.

5.6.2. Hedging effectiveness and statistical significance

The hedging effectiveness (*HE*) values quantify the risk reduction achieved through hedging strategies. These are shown in both Tables ?? and ??. Higher, positive and statistically significant *HE* values, such as for *GLOBALX_ETF – ISHARES_TRVL_ETF* (0.193, p = 0.000) and *ISHARES_TRVL_ETF – SPDR_ETF* (0.213, p = 0.002) from Table ??, indicate meaningful risk mitigation opportunities for these pairs. On the other hand, negative and highly significant *HE* values for cryptocurrency-related pairs, such as *GLOBALX_ETF – ETH* (-5.918, p = 0.000) and *GLOBALX_ETF – BNB* (-6.821, p = 0.000) from Table ??, reveal substantial inefficiencies in risk reduction. Surprisingly, we observe that several of the *HE*s for asset pairs where cryptocurrency assets are used as a hedge were negative and mostly statistically significant. These results are consistent with those of the bilateral portfolio weights in Table **??**. From Table **??**, the highest positive and statistically significant *HE* was between *ETH* and *US_GLOBALJETS_ETF* (0.324, $p = 0.000$). *BTC* is the only other crypto paring with *US_GLOBALJETS_ETF* ($HE = 0.210$, $p = 0.000$). These results are consistent with those of the bilateral portfolio weights shown in Table **??**.

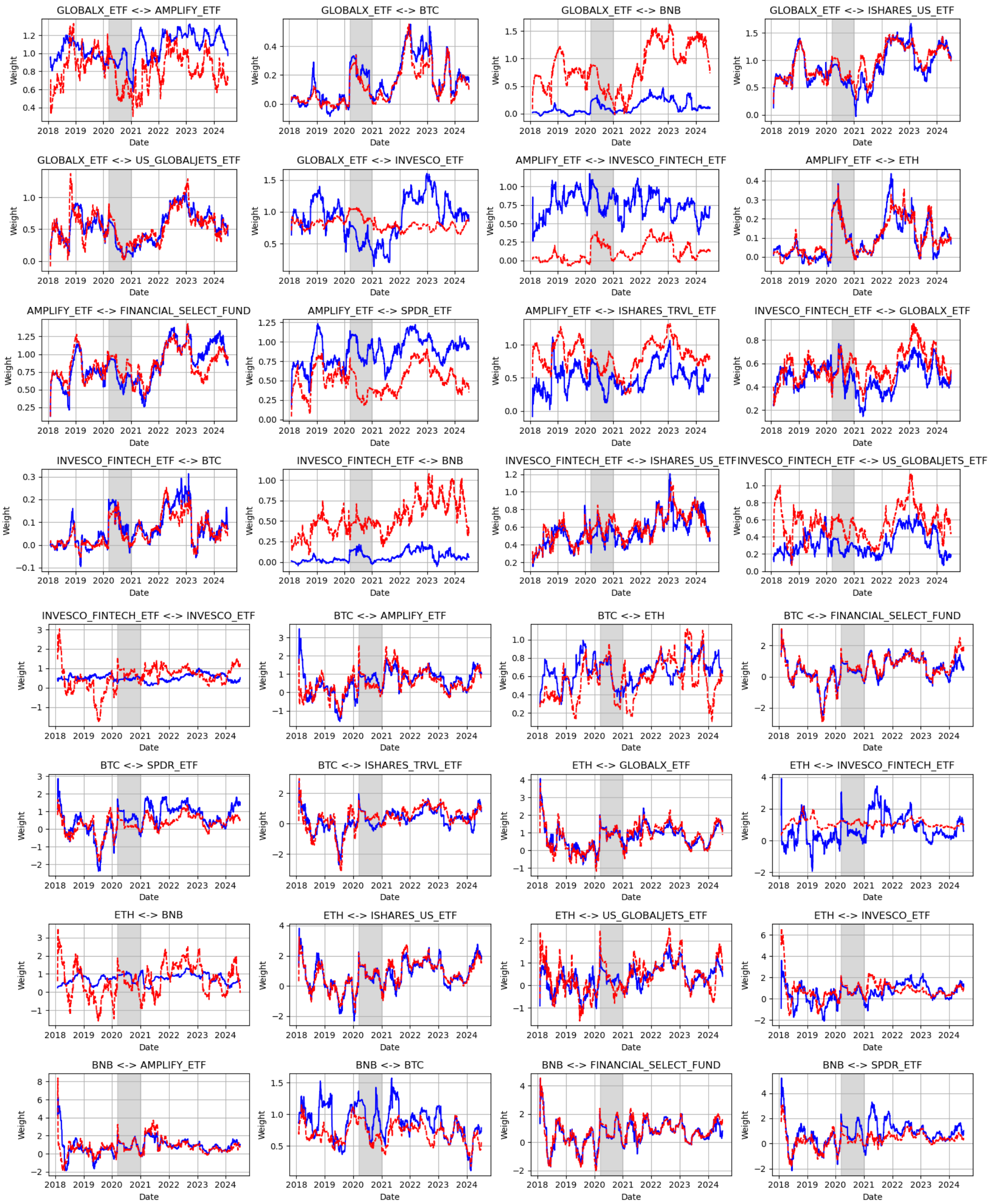
These results may highlight the challenges of using cryptocurrency-based assets as reliable hedging instruments even though they were the cheapest hedge for most assets. The ineffectiveness of cryptocurrencies as a hedge may be due to their high volatility and idiosyncratic risk. Overall, the results emphasize the asymmetric hedging potential across markets. While traditional financial and tourism-related ETFs emerge as reliable hedging options, cryptocurrency assets demonstrate significant challenges in their application for risk management.

5.6.3. Cumulative profits of diversification strategies

Again, of interest to investors will be to access the cumulative profitability of the various diversification strategies discussed earlier. We use the dynamic optimal hedge ratios and portfolio weights over time to construct the portfolios.[3] As robustness checks, we also include the cumulative profits based on an equality-weighted portfolio and the buy-and-hold (unhedged) strategy. We also construct a portfolio with constant median hedge ratios and portfolio weights. These results are presented in Figure 11 Table 4. We observe the dynamic cumulative profits in Figure 11. The results are generally heterogeneous depending on the asset allocation strategy and portfolio composition. Generally, there is an upward trend of profits in all the types of strategies except for some asset pairs (excluding crypto assets as long position) when using the hedge ratios strategy; We generally observe that portfolios with crypto assets in long positions using the hedge ratios have the most profit mostly after the first year of the COVID-19 pandemic. For instance, in the graph of *AMPLIFY_ETF – BNB*, taking *BNB* as the long position has cumulative profits ending at almost 500% using the hedge ratios. Notably, most of the

