On the determinants of price fluctuations during the COVID-19 pandemic: Evidence from US equity markets

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Abstract:

Global crises often present significant threats to the well-being of individuals, businesses, and entire economies because of their widespread impact and severe repercussions. This study aims to pinpoint crucial factors influencing volatility in US sectoral stock indices during the COVID-19 pandemic. A Beta-Skew-t-EGARCH framework is used to model the changing patterns of volatility in each sector's returns over time. The empirical analysis relies on both the elastic net penalization approach and the partialing-out LASSO instrumental-variables regression. The findings reveal that the predominant variables explaining sectoral volatility include trading volume, stringency of US policy responses, volatility of broad USD exchange rates, Google search trends of market sectors, positive cases of coronavirus, US economic policy uncertainty, Google search volume for coronavirus, VIX, and the roll-out of vaccination programs. On the other hand, Bitcoin, treasury bills, gold, default risk, and Chinese stock prices do not have a meaningful impact on the price swings for all sectors. A thorough understanding of the factors underlying sectoral volatility enables portfolio managers to devise sensible investment decisions, and policy makers to lay down regulations intended to curb excessive volatility.

Keywords: US stock market, Price swings, Endogeneity, COVID-19 pandemic; Elastic net technique.

محددات تقلبات الأسعار في سوق الأسهم الأمريكية خلال جائحة فيروس كورونا

ملخص:

تُشكل الأزمات العالمية تهديدات كبيرة لرفاهية الأفراد والشركات والاقتصادات بأكملها بسبب تأثيرها واسع النطاق وتداعياتها الشديدة. تسعى هذه الورقة إلى تحديد المتغيرات الرئيسية وراء تقلبات سوق الأسهم القطاعية الأمريكية تحت ضغط جائحة كوفيد-19، من خلال اختبار القوة التفسيرية لمجموعة كبيرة من العوامل المحتملة. تم تقدير تقلبات أسعار الأسهم في القطاعات المختلفة باستخدام نموذج Beta-Skew-t-EGARCH model، والذي يعالج بعض المشاكل الموجودة عادةً في السلاسل الزمنية مثل عدم تماثل التوزيعات والالتواء والقيم المتطرفة. يعتمد التحليل العملي للبيانات لتحديد المتغيرات الأكثر تأثيراً على تقلبات أسعار الأسهم على أسلوب Elastic-net Regularized Regression، والذي يُعد أحد الأساليب الهامة المستخدمة في معالجة مشكلة التعددية المتعلقة بالمتغيرات التنبؤية، وأيضاً تحسين أداء النموذج وزيادة قدرته على التنبؤ بالبيانات بشكل دقيق وموثوق.

أشارت نتائج البحث أن حجم التداول، وتقلب أسعار صرف الدولار الأمريكي، ومعدلات الإصابة بفيروس كورونا، ومؤشر VIX، واتجاهات بحث Google، وعدم اليقين في السياسة الاقتصادية الأمريكية، وبدء برامج التطعيم هي المحددات الأكثر شيوعًا للتقلبات القطاعية. من ناحية أخرى، أشارت النتائج أن تحركات أسعار الذهب والبيتكوين والنفط والأسهم الأوروبية والصينية ليس لها تأثير جوهري على تقلبات مؤشرات الأسعار لجميع القطاعات تقريبًا. هناك مجموعة هامة من المضامين والتوصيات التي يمكن استنتاجها من هذه النتائج.

الكلمات المفتاحية: سوق الأسهم الأمريكية، التقلب في أسعار الأسهم، أسلوب الشبكة المرنة، جائحة كوفيد-19.

1. Introduction

Global catastrophes tend to pose substantial threats to the welfare of individuals, business entities, and entire economies, due to their extensive reach and profound consequences. A prime illustration of such crises is the implacable pandemic of the novel Coronavirus disease, which indeed instigated monumental transformations, both domestically and internationally. The repercussions of this pandemic have been far-reaching, affecting nearly every facet of life, from public health and societal standards to economic systems and global linkages. With seemingly no end in sight to the ongoing health emergency, countries continue to grapple with heightened unpredictability and uncertainty shrouding most aspects of life. Notably, the United States has borne a significant burden of the pandemic's toll, experiencing higher infection rates and casualties compared to other parts of the world. By the end of November 2023, the cumulative nationwide tally of COVID-19 positive cases and fatalities surged to 103,44 and 1,13 million, respectively, accounting for nearly 13.47 and 16.22 percent of the world's cumulative confirmed cases and mortality, respectively.[1] As a principal barometer of future economic conditions, financial markets are no exception to the vicissitudes of the pandemic and its aftermath. During February-March 2020, major benchmark stock indices underwent an all-time collapse on the back of negative economic sentiment and poor business confidence. In particular, the circuit breakers that apply to the entire US stock market were activated on March 9, 12, 16, and 18. This action temporarily paused trading with the aim of soothing investor anxiety.

