Digital Finance (2026) 8:22
https://doi.org/10.1007/s42521-026-00190-7

RESEARCH

Understanding sectoral co-movement and investor behaviour during black swan events: a study of tech and pharma stocks during the global pandemic

František Pollák[1,2] · Kristián Kalamen[1] · Roman Vavrek[3] · Mónica García-Melón[4]

Received: 5 August 2025 / Accepted: 18 March 2026

Abstract

The COVID-19 pandemic exposed vulnerabilities in global financial markets and altered investor behaviour across sectors under conditions of heightened uncertainty. This study examines whether the technology and pharmaceutical sectors exhibited distinct patterns of synchronization with the S&P 500 during pandemic waves and inter-wave periods. Sector–benchmark co-movement is evaluated using rank-based correlation measures across short lead–lag structures and epidemiologically defined phases spanning March 2019 to December 2022. To capture potential changes in sectoral alignment with the market benchmark, the analysis adopts a phase-sensitive framework that allows co-movement to vary across different stages of the pandemic. Sector-level evidence is complemented by firm-level illustrations using representative companies from each sector. This approach enables an assessment of whether observed synchronization reflects contemporaneous market integration or more episodic, sector-specific dynamics during periods of systemic stress. The findings indicate that the technology sector displayed relatively stronger and more contemporaneous alignment with the S&P 500, particularly during periods of elevated uncertainty, whereas the pharmaceutical sector exhibited more irregular and event-driven co-movement patterns. These results suggest that sectoral synchronization during the pandemic was heterogeneous and evolved over time rather than remaining constant across sectors or phases. By focusing on sector–benchmark interactions during an extreme global shock, this study contributes to the literature on financial market behaviour under crisis conditions. The results highlight the importance of sector-level analysis when assessing diversification properties and market integration during periods of heightened uncertainty.

Keywords Sectoral synchronization · Investor behavior · Market integration under uncertainty · COVID-19 pandemic · Rank correlation

JEL Classification G01 · G10 · G12

Extended author information available on the last page of the article

1 Introduction

Sector diversification is a central principle of portfolio construction and risk management. By allocating capital across industries with heterogeneous economic fundamentals, investors aim to reduce exposure to aggregate shocks and preserve the informational content of sector-specific returns. This mechanism, however, relies on the assumption that sectors remain imperfectly correlated with the broader market. When sectoral returns become highly synchronized with a market benchmark such as the S&P 500 or Nasdaq, diversification benefits deteriorate, common risk pricing dominates sectoral fundamentals, and shocks are more likely to propagate systemically. Whether sector diversification continues to function during periods of extreme uncertainty is therefore an economically meaningful question with direct implications for investors, regulators, and financial stability.

The COVID-19 pandemic provides an exceptional setting in which to examine this issue. Unlike crises originating within the financial system, the pandemic emerged as an exogenous public-health shock that disrupted real economic activity through lockdowns, mobility restrictions and policy interventions. These measures generated unprecedented uncertainty about growth prospects, cash flows, and the duration of economic disruption, forcing investors to rapidly reassess risk and reallocate capital. Evidence from financial markets indicates that this uncertainty was immediately reflected in sharp repricing of expected growth, highlighting the pandemic's relevance for asset pricing and portfolio decisions (Gormsen & Koijen, 2020; Goodell, 2020; Yousaf & Yarovaya, 2022).

From an economic perspective, synchronization between sectoral returns and the S&P 500 (see slickchart.com for its current market share – capitalization) during such a shock is not merely a statistical regularity. It reflects how investors balance sector-specific information against market-wide discount-rate shocks under stress. When uncertainty is elevated, investors may rely more heavily on benchmarks, reduce differentiation across sectors and price assets primarily through common risk factors. Conversely, persistent differentiation in sector–benchmark relationships would suggest that sector-specific fundamentals continue to play a meaningful role in valuation even during systemic crises. Understanding which of these mechanisms dominates is essential for interpreting market behaviour during extreme events. The pandemic is particularly informative because its economic impact was highly asymmetric across sectors. Some industries experienced abrupt contractions due to containment measures, while others became critical to maintaining economic continuity. Technology firms, embedded in digital infrastructure, remote communication, and cloud-based services, assumed an increasingly central role as economic activity shifted online. Pharmaceutical firms, by contrast, were shaped by innovation pipelines, regulatory approvals, and discrete information events related to vaccines and treatments. These structural differences imply that the two sectors may have interacted with aggregate market risk in fundamentally different ways during the pandemic, despite being exposed to the same global shock.

Investor behaviour provides a crucial channel linking these sectoral characteristics to observed market outcomes. Under conditions of extreme uncertainty, behavioural responses such as herding, benchmark-oriented trading, and heightened sensitivity to policy and health-related news can compress sectoral differences and increase co-movement with the market index (Hasan, 2022; Harb & Umutlu, 2024). As uncertainty evolves and information becomes more differentiated, investors may gradually re-price sector-specific risks, leading to changes in sector–benchmark dependence over time. Whether sectoral synchronization during COVID-19 reflected temporary crisis behaviour or more persistent structural integration remains an open empirical question. Existing research on financial markets during the pandemic documents substantial increases in volatility, spillovers, and market-wide connectedness. While these findings confirm the systemic nature of the shock, they provide limited insight into how sectoral risk was priced relative to the market benchmark over the course of the crisis. Aggregate analyses obscure sector-level heterogeneity, and cross-market studies often abstract from differences in economic roles across industries. Against this background, understanding how sectoral returns interacted with the broader market during the COVID-19 shock is essential for interpreting investor behaviour and assessing the limits of sector diversification under extreme uncertainty.

Positioned within this framework, the present study examines how the technology and pharmaceutical sectors co-moved with the S&P 500 during the COVID-19 pandemic, with particular attention to the evolution of synchronization across different stages of the crisis. By focusing on sector–benchmark relationships rather than aggregate market spillovers, the analysis seeks to shed light on whether pandemic-era synchronization reflects temporary behavioral reactions, structural integration driven by digitalization, or event-driven pricing linked to sector-specific information. This perspective allows for a more nuanced interpretation of co-movement dynamics and contributes to a deeper understanding of how investors reprice sectoral risk under extreme uncertainty. In doing so, the study aligns with the broader literature's call for economically grounded, dynamic analyses of financial market behavior during crises. Rather than treating synchronization as an end, it conceptualizes sectoral co-movement with the S&P 500 as an indicator of how market participants process uncertainty, allocate capital, and reassess the relative importance of different sectors in the face of a global shock. This positioning bridges the gap between descriptive evidence on crisis volatility and a theoretically informed interpretation of sectoral behavior during Black Swan events.

Rather than modeling long-run equilibrium relationships, this study focuses on short to medium horizon behavioral synchronization under extreme uncertainty. Rank-based dependence measures are particularly suitable in this context, as they are robust to non-normal return distributions, outliers, and abrupt regime shifts that characterize crisis periods. By combining lag-specific rank correlations with monotonic trend detection, the analysis captures how sector–benchmark dependence emerges, intensifies, or dissipates across distinct uncertainty regimes, without imposing linearity or long-run equilibrium assumptions.

The objective of this study is to examine how synchronization between the technology and pharmaceutical sectors and the S&P 500 evolved during the COVID-19 pandemic, and whether sector–benchmark co-movement differed across pandemic waves and inter-wave periods in terms of strength, timing, and persistence, reflecting heterogeneous investor responses under extreme uncertainty. The remainder of the paper is organized as follows. Section 2 reviews the relevant theoretical and empirical literature on financial market co-movement, crisis dynamics, and investor behavior. Section 3 describes the data, temporal segmentation, and empirical methodology. Section 4 presents and discusses the empirical results, while Sect. 5 concludes with implications for portfolio diversification, market stability, and future research.