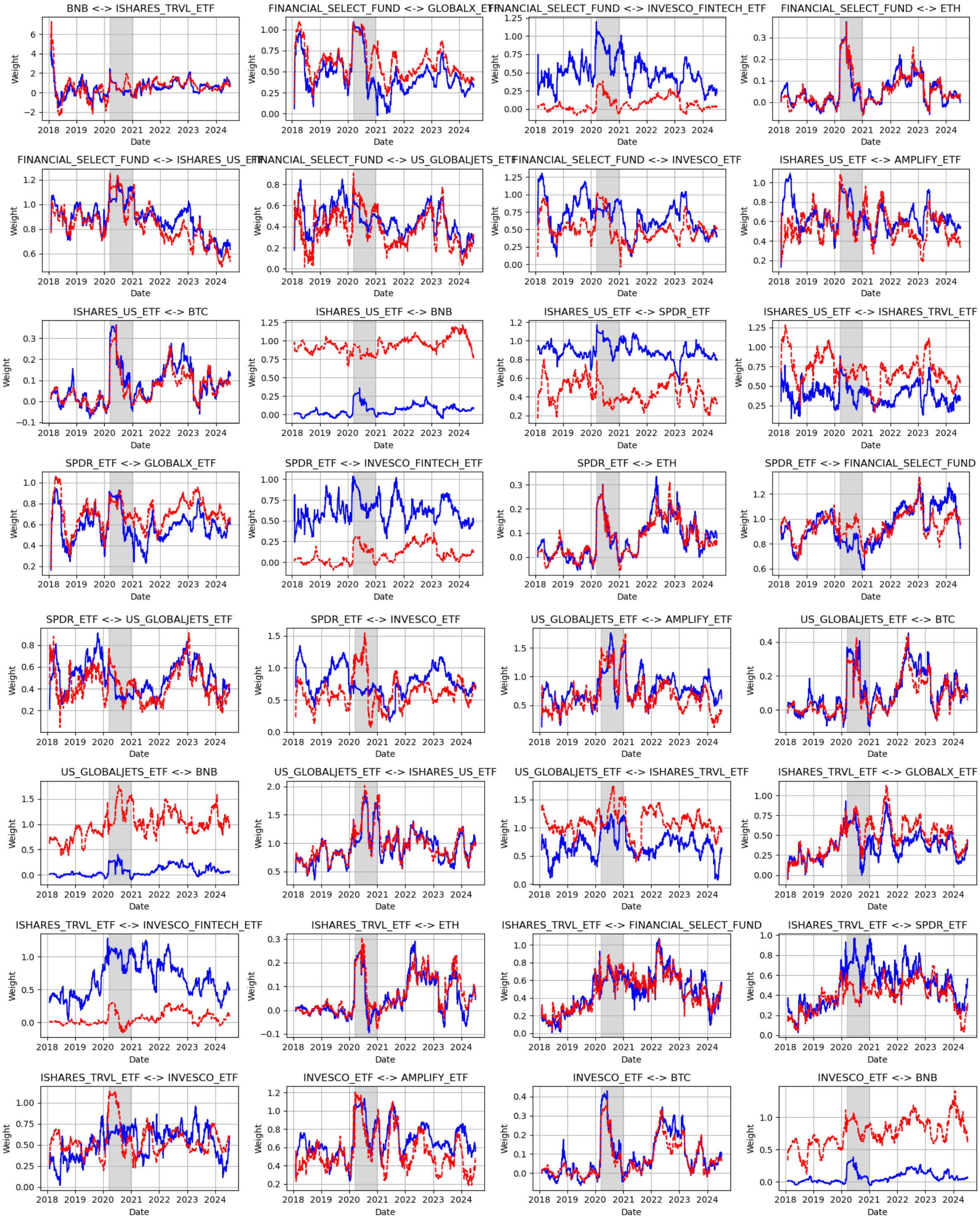
[3] The results for the dynamic cumulative portfolio returns based on the constant median of hedge ratios and portfolio weights are presented in the Appendix in Figure **??**.

Figure 5: Dynamic hedge ratios (Part 1)



Note: The blue continuous line represents the dynamic optimal bilateral hedge ratio between the first (long) and second assets (short), while the red broken lines represent the reverse order of the two assets. The grey-shaded area is the first year when COVID-19 was declared a pandemic (2020-03-11 to 2020-12-31).

Figure 6: Dynamic hedge ratios (Part 2)



Note: The blue continuous line represents the dynamic optimal bilateral hedge ratio between the first (long) and second assets (short), while the red broken lines represent the reverse order of the two assets. The grey-shaded area is the first year when COVID-19 was declared a pandemic (2020-03-11 to 2020-12-31).

portfolios with tourism ETFs in long positions recorded the highest drops and losses during the COVID-19 pandemic and ended the period with the least (most) cumulative profits (losses) using the hedge ratios strategy. Similarly, portfolios with tourism ETFs in the portfolio weight strategies also saw some of the lowest cumulative profits.

These results are confirmed by the summary in Table 4, which provides the cumulative end-period profit of the various portfolio strategies. We see that, on average, except for the 50/50 allocation strategy, the portfolio weights have the highest cumulative profits, with the median strategy ending with an average of about 100% followed by the dynamic weighting recording 92% average cumulative returns. This is followed by the unhedged strategy (84%) and then the dynamic hedge ratios strategy (Asset1–Asset2 80%). This is consistent with Antonakakis et al. (2020a), who also found that the dynamic portfolio weights and unhedged strategies outperform the hedge ratios strategy. Meanwhile, as observed earlier, all the portfolios with cryptocurrency recorded positive and highest cumulative returns in all strategies except in some dynamic hedge ratios portfolios where crypto is in a short position. We generally see lower portfolio returns between asset pairs from the same market. Under the unhedged strategy, the tourism ETFs recorded the least portfolio returns, with all of them recording losses.

5.7. Multivariate portfolio analysis

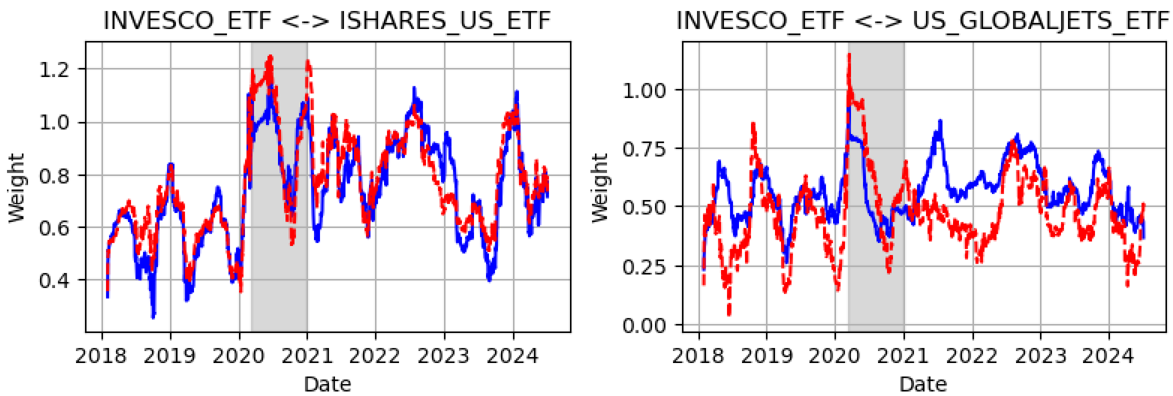
We also construct a multivariate investment portfolio based on the minimum variance portfolio (*MVP*), minimum correlation portfolio (*MCP*) and minimum connectedness portfolio (*MCoP*). Each of these strategies has its key advantage. MVP seeks to construct the portfolio through the minimization of portfolio volatility while MCP seeks to minimize the correlations across the assets. Meanwhile, MCoP is constructed on the basis of minimizing the pairwise connectedness or bilateral spillovers between pairs of assets.

