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Volatility spillovers, structural breaks and uncertainty in technology sector markets

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Abstract

This study uses the dynamic conditional correlation to investigate how technology subsector stocks interact with financial assets in the face of economic and financial uncertainty. Our results suggest that structural breaks have diverse effects on financial asset connectedness and that the level of bond linkage increases when the trend breaks. We see a growing co-movement between the technology sector and major financial assets when uncertainty is considered. Overall, our findings indicate that the connectedness response varies depending on the type of uncertainty shock.

Keywords: Technology sector, Diversification, Dynamic conditional correlation, Uncertainty, Structural breaks

Introduction

Nowadays, investment in technology and innovation is a critical component of creating a favorable market environment and promoting social development (Ma et al. 2021). With ever-increasing market competitiveness, technological investment and development in the manufacturing process have become hot areas for study in recent years (Metzger and Schinas 2019; Chen et al. 2020; Liu and De Giovanni 2019). In this study, we focus on the entire tech sector and its sub-sectors—information technology (IT), biotech, cleantech, fintech, and cryptocurrency—to explore their hedging and diversification opportunities. Portfolio diversification is a fundamental financial strategy in which the common practice is to allocate the portfolio between different asset classes and industries, resulting in minimizing the portfolio's risk. The technology sector might have diversification and hedging features, including several subsectors engaging different businesses. Therefore, advancing technology sectors through investments may establish a promising market atmosphere and social development and improve the business's scope worldwide (Ma et al. 2021).

The global financial crisis (GFC) in 2008 started in the banking system and spread throughout international financial markets (Hasan et al. 2021b), affecting most industries, including the tech sectors. With the spread of the COVID-19 pandemic, people, businesses, and governments again face uncertainty (Ji et al. 2020; Hasan et al. 2021c). However, in this case, the tech industry can play a critical role in transitioning to a different way of living. Companies specializing in facilitating operations, such as video-conference newcomer Zoom and food delivery, have surged during the virus outbreak (Economist 2020a). Given the various causes of uncertainty and the channels by which it influences tech, the impacts of uncertainty in the tech sector and its subsectors are likely to vary. For investment purposes, it is therefore essential to analyze the dynamics of the tech sector in its entirety as well as within its subsectors. According to IDC's forecast for 2018, 60% of the global gross domestic product will be digitalized by 2022.[1]

The potential of the tech sector and its subsectors indicates the need for further knowledge of its relationship with the financial markets. Furthermore, we should acknowledge the risks and uncertainties associated with these sectors. Bloom (2014) shows that rising uncertainty adversely impacts some industries. Adverse events such as cyberattacks increase uncertainty, and investment behavior tends to change during uncertain times.

During uncertain times, investors show higher risk aversion (Bloom 2014; Matkovskyy and Jalan 2019). Due to the significant risk and uncertainty in the biotech industry, a lack of investment endangers its development. According to Statista (2020), the predicted internal rate of return on investment in biotech R&D for large-cap corporations fell from 10.1% to around 2% between 2010 and 2018. Although uncertainty appears to deter investment in tech, Bloom (2014) shows that it may drive R&D, which is critical in the tech industry. As a result, studying how uncertainty impacts the tech subsectors is of particular interest.

For tech companies to seize investment opportunities and attract investors, it is vital to understand the movements over the business cycle, how the sector correlates to the rest of the financial markets, and how uncertainty affects market co-movement. Therefore, our primary purpose is to investigate the characteristics of several technology subsectors and their dependency on the financial markets. Second, we analyze the impacts of uncertainty on market connectedness. We address these aims by posing the following research questions, having investor implications.

1. How are the different technology subsectors correlated with the financial market, and how does this dependency structure differ over time?
2. How do breakpoints and uncertainty impact the connectedness between the technology subsectors and the financial market?

We compile daily price data from 2000 to 2020 for six tech variables and seven financial assets indices. We then estimate multivariate generalized autoregressive conditional heteroscedasticity (GARCH)-type models based on the dynamic conditional correlation (DCC) method. Furthermore, we include structural breaks, identified by Bai and Perron (1998, 2003) tests, and uncertainty measures. The results indicate that breaks and uncertainty affect the correlation between the studied variables. Multiple breakpoints in the same series may cause the level of connection to increase after one break and decrease after another. However, we note that the connectedness between all tech variables and bonds increases over time following a breakpoint in the trend. The uncertainties have

[1] https://www.businesswire.com/news/home/20171215005055/en/IDC-Forecasts-Worldwide-Spending-on-Digital-Transformation-Technologies-in-2018-to-Reach-1.3-Trillion-in-2018.

diverse effects on the interconnectivity, but uncertainty generally increases the correlation between the tech variables and financial assets.

This study offers four significant contributions to the extant literature. First, the study brings a new perspective to the economic literature by scrutinizing the relationship between the financial market and the overall technology sector and its subsectors in a cohesive way, different from existing studies that concentrate on a single subsector or a subset of subsectors (e.g., Thakor et al. 2017; Bouri et al. 2017a, b; Unsal and Rayfield 2019). Second, given the constant evolution of technology, the attempt to capture changes in the dynamic time-varying correlations between tech variables and financial assets. Moreover, the study investigates the dynamic correlation structure using structural breaks and different uncertainty measures, providing insights into uncertain periods. Finally, the study utilizes empirical findings to create optimal portfolio strategies with important implications for tech investors.

The remainder of this paper proceeds as follows. "Literature review" section provides a review of the previous literature. "Methodology" section describes the methodology, while the data and the preliminary analysis are presented in "Data and preliminary analysis" section. "Empirical results and discussion" section analyzes the empirical results. "Conclusion and policy implications" section provides conclusions and policy implications.

Literature review

In this section, we discuss previous academic research on technology from economic and financial perspectives. As we investigate different tech sectors and their relationships with the financial market, we focus on the literature on the business cycles of tech sectors, financial properties, diversification opportunities, and risk measurement.

Business cycles of the technology sector

New emerging technologies have recently boosted enterprises' speed and magnitude of change. The historic decline in the average life span of a firm included in the S&P 500 demonstrates that technology significantly impacts business and necessitates regular adjustments for a company with speed and alertness to maintain its competitiveness (Schwab 2017). These circumstances are especially applicable to tech-based businesses. In particular, clean energy stocks are vulnerable to business cycle fluctuations, implying that investors tend not to invest in clean energy stocks during low economic activity (Kocaarslan and Soytas 2019).

Despite the decades-long existence of the biotech sector, biotech-based products usually take between 1 and 2 decades and millions of dollars to develop, and the industry is slow-moving (Thakor et al. 2017). Lo (2015) finds that the biotech and pharmaceutical industries face considerable challenges because investors withdrew capital from this sector due to weak investment returns.

Following the 2008 GFC, the fintech sector has evolved rapidly, changing the financial landscape in banking, payments, investments, and money systems (Palmié et al. 2020). The fintech ecosystem is driven mainly by entrepreneurial and innovative start-up companies (Lee and Shin 2018). In addition to incumbents in the traditional financial market, venture capital investment plays a critical role in creating pioneering enterprises in this area (Cumming and Schwienbacher 2018; Haddad and Hornuf 2019). They discovered that following the 2008 GFC, investments in fintech surged, with more noticeable in nations lacking a significant financial hub. Unsal and Rayfield (2019) analyze trends in financial innovations by looking at the number of patent filings by fintech firms and find that patent activity decreased in 2000 and 2008, attributed to the dot-com bubble and the financial crisis, respectively, suggesting that the fintech sector moves in lockstep with the financial market. Recently, during COVID-19, according to Bao and Huang (2021), fintech firms favored financing for new and financially constrained firms, influencing business behavior through shadow banking. Similarly, Zachariadis et al. (2020) suggest that investors support fintech investments whose services may improve clients' financial well-being, despite the projected economic catastrophe following COVID-19.

Recently, cryptocurrency has become the top research agenda for researchers. Most studies focus on Bitcoin, revealing inconclusive outcomes. Dyhrberg (2016) finds that Bitcoin has financial asset properties between gold and USD, while Baur et al. (2018) suggest it as a distinct asset from both fiat currency and gold. Alfieri et al. (2019) argue that Bitcoin has the nature of common stocks, and their performance should be assessed accordingly.

Portfolio diversification properties of the technology sector

Diversification benefits have long been recognized in the biopharma industry; however, achieving them is difficult due to the huge capital required, the long time horizon, and private partnerships. However, Lo (2015) and Lo and Pisano (2016) propose an alternative for funding biomedical innovation: forming an extensive diversified portfolio of biomedical projects at various stages of development.

Bitcoin recently emerged as an effective diversifier when included in traditional portfolios (Bouri et al. 2017a; Alfieri et al. 2019). Baur et al. (2018) and Corbet et al. (2018) show that cryptocurrencies have unique risk-return characteristics, are uncorrelated with other financial assets, and thus have diversification benefits. Bouri et al. (2020) find evidence that cryptocurrencies are hedges against the equity market, but none are safe havens. However, an asymmetric correlation exists between cryptocurrencies and equities, indicating cross-relationship heterogeneity (Kristjanpoller et al. 2020). Also, Ji et al. (2019) and Kurka (2019) find that cryptocurrencies are strongly associated with commodities.

There is a strong correlation between clean energy and technology companies (Nasreen et al. 2020). Ahmad et al. (2018) find that clean energy equities are effective hedges for crude oil futures and technology, with more effective for crude oil futures. Dutta et al. (2020) report similar conclusions, claiming that commodity market volatility indexes can help diversify clean energy equity market risks. Nasreen et al. (2020) find that clean energy and technology stock indices are a good hedge for the oil market. According to Kocaarslan and Soytas (2019), investments in clean energy stocks grow positively and negatively associated with an increase in oil prices in the short and long runs, respectively.

Uncertainty and risk in the technology sector

As the tech sector is driven by innovation and inventions, the technological revolution is associated with periods of greater experimentation, with a few successful projects and a larger number of failures (Schwab 2017). This is referred to as financing risk by Nanda and Rhodes-Kropf (2017), which means that funding in innovative firms is erratic. Ryu and Ko (2020) suggest that because of the intricacy and unpredictability, though innovative, of Fintech transactions compared with the other traditional means, uncertainty is inextricably linked with it. However, the lower the level of uncertainty and the higher the usefulness, ease, and innovation of fintech, the greater the intention to utilize fintech (Um et al. 2020). For instance, economic policy uncertainty (EPU) and cryptocurrencies are shown to be intertwined (Koumba et al. 2020). The result is supported by Dyhrberg (2016) and Platanakis and Urquhart (2019), who find that Bitcoin is a suitable asset for the risk-averse investor when anticipating adverse times. Bouri et al. (2017b) and Demir et al. (2018) show that Bitcoin can act as a hedge against global uncertainty.

Furthermore, Wu et al. (2019) reveal that Bitcoin doesn't act as a strong hedge or a safe haven; instead, it can provide weak safe-haven property against EPU. Conversely, Yen and Cheng (2021) suggest that Bitcoin can be utilized as a hedge or diversifier against EPU. However, Hasan et al. (2021a) argue that Bitcoin cannot exhibit a hedge and safe haven against cryptocurrency policy uncertainty. On the other hand, Corbet et al. (2019) discovered that the US monetary policy changes have a significant volatility spillover on currency-based assets, but protocol and application-based assets are mostly immune.[2]

The prior studies suggest that the banking industry must shift from traditional financial institutions and firms to meet customer demand for fintech services (Romanova and Kudinska 2016; Navaretti et al. 2018; Zveryakov et al. 2019). Moreover, Banna et al. (2021) unearth that the more fintech-based financial inclusion in the banking industry, the more the risk-taking behavior of banks is observed. Accepting an innovative financial landscape might benefit incumbents, increasing efficiency and competitiveness. However, a regulatory perspective, along with adaptation, is needed to ensure financial stability (He et al. 2017).

A few attributes have been identified from the earlier literature discussed above, which aided us in finding lacunas regarding the tech sector literature. The literature on the tech sector has primarily focused on the diversification and portfolio implications of the Bitcoin market, but little attention has been given to other critical sub-sectors of the tech sector, such as IT, biotech, cleantech, and fintech. These sectors play a vital role in promoting technological innovation and societal development, yet their potential for diversification and hedging opportunities against various financial markets and uncertainty indicators has been overlooked in earlier research. Furthermore, earlier studies have failed to assess the link between tech sectors and the financial market and the impact of uncertainties. Understanding the movements of tech sectors throughout the business cycle and their interaction with financial markets is crucial, especially in light of market uncertainty. Therefore, this study aims to bridge these gaps in the existing literature by

[2] Protocol-based assets are usually digital assets used as a blockchain foundation, which serve as a platform for building other applications. Similarly, the application-based assets are the applications integrate a user-friendly interface with a decentralized back-end, constracted on top of an existing blockchain.

exploring the diversification and hedging opportunities of critical sub-sectors within the tech sector and assessing their interactions with the financial market while considering the impact of structural time breaks and uncertainties.