2 Literature review

Empirical finance has long examined co-movement among asset returns as a manifestation of shared exposure to macroeconomic risk factors and evolving market integration. Early studies document that correlations across assets and sectors are time-varying and tend to increase during periods of financial stress, altering the transmission of shocks and the structure of systemic risk (Forbes & Rigobon, 2002; Solnik et al., 1996). Subsequent research extends this insight by exploring the mechanisms through which co-movement intensifies during crises, including portfolio rebalancing, information spillovers, and market-wide shocks. Early theoretical and empirical work on contagion challenged the notion that increased correlations during crises necessarily reflect irrational panic. Kodres and Pritsker (2002) show that contagion can arise endogenously as a rational equilibrium outcome driven by portfolio rebalancing, cross-market hedging and information effects. When investors face shocks to one asset or market, they may rebalance positions elsewhere to manage risk exposure, generating excess co-movement even in the absence of direct fundamental linkages. This framework established contagion and synchronization as economically meaningful phenomena rooted in financial interdependence rather than behavioral anomalies.

Beyond the core strands of contagion, connectedness and crisis co-movement a wide range of empirical studies has further refined the analysis of dynamic dependence across financial markets using alternative econometric, network-based and nonlinear frameworks. Research examining spillovers between equity, commodity and foreign exchange markets consistently documents strong time variation and asymmetry in transmission mechanisms, particularly during periods of heightened uncertainty (Tilfani et al., 2019; Hu et al., 2020; Adekoya & Oliyide, 2021; Yang et al., 2021). Studies focusing on cross-asset and cross-market interactions show that lead–lag relationships and directional spillovers evolve over time and intensify during crisis episodes, reinforcing the need for dynamic rather than static dependence measures (Solnik et al., 1996; Vyrost et al., 2015; He et al., 2021). Empirical research following major crisis episodes confirmed that both return and volatility spillovers intensify during turbulent periods and that these spillovers are directional rather than symmetric. Diebold and Yilmaz (2009) introduced a framework for measuring volatility spillovers based on forecast error variance decompositions, demonstrating that shocks propagate unevenly across markets. Subsequent extensions emphasized directional connectedness, distinguishing between net transmitters and net receivers of volatility (Diebold & Yilmaz, 2012). This line of research fundamentally reframed co-movement as a system-wide property of financial networks rather than a pairwise correlation between assets.

Later work expanded this framework to capture the topology of financial networks more explicitly. Diebold and Yilmaz (2014) showed that connectedness measures can be interpreted as weighted, directed networks that evolve over time, with network density increasing during crises. Empirical applications across equity, banking, commodity, and foreign exchange markets consistently reveal that financial systems become more tightly connected under stress, increasing the potential for systemic risk transmission (Billio et al., 2012; Demirer et al., 2018). A key limitation of early connectedness and correlation-based approaches is their implicit assumption that dependence operates uniformly across time horizons. More recent research addresses this issue by decomposing co-movement into frequency components. Baruník and Křehlík (2018) propose a frequency-domain connectedness framework that distinguishes between short-term and long-term spillovers. Their results show that during crisis periods, low-frequency connectedness dominates, indicating persistent integration driven by macroeconomic uncertainty and long-run expectations rather than transient trading effects. Similar conclusions emerge from wavelet-based and multiscale analyses of financial markets, which document that correlations differ substantially across time scales and intensify at longer horizons during systemic events (Wang et al., 2017, 2018).

Another strand of the literature emphasizes that linear correlation measures underestimate dependence during extreme market movements. Copula-based models and tail-dependence frameworks reveal that financial assets often exhibit weak dependence in normal times but strong co-movement in the tails of the return distribution (Patton, 2006; Sukcharoen et al., 2014). Wen et al. (2019) extends this insight by constructing tail-dependence networks of global stock markets, showing that network structure and systemic importance differ markedly between normal and extreme market conditions. These findings suggest that crisis-time synchronization is inherently nonlinear and that average correlation measures fail to capture the most economically relevant forms of dependence. Furthermore, network approaches rooted in economy-physics support this view. Hierarchical clustering and minimum spanning tree analyses reveal that market structure becomes more compact and centralized during crises, with dominant markets exerting stronger influence over peripheral ones (Mantegna, 1999; Tumminello et al., 2005, 2010). These structural changes imply that synchronization during crises reflects a reorganization of the financial system rather than a uniform increase in pairwise correlations.

Goodell (2020) characterizes the pandemic as a unique event for financial research due to its global simultaneity, policy-driven economic disruption, and profound uncertainty regarding duration and outcomes. The COVID-19 pandemic has also been examined through a variety of complementary empirical lenses, including studies of uncertainty transmission, policy effects, and information-driven volatility. Evidence shows that pandemic-related news, health indicators and policy responses played a central role in shaping financial market dynamics, amplifying spillovers and altering dependence structures across assets and markets (Ozili & Arun, 2020; Salisu & Vo, 2020; Sharif et al., 2020; Albulescu, 2021). Analyses of market reactions to COVID-19 further highlight the heterogeneity of responses across regions, asset classes, and time periods, underscoring the importance of time-varying frameworks and careful periodization in empirical research (Bissoondoyal-Bheenick et al., 2020;

Zhang et al., 2020; Aharon et al., 2021; Wang et al., 2022). Empirical evidence from early 2020 documents extreme volatility spikes, abrupt liquidity shortages, and sharp increases in cross-market spillovers across global equity markets (Baker et al., 2020; Albulescu, 2021). Studies applying connectedness and spillover frameworks show that volatility transmission surged dramatically during the initial phase of the pandemic, consistent with heightened uncertainty and synchronized investor reactions (Bissoondoyal-Bheenick et al., 2020; Aharon et al., 2021).

Within this context, technology and pharmaceutical sectors occupy distinct economic roles that motivate a comparative analysis of their synchronization with the S&P 500. Technology firms are deeply embedded in the digital infrastructure that underpins modern economic activity. During the pandemic, remote work, digital communication, cloud services and e-commerce became essential rather than complementary, potentially increasing the macroeconomic relevance of large technology firms. The literature on the digital economy emphasizes that digitalization strengthens scale effects, increases market concentration and ties firm performance more closely to aggregate productivity and demand conditions (Chen, 2020) From an asset-pricing perspective, this suggests that technology sector returns may become more tightly linked to market wide discount-rate shocks during periods when digital services are central to economic resilience. Pharmaceutical firms, by contrast, are characterized by innovation-driven and regulation-sensitive cash flows. Empirical evidence indicates that such event-driven dynamics can generate asymmetric and episodic spillovers rather than persistent synchronization with aggregate market indices (Wen et al., 2019; Yang et al., 2021). This asymmetry implies that synchronization patterns for pharmaceuticals may differ not only in magnitude but also in stability and timing compared to technology. Investor behavior provides a critical link between these sectoral characteristics and observed co-movement dynamics. Behavioral finance research shows that under extreme uncertainty, investors tend to engage in herding, benchmarked trading, and flight-to-liquidity, which amplify the common component in asset returns (Antonakakis et al., 2020; Sharif et al., 2020). In the early phase of the pandemic, such behavior likely contributed to broad based selloffs and heightened synchronization across sectors.

Time-varying and frequency-domain analyses of COVID-19 market dynamics reveal that these effects were not constant over time. Wang et al. (2022) find that spillovers intensified sharply during the first wave of the pandemic and declined gradually as policy interventions stabilized markets. Frequency-based decompositions indicate that low-frequency spillovers dominated during peak uncertainty, suggesting persistent systemic integration rather than short-lived speculative co-movement. Similar patterns are documented in studies examining volatility transmission across commodities, equities, and foreign exchange markets during the pandemic (Hu et al., 2020; Yang et al., 2021). A growing literature also examines the role of uncertainty, sentiment, and information flow during COVID-19. Sharif et al. (2020) show that pandemic-related news and policy announcements had immediate and significant effects on financial markets, amplifying volatility and co-movement across assets. Salisu and Vo (2020) demonstrate that health-related information became a significant predictor of stock returns during the pandemic, underscoring the role of non-economic news in shaping financial dynamics. While much of the COVID-19 literature focuses on aggregate indices and cross-country spillovers, several studies highlight substantial heterogeneity across markets and assets. Ramelli and Wagner (2020) document pronounced differences in firm-level and sectoral responses to the pandemic, reflecting exposure to lockdown measures, supply chain disruptions, and shifts in consumer behavior. Zhang et al. (2020) similarly show that financial markets responded heterogeneously across regions and sectors despite synchronized global volatility spikes.