These results, along with the hedging effectiveness (*HE*), are presented in Tables 5 and 6 and Figure 14. From Table 5, we observe some similarities as well as differences in the portfolio allocation. For instance, both the *MVP* and *MCP* strategies assigned the highest portfolio mean weight to the *FINANCIAL_SELECT_FUND* (*MVP*: 21.9%, *MCP*: 15%). This is consistent with our earlier results that showed the dominance of the traditional financial sector in the transmission of spillovers. What is rather surprising is that the *MCP* assigned the least weight to *SPDR_ETF* (0.7%), which contributed the largest spillovers in the system. This may be because the asset correlates highly with other assets in the system. The *MVP* strategy, however, assigned *US_GLOBALJETS_ETF* (0.1%) the least weight. These results are interesting given that our earlier results showed *SPDR_ETF*.

Meanwhile, for the *MCoP* strategy, the highest allocation went to three assets: *FINANCIAL_SELECT_FUND*, *ETH*, and *INVESCO_ETF* – with a portfolio allocation of 8.6% each. From the table, we can see that while the *MVP* and *MCP* strategies have relatively large differences in the portfolio allocation of the assets, the *MCoP* strategy has marginal differences in the portfolio weights of all assets. The *HE*s for all assets under the three strategies show high hedging effectiveness and are significant. Investing in either of the portfolio strategies with the mean weights will reduce the volatility of each asset ranging from 95% (*INVESCO_ETF*) to as high as 100% for *BTC*, *BNB* and *US_GLOBALJETS_ETF* all in the MVP strategy.

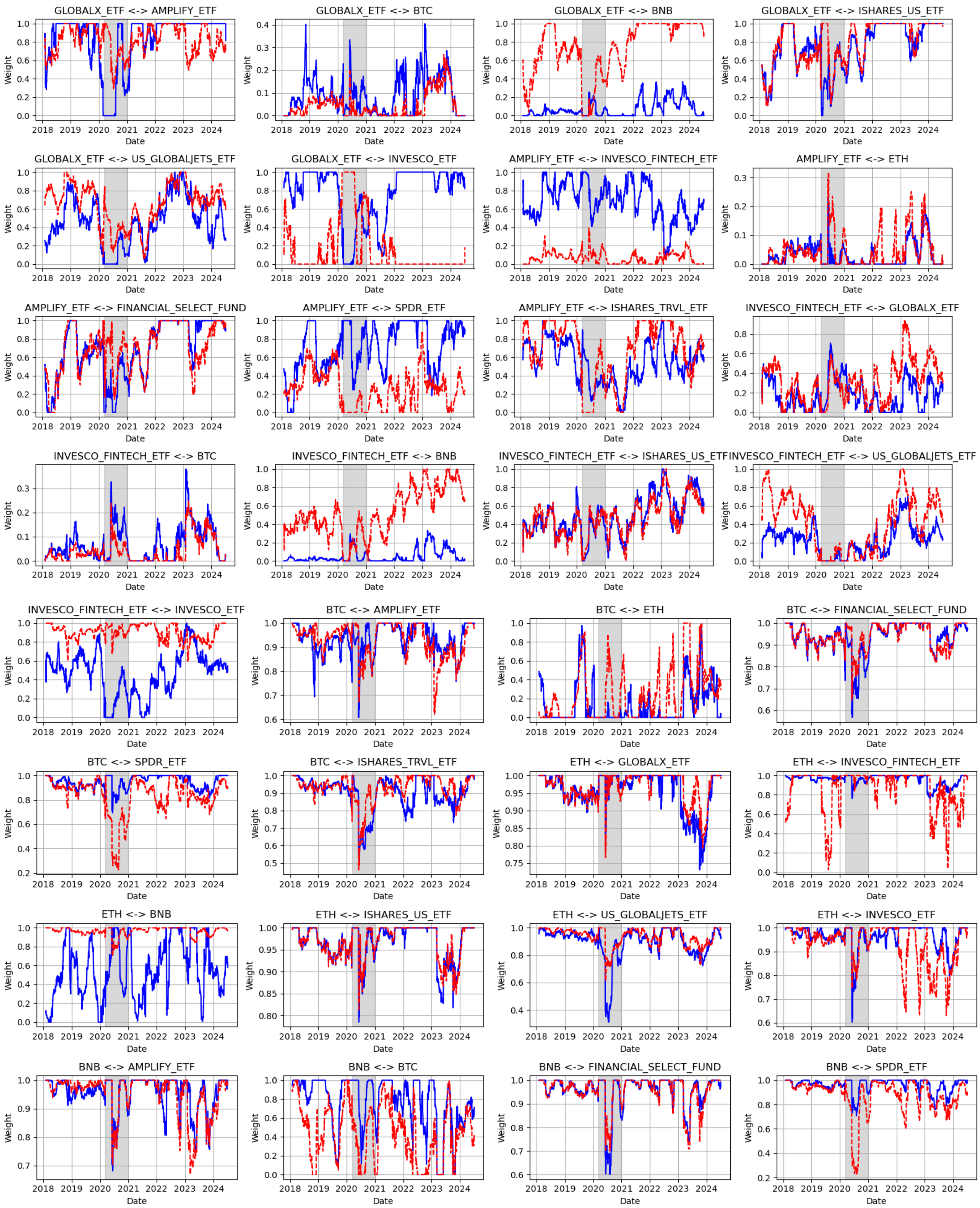
We then evaluate the three strategies using the shape ratios in Table 6. From the table, the MCoP performs best (Sharpe ratio = 0.037), followed by MCP (Sharpe ratio = 0.035) and MVP (Sharpe ratio = 0.022), respectively. The results are consistent with Tiwari et al. (2022), who also found that the MCoP outperforms MCP and MVP strategies. These results are further confirmed by the cumulative portfolio returns based on MVP, MCP and MCoP shown in Figure 14. From the figure, we can see that the cumulative portfolio profits for MCP and MCoP follow a very similar pattern and outperform the MVP strategy. The figure also shows that the highest loss, reaching a cumulative loss of around 50%, was observed during the COVID-19 pandemic for all strategies.