Methodology

The multivariate GJR-GARCH-DCC model

This study employs Engle's (2002) multivariate dynamic conditional correlation (DCC) model, which captures the time variation of the conditional correlations between tech investments. Unlike other multivariate GARCH models, the DCC model can handle the dimensionality problem by decomposing the conditional covariance matrix (Pham 2019). Using the Glosten et al. (1993) (GJR) model, which is based on the Generalized Autoregressive Conditional Heteroscedasticity (GARCH), the DCC method is thus termed the DCC-GJR-GARCH-model. The GJR-GARCH model may handle asymmetric consequences, including leverage effects, by responding to lower or higher volatility for favorable or unfavorable shocks, respectively (Al Mamun et al. 2020; Hassan et at. 2021). Consider a vector of n return series $r_{i,t} = [r_{1,t}, \ldots, r_{n,t}]$. We assume that following AR(1), DCC-GJR-GARCH[3] model describes the return-generating process:

$$r_{i,t} = \mu_i + \psi_i r_{i,t-1} + \varepsilon_{i,t}, \tag{1}$$

where $|\mu_i| \in [0, \infty)$,$|\psi_i| < 1$, and $\varepsilon_{i,t} = [\varepsilon_{i,t}, \ldots, \varepsilon_{n,t}]$ is the vector of the residuals. We specify the conditional volatilities $h_{i,t}$ from the univariate GARCH (1,1) as

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta h_{i,t-1}^2, \tag{2}$$

where $\omega_i > 0$, $\alpha_i \geq 0$, and $\beta_i \geq 0$. Next, we apply the GJR-GARCH model by Glosten et al. (1993) to capture the asymmetric effects of volatility. We can describe the univariate GJR-GARCH (1,1) processed by

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}^2 + \gamma_i I_{t-1} \varepsilon_{i,t-1}^2, \tag{3}$$

where I_{t-1} is an indicator that takes the value of unity if $\varepsilon_{t-1} > 0$ and zero otherwise. The parameter γ_i captures the asymmetric impact of positive and negative shocks. When $\gamma_i > 0$, negative shocks have more impact on volatility than positive shocks.

To estimate the conditional correlation matrix across tech investment returns, we obtain the dynamic correlations using the conditional variance—covariance matrix,H_t:

$$H_t = D_t^{1/2} R_t D_t^{1/2}, \tag{4}$$

where $D_t = diag\left(\sqrt{h_{i,t}}, \ldots, \sqrt{h_{n,t}}\right)$ is a diagonal matrix of time-varying variances H_t from the univariate GJR-GARCH process and R_t is the $n \times n$ time-varying conditional correlation matrix of the standardized residuals. The conditional correlation matrix R_t is

$$R_t = \left\{Q_t^*\right\}^{-1/2} Q_t \left\{Q_t^*\right\}^{-1/2}, \tag{5}$$

[3] The GJR-GARCH (1, 1) model is used with one lag for both the variance and squared residual terms in the GARCH-part based on the Schwarz Information Criterion (SIC).

where an element of R_t has the following form:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{ii,t} q_{jj,t}}}, \tag{6}$$

where $Q_t^* = diag[Q_t]$ are the diagonal elements of the covariance matrix Q_t. The covariance matrix Q_t of the DCC model evolves according to

$$Q_t \equiv \left[q_{i,j,t}\right] = (1 - \alpha_{dcc} - \beta_{dcc})S + a\left(z_{t-1}z_{t-1}^{'}\right) + bQ_{t-1}, \tag{7}$$

where $z_t = [z_{1,t}, \cdots, z_{n,t}]^{'}$ is the standardized residual (i.e., $z_{i,t} = \varepsilon_{i,t}/\sqrt{h_{i,t}}$), $S \equiv \left[s_{i,j}\right] = E\left[z_t z_t^{'}\right]$ is the $(n \times n)$ unconditional covariance matrix of z_t, and α_{dcc} and β_{dcc} are non-negative scalars satisfying $(\alpha_{dcc} + \beta_{dcc}) < 1$.

Note that following Engle (2002), we estimate the DCC model using a two-step maximum likelihood estimation method in which the log-likelihood is

$$l_t(\theta, \phi) = -\frac{1}{2}\left[\sum_{t=1}^{T}\left(nlog(2\pi) + log|D_t|^2 + \varepsilon_t^{'}D_t^{-2}\varepsilon_t\right) + \sum_{t=1}^{T}\left(log|R_t| + z_t^{'}R_t^{-1}z_t - z_t^{'}z_t\right)\right], \tag{8}$$

where θ and ϕ are the parameters in D_t and R_t, respectively. We maximize the log-likelihood function using a two-stage approach. In the first stage, we maximize the log-likelihood function over the D_t parameters in the first part of Eq. (8). In the second stage, given the estimated parameters in the first stage, we maximize the correlation component of the likelihood function (the second part of Eq. [8]) to estimate the correlation coefficients.

Structural breaks

The structural variations or structural breaks are unforeseen shifts that arise in time-series data as a result of any event, which may cause predicting errors or render the model unreliable. In this case, Bai and Perron's (2003) multiple structural break test can be suggested, as it captures multiple breaks in a time series. The Bai—Perron test captures structural fractures better than the Chow or other tests because it allows for many structural breaks and automatically recognizes them. The Bai—Perron test also results for different periods identified by breaks. This allows for a better understanding of the influence over time. Since it is preferable to avoid predetermining the number of breaks and it may be unknown whether there are none or several breakpoints in the series, they propose that it is useful to first check for at least one break using the double maximum tests: UDmax and VDmax. If the double maximum tests identify breaks, then the second step is to use a sequential examination of $supF(\ell + 1|\ell)$, which is a test of ℓ against $\ell + 1$ number of breaks. The null hypothesis is no structural break against the alternative hypothesis of a single break.

Data and preliminary analysis

The data set consists of two parts. The first includes six variables representing the tech sector and its subsectors, namely the NYSE Arca Technology 100 Index (ATE), MSCI World Information Technology (MIT), NYSE Arca Biotechnology (ABI), S&P Clean

Energy (SPC), Global X Fintech ETF (FIN), and Bitcoin/USD exchange rate (BTC). The second part consists of conventional financial assets: S&P 500 (SP5), MSCI World (MWO), MSCI World ESG Leaders (ESG), crude oil (OIL), gold (GLD), US dollar and Euro (USD), and the 5-year US Treasury bond rate (BND). Given the novelty of some of the tech indices, specifically the SPC, FIN, BTC, and ESG index, we account for different start dates and use a spatial sample for these indices. The start date for the remaining ten variables is 01/01/2000, which yields 5240 daily observations for the entire sample. We chose this start date for the full sample to capture the potential effects of the dot-com bubble (2000−2002). All the variables used in the estimations are the first difference of the natural logarithm. Stock returns are collected from Thomson Reuters Eikon. We collect the Bitcoin data from CoinMarketCap. All indices are denominated in USD.

Panel A of Fig. 1 presents the price dynamics of the tech indices. Unsurprisingly, the negative effect of the dot-com bubble is most evident in the IT sector, seen by the substantial decline in MIT. However, the simultaneous decreases in ATE and ABI may indicate that the IT dot-com crisis affected the entire tech sector. Interestingly, the 2008 GFC had a minor effect on these three indices. SPC, however, declined sharply around the crisis and has not recovered to prior price levels. The biotech index showed significant drops around 2015, a clear break in the upward trend, which some suggest was a “biotech bubble burst.” The FIN and BTC price levels fell around 2018, but the remaining tech sectors also saw drops simultaneously, albeit insignificant. The price level for BTC was just about stagnant until 2017 when it increased vigorously. In the following years, BTC continued to fluctuate frequently.

Furthermore, Panel B of Fig. 1 illustrates the evolution of the stock returns of the tech indices. The return graphs confirm the suspicion that the financial crisis did not have as strong an impact on the tech sectors as the tech crisis; the spikes were not as long, and the increased volatility was not as persistent over time. Around 2012, during the European sovereign debt crisis, volatility in stock returns seemed to increase briefly. The drop in the price level for ABI around 2015 did not affect the returns as much as the financial crisis but caused a positive volatility spike. FIN return fluctuations are visible at the beginning and end of 2018. We see variations in BTC from 2018 until the end of the period, while the stock return for BTC is highly volatile over the entire sample. This finding is strengthened by the relatively high standard deviation of BTC, confirming the currency’s high volatility trait.

Table 1 presents the descriptive statistics for ten tech and financial asset returns. All the return series have positive returns during the sample periods. However, they do not follow a lognormal distribution, which we can infer from the positive skewness values for ATE, MIT, and USD and the negative values for the remaining variables. The high kurtosis values reinforce the rejection of the null hypothesis of a normal distribution, which is confirmed by the Jarque−Bera tests. Therefore, our return series follow a leptokurtic distribution, having fat tails. However, the Portmanteau Q(10) results confirm that our time series has no autocorrelation issues and the ARCH-LM test with 10 lags checks for the presence of heteroscedasticity.

Furthermore, the ADF and the PP tests convey that all the return series are stationary; thus, our non-normal or leptokurtic distribution of return series evidence a heterogeneous dependence structure. Hence, the data characteristics suggest dynamic methods

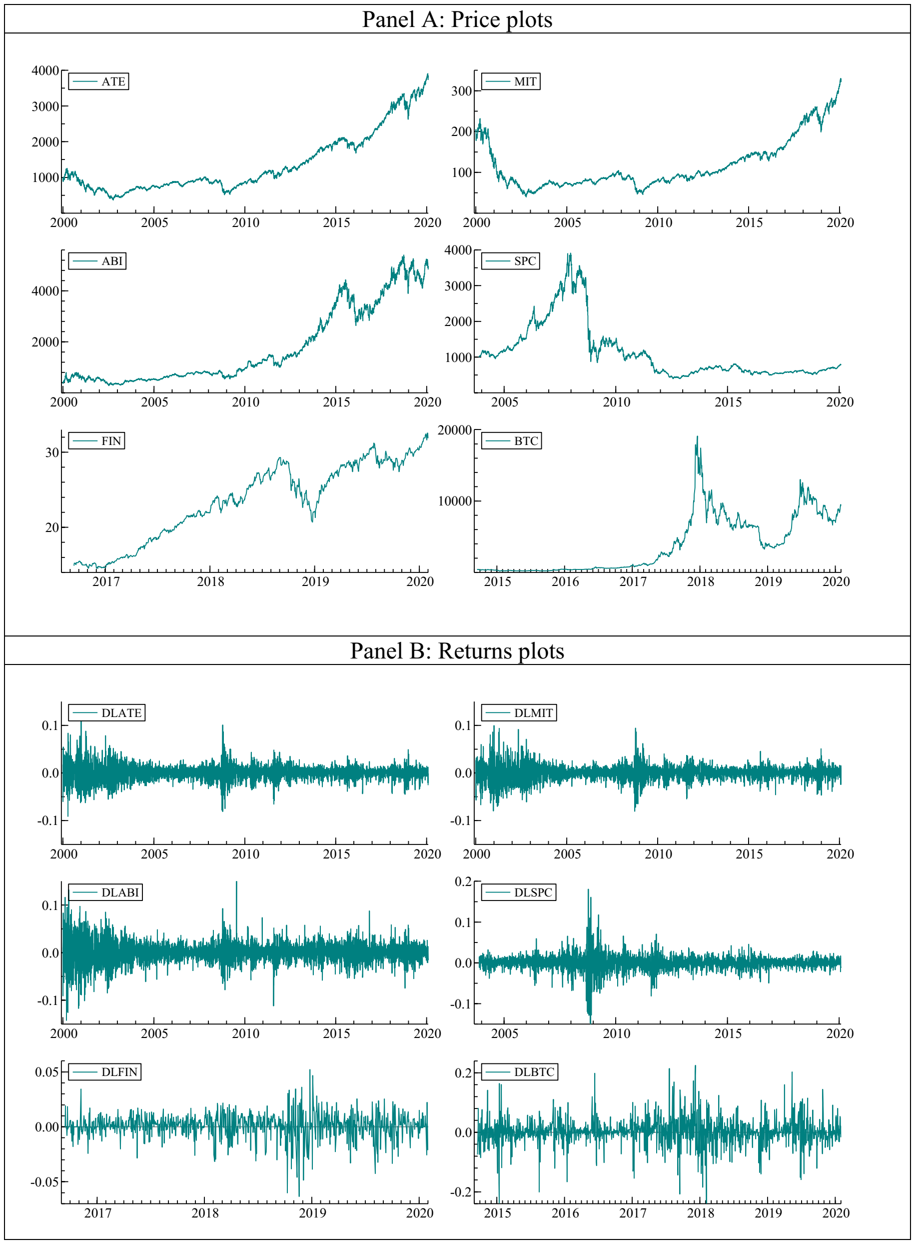


Fig. 1 Price and return plots of tech investment

such as Dynamic Conditional Correlation (DCC) model, as traditional methods may deliver an imprecise assessment of interconnectedness.