Methodologically, the COVID-19 literature reinforces the limitations of static descriptive approaches. Studies relying on rolling-window estimation, time-varying parameter VAR models, and network-based measures consistently provide richer insights into the evolution of market dependence than those based on fixed-sample correlations (Demirer et al., 2018; Antonakakis et al., 2020). These approaches reveal that both the magnitude and direction of spillovers change over time, often in response to policy interventions and shifts in uncertainty regimes.

Financial market co-movement is a dynamic and state-dependent process, influenced by macroeconomic shocks, behavioral responses of investors, and institutional mechanisms that govern risk transmission across markets. From an economic perspective, synchronization between sectoral returns and a broad market benchmark such as the S&P 500 matters because it reveals how investors price sector-specific cash flows under varying uncertainty regimes. When sectoral returns become highly synchronized with the benchmark, diversification benefits deteriorate and sectoral shocks are more likely to propagate systemically. Conversely, weaker or unstable synchronization may indicate that sector-specific information continues to dominate pricing, preserving heterogeneity in risk assessment even during crises (Kodres & Pritsker, 2002; Diebold & Yilmaz, 2014). The economic logic underpinning sector benchmark synchronization rests on the interaction between common discount-rate shocks and sectoral cash-flow expectations. During tranquil periods, sector returns reflect heterogeneous fundamentals, technological cycles, regulatory environments and demand conditions. In crisis periods, however, heightened uncertainty and liquidity constraints tend to elevate the role of common risk factors, increasing the weight of aggregate discount-rate shocks relative to idiosyncratic cash-flow news. This mechanism has been widely documented in studies showing that correlations and spillovers intensify during periods of market stress (Forbes & Rigobon, 2002; Baruník & Křehlík, 2018; Kalamen et al., 2023). Importantly, the strength and persistence of this synchronization are not uniform across sectors, as different industries vary in their exposure to macroeconomic conditions, policy interventions, and investor sentiment. COVID-19 provides a particularly informative setting for examining these mechanisms because it represents an exogenous shock that altered both the level and the structure of uncertainty. Unlike financial crises driven by balance-sheet weaknesses or asset-price bubbles, the pandemic disrupted real economic activity through lockdowns, mobility restrictions, and public health interventions, while simultaneously prompting unprecedented monetary and fiscal responses. As a result, investors faced not only heightened volatility but also deep uncertainty regarding the duration of restrictions, the pace of recovery, and the long-term transformation of economic activity (Baker et al., 2020; Goodell, 2020; Akhtaruzzaman et al., 2021; Pollák et al., 2026).

A growing strand of COVID-19 finance literature emphasizes that market reactions during the pandemic were not continuous or homogeneous but unfolded across distinct epidemiological and policy-driven phases. Studies documenting pandemic-induced market dynamics consistently identify sharp discontinuities in volatility, spillovers, and return co-movement corresponding to infection waves (Ashraf 2020a; Baker et al. 2020; Goodell 2020; Narayan 2022). Rather than treating the pandemic as a single event or relying exclusively on rolling windows, several authors adopt phase-based or regime-oriented approaches to capture shifts in investor behavior between acute shock phases and calmer inter-wave periods, arguing that behavioral responses differ fundamentally across these stages (Ramelli & Wagner, 2020; Harjoto et al., 2021; Yuan et al., 2022). Importantly, these phases are not defined by equal economic conditions but by transitions in uncertainty regimes shaped by epidemiological developments and policy interventions. Aligning empirical segmentation with World Health Organization updates, major containment measures, and vaccine milestones allows researchers to isolate periods of heightened systemic stress from intervals of partial normalization, even if calendar lengths appear similar. This literature suggests that phase-based segmentation provides a more economically meaningful framework for analyzing investor synchronization than purely mechanical time windows, particularly when the objective is to assess how sector–benchmark dependence evolves across qualitatively different crisis stages. From an economic and behavioral perspective, pandemic waves and inter-wave periods are associated with fundamentally different uncertainty regimes, which implies systematic differences in sector–benchmark synchronization. During pandemic waves, elevated health risk, policy uncertainty, and abrupt macroeconomic disruptions tend to amplify common discount-rate shocks, leading investors to rely more heavily on market benchmarks and to reduce differentiation across assets. This mechanism is consistent with crisis-period evidence showing rising correlations, intensified spillovers, and benchmark-oriented trading when uncertainty peaks (Forbes & Rigobon, 2002; Baker et al., 2020; Sharif et al., 2020). In contrast, inter-wave periods are typically characterized by lower uncertainty, partial policy stabilization, and improved information about economic adaptation, allowing sector-specific fundamentals to regain importance in valuation. As a result, sector–benchmark dependence may weaken or become more heterogeneous outside acute crisis phases. Importantly, these effects are not expected to be uniform across sectors. Industries whose cash flows are closely tied to aggregate economic activity may exhibit stronger and more persistent synchronization during waves, whereas sectors driven by innovation cycles or event-specific information may display episodic or asymmetric co-movement.

Despite the richness of the existing literature, several gaps remain. While numerous studies document increased volatility and connectedness during COVID-19, much of this work focuses on aggregate indices or cross-country spillovers, offering limited insight into sector benchmark relationships. Sector-level analyses are often descriptive or confined to short windows, leaving open questions about the persistence and economic interpretation of synchronization patterns. Moreover, although dynamic and frequency-domain methods are increasingly used, they are rarely applied within a comparative sectoral framework that explicitly links co-movement dynamics to sector-specific economic roles. Finally, the literature frequently documents dynamic spillovers without directly connecting them to investor behavior and benchmark oriented trading that explain why synchronization should strengthen or weaken across different phases of a crisis. As a result, it remains unclear whether pandemic-era sector benchmark co-movement reflects temporary behavioral reactions, structural integration, or event-driven repricing of sector-specific risk an issue this study explicitly addresses.

These gaps point to the need for a sector-focused analysis that treats synchronization with the S&P 500 as an economically meaningful outcome rather than a purely statistical artifact. Such an analysis should account for time variation in dependence structures, recognize the role of extreme events and tail dependence, and interpret results through the lens of investor behavior and sectoral economics. The existing evidence on dynamic connectedness, tail dependence, and frequency-specific spillovers provides the methodological foundation for this approach (Diebold & Yilmaz, 2014; Baruník & Křehlík, 2018; Wen et al., 2019).

In the context of the above, the research objective of this study is to determine whether the technology and pharmaceutical sectors exhibited statistically significant, lag-specific synchronization with the S&P 500 index during pandemic waves and inter-wave periods. In order to achieve this research objective, the research aims to answer two research questions:

RQ1: Can the impact of individual waves of the COVID-19 pandemic be considered homogeneous across the SP500 index and two selected sectors (PHA, TECH)?

RQ2: Is it possible to observe a time lag in the development of the S&P 500 index and the two selected sectors (PHA, TECH)?

3 Methodology

This study aims to determine whether the technology and pharmaceutical sectors exhibited statistically significant, lag-specific synchronization with the S&P 500 index during pandemic waves and inter-wave periods. Specifically, we test whether the absolute level of correlation between sectoral median returns and the S&P 500 index increased during pandemic induced systemic shocks, and whether any lead-lag relationships emerged. Our analysis seeks to describe the adaptive markets hypothesis (Lo, 2004) in a high volatility setting, examining how investor adaptation manifested across two structurally different sectors. Technology, associated with innovation and long-term growth, and pharmaceuticals, perceived as a defensive sector with episodic price movements during health crises.

This methodology is inspired by and expands upon prior studies such as Albuquerque et al. (2020), Haroon and Rizvi (2020), who identified shifts in investor sentiment during pandemic peaks but lacked a temporal granularity based on epidemiological segmentation.