Figure 7: Dynamic hedge ratios (Part 3)



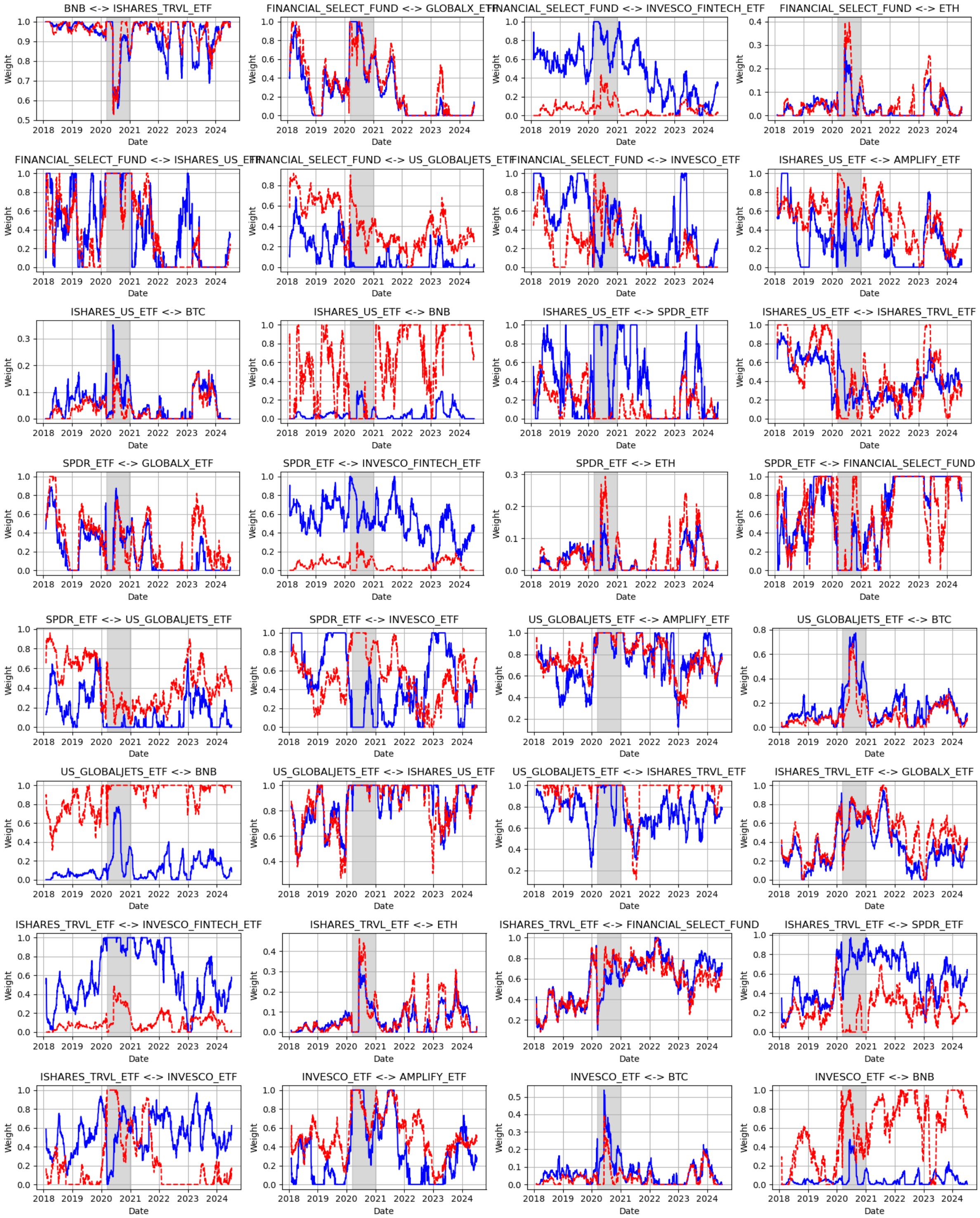
Note: The blue continuous line represents the dynamic optimal bilateral hedge ratio between the first (long) and second assets (short), while the red broken lines represent the reverse order of the two assets. The grey-shaded area is the first year when COVID-19 was declared a pandemic (2020-03-11 to 2020-12-31).

Figure 8: Dynamic portfolio weights (Part 1)



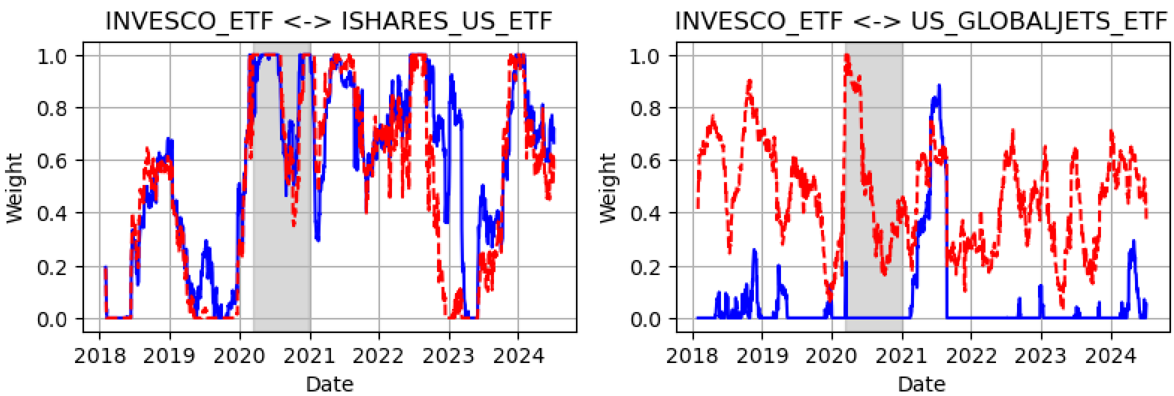
Note: The blue continuous line represents the dynamic portfolio weights between the first and second assets, while the red broken lines represent the reverse order of the two assets. The grey-shaded area is the first year when COVID-19 was declared a pandemic (2020-03-11 to 2020-12-31).