The evolving global health threats have cast a shadow over financial market performance, prompting a growing body of research evaluating the distinct effects of the COVID-19 pandemic on many business and industry domains (e.g., Ahmad et al., 2021; Alomari et al., 2022; Baek and Lee, 2021; Baig et al., 2021; Choi, 2022; Curto and Serrasqueiro, 2022; Laborda and Olmo, 2021; Liu et al., 2023; Wang et al., 2023; Xu, 2022; Yu and Xiao, 2023). Choi (2022), for example, documents that, when the pandemic started, there was an increased degree of volatility spillovers among market sectors in the US. Alomari et al. (2022) provide evidence of a positive linkage between most US sectoral stock returns and COVID-19-related news, measured via a newspaper-based infectious diseases tracking index, during optimistic market conditions. Conversely, during pessimistic market conditions, they observe a negative correlation between most US sectoral stock returns and news regarding COVID-19. Laborda and Olmo (2021) find that the energy sector played a significant role as the primary source of transmitting volatility shocks in

1 Source: https://covid.cdc.gov/covid-data-tracker

the wake of the pandemic outbreak. Ngene (2021) shows that the intensity and direction of volatility shock transmissions across US equity market sectors tend to differ between times of economic recession and expansion. The results also show that domestic credit market conditions proxied by default spread, stock market uncertainty proxied by VIX, and global credit market uncertainty proxied by TED spread have substantial impact on cross-sector volatility spillovers at lower and higher quantiles. Baig et al. (2021) report evidence that COVID-19 positive cases and fatalities, investor sentiment, and lockdown-related measures lead to less (more) firm-level liquidity (volatility) levels in the US. Ahmad et al. (2021) show that US sectoral returns are more sensitive to changes in VIX than to changes in implied volatility of oil (OVX). Energy and materials (information technology, healthcare, and consumer discretionary) sectors are the most receptive of volatility shocks from OVX (VIX). The results of Bouri et al. (2023a) suggest that the correlations between expected inflation and US sector indices vary not only over time, but also across different frequencies Based on high-frequency data from the US, Eurozone, UK, Japan, China, and India, Bouri and Harb (2022) show that the propagation of volatility shocks within the system is shaped by the size (i.e., small, medium, large) of good and bad volatility.

Expanding on this research trajectory, our study endeavors to uncover the most important factors contributing to the volatility of US stock returns within specific industry sectors, amidst the influence of the COVID-19 pandemic. Due to its paramount leadership role in the global financial landscape and the lion's share of investor attention, the US stock market is the principal subject of our empirical inquiry. According to data from the World Bank, the US stock market, by the end of 2022, constitutes nearly 60% of all equities traded in the world and about 40% of global market capitalization as a proportion of GDP.[2] There are, indeed, two reasons underlying this empirical inquiry. First, our primary motivation is to investigate and understand the specific factors that contributed to the volatilities observed in different sectors of the US equity market during the Coronavirus pandemic. This helps shed light on the unique challenges and market dynamics faced by different sectors during this unprecedented crisis. Besides, with its focus on the sector-specific volatilities rather than the entire market volatility, our work fills an existing gap in the literature and provides a comprehensive analysis of the US equity market dynamics during such a tumultuous period. Since market-level data covers diverse businesses with varying market capitalizations, trading activity levels, and responses to market cycles, it may, on the one hand, introduce aggregation bias into empirical analysis (Salisu et al.,

2 Source: https://data.worldbank.org/indicator/CM.MKT.TRAD.CD

2021). On the other hand, a thorough understanding of the market dynamics may not be possible from the examination of sample firm-level data. Arguably, the sector-based inquiry is highly likely to produce more accurate results and fresh perspectives that might otherwise be challenging to discover using the other two approaches. It may also be a useful addition to conventional analyses relying on highly aggregated market data or firm-level information (Laborda and Olmo, 2021). Second, we seek to provide practical implications for investors, portfolio managers, and financial institutions. By identifying the underlying causes of sector volatilities, our study can help market participants develop more informed risk management strategies and make investment decisions during similar crises in the future.