Table 2 shows the correlation matrix for the tech variables and financial assets. All tech variables correlate negatively with BND and GLD, except for SPC and BTC with GLD. With some exceptions, the rest of the financial assets positively correlate with tech variables. It is observed that the tech variables: ATE, MIT, ABI, and FIN are highly positively correlated with the SP5, MWO, and ESG indices.

Table 3 reports the structural break dates in the tech returns. We conduct separate Bai and Perron (2003) multiple break tests for breakpoints in constant only and trend

Table 1 Descriptive statistics for tech and financial assets

	Mean (%)	SD	Skewness	Kurtosis	Jarque−Bera	ADF(c)	ADF(ct)	PP	Q (10)	ARCH−LM(10)	Obs
Panel A: Technology assets											
ATE	0.026	0.015	0.047	7.670	4769.4***	−31.71(5)***	−31.77(5)***	−74.25***	16.36**	1026.0***	5240
MIT	0.009	0.014	0.016	8.305	6152.8***	−36.71(3)***	−36.83(3)***	−67.24***	23.88***	888.58***	5240
ABI	0.048	0.020	−0.080	7.766	4971.3***	−31.37(5)***	−31.37(5)***	−70.96***	24.23***	828.39***	5240
SPC	0.006	0.017	−0.569	18.21	41,034.0***	−55.59(0)***	−55.58(0)***	−55.24***	117.7***	1462.5***	4225
FIN	0.086	0.011	−0.772	6.844	636.12***	−28.70(0)***	−28.69(0)***	−28.67***	7.693	86.391***	883
BTC	0.215	0.044	−0.141	7.839	1378.9***	−36.42 (0)***	−36.41(0)***	−36.43***	7.180	96.661***	1402
Panel B: Financial assets											
SP5	0.015	0.012	−0.232	12.08	18,068.7***	−55.89(1)***	−55.93(1)***	−78.66***	59.38***	1337.5***	5240
MWO	0.010	0.010	−0.387	11.21	14,876.5***	−51.08(1)***	−51.10(1)***	−63.65***	70.64***	1519.9***	5240
ESG	0.028	0.010	−0.318	9.085	7480.3***	−61.72(0)***	−61.71(0)***	−61.41***	58.70***	1138.2***	4790
OIL	0.013	0.023	−0.112	7.427	4295.4***	−75.42(0)***	−75.42(0)***	−75.54***	26.20***	594.52***	5240
GLD	0.032	0.011	−0.216	9.267	8624.8***	−52.42(1)***	−52.43(1)***	−73.36***	10.58	224.86***	5240
USD	0.002	0.006	0.138	5.787	1715.3***	−71.63(0)***	−71.64(0)***	−71.63***	4.840	300.95***	5240
BND	0.007	0.003	−0.079	7.298	4044.5***	−54.51(1)***	−54.51(1)***	−73.79***	24.65	458.28***	5240

Jarque−Bera tests for normality. Augmented Dickey−Fuller (ADF) with constant (c) and constant plus trend (ct) test for unit roots. Philip−Perron (PP) test for unit roots. Portmanteau (Q) tests for no serial correlation. ARCH-LM test with 10 lags checks for the presence of heteroscedasticity. **, and *** indicate rejection of the null hypothesis at the 5%, and 1% significance levels, respectively

Table 2 Correlation matrix for tech and financial assets

	ATE	MIT	ABI	SPC	FIN	BTC	SP5	MWO	ESG	OIL	GLD	USD	BND
ATE	1												
MIT	0.936	1											
ABI	0.728	0.608	1										
SPC	0.169	0.151	0.135	1									
FIN	0.838	0.842	0.573	0.099	1								
BTC	0.023	0.020	0.029	0.056	0.052	1							
SP5	0.873	0.838	0.643	0.172	0.785	0.014	1						
MWO	0.781	0.813	0.57	0.137	0.778	0.012	0.894	1					
ESG	0.628	0.673	0.45	0.075	0.541	0.001	0.676	0.849	1				
OIL	0.151	0.155	0.092	0.034	0.152	−0.016	0.211	0.279	0.270	1			
GLD	−0.034	−0.015	−0.032	0.016	−0.077	0.046	−0.032	0.074	−0.029	0.207	1		
USD	0.018	0.048	0.021	0.066	0.017	0.023	0.063	0.262	−0.028	0.147	0.357	1	
BND	−0.324	−0.322	−0.222	−0.031	−0.294	−0.008	−0.362	−0.345	−0.373	−0.148	0.143	0.089	1

Table 3 Structural breaks in the tech variables

Variables	No. of breaks	Constant only	Trend only
ATE	1	11/03/2003[b]	13/02/2003[b]
	2	09/03/2009[b]	–
	3	11/02/2016[b]	–
MIT	1	11/03/2003[a]	10/02/2003[b]
ABI	1	–	12/03/2003[b]
SPC	1	26/12/2007[a]	20/11/2008[a]
	2	–	24/07/2012[a]
FIN	1	17/04/2017[b]	22/03/2017[b]
	2	25/12/2018[a]	25/12/2018[b]
BTC	1	18/12/2017[a]	18/12/2017[a]

Structural breaks are identified by the Bai−Perron Multiple Breakpoint test. The symbols [a] and [b] indicate significance at 1% and 5% levels, respectively

only. All the tech assets display breakpoint dates in the trend term at the 5% significance level, and all the variables except ABI have statistically significant breakpoints in the constant. We identify the potential causes of the structural breaks by searching for news and events around the specific dates.[4]

Empirical results and discussion

This section discusses the estimated results from the DCC-GJR-GARCH model, which allows us to investigate the dynamic relationship between the tech sectors and the financial market. Furthermore, considering structural breaks and uncertainty allows us to clarify how the relationship between the tech sectors and the financial market responds to macro fundamentals and financial turmoil. Finally, we present and compare diversified portfolios with optimal weights and hedged portfolios.

DCC-GARCH model results

Based on the Schwarz information criterion,[5] we select the GARCH model for cleantech, Bitcoin, and fintech, and the GJR-GARCH model for tech, IT, and biotech.[6] Table 4 (Panels A−F) presents the results from these models.In the estimated models, all the ARCH (α) and GARCH (β) values combined are high and close to one, and particularly the GARCH coefficients are positive and significant for all the models, implying the persistence of high volatility over time. The mean equations' results indicate that the autoregressive coefficients are statistically significant for the S&P 500, MSCI World, ESG, and oil, with MSCI World and ESG having positive signs, while the other variables have negative signs. These findings suggest the presence of a linear trend in the returns of the significant variables, meaning that past values of the

[4] We collected news from the Financial Times, BBC News, The Guardian, National Public Radio, CNN, DN, and The World Bank Group.

[5] Based on the SIC, we compare the estimated set of maximum likelihood-based models, where the numerical values for our time series and linear regression of dependent variable is identical for all estimates being compared.

[6] Appendix 1 provides the identification of best fitted GARCH model for each tech asset.

Table 4 Estimation results: DCC-GARCH models

	ATE	**SP5**	**MWO**	**ESG**	**OIL**	**GLD**	**USD**	**BND**
Panel A: DCC-GJR-GARCH (1,1) model for ATE								
Estimated parameters—mean equation AR(1)								
AR(1)	−0.020	−0.051***	0.117***	0.131***	−0.033**	−0.022	0.012	−0.017
	(0.014)	(0.015)	(0.016)	(0.016)	(0.015)	(0.016)	(0.013)	(0.014)
	Estimated parameters—variance equation							
ARCH (α)	0.010	−0.015**	0.005	0.0048	0.019**	0.034***	0.01***	0.039***
	(0.007)	(0.007)	(0.010)	(0.0083)	(0.007)	(0.008)	(0.004)	(0.008)
GARCH (β)	0.911***	0.899***	0.902***	0.9018***	0.950***	0.963***	0.972***	0.960***
	(0.011)	(0.011)	(0.014)	(0.0127)	(0.008)	(0.009)	(0.003)	(0.008)
Gamma (γ)	0.125***	0.189***	0.152***	0.1529***	0.050***	−0.008	0.013**	−0.007
	(0.017)	(0.021)	(0.020)	(0.0195)	(0.010)	(0.011)	(0.005)	(0.007)
ρ with ATE		0.900***	0.820***	0.6171***	0.1762**	−0.011	0.027	−0.311***
	MIT	**SP5**	**MWO**	**ESG**	**OIL**	**GLD**	**USD**	**BND**
Panel B: DCC-GJR-GARCH (1,1) model for MIT								
Estimated parameters—mean equation AR(1)								
AR(1)	0.073***	−0.051***	0.117***	0.131***	−0.033**	−0.022	0.012	−0.017
	(0.014)	(0.015)	(0.016)	(0.016)	(0.015)	(0.016)	(0.013)	(0.014)
	Estimated parameters—variance equation							
ARCH (α)	0.016*	−0.015**	0.005	0.004	0.019**	0.034***	0.010***	0.039***
	(0.008)	(0.007)	(0.010)	(0.008)	(0.007)	(0.008)	(0.004)	(0.008)
GARCH (β)	0.905***	0.899***	0.902***	0.901***	0.950***	0.963***	0.972***	0.960***
	(0.013)	(0.011)	(0.014)	(0.012)	(0.008)	(0.009)	(0.003)	(0.008)
Gamma (γ)	0.122***	0.189***	0.152***	0.152***	0.050***	−0.008	0.013**	−0.007
	(0.018)	(0.021)	(0.020)	(0.019)	(0.010)	(0.011)	(0.005)	(0.007)
ρ with MIT		0.863***	0.841***	0.643***	0.190***	0.028	0.067	−0.289***
	ABI	**SP5**	**MWO**	**ESG**	**OIL**	**GLD**	**USD**	**BND**
Panel C: DCC-GJR-GARCH (1,1) model for ABI								
Estimated parameters—mean equation AR(1)								
AR(1)	−0.003	−0.051***	0.117***	0.131***	−0.033**	−0.022	0.012	−0.017
	(0.015)	(0.015)	(0.016)	(0.016)	(0.015)	(0.016)	(0.013)	(0.014)
	Estimated parameters—variance equation							
ARCH (α)	0.031***	−0.015**	0.005	0.004	0.019**	0.034***	0.010***	0.039***
	(0.009)	(0.007)	(0.010)	(0.008)	(0.007)	(0.008)	(0.004)	(0.008)
GARCH (β)	0.927***	0.899***	0.902***	0.901***	0.950***	0.963***	0.972***	0.960***
	(0.012)	(0.011)	(0.014)	(0.012)	(0.008)	(0.009)	(0.003)	(0.008)
Gamma (γ)	0.059	0.189***	0.152***	0.152***	0.050***	−0.008	0.013**	−0.007
	(0.014)	(0.021)	(0.020)	(0.019)	(0.010)	(0.011)	(0.005)	(0.007)
ρ with ABI		0.662***	0.587***	0.427***	0.094**	−0.011	0.013	−0.213***
	SPC	**SP5**	**MWO**	**ESG**	**OIL**	**GLD**	**USD**	**BND**
Panel D: DCC− GARCH (1,1) model for SPC								
Estimated parameters—mean equation ARMA (1,0)								
AR(1)	0.157***	−0.056***	0.119***	0.123***	−0.034**	−0.015	0.006	−0.029*
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.015)	(0.015)
	Estimated parameters—variance equation							
ARCH (α)	0.088***	0.115***	0.1097***	0.105***	0.053***	0.035***	0.029***	0.032***
	(0.012)	(0.014)	(0.016)	(0.016)	(0.008)	(0.009)	(0.003)	(0.007)
GARCH (β)	0.902***	0.861***	0.878***	0.878***	0.941***	0.959***	0.969***	0.963***
	(0.013)	(0.015)	(0.017)	(0.017)	(0.009)	(0.010)	(0.003)	(0.008)

Table 4 (continued)

	SPC	SP5	MWO	ESG	OIL	GLD	USD	BND
ρ with SPC		0.088***	0.049***	0.017	0.033	0.005	−0.007	−0.002
	FIN	**SP5**	**MWO**	**ESG**	**OIL**	**GLD**	**USD**	**BND**
Panel E: DCC-GARCH (1,1) model for FIN								
Estimated parameters—mean equation AR(1)								
AR(1)	0.000	−0.053	0.073*	0.101***	−0.032	−0.026	0.062*	−0.049
	(0.038)	(0.041)	(0.039)	(0.036)	(0.033)	(0.028)	(0.034)	(0.035)
	Estimated parameters—variance equation							
ARCH (α)	0.130**	0.198***	0.213***	0.173***	0.039***	0.005	0.020	0.036
	(0.054)	(0.049)	(0.059)	(0.048)	(0.0131)	(0.006)	(0.013)	(0.029)
GARCH (β)	0.830***	0.763***	0.742***	0.686***	0.937***	0.975***	0.978***	0.941***
	(0.064)	(0.038)	(0.052)	(0.084)	(0.022)	(0.011)	(0.013)	(0.058)
ρ with FIN		0.734***	0.729***	0.531***	0.128**	−0.069	−0.000	−0.275***
	BTC	**SP5**	**MWO**	**ESG**	**OIL**	**GLD**	**USD**	**BND**
Panel F: DCC-GARCH (1,1) model for BTC								
Estimated parameters—mean equation AR(1)								
AR(1)	0.067**	−0.053*	0.095***	0.130***	−0.048*	−0.043*	0.030	−0.057**
	(0.033)	(0.031)	(0.031)	(0.029)	(0.028)	(0.024)	(0.028)	(0.028)
	Estimated parameters—variance equation							
ARCH (α)	0.134***	0.211***	0.212***	0.138***	0.058***	0.012***	0.018***	0.020**
	(0.033)	(0.040)	(0.048)	(0.034)	(0.014)	(0.004)	(0.006)	(0.010)
GARCH (β)	0.818***	0.742***	0.749***	0.838***	0.922***	0.984***	0.981***	0.974***
	(0.041)	(0.034)	(0.040)	(0.037)	(0.021)	(0.006)	(0.006)	(0.013)
ρ with BTC		−0.017	0.0008	−0.0072	−0.0048	0.0380	0.0333	−0.0087

Values () are the standard deviation of the estimated parameters in mean and variance equations. The asterisk *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels. The ρ indicates a conditional correlation coefficient

series can predict current values. Conversely, the insignificant autoregressive coefficients for the remaining variables suggest an absence of a linear trend in their returns, implying that they may not be useful predictors when using one-period lags to predict current values, although it ultimately depends on a specific model and data set (Bollerslev 2008).