Figure 9: Dynamic portfolio weights (Part 2)



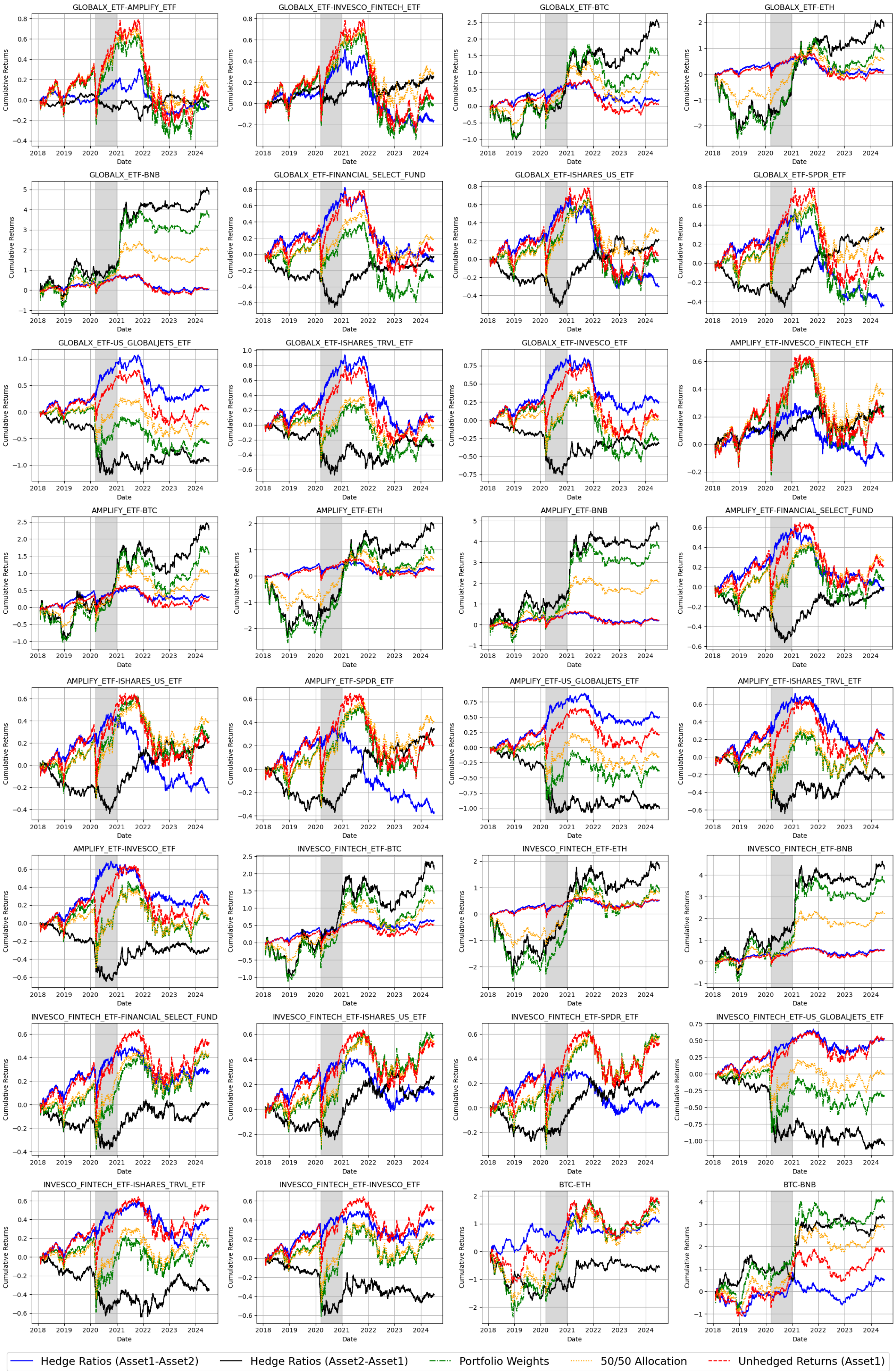
Note: The blue continuous line represents the dynamic portfolio weights between the first and second assets, while the red broken lines represent the reverse order of the two assets. The grey-shaded area is the first year when COVID-19 was declared a pandemic (2020-03-11 to 2020-12-31).

Figure 10: Dynamic portfolio weights (Part 3)



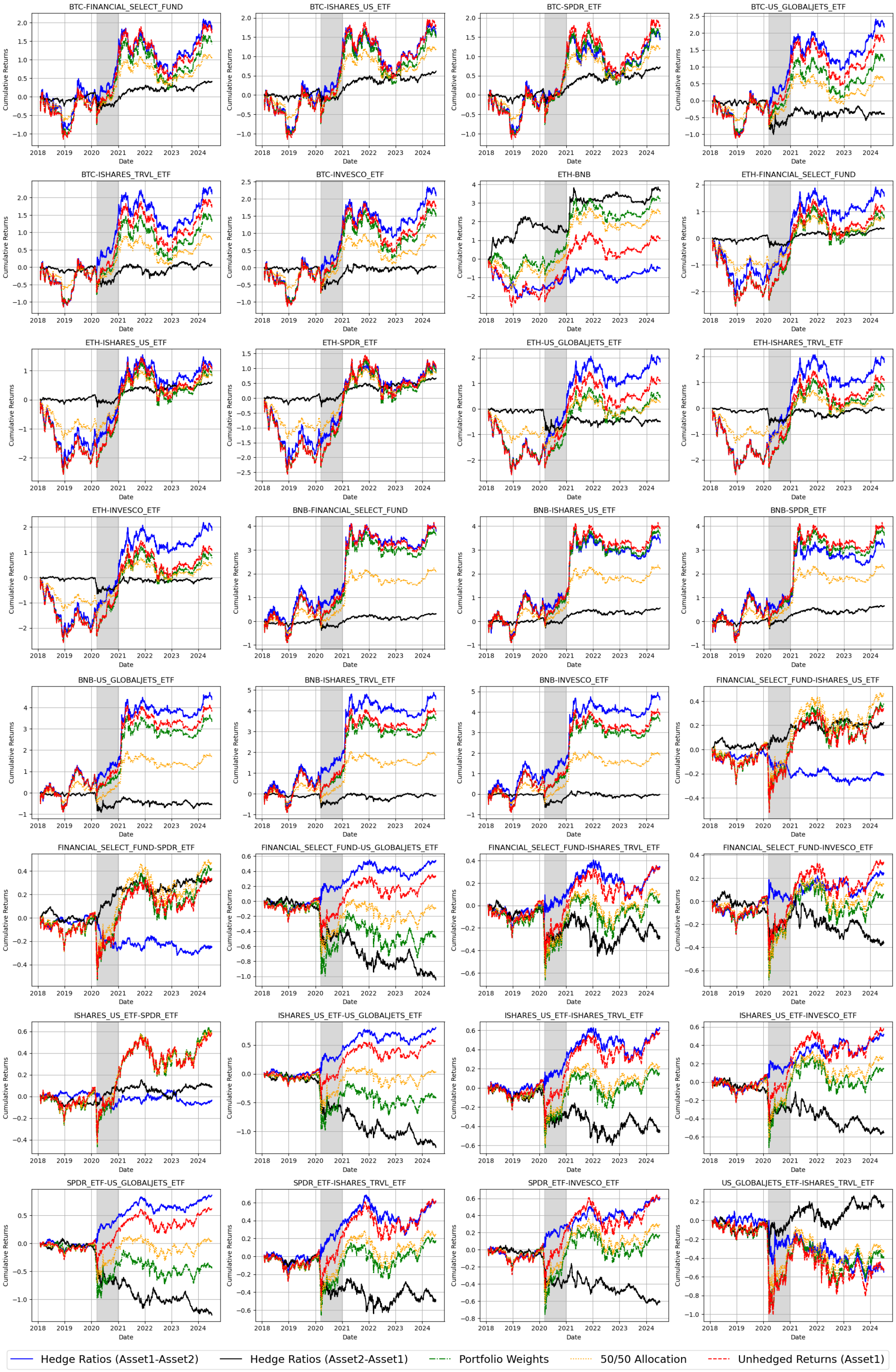
Note: The blue continuous line represents the dynamic portfolio weights between the first and second assets, while the red broken lines represent the reverse order of the two assets. The grey-shaded area is the first year when COVID-19 was declared a pandemic (2020-03-11 to 2020-12-31).