The study aims to offer a greater understanding of market behaviour by looking at the factors that contribute to sector volatility, potentially lowering uncertainty and boosting investor confidence in the market's ability to accurately reflect underlying values. Furthermore, understanding the unique drivers of volatility could aid policymakers in the formulation of targeted policies and regulations aimed at stabilizing the market and mitigating risks associated with future crises.

In more detail, our aim is to thoroughly address these chief inquiries:

- What influences the fluctuations in sector-specific volatilities within the US stock market during the COVID-19 outbreak?
- Do these influencing factors demonstrate variations across different sectors within the market?

Our work contributes to the rapidly expanding literature on the financial and economic implications of the ongoing pandemic in at least three prime ways. Firstly, relevant studies (e.g., Ahmad et al., 2021; Baek and Lee, 2021; Baig et al., 2021; Bouteska et al., 2023; Chatjuthamard et al., 2021; Kamal and Wohar, 2023; Kanamura, 2022; Ngene, 2021; Salisu et al., 2021; Wang et al., 2021a) examine the factors that influence market volatility in both normal and stressful circumstances, with the goal of illuminating the potential for portfolio diversification and hedging. However, in doing so, these papers tend to concentrate their analysis on a small group of candidate predictors, giving rise to a partial understanding of the factors affecting the price volatility of US equities. To our knowledge, no empirical investigation has been undertaken to uncover the factors influencing the price volatility of sector indices. We add to the extant research by evaluating the explanatory power of an expansive collection of thirty two factors epitomizing important financial, economic, political, and health dimensions. Notably, the collection also incorporates dummy variables that serve as proxies for significant events with the potential to impact volatility. These events include the price crash of the US stock market, the oil price rift between Saudi Arabia and Russia, the mass vaccination roll-out in the US, the presidential race in the US, and the detection of the Omicron variant infection. Secondly, considering the extensive range of factors under examination, our analysis leans on the elastic net technique developed by Zou and Hastie (2005). An extension of the Least Absolute Shrinkage and Selection Operator (LASSO) proposed by Tibshirani (1996), the elastic net method enables us to navigate the challenge posed by a vast array of variables by handling high-dimensional data and enhancing the accuracy of our predictions by incorporating both Lasso and Ridge regression penalties. In a data-rich environment, the variable selection problem is highly likely to emerge, since one could be lured to experiment with numerous combinations of candidate factors, each yielding different results. The elastic net method handles this problem and identifies the most informative predictors, while achieving a balance between model accuracy and model complexity. To our best knowledge, our approach marks the inaugural attempt to employ a lasso-type penalization technique specifically aimed at identifying the primary contributors to the volatility observed within sectors of the US equity market. This method allows us to pinpoint and prioritize the most influential factors driving sector-specific market volatility during the specified period. Thirdly, as pointed out by Ahmed (2018), Bampinas and Panagiotidis (2016), and Salisu et al. (2021), the examination of firm-level data may fail to provide a thorough picture of a country's market dynamics, while the use of market-level data may induce aggregation bias into empirical analysis. Owing to the heterogeneity of market industries, it is unlikely that the factors affecting volatility to be the same across them. Thus, our sector-level assessment serves as an indispensable complement to both firm- and aggregate market-level analyses. The results offer practical implications for investors wishing to diversify within multiple industries.

After this introduction, the rest of the paper proceeds as follows. Section 2 provides a brief overview of the extant literature. Section 3 outlines the datasets and the volatility modelling approach. Section 4 presents the methodology, whereas Section 5 shows the empirical findings. A discussion of our results and their policy implications are given in the penultimate section, while the final section concludes.

2. Related research

The literature on the factors driving the volatility of financial markets, particularly in chaotic times, is extensive and has garnered huge attention from academic and professional communities. During turbulent times, factors such as uncertainty, investor panic, deteriorating economic conditions, and financial system vulnerabilities play crucial roles in driving market volatility. Studies have examined the impact of specific events, such as the global financial crisis of 2008, the European sovereign debt crisis of 2010, and the COVID-19 pandemic, to understand how these crises have affected market volatility. Additionally, relevant literature explores the role of policy responses, including monetary and fiscal measures, as well as regulatory interventions, in mitigating or exacerbating market volatility during anxiety-ridden times. Market-specific factors, such as liquidity constraints, flight to safety, and contagion effects, have also been investigated to comprehend their impact on financial market volatility during periods of crisis. In reality, the literature on the potential determinants of market volatility can by no means be exhaustively reviewed, due to its breadth and diversity. In this section, therefore, we concentrate on two distinct strands of research to gain a more comprehensive understanding of the factors influencing stock price volatility. This helps to deepen our understanding of the key drivers and their interrelationships, allowing for a more insightful examination of stock market volatility.

