From Beaches to Fintech: Exploring the Connectedness of Tourism, Fintech, and Cryptocurrency

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Abstract

This paper examines spillover dynamics, hedging effectiveness, and portfolio optimisation across tourism, cryptocurrency, and Fintech markets within a time-varying connectedness framework that incorporates traditional financial markets. We document pronounced time-varying spillovers, peaking during the COVID-19 pandemic, with traditional finance emerging as the dominant shock transmitter and the tourism sector as a key net receiver. Transmission-channel evidence suggests that total connectedness increases with credit stress and is positively correlated with market uncertainty and tourism mobility, with these effects intensifying during the COVID-19 pandemic. Cryptocurrencies offer the least costly but weakest hedges, while tourism assets hedge crypto exposure more effectively, albeit with greater downside risk. Dynamic portfolio weight strategies outperform hedge-ratio strategies, and the minimum connectedness portfolio (MCoP) delivers the highest risk-adjusted returns. Diebold–Mariano tests indicate no significant differences in return predictability, whereas Jobson–Korkie results show that minimum correlation portfolio (MCP) and MCoP significantly outperform the minimum-variance portfolio (MVP). Downside risk measures highlight the superior performance of MCoP at the cost of deeper drawdowns. These findings underscore the value of connectedness-based strategies for portfolio design in increasingly integrated markets.

Keywords: Fintech, Cryptocurrency, Blockchain, Tourism, Bitcoin, Portfolio optimisation
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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 decentralised 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 decentralised 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, globalisation and digitalisation 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 personalised 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. Tokenisation, 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 decentralised 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 analysing 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.

Overall, this study fills a critical void in the literature by jointly examining the dynamic connectedness among tourism, Fintech, and cryptocurrency markets—three sectors that have been largely analysed in isolation. Unlike previous studies that explore bilateral linkages (e.g., Fintech–Finance or Tourism–Crypto), this paper develops a unified framework capturing tri-sectoral interdependencies under varying market conditions. By integrating a time-varying parameter VAR model with portfolio optimisation techniques, the study advances understanding of how digital and real sectors co-move, particularly during systemic shocks such as the COVID-19 pandemic. This approach contributes both methodologically—by applying an order-invariant spillover framework—and practically—by informing optimal diversification strategies in digitally integrated markets.

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 optimising risk-adjusted returns in dynamic 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 interests 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 tokenised 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 travellers. 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 emphasises 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.

The reviewed literature collectively indicates growing intersections among digital finance, tourism, and crypto-economies, yet no unified empirical model has captured their joint evolution. Existing studies provide fragmented evidence—Fintech improving transaction efficiency in tourism, blockchain enhancing trust, and cryptocurrencies enabling payment diversification—but overlook systemic linkages and risk transmission. By modelling these sectors within a time-varying connectedness framework, this paper extends the literature to an integrated quantification of cross-sector spillovers and portfolio implications. 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:

[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

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, 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.

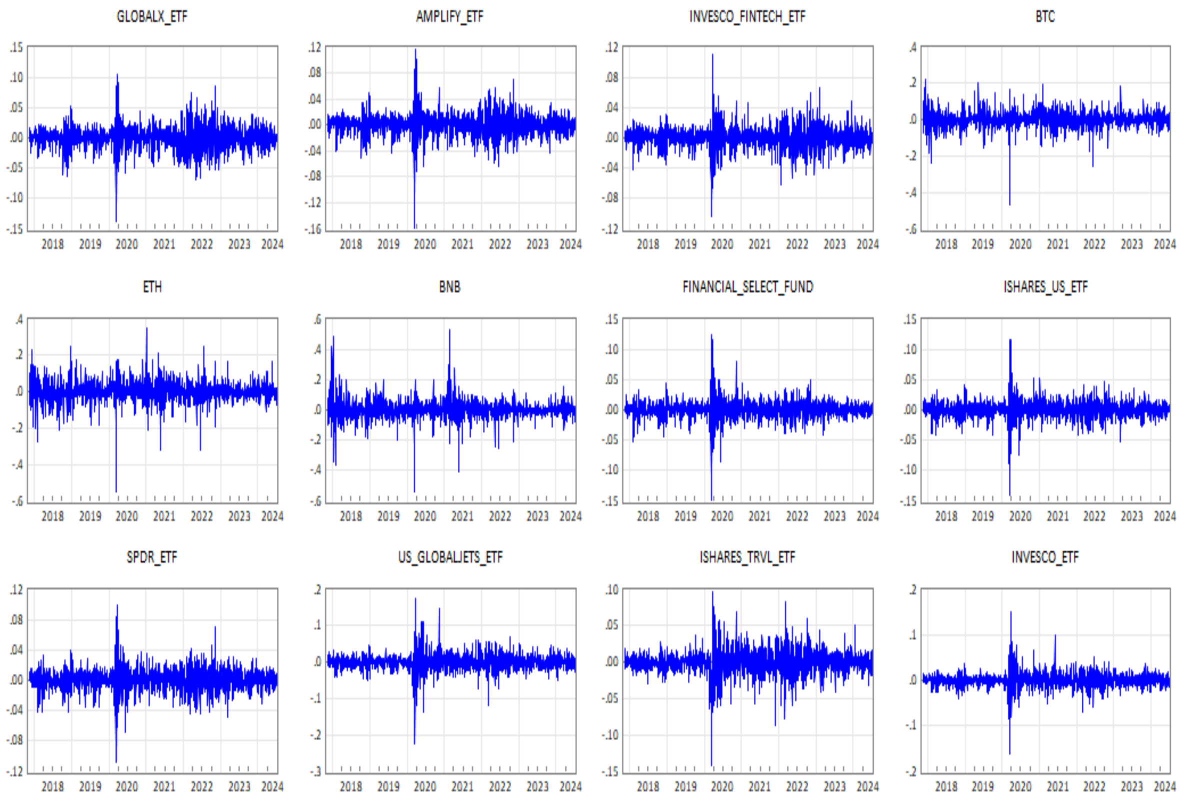
For data on cryptocurrency, we use Bitcoin, the world's largest cryptocurrency according to its market CAP. We also include two alternative coins, namely Ethereum, the second largest coin, and *BNB*, the native coin for Binance and the largest cryptocurrency trading exchange. While Bitcoin is designed 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 the terms "connectedness" and "spillovers" interchangeably Diebold & Yılmaz (2012). To estimate spillovers among Fintech, cryp-

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.

tocurrency and tourism sectors, we use a TVP-VAR model with heteroscedastic variance-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, rather than 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

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

the TVP-VAR to its TVP-VMA representation by the Wold representation theorem: $\boldsymbol{y}_t = \sum_{h=0}^{\infty} \boldsymbol{A}_{h,t}\boldsymbol{\epsilon}_{t-i}$ 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 centre 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,

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

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

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

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

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,

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

If $S_{ij,t}^{gen,net} > 0$ ($S_{ij,t}^{gen,net} < 0$), 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 that highlights the degree of network interconnectedness and, consequently, 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:

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

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 utilise portfolio back-testing techniques to evaluate the investment performance of these assets, while also exploring any potential hedging advantages. To examine the investment performance of the assets under examination, we use different measures of constructing portfolios that have been traditionally used, 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 it presents different assets from various markets, allowing investors to make efficient portfolio allocations and diversifications. 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:

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

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 has emerged, namely the *MCP*, introduced by Christoffersen et al. (2014). This approach is similar to the MVP; however, in this case, the portfolio weights are obtained by minimising 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 offers a portfolio procedure that is not affected heavily by network shocks. Thus, assets that are neither influencing nor influenced by others are allocated 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:

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

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

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

where $\text{Var}\,(r_{\text{unhedged}})$ denotes the variance of the unhedged position between variable i and j and $\text{Var}\,(r_{w,\beta})$ 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.

4.3.6. Statistical Evaluation of Performance Measures

To determine whether there are statistically significant differences in portfolio performance across the Minimum Variance Portfolio (MVP), Minimum Correlation Portfolio (MCP), and Minimum Connectedness Portfolio (MCoP), we employ two formal hypothesis tests. First, the robust Diebold–Mariano (DM) test assesses whether differences in portfolio return dynamics reflect unequal predictive accuracy. Second, the Jobson–Korkie (JK) test evaluates whether the Sharpe ratios of competing portfolios differ significantly. A concise description of both tests follows[3].

(i) Diebold–Mariano Test for Predictive Accuracy

The Diebold–Mariano (DM) test (Diebold & Mariano, 1995, 2002) evaluates whether two competing portfolio strategies exhibit equal predictive accuracy. Let $r_{1,t}$ and $r_{2,t}$ denote the returns of two portfolios. Following standard practice in the portfolio literature, we define forecast errors as negative returns, $e_{i,t} = -r_{i,t}$, and employ a squared-error loss function, $L(e_{i,t}) = e_{i,t}^2$. The loss differential is then given by:

$$d_t = L(e_{1,t}) - L(e_{2,t}). \tag{22}$$

The null hypothesis of equal predictive accuracy is:

$$H_0 : \mathbb{E}[d_t] = 0.$$

Let $\bar{d} = \frac{1}{T}\sum_{t=1}^{T} d_t$ denote the sample mean loss differential. Because d_t may exhibit serial correlation and conditional heteroskedasticity, inference is conducted using the heteroskedasticity- and autocorrelation-consistent (HAC) variance estimator proposed by Diebold & Mariano (1995). Specifically, the long-run variance of d_t is estimated using a Newey–West estimator with a Bartlett kernel:

$$\hat{\delta}_d^2 = \hat{\gamma}_0 + 2\sum_{\tau=1}^{h-1}\left(1 - \frac{\tau}{h}\right)\hat{\gamma}_\tau, \tag{23}$$

where $\hat{\gamma}_\tau$ denotes the sample autocovariance of d_t at lag τ. The bandwidth h is selected

[3]Additional methodological details are provided in Appendix A.1.

using the standard Newey–West data-dependent rule, ensuring robustness to weak serial dependence in daily returns.

The robust Diebold–Mariano statistic is given by:

$$DM = \frac{\bar{d}}{\sqrt{\hat{\delta}_d^2/T}} \xrightarrow{d} \mathcal{N}(0,1), \tag{24}$$

under the null hypothesis. A statistically significant DM statistic indicates differential predictive performance between portfolio strategies.

(ii) Jobson–Korkie Test for Sharpe Ratio Differences

The Jobson–Korkie test (Jobson & Korkie, 1981) evaluates whether the Sharpe ratios of two portfolios differ significantly. The null hypothesis is:

$$H_0 : SR_i = SR_j,$$

where the Sharpe ratio is defined as $SR = (\mu - r_f)/\sigma$. Throughout the analysis, we assume a zero risk-free rate.

The test statistic is given by:

$$JK = \frac{SR_i - SR_j}{\sqrt{\frac{1}{T}\left(\sigma_i^2 + \frac{SR_i^2}{2} + \sigma_j^2 + \frac{SR_j^2}{2} - 2SR_iSR_j\,\mathrm{Cov}(r_i, r_j)\right)}}, \tag{25}$$

which is asymptotically standard normal. The variance term explicitly accounts for contemporaneous correlation between portfolio returns. Given the large sample size of daily observations, asymptotic inference is appropriate.

4.3.7. Downside Risk Measures: Sortino Ratio, Maximum Drawdown, and CVaR

While the Sharpe ratio evaluates risk-adjusted performance using total return volatility, it does not distinguish between upside and downside risk. We therefore complement the analysis with three downside risk measures.

(i) Sortino Ratio. The Sortino ratio penalises only negative deviations from the target return:

$$\text{Sortino} = \frac{R_p - r_f}{\sigma_d}, \tag{26}$$

where R_p denotes the mean portfolio return and σ_d is the downside deviation,

$$\sigma_d = \sqrt{\frac{1}{T}\sum_{t=1}^{T} \min(r_{p,t} - r_f, 0)^2}. \tag{27}$$

(ii) Maximum Drawdown (MDD). Maximum drawdown measures the largest peak-to-trough decline in cumulative portfolio value:

$$\text{MDD} = \max_{t\in[0,T]} \left(\frac{\max_{\tau\leq t} V_\tau - V_t}{\max_{\tau\leq t} V_\tau} \right), \tag{28}$$

where V_t denotes cumulative portfolio value.

(iii) Conditional Value-at-Risk (CVaR). Conditional Value-at-Risk (CVaR), or Expected Shortfall, captures the expected loss conditional on returns falling below the α-quantile:

$$\text{CVaR}_\alpha = \mathbb{E}\left[r_{p,t} \mid r_{p,t} \leq \text{VaR}_\alpha\right]. \tag{29}$$

Unlike VaR, CVaR accounts for the magnitude of extreme losses and is therefore a coherent measure of tail risk. Together, these indicators provide a comprehensive assessment of downside risk and crisis vulnerability across portfolio strategies.

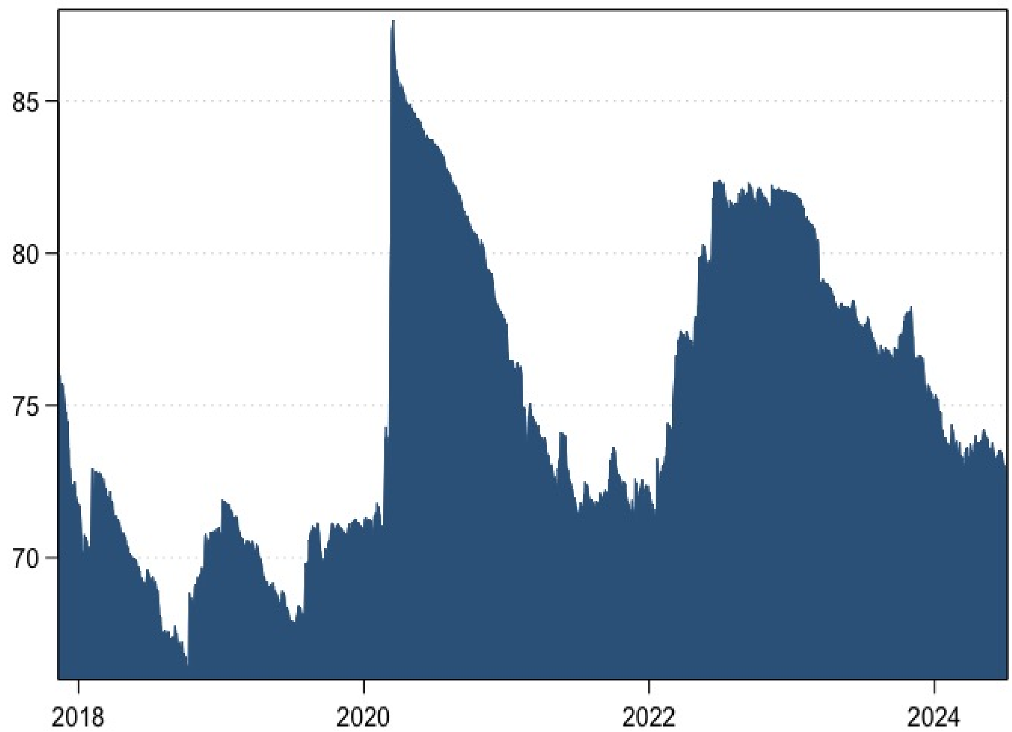
5. Results and Discussions

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 emphasises 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 travellers 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 decentralised 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 emphasise 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 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,

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

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.