Data sources and sampling strategy

We employ historical daily return data for a total of 10 firms, 7 in the technology sector (Apple Inc., Amazon, Alphabet, Microsoft, Nvidia, Meta, and Tesla) and 3 in the pharmaceutical sector (Pfizer, Moderna, and Johnson & Johnson) as well as the S&P 500 Index, covering the period March 8, 2019 to December 12, 2022. These firms were chosen based on market capitalization, sectoral relevance, and investor interest volume, consistent with methodologies used by and Zhang et al. (2020). The selected firms represent economically meaningful but not exhaustive portions of their respective sectors within the S&P 500 index. During 2019–2022, the information technology sector accounted for approximately 27–30% of total S&P 500 market capitalization, with the technology firms included in this study jointly representing roughly 22–24% of the index. In contrast, the pharmaceutical firms considered represented approximately 6–7% of index capitalization, despite belonging to the broader healthcare sector, which accounted for about 13–15% of the index. Data for this research were obtained from:

Yahoo Finance - used for extracting historical daily adjusted closing prices of all 10 companies (7 technology, 3 pharmaceutical) and the S&P 500 index.

Investing.com - used as a secondary verification source for cross-checking market prices and benchmark index consistency during known volatility windows.

Microsoft Excel - used for manual preprocessing steps, inspection of data integrity, and export of summary statistics and return matrices.

Daily closing prices were retrieved from Yahoo Finance and Investing.com, from which daily returns were calculated:

$$r_{i,t} = \frac{\mathrm{P}_{i,t} - \mathrm{P}_{i,t-1}}{\mathrm{P}_{i,t-1}} \tag{1}$$

where $r_{i,t}$ is the return of stock on day and $P_{i,t}$ is the closing price on that day. For each day, we compute the median return for each sector to mitigate outlier bias. Median returns are preferred over mean values due to the presence of non normal return distributions during high volatility periods, as documented by Mazur et al. (2021). This is also the reason why we work with this mean value (median) in the next stages of the research. To account for the dynamic nature of investor behavior during the COVID-19 crisis, the entire analysis period (from 8 March 2019 to 12 December 2022) was divided into 11 discrete segments, comprising 6 pandemic waves and 5 inter-wave periods, see Table 1.

The **first wave** led to massive sell-offs and extreme volatility in financial markets. The S&P 500 index fell by more than 30% in March 2020, and many stock markets experienced significant declines (Chebbi et al., 2021). During this period, investors also shifted their capital to less risky assets such as government bonds and gold. Dharani et al. (2021) noted that Sharia-compliant indices performed better during this phase due to lower leverage and less exposure to highly volatile sectors, which made them attractive to investors seeking stability. The responses of individual governments around the world included social measures and economic stimulus packages to mitigate the economic impact. Ashraf (2020b) mapped and found that government interventions had a mixed impact, reducing infections but also adversely affecting economic activity and contributing to market uncertainty. The **second wave** was marked by hope and the end of the pandemic, as the first reports of vaccines began to emerge in December 2020, with Pfizer and Moderna receiving emergency use authorizations. Goodell (2020) noted that vaccination led to increased investor optimism, particularly in the healthcare and pharmaceutical sectors, which saw outsized

Table 1 Phases of the COVID-19 pandemic for research setting

code	Segment	Description	Start Date	End Date	Trading Days
0	**Pre-COVID Period**	Baseline, pre-pandemic phase	03/08/2019	03/10/2020	254
1	**First Wave**	Initial global outbreak	03/11/2020	05/31/2020	56
2	**Post-First Wave**	Temporary stabilization	06/01/2020	08/31/2020	65
3	**Second Wave**	Second surge (Europe/US)	09/01/2020	12/31/2020	85
4	**Post-Second Wave**	Vaccine rollout optimism	01/01/2021	03/31/2021	61
5	**Third Wave**	Delta variant emergence	04/01/2021	06/30/2021	63
6	**Post-Third Wave**	Delta mitigation lull	07/01/2021	09/30/2021	64
7	**Fourth Wave**	Omicron early warnings	10/01/2021	12/31/2021	64
8	**Post-Fourth Wave**	Early 2022 stabilization	01/01/2022	03/31/2022	62
9	**Fifth Wave**	Omicron global surge	04/01/2022	06/30/2022	62
10	**Post-Fifth Wave**	Residual volatility and geopolitical risk	07/01/2022	12/12/2022	113

Source: Own processing based on World Health Organization (WHO) epidemiological updates, *Johns Hopkins University COVID-19 dashboards and local case surge timelines. Together consistent with prior crisis-phase and pandemic-finance literature (*Goodell, 2020; Ramelli & Wagner, 2020; Narayan, 2022*), the empirical period was segmented into epidemiologically and policy-defined phases.*

returns. Investor attention thus turned to sectors that could benefit from the rollout of vaccines. Sectors such as technology and healthcare performed better, while sectors such as travel and entertainment struggled due to ongoing restrictions. Chebbi et al. (2021) found that although stock liquidity declined during the second wave of Alpha, the rollout of vaccines had a positive impact on market sentiment. The **third wave** saw the emergence of the Delta variant, which was highly contagious, leading to a renewed increase in the number of cases and hospitalizations, even among the vaccinated population. During this variant, investors began to differentiate more between sectors. Dharani et al. (2021) report that sectors such as technology and healthcare maintained their value, while sectors such as tourism and entertainment suffered due to pandemic measures. Yuan et al. (2022) pointed out differences in investor behavior during the Delta wave compared to previous variants. Investors adapted to the environment, making more rational decisions than before and focusing their strategic investment decisions on sectors perceived as crisis-resistant. During the **fourth wave**, investors were more accustomed to pandemic-related news. Milder symptoms of the Omicron virus, coupled with increasing global vaccination rates, led to a more moderate market reaction. Yuan et al. (2022) found that the panic index (VIX) rose sharply but did not reach the levels seen during previous waves, and markets were resilient, with investment continuing in the healthcare and technology sectors. On the other hand, according to Ullah et al. (2023), investors showed increased interest in companies that would benefit from the reopening of the economy, including the travel and retail sectors, reflecting increased confidence in a broader economic recovery. Omicron had a milder economic impact than Delta in the third wave, which supported investors' decisions. A study by Yuan et al. (2022) highlighted that investor behavior during the **fifth wave** showed increased complexity, with investor attention, sentiment, and fear playing a significant role in driving market reactions and contagion across global equity markets. This pointed to a higher level of sophistication in investment strategies, as investors drew on their experience from previous waves in their decisions. Caution still prevailed in the market, as it was unclear what further waves might follow.

During the first wave, according to Liu et al. (2021), we saw panic, high volatility, and sharp declines in indices. The second wave, according to Ashraf (2020a), was marked by bans, reduced liquidity, and mixed government interventions. The third wave, according to Goodell (2020), saw optimism, market recovery, and positive sentiment driven by vaccines. The fourth wave of omicron, according to Yuan et al. (2022), still had investor concerns or was better managed with continued volatility and specific sectors profiting. Investor behavior changed dramatically from the initial panic and fear-driven sell-offs during the first wave to more strategic investment decisions in subsequent waves. Investors gradually learned to navigate uncertainty, leading to less radical market reactions in later waves. Yuan et al. highlighted the role of investor psychology, such as fear and sentiment, in creating financial contagion in markets, especially during times of extreme uncertainty. Google search volumes were used as a proxy to measure investor attention and sentiment, which showed that investor psychology continued to be a major driver of market behavior throughout the pandemic. According to Curto and Serrasqueira (2021), the COVID-19 pandemic brought several threats, each caused by different variants of the virus, and this was reflected in corresponding changes in investor behavior and developments in financial markets.

This phase structure enables us to test whether the intensity and direction of investor synchronization with the S&P 500 index varied depending on the macroeconomic stress and epidemiological uncertainty of each phase. The segmentation approach closely mirrors prior crisis-phase literature such as Harjoto et al. (2021) and Narayan (2022), which emphasize the behavioral distinctiveness of acute vs. latent pandemic stages.

The entire analytical workflow was designed to prioritize reproducibility, transparency, and rigorous documentation. The dataset used is available here: https://doi.org/10.5281/zenodo.18206306.

A combination of Python, Statgraphics, Microsoft Excel, and external financial APIs and platforms was used to collect, process, compute, visualize, and validate all empirical outputs.