The first line of research investigates the explanatory potential of macroeconomic fundamentals (e.g., Bouri et al., 2023a; Cai et al., 2017; Demirer et al., 2020; Dinh et al., 2022; Engle et al., 2013; Girardin and Joyeux, 2013; Lu et al., 2021; Lyócsa et al., 2020; Schwert, 1989; Si et al., 2021). Changes in macroeconomic conditions can have a significant impact on the level of uncertainty and risk perception, which can subsequently influence financial market volatility. For example, Dinh et al. (2022) find that stock returns, interest rates, money supply, inflation, trade balance growth, and consumer confidence are the most important predictors of the time-varying volatility and correlation of precious metals in G7 and BRICS countries. Mittnik et al. (2015) show that new orders of consumer goods and materials, VIX, TED spread, and realized variance are the most significant drivers of the volatility of S&P 500 index. Hernandez et al. (2022) document that oil volatility has a substantial causal effect on the spillover dynamics of US stock market sectors, and such an effect is amplified in a high volatility environment. Despite being one of the smallest on the US stock market, the energy sector is very important to the network connectedness of other stock sectors. Demirer et al. (2020) and Lu et al. (2021) show that oil price changes are a chief influence of stock market volatility. Mo et al. (2018) demonstrate that changes in consumer price index, money supply, short-term interest rates, and real effective exchange rates are negatively related to the commodity futures volatility in India. Chen et al. (2023) find that climate policy uncertainty is a viable determinant of stock market volatility in China.

The second strand of literature assesses the extent to which market volatility is induced by global events and different crises, whether of a political, economic, biological, or military nature (e.g., Apergis et al., 2022; Bakry et al., 2022; Bora and Basistha, 2021; Chatjuthamard et al., 2021; Choi, 2022; Curto and Serrasqueiro, 2022; Demir et al., 2022; Lúcio and Caiado, 2022; Mnasri and Essaddam, 2021; Rouatbi et al., 2021; Uddin et al., 2021). These types of crises can introduce uncertainty, disrupt economic activities, and alter investor sentiment, leading to increased volatility in financial markets. The interconnectedness of global financial markets implies that crises in one region or sector can potentially have spillover effects on other markets worldwide. For example, Shahzad et al. (2021) find that sectoral spillovers of US equity market tend to rise in the wake of global crises. Moreover, the financial sector exhibits a striking change in dynamics, because of being an information leader (receiver) during the 2008 global financial crisis (the COVID-19 pandemic period). Dufrénot et al. (2011) document that the deteriorating financial situation in the US market following the 2007-2008 subprime crisis exacerbates the level of stock price volatility in Latin American countries. Bakry et al. (2022) report evidence of a positive association between daily announcements of COVID-19 confirmed cases and market volatility in both developed and emerging economies. Their results are analogous to those of Uddin et al. (2021). Curto and Serrasqueiro (2022) establish that the spread of the COVID-19 exerts discrepant volatility effects on US stock sectors. Particularly, the most positively affected ones are information technology, telecom services, industrials, consumer discretionary, consumer staples, and energy. Wu et al. (2023) document that stock market volatilities of NATO and non-NATO countries decrease at the initial period of the conflict between Russia and Ukraine; nevertheless, as the crisis intensifies, stock market volatility starts to rise.

A main conclusion deduced from the above survey of related studies is that the current body of literature typically tends to examine only a limited set of potential predictors, leading to an incomplete comprehension of the factors that influence stock price volatility. Motivated by this research gap, our work contributes to the extant research by evaluating the explanatory power of a comprehensive collection of candidate factors representing global financial, political, health, and economic developments.