Figure 11: Cumulative profits of diversification strategies (Part 1)



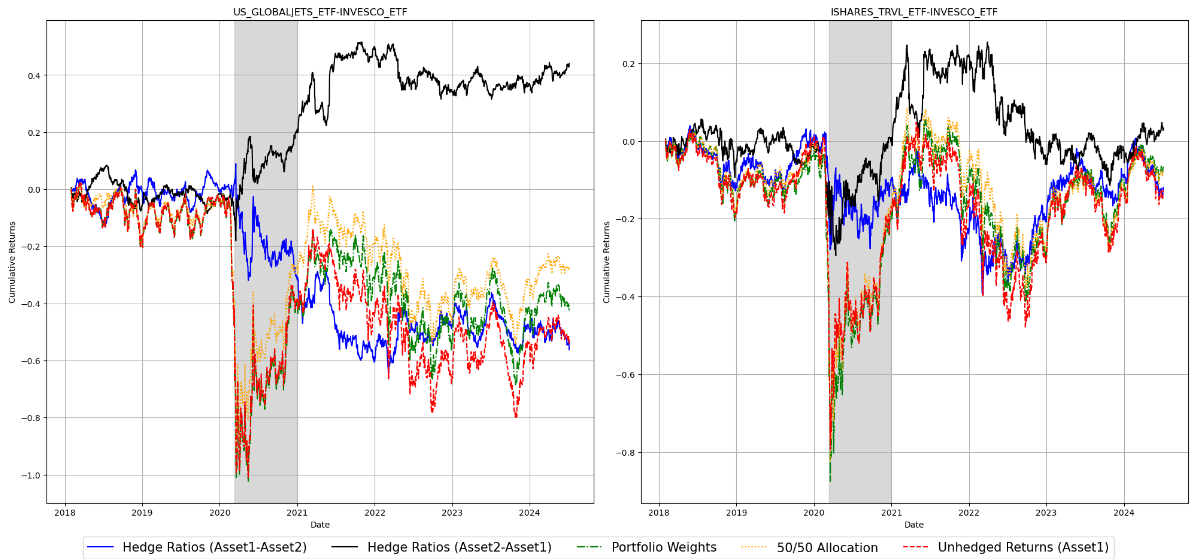
Note: The grey-shaded area is the first year when COVID-19 was declared a pandemic (2020-03-11 to 2020-12-31).

Figure 12: Cumulative profits of diversification strategies (Part 2)



Note: The grey-shaded area is the first year when COVID-19 was declared a pandemic (2020-03-11 to 2020-12-31).

Figure 13: Cumulative profits of diversification strategies (Part 3)



Note: The grey-shaded area is the first year when COVID-19 was declared a pandemic (2020-03-11 to 2020-12-31).