Statistical approach and model specification

To examine the synchronization between sectoral returns and the broader market during pandemic and non-pandemic periods, we adopt a rank dependence modeling approach using the Mann-Kendall test and Kendall's τ coefficient. This choice is motivated by the non-normal, fat-tailed nature of financial return distributions during systemic events such as COVID-19 (Albuquerque et al., 2020). Kendall's τ handles noisy, discontinuous data more effectively and yields a more consistent and interpretable measure of directional co-movement, especially in turbulent market environments. Kendall's τ is calculated:

$$\tau = \frac{n_c - n_d}{\frac{n(n-1)}{2}} \tag{2}$$

where n is the number of paired observations, n_c is the number of concordant pairs, and n_d is the number of discordant pairs.

The Mann-Kendall (S) test is used to detect monotonic trends (consistently increasing or decreasing) in time series data (in our case, individual waves of the COVID-19 pandemic, see Table 1). This is a proven method for working with time series, as documented by its use in connection with the COVID-19 pandemic, see Shaharudin et al. (2021), Goulet et al. (2024) or Liu et al. (2024), and it is calculated:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(x_j - x_i) \tag{3}$$

where n is the number of data points, x_j and x_i are data values at times j and i.

Specifically, we examined rank relationships in the range of fifteen-time lags (t), where t =-7, -6, …, 0, …, 6, 7. We assume that a time lag of seven days (one week) is sufficient to identify correlations between the variables under observation. A positive τ indicates a direct linear rank relationship between the sector and the market index, meaning that when the S&P 500 index rises (or falls), the sector tends to do the same. A negative τ indicates the opposite relationship, meaning that when the S&P 500 index rises (or falls), the sector trends to move in the opposite direction.

The rank correlation is calculated between today's sector return and the index from previous days (negative t). We test whether market developments (S&P 500) have outpaced sector developments. A high rank correlation with a negative time lag may indicate that the sector has reacted late to market movements. The rank correlation is calculated between today's index and future sector returns (positive t). We test whether the sector outperformed the market. A high rank correlation with a positive time lag may indicate that the sector had predictive value relative to the benchmark.

Case study integration S&P500 as a benchmark for sectoral development.

The first wave led to massive sell-offs and extreme volatility in the stock markets. The S&P 500 index fell by more than 30% in March 2020, and many stock markets experienced significant declines (Chebbi et al., 2021). The second wave brought hope for an end to the pandemic as the first reports of vaccines began to emerge in December 2020, with Pfizer and Moderna receiving emergency use authorizations, and Goodell (2020) noting that vaccination led to increased investor optimism. The third wave of the Delta variant was highly contagious, leading to a resurgence in cases and hospitalizations, even among the vaccinated population. During this variant, investors began to differentiate more between sectors. Dharani et al. (2021) report that sectors such as technology and healthcare maintained their value, the technology (IT) sector showed an average return of 0.126% with a standard deviation of

1.66, while the healthcare sector showed an average return of 0.011% with a standard deviation of 1.5. Meanwhile, sectors such as tourism and gastronomy suffered due to pandemic measures. During the fourth wave, investors were more accustomed to pandemic-related news. The milder symptoms of the Omicron virus, coupled with increasing global vaccination rates, led to a milder market reaction, and Yuan et al. (2022) found that the panic index (VIX) rose sharply but did not reach the levels seen during previous waves. The latest fifth wave highlighted that investor behavior during this wave showed increased complexity, with investor attention, sentiment, and fear playing a significant role in driving market reactions and contagion across global equity markets. This pointed to a higher level of sophistication in investment strategies, as investors drew on their experience from previous waves in their decisions. The reaction of the S&P 500 index to the above facts is captured in Fig. 1.

Using the Mann-Kendall test we did not identify the monotonic (consistently increasing or decreasing) trend in time series under evaluation (S = -1,777; p = 0,075). In the context of the above, this result was to be expected, as the trend across the individual waves of the pandemic has not been confirmed by other studies. However, we can observe obvious differences in the variability of daily returns on the S&P 500 index. The analytical part of this study focuses on the volatility of the S&P500 index and compares it with the volatility of two selected sectors - the pharmaceutical sector and the technology sector.

Daily returns responded positively to the first wave of the pandemic. In the following period, this optimism reversed and returns declined. We are seeing growth rates in connection with the third wave (although growth is minimal), when we are also seeing lower volatility and thus signs of stabilization. However, as time goes on, the medium-term consequences and impacts of the COVID-19 pandemic are becoming apparent, and daily returns on the S&P 500 index are declining.

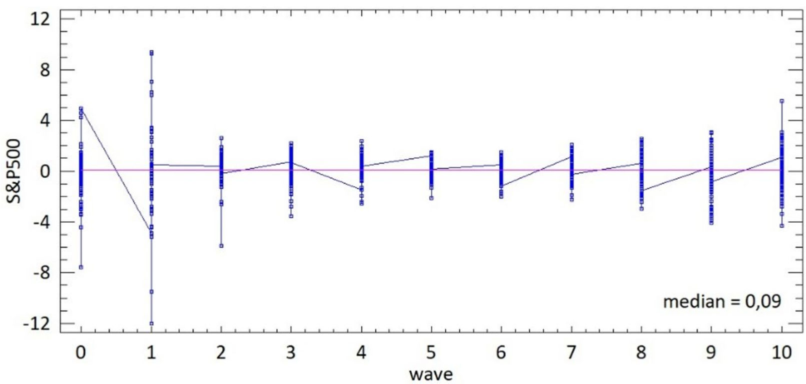

Fig. 1 Run chart of the S&P500 index across the entire evaluated period (daily returns in %). note: codes of individual waves are contained in Table 1. *Source: own processing*

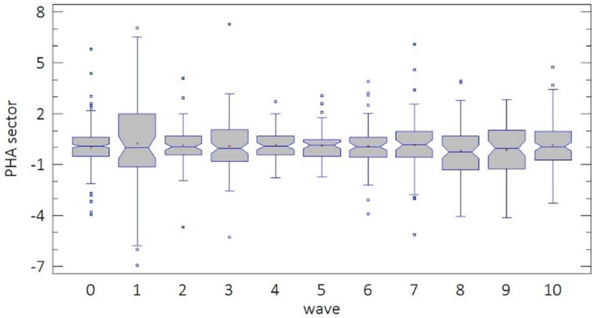

Fig. 2 Boxplot of the pharmaceutical index (median) across the entire evaluated period (daily returns in %). note: codes of individual waves are contained in Table 1.Source: own processing

Table 2 Wave of the COVID-19 pandemic and the change from the previous/next wave

Segment	Before / After	Δ median (*p.p.*)	Change
First Wave (1)	vs. Pre-COVID Period (0)	,315	positive
	Post-First Wave (2) vs.	-,047	negative
Second Wave (3)	vs. Post-First Wave (2)	-,227	negative
	Post-Second Wave (4) vs.	-,033	negative
Third Wave (5)	vs. Post-Second Wave (4)	,015	positive
	Post-Third Wave (6) vs.	,004	positive
Fourth Wave (7)	vs. Post-Third Wave (6)	,091	positive
	Post-Fourth Wave (8) vs.	-,359	negative
Fifth Wave (9)	vs. Post-Fourth Wave (8)	,017	positive
	Post-Fifth Wave (10) vs.	-,032	negative

Source: own processing

4 Results and discussion

In terms of content, the presented analysis compares the performance of the S&P500 index and the index created for the pharmaceutical and technology sectors.

Comparison of pharmaceutical sector development with the S&P 500 index.

The development of the pharmaceutical index (median of three companies in the sector, see methodology) is shown in Fig. 2. From the perspective of the median value, daily returns are not affected by the COVID-19 pandemic. However, what could be expected and was also confirmed are differences in volatility, or rather variability of returns. Based on this result, we can conclude that the pharmaceutical sector was significantly affected by the waves of the COVID-19 pandemic.

The impact of each wave of the COVID-19 pandemic on the median development for the pharmaceutical sector mirrors the SP500 index trend in 50% of cases. On the other hand, however, in 50% of cases the trend is reversed, see Table 3. In the case of the same trend (whether positive or negative), the performance of the pharmaceutical sector did not match that of the S&P 500 index. It appears that this sector was less volatile, which brought greater profits but also greater losses depending on the wave of the COVID-19 pandemic.