The conditional variance equations show that the GJR leverage coefficient (γ) is significant and positive for all returns except for gold and bonds, implying that negative shocks have a greater impact on conditional volatility than positive shocks, supporting the leverage effect. In the correlation coefficient, ρ, we observe different results for fintech and USD, as well as for cleantech and USD, where the correlation is negative. This result is consistent with Ahmad's (2017) findings of time variations in the cleantech stock price hedge ratios.

The DCC model investigates the dynamic correlation between tech sectors and financial assets. Table 5 presents estimates of the DCC parameters ($\alpha_{dcc} and \beta_{dcc}$) for each tech variable and the corresponding financial assets. Both α_{dcc} and β_{dcc} are significant for tech, IT, and biotech and their corresponding assets, indicating that the volatility of previous returns significantly impacts the dynamic correlation between the tech sectors and financial assets. Further, the value of β_{dcc} is close to one, indicating that the dynamic correlation will continue long. The α_{dcc} for fintech is significant

Table 5 DCC estimates between the tech sectors and financial assets

	ATE-SP5	ATE-MWO	ATE-ESG	ATE-OIL	ATE-GLD	ATE-USD	ATE-BND
alpha (α_{dcc})	0.0492***	0.0300***	0.0112	0.027***	0.0195**	0.0138***	0.0303***
beta (β_{dcc})	0.9327***	0.9615***	0.9781***	0.9673***	0.9698***	0.9828***	0.9489***
($\alpha_{dcc}+\beta_{dcc}$)	0.9819	0.9915	0.9893	0.9943	0.9893	0.9966	0.9792
	MIT-SP5	**MIT-MWO**	**MIT-ESG**	**MIT-OIL**	**MIT-GLD**	**MIT-USD**	**MIT-BND**
alpha (α_{dcc})	0.0401***	0.0346***	0.021***	0.0278***	0.0225***	0.013***	0.022***
beta (β_{dcc})	0.9388***	0.932***	0.9569***	0.9669***	0.9671***	0.9846***	0.9635***
($\alpha_{dcc}+\beta_{dcc}$)	0.9789	0.9666	0.9779	0.9947	0.9896	0.9976	0.9855
	ABI-SP5	**ABI-MWO**	**ABI-ESG**	**ABI-OIL**	**ABI-GLD**	**ABI-USD**	**ABI-BND**
alpha (α_{dcc})	0.0274***	0.0280***	0.02***	0.0236***	0.0081**	0.0072**	0.0203***
beta (β_{dcc})	0.9456***	0.9411***	0.9464***	0.965***	0.9845***	0.99***	0.9642***
($\alpha_{dcc}+\beta_{dcc}$)	0.973	0.9691	0.9664	0.9886	0.9926	0.9972	0.9845
	SPC-SP5	**SPC-MWO**	**SPC-ESG**	**SPC-OIL**	**SPC-GLD**	**SPC-USD**	**SPC-BND**
alpha (α_{dcc})	0.0000	0.0000	0.0000	0.0045	0.0024	0.0072	0.0058
beta (β_{dcc})	0.8509	0.8375*	0.8229*	0.9912***	0.9701***	0.9434***	0.8389**
($\alpha_{dcc}+\beta_{dcc}$)	0.8509	0.8375	0.8229	0.9957	0.9725	0.9506	0.8447
	FIN-SP5	**FIN-MWO**	**FIN-ESG**	**FIN-OIL**	**FIN-GLD**	**FIN-USD**	**FIN-BND**
alpha (α_{dcc})	0.0719***	0.1034***	0.0409**	0.0411**	0.0193	0.0000	0.0356
beta (β_{dcc})	0.8617***	0.8249***	0.7416***	0.9061***	0.8714***	0.7929	0.8222***
($\alpha_{dcc}+\beta_{dcc}$)	0.9336	0.9283	0.7825	0.9472	0.8907	0.7929	0.8578
	BTC-SP5	**BTC-MWO**	**BTC-ESG**	**BTC-OIL**	**BTC-GLD**	**BTC-USD**	**BTC-BND**
alpha (α_{dcc})	0.0076	0.0000	0.0006	0.0000	0.0054	0.0000	0.0000
beta (β_{dcc})	0.9483***	0.8212	0.8472**	0.8404	0.9676***	0.8486***	0.8681***
($\alpha_{dcc}+\beta_{dcc}$)	0.9559	0.8212	0.8478	0.8404	0.973	0.8486	0.8681

The asterisk *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively

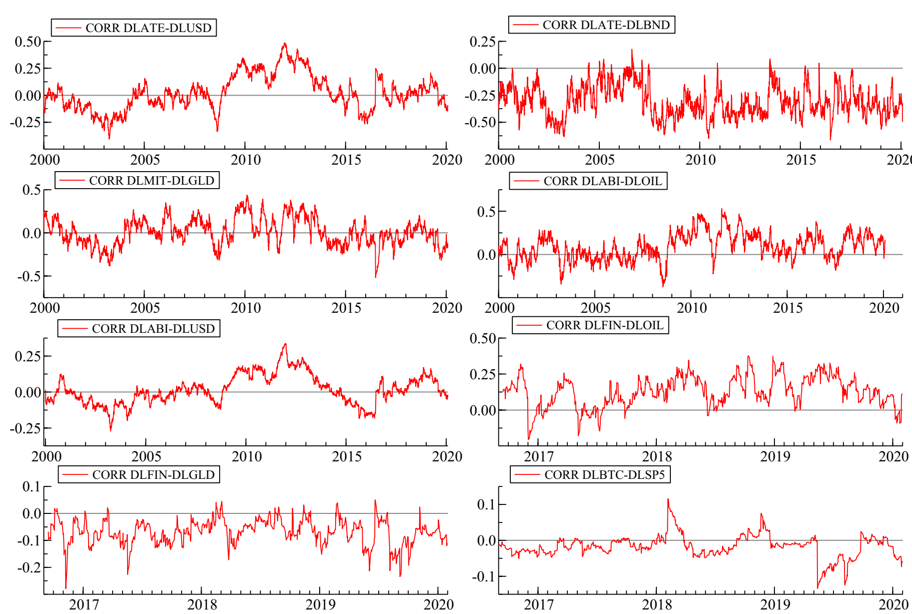


Fig. 2 DCC graphs for selected assets

for the S&P 500, MSCI World, ESG, and oil. For cleantech and Bitcoin, the α_{dcc} for all corresponding variables are insignificant, implying some different dynamics compared to the other tech variables. Conversely, Bitcoin significantly correlates with all other variables (except OIL and MWO), implying that only the long-run dynamic correlation between them can continue.

Figure 2 depicts the time-varying conditional correlations between the tech variables and financial assets. The conditional correlations fluctuate and differ across commodities and financial assets. We observe that tech and USD were negatively correlated before the 2008 GFC but became positive after that. The same holds for the correlation between biotech and USD.

Tech and bonds, as well as fintech and gold, are negatively correlated throughout the sample period. IT and gold switch between positive and negative correlations. Subsequent to the dot-com bubble and during macro events such as the financial crisis and the US election, the correlation between IT and gold became negative. Bitcoin and S&P 500 have a negative correlation most of the time. We observed a positive spike in 2018 and a negative spike in 2019, which indicates that Bitcoin and S&P 500 are sensitive to the type of "macro fundamentals" or shock. Biotech and oil show sharp turns in correlations; at the beginning of the financial crisis, it rapidly decreased and then quickly bounced back and became positive. Common for all the tech variables and the correlation between the financial assets are the fluctuations around the 2008 GFC. The main difference here is that biotech, IT, and tech all have negative spikes concerning bonds and gold, whereas, for the other tech variables and their corresponding financial assets, the spikes are positive during this period.

The impact of structural breaks and uncertainty

We further account for structural breaks and uncertainty, which will give us a better understanding of the relationship between the tech sectors and financial assets. Some prior studies (e.g., Mensi et al. 2015; Dong and Yoon 2018) also use this technique to capture the same. We use the results from the Bai−Perron test (Table 3) and examine if and how the breakpoints affect the correlation between the tech variables and financial assets. We conduct the breakpoint regression using two model specifications: a breakpoint in the constant only and a breakpoint in the time trend only, given respectively by

$$DCC_t = \alpha_0 + \lambda_0 t + \lambda_1 t * break_t + e_t \quad (9)$$

$$DCC_t = \alpha_0 + \lambda_1 * break_t + \lambda_0 t + e_t, \quad (10)$$

where the variable ($break_t$) takes the zero value for all observations before the identified structural break and the value one for all subsequent observations. We represent the level of interconnectedness by changes in the constant term α_0 and the rate of comovement by changes in the time-trend parameter $\lambda_0 * t$.

Further, we examine whether different types of uncertainty affect the correlation differently by including four uncertainty measures: the EPU, VIX, OVX, and currency volatility indices. For three out of the four uncertainty measures, suitable indices are available. However, we create an index to measure currency volatility by modeling a GARCH process and extracting the residuals.

In the linear time-trend regression, shocks in the constant and time-trend only increase when volatility increases, where the variable $\left(uncertainty_t\right)$ is the natural logarithm of each uncertainty index. We define the following two regressions:

$$DCC_t = \alpha_0 + \delta_0 t + \delta_1 t * uncertainty_t + e_t \tag{11}$$

$$DCC_t = \alpha_0 + \delta_1 * uncertainty_t + \delta_0 t + e_t. \tag{12}$$

We capture the level of connectivity by changes in the constant term α_0 and the rate of connectivity by changes in the time-trend parameter $\delta_0 * t$. In line with Berger et al. (2011), we interpret the level of connectivity as the instant change and the rate as the connection over time. In particular, we are looking for diversification opportunities, that is, negative co-movement. We present the structural breaks and uncertainty results in Table 6 (Panels A−F).

Table 2 and the estimated parameters in Table 5 show that both the unconditional and dynamic conditional correlation between tech and the S&P 500 is positive and significant. Including the breakpoints strengthens this result, as the trend, δ_0, in Panel A of Table 6 is positive and significant when allowing for breakpoints in both the constant and time trend. Interestingly, all four identified breakpoints in the tech time series had a decreasing effect on the level of correlation and the correlation trend with the S&P 500. This result suggests that tech and S&P 500 do not follow the same business cycle, and the two variables combined could stabilize a portfolio return (Bodie et al. 2018). Uncertainty in EPU, VIX, and CVX positively affects the level of correlation for most financial assets and tech. When markets become more interlinked, Lehkonen and Heimonen (2014) suggest that a potential cyber-attack or financial turmoil could have potential contagion effects on multiple firms simultaneously. Thus, the contagion could cause higher interconnection.

The connectivity rate between biotech and S&P 500, MSCI World, and oil was positive before the breakpoint in 2003 but subsequently became negative. Conversely, the opposite held for gold, USD, and bonds. This result indicates that the biotech sector behaves somewhat differently than the financial market. Because biotech is a slow-moving sector and an ethical investment choice, other factors and incentives might affect its business cycle. Biotech, already characterized by uncertainty, also seems to correspond differently to uncertainty. EPU causes an increase in the correlation for all financial variables except bonds, which decreases with uncertainty. The VIX and OVX adversely affect the correlation with bonds and gold but positively affect the remaining assets. Lazonick and Tulum (2011) explain that the biotech sector behaves like an emerging market, and hence, our results are somewhat in line with the findings of Lehkonen and Heimonen (2014) that connection increases for emerging markets during crises.