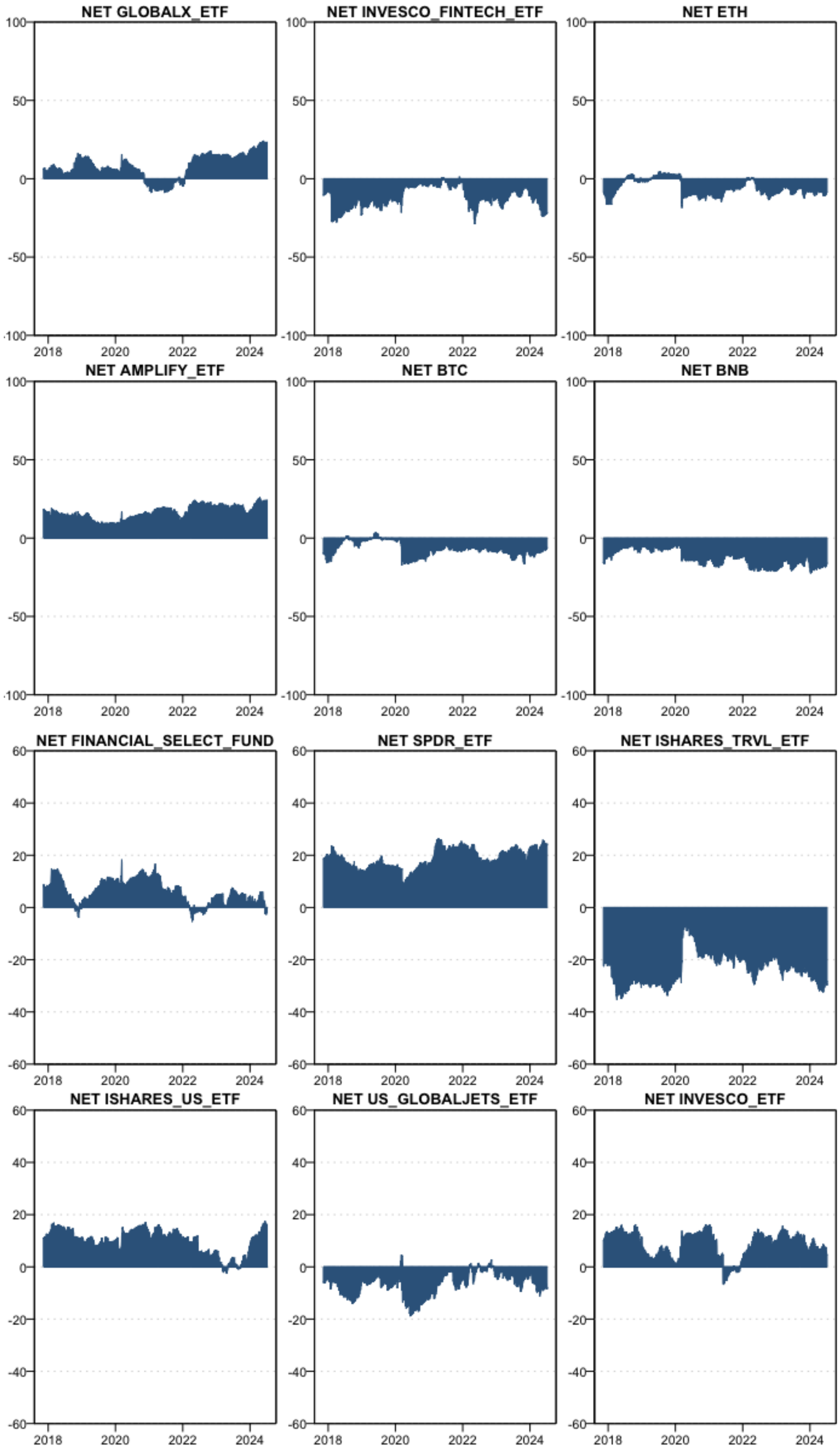
5.4. Network analysis of spillovers

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 colour represent that particular variable's net spillover/spillback to all other variables; these represent the values on the last row of Table 2. The colour 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 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.

5.5. Dynamic net pairwise directional spillovers

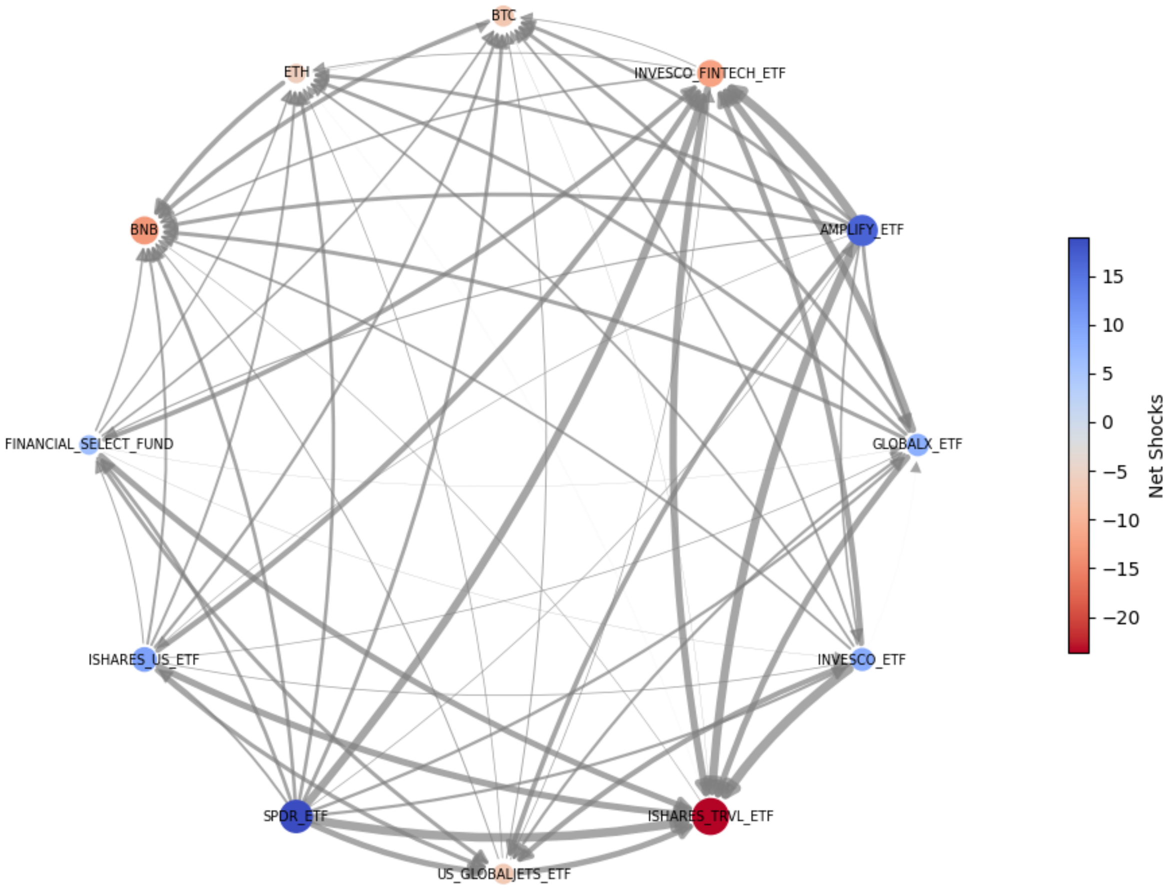
Due to the large net pairwise connectedness among all 12 assets, the results are presented in the Appendix. We highlight some key observations from these results. The net pairwise spillovers, as depicted in Figure A.1, provide valuable insights into the interconnectedness among the individual assets from the Fintech, cryptocurrency, tourism,

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.

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, emphasising 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, combined with the vulnerability of the tourism sector, underscores the need for strategic portfolio diversification and targeted 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 backtesting.

5.6. Economic Channels of Spillover Transmission

The spillover dynamics observed across Fintech, tourism, and cryptocurrency sectors can be rationalised through several economic channels. These channels explain how shocks in one sector propagate to others, influencing asset valuations, investor behaviour, and market stability. By linking empirical findings to theoretical mechanisms, we address the interconnectedness highlighted in the results, such as the dominance of traditional financial markets as net transmitters and tourism's vulnerability as a net receiver.

First, the dominance of traditional financial markets as net transmitters reflects credit supply constraints and funding dependencies that propagate through financial intermediation chains. Traditional banks and financial institutions often face balance-sheet constraints, such as limited capital or liquidity requirements, which can lead to tighter lending conditions. These constraints are transmitted to Fintech valuations via sponsor or partner banks and acquirers, who provide essential funding and infrastructure. For tourism firms, this manifests in restricted access to working-capital lines, fleet financing, or capital expenditures (capex) needed for operations like hotel expansions or airline fleet renewals. Tighter financial conditions raise the external finance premium—the additional cost of borrowing due to market imperfections—depressing cash-flow valuations in both tourism and Fintech sectors. Additionally, shifts in the risk-bearing capacity of intermediaries, such as market dealers or ETF Authorised Participants (APs), increase bid–ask spreads and price impact. This elevates cross-asset covariance and the total connectedness index (TCI), as observed in our empirical results, where traditional finance contributes the highest net spillovers (35.08%, see Table 3).

Second, Fintech-driven liquidity and payment innovations amplify contagion via synchronised investor sentiment and technology-linked exposure. Tourism revenues heavily depend on seamless checkout conversions, low cross-border fees, minimal chargeback risks, and the availability of Buy Now, Pay Later (BNPL) or credit options supplied by Fintech platforms. Shocks to Fintech, such as cyber events, system outages, or policy shifts on interchange fees and data privacy, directly impact tourism cash flows and equity valuations. For example, a Fintech outage could disrupt payment processing for travel bookings, resulting in lost revenue for tourism firms. Dynamic pricing algorithms, fraud detection models, and adtech budgets often co-move across integrated platforms, synchronising demand fluctuations and investor reactions. Consequently, Fintech acts as a secondary transmitter to tourism; pairwise connectedness intensifies around events like payment policy changes or outages, aligning with our aggregate net spillover from Fintech to tourism of 10.19%.

Third, tourism-driven spillovers could emerge through demand and revenue shocks. Travel restrictions, rising fuel costs, or geopolitical events can alter cash flows in airlines and hospitality sectors, impacting collateral values and loan covenants. Lenders and payment processors (often Fintech-integrated) then adjust credit limits or pricing, feeding back into the broader financial system. For instance, a decline in tourism revenues might lead to higher default risks on loans, prompting banks to tighten credit supply economy-wide. Hence, tourism is typically a net recipient but can also transmit during large real-sector shocks, such as pandemics or fuel price spikes, consistent with the heightened spillovers observed during COVID-19 in our dynamic analysis.

Fourth, the limited hedging capacity of cryptocurrencies (as we provide more empirical evidence in the next section) could be attributable to asymmetric volatility, speculative behaviour, and weak safe-haven demand, especially during high-uncertainty periods. Cryptocurrencies exhibit high, state-dependent volatility, where price swings are amplified in downward markets due to asymmetric leverage effects—investors facing margin calls or liquidations exacerbate sell-offs. Leverage and margin constraints in derivatives markets, combined with basis risk (dislocations between spot and futures prices), undermine their reliability as hedges. Moreover, depeg episodes in stablecoins or constraints in banking rails (e.g., restrictions on fiat-to-crypto conversions) feed back into processor and merchant settlements, affecting the reliability of tourism checkout. Hence, crypto is predominantly a net receiver in normal times; during risk-on episodes, it can temporarily transmit wealth effects or sentiment channels to Fintech, as evidenced by our findings, which show that cryptocurrencies receive net spillovers of -26.06% aggregately.

Fifth is crisis amplification and regime dependence spillover channels. In periods of stress, such as the COVID-19 pandemic, risk tolerance decreases, and margins increase; de-risking behaviours elevate cross-hedging correlations (often approaching one), weakening hedge ratios and increasing portfolio tail risk. This amplification is evident in our results, where the total spillover index peaked near 90% in early 2020, reflecting synchronised market reactions across sectors.

Together, these mechanisms suggest that shocks in credit and liquidity conditions transmit rapidly across digital and real sectors, producing the high time-varying connectedness observed empirically. Understanding these channels provides investors and policymakers with tools to mitigate risks, such as through diversified portfolios or regulatory oversight of integrated Fintech-tourism systems.

5.6.1. External Validation of Connectedness Dynamics

This section provides quantitative evidence linking the Total Connectedness Index (TCI) to observable measures of financial stress, credit conditions, and tourism-related economic activity. The objective is to assess whether the time variation and regime shifts in connectedness documented earlier correspond to economically meaningful changes in external conditions, particularly during periods of heightened uncertainty such as the COVID-19 pandemic. The results are presented in Tables 5 to 6.

The TCI is computed from the baseline TVP-VAR specification and summarises the aggregate strength of cross-market spillovers across tourism, cryptocurrency, Fintech, and traditional financial markets. To proxy financial market uncertainty, we employ the CBOE Volatility Index (VIX), obtained from the Chicago Board Options Exchange, which captures forward-looking equity market risk. Credit conditions are measured using the ICE BofA U.S. High Yield Option-Adjusted Spread (OAS), sourced from the Federal Reserve of St. Louis (ICE Data Indices, LLC, 2025), which reflects economy-wide funding stress and shifts in risk premia faced by non-investment-grade borrowers.

Tourism activity is proxied using mobility indicators constructed from Google's Global Mobility Reports (Google LLC, 2025). Specifically, we extract daily percentage deviations from baseline for mobility related to retail and recreation, transit stations, and workplaces, and aggregate these into a tourism-relevant activity index. We use U.S. data as the proxy for tourism activity. Higher (lower) values indicate stronger (weaker) tourism-related activity relative to the pre-pandemic baseline.

Regime differences in connectedness.. Table 4 reports mean differences in TCI across Pre-COVID, COVID, and Post-COVID regimes using Welch tests, alongside effect sizes. The results indicate pronounced and statistically significant increases in connectedness during the COVID period, relative to both the pre-COVID and post-COVID regimes. Importantly, post-COVID connectedness remains significantly elevated compared to pre-COVID levels, suggesting a persistent upward shift in cross-market spillovers even after the initial crisis phase. The large Cohen's d values confirm that these differences are economically meaningful rather than driven solely by sampling variation.

Table 4: Mean Differences in Total Connectedness Index (TCI) Across Regimes

Comparison	Mean Difference	t-statistic	p-value	Cohen's d
COVID minus Pre-COVID	11.9376	65.160	0.0000	5.542
COVID minus Post-COVID	5.8939	28.885	0.0000	1.946
Post-COVID minus Pre-COVID	6.0437	43.852	0.0000	2.156

Notes: TCI denotes the Total Connectedness Index obtained from the TVP-VAR model. Regimes are defined as Pre-COVID (up to 10 March 2020), COVID (11 March 2020–31 December 2020), and Post-COVID (from 1 January 2021 onward). Mean differences are evaluated using Welch unequal-variance t-tests. Cohen's d reports standardised effect sizes.

Period summaries and external conditions. Table 5 summarises average TCI levels alongside VIX, high-yield credit spreads, and U.S. tourism mobility across regimes. The COVID period is characterised by the highest average connectedness, coinciding with elevated market volatility, wider credit spreads, and sharply depressed tourism activity. Pre-COVID observations exhibit the lowest TCI and comparatively benign financial conditions, while Post-COVID values lie between the two, indicating partial normalisation. The alignment of TCI with both financial stress indicators and real-sector tourism activity provides descriptive evidence in support of the proposed transmission channels.

Table 5: Period Summary: TCI and External Indicators

Period	N	Mean TCI	SD TCI	Mean VIX	Mean HY OAS	Mean Tourism
Pre-COVID	608	70.358	1.822	17.407	3.853	3.147
COVID	212	82.296	2.441	26.267	5.915	-27.986
Post-COVID	916	76.401	3.521	19.585	3.872	-15.415

Notes: TCI is the Total Connectedness Index from the TVP-VAR model. VIX denotes the CBOE Volatility Index (Chicago Board Options Exchange). HY OAS is the ICE BofA U.S. High Yield Option-Adjusted Spread, capturing economy-wide credit stress. Tourism activity is proxied by a composite U.S. tourism mobility index constructed from Google Global Mobility Reports, averaging retail and recreation, transit stations, and workplace mobility.

Correlation evidence. Table 6 presents Pearson correlations between TCI and external indicators in levels. TCI is positively correlated with VIX and high-yield OAS, indicating that higher market uncertainty and tighter credit conditions are associated with stronger spillover intensity. In contrast, TCI is negatively correlated with the U.S. tourism mobility measures, implying that contractions in tourism-related activity coincide with increased interconnectedness across markets. These correlations are statistically significant and consistent with the view that financial stress and real-sector disruptions jointly amplify spillover dynamics.

Table 6: Correlations Between TCI and External Indicators

Indicator	N	Correlation	p-value
VIX	1714	0.379	0.000
HY OAS	1736	0.698	0.000
Tourism (U.S.)	1145	-0.340	0.000

Notes: Reported values are Pearson correlations computed in levels. TCI is the Total Connectedness Index. VIX proxies market uncertainty, while HY OAS captures credit market stress. Tourism mobility indices are derived from the Google Global Mobility Reports. The U.S. index is used in the period summaries. Negative correlations indicate higher connectedness during periods of tourism contraction.

Regression Results: Drivers of Total Connectedness. To empirically link the dynamics of the TCI to observable economic conditions, we estimate a set of time-series regressions relating TCI to market uncertainty, credit conditions, and tourism activity. We estimate three complementary specifications: (i) a levels specification capturing long-run associations and (ii) a crisis-interaction specification allowing relationships to differ during the COVID-19 period. Each specification is estimated separately using Newey–West heteroskedasticity- and autocorrelation-consistent standard errors, which explains the presence of different intercepts across models.

The regression results are reported in Table 7, with coefficients interpreted as marginal effects on aggregate spillovers. The regression results provide quantitative support for the economic channels underlying the observed spillover dynamics. Across all specifications, credit market stress emerges as the most robust determinant of total connectedness. In the levels specification, wider credit spreads are associated with significantly higher TCI, indicating that tighter financial conditions amplify cross-market spillovers. This effect strengthens markedly during the COVID-19 period. This finding is consistent with the interpretation that deteriorating credit conditions amplify cross-market spillovers by tightening funding constraints and increasing balance-sheet interdependencies.