Based on the above, it is not possible to observe the same development or trend between the monitored variables, see Table 2. The pharmaceutical sector did not mirror the benchmark performance of the S&P 500 index. For this sector, changes in the development of the COVID-19 pandemic represented a different kind of stimulus, which was reflected in the above results.

Comparison of technology sector development with the S&P 500 index.

From the perspective of the development of the median daily returns of the technology sector across the 11 waves of the COVID-19 pandemic, we do not observe any differences. On the other hand, differences in standard deviation proved to be significant, i.e., heteroscedasticity across individual waves can be confirmed. Although the COVID-19 pandemic itself did not affect the sector's performance, it had an undeniable impact on its volatility, see Fig. 3.

In 7 out of 10 cases, the trend for both variables is the same, i.e., the change in the median in a given pandemic wave in the technology sector mirrors 70% of the change in the S&P 500 index. With one exception (see Table 3), volatility in this sector is higher than that of the S&P 500 index, i.e., it appears that the COVID-19 pandemic has had a greater impact on the technology sector.

Based on the above, it is only possible to partially observe the same development or trend between the monitored variables, see Table 3. Given the composition of the S&P 500 index, it turned out that the technology sector largely mirrored its performance. The volatility of this sector proved to be higher, which underscores the sensitivity of investors in this sector. They considered individual changes to be more significant from the perspective of the specifics of this particular sector.

Sectoral lag comparison over pandemic waves.

The above results pointed to (partially) different responses in the development of the S&P 500 index and two selected sectors to individual waves of the COVID-19 pandemic. Table 4 confirms these conclusions. The rank correlation of the S&P 500 index is positive in both cases. In the technology sector, the strength of the rank correlation is higher, reflecting the aforementioned agreement in 7 out of 10 cases, see previous analysis.

In the pharmaceutical sector, none of the 14 defined time lags show statistically significant results. In this case, the change in the daily returns of the S&P 500 index will be partially reflected in the pharmaceutical sector on the same day. In the case of the second sector, the immediate response rate is higher (double). A statistically significant linear relationship was confirmed after a certain time lag (t=-7 and 1). Given its strength, it is not possible to conclude that the S&P 500 index or the technology sector reacted late to developments in the other.

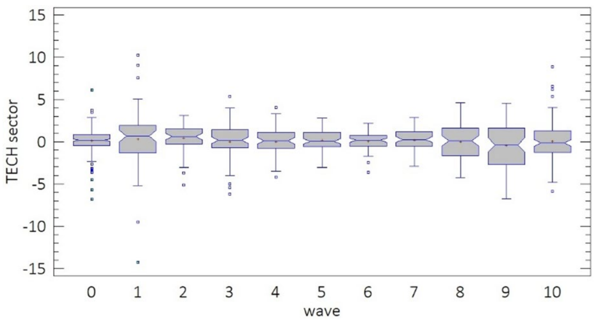

Fig. 3 Boxplot of the technology index (median) across the entire evaluated period (daily returns in %). note: codes of individual waves are contained in Table 1. Source: own processing

Table 3 Wave of the COVID-19 pandemic and the change from the previous/next wave – TECH sector vs. S&P 500

Segment	Before / After	Δ median (*p.p.*)	Change	Change (vs. S&*P* 500)
First Wave (1)	vs. Pre-COVID Period (0)	,514	positive	the same
	Post-First Wave (2) vs.	-,060	negative	the same
Second Wave (3)	vs. Post-First Wave (2)	-,450	negative	the same
	Post-Second Wave (4) vs.	-,031	negative	the same
Third Wave (5)	vs. Post-Second Wave (4)	-,086	negative	differ-ent
	Post-Third Wave (6) vs.	,123	positive	the same
Fourth Wave (7)	vs. Post-Third Wave (6)	,094	positive	the same
	Post-Fourth Wave (8) vs.	-,156	negative	the same
Fifth Wave (9)	vs. Post-Fourth Wave (8)	-,461	negative	differ-ent
	Post-Fifth Wave (10) vs.	,236	positive	differ-ent

Source: own processing

Table 4 Rank correlation of the S&P 500 index with selected sectors with a various time lags

lag	PHA sector		TECH sector	
	τ	*p*-value	τ	*p*-value
lag (-7)	,020	,353	,071	,001
lag (-6)	-,011	,606	-,031	,150
lag (-5)	,004	,854	,001	,950
lag (-4)	,005	,787	-,022	,312
lag (-3)	-,003	,878	-,016	,441
lag (-2)	0,02	,360	-,007	,725
lag (-1)	-,019	,383	-,034	,118
lag (0)	0,327	0	,668	0
lag (+1)	-,007	,719	-,054	,012
lag (+2)	,009	,676	,007	,731
lag (+3)	-,009	,671	-,015	,476
lag (+4)	,011	0,610	-,015	,492
lag (+5)	,037	,087	-,011	,584
lag (+6)	-,037	,084	-,034	,112
lag (+7)	,027	,215	,007	,726

Source: own processing

Based on the results shown in Table 4, we can conclude that developments and changes in the S&P 500 index will be reflected in both sectors on the same day. The strength of this reaction remains different. The pharmaceutical sector reacts more moderately, while the reaction in the technology sector is much more pronounced.

5 Conclusion

This study contributes a novel, phase sensitive analytical framework to the growing body of literature examining investor behavior during systemic crises. The primary objective of this study was to examine how synchronization between the technology and pharmaceutical sectors and the S&P 500 evolved during the COVID-19 pandemic, and whether sector–benchmark co-movement differed across pandemic waves and inter-wave periods in terms of strength, timing, and persistence, reflecting heterogeneous investor responses under extreme uncertainty.

By decomposing the COVID-19 pandemic into distinct waves and inter-wave periods and applying the Mann-Kendall test and lag-based Kendall's τ rank correlation coefficient between sectoral median returns and the S&P 500 index, we demonstrate that investor synchronization is not static but highly contextual, sector dependent and sensitive to the temporal structure of shocks.

In comparative context our results show that the technology sector exhibited significantly higher correlation with the S&P 500 during pandemic waves, responding to RQ1. These findings reinforce conclusions from Albuquerque et al. (2020) and Narayan (2022). The pharmaceutical sector showed lower correlation without any time lag, aligning with the findings of Kizys et al. (2021) on headline-driven speculation. We therefore consider RQ2 to be answered as well. The study's key innovation lies in its temporal architecture. Rather than employing arbitrary pre/post-event windows or static crisis periods, we map rank correlation behavior across epidemiologically defined segments. This approach captures how investor psychology and expectation formation evolve alongside external shocks. Moreover, the use of non-parametric Kendall's τ across lags (t), where t = -7, -6, …, 0, …, +6, +7, allows us to detect lead–lag effects in sectoral responsiveness, an aspect often overlooked in traditional event studies.

The findings advance the adaptive markets hypothesis (Lo, 2004) by showing that investors dynamically recalibrate their behavior not only in response to market wide information, but also to sector-specific narratives. The stronger alignment of the technology sector with the benchmark during crisis waves suggests the emergence of temporary efficiency, as market actors converged on a consensus regarding the systemic importance of tech. In contrast, the pharmaceutical sector remained dominated by episodic, speculative behavior, reflecting bounded rationality and fragmented information processing. For financial analysts and portfolio managers, this research demonstrates that crisis-time sector strategies must differentiate between structurally integrative sectors (e.g., technology) and reactive sectors (e.g., pharma). Investors seeking systemic alignment during crises may prefer the former, while speculative or alpha seeking strategies might engage with the latter, albeit with higher volatility risk.