Considering the graphical illustration of cleantech in Figs. 1 and 2, the spikes around 08/09 indicate that the financial crisis considerably impacted the series. The identified breakpoints in constant, 2007, and trend, 2008, also suggest that the crisis caused heightened volatility in the series. This may be due to the rapid increase in energy prices, specifically oil, before plunging as the financial crisis spread. This aligns with

Ahmad (2017), who finds that oil prices affect clean energy stock prices. He concludes that there are volatility spillovers from oil prices to clean energy stock prices. Figure 1 shows that cleantech has not recovered from the 2008 break since the index is now lower than before the downturn. When we consider the dynamic correlation with the breakpoints, we notice that the break in constant resulted in a decrease in the level of connectivity with all financial assets except the S&P 500, for which the level of correlation increased. Surprisingly, the correlation rate decreased for S&P 500 and USD but was positive for the remaining financial variables. Uncertainty negatively affects the level and rate of connectivity between cleantech, oil, and gold; however, in contrast to the other tech variables, the level and the connectivity rate increase with EPU for cleantech and bonds. Uncertainty, measured by VIX, has adverse effects on both the level and the connectivity rate for cleantech and bonds. These results align with Ahmad et al. (2018) and Dutta et al. (2020), who find that volatility indexes such as the VIX and OVX effectively hedge assets for clean energy equities. These results could imply a higher sensitivity in the relationship between cleantech and bonds to financial market shocks than economic shocks.

Table 6 DCC regression results with structural breakpoints and uncertainty measures

Panel A: ATE										
	Breakpoint in constant						Breakpoint in trend			
	α_0	α_1	α_2	α_3	λ_0	λ_1	α_0	α_1	λ_0	λ_1
SP5	(+)***	(–)***	(–)***	(–)***	(+)***	-	(+)***	-	(+)***	(–)***
MWO	(+)***	(–)***	(+)***	(–)***	(+)***	-	(+)***	-	(+)***	(–)***
ESG	(+)***	(–)***	(+)***	(–)***	(–)***	-	(+)***	-	(+)***	(–)***
OIL	(+)***	(–)***	(+)***	(–)***	(–)***	-	(–)***	-	(+)***	(–)***
GLD	(–)***	(+)***	(+)***	(–)***	(–)***	-	(+)***	-	(–)***	(+)***
USD	(–)***	(+)***	(+)***	(–)***	(–)***	-		-	(–)***	(+)***
BND	(–)***	(+)***		(+)***	(–)***	-	(–)***	-	(–)***	(+)***
	Uncertainty effect in constant						Uncertainty effect in trend			
		α_0	α_1	δ_0	δ_1		α_0	α_1	δ_0	δ_1
SP5	EPU	(+)***	(+)***	(+)***	-		(+)***	-	(–)*	(+)***
MWO	EPU	(+)***	(+)***	(+)***	-		(+)***	-	(–)***	(+)***
ESG	EPU	(+)***	(+)***	(+)***	-		(+)***	-	(–)***	(+)***
OIL	EPU	(–)***	(+)***	(+)***	-			-	(–)***	(+)***
GLD	EPU			(–)***	-		(–)***	-	(–)***	(+)***
USD	EPU	(–)***	(+)***	(+)***	-		(–)***	-	(–)***	(+)***
BND	EPU	(+)**	(–)***	(–)***	-		(–)***	-	(+)***	(–)***
SP5	VIX	(+)***	(+)***	(+)***	-		(+)***	-	(–)***	(+)***
MWO	VIX	(+)***	(+)***	(+)***	-		(+)***	-	(–)**	(+)***
ESG	VIX	(+)***	(+)***	(+)***	-		(+)***	-	(–)***	(+)***
OIL	VIX	(–)***	(+)***	(+)***	-		(–)***	-	(–)***	(+)***
GLD	VIX	(+)***	(–)***	(–)***	-		(–)***	-	(–)***	(+)***
USD	VIX	(–)***	(+)***	(+)***	-		(–)***	-	(–)***	(+)***
BND	VIX	(+)***	(–)***	(–)***	-		(–)***	-	(+)***	(–)***
SP5	CVX	(+)***	(+)***	(+)***	-		(+)***	-	(+)***	(+)***
MWO	CVX	(+)***	(+)***	(+)***	-		(+)***	-	(+)***	(+)***
ESG	CVX	(+)***	(+)***	(+)***	-		(+)***	-	(+)***	(+)***
OIL	CVX	(–)**	(+)***	(+)***	-			-	(+)***	(+)***
GLD	CVX	(–)**		(–)***	-		(–)***	-	(–)***	
USD	CVX	(–)***	(+)***	(+)***	-		(–)***	-	(+)***	(+)***
BND	CVX	(–)***	(–)***	(–)***	-		(–)***	-	(–)***	(–)***
SP5	OVX	(+)***	(+)***		-		(+)***	-	(–)***	(+)***
MWO	OVX	(+)***	(+)***	(+)***	-		(+)***	-	(–)***	(+)***
ESG	OVX	(+)***	(+)***	(–)***	-		(+)***	-	(–)***	(+)***
OIL	OVX		(+)***		-		(+)***	-	(–)***	(+)***
GLD	OVX	(+)***	(–)***	(–)***	-		(+)***	-	(+)***	(–)***
USD	OVX	(+)***	(–)***	(–)***	-		(+)***	-	(+)***	(–)***
BND	OVX	(–)***	(–)***	(+)***	-		(–)***	-	(+)***	(–)***

Panel B: MIT									
		Breakpoint in constant				Breakpoint in trend			
		α_0	α_1	λ_0	λ_1	α_0	α_1	λ_0	λ_1
SP5		(+)***		(+)***	-	(+)***	-	(+)***	(–)***
MWO		(+)***	(–)***	(+)***	-	(+)***	-	(+)***	(–)***
ESG		(+)***	(–)***	(–)***	-	(+)***	-	(+)***	(–)***
OIL		(+)***	(–)***	(+)***	-	(–)***	-	(+)***	(–)***
GLD		(–)***	(+)***	(+)***	-	(+)***	-	(–)***	(+)***
USD		(–)***	(+)***	(+)***	-	(+)***	-	(–)***	(+)***
BND		(–)***	(+)***	(+)***	-	(–)***	-	(–)***	(+)***
		Uncertainty effect in constant				Uncertainty effect in trend			
		α_0	α_1	δ_0	δ_1	α_0	α_1	δ_0	δ_1
SP5	EPU	(+)***	(+)***	(+)***	-	(+)***	-	(–)***	(+)***
MWO	EPU	(+)***	(+)***	(+)***	-	(+)***	-	(–)***	(+)***
ESG	EPU	(+)***	(+)***	(–)***	-	(+)***	-	(–)***	(+)***
OIL	EPU	(–)***	(+)***	(+)***	-	(+)**	-	(–)***	(+)***
GLD	EPU	(+)***	(–)**	(–)***	-	(+)***	-	(–)***	(+)***
USD	EPU	(–)***	(+)***	(+)***	-	(–)***	-	(–)***	(+)***
BND	EPU	(+)***	(–)***	(–)***	-	(–)***	-	(+)***	(–)***
SP5	VIX	(+)***	(+)***	(+)***	-	(+)***	-	(–)***	(+)***
MWO	VIX	(+)***	(+)***	(+)***	-	(+)***	-	(–)***	(+)***
ESG	VIX	(+)***	(+)***	(+)***	-	(+)***	-	(–)***	(+)***
OIL	VIX	(–)***	(+)***	(+)***	-	(–)***	-	(–)***	(+)***
GLD	VIX	(+)***	(–)***	(–)***	-	(+)***	-	(–)***	(+)***
USD	VIX	(–)***	(+)***	(+)***	-	(–)***	-	(–)***	(+)***
BND	VIX	(+)***	(–)***	(–)***	-	(–)***	-	(+)***	(–)***
SP5	CVX	(+)***	(+)***	(+)***	-	(+)***	-	(+)***	(+)***
MWO	CVX	(+)***	(+)***	(+)***	-	(+)***	-	(+)***	(+)***
ESG	CVX	(+)***	(+)***	(–)***	-	(+)***	-	(–)***	(+)***
OIL	CVX		(+)***	(+)***	-	(+)*	-	(+)***	(+)***
GLD	CVX	(+)***		(–)***	-	(+)***	-	(–)***	
USD	CVX	(–)***	(+)***	(+)***	-	(–)***	-	(+)***	(+)***
BND	CVX	(–)***	(–)***	(–)***	-	(–)***	-	(–)***	(–)***
SP5	OVX	(+)***	(+)***		-	(+)***	-	(–)***	(+)***
MWO	OVX	(+)***	(+)***		-	(+)***	-	(–)***	(+)***
ESG	OVX	(+)***	(+)***	(–)***	-	(+)***	-	(–)***	(+)***
OIL	OVX	(+)**	(+)***	(–)***	-	(+)***	-	(–)***	(+)***
GLD	OVX	(+)***	(–)***	(–)***	-	(+)***	-	(+)***	(–)***
USD	OVX	(+)***	(–)***	(–)***	-	(+)***	-	(+)***	(–)***
BND	OVX		(–)***	(+)**	-	(–)***	-	(+)***	(–)***

Panel C: ABI									
		No breakpoint in constant				Breakpoint in trend			
		α_0	α_1	λ_0	λ_1	α_0	α_1	λ_0	λ_1
SP5					-	(+)***	-	(+)***	(–)***
MWO					-	(+)***	-	(+)***	(–)***
ESG					-	(+)***	-		(–)**
OIL					-	(–)***	-	(+)***	(–)***
GLD					-	(+)***	-	(–)***	(+)***
USD					-	(–)***	-	(–)***	(+)***
BND					-	(–)***	-	(–)***	(+)***
		Uncertainty effect in constant				Uncertainty effect in trend			
		α_0	α_1	δ_0	δ_1	α_0	α_1	δ_0	δ_1
SP5	EPU	(+)***	(+)***	(+)***	-	(+)***	-	(–)***	(+)***
MWO	EPU	(+)***	(+)***	(–)***	-	(+)***	-	(–)***	(+)***
ESG	EPU	(+)***	(+)***	(–)***	-	(+)***	-	(–)***	(+)***
OIL	EPU	(+)***	(+)***	(+)***	-		-	(–)***	(+)***
GLD	EPU	(–)*		(–)**	-	(–)***	-	(–)***	(+)***
USD	EPU	(–)***	(+)***	(+)***	-	(–)***	-	(–)***	(+)***
BND	EPU	(+)***	(–)***	(–)***	-	(–)***	-	(+)***	(–)***
SP5	VIX	(+)***	(+)***	(+)**	-	(+)***	-	(–)***	(+)***
MWO	VIX	(+)***	(+)***	(+)***	-	(+)***	-	(–)***	(+)***
ESG	VIX	(+)***	(+)***		-	(+)***	-	(–)***	(+)***
OIL	VIX	(+)***	(+)***	(+)***	-	(–)***	-	(–)***	(+)***
GLD	VIX	(+)***	(–)***	(–)***	-	(–)***	-	(–)***	(+)***
USD	VIX	(–)***	(+)***	(+)***	-	(–)***	-	(–)***	(+)***
BND	VIX	(+)***	(–)***	(–)***	-	(–)***	-	(+)***	(–)***
SP5	CVX	(+)***	(+)***	(–)***	-	(+)***	-	(–)***	(+)***
MWO	CVX	(+)***	(+)**		-	(+)***	-	(–)*	(+)*
ESG	CVX	(+)***	(+)**	(–)***	-	(+)***	-	(–)***	(+)***
OIL	CVX	(–)***	(+)**	(+)**	-	(–)*	-	(+)***	(+)***
GLD	CVX	(–)***	(–)***	(–)**	-	(–)***	-		(–)***
USD	CVX	(–)***		(+)***	-	(–)***	-	(+)***	
BND	CVX	(–)***	(–)***	(–)***	-	(–)***	-	(–)***	(–)***
SP5	OVX	(+)***	(+)***	(–)***	-	(+)***	-	(–)***	(+)***
MWO	OVX	(+)***	(+)***		-	(+)***	-	(–)***	(+)***
ESG	OVX	(+)***	(+)***	(–)***	-	(+)***	-	(–)***	(+)***
OIL	OVX	(+)***	(+)**		-	(+)***	-	(–)***	(+)***
GLD	OVX	(+)**	(–)***	(–)***	-	(+)***	-	(+)***	(–)***
USD	OVX	(+)***	(–)***	(–)***	-	(+)***	-	(+)***	(–)***
BND	OVX	(+)*	(–)***	(+)**	-	(–)***	-	(+)***	(–)***

Note: The asterisk *, ** and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 6 (continued)