In contrast, market uncertainty measured by the VIX and tourism mobility do not exert statistically significant effects in normal times, suggesting that short-run fluctuations in risk sentiment and tourism activity are not sufficient, on their own, to alter aggregate connectedness outside crisis periods

The *COVID interaction specification* (Panel B) reveals substantial regime shifts. The COVID dummy enters with a large and highly significant positive coefficient, confirming that total connectedness rose sharply during the pandemic. More importantly, the interaction terms show that the transmission mechanisms operating during COVID differ markedly from those prevailing in normal periods. The interaction between credit spreads and COVID is negative and significant, implying that although credit stress remains a key driver of connectedness, its marginal impact was partially attenuated during the crisis—consistent with policy interventions that stabilised credit markets despite elevated spreads.

Tourism activity exhibits pronounced regime dependence. Outside the pandemic, while its level effect is weak in tranquil periods, during COVID, however, the positive and highly significant interaction term implies a reversal: declines in tourism mobility became an important amplifier of connectedness. This pattern reflects the role of tourism as a real-sector shock transmission channel during the pandemic, where collapses in travel demand propagated stress across financial, Fintech, and cryptocurrency markets.

Finally, the interaction between VIX and the COVID dummy is positive and marginally significant, suggesting that uncertainty shocks became more potent in driving connectedness during the crisis, even though their effects are muted in normal times.

Taken together, the results confirm that total connectedness is primarily driven by credit conditions, with uncertainty and tourism activity becoming economically and statistically relevant during crisis periods. These findings provide an explicit empirical linkage between the theoretical spillover mechanisms and the observed dynamics of the connectedness index.

Table 7: HAC Regressions Linking Total Connectedness to Financial Stress and Tourism Activity

Specification	**Variable**	**Coefficient**	**Std. Error**	**HAC t-Stat**	**NW Lag**
Panel A: Levels Specification					
Intercept	–	64.799***	0.877	73.93	6
Market Uncertainty	VIX	0.036	0.029	1.25	6
Credit Stress	Credit Spread	2.976***	0.247	12.04	6
Tourism Activity	Tourism Mobility	0.045	0.035	1.29	6
Panel B: COVID Interaction Specification					
Intercept	–	57.818***	0.781	74.01	6
Market Uncertainty	VIX	-0.052	0.032	-1.60	6
Credit Stress	Credit Spread	4.759***	0.216	22.08	6
Tourism Activity	Tourism Mobility	-0.070*	0.038	-1.87	6
COVID Dummy	COVID	16.598***	1.127	14.73	6
VIX × COVID	Interaction	0.056*	0.033	1.71	6
Credit Spread × COVID	Interaction	-3.174***	0.244	-13.01	6
Tourism Mobility × COVID	Interaction	0.128***	0.037	3.46	6

Notes: The dependent variable is the **Total Connectedness Index (TCI)**. **Market Uncertainty** is measured by the CBOE Volatility Index (VIX). **Credit Stress** is the ICE BofA U.S. High Yield Option-Adjusted Spread (OAS). **Tourism Mobility** is constructed from Google Mobility indicators capturing tourism-related activity. **COVID** equals one from 11 March 2020 onward. All models are estimated separately using Newey–West HAC standard errors with a Bartlett kernel. **NW Lag** reports the Newey–West bandwidth. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.7. Hedging and portfolio Analysis

5.7.1. 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 A.1, 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 summarised in Table A.2. 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 a higher weight for tourism while others assume a 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.

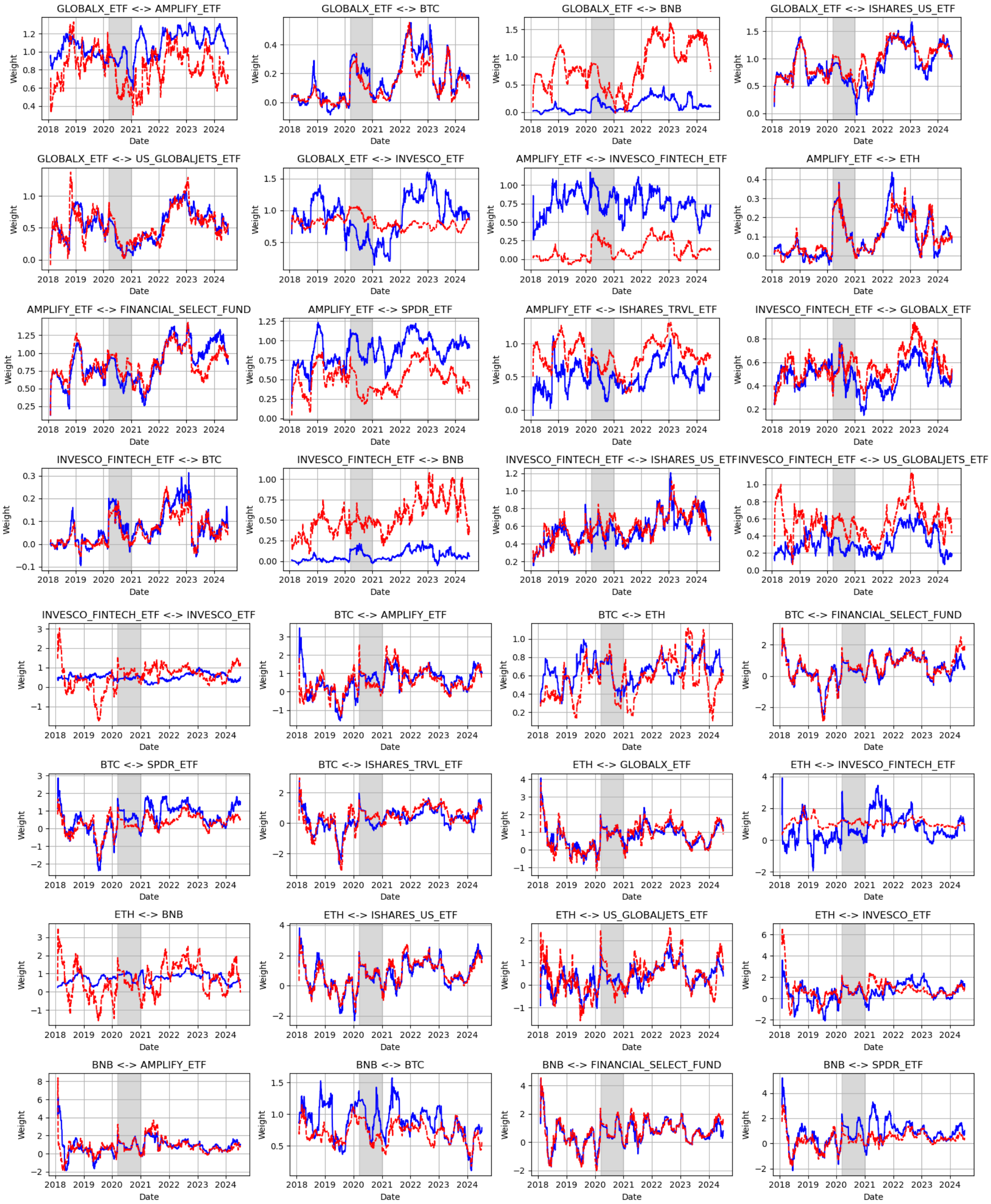
5.7.2. Hedging effectiveness and statistical significance

The hedging effectiveness (*HE*) values quantify the risk reduction achieved through hedging strategies. These are shown in both Tables A.1 and A.2. 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 A.1, 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 A.1, 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 A.2. From Table A.1, 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 A.2.

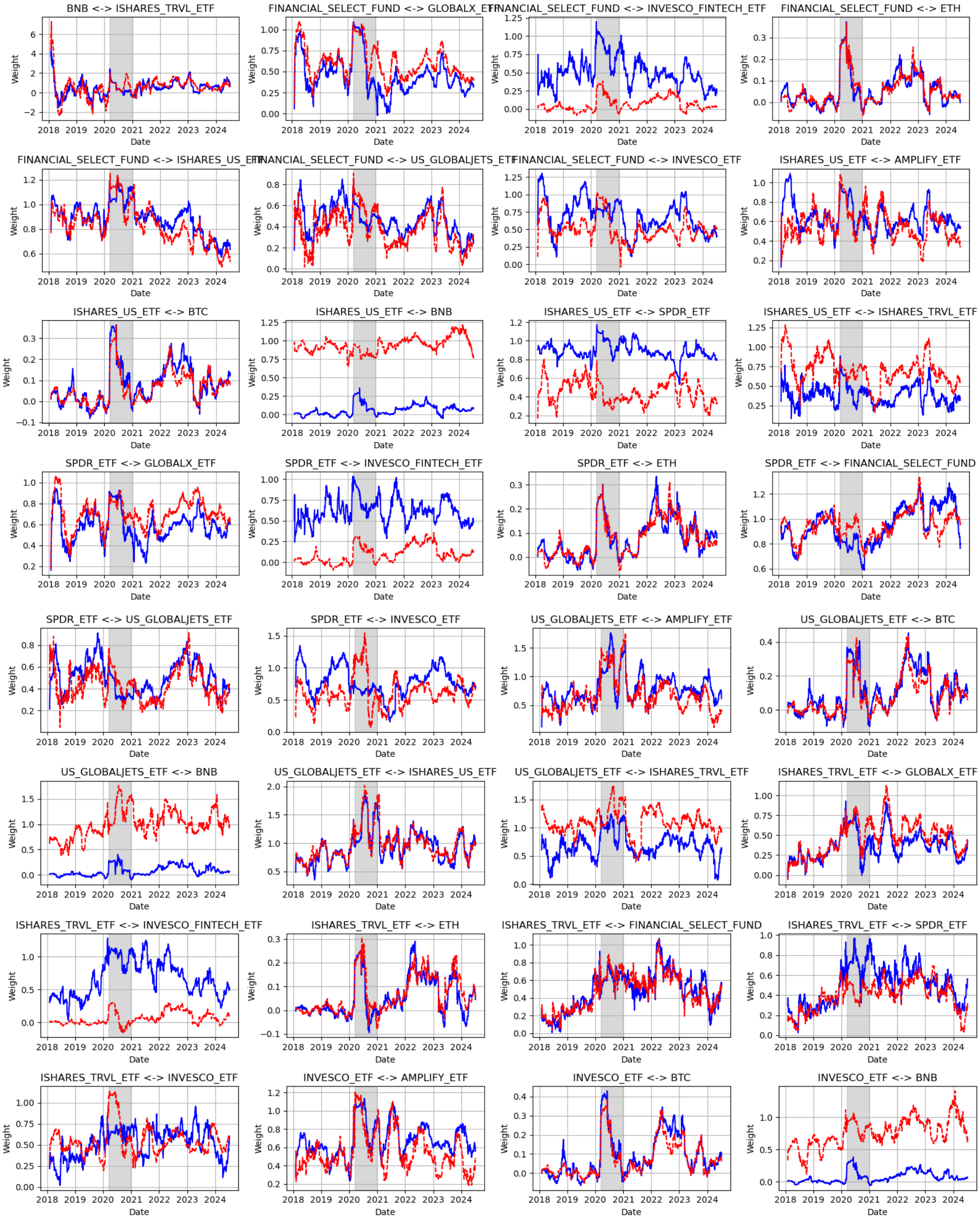
These results may highlight the challenges of using cryptocurrency-based assets as reliable hedging instruments, even though they were the cheapest hedge for most assets. The ineffectiveness of cryptocurrencies as a hedge may be due to their high volatility and idiosyncratic risk. Overall, the results emphasise 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.

Figure 5: Dynamic hedge ratios (Part 1)



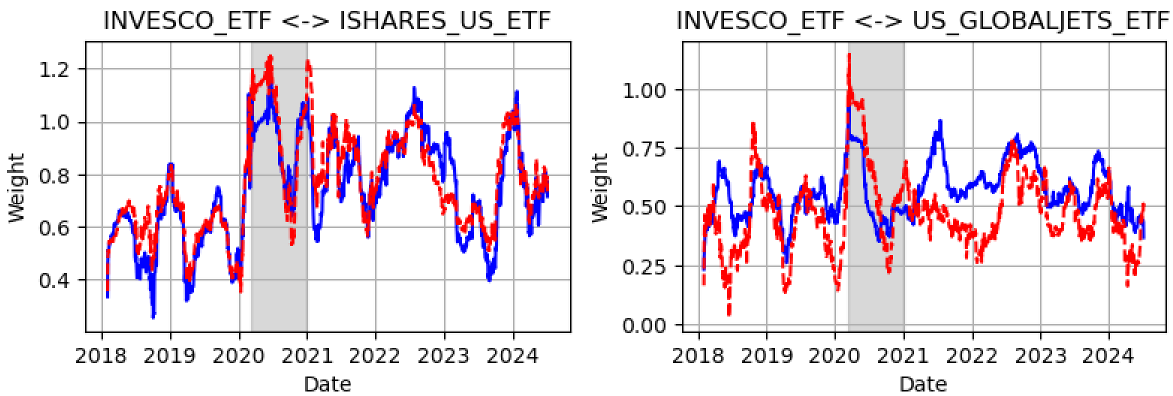
Note: The blue continuous line represents the dynamic optimal bilateral hedge ratio between the first (long) and second assets (short), while the red broken lines represent the reverse order of the two assets. The grey-shaded area is the first year when COVID-19 was declared a pandemic (2020-03-11 to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

Figure 6: Dynamic hedge ratios (Part 2)



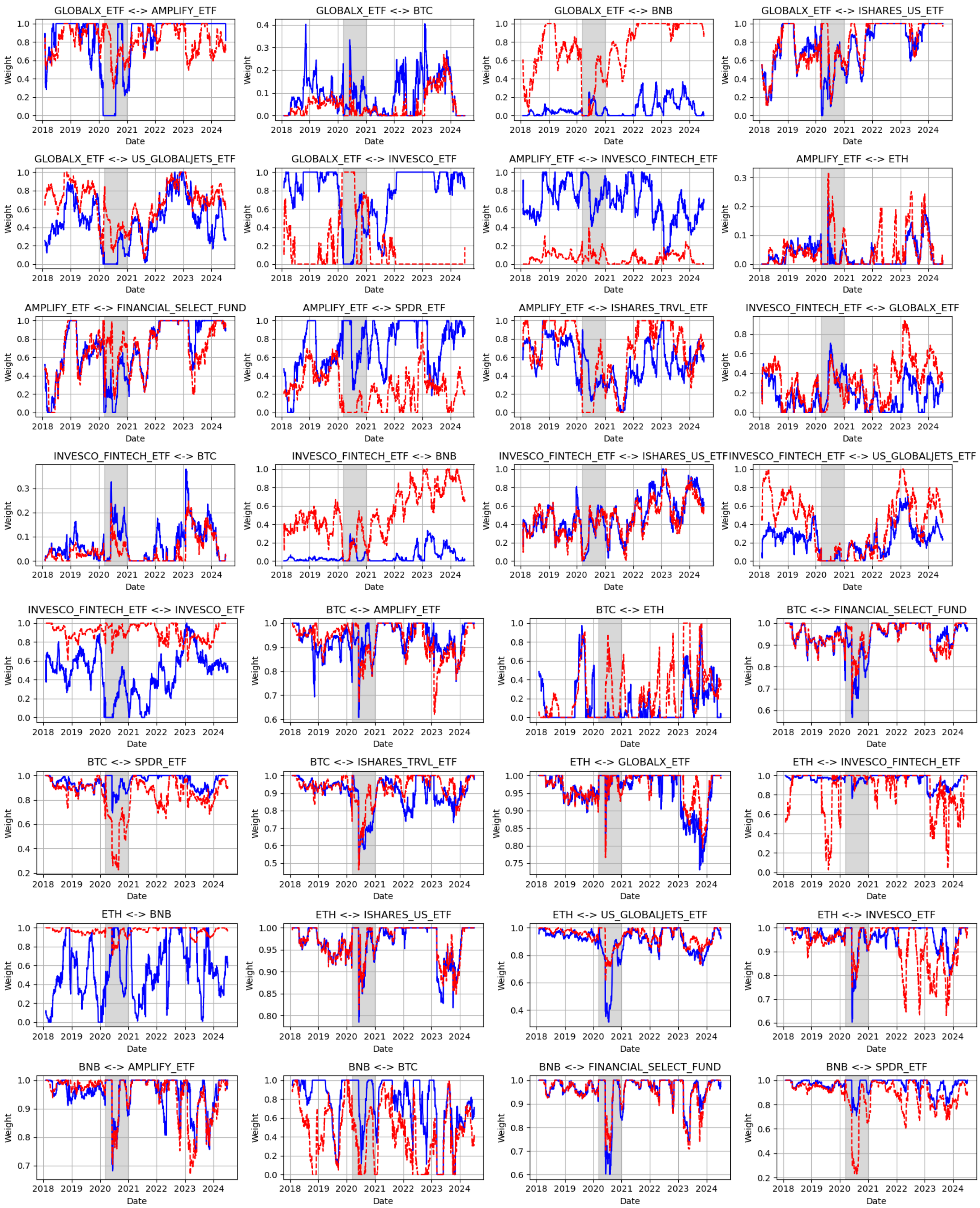
Note: The blue continuous line represents the dynamic optimal bilateral hedge ratio between the first (long) and second assets (short), while the red broken lines represent the reverse order of the two assets. The grey-shaded area is the first year when COVID-19 was declared a pandemic (2020-03-11 to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