Importantly, the evidence presented in this study does not seek to estimate structural risk pricing or long-run equilibrium relationships. Instead, the analysis provides empirical insight into how sector–benchmark synchronization behaves as a short- to medium-horizon outcome of investor reactions under extreme uncertainty. By focusing on rank-based dependence, lag structures, and epidemiologically defined phases, the study captures behavioral alignment and divergence without imposing parametric asset-pricing assumptions. In this sense, the contribution of the paper lies in documenting how and when sectoral returns align with the market benchmark during crisis phases, rather than explaining why such alignment arises from specific pricing mechanisms. This distinction ensures that conclusions remain firmly grounded in observable synchronization dynamics rather than inferred structural drivers.

Several limitations warrant discussion. First, our analysis focused on two sectors and a single systemic shock. While this improves internal validity, future work should examine whether this framework generalizes across different crisis types (e.g., inflation shocks, geopolitical events) and sectors (e.g., energy, finance). Second, while Mann-Kendall test and also Kendall's τ are robust for ordinal rank correlation, future studies could incorporate dynamic conditional correlation (DCC) models, regime switching frameworks, or network-based contagion analysis to enrich the temporal resolution of findings. Third, in the context of the methodological approaches used, it should be noted that the presented study is strictly descriptive / non-parametric and does not attempt to estimate structural asset-pricing models or long-run equilibrium relationships. Fourth, in future research, it would be valuable to apply such models as demonstrated by Narayan et al. (2020) to capture time-varying co-movements and better reflect evolving investor behavior during systemic crises. Additionally, integrating investor sentiment data (e.g., social media indices or Google trends) could better contextualize the psychological dynamics behind the correlation patterns identified.

In crises, markets do not speak with one voice. They fragment, then coalesce, around narratives, expectations and sectoral archetypes. This study shows that temporal structure, not just event magnitude, determines whether investors act collectively or reactively. By anchoring behavioral finance in a precise, phase-aligned, and lag-aware empirical model, this paper lays the groundwork for a new generation of market synchronization research, one that is better attuned to the real time rhythm of global shocks.

Author contributions Kristián Kalamen has collected data from different resources, Roman Vavrek and Kristián Kalamen performed formal analysis, and contributed to writing original draft preparation; František Pollák, Roman Vavrek and Mónica García-Melón have performed supervision. Roman Vavrek and Kristián Kalamen covered task writing review & editing, drafted pictures and tables; Roman Vavrek performed revisions and improved the quality of the draft. All authors have read and agreed to the published version of the manuscript.

Funding Open access funding provided by The Ministry of Education, Science, Research and Sport of the Slovak Republic in cooperation with Centre for Scientific and Technical Information of the Slovak Republic. This article is one of the partial outputs of the currently implemented research grant VEGA no. 1/0110/24.

Data availability Dataset available at [https://doi.org/10.5281/zenodo.18206306](https:/doi.org/10.5281/zenodo.18206306) ; raw prices sourced from Yahoo Finance and Investing.com.

Declarations

Conflict of interests The authors declare no competing interests.

Ethical approval Not applicable.

Consent to participate and consent to publish Not applicable.

References

Adekoya, O. B., & Oliyide, J. A. (2021). How COVID-19 drives connectedness among commodity and financial markets: Evidence from TVP-VAR and causality-in-quantiles techniques. *Resources Policy*, *70*, 101898. https://doi.org/10.1016/j.resourpol.2020.101898

Aharon, D. Y., Umar, Z., & Vo, X. V. (2021). Dynamic spillovers between the term structure of interest rates, bitcoin, and safe-haven currencies. *Financial Innovation*, *7*, 59. https://doi.org/10.1186/s40854-021-00274-w

Akhtaruzzaman, M., Boubaker, S., & Sensoy, A. (2021). Financial contagion during COVID-19 crisis. *Finance Research Letters*, *38*, 101604. https://doi.org/10.1016/j.frl.2020.101604

Albulescu, C. T. (2021). COVID-19 and the United States financial markets' volatility. *Finance Research Letters*, *38*, 101699. https://doi.org/10.1016/j.frl.2020.101699

Albuquerque, R., Koskinen, Y., Yang, S., & Zhang, C. (2020). Resiliency of environmental and social stocks: An analysisof the exogenous COVID-19 market crash. *The Review of Corporate Finance Studies, 9*(3), 593–621.

Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management*, *13*(4), 84. https://doi.org/10.3390/jrfm13040084

Ashraf, B. N. (2020a). Stock markets' reaction to COVID-19: Cases or fatalities? *Research in International Business and Finance*, *54*, 101249. https://doi.org/10.1016/j.ribaf.2020.101249

Ashraf, B. N. (2020b). Economic impact of government interventions during the COVID-19 pandemic: International evidence from financial markets. *Journal of Behavioral and Experimental Finance*, *27*, 100371. https://doi.org/10.1016/j.jbef.2020.100371

Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyosin, T. (2020). The unprecedented stock market reaction to COVID-19. *The Review of Asset Pricing Studies*, *10*(4), 742–758. https://doi.org/10.1093/rapstu/raaa008

Baruník, J., & Křehlík, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics*, *16*(2), 271–296. https://doi.org/10.1093/jjfinec/nby001

Billio, M., Getmansky, M., Lo, A. W., & Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, *104*(3), 535–559. https://doi.org/10.1016/j.jfineco.2011.12.010

Chebbi, K., Ammer, M. A., & Hameed, A. (2021). The COVID-19 pandemic and stock liquidity: Evidence from S&P 500. *The Quarterly Review of Economics and Finance*, *81*, 134–142. https://doi.org/10.1016/j.qref.2021.05.008

Chen, Y. (2020). Improving market performance in the digital economy. *China Economic Review*, *62*, 101482. https://doi.org/10.1016/j.chieco.2020.101482

Demirer, M., Diebold, F. X., Liu, L., & Yilmaz, K. (2018). Estimating global bank network connectedness. *Journal of Applied Econometrics*, *33*(1), 1–15. https://doi.org/10.1002/jae.2585

Dharani, M., Hassan, M. K., Rabbani, M. R., & Huq, T. (2021). Does the Covid-19 pandemic affect faith-based investments? Evidence from global sectoral indices. *Research in International Business and Finance*, *59*, 101537. https://doi.org/10.1016/j.ribaf.2021.101537

Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, *119*(534), 158–171. https://doi.org/10.1111/j.1468-0297.2008.02208.x

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, *28*(1), 57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006

Diebold, F. X., & Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, *182*(1), 119–134. https://doi.org/10.1016/j.jeconom.2014.04.012

Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market co-movements. *The Journal of Finance*, *57*(5), 2223–2261.

Goodell, J. W. (2020). COVID-19 and finance: agendas for future research. *Finance Research Letters*, *35*, 101512. https://doi.org/10.1016/j.frl.2020.101512

Gormsen, N. J., & Koijen, R. S. (2020). Coronavirus: Impact on stock prices and growth expectations. *The Review of Asset Pricing Studies*, *10*(4), 574–597. https://doi.org/10.1093/rapstu/raaa013

Goulet, M. H., Cassivi, C., Hupé, C., Jean-Baptiste, F., & Dumais, A. (2024). Seclusion and mechanical restraint in the wake of the COVID-19 pandemic: an increased use in mental health settings. *Frontiers in Psychiatry*, *15*, 1428599. https://doi.org/10.3389/fpsyt.2024.1428599

Harb, A. M., & Umutlu, M. (2024). Shock resistors or transmitters? Contagion across industries and countries during the COVID-19 pandemic and the global financial crisis. *Economics Letters*, *244*, 112026. https://doi.org/10.1016/j.econlet.2024.112026

Harjoto, M. A., Hoepner, A. G. F., & Li, Q. (2021). Corporate social irresponsibility and portfolio performance: A cross–national study. *Journal of International Financial Markets Institutions and Money*, *70*, 101274. https://doi.org/10.1016/j.intfin.2020.101274

Hasan, M. T. (2022). The sum of all SCARES COVID-19 sentiment and asset return. *The Quarterly Review of Economics and Finance*, *86*, 332–346. https://doi.org/10.1016/j.qref.2022.08.005

Hu, M., Zhang, D., Ji, Q., & Wei, L. (2020). Macro factors and the realized volatility of commodities: A dynamic network analysis. *Resources Policy*, *68*, 101813. https://doi.org/10.1016/j.resourpol.2020.101813

Kalamen, K., Pollák, F., & Markovič, P. (2023). *Pandemic Economic Crises Encyclopedia*, 3(4), 1489–1497. https://doi.org/10.3390/encyclopedia3040106.