Panel D: SPC

		Breakpoint in constant				Breakpoint in trend				
		α_0	α_1	λ_0	λ_1	α_0	α_1	λ_0	λ_1	λ_2
SP5		(+)***	(+)***	(+)***	-	(+)***	-	(+)***	(–)***	(–)***
MWO		(+)***	(–)**	(+)***	-	(+)***	-	(–)***	(+)***	(+)***
ESG		(+)***	(–)**	(+)***	-	(+)***	-	(–)***	(+)***	(+)***
OIL		(+)***	(–)***	(+)***	-	(+)***	-	(–)***	(+)***	(+)***
GLD		(+)***	(–)***	(+)***	-	(+)***	-	(–)***	(+)***	(+)***
USD		(–)***	(–)*		-	(–)***	-	(+)***	(–)***	(–)***
BND		(–)***	(–)*	(+)***	-		-	(–)***	(+)***	(+)***

		Uncertainty effect in constant				Uncertainty effect in trend			
		α_0	α_1	β_0	β_1	α_0	α_1	δ_0	δ_1
OIL	EPU	(+)***	(–)***		-	(+)***	-	(+)***	(–)***
GLD	EPU	(+)***	(–)***	(–)*	-	(+)***	-	(+)***	(–)***
USD	EPU	(–)***	(+)*	(–)***	-	(–)***	-		
BND	EPU	(–)***	(+)***		-	(–)***	-	(–)**	(+)**
OIL	VIX	(+)***	(–)***	(–)***	-	(+)***	-	(+)***	(–)***
GLD	VIX	(+)***	(–)***		-	(+)***	-		
USD	VIX	(–)***	(+)***		-	(–)***	-	(–)***	(+)***
BND	VIX		(–)*	(+)***	-	(–)***	-	(+)***	(–)***
OIL	CVX	(+)***	(–)***	(–)***	-	(+)***	-	(–)***	
GLD	CVX	(+)***			-	(+)***	-		
USD	CVX	(–)***	(+)**	(–)***	-	(–)***	-	(–)***	
BND	CVX	(–)***	(+)**		-	(–)***	-		(+)**
OIL	OVX	(+)**		(+)***	-	(+)**	-	(–)***	(+)***
GLD	OVX	(–)***	(+)***	(+)***	-	(+)**	-	(–)***	(+)***
USD	OVX	(–)***	(+)***		-	(–)***	-		
BND	OVX	(–)***	(+)***	(+)***	-	(–)***	-		

Panel E: FIN

	Breakpoint in constant					Breakpoint in trend				
	α_0	α_1	α_2	λ_0	λ_1	α_0	α_1	λ_0	λ_1	λ_2
SP5	(+)***	(+)***			-	(+)***	-	(–)***	(+)***	
MWO	(+)***	(+)***	(+)**		-	(+)***	-	(–)***	(+)***	
ESG	(+)***				-	(+)***	-		(+)*	
OIL	(+)***	(–)*		(+)***	-	(+)***	-		(+)*	(–)*
GLD	(–)***	(–)***	(–)***	(+)***	-	(–)***	-	(+)***	(–)***	(–)***
USD	(–)***	(–)***		(–)*	-	(–)***	-	(–)*	(+)*	
BND	(–)***			(–)*	-	(–)***	-			(+)***

		Uncertainty effect in constant				Uncertainty effect in trend			
		α_0	α_1	β_0	β_1	α_0	α_1	δ_0	δ_1
SP5	EPU	(+)***		(+)***	-	(+)***	-		(+)***
MWO	EPU	(+)***	(+)*	(+)***	-	(+)***	-		(+)***
ESG	EPU	(+)***		(+)***	-	(+)***	-		(+)**
OIL	EPU	(+)***		(+)***	-	(+)***	-		
GLD	EPU		(–)***		-	(–)***	-	(+)***	(–)***
USD	EPU	(–)***	(+)***		-	(–)***	-	(+)***	(–)***
BND	EPU	(–)***	(–)***	(–)***	-	(–)***	-	(+)***	(–)***
SP5	VIX	(+)***	(+)***	(+)***	-	(+)***	-	(–)***	(+)***
MWO	VIX	(+)*	(+)***	(+)***	-	(+)***	-	(–)***	(+)***
ESG	VIX	(+)***	(+)***		-	(+)***	-	(–)***	(+)***
OIL	VIX	(–)***	(+)***	(+)***	-	(+)***	-	(–)***	(+)***
GLD	VIX	(–)***			-	(–)***	-	(+)***	(–)***
USD	VIX	(–)***			-	(–)***	-		(–)*
BND	VIX		(–)***		-	(–)***	-	(+)***	(–)***
SP5	CVX	(+)***		(+)***	-	(+)***	-	(+)***	
MWO	CVX	(+)***	(–)*	(+)***	-	(+)***	-	(+)***	
ESG	CVX	(+)***	(–)*	(+)***	-	(+)***	-	(+)***	(–)*
OIL	CVX	(+)***	(–)*	(+)***	-	(+)***	-	(+)***	
GLD	CVX	(–)***			-	(–)***	-	(–)*	(+)***
USD	CVX	(–)***			-	(–)***	-		
BND	CVX	(–)***		(–)***	-	(–)***	-	(–)***	
SP5	OVX	(+)***	(+)***	(+)***	-	(+)***	-	(–)***	(+)***
MWO	OVX	(+)**	(+)***	(+)***	-	(+)***	-	(–)***	(+)***
ESG	OVX	(+)***	(+)***	(+)***	-	(+)***	-	(–)***	(+)***
OIL	OVX			(+)***	-	(+)***	-		
GLD	OVX	(+)***	(–)***		-	(–)***	-	(+)***	(–)***
USD	OVX	(–)***			-	(–)***	-		
BND	OVX	(–)***	(–)**	(–)***	-	(–)***	-	(+)***	(–)***

Panel F: BTC

		Breakpoint in constant				Breakpoint in trend			
		α_0	α_1	λ_0	λ_1	α_0	α_1	β_0	β_1
SP5		(–)***	(+)***	(–)***	-	(–)***	-	(–)***	(+)***
MWO		(+)***	(+)***	(+)***	-	(+)***	-	(–)**	
ESG		(–)***	(+)***	(–)***	-	(–)***	-	(–)**	
OIL		(–)***			-	(–)***	-		
GLD		(+)***	(–)***	(+)***	-	(+)***	-	(+)***	(–)***
USD		(+)***	(+)***	(+)**	-	(+)***	-	(+)**	(+)***
BND		(–)***		(+)***	-	(–)***	-	(+)***	(+)***

		Uncertainty effect in constant				Uncertainty effect in trend			
		α_0	α_1	β_0	β_1	α_0	α_1	δ_0	δ_1
SP5	EPU	(+)*	(–)***		-	(–)***	-	(+)***	(–)***
MWO	EPU	(+)***		(–)**	-	(+)***	-	(+)***	(+)***
ESG	EPU	(–)***	(–)***		-	(–)***	-	(+)***	(+)***
OIL	EPU	(–)***	(–)*		-	(–)***	-	(+)***	(+)***
GLD	EPU		(+)***	(+)***	-	(+)***	-	(–)***	(+)***
USD	EPU	(+)***	(+)**		-	(+)***	-	(+)***	(+)***
BND	EPU	(–)***	(+)***		-	(–)***	-	(+)***	(+)***
SP5	VIX	(–)***	(+)***	(–)***	-	(–)***	-	(–)***	(+)***
MWO	VIX	(+)***		(+)***	-	(+)***	-		
ESG	VIX	(–)***	(+)***		-	(–)***	-		
OIL	VIX	(–)***			-	(–)***	-		
GLD	VIX	(+)***	(–)**	(+)***	-	(+)***	-	(+)***	
USD	VIX	(+)***	(+)***		-	(+)***	-	(+)***	(+)***
BND	VIX	(–)***	(+)***	(+)***	-	(–)***	-	(+)***	(+)***
SP5	CVX	(–)***		(–)***	-	(–)***	-	(–)***	
MWO	CVX	(–)***		(–)***	-	(+)***	-	(–)***	
ESG	CVX	(–)***		(–)*	-	(–)***	-	(–)*	
OIL	CVX	(–)***	(–)***		-	(–)***	-		
GLD	CVX	(+)***		(+)***	-	(+)***	-	(+)***	
USD	CVX	(+)***			-	(+)***	-		
BND	CVX	(–)***		(+)***	-	(–)***	-	(+)***	
SP5	OVX			(–)***	-	(–)***	-	(+)***	(–)***
MWO	OVX	(+)***		(–)***	-	(+)***	-		(–)*
ESG	OVX	(–)***			-	(–)***	-	(+)**	(–)**
OIL	OVX	(–)***			-	(–)***	-	(+)*	(–)*
GLD	OVX	(+)***	(–)**	(+)***	-	(+)***	-	(–)**	(+)***
USD	OVX	(+)***	(–)***	(–)**	-	(+)***	-		
BND	OVX	(–)***	(–)***		-	(–)***	-	(+)**	

The asterisk *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively

When applying structural breaks and uncertainty, the correlation between Bitcoin and MSCI World, USD, and bonds remains positive and unchanged. The S&P 500 and Bitcoin, as well as ESG and Bitcoin, are negatively correlated before the break but become positive thereafter. The positive correlation aligns with the results of Kurka (2019) and Ji et al. (2019), who explain that Bitcoin becomes more correlated with financial assets over time. During uncertain times, however, the correlation between the S&P 500 and Bitcoin seems to remain negative, in line with Bouri et al. (2017a) and Alfieri et al. (2019). These authors conclude that Bitcoin is an effective diversifier. The association between Bitcoin and ESG seems to be affected differently depending on the type of uncertainty. This is also true for gold, where the connectivity reacts differently for each type of uncertainty.

To summarize, we draw several notable conclusions about the correlation dynamics when we account for structural breaks and uncertainty when analyzing the time-varying correlations. Multiple breaks in a variable can lead to different effects on the connection with financial assets. For example, tech has three identified breakpoints in the constant, which affect the conditional correlation with the same asset differently. As Panel A of Table 6 shows, the connectivity between tech and MSCI World decreased after the 2003 break but increased after the break in 2009 and finally decreased again after the break in 2016. In other words, connectivity decreased due to the turbulence caused by the Iraq war. It increased after the financial crisis but decreased again after the 2016 US presidential campaign. Similarly, we show in Panel E that the first and second breakpoints in the trend had opposing effects on the connectivity between fintech and oil. The breakpoints identified in fintech coincide with when the fintech price went from bullish to bearish. It is difficult to determine the underlying factors that trigger breaks in a time series, but the differing connectivity reactions due to breaks could be due to variations in the events occurring around the breakpoint, such as a war or a financial crisis.

Second, structural breaks in the series and external uncertainty measures affect connectedness differently. In Panel B, we infer that the connectivity rate between IT and bonds increased after the break in the trend, while it decreased after including uncertainty. In uncertain times, when the equity market faces downturns, bonds work as a diversifier or a hedge due to the "flight to quality." Bloom (2014), however, states that the volatility of bonds increases during uncertain times and that R&D-intense firms may instead be "stimulated." Therefore, the results indicate that IT, an R&D-intense sector, and bonds may complement each other in a portfolio, thus reducing the risk during uncertain times. This could explain the results. Interestingly, we find that the connectedness rate between the tech variables and bonds consistently increases after breakpoints in the trend.

The results for cleantech and Bitcoin, presented in Panel E and G, respectively, show that the different uncertainty measures lead to different reactions in the connectedness. The connectivity level between cleantech and bonds increases with EPU but decreases with the VIX. The dynamics between Bitcoin and the financial variables differ both in the level and the rate of co-movement. EPU causes a downshift in the level of connectivity between Bitcoin and the S&P 500 and ESG, whereas the VIX and OVX have the opposite effect. The co-movement rate also shows contrasting signs for the S&P 500, where EPU decreases the rate, and VIX increases it. Additionally, OVX has a negative effect on the S&P 500, MSCI World, ESG, and oil. The differing results are unsurprising because the uncertainty measures have different objectives. It could imply that the correlation between some variables is more susceptible to financial uncertainty in the short term, but economic uncertainty has a different effect over time or vice versa. Such is the case for Bitcoin and the S&P 500, for which the level of connection increases with the VIX, but over time, the VIX causes the connectedness rate to decrease. Furthermore, the volatility measure for oil, OVX, seems to have a negative effect on oil and Bitcoin in both constant and trend, but for all the other tech variables, the relationship with oil seems to become positive or unchanged.

Finally, the findings show that the level and rate of connection take on the same values when introducing uncertainty for some tech variables. This is true for all significant parameters for cleantech, as Panel D shows. Thus, we find a direct reaction in the level of affiliation and that over time, the connectivity rate will move in the same direction as the instantaneous effect. This result would imply that uncertainty boosts the increase or decrease in the linkage for the stated variables and possibly makes the relationship more sensitive to uncertainty.