Figure 7: Dynamic hedge ratios (Part 3)



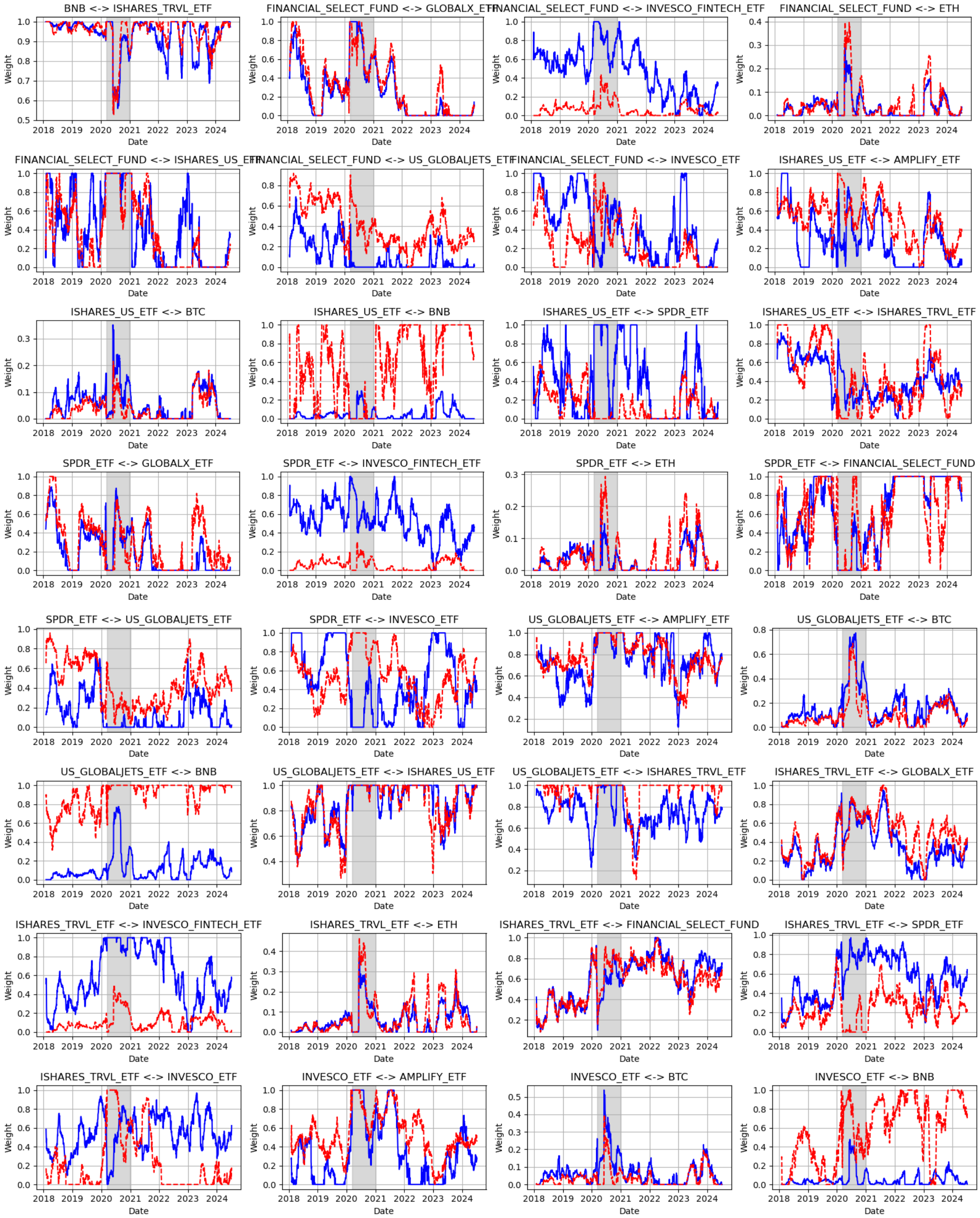
Note: The blue continuous line represents the dynamic optimal bilateral hedge ratio between the first (long) and second assets (short), while the red broken lines represent the reverse order of the two assets. The grey-shaded area is the first year when COVID-19 was declared a pandemic (2020-03-11 to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

Figure 8: Dynamic portfolio weights (Part 1)



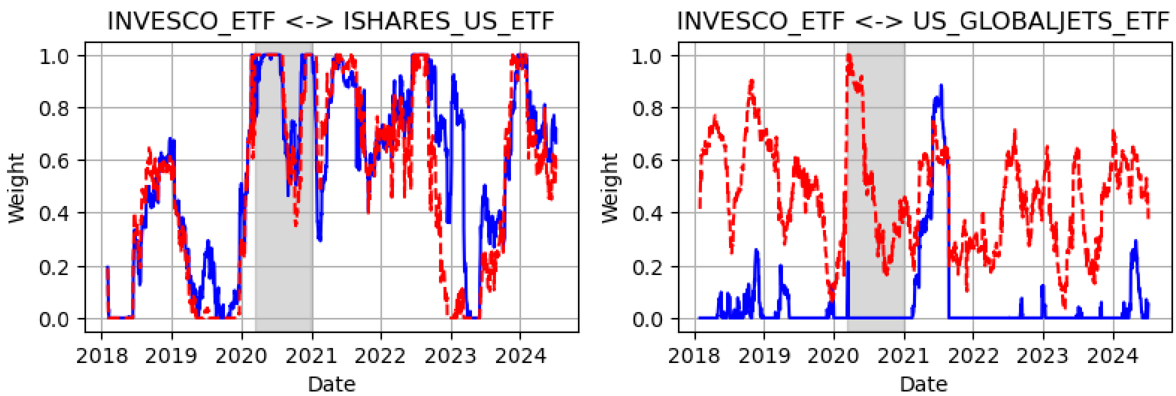
Note: The blue continuous line represents the dynamic portfolio weights between the first and second assets, while the red broken lines represent the reverse order of the two assets. The grey-shaded area is the first year when COVID-19 was declared a pandemic (2020-03-11 to 2020-12-31).

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).

5.7.3. Cumulative profits of diversification strategies

Again, of interest to investors will be to assess 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.[4] 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 and Table 8. From 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 positions) 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 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 8. 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 the 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

[4]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 A.3.

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.

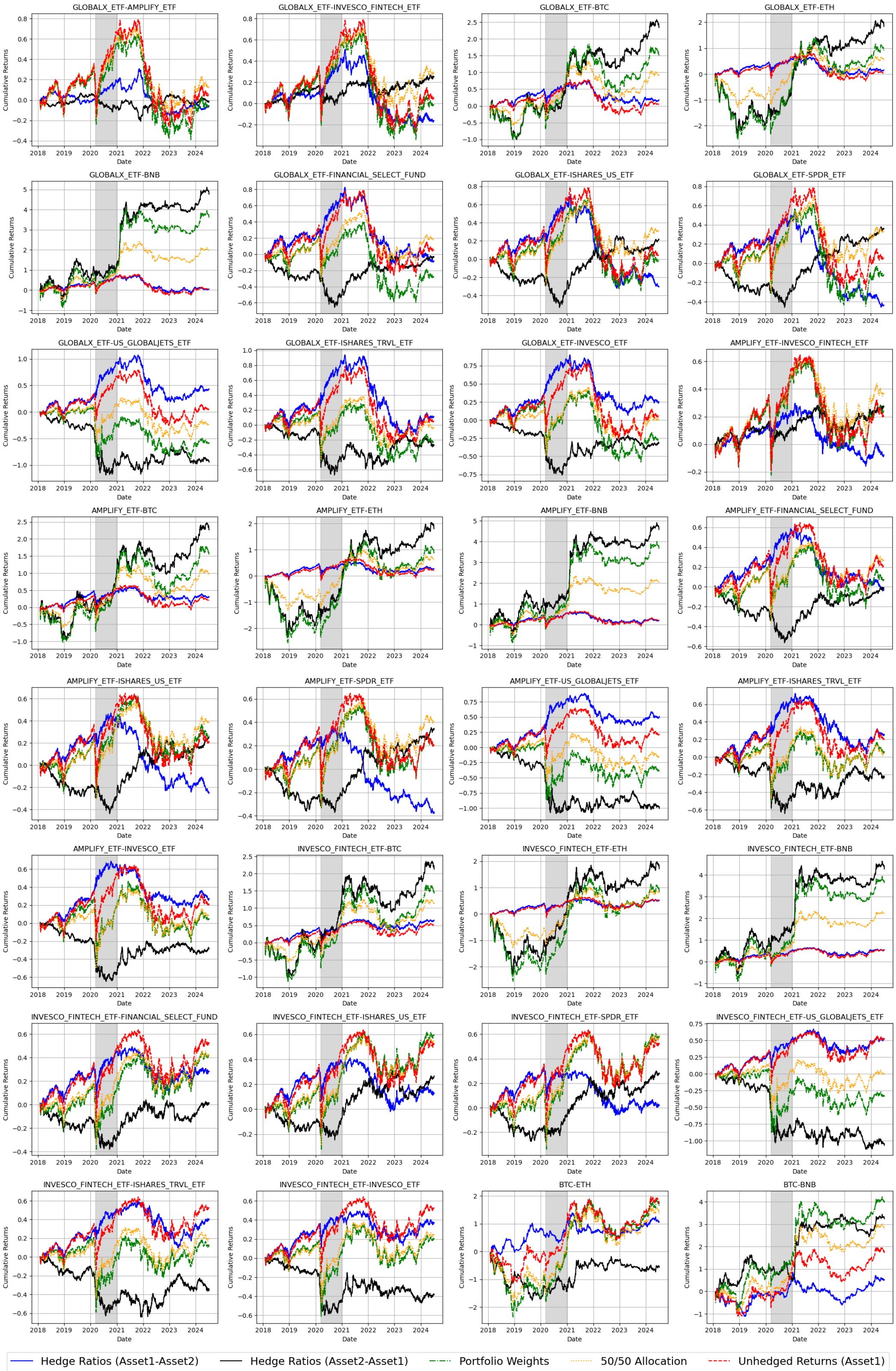
5.8. Multivariate portfolio analysis

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 minimisation of portfolio volatility, while MCP seeks to minimise the correlations across the assets. Meanwhile, MCoP is constructed on the basis of minimising the pairwise connectedness or bilateral spillovers between pairs of assets.

These results, along with the hedging effectiveness (*HE*), are presented in Table 9 and Figure 14. From Table 9, 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*.

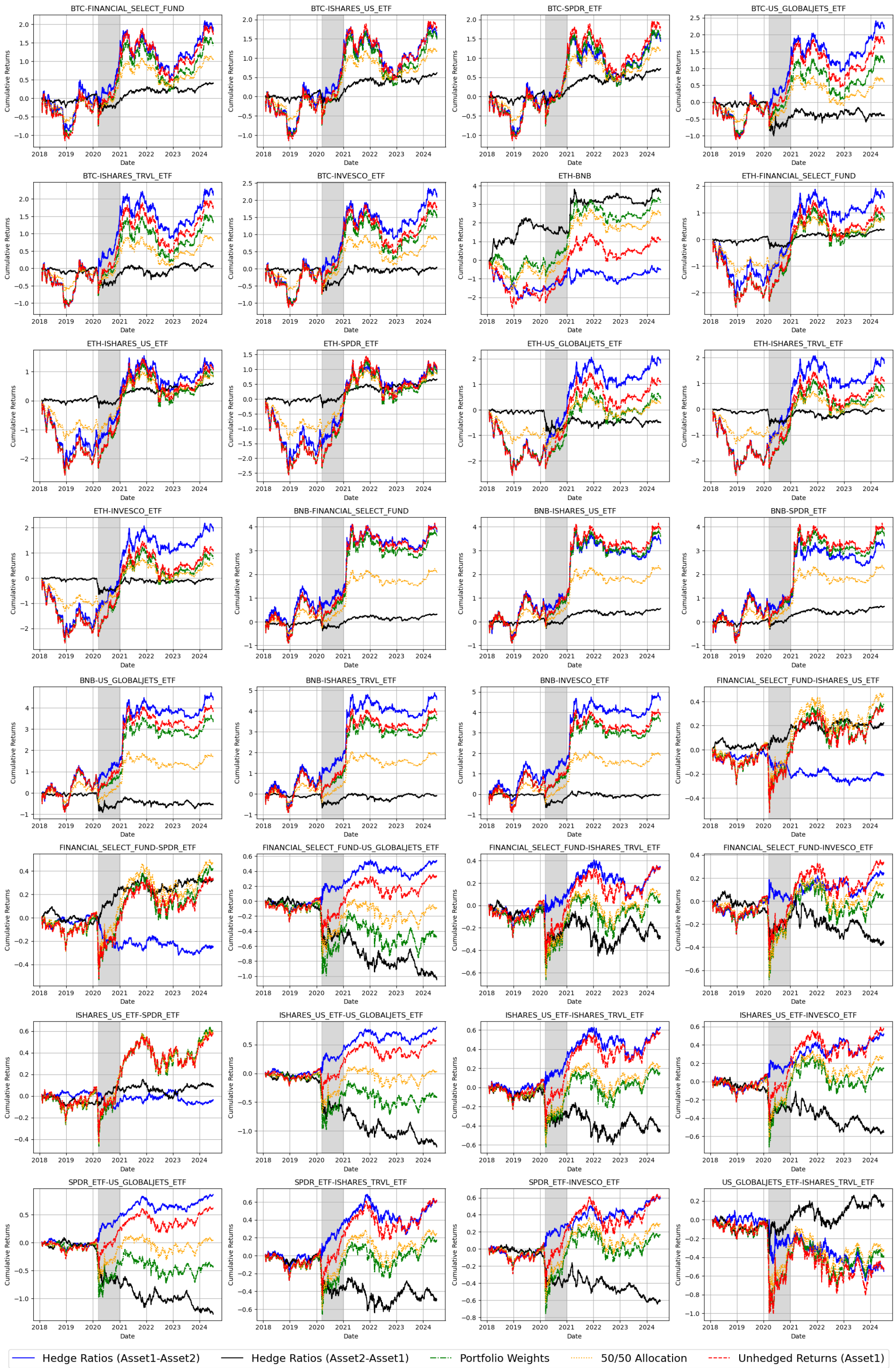
Meanwhile, for the *MCoP* strategy, the highest allocation went to three assets: *FINANCIAL_SELECT_FUND*, *ETH*, and *INVESCO_ETF* – with a portfolio allocation of 8.6% each. From the table, we can see that while the *MVP* and *MCP* strategies have relatively large differences in the portfolio allocation 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.

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



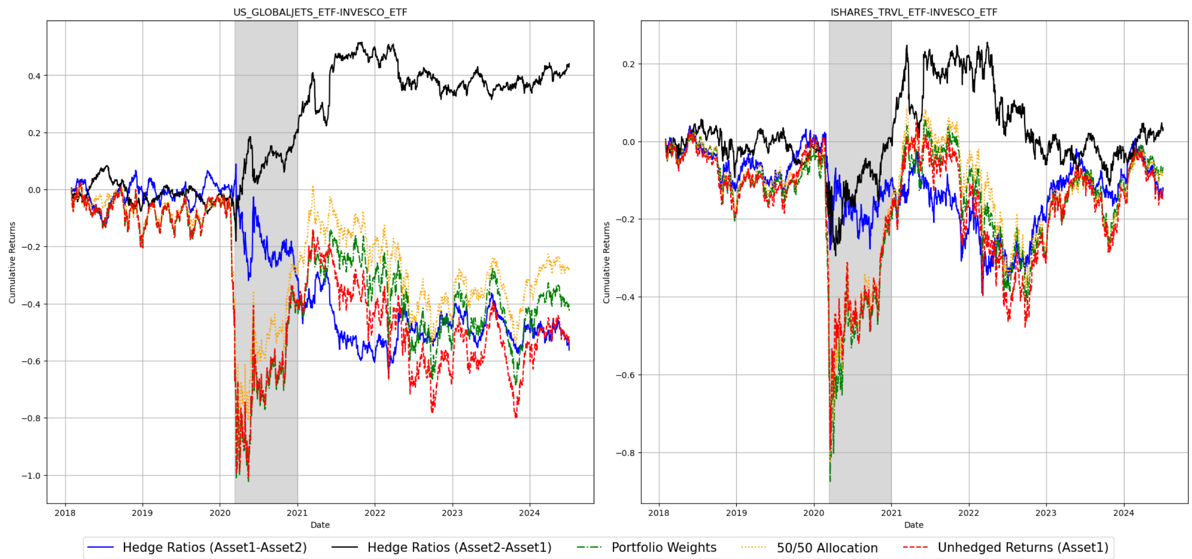
Note: The grey-shaded area is the first year when COVID-19 was declared a pandemic (2020-03-11 to 2020-12-31).