3. Data description

We gather diverse daily time-series data over the period from 22/01/2020 to 08/12/2023, in order to deal with the issues of interest. The day the first COVID-19 case emerged in the US marks the beginning of the sample period. The selected sample encompasses the COVID-19 pandemic, which began to significantly impact global markets and economies from early 2020. Thus, this sample period presents a unique and relevant context for exploring market volatility due to the unprecedented disruptions caused by the pandemic. We fill in the blanks on weekends and other non-working days using a piecewise constant interpolation for variables that have only weekday data. With this process, the sample size for each variable amounts to 1417 observations. The focus of our empirical part is on the six most significant S&P 500 sector groups based on market capitalization. They are Information Technology (IT), Consumer Discretionary (CD), Industrials (ND), Financials (FN), Healthcare (HC), and Energy (NG), collectively constituting over 77 percent of the total S&P sector weightings (S&P Dow Jones Indices, 2023). During the pandemic, such sectors appear to play critical roles in shaping the economy and societal responses. For example, IT sector became pivotal as remote work and digital connectivity surged, relying heavily on tech services and products. Healthcare bore the brunt of the crisis, focusing on treatments, vaccines, and healthcare system resilience. Energy encountered volatility due to reduced travel and fluctuating oil demands, impacting global energy markets. The next subsections shed light on the volatility proxy and its putative determinants.

3.1 Volatility modelling

Financial and economic time series commonly exhibit distinctive features, including nonnormality, fat-tailedness, and leverage effects. These stylized facts are crucial considerations in empirical analyses, since they bear significant implications for asset pricing, risk management, and portfolio construction. Acknowledging and appropriately addressing these empirical regularities is essential for a more robust and realistic understanding of market dynamics and associated risks. Smales (2021) find that the distributions of daily returns of all US market sectors are fat-tailed and negatively skewed during the COVID-19 pandemic period. Ngene (2021) reports analogous results prior to and throughout the global health crisis. To tackle these potential issues in our analysis, we employ a Beta-Skew-t-EGARCH model developed by Harvey and Sucarrat (2014). Sucarrat (2013) shows that such modeling approach not only possesses the capability to effectively manage outliers or abrupt jumps in the data but also demonstrates a capacity to discern between short-term and long-term constituents of price volatility.

To start with, suppose a closing-price time series observed over a time period of days. Let be the log-price level at time , then the corresponding return is given as:

$$r_t = p_t - p_{t-1}, \qquad t = 1,2,..,T \qquad (1)$$

The first order one-component Beta-skew-t-EGARCH model with a martingale difference property is expressed as:

$$r_t = exp(\lambda_t)\,\varepsilon_t = \sigma_t\,\varepsilon_t, \;\; \varepsilon_t \sim st\,(0,\sigma_\varepsilon^2,\nu,\gamma), \;\; \nu > 2, \;\; \gamma \in (0,\infty), \qquad (2)$$

$$\lambda_t = \omega + \lambda_t^\dagger, \qquad (3)$$

$$\lambda_t^\dagger = \phi_1\,\lambda_{t-1}^\dagger + \kappa_1\,u_{t-1} + \kappa^*\,sgn(-r_{t-1})(u_{t-1} + 1), \;\; |\phi_1| < 1 \qquad (4)$$

$$\varepsilon_t = \varepsilon_t^* + \mu_{\varepsilon^*} \qquad (5)$$

where denotes the conditional volatility of , and is the conditional error, which is distributed as a skewed *t* with zero mean, variance , degrees of freedom parameter , and skewness parameter . is the sign function, is the log-scale intercept (i.e., the long-run log-volatility), while denote the GARCH, ARCH, and leverage parameters, respectively. represents an uncentered skewed *t* variable with degrees of freedom parameter , skewness parameter and mean Further, is the conditional score defined as:

$$u_t = \frac{(\nu + 1)[r_t^2 + r_t\,\mu_{\varepsilon^*}\,exp(\lambda_t)]}{\nu\,exp(2\,\lambda_t)\,\gamma^{2\,sgn\,[r_t + \mu_{\varepsilon^*}\,exp(\lambda_t)]} + [r_t + \mu_{\varepsilon^*}\,exp(\lambda_t)]^2} - 1 \qquad (6)$$