Optimal portfolio weights and hedging strategies

To construct effective diversified or hedged portfolios, we consider portfolios consisting of two assets with optimal weights (PFI) and hedged portfolios without shorting constraints (PFII). In this application, we focus on minimizing the portfolio risk and do not focus on forecasting expected returns. Hence, we assume an expected return of zero. We calculate the optimal portfolio weights concerning time-varying covariance matrices following Kroner and Ng (1998), who define the portfolio weight (w_t) of the commodity asset holdings as

$$w_t = \frac{h_t^{fa} - h_t^{fa,te}}{h_t^{te} - 2h_t^{fa,te} + h_t^{fa}}, \quad \text{with} \quad \begin{cases} 0 & \text{if } w_t < 0 \\ w_t^* & \text{if } 0 \leq w_t \leq 1 \\ 1 & \text{if } w_t > 1 \end{cases} \tag{13}$$

where h_t^{fa} is the conditional volatility of a financial asset, h_t^{te} is the conditional volatility of a tech asset, and $h_t^{fa,te}$ is the conditional covariance between the returns of a financial asset and a tech asset. The calculated, w_t^*, is the optimal holding weight for the tech variable, which by definition gives the weight for the financial asset equal to $\left(1 - w_t^*\right)$. The hedging strategies include the determination of risk-minimizing hedge ratios. In this case, we determine how a one-dollar long position in a financial asset is hedged through a short position of β dollars in the tech sector. Following Kroner and Sultan (1993), the optimal hedge ratio is

$$\beta_t = \frac{h_t^{fa,te}}{h_t^{fa}}. \tag{14}$$

We construct the two-asset portfolios with each tech variable and a financial asset that minimizes the volatility. Figures 3 and 4 show the results for the tech weights and hedging ratios, respectively.[7] As the figures show, both the optimal weights and the hedge ratios vary over time, implying that the portfolios need revisions to be effective. We can also conclude that there is heterogeneity between the tech sectors, as the results show that we should apply different weights and ratios for each sector. In the diversified portfolios, Bitcoin should occupy the lowest weight for all financial assets, most likely due to its high volatility. This result is supported by Conlon and McGee (2020), who claim that a small allocation to Bitcoin substantially increases the portfolio downside risk. Further, Wu et al. (2019), Ji et al. (2020), and Hasan et al. (2021b) suggest that Bitcoin cannot be utilized as a hedging and diversification instrument against uncertainties and stock markets. After January 2018, cleantech is the best diversifier for ESG, indicating that a diverse and ethical portfolio could be created with these two assets. However, biotech is not an effective diversifier for ESG.

In the diversified portfolios containing bonds, less weight is given to the tech variables, as bonds have low volatility. IT, cleantech, and tech alternate as the biggest

[7] See Appendix 2 for other weight and hedging ratios.

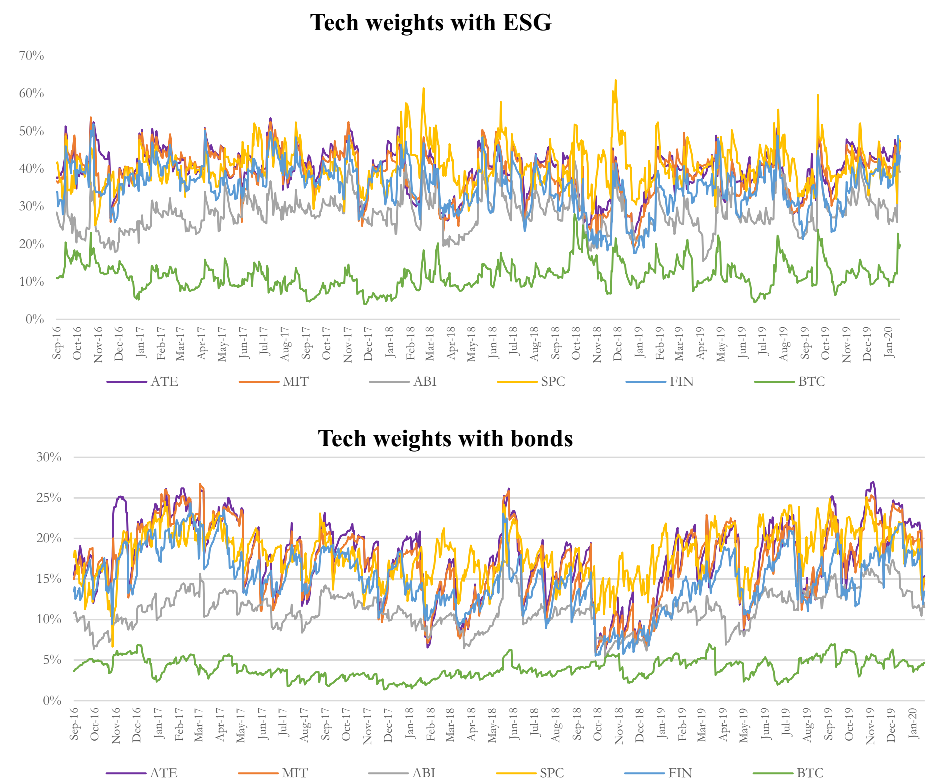


Fig. 3 Optimal tech weights with ESG and bonds

diversifier with bonds. In the hedged portfolios, Bitcoin fluctuates the most over time. A long position in the S&P 500 and oil should sometimes be hedged by a short position in Bitcoin, as the spikes below zero in the figures indicate. For a long position in the S&P 500, fintech provides the highest positive hedge ratio, implying that a larger short position in fintech is needed to hedge against the S&P 500 compared to the other tech variables.

To provide a comparative perspective of the two strategies, we presented the annual volatility for the diversified portfolio (PFI) and hedged portfolio (PFII) in Table 7. We generally find that tech assets are better diversification tools than hedges. Cleantech is the best diversifier for the S&P 500, MSCI World, ESG, and oil, suggesting that investors should include cleantech in their portfolio to reduce risk. This result is supported by Saeed et al. (2020) and Kuang (2021), who state that clean energy is an effective diversifier or hedging tool for international stocks. Diversifying with tech generates the lowest volatility for gold, USD, and bonds. The results for bonds imply that the tech variables should not be used to hedge against the market risk of bonds but to generate diversified portfolios with low volatility. This result is natural because bonds tend to have low market risk and should generally not be diversified with stocks to decrease risk. On the contrary, it is common to include bonds in stock portfolios to decrease risk.

Moreover, it observes that including Bitcoin in the portfolio generates a higher risk than other tech assets. This phenomenon is corroborated by Conlon and McGee (2020),

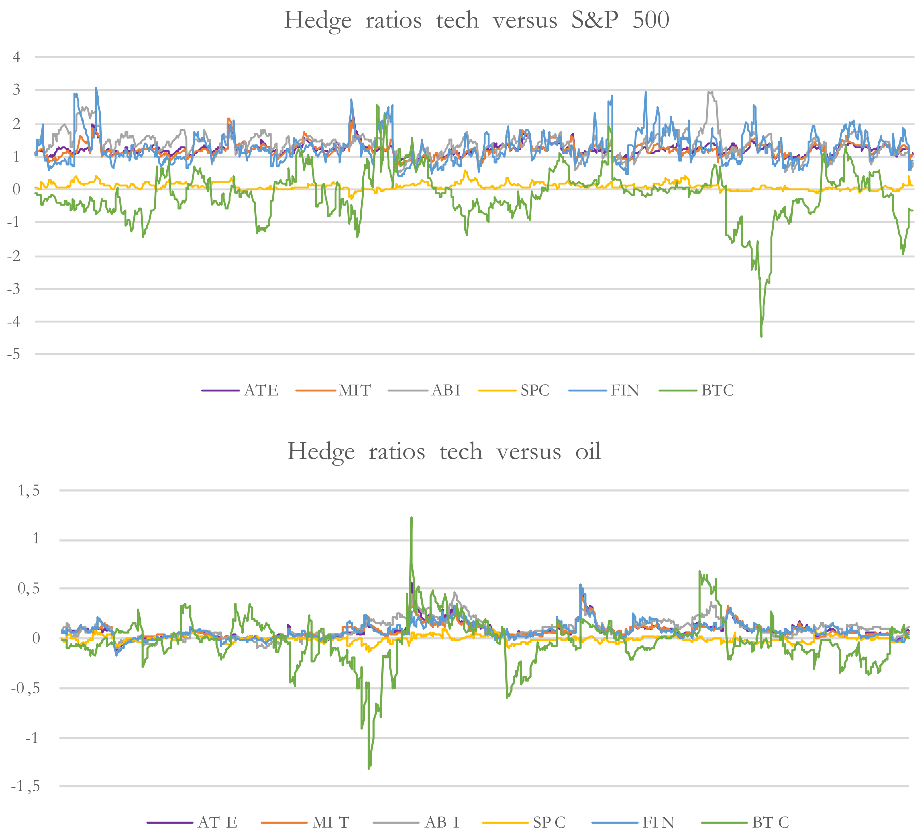


Fig. 4 Hedging ratios for tech assets against the S&P 500 and oil

who claim that, rather than offering hedging or safe-haven features, Bitcoin increases downside risk when incorporated into a portfolio due to its high price volatility. Contrary to diversification, suitable hedging tools are assets with strong absolute correlations. As such, Bitcoin generates greater risk than other tech variables because its correlations with financial assets are pretty low.

Conclusion and policy implications

In this study, we analyze the characteristics of tech subsectors and how they are connected with the financial market over time, considering breaks and uncertainty. We find heterogeneity in the relationships between the subsectors and the financial market, with differences in the correlations and movements over the business cycle. When we include time variation in the analysis of the relationships, we find that the unconditional and average dynamic conditional correlations show similar patterns. Tech, IT, biotech, and fintech highly positively correlate with the stock indices, and all tech variables negatively correlate with bonds. Bitcoin and cleantech diverge, with a positive correlation to gold. In addition, they are weakly correlated with the remaining financial assets. From the DCC graphs, we note that the correlation differs over time, which has implications for investors when creating effective portfolios. Our construction and testing of diversified

Table 7 Annual volatility in the diversified portfolio (PFI) and hedged portfolio (PFII)

	SP5 (%)		MWO (%)		ESG (%)		OIL (%)		GLD (%)		USD (%)		BND (%)	
	PFI	PFII	PFI	PFII	PFI	PFII	PFI	PFII	PFI	PFII	PFI	PFII	PFI	PFII
ATE	13.4	8.5	11.6	13.6	10.3	14.5	15.5	30.1	8.1	11.1	5.8	8.9	2.6	42.7
MIT	13.6	10.0	11.7	15.3	10.4	15.7	15.9	30.1	8.4	11.2	5.9	9.2	2.7	39.6
ABI	14.5	27.9	12.4	32.3	11.1	20.6	19.7	30.1	10.1	11.8	7.0	12.5	3.0	62.7
SPC	9.4	12.3	8.4	9.8	8.0	9.6	12.8	30.4	8.6	11.0	5.9	7.1	3.3	6.8
FIN	13.7	17.6	11.9	22.7	10.8	22.7	17.1	30.2	8.9	11.6	6.2	11.8	2.8	45.0
BTC	14.5	76.1	11.9	98.9	11.5	89.9	28.9	40.2	13.7	56.7	8.3	114	3.8	218

and hedged portfolios also strengthen the conclusion of heterogeneity in the subsectors since the weights and ratios vary between sectors.

We conclude that structural breaks in the tech variables lead to different effects on the relationship with the financial market. The dynamic correlation between the tech subsectors and the financial market is vital for investors to understand but not always sufficient. A risk-averse investor seeks assets that are uncorrelated to each other to diversify risk. Based on our findings, investors can use the tech sectors as a hedge or diversifier for different financial assets to protect their investments from various crises. However, political events and times of uncertainty affect the interaction, which could have significant consequences. Our results show that the effects on the interconnection between the tech subsectors and the financial market may depend on the types of political events. The effects of uncertainty on the linkage between tech variables and the financial market also vary and do not always follow the same pattern as structural breaks. Different uncertainty measures affect both the level and the rate of connectivity differently. When we include EPU, we find different reactions in the level and rate of connectivity between Bitcoin and ESG, where the former becomes negative and the latter becomes positive. Further, the connection between Bitcoin and bonds responds differently depending on the types of uncertainty. Including EPU in the analysis has a negative effect on the level of connection, whereas VIX has a positive effect.

Moreover, we find that for some tech variables, the level and rate of connectivity take the same values for both structural breaks and uncertainty. An investor would be more prepared for such pairs of subsectors and financial assets, and the outcome should be more predictable during such times. Finally, we find that the tech variables are more suitable for diversifying portfolios consisting of other financial assets, such as stocks, oil, and gold, rather than hedging tools. To further understand the tech-financial market relationship, it would be interesting to investigate the directionality between the subsectors and financial assets. Moreover, an important extension would be to analyze the dependency and directionality between the tech subsectors over time and design a risk-managing portfolio containing different tech assets.