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 8: Summary of cumulative profits from diversification strategies

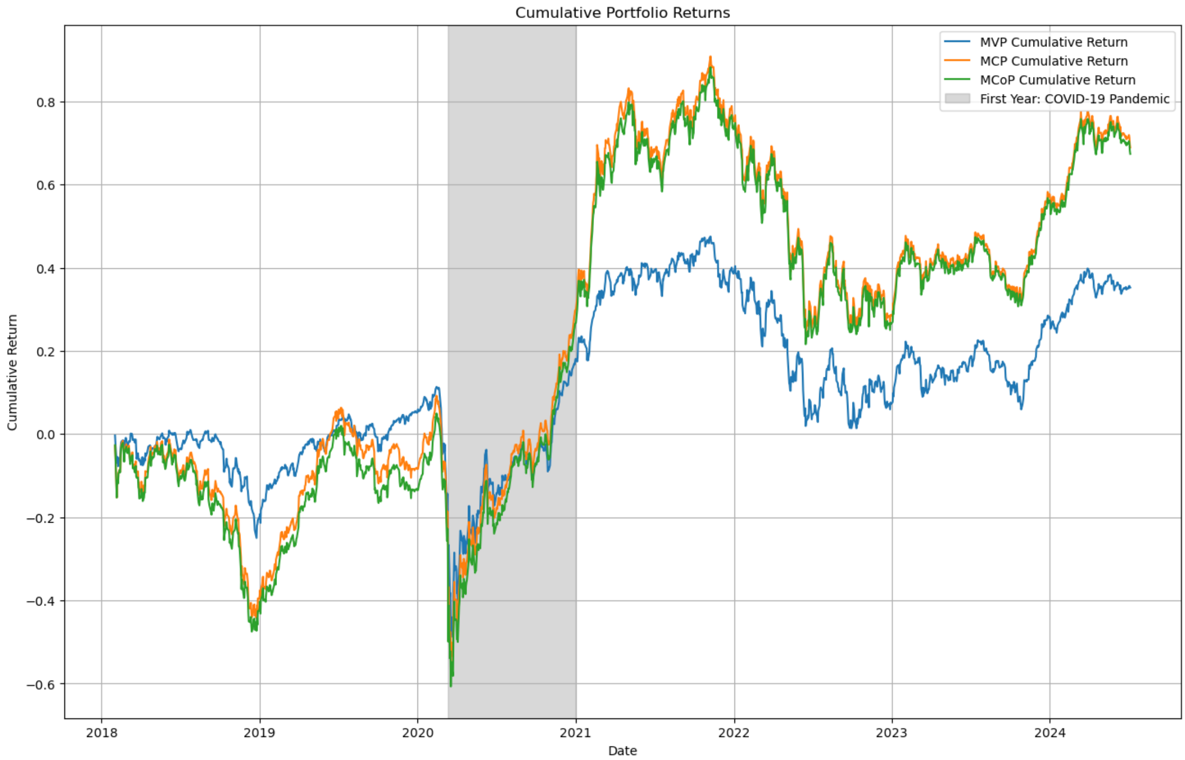
Asset Pair	Dynamic hedge ratios		Median hedge ratios		Portfolio weight			Buy and hold
	(Asset1-Asset2)	(Asset2-Asset1)	(Asset1-Asset2)	(Asset2-Asset1)	Dynamic	Median	50/50 Allocation	Unhedged
GLOBALX_ETF – AMPLIFY_ETF	-6%	-1%	-18%	17%	-5%	6%	14%	6%
GLOBALX_ETF – INVESCO_FINTECH_ETF	-16%	25%	-39%	50%	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.

Table 9: 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

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).

5.8.1. Results of Statistical Evaluation of Portfolio Performance

To rigorously assess the profitability and robustness of the MVP, MCP, and MCoP strategies, we evaluate their performance along two complementary dimensions: risk-adjusted returns and statistical significance of performance differences.

The Diebold–Mariano test confirms that differences in cumulative return predictability are statistically insignificant across all strategies and across all market regimes, as all DM statistics are small in magnitude and associated p-values exceed conventional significance thresholds. Hence, none of the portfolios demonstrate superior forecasting accuracy in terms of return dynamics.

In contrast, the Jobson–Korkie test provides strong statistical evidence of differences in risk-adjusted performance. Across the full sample and in each subperiod, MVP exhibits significantly lower Sharpe ratios than both MCP and MCoP ($p < 0.01$). During

Table 10: Diebold–Mariano and Jobson–Korkie Test Results by Period

Period	Comparison	DM Stat	DM p-value	JK Stat	JK p-value
Full Sample	MVP vs MCP	0.2904	0.7715	-14.7263	0.0000
Full Sample	MVP vs MCoP	0.3095	0.7569	-16.1686	0.0000
Full Sample	MCP vs MCoP	0.2613	0.7938	-1.8332	0.0668
Pre-COVID	MVP vs MCP	0.2238	0.8229	-26.1527	0.0000
Pre-COVID	MVP vs MCoP	0.1927	0.8472	-23.5864	0.0000
Pre-COVID	MCP vs MCoP	0.0248	0.9802	1.5220	0.1280
COVID	MVP vs MCP	0.3631	0.7165	-3.7317	0.0002
COVID	MVP vs MCoP	0.3024	0.7623	-2.8676	0.0041
COVID	MCP vs MCoP	0.0113	0.9910	0.8400	0.4009
Post-COVID	MVP vs MCP	0.1554	0.8765	-6.2324	0.0000
Post-COVID	MVP vs MCoP	0.2406	0.8099	-12.2343	0.0000
Post-COVID	MCP vs MCoP	0.4472	0.6547	-6.0031	0.0000

the COVID-19 period, although risk increased substantially, the statistical dominance of MCP and MCoP over MVP persists. The comparison between MCP and MCoP is generally statistically insignificant pre-COVID and during COVID, but becomes strongly significant post-COVID ($p < 0.01$), favouring MCoP. Over the full sample, the MCP–MCoP difference is marginally significant at the 10% level ($p = 0.0668$), suggesting a slight advantage of MCoP in long-run risk–return efficiency.

Overall, while all three portfolio strategies display statistically similar return predictability, portfolios that minimise correlations (MCP) or connectedness (MCoP) consistently deliver superior risk-adjusted outcomes relative to the traditional minimum-variance approach. MCoP provides the most favourable performance, particularly in the long run and in the post-pandemic recovery phase.

5.8.2. Downside Risk and Crisis Performance of Portfolio Strategies

Table 11 reports the Sharpe ratio, Sortino ratio, Maximum Drawdown (MDD), and Conditional Value-at-Risk at 5% ($\mathrm{CVaR}_{0.05}$) for the Minimum Variance Portfolio (MVP), Minimum Correlation Portfolio (MCP), and Minimum Connectedness Portfolio (MCoP) across the full sample, and the pre-COVID, COVID, and post-COVID periods.

Full Sample Performance.. Over the entire period, both MCP and MCoP outperform MVP in terms of risk-adjusted returns. MCoP achieves the highest Sharpe ratio (0.0367) and Sortino ratio (0.0335), followed closely by MCP (Sharpe = 0.0347). MVP delivers the lowest performance (Sharpe = 0.0216). However, this higher return comes at the cost of deeper losses during market stress — MCoP exhibits the largest maximum drawdown (−58.82%) and worst tail losses (CVaR = −5.07%), followed by MCP. This suggests that reducing variance alone (MVP) yields stability, but accounting for cross-market spillovers enhances returns at the cost of higher downside exposure.

Pre-COVID Period.. Before the pandemic, MVP shows slightly negative Sharpe and Sortino ratios, indicating poor performance even after accounting for volatility and downside risk. MCP and MCoP generate positive Sharpe ratios of 0.0251 and 0.0229, respectively, confirming superior risk-adjusted returns. Nonetheless, both MCP and MCoP suffer larger drawdowns (up to −52.20%), while MVP is comparatively more stable (MDD = −24.58%). Thus, prior to systemic stress, connectedness- and correlation-based allocations improve performance but increase vulnerability to deep portfolio losses.

During COVID-19.. The COVID-19 crisis reverses this risk–return trade-off. All strategies improve in terms of Sharpe and Sortino ratios, reflecting heightened return volatility and subsequent recovery. MCP delivers the strongest performance (Sharpe = 0.0813), followed by MCoP (0.0762) and MVP (0.0606). At the same time, maximum drawdowns remain severe but relatively similar across strategies (−27% to −32%), while tail losses intensify substantially — CVaR ranges from −6.11% (MVP) to −7.86% (MCoP). This indicates that, during extreme market turmoil, portfolios exploiting diversification through correlation or connectedness achieve higher returns, despite experiencing deeper losses in the worst cases.

Post-COVID Recovery.. Following the pandemic, all portfolios stabilise. MCoP maintains the highest Sharpe ratio (0.0325), followed by MCP (0.0248) and MVP (0.0185). However, both MCP and MCoP continue to exhibit higher maximum drawdowns (−53%), whereas MVP remains more conservative (MDD = −35.97%). Tail-risk (CVaR) is also lowest for MVP (−2.69%), implying better downside protection but at the expense of lower returns.

Across all periods, MVP offers the lowest returns but also the most controlled downside risk. MCP and MCoP consistently generate higher Sharpe and Sortino ratios,

Table 11: Downside Risk Metrics by Portfolio and Period

Period	Portfolio	Sharpe	Sortino	Max Drawdown	CVaR (5%)
Full Sample	MVP	0.0216	0.0199	-0.4631	-0.0316
Full Sample	MCP	0.0347	0.0313	-0.5311	-0.0466
Full Sample	MCoP	0.0367	0.0335	-0.5882	-0.0507
Pre-COVID	MVP	-0.0028	-0.0023	-0.2458	-0.0247
Pre-COVID	MCP	0.0251	0.0226	-0.4462	-0.0416
Pre-COVID	MCoP	0.0229	0.0208	-0.5220	-0.0474
COVID	MVP	0.0606	0.0563	-0.2745	-0.0611
COVID	MCP	0.0813	0.0655	-0.3122	-0.0747
COVID	MCoP	0.0762	0.0634	-0.3209	-0.0786
Post-COVID	MVP	0.0185	0.0177	-0.3597	-0.0269
Post-COVID	MCP	0.0248	0.0234	-0.5311	-0.0424
Post-COVID	MCoP	0.0325	0.0311	-0.5358	-0.0455

particularly during crisis and recovery phases, but are more exposed to extreme losses and deeper drawdowns. MCoP is marginally more profitable than MCP, but also carries slightly higher tail-risk, reflecting its sensitivity to spillover dynamics.

Overall, correlation- and connectedness-based allocation (MCP and MCoP) enhance performance relative to variance-based allocation (MVP), especially during periods of high uncertainty. However, this comes at the cost of higher exposure to extreme downside events.

6. Conclusion and Policy Implications

This study provides new evidence on the dynamic spillover structure between tourism, Fintech, cryptocurrency, and traditional financial markets, emphasising how these interdependencies evolve across tranquil and turbulent periods such as the COVID-19 crisis. Traditional financial markets consistently emerge as the dominant net transmitters of shocks, reinforcing their systemic role in propagating risks to emerging digital and tourism-based assets. Conversely, cryptocurrencies behave largely as net receivers of spillovers and exhibit limited effectiveness as hedging instruments, while tourism assets—despite their higher volatility—serve as comparatively stronger hedges.

Portfolio analysis reveals that incorporating cross-market connectedness into optimisation significantly improves performance relative to conventional variance- or correlation-based approaches. The Minimum Connectedness Portfolio (MCoP) consistently delivers higher risk-adjusted returns, particularly during crisis periods, even though it is more exposed to tail risks and drawdowns. In contrast, the Minimum Variance Portfolio (MVP) provides the most stable downside protection but offers inferior returns.

The statistical evaluation confirms these insights. Across the full and sub-sample periods, the Diebold–Mariano test suggests no significant differences in return predictability between MVP, MCP, and MCoP, implying that no strategy systematically outperforms in terms of forecasting accuracy. However, the Jobson–Korkie test indicates that MVP delivers significantly lower Sharpe ratios than MCP and MCoP, especially during COVID-19 and post-crisis periods. The difference between MCP and MCoP is generally insignificant or marginal, suggesting comparable efficiency, though MCoP has a marginal advantage. Downside risk metrics reinforce this asymmetry: MCP and MCoP yield higher returns but experience deeper drawdowns and more severe tail losses, while MVP remains more conservative.

These findings carry important policy and investment implications. For investors, they demonstrate that accounting for cross-market connectedness—rather than solely minimising variance—can yield superior returns, particularly in high-uncertainty environments. However, this comes at the cost of greater exposure to extreme losses, necessitating active risk management. Policymakers and financial regulators should recognise that spillovers between traditional and alternative markets amplify systemic risks, especially during crises. Stronger regulatory oversight and transparency in emerging markets, such as cryptocurrency and Fintech, are essential to mitigating instability.

Overall, this study concludes that while return predictability does not differ statistically across portfolio strategies, risk-adjusted performance and downside resilience vary markedly. Integrating connectedness into portfolio construction offers meaningful benefits, underscoring the importance of network-based risk management in an increasingly interconnected global financial system.

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Appendix A. Appendix

Here, we present a brief additional methodological details and some extra tables and figures related to net pairwise spillovers and dynamic hedge ratios and optimal portfolio weights.

Appendix A.1. ***Methodological Details for Downside and Tail Risk Measures***

The Sortino ratio, maximum drawdown (MDD), and Conditional Value-at-Risk (CVaR) are computed using daily portfolio returns. The Sortino ratio penalises only downside volatility and is calculated using a zero minimum acceptable return, consistent with the assumption of a zero risk-free rate.

The maximum drawdown is defined as the maximum peak-to-trough decline in cumulative portfolio value over the sample period and is computed using cumulative returns constructed through simple return aggregation.

Conditional Value-at-Risk (CVaR) is estimated at the 5% confidence level ($\alpha = 0.05$) using a historical (non-parametric) approach. Specifically, CVaR is computed as the average of portfolio returns falling below the empirical 5th percentile of the return distribution. This approach avoids distributional assumptions and is standard in empirical finance applications.

To account for sampling uncertainty, CVaR standard errors are obtained via a non-parametric block bootstrap with 1,000 replications, preserving the time-series dependence in returns. Confidence intervals are constructed using the percentile method. These uncertainty measures are reported for robustness and do not alter the ranking of portfolio strategies across sample periods.

Appendix A.2. ***Extra Figures and Tables***

The additional supporting figures and tables on net pairwise spillovers, dynamic optimal bilateral hedge ratios, dynamic optimal bilateral portfolio weights and Cumulative profits of diversification strategies with median hedge ratios and portfolio weights to construct the portfolios.