Table 4: Summary of cumulative profits from diversification strategies

Asset Pair	Dynamic hedge ratios		Median hedge ratios		Portfolio weight			Buy and hold
	(Asset1-Asset2)	(Asset2-Asset1)	(Asset1-Asset2)	(Asset2-Asset1)	Dynamic	Median	50/50 Allocation	Unhedged
GLOBALX_ETF – AMPLIFY_ETF	-6%	-1%	-18%	17%	-5%	6%	14%	6%
GLOBALX_ETF – INVESCO_FINTECH_ETF	-16%	25%	-39%	50%	0%	12%	29%	6%
GLOBALX_ETF – BTC	18%	234%	-15%	167%	150%	159%	89%	6%
GLOBALX_ETF – ETH	15%	184%	-3%	93%	87%	96%	52%	6%
GLOBALX_ETF – BNB	6%	477%	-27%	376%	360%	365%	193%	6%
GLOBALX_ETF – FINANCIAL_SELECT_FUND	-8%	-3%	-21%	31%	-27%	11%	20%	6%
GLOBALX_ETF – ISHARES_US_ETF	-30%	22%	-43%	55%	-1%	16%	32%	6%
GLOBALX_ETF – SPDR_ETF	-44%	36%	-54%	58%	-12%	8%	34%	6%
GLOBALX_ETF – US_GLOBALJETS_ETF	44%	-94%	36%	-58%	-60%	-27%	-24%	6%
GLOBALX_ETF – ISHARES_TRVL_ETF	11%	-27%	13%	-15%	-22%	0%	-4%	6%
GLOBALX_ETF – INVESCO_ETF	25%	-32%	8%	-6%	-26%	5%	2%	6%
AMPLIFY_ETF – INVESCO_FINTECH_ETF	-8%	27%	-18%	40%	24%	31%	37%	22%
AMPLIFY_ETF – BTC	32%	227%	6%	156%	155%	163%	97%	22%
AMPLIFY_ETF – ETH	28%	180%	15%	79%	86%	97%	60%	22%
AMPLIFY_ETF – BNB	21%	458%	-5%	363%	365%	371%	201%	22%
AMPLIFY_ETF – FINANCIAL_SELECT_FUND	-3%	-1%	-6%	21%	8%	25%	28%	22%
AMPLIFY_ETF – ISHARES_US_ETF	-25%	25%	-26%	45%	27%	31%	40%	22%
AMPLIFY_ETF – SPDR_ETF	-37%	34%	-32%	46%	22%	30%	42%	22%
AMPLIFY_ETF – US_GLOBALJETS_ETF	51%	-101%	49%	-71%	-40%	-35%	-16%	22%
AMPLIFY_ETF – ISHARES_TRVL_ETF	26%	-22%	28%	-23%	7%	6%	4%	22%
AMPLIFY_ETF – INVESCO_ETF	27%	-29%	24%	-17%	5%	16%	10%	22%
INVESCO_FINTECH_ETF – BTC	65%	213%	43%	150%	142%	166%	112%	52%
INVESCO_FINTECH_ETF – ETH	51%	172%	48%	70%	83%	97%	75%	52%
INVESCO_FINTECH_ETF – BNB	55%	428%	34%	346%	359%	375%	216%	52%
INVESCO_FINTECH_ETF – FINANCIAL_SELECT_FUND	28%	1%	35%	8%	42%	43%	43%	52%
INVESCO_FINTECH_ETF – ISHARES_US_ETF	13%	26%	20%	29%	60%	56%	55%	52%
INVESCO_FINTECH_ETF – SPDR_ETF	2%	28%	17%	29%	58%	57%	57%	52%
INVESCO_FINTECH_ETF – US_GLOBALJETS_ETF	52%	-107%	68%	-87%	-35%	-29%	-1%	52%
INVESCO_FINTECH_ETF – ISHARES_TRVL_ETF	40%	-34%	60%	-47%	13%	17%	20%	52%
INVESCO_FINTECH_ETF – INVESCO_ETF	37%	-38%	54%	-29%	20%	25%	25%	52%
BTC – ETH	107%	-57%	107%	-80%	159%	98%	135%	171%
BTC – BNB	52%	324%	-46%	229%	391%	352%	276%	171%
BTC – FINANCIAL_SELECT_FUND	181%	41%	155%	26%	141%	165%	102%	171%
BTC – ISHARES_US_ETF	154%	62%	141%	48%	148%	166%	115%	171%
BTC – SPDR_ETF	143%	73%	134%	48%	149%	167%	116%	171%
BTC – US_GLOBALJETS_ETF	218%	-40%	189%	-67%	116%	145%	59%	171%
BTC – ISHARES_TRVL_ETF	211%	8%	175%	-18%	131%	158%	79%	171%
BTC – INVESCO_ETF	209%	4%	173%	-12%	148%	162%	84%	171%
ETH – BNB	-52%	363%	-197%	310%	309%	233%	239%	98%
ETH – FINANCIAL_SELECT_FUND	157%	37%	76%	30%	73%	97%	66%	98%
ETH – ISHARES_US_ETF	105%	60%	59%	53%	81%	97%	78%	98%
ETH – SPDR_ETF	91%	67%	48%	55%	83%	98%	80%	98%
ETH – US_GLOBALJETS_ETF	183%	-50%	118%	-59%	39%	88%	22%	98%
ETH – ISHARES_TRVL_ETF	178%	-5%	103%	-15%	70%	94%	43%	98%
ETH – INVESCO_ETF	187%	-3%	100%	-7%	74%	96%	48%	98%
BNB – FINANCIAL_SELECT_FUND	379%	32%	357%	22%	355%	373%	207%	380%
BNB – ISHARES_US_ETF	329%	56%	340%	38%	357%	374%	219%	380%
BNB – SPDR_ETF	311%	65%	333%	39%	360%	374%	221%	380%
BNB – US_GLOBALJETS_ETF	437%	-56%	399%	-73%	332%	349%	163%	380%
BNB – ISHARES_TRVL_ETF	455%	-8%	386%	-24%	350%	367%	184%	380%
BNB – INVESCO_ETF	460%	-2%	382%	-20%	353%	371%	189%	380%
FINANCIAL_SELECT_FUND – ISHARES_US_ETF	-21%	22%	-18%	27%	38%	49%	46%	33%
FINANCIAL_SELECT_FUND – SPDR_ETF	-25%	32%	-17%	30%	42%	54%	47%	33%
FINANCIAL_SELECT_FUND – US_GLOBALJETS_ETF	54%	-105%	58%	-87%	-49%	-53%	-10%	33%
FINANCIAL_SELECT_FUND – ISHARES_TRVL_ETF	34%	-28%	38%	-30%	4%	3%	10%	33%
FINANCIAL_SELECT_FUND – INVESCO_ETF	24%	-36%	35%	-28%	6%	11%	15%	33%
ISHARES_US_ETF – SPDR_ETF	-3%	8%	4%	6%	61%	60%	60%	58%
ISHARES_US_ETF – US_GLOBALJETS_ETF	80%	-128%	82%	-107%	-43%	-47%	2%	58%
ISHARES_US_ETF – ISHARES_TRVL_ETF	62%	-45%	63%	-41%	16%	15%	23%	58%
ISHARES_US_ETF – INVESCO_ETF	52%	-55%	60%	-45%	15%	20%	28%	58%
SPDR_ETF – US_GLOBALJETS_ETF	86%	-128%	88%	-110%	-45%	-45%	4%	61%
SPDR_ETF – ISHARES_TRVL_ETF	61%	-49%	67%	-45%	17%	19%	24%	61%
SPDR_ETF – INVESCO_ETF	60%	-61%	63%	-48%	17%	25%	29%	61%
US_GLOBALJETS_ETF – ISHARES_TRVL_ETF	-55%	17%	-46%	9%	-41%	-44%	-34%	-54%
US_GLOBALJETS_ETF – INVESCO_ETF	-56%	44%	-51%	27%	-42%	-54%	-29%	-54%
ISHARES_TRVL_ETF – INVESCO_ETF	-12%	3%	-11%	3%	-7%	-8%	-8%	-13%
Average	**80%**	**42%**	**64%**	**30%**	**92%**	**100%**	**68%**	**84%**

Note: The buy and hold unhedged strategy is for Asset 1.

6. Conclusion and Policy Implications

This study underscores the dynamic interconnectedness among tourism, cryptocurrency, and Fintech markets, emphasizing the heterogeneity of spillovers over time, particularly during periods of heightened uncertainty such as the COVID-19 pandemic. Traditional financial markets emerge as dominant spillover transmitters, shaping risk