The main limitation of this study is the separate data periods used because of the data availability. In addition, this study considers only the VIX as the proxy of stock market volatility. Future research could employ the uncertainty indices to investigate its impact on sector-specific or firm-level technological investment, as well as how several policy uncertainties are relevant to green technology investments.

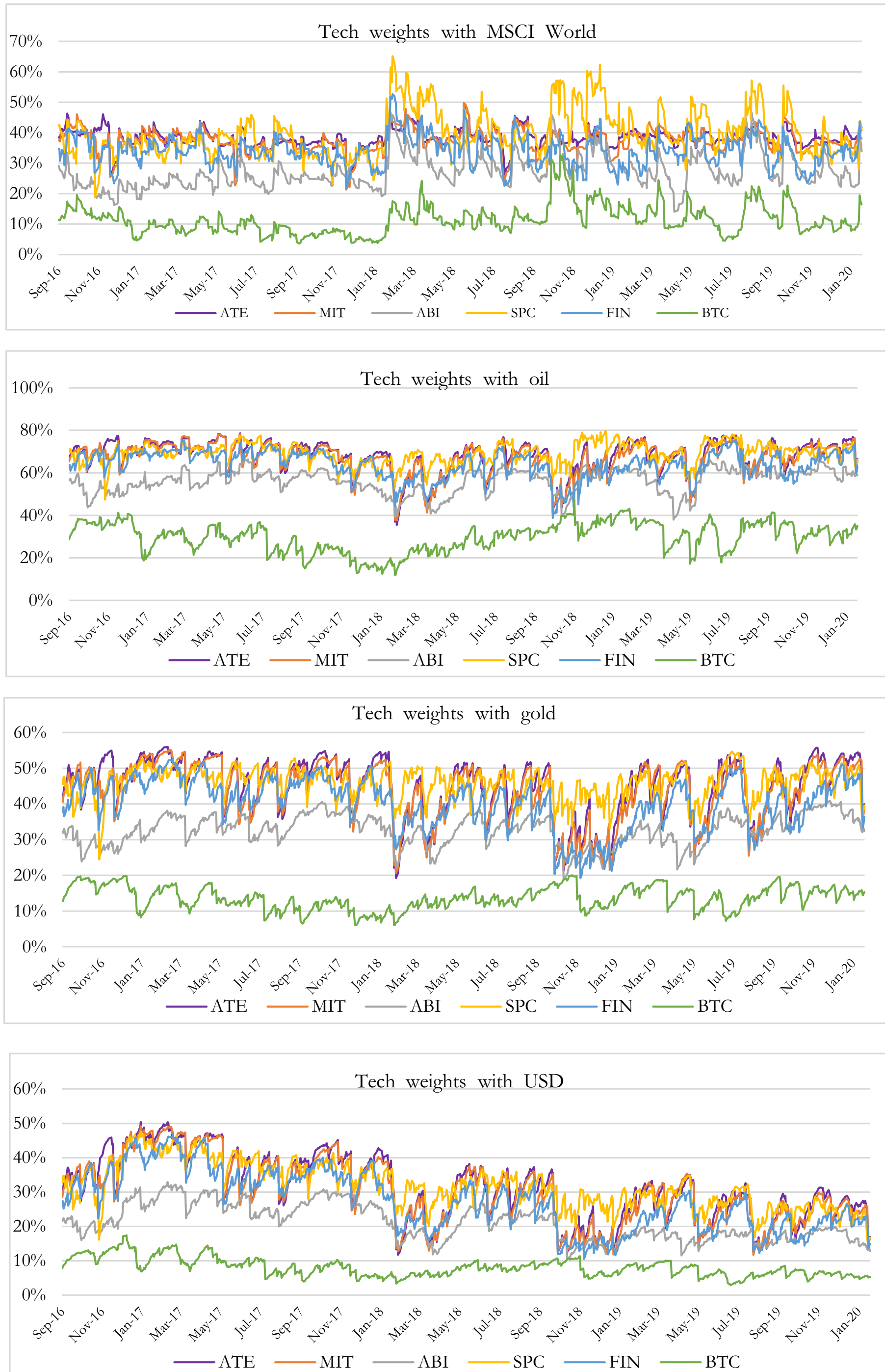
Appendix 1: Identification of best-fitted GARCH-model

ATE		1	2	3	4	5	6	MIT		1	2	3	4	5	6
ARMA	*(p, q)*	(1, 0)	(0, 1)	(1, 1)	(2, 0)	(0, 2)	(2, 1)	ARMA	*(p, q)*	(1, 0)	(0, 1)	(1, 1)	(2, 0)	(0, 2)	(2, 1)
GARCH	*LOG (L)*	136,197	136,186	136,112	136,213	136,189	136,217	GARCH	*LOG (L)*	135,884	135,872	135,841	135,895	135,875	135,904
	AIC	− 51,96,139	− 51,95,717	− 51,92,631	− 51,96,507	− 51,95,587	− 51,96,358		*AIC*	− 51,84,185	− 51,83,737	− 51,82,272	− 51,84,362	− 51,8357	− 51,84,447
	BIC	− 51,88,874	− 51,88,451	− 51,84,488	− 51,88,365	− 51,87,445	− 51,87,339		*BIC*	− 51,7692	− 51,76,472	− 51,7413	− 51,76,219	− 51,75,427	− 51,75,427
EGARCH	*LOG (L)*	134,771	134,655	134,652	134,848	134,841	134,313	EGARCH	*LOG (L)*	134,470	134,535	134,264	134,552	134,552	134,140
	AIC	− 51,41,166	− 51,36,745	− 51,3638	− 51,43,855	− 51,43,571	− 51,2316		*AIC*	− 51,29,709	− 51,3216	− 51,21,571	− 51,32,544	− 51,3257	− 51,16,572
	BIC	− 51,32,146	− 51,27,725	− 51,26,483	− 51,33,959	− 51,33,675	− 51,12,387		*BIC*	− 51,2069	− 51,2314	− 51,11,674	− 51,22,648	− 51,22,673	− 51,05,798
GJR	*LOG (L)*	136,268	136,256	136,249	136,277	136,258	136,281	GJR	*LOG (L)*	135,983	135,971	135,980	135,991	135,975	135,998
	AIC	− 51,98,581	− 51,9812	− 51,97,604	− 51,98,683	− 51,97,955	− 51,98,564		*AIC*	− 51,87,727	− 51,87,259	− 51,87,341	− 51,87,745	− 51,87,148	− 51,87,766
ABI		**1**	**2**	**3**	**4**	**5**	**6**	**SPC**		**1**	**2**	**3**	**4**	**5**	**6**
ARMA	*(p, q)*	(1, 0)	(0, 1)	(1, 1)	(2, 0)	(0, 2)	(2, 1)	ARMA	*(p, q)*	(1, 0)	(0, 1)	(1, 1)	(2, 0)	(0, 2)	(2, 1)
GARCH	*LOG (L)*	131,241	131,233	131,197	131,257	131,235	131,261	GARCH	*LOG (L)*	125,709	125,690	125,631	125,701	125,673	125,674
	AIC	− 50,06,973	− 50,06,696	− 50,0504	− 50,07,321	− 50,06,482	− 50,07,229		*AIC*	− 59,47,405	− 59,46,531	− 59,43,340	− 59,46,663	− 59,45,342	− 59,45,002
	BIC	− 49,99,707	− 49,99,431	− 49,96,898	− 49,99,179	− 49,98,339	− 49,9821		*BIC*	− 59,36,887	− 59,36,012	− 59,3162	− 59,34,942	− 59,33,621	− 59,32,079
EGARCH	*LOG (L)*	130,001	130,037	129,856	130,053	130,047	129,688	EGARCH	*LOG (L)*	123,746	123,323	123,668	123,721	123,244	123,585
	AIC	− 49,5912	− 49,60,495	− 49,53,317	− 49,60,848	− 49,60,603	− 49,46,632		*AIC*	− 58,53,719	− 58,33,715	− 58,49,651	− 58,52,153	− 58,2959	− 58,45,335
	BIC	− 49,50,101	− 49,51,475	− 49,4342	− 49,50,952	− 49,50,707	− 49,35,859		*BIC*	− 58,40,796	− 58,20,792	− 58,35,526	− 58,38,028	− 58,15,465	− 58,30,008
GJR	*LOG (L)*	131,381	131,373	131,377	131,392	131,376	131,399	GJR	*LOG (L)*	125,704	125,699	125,683	125,708	125,689	125,693
	AIC	− 50,12,044	− 50,11,766	− 50,11,647	− 50,12,223	− 50,11,591	− 50,12,215		*AIC*	− 59,46,781	− 59,46,533	− 59,45,412	− 59,46,591	− 59,45,706	− 59,45,524
	BIC	− 50,03,901	− 50,03,623	− 50,02,628	− 50,03,204	− 50,02,572	− 50,02,319		*BIC*	− 59,3506	− 59,34,812	− 59,32,489	− 59,33,668	− 59,32,783	− 59,31,399

FIN		1	2	3	4	5	6	BTC		1	2	3	4	5	6
ARMA	*(p, q)*	(1, 0)	(0, 1)	(1, 1)	(2, 0)	(0, 2)	(2, 1)	ARMA	*(p, q)*	(1, 0)	(0, 1)	(1, 1)	(2, 0)	(0, 2)	(2, 1)
GARCH	*LOG (L)*	28,641,6	28,629,7	28,583,2	28,635	28,632,1	28,612,4	GARCH	*LOG (L)*	41,420,5	41,413,4	41,410,9	41,417		
	AIC	− 64,71,487	− 64,68,781	− 64,56,438	− 64,6817	− 64,67,526	− 64,61,239		*AIC*	− 58,98,784	− 58,97,774	− 58,96,282	− 58,97,144		
	BIC	− 64,33,568	− 64,30,861	− 64,14,185	− 64,25,916	− 64,25,273	− 64,14,651		*BIC*	− 58,72,593	− 58,71,583	− 58,67,098	− 58,6796		
EGARCH	*LOG (L)*	27,383,9	27,430,5	27,364,9	27,402,5	27,421	24,745,4	EGARCH	*LOG (L)*	40,073,2	40,100,3	40,133,6	40,096,5		
	AIC	− 61,8298	− 61,9355	− 61,76,867	− 61,8539	− 61,89,576	− 55,81,745		*AIC*	− 57,04,313	− 57,0817	− 57,11,782	− 57,06,495		
	BIC	− 61,36,393	− 61,46,963	− 61,25,946	− 61,34,469	− 61,38,655	− 55,26,491		*BIC*	− 56,72,136	− 56,75,993	− 56,76,611	− 56,71,325		
GJR	*LOG (L)*	28,648,6	28,650,6	28,629,7	28,646,4	NA	28,657,3	GJR	*LOG (L)*	41,436,7	41,439,5	41,413,1	41,443,4		
	AIC	− 64,71,265	− 64,71,714	− 64,65,168	− 64,68,944	NA	− 64,69,595		*AIC*	− 58,99,962	− 59,0035	− 58,95,443	− 58,99,773		
	BIC	− 64,29,011	− 64,2946	− 64,1858	− 64,22,357	NA	− 64,18,674		*BIC*	− 58,70,778	− 58,71,166	− 58,63,266	− 58,67,595		

Schwartz information criterion is denoted as BIC, where the best (lowest) value is highlighted with shading. We proceeded with tests of ARMA orders until the higher-order (p + 1 and q + 1) did not yield better BIC values than p − 1 and q − 1. As an example, if the lowest BIC is (1,0), we proceed until (2,1) and then stop if BIC (1,0) ≤ BIC (2,1).Appendix 2

Panel A: Optimal tech weights for S&P 500, MSCI World, oil, gold, and USD.



Panel B: Hedging ratios for tech assets, MSCI World, ESG, gold, USD, and bond.

Abbreviations

ABI	NYSE Arca Biotechnology
ATE	NYSE Arca Technology 100 Index
BND	Five-year US Treasury bond rate
BTC	Bitcoin/USD exchange rate
DCC	Dynamic Conditional correlation
ESG	MSCI World ESG Leaders
FIN	Global X Fintech ETF
GARCH	Generalized Autoregressive conditional heteroskedasticity
GJR	Glosten, Jagannathan, and Runkle (1993)
GFC	Global financial crisis
GLD	Gold
IDC	International Data Corporation
MIT	MSCI World Information Technology
MWO	MSCI World
OIL	Crude oil
SIC	Schwarz information criterion
SP5	S&P 500
SPC	S&P clean energy
USD	US dollar and Euro

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Author contributions
LA: conceptualization, investigation, EE: data curation, data analysis and investigation, GSU: supervision, writing-review and editing, MBH: writing-final revision, SHK: writing-review and editing, funding acquisition. All authors read and approved the final manuscript.

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Availability of data and materials
The datasets generated and/or analysed during the current study are not publicly available due to data security but are available from the corresponding author on reasonable request.

Declaration

Competing interests
There are no conflict of interest to declare.

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