Figure A.1: Net pairwise spillover (Part 1)

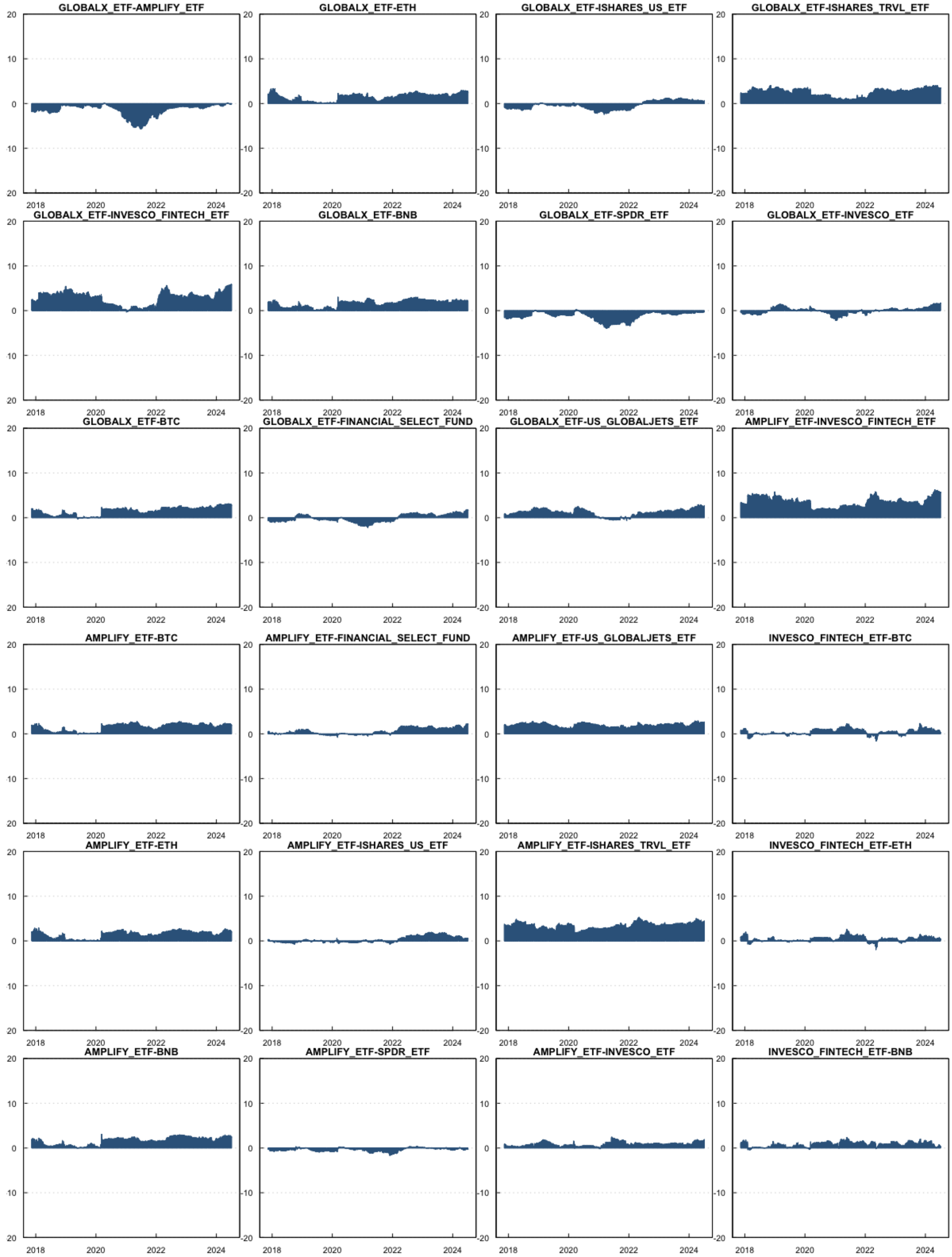

Figure A.1: Net pairwise spillover (Part 2)

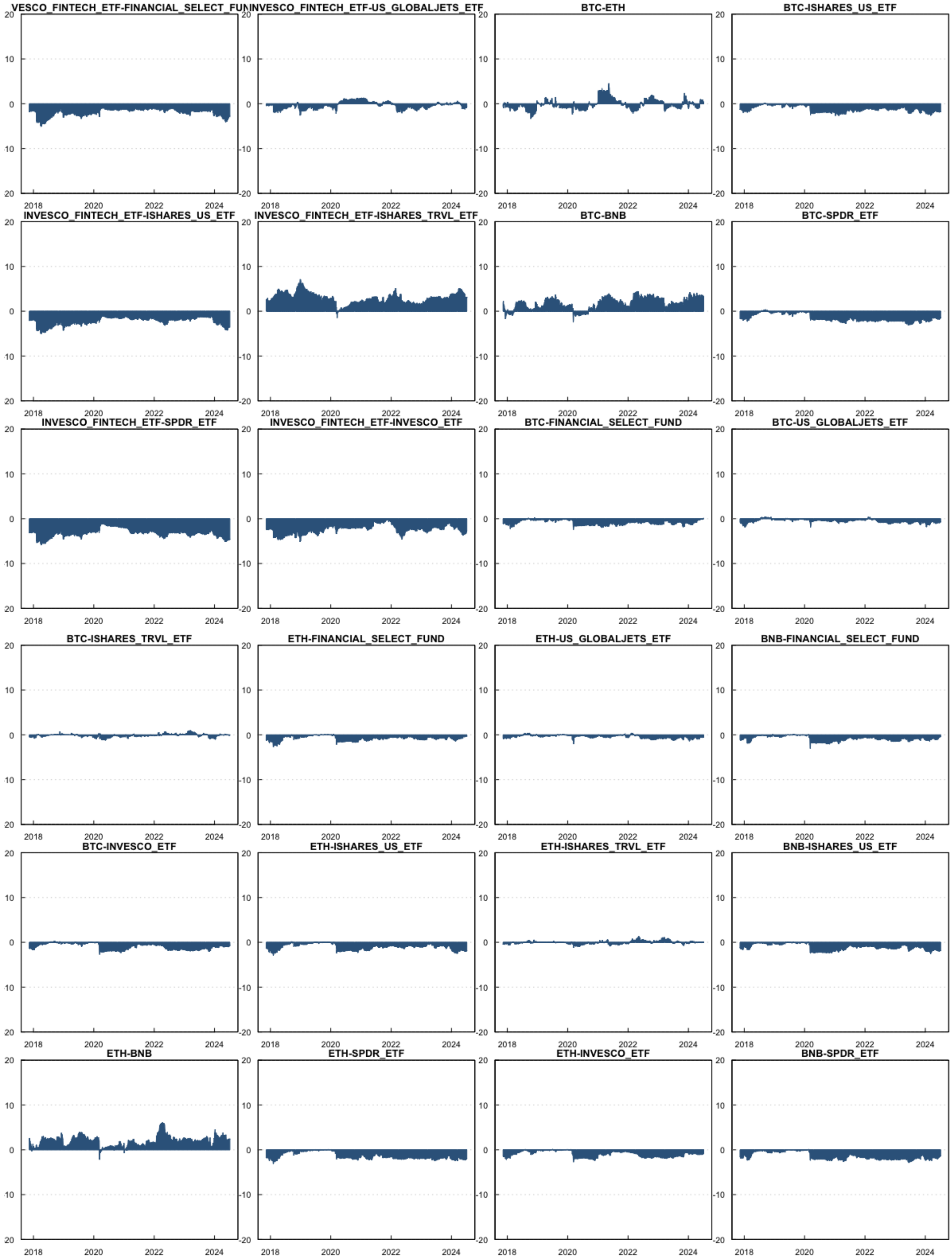

Figure A.1: Dynamic pairwise spillover (Part 3)

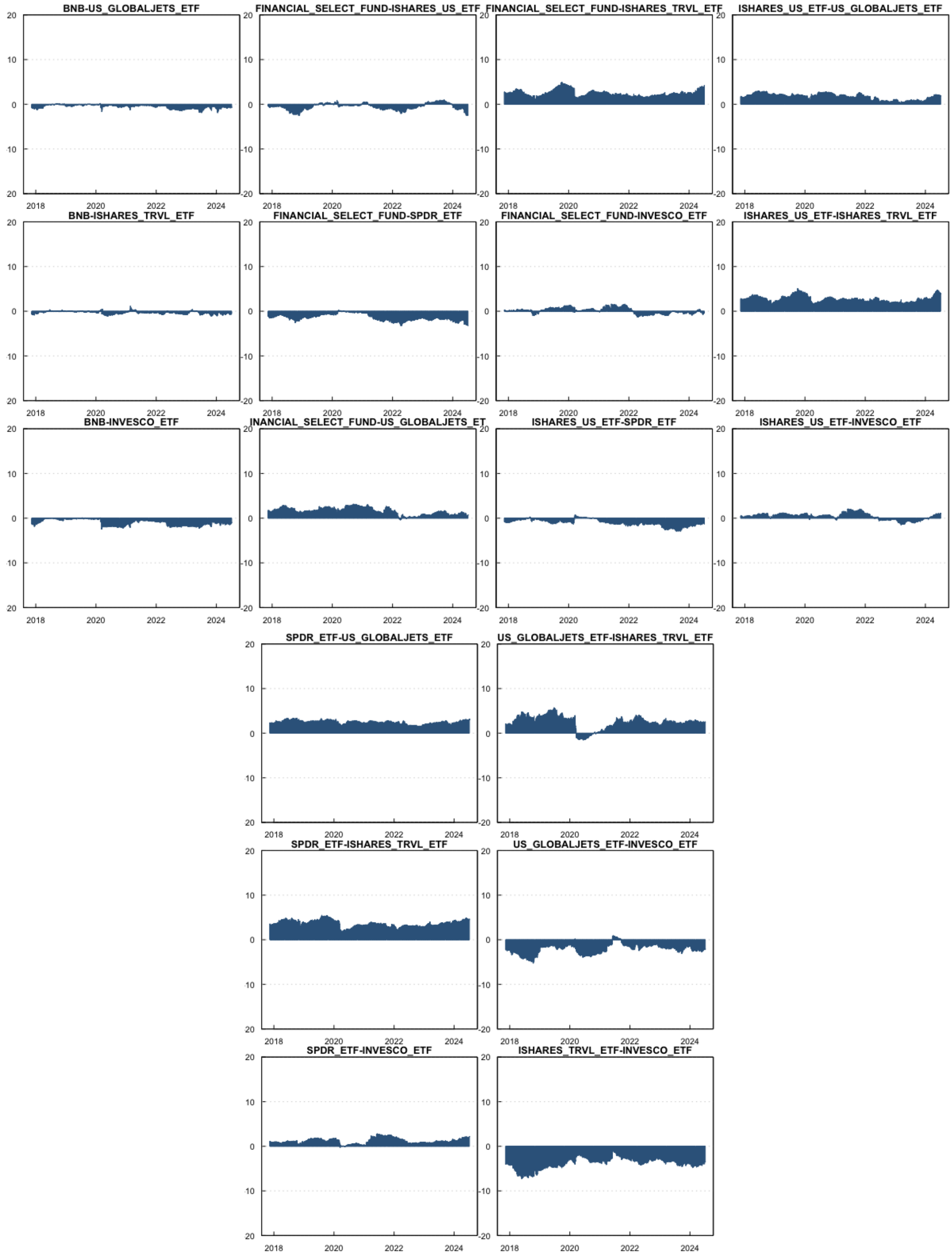

Table A.1: Summary of dynamic optimal bilateral hedge ratios

Pair	Mean	Std. Dev.	5%	95%	HE	p-value
GLOBALX_ETF – AMPLIFY_ETF	1.061	0.141	0.841	1.265	-0.048	0.516
GLOBALX_ETF – INVESCO_FINTECH_ETF	0.828	0.196	0.495	1.123	0.074*	0.077
GLOBALX_ETF – BTC	0.155	0.149	-0.029	0.442	-3.028***	0.000
GLOBALX_ETF – ETH	0.124	0.126	-0.014	0.360	-5.918***	0.000
GLOBALX_ETF – BNB	0.120	0.114	-0.019	0.326	-6.821***	0.000
GLOBALX_ETF – FINANCIAL_SELECT_FUND	0.849	0.399	0.235	1.461	-0.092	0.821
GLOBALX_ETF – ISHARES_US_ETF	0.881	0.330	0.362	1.394	-0.082	0.894
GLOBALX_ETF – SPDR_ETF	0.946	0.282	0.544	1.380	-0.087	0.630
GLOBALX_ETF – US_GLOBALJETS_ETF	0.543	0.248	0.140	0.943	-0.093	0.906
GLOBALX_ETF – ISHARES_TRVL_ETF	0.542	0.249	0.198	0.966	0.193***	0.000
GLOBALX_ETF – INVESCO_ETF	0.904	0.319	0.344	1.376	-0.085	0.582
AMPLIFY_ETF – GLOBALX_ETF	0.809	0.092	0.677	1.032	-0.050	0.436
AMPLIFY_ETF – INVESCO_FINTECH_ETF	0.754	0.167	0.456	1.009	0.080*	0.076
AMPLIFY_ETF – BTC	0.118	0.122	-0.033	0.336	-4.162***	0.000
AMPLIFY_ETF – ETH	0.095	0.103	-0.012	0.289	-7.861***	0.000
AMPLIFY_ETF – BNB	0.096	0.093	-0.018	0.270	-8.965***	0.000
AMPLIFY_ETF – FINANCIAL_SELECT_FUND	0.849	0.267	0.441	1.278	0.001	0.654
AMPLIFY_ETF – ISHARES_US_ETF	0.840	0.212	0.523	1.197	0.016	0.510
AMPLIFY_ETF – SPDR_ETF	0.870	0.178	0.583	1.164	0.008	0.576
AMPLIFY_ETF – US_GLOBALJETS_ETF	0.512	0.176	0.251	0.820	-0.186	0.146
AMPLIFY_ETF – ISHARES_TRVL_ETF	0.504	0.192	0.225	0.846	0.154***	0.002
AMPLIFY_ETF – INVESCO_ETF	0.835	0.221	0.439	1.155	-0.008	0.831
INVESCO_FINTECH_ETF – GLOBALX_ETF	0.482	0.117	0.296	0.679	-0.209***	0.004
INVESCO_FINTECH_ETF – AMPLIFY_ETF	0.572	0.127	0.373	0.805	-0.050	0.921
INVESCO_FINTECH_ETF – BTC	0.072	0.076	-0.021	0.217	-6.620***	0.000
INVESCO_FINTECH_ETF – ETH	0.060	0.064	-0.013	0.179	-12.072***	0.000
INVESCO_FINTECH_ETF – BNB	0.064	0.063	-0.014	0.183	-13.593***	0.000
INVESCO_FINTECH_ETF – FINANCIAL_SELECT_FUND	0.537	0.201	0.233	0.918	0.048*	0.094
INVESCO_FINTECH_ETF – ISHARES_US_ETF	0.559	0.161	0.308	0.842	0.085*	0.055
INVESCO_FINTECH_ETF – SPDR_ETF	0.588	0.160	0.327	0.860	0.089	0.141
INVESCO_FINTECH_ETF – US_GLOBALJETS_ETF	0.324	0.137	0.155	0.573	-0.684***	0.000
INVESCO_FINTECH_ETF – ISHARES_TRVL_ETF	0.555	0.185	0.264	0.876	-0.047	0.681
INVESCO_FINTECH_ETF – INVESCO_ETF	0.509	0.168	0.218	0.805	-0.076	0.530
BTC – GLOBALX_ETF	0.562	0.613	-0.530	1.275	-0.187**	0.035
BTC – AMPLIFY_ETF	0.586	0.680	-0.499	1.510	-0.307	0.126
BTC – INVESCO_FINTECH_ETF	0.526	0.642	-0.460	1.712	-0.325***	0.001
BTC – ETH	0.662	0.145	0.431	0.911	-0.173**	0.025
BTC – BNB	0.564	0.215	0.217	0.936	-0.322***	0.001
BTC – FINANCIAL_SELECT_FUND	0.463	0.776	-0.797	1.600	-0.357**	0.031
BTC – ISHARES_US_ETF	0.524	0.843	-1.008	1.747	-0.531	0.415
BTC – SPDR_ETF	0.584	0.781	-0.813	1.669	-0.478	0.579
BTC – US_GLOBALJETS_ETF	0.296	0.522	-0.636	1.046	0.210***	0.000
BTC – ISHARES_TRVL_ETF	0.262	0.673	-0.836	1.297	-0.222***	0.000
BTC – INVESCO_ETF	0.379	0.787	-1.225	1.362	-0.326***	0.004
ETH – GLOBALX_ETF	0.768	0.631	-0.277	1.694	-0.368	0.106
ETH – AMPLIFY_ETF	0.781	0.712	-0.308	1.790	-0.438	0.453
ETH – INVESCO_FINTECH_ETF	0.742	0.840	-0.301	2.251	-1.303	0.765
ETH – BTC	1.074	0.236	0.769	1.434	-0.107	0.252
ETH – BNB	0.745	0.258	0.296	1.149	-0.069	0.523
ETH – FINANCIAL_SELECT_FUND	0.662	0.868	-0.662	2.039	-0.463	0.432
ETH – ISHARES_US_ETF	0.725	0.942	-0.774	2.198	-0.682	0.532
ETH – SPDR_ETF	0.790	0.872	-0.674	2.192	-0.703	0.253
ETH – US_GLOBALJETS_ETF	0.349	0.537	-0.564	1.276	0.324***	0.000
ETH – ISHARES_TRVL_ETF	0.426	0.730	-0.705	1.677	-0.173***	0.000
ETH – INVESCO_ETF	0.596	0.847	-0.961	1.838	-0.355*	0.079
BNB – GLOBALX_ETF	0.784	0.906	-0.515	2.086	-2.391*	0.051
BNB – AMPLIFY_ETF	0.824	0.915	-0.560	2.201	-2.226**	0.012
BNB – INVESCO_FINTECH_ETF	0.773	0.859	-0.418	2.570	-3.044*	0.081
BNB – BTC	0.880	0.260	0.428	1.289	0.038	0.612
BNB – ETH	0.705	0.165	0.436	0.967	0.159	0.155
BNB – FINANCIAL_SELECT_FUND	0.636	0.854	-0.978	1.815	-0.817	0.749

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Table A.1: Summary of dynamic optimal bilateral hedge ratios (continued)