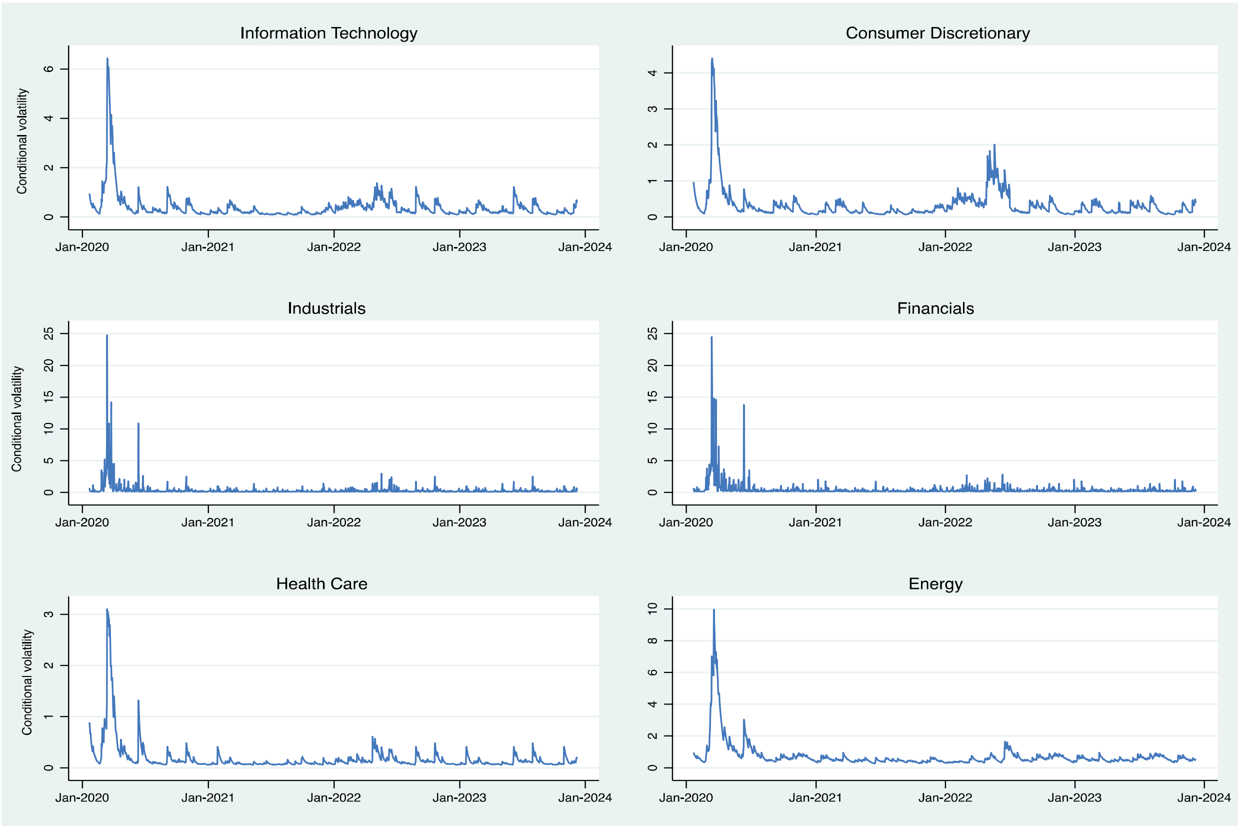

Fig. 1. The time evolution of conditional volatilities of US stock sector returns

Fig. 1 illustrates the time trend of the sectoral conditional volatilities throughout the sample period. Without exception, the individual sector indices experienced wildly elevated volatility spikes throughout the first half of 2020, which saw traumatic events centered on the COVID-19 disease, lockdowns and economic shutdown, the sudden spike in unemployment rates, Federal Reserve actions, and the outbreak and the Russia-Saudi Arabia oil price rift. For the rest of the sample period, sectoral volatilities are fairly stable, except for some spikes particularly during January 2022-November 2023. We observe that the sectors of Industrials, Financials, and Energy (Healthcare, Information Technology, and Consumer Discretionary) exhibit the greatest (lowest) magnitude of index price fluctuations. Moreover, Industrials and Financials tend to show similar volatility patterns over time.

3.2 Candidate volatility drivers

Although extant literature presents a broad universe of variables contributing to stock price swings, there is no manifest consensus on a single factor that can consistently explain such fluctuations across markets and over time. Our primary goal in this paper is to investigate the relevancy of a wide variety of factors as robust catalysts of US stock sector volatilities throughout the course of the pandemic. The pool of factors being considered consists of thirty two variables, including 5 dummy variables that represent significant occurrences during the period under study. Those potential determinants capture global economic and financial market influences, which comprise macroeconomic fundamentals (US inflation expectation rates, real economic activity, default spread, term spread, treasury bill interest rates), market sectors' exposure to the pandemic (US coronavirus positive cases, death counts, stringency of US policy responses, infectious disease equity market volatility), public attention (Google search queries for COVID-19 and US equities), financial markets (aggregate trading volume, broad US dollar index, European and Chinese stocks, Bitcoin, gold, and oil), global uncertainty and angst (Twitter-based economic uncertainty, policy uncertainty in US and China, forward-looking volatility indices for gold, oil, Bitcoin, and for stock markets of the US and Europe), and milestone events (the equity market collapse, the oil price crash, US presidential race, the commencement of COVID-19 pandemic vaccination campaign, detection of the first Omicron infection). In general, the rationale behind selecting these candidate variables stems from three main reasons. Firstly, these variables are chosen due to their theoretical relevance in understanding market volatility specifically during the pandemic. We consider the variables related to government interventions, economic indicators, public health conditions, and investor sentiment, since they are likely to have a direct or indirect impact on market volatility during crisis times. Secondly, empirical evidence provides a foundation for selecting those variables that have demonstrated a robust association with market volatility. Through examining relevant works and empirical research, we choose variables that have shown significant relationships with market volatility in similar contexts or during periods of market turmoil. This empirical evidence is basically informed by financial theories and models that explain the link between certain variables (e.g., trading volume, investor sentiment) and market volatility. Finally, data availability constraints are the last factor governing the choice of our candidate determinants of volatility.