Table 5: Multivariate portfolio weights

Variable	Minimum Variance Portfolio (MVP)					
	Mean	Std. Dev.	5%	95%	HE	P-value
GLOBALX_ETF	0.063	0.102	0.000	0.303	0.984***	0.000
AMPLIFY_ETF	0.069	0.093	0.000	0.252	0.988***	0.000
INVESCO_FINTECH_ETF	0.142	0.102	0.000	0.348	0.965***	0.000
BTC	0.039	0.041	0.000	0.116	0.998***	0.000
ETH	0.006	0.012	0.000	0.027	1.000***	0.000
BNB	0.014	0.023	0.000	0.068	1.000***	0.000
FINANCIAL_SELECT_FUND	0.219	0.177	0.000	0.547	0.966***	0.000
ISHARES_US_ETF	0.100	0.123	0.000	0.328	0.980***	0.000
SPDR_ETF	0.040	0.080	0.000	0.231	0.977***	0.000
US_GLOBALJETS_ETF	0.001	0.007	0.000	0.005	1.000***	0.000
ISHARES_TRVL_ETF	0.112	0.096	0.000	0.293	0.992***	0.000
INVESCO_ETF	0.196	0.128	0.000	0.415	0.950***	0.000
Variable	**Minimum Correlation Portfolio (MCP)**					
	Mean	Std. Dev.	5%	95%	HE	P-value
GLOBALX_ETF	0.134	0.136	0.000	0.383	0.967***	0.000
AMPLIFY_ETF	0.041	0.073	0.000	0.204	0.983***	0.000
INVESCO_FINTECH_ETF	0.081	0.058	0.000	0.183	0.990***	0.000
BTC	0.097	0.071	0.000	0.227	0.984***	0.000
ETH	0.063	0.065	0.000	0.185	0.994***	0.000
BNB	0.092	0.062	0.003	0.226	0.989***	0.000
FINANCIAL_SELECT_FUND	0.150	0.110	0.000	0.323	0.957***	0.000
ISHARES_US_ETF	0.097	0.107	0.000	0.304	0.984***	0.000
SPDR_ETF	0.007	0.021	0.000	0.050	0.999***	0.000
US_GLOBALJETS_ETF	0.083	0.064	0.000	0.194	0.972***	0.000
ISHARES_TRVL_ETF	0.099	0.051	0.020	0.186	0.991***	0.000
INVESCO_ETF	0.057	0.052	0.000	0.151	0.997***	0.000
Variable	**Minimum Connectedness Portfolio (MCoP)**					
	Mean	Std. Dev.	5%	95%	HE	P-value
GLOBALX_ETF	0.083	0.083	0.000	0.200	0.987***	0.000
AMPLIFY_ETF	0.085	0.091	0.000	0.200	0.984***	0.000
INVESCO_FINTECH_ETF	0.081	0.085	0.000	0.200	0.988***	0.000
BTC	0.083	0.084	0.000	0.200	0.986***	0.000
ETH	0.086	0.091	0.000	0.200	0.984***	0.000
BNB	0.083	0.082	0.000	0.200	0.987***	0.000
FINANCIAL_SELECT_FUND	0.086	0.085	0.000	0.200	0.986***	0.000
ISHARES_US_ETF	0.081	0.086	0.000	0.200	0.985***	0.000
SPDR_ETF	0.082	0.086	0.000	0.200	0.985***	0.000
US_GLOBALJETS_ETF	0.085	0.085	0.000	0.200	0.983***	0.000
ISHARES_TRVL_ETF	0.079	0.082	0.000	0.200	0.987***	0.000
INVESCO_ETF	0.086	0.088	0.000	0.200	0.986***	0.000

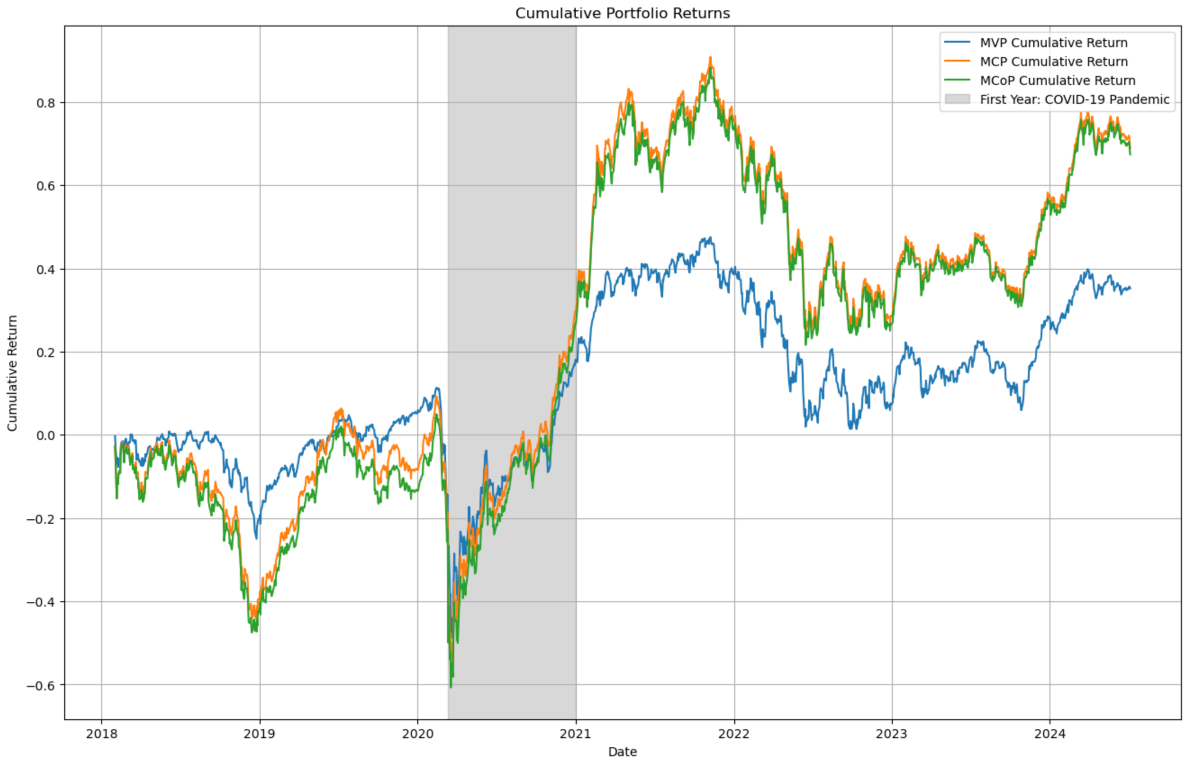
Table 6: Sharpe ratio

Portfolio construction	Sharpe ratio
Minimum Variance Portfolio (MVP)	0.022
Minimum Correlation Portfolio (MCP)	0.035
Minimum Connectedness Portfolio (MCoP)	0.037

dynamics across these alternative asset classes. Despite their cost-efficiency, cryptocurrency assets prove ineffective as hedges, while tourism assets demonstrate superior hedging capabilities, albeit at higher risk levels. Cross-sectoral hedges between Fintech and traditional financial markets, alongside sectoral hedges, are both revealed as costly and inefficient due to strong co-movements. The superiority of minimum connectedness portfolio strategies over traditional variance and correlation-based approaches highlights the importance of accounting for bilateral spillovers in portfolio optimization.

Policymakers and financial regulators should recognize the systemic risk implications of spillovers between traditional and alternative asset markets, particularly during crises. Enhanced disclosure requirements and transparency in emerging markets such as cryptocurrency and Fintech are critical to mitigating uncertainty and promoting market stability. For investors, the findings advocate for the adoption of dynamic portfolio strategies that balance risk reduction and return optimization. Tourism assets' effectiveness in hedging cryptocurrency risks suggests the potential for diversified investment strategies that bridge traditional and alternative sectors, especially in regions where tourism is a key economic driver. Finally, the interconnectedness dynamics observed in this study call for coordinated regulatory frameworks that account for cross-market spillovers to safeguard financial stability in an increasingly interlinked global financial system.

Figure 14: Plot of the cumulative sum of portfolio returns



Note: MCoP: minimum connectedness portfolio; MVP: minimum variance portfolio; and MCP: minimum correlation portfolio. The grey-shaded area is the first year when COVID-19 was declared a pandemic (2020-03-11 to 2020-12-31).

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