Pair	Mean	Std. Dev.	5%	95%	HE	p-value
BNB – ISHARES_US_ETF	0.693	0.913	-1.212	1.929	-1.138	0.225
BNB – SPDR_ETF	0.799	0.955	-0.849	2.380	-1.918***	0.006
BNB – US_GLOBALJETS_ETF	0.328	0.637	-0.875	1.276	-0.018***	0.000
BNB – ISHARES_TRVL_ETF	0.469	0.706	-0.688	1.517	-0.791***	0.000
BNB – INVESCO_ETF	0.554	0.986	-1.102	1.609	-1.981	0.892
FINANCIAL_SELECT_FUND – GLOBALX_ETF	0.453	0.223	0.176	0.964	-0.254***	0.000
FINANCIAL_SELECT_FUND – AMPLIFY_ETF	0.603	0.192	0.357	0.985	-0.057	0.382
FINANCIAL_SELECT_FUND – INVESCO_FINTECH_ETF	0.506	0.198	0.213	0.900	0.043	0.262
FINANCIAL_SELECT_FUND – BTC	0.067	0.092	-0.046	0.243	-5.801***	0.000
FINANCIAL_SELECT_FUND – ETH	0.056	0.075	-0.029	0.212	-10.539***	0.000
FINANCIAL_SELECT_FUND – BNB	0.056	0.074	-0.034	0.224	-11.898***	0.000
FINANCIAL_SELECT_FUND – ISHARES_US_ETF	0.881	0.129	0.644	1.106	-0.013	0.900
FINANCIAL_SELECT_FUND – SPDR_ETF	0.834	0.152	0.589	1.142	-0.043	0.647
FINANCIAL_SELECT_FUND – US_GLOBALJETS_ETF	0.461	0.142	0.251	0.693	-0.393***	0.000
FINANCIAL_SELECT_FUND – ISHARES_TRVL_ETF	0.377	0.167	0.113	0.653	0.043	0.624
FINANCIAL_SELECT_FUND – INVESCO_ETF	0.685	0.241	0.283	1.117	-0.035	0.839
ISHARES_US_ETF – GLOBALX_ETF	0.506	0.180	0.264	0.915	-0.194***	0.004
ISHARES_US_ETF – AMPLIFY_ETF	0.639	0.146	0.447	0.925	-0.023	0.785
ISHARES_US_ETF – INVESCO_FINTECH_ETF	0.563	0.160	0.359	0.875	0.088*	0.066
ISHARES_US_ETF – BTC	0.077	0.092	-0.042	0.246	-5.924***	0.000
ISHARES_US_ETF – ETH	0.064	0.076	-0.031	0.225	-10.837***	0.000
ISHARES_US_ETF – BNB	0.062	0.073	-0.034	0.202	-12.274***	0.000
ISHARES_US_ETF – FINANCIAL_SELECT_FUND	0.941	0.099	0.791	1.135	-0.011	0.927
ISHARES_US_ETF – SPDR_ETF	0.891	0.090	0.780	1.051	-0.012	0.941
ISHARES_US_ETF – US_GLOBALJETS_ETF	0.451	0.122	0.269	0.651	-0.421***	0.000
ISHARES_US_ETF – ISHARES_TRVL_ETF	0.386	0.125	0.211	0.617	0.064	0.268
ISHARES_US_ETF – INVESCO_ETF	0.699	0.195	0.351	1.061	-0.018	0.862
SPDR_ETF – GLOBALX_ETF	0.580	0.148	0.337	0.866	-0.151**	0.043
SPDR_ETF – AMPLIFY_ETF	0.705	0.136	0.482	0.926	-0.022	0.957
SPDR_ETF – INVESCO_FINTECH_ETF	0.621	0.144	0.406	0.897	0.123**	0.015
SPDR_ETF – BTC	0.094	0.103	-0.043	0.288	-5.848***	0.000
SPDR_ETF – ETH	0.077	0.082	-0.025	0.242	-10.718***	0.000
SPDR_ETF – BNB	0.075	0.077	-0.029	0.220	-12.182***	0.000
SPDR_ETF – FINANCIAL_SELECT_FUND	0.946	0.151	0.707	1.175	-0.038	0.767
SPDR_ETF – ISHARES_US_ETF	0.945	0.103	0.763	1.093	-0.014	0.949
SPDR_ETF – US_GLOBALJETS_ETF	0.499	0.149	0.297	0.759	-0.433***	0.000
SPDR_ETF – ISHARES_TRVL_ETF	0.438	0.148	0.243	0.694	0.066*	0.095
SPDR_ETF – INVESCO_ETF	0.777	0.226	0.373	1.160	-0.062	0.781
US_GLOBALJETS_ETF – GLOBALX_ETF	0.612	0.234	0.261	1.116	0.016	0.333
US_GLOBALJETS_ETF – AMPLIFY_ETF	0.795	0.262	0.468	1.363	-0.042	0.680
US_GLOBALJETS_ETF – INVESCO_FINTECH_ETF	0.674	0.303	0.318	1.361	-0.065*	0.083
US_GLOBALJETS_ETF – BTC	0.105	0.121	-0.053	0.339	-1.961***	0.000
US_GLOBALJETS_ETF – ETH	0.083	0.107	-0.037	0.288	-4.072***	0.000
US_GLOBALJETS_ETF – BNB	0.078	0.097	-0.042	0.263	-4.740***	0.000
US_GLOBALJETS_ETF – FINANCIAL_SELECT_FUND	1.003	0.268	0.540	1.490	-0.153	0.289
US_GLOBALJETS_ETF – ISHARES_US_ETF	0.934	0.284	0.557	1.532	-0.138	0.631
US_GLOBALJETS_ETF – SPDR_ETF	0.961	0.283	0.606	1.654	-0.217	0.320
US_GLOBALJETS_ETF – ISHARES_TRVL_ETF	0.683	0.216	0.343	1.104	0.098**	0.010
US_GLOBALJETS_ETF – INVESCO_ETF	1.095	0.222	0.719	1.487	-0.159	0.135
ISHARES_TRVL_ETF – GLOBALX_ETF	0.367	0.175	0.142	0.686	0.022	0.496
ISHARES_TRVL_ETF – AMPLIFY_ETF	0.468	0.210	0.149	0.808	0.132*	0.094
ISHARES_TRVL_ETF – INVESCO_FINTECH_ETF	0.672	0.274	0.293	1.111	0.007	0.686
ISHARES_TRVL_ETF – BTC	0.061	0.097	-0.047	0.260	-4.633***	0.000
ISHARES_TRVL_ETF – ETH	0.054	0.083	-0.042	0.228	-8.603***	0.000
ISHARES_TRVL_ETF – BNB	0.064	0.079	-0.021	0.219	-9.743***	0.000
ISHARES_TRVL_ETF – FINANCIAL_SELECT_FUND	0.479	0.215	0.109	0.796	0.207***	0.000
ISHARES_TRVL_ETF – ISHARES_US_ETF	0.472	0.199	0.171	0.783	0.230***	0.000
ISHARES_TRVL_ETF – SPDR_ETF	0.499	0.200	0.195	0.815	0.213***	0.002
ISHARES_TRVL_ETF – US_GLOBALJETS_ETF	0.399	0.146	0.132	0.617	-0.196*	0.074
ISHARES_TRVL_ETF – INVESCO_ETF	0.519	0.176	0.210	0.752	0.146***	0.004

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Table A.1: Summary of dynamic optimal bilateral hedge ratios (continued)

Pair	Mean	Std. Dev.	5%	95%	HE	p-value
INVESCO_ETF – GLOBALX_ETF	0.546	0.173	0.328	0.987	-0.112**	0.047
INVESCO_ETF – AMPLIFY_ETF	0.677	0.176	0.397	1.042	-0.011	0.806
INVESCO_ETF – INVESCO_FINTECH_ETF	0.551	0.216	0.275	1.014	0.081*	0.090
INVESCO_ETF – BTC	0.088	0.111	-0.041	0.298	-4.362***	0.000
INVESCO_ETF – ETH	0.073	0.094	-0.025	0.284	-8.142***	0.000
INVESCO_ETF – BNB	0.070	0.086	-0.033	0.238	-9.363***	0.000
INVESCO_ETF – FINANCIAL_SELECT_FUND	0.762	0.214	0.352	1.122	0.050	0.407
INVESCO_ETF – ISHARES_US_ETF	0.740	0.194	0.421	1.039	0.035	0.460
INVESCO_ETF – SPDR_ETF	0.767	0.190	0.479	1.128	-0.030	0.988
INVESCO_ETF – US_GLOBALJETS_ETF	0.566	0.116	0.394	0.779	-0.182**	0.022
INVESCO_ETF – ISHARES_TRVL_ETF	0.472	0.166	0.222	0.767	0.089	0.116

Table A.2: Summary of dynamic optimal bilateral portfolio weights

Pair	Mean	Std. Dev.	5%	95%	HE	p-value
GLOBALX_ETF – AMPLIFY_ETF	0.835	0.298	0.000	1.000	-0.020	0.984
GLOBALX_ETF – INVESCO_FINTECH_ETF	0.824	0.158	0.548	1.000	0.091*	0.058
GLOBALX_ETF – BTC	0.093	0.080	0.000	0.230	-3.363***	0.000
GLOBALX_ETF – ETH	0.043	0.056	0.000	0.162	-6.774***	0.000
GLOBALX_ETF – BNB	0.070	0.087	0.000	0.268	-7.506***	0.000
GLOBALX_ETF – FINANCIAL_SELECT_FUND	0.735	0.300	0.063	1.000	0.009	0.274
GLOBALX_ETF – ISHARES_US_ETF	0.757	0.252	0.249	1.000	0.052	0.124
GLOBALX_ETF – SPDR_ETF	0.806	0.235	0.298	1.000	0.039	0.281
GLOBALX_ETF – US_GLOBALJETS_ETF	0.464	0.260	0.000	0.891	-0.361	0.112
GLOBALX_ETF – ISHARES_TRVL_ETF	0.655	0.226	0.207	0.971	0.157***	0.005
GLOBALX_ETF – INVESCO_ETF	0.777	0.303	0.011	1.000	-0.091	0.953
AMPLIFY_ETF – GLOBALX_ETF	0.165	0.298	0.000	1.000	-0.274***	0.000
AMPLIFY_ETF – INVESCO_FINTECH_ETF	0.688	0.207	0.360	1.000	0.089*	0.055
AMPLIFY_ETF – BTC	0.066	0.061	0.000	0.173	-4.551***	0.000
AMPLIFY_ETF – ETH	0.032	0.042	0.000	0.128	-8.767***	0.000
AMPLIFY_ETF – BNB	0.045	0.060	0.000	0.175	-9.765***	0.000
AMPLIFY_ETF – FINANCIAL_SELECT_FUND	0.685	0.313	0.042	1.000	0.012	0.439
AMPLIFY_ETF – ISHARES_US_ETF	0.698	0.273	0.207	1.000	0.050	0.240
AMPLIFY_ETF – SPDR_ETF	0.719	0.274	0.255	1.000	0.036	0.358
AMPLIFY_ETF – US_GLOBALJETS_ETF	0.257	0.195	0.000	0.627	-0.663***	0.000
AMPLIFY_ETF – ISHARES_TRVL_ETF	0.541	0.225	0.161	0.859	0.106**	0.037
AMPLIFY_ETF – INVESCO_ETF	0.679	0.322	0.000	1.000	-0.116	0.717
INVESCO_FINTECH_ETF – GLOBALX_ETF	0.176	0.158	0.000	0.452	-0.614***	0.000
INVESCO_FINTECH_ETF – AMPLIFY_ETF	0.312	0.207	0.000	0.640	-0.297**	0.019
INVESCO_FINTECH_ETF – BTC	0.069	0.071	0.000	0.197	-6.926***	0.000
INVESCO_FINTECH_ETF – ETH	0.040	0.053	0.000	0.161	-12.836***	0.000
INVESCO_FINTECH_ETF – BNB	0.048	0.073	0.000	0.221	-14.366***	0.000
INVESCO_FINTECH_ETF – FINANCIAL_SELECT_FUND	0.520	0.257	0.095	0.947	-0.142	0.825
INVESCO_FINTECH_ETF – ISHARES_US_ETF	0.490	0.217	0.120	0.856	-0.043	0.314
INVESCO_FINTECH_ETF – SPDR_ETF	0.464	0.197	0.145	0.816	0.006	0.521
INVESCO_FINTECH_ETF – US_GLOBALJETS_ETF	0.230	0.158	0.000	0.565	-1.260***	0.000
INVESCO_FINTECH_ETF – ISHARES_TRVL_ETF	0.402	0.306	0.000	0.899	-0.354***	0.001
INVESCO_FINTECH_ETF – INVESCO_ETF	0.469	0.236	0.000	0.877	-0.304	0.459
BTC – GLOBALX_ETF	0.907	0.080	0.770	1.000	0.099	0.141
BTC – AMPLIFY_ETF	0.934	0.061	0.827	1.000	0.083	0.210
BTC – INVESCO_FINTECH_ETF	0.931	0.071	0.803	1.000	0.079	0.183
BTC – ETH	0.132	0.217	0.000	0.604	-0.645***	0.000
BTC – BNB	0.234	0.278	0.000	0.886	-0.700***	0.000
BTC – FINANCIAL_SELECT_FUND	0.937	0.072	0.786	1.000	0.088	0.186
BTC – ISHARES_US_ETF	0.942	0.059	0.833	1.000	0.079	0.230
BTC – SPDR_ETF	0.947	0.056	0.843	1.000	0.071	0.281
BTC – US_GLOBALJETS_ETF	0.838	0.151	0.542	1.000	0.164**	0.013
BTC – ISHARES_TRVL_ETF	0.900	0.094	0.686	1.000	0.123**	0.041
BTC – INVESCO_ETF	0.931	0.076	0.802	1.000	0.094	0.152
ETH – GLOBALX_ETF	0.957	0.056	0.838	1.000	0.046	0.450
ETH – AMPLIFY_ETF	0.968	0.042	0.872	1.000	0.040	0.522
ETH – INVESCO_FINTECH_ETF	0.960	0.053	0.839	1.000	0.044	0.441
ETH – BTC	0.868	0.217	0.396	1.000	0.022	0.756
ETH – BNB	0.555	0.301	0.042	1.000	-0.060	0.626
ETH – FINANCIAL_SELECT_FUND	0.965	0.047	0.862	1.000	0.050	0.433
ETH – ISHARES_US_ETF	0.966	0.042	0.878	1.000	0.044	0.475
ETH – SPDR_ETF	0.970	0.038	0.890	1.000	0.039	0.526
ETH – US_GLOBALJETS_ETF	0.898	0.119	0.745	1.000	0.117*	0.062
ETH – ISHARES_TRVL_ETF	0.939	0.066	0.828	1.000	0.076	0.188
ETH – INVESCO_ETF	0.963	0.054	0.841	1.000	0.051	0.426
BNB – GLOBALX_ETF	0.930	0.087	0.732	1.000	0.050	0.356
BNB – AMPLIFY_ETF	0.955	0.060	0.825	1.000	0.038	0.484
BNB – INVESCO_FINTECH_ETF	0.952	0.073	0.779	1.000	0.035	0.487
BNB – BTC	0.766	0.278	0.114	1.000	0.081	0.341
BNB – ETH	0.445	0.301	0.000	0.958	0.037	0.988
BNB – FINANCIAL_SELECT_FUND	0.956	0.072	0.780	1.000	0.042	0.442

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Table A2: Summary of dynamic optimal bilateral portfolio weights (continued)