To address the challenge posed by non-synchronicity of dataset releases, we adopt a method similar to Forbes and Rigobon (2002) and Hon et al. (2004) by employing two-day rolling averages across all factors. This helps us create a more consistent and comparable series. To meet the stationarity requirement, we transform our variables into the logarithmic form of the first difference. In Table 1, we provide a summary of the variables along with their respective data sources.

Table 1

A summary of variable description

Dimension	Variable (Symbol)	Definition	Raw data source
Financial markets	Trading volume (	denotes the aggregate daily dollar value of stocks traded on US equity markets, acting as a gauge of the overall liquidity present in the market.	https://www.backtestmarket.com/en/
	Broad US dollar exchange rate index ()	index is a measure that indicates the comparative strength of the US dollar's foreign exchange value vis-à-vis a range of major currencies from both developed and developing economies.	https://fred.stlouisfed.org/
	Volatility of USD index ()	A first order one-component Beta-skew-t-EGARCH model is employed to capture the fluctuations of the BUD index.	Own calculation
	China's stock market ()	The S&P China 500 index mirrors the stock market performance of China, encompassing the 500 most significant and highly liquid equities across a diverse spectrum of industry sectors.	https://www.spglobal.com/en/
	European stock market ()	The S&P Europe 350 index serves as a representation of stock price fluctuations within European markets. It monitors the performance of the 350 most prominent and highly liquid stocks from a set of 16 developed markets in Europe.	https://www.spglobal.com/en/
	Gold prices ()	The spot prices of the yellow metal are expressed in US dollars per troy ounce, commonly abbreviated as (USD/Oz).	https://www.gold.org/
	Oil prices ()	The spot prices of West Texas Intermediate (WTI) oil, expressed in US dollars per barrel.	https://fred.stlouisfed.org/
	Bitcoin prices ()	The price of a single unit of Bitcoin in US dollars on the Bitstamp trading platform.	https://bitcoincharts.com/

Pandemic risk	US coronavirus cases ()	In accordance with Ding et al. (2021), INF is quantified as the rate of growth of cumulative infections recorded on a specific day.	https://covid.cdc.gov/covid-data-tracker
	US coronavirus fatalities ()	is calculated using the same methodology as .	https://covid.cdc.gov/covid-data-tracker
	Stringency of US policy responses ()	The Oxford COVID-19 Government Response Tracker (STR) is employed as a comprehensive metric reflecting the actions taken by the US government in response to the pandemic.	https://covidtracker.bsg.ox.ac.uk/
	Infectious disease equity market volatility ()	Introduced by Baker et al. (2020), is derived from newspaper reports. It quantifies how infectious disease developments related to pandemics impact the overall volatility of the US stock market.	https://www.policyuncertainty.com/infectious_EMV.html
Public attention	Search volume for stock market sectors ()	Google Search offers a powerful means to capture public attention to a specific keyword or topic. In our case, the search terms under scrutiny revolve around the sector-specific names, which include Information Technology, Consumer Discretionary, Industrials, Financials, Healthcare, and Energy. We follow the approach outlined in Lyócsa et al. (2020) to produce at a daily granularity.	https://trends.google.com/trends/?geo=QA
	Search trends for coronavirus ()	monitors the level of search attention throughout the US specifically to the term “coronavirus”. Daily values are produced using a methodology akin to that of data.	https://trends.google.com/trends/?geo=QA