Kizys, R., Tzouvanas, P., & Donadelli, M. (2021). From COVID-19 herd immunity to investor herding in international stock markets: The role of government and regulatory restrictions. *International Review of Financial Analysis*, *74*, 101663. https://doi.org/10.1016/j.irfa.2021.101663

Kodres, L. E., & Pritsker, M. (2002). A rational expectations model of financial contagion. *The Journal of Finance*, *57*(2), 769–799.

Liu, Z., Huynh, T. L. D., & Dai, P. F. (2021). The impact of COVID-19 on the stock market crash risk in China. *Research in International Business and Finance*, *57*, 101419. https://doi.org/10.1016/j.ribaf.2021.101419

Liu, J. W., Zeng, W., Zhuo, C., Liu, Y., Zhu, L., & Zou, G. Y. (2024). Impact of the COVID-19 Pandemic on the Incidence of Notifiable Infectious Diseases in China Based on SARIMA Models Between 2013 and 2021. *Journal of Epidemiology and Global Health*, *14*(3), 1191–1201. https://doi.org/10.1007/s44197-024-00273-x

Lo, A. W. (2004). The adaptive markets hypothesis: Market efficiency from an evolutionary perspective. *The Journal of Portfolio Management*, *30*(5), 15–29. https://doi.org/10.3905/jpm.2004.442611

Mantegna, R. N. (1999). Hierarchical structure in financial markets. *The European Physical Journal B*, *11*, 193–197. https://doi.org/10.1007/s100510050929

Narayan, P. K. (2022). Understanding exchange rate shocks during COVID-19. *Finance Research Letters*, *45*, 102181. https://doi.org/10.1016/j.frl.2021.102181

Narayan, P. K., Devpura, N., & Wang, H. (2020). Japanese currency and stock market—What happened during the COVID-19 pandemic? *Economic Analysis and Policy*, *68*, 191–198. https://doi.org/10.1016/j.eap.2020.09.014

Ozili, P. K., & Arun, T. (2020). Spillover of COVID-19: Impact on the global economy. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3562570

Patton, A. J. (2006). Modelling asymmetric exchange rate dependence. *International Economic Review*, *47*(2), 527–556.

Pollák, F., Kalamen, K., Vavrek, R., & Gbúrová, J. (2026). Resilient innovation and entrepreneurial responses to systemic shocks: Economic insights into sustainable business ecosystems. *Sustainable Technology and Entrepreneurship*, *5*(1), 100123.

Ramelli, S., & Wagner, A. F. (2020). Feverish stock price reactions to COVID-19. *Review of Corporate Finance Studies*, *9*(3), 622–655.

Salisu, A. A., & Vo, X. V. (2020). Predicting stock returns in the presence of COVID-19 pandemic: The role of health news. *International Review of Financial Analysis*, *71*, 101546. https://doi.org/10.1016/j.irfa.2020.101546

Shaharudin, S. M., Ismail, S., Samsudin, M. S., Azid, A., Tan, M. L., & Basri, M. A. A. (2021). Prediction of Epidemic Trends in COVID-19 with Mann-Kendall and Recurrent Forecasting-Singular Spectrum Analysis. *Sains Malaysiana*, *50*(4), 1131–1142. https://doi.org/10.17576/jsm-2021-5004-23

Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International Review of Financial Analysis*, *70*, 101496. https://doi.org/10.1016/j.irfa.2020.101496

slickchart.com (2026). S&P 500 Companies by Market Cap. Retrieved January 7, 2026, from: https://www.slickcharts.com/sp500

Solnik, B., Boucrelle, C., & Le Fur, Y. (1996). International market correlation and volatility. *Financial Analysts Journal*, *52*(5), 17–34.

Sukcharoen, K., Zohrabyan, T., Leatham, D., & Wu, X. (2014). Interdependence of oil prices and stock market indices: A copula approach. *Energy Economics*, *44*, 331–339. https://doi.org/10.1016/j.eneco.2014.04.012

Tilfani, O., Ferreira, P., & Boukfaoui, M. Y. E. (2021). Dynamic cross-correlation and dynamic contagion of stock markets: a sliding windows approach with the DCCA correlation coefficient. *Empirical Economics*, *60*, 1127–1156. https://doi.org/10.1007/s00181-019-01806-1

Tumminello, M., Aste, T., Di Matteo, T., & R MantegnaN (2005). A tool for filtering information in complex systems. *Proceedings of the National Academy of Sciences*, *102*(30), 10421–10426. https://doi.org/10.1073/pnas.0500298102

Tumminello, M., Lillo, F., & Mantegna, R. N. (2010). Correlation, hierarchies, and networks in financial markets. *Journal of Economic Behavior & Organization*, *75*(1), 40–58. https://doi.org/10.1016/j.jebo.2010.01.004

Ullah, S., Khan, S., Hashmi, N. I., & Alam, M. S. (2023). COVID-19 pandemic and financial market volatility: A quantile regression approach. *Heliyon*, *9*(10), e21131. https://doi.org/10.1016/j.heliyon.2023.e21131

Výrost, T., Lyócsa, Š., & Baumöhl, E. (2015). Granger causality stock market networks: Temporal proximity and preferential attachment. *Physica A: Statistical Mechanics and Its Applications*, *427*, 262–276. https://doi.org/10.1016/j.physa.2015.02.017

Wang, G. J., Xie, C., & Chen, S. (2017). Multiscale correlation networks analysis of the U.S. stock market: A wavelet analysis. *Journal of Economic Interaction and Coordination*, *12*, 561–594. https://doi.org/10.1007/s11403-016-0176-x

Wang, G. J., Xie, C., & Stanley, H. E. (2018). Correlation structure and evolution of world stock markets: Evidence from Pearson and partial correlation-based networks. *Computational Economics*, *51*, 607–635. https://doi.org/10.1007/s10614-016-9627-7

Wang, D., Li, P., & &Huang, L. (2022). Time-frequency volatility spillovers between major international financial markets during the COVID-19 pandemic. *Finance Research Letters 46(Part A)*, 102244. https://doi.org/10.1016/j.frl.2021.102244

Wen, F., Yang, X., & Zhou, W. X. (2019). Tail dependence networks of global stock markets. *International Journal of Finance & Economics*, *24*(1), 558–567. https://doi.org/10.1002/ijfe.1679

Yang, J., Li, Z., & Miao, H. (2021). Volatility spillovers in commodity futures markets: A network approach. *The Journal of Futures Markets*, *41*(12), 1959–1987. https://doi.org/10.1002/fut.22270

Yousaf, I., & Yarovaya, L. (2022). Herding behavior in conventional cryptocurrency market, non-fungible tokens, and DeFi assets. *Finance Research Letters*, *50*, 103299. https://doi.org/10.1016/j.frl.2022.103299

Yuan, Y., Wang, H., & Jin, X. (2022). Pandemic-driven financial contagion and investor behavior: Evidence from the COVID-19. *International Review of Financial Analysis*, *83*, 102315. https://doi.org/10.1016/j.irfa.2022.102315

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, *36*, 101528. https://doi.org/10.1016/j.frl.2020.101528

Authors and Affiliations

František Pollák[1,2] · Kristián Kalamen[1] · Roman Vavrek[3] · Mónica García-Melón[4]

✉ Kristián Kalamen
kristian.kalamen@euba.sk

František Pollák
frantisek.pollak@euba.sk

Roman Vavrek
roman.vavrek@vsb.cz

Mónica García-Melón
mgarciam@upv.es

1 Faculty of Business Management, Department of Corporate Finance, Bratislava University of Economics and Business, Bratislava, Slovakia

2 Faculty of Corporate Strategy, Department of Marketing and Tourism, Institute of Technology and Business in České Budějovice, České Budějovice, Czech Republic

3 Faculty of Economics, Department of Management , VŠB – Technical University of Ostrava, Ostrava, Czech Republic

4 Department of Engineering Projects, Universitat Politècnica de València, Valencia, Spain