Pair	Mean	Std. Dev.	5%	95%	HE	p-value
BNB – ISHARES_US_ETF	0.956	0.065	0.790	1.000	0.041	0.469
BNB – SPDR_ETF	0.959	0.059	0.826	1.000	0.037	0.499
BNB – US_GLOBALJETS_ETF	0.876	0.147	0.652	1.000	0.103*	0.076
BNB – ISHARES_TRVL_ETF	0.931	0.091	0.736	1.000	0.067	0.223
BNB – INVESCO_ETF	0.951	0.076	0.834	1.000	0.047	0.401
FINANCIAL_SELECT_FUND – GLOBALX_ETF	0.265	0.300	0.000	0.937	-0.539***	0.000
FINANCIAL_SELECT_FUND – AMPLIFY_ETF	0.315	0.313	0.000	0.958	-0.228***	0.001
FINANCIAL_SELECT_FUND – INVESCO_FINTECH_ETF	0.480	0.257	0.053	0.905	0.002	0.881
FINANCIAL_SELECT_FUND – BTC	0.063	0.072	0.000	0.214	-5.862***	0.000
FINANCIAL_SELECT_FUND – ETH	0.035	0.047	0.000	0.138	-11.020***	0.000
FINANCIAL_SELECT_FUND – BNB	0.044	0.072	0.000	0.220	-12.327***	0.000
FINANCIAL_SELECT_FUND – ISHARES_US_ETF	0.424	0.380	0.000	1.000	-0.050	0.361
FINANCIAL_SELECT_FUND – SPDR_ETF	0.360	0.369	0.000	1.000	-0.108**	0.042
FINANCIAL_SELECT_FUND – US_GLOBALJETS_ETF	0.104	0.149	0.000	0.409	-1.164***	0.000
FINANCIAL_SELECT_FUND – ISHARES_TRVL_ETF	0.406	0.217	0.138	0.796	-0.044	0.592
FINANCIAL_SELECT_FUND – INVESCO_ETF	0.426	0.334	0.000	1.000	-0.191	0.122
ISHARES_US_ETF – GLOBALX_ETF	0.243	0.252	0.000	0.751	-0.526***	0.000
ISHARES_US_ETF – AMPLIFY_ETF	0.302	0.273	0.000	0.793	-0.225***	0.004
ISHARES_US_ETF – INVESCO_FINTECH_ETF	0.510	0.217	0.144	0.880	0.056	0.277
ISHARES_US_ETF – BTC	0.058	0.059	0.000	0.167	-6.183***	0.000
ISHARES_US_ETF – ETH	0.034	0.042	0.000	0.122	-11.531***	0.000
ISHARES_US_ETF – BNB	0.044	0.065	0.000	0.210	-12.828***	0.000
ISHARES_US_ETF – FINANCIAL_SELECT_FUND	0.576	0.380	0.000	1.000	-0.088	0.452
ISHARES_US_ETF – SPDR_ETF	0.385	0.368	0.000	1.000	-0.065	0.225
ISHARES_US_ETF – US_GLOBALJETS_ETF	0.137	0.163	0.000	0.481	-1.203***	0.000
ISHARES_US_ETF – ISHARES_TRVL_ETF	0.424	0.207	0.139	0.806	-0.029	0.917
ISHARES_US_ETF – INVESCO_ETF	0.433	0.331	0.000	1.000	-0.246	0.119
SPDR_ETF – GLOBALX_ETF	0.194	0.235	0.000	0.702	-0.555***	0.000
SPDR_ETF – AMPLIFY_ETF	0.281	0.274	0.000	0.745	-0.249**	0.040
SPDR_ETF – INVESCO_FINTECH_ETF	0.536	0.197	0.184	0.855	0.094**	0.043
SPDR_ETF – BTC	0.053	0.056	0.000	0.157	-6.284***	0.000
SPDR_ETF – ETH	0.030	0.038	0.000	0.110	-11.669***	0.000
SPDR_ETF – BNB	0.041	0.059	0.000	0.174	-12.959***	0.000
SPDR_ETF – FINANCIAL_SELECT_FUND	0.640	0.369	0.000	1.000	-0.154	0.452
SPDR_ETF – ISHARES_US_ETF	0.615	0.368	0.000	1.000	-0.071	0.977
SPDR_ETF – US_GLOBALJETS_ETF	0.152	0.181	0.000	0.542	-1.226***	0.000
SPDR_ETF – ISHARES_TRVL_ETF	0.446	0.227	0.132	0.821	-0.041	0.879
SPDR_ETF – INVESCO_ETF	0.495	0.363	0.000	1.000	-0.317	0.111
US_GLOBALJETS_ETF – GLOBALX_ETF	0.536	0.260	0.109	1.000	0.045	0.617
US_GLOBALJETS_ETF – AMPLIFY_ETF	0.743	0.195	0.373	1.000	0.065	0.215
US_GLOBALJETS_ETF – INVESCO_FINTECH_ETF	0.770	0.158	0.435	1.000	0.107**	0.037
US_GLOBALJETS_ETF – BTC	0.162	0.151	0.000	0.458	-1.844***	0.000
US_GLOBALJETS_ETF – ETH	0.102	0.119	0.000	0.255	-4.046***	0.000
US_GLOBALJETS_ETF – BNB	0.124	0.147	0.000	0.348	-4.638***	0.000
US_GLOBALJETS_ETF – FINANCIAL_SELECT_FUND	0.896	0.149	0.591	1.000	0.022	0.512
US_GLOBALJETS_ETF – ISHARES_US_ETF	0.863	0.163	0.519	1.000	0.039	0.315
US_GLOBALJETS_ETF – SPDR_ETF	0.848	0.181	0.458	1.000	0.035	0.397
US_GLOBALJETS_ETF – ISHARES_TRVL_ETF	0.759	0.155	0.488	1.000	0.116**	0.030
US_GLOBALJETS_ETF – INVESCO_ETF	0.946	0.155	0.630	1.000	0.008	0.790
ISHARES_TRVL_ETF – GLOBALX_ETF	0.345	0.226	0.029	0.793	-0.086**	0.049
ISHARES_TRVL_ETF – AMPLIFY_ETF	0.459	0.225	0.141	0.839	0.078	0.207
ISHARES_TRVL_ETF – INVESCO_FINTECH_ETF	0.598	0.306	0.101	1.000	0.018	0.799
ISHARES_TRVL_ETF – BTC	0.100	0.094	0.000	0.314	-4.474***	0.000
ISHARES_TRVL_ETF – ETH	0.061	0.066	0.000	0.172	-8.704***	0.000
ISHARES_TRVL_ETF – BNB	0.069	0.091	0.000	0.264	-9.767***	0.000
ISHARES_TRVL_ETF – FINANCIAL_SELECT_FUND	0.594	0.217	0.204	0.862	0.133***	0.005
ISHARES_TRVL_ETF – ISHARES_US_ETF	0.576	0.207	0.194	0.861	0.176***	0.002
ISHARES_TRVL_ETF – SPDR_ETF	0.554	0.227	0.179	0.868	0.171**	0.024
ISHARES_TRVL_ETF – US_GLOBALJETS_ETF	0.241	0.155	0.000	0.512	-0.624***	0.000
ISHARES_TRVL_ETF – INVESCO_ETF	0.537	0.197	0.200	0.828	0.038**	0.021

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Table A2: Summary of dynamic optimal bilateral portfolio weights (continued)

Pair	**Mean**	**Std. Dev.**	**5%**	**95%**	**HE**	**p-value**
INVESCO_ETF – GLOBALX_ETF	0.223	0.303	0.000	0.989	-0.372***	0.000
INVESCO_ETF – AMPLIFY_ETF	0.321	0.322	0.000	1.000	-0.124**	0.026
INVESCO_ETF – INVESCO_FINTECH_ETF	0.531	0.236	0.123	1.000	0.077	0.206
INVESCO_ETF – BTC	0.069	0.076	0.000	0.198	-4.522***	0.000
INVESCO_ETF – ETH	0.037	0.054	0.000	0.159	-8.720***	0.000
INVESCO_ETF – BNB	0.049	0.076	0.000	0.166	-9.740***	0.000
INVESCO_ETF – FINANCIAL_SELECT_FUND	0.574	0.334	0.000	1.000	0.035	0.614
INVESCO_ETF – ISHARES_US_ETF	0.567	0.331	0.000	1.000	0.026	0.721
INVESCO_ETF – SPDR_ETF	0.505	0.363	0.000	1.000	-0.024	0.494
INVESCO_ETF – US_GLOBALJETS_ETF	0.054	0.155	0.000	0.370	-0.778***	0.000
INVESCO_ETF – ISHARES_TRVL_ETF	0.463	0.197	0.172	0.800	0.061	0.277

Figure A.2: Cumulative profits of diversification strategies with median hedge ratios and portfolio weights to construct portfolio (Part 1)

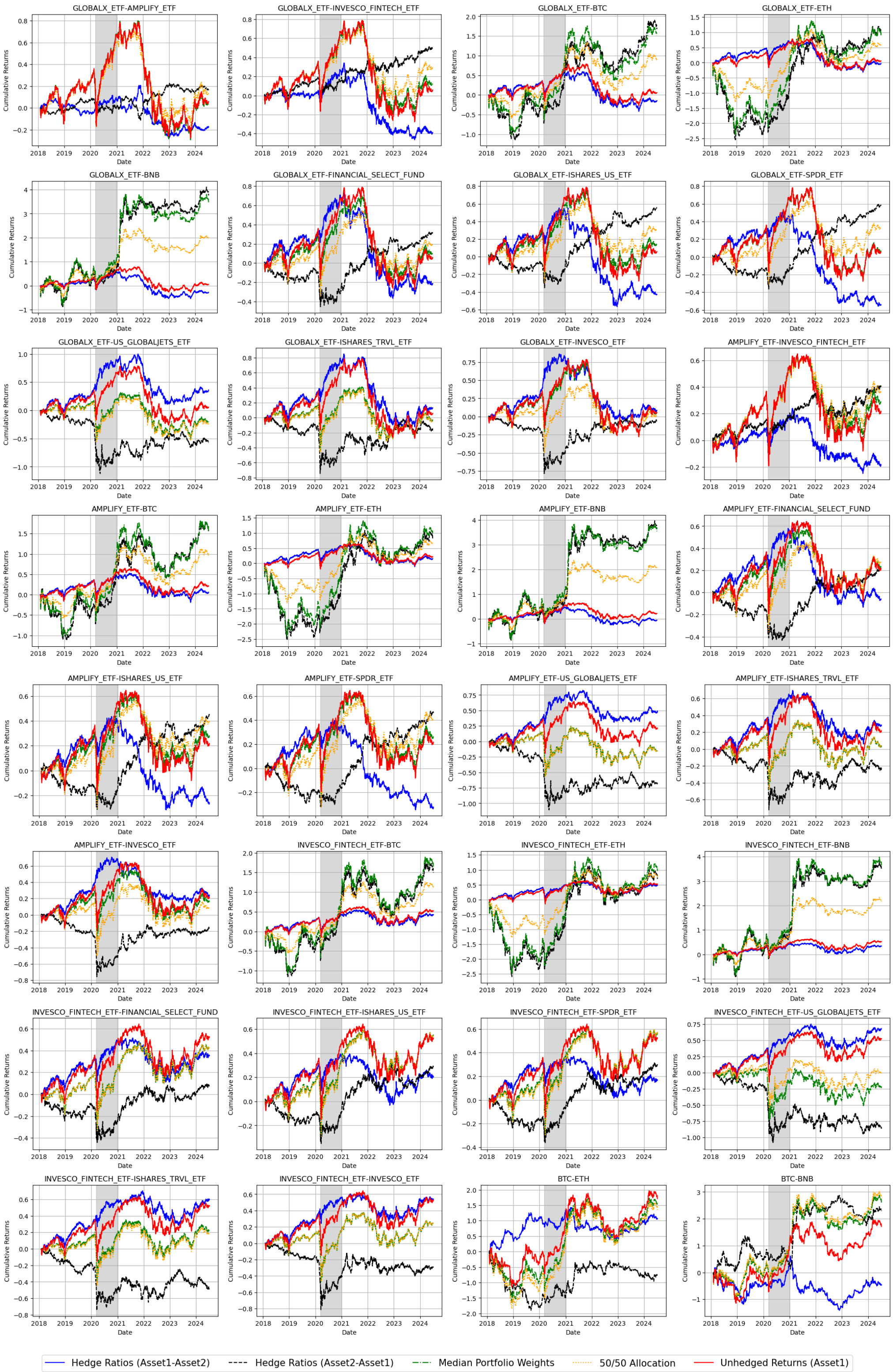
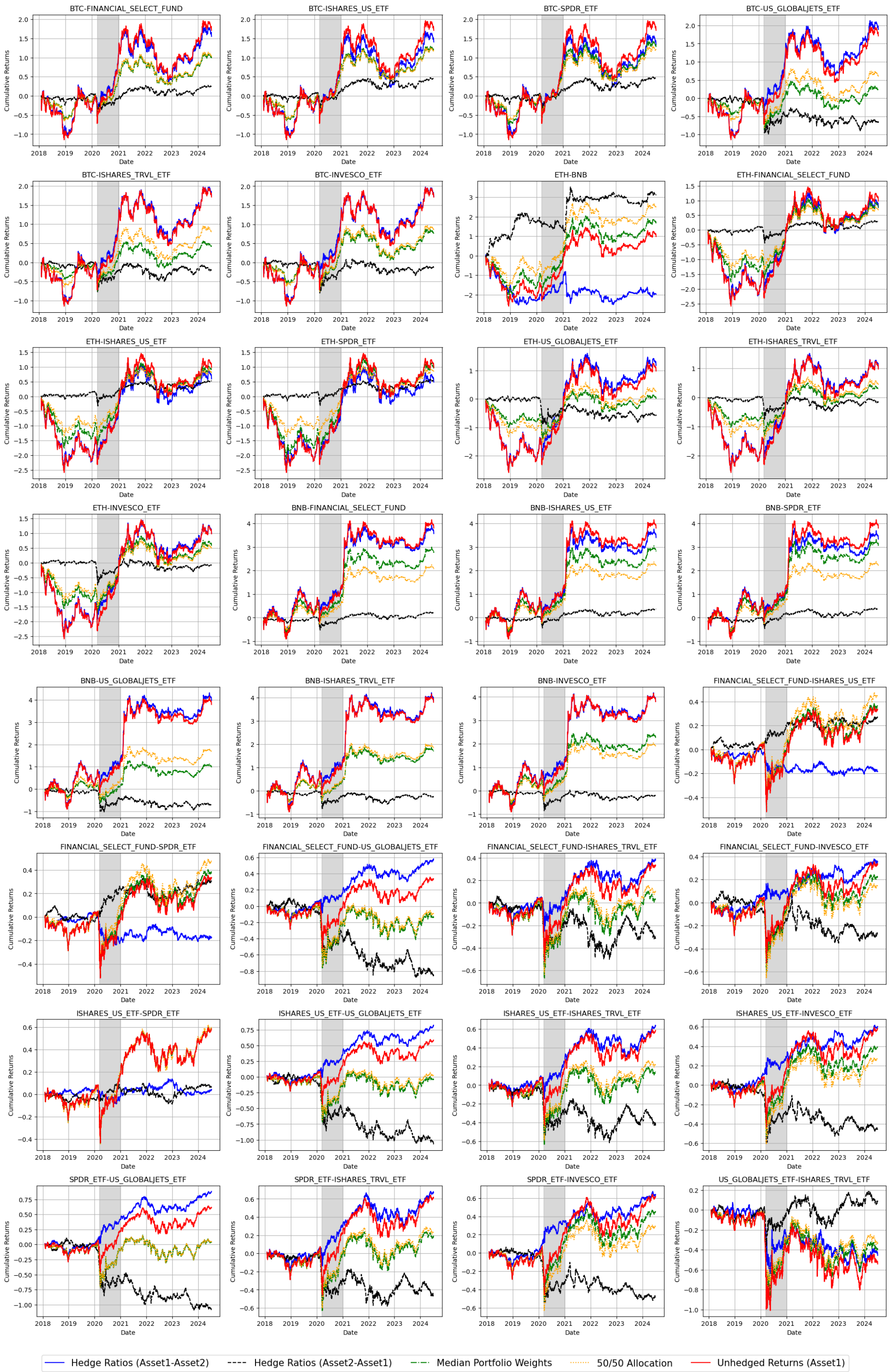


Figure A.3: Note: The grey-shaded area is the first year when COVID-19 was declared a pandemic (2020-03-11 to 2020-12-31).

Figure A.3: Cumulative profits of diversification strategies with median hedge ratios and portfolio weights to construct portfolio (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 A.3: Cumulative profits of diversification strategies with median hedge ratios and portfolio weights to construct portfolio (Part 3)

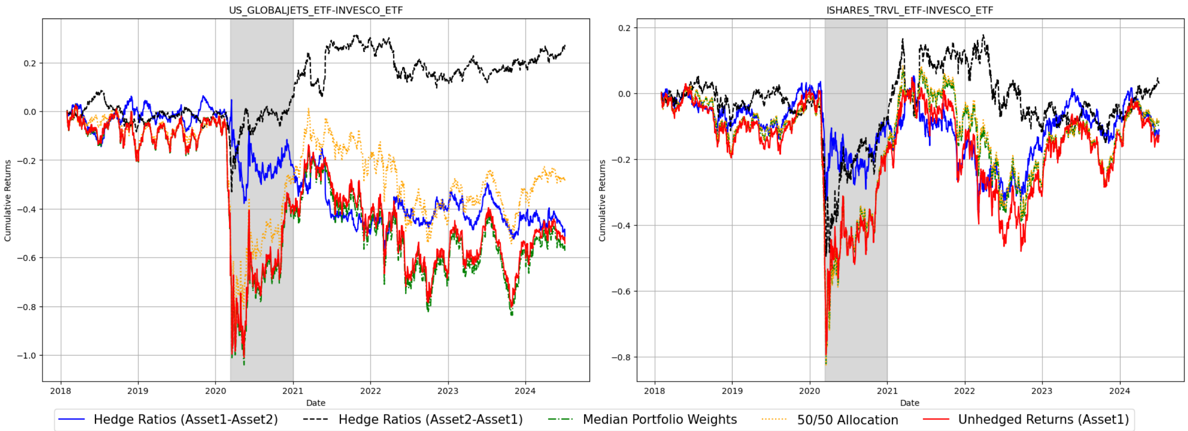


Figure A.4: Note: The grey-shaded area is the first year when COVID-19 was declared a pandemic (2020-03-11 to 2020-12-31).