Macroeconomic fundamentals	US real economic activity ()	The Aruoba-Diebold-Scotti (REA) index, as introduced by Aruoba et al. (2009), serves as a real-time gauge of the general economic activity within the US. index has a zero average value, and hence incrementally larger positive (negative) values indicate steadily better- (worse)-than-average general conditions.	https://www.philadelphiafed.org/
	Relative treasury bill rate ()	Treasury bills are often used as a proxy for short-term interest rate developments and are considered an essential component in assessing monetary policy. In the spirit of Peña et al. (1999), is calculated as	https://fred.stlouisfed.org/
	Term spread ()	We adopt as a proxy for determining the stance of US monetary policy.	https://fred.stlouisfed.org/
	Default spread ()	We use as an indicator of market sentiment regarding credit conditions and corporate borrowing costs.	https://fred.stlouisfed.org/
	Inflation expectation rates ()	represents the forecast of average inflation over a five-year period, reflecting the US market's outlook on future inflation trends.	https://fred.stlouisfed.org/

Global fear and uncertainty		Derived from S&P 500 call and put option prices, quantifies investors' sentiment and the anticipated market volatility over the next 30 days.	https://fred.stlouisfed.org/
		mirrors the degree of fluctuation in the prices of the 50 major blue-chip stocks from eurozone countries included in the Euro STOXX 50 index.	https://www.stoxx.com/index-details?symbol=v2tx
	Implied volatility of Bitcoin ()	is an index that reflects the market's anticipation of 30-day volatility based on Bitcoin option prices from various exchanges.	https://t3index.com/indices/bit-vol/
		index measures the market's expectation of 30-day fluctuation in crude oil prices.	https://www.cboe.com/us/indices/dashboard/ovx/
		index tracks the market's expectation of 30-day volatility in gold prices.	https://www.cboe.com/us/indices/dashboard/gvz/
	Twitter-based economic uncertainty ()	Proposed by Baker et al. (2021), functions as a real-time measure capturing the perception of economic uncertainty worldwide among Twitter users.	https://www.policyuncertainty.com/twitter_uncert.html
	US economic policy uncertainty ()	Introduced by Baker et al. (2016), index quantifies policy economic uncertainty within the US. It provides insights into the impact of policy changes on economic conditions and market behavior.	https://www.policyuncertainty.com/us_monthly.html
	China economic policy uncertainty ()	Developed by Huang and Luk (2020), index serves as a proxy indicator measuring policy economic uncertainty specifically within mainland China.	https://economicpolicyuncertaintyinchina.weebly.com/

Crucial events	Equity market unrest ()	, a dummy variable, symbolizes the stock market collapse in the US during the initial turmoil of the coronavirus outbreak. Specifically, it takes on a value of one between 24/02/2020 and 23/03/2020, signifying the crash period, and holds a value of zero otherwise.	-
	Oil price war ()	is a dummy variable representing the period of the Saudi Arabia-Russia oil price war. It takes on a value of one between 06/03/2020, and 13/04/2020, signifying the approximate duration of the rift, and holds a value of zero otherwise.	-
	US presidential elections (USP)	is a dummy variable that reflects the US presidential race in 2020. Between 03/11/2020, the day of the election, until 20/01/2021, Joe Biden's inauguration, is equal to one; otherwise, it is zero.	-
	COVID-19 vaccination campaign ()	a dummy variable, designates the initiation of the vaccination campaign in the US. It is set to one starting from 14/12/2020, indicating the commencement of this campaign, and holds a value of zero otherwise.	-
	Detection of a new COVID-19 variant ()	a dummy variable, denotes the identification of a new version of the pandemic. It is set to one from 26/11/2021, marking the date of the first reported Omicron infection case in the US, and retains a value of zero otherwise.	-

Notes: A quick overview of the potential factors influencing the sector volatility of the US stock market appears in this table.

Since our inquiry comprises a great deal of covariates, it is of particular interest at this early level of analysis to shed light on their interrelationships. The pairwise correlations between continuous variables are displayed as a heatmap visualization in Fig. 2. Cross-correlation coefficients lacking statistical significance (i.e.,) are shown in blank cells. Very weak positive (negative) coefficients (i.e.,) are illustrated in turquoise (yellow), whereas very strong positive (negative) ones (i.e.,) are colored in dark blue (dark brown). It is obvious that the entire dependence structure is dominated by either statistically insignificant or very weak pairwise relationships. Nonetheless, there exist some exceptions that include cross-sector correlations of volatility, and correlations between almost all sectoral volatilities on the one hand and trading volume, volatility of USD exchange rates, COVID-19 positive cases and deaths, Google search volume for coronavirus, and default spread on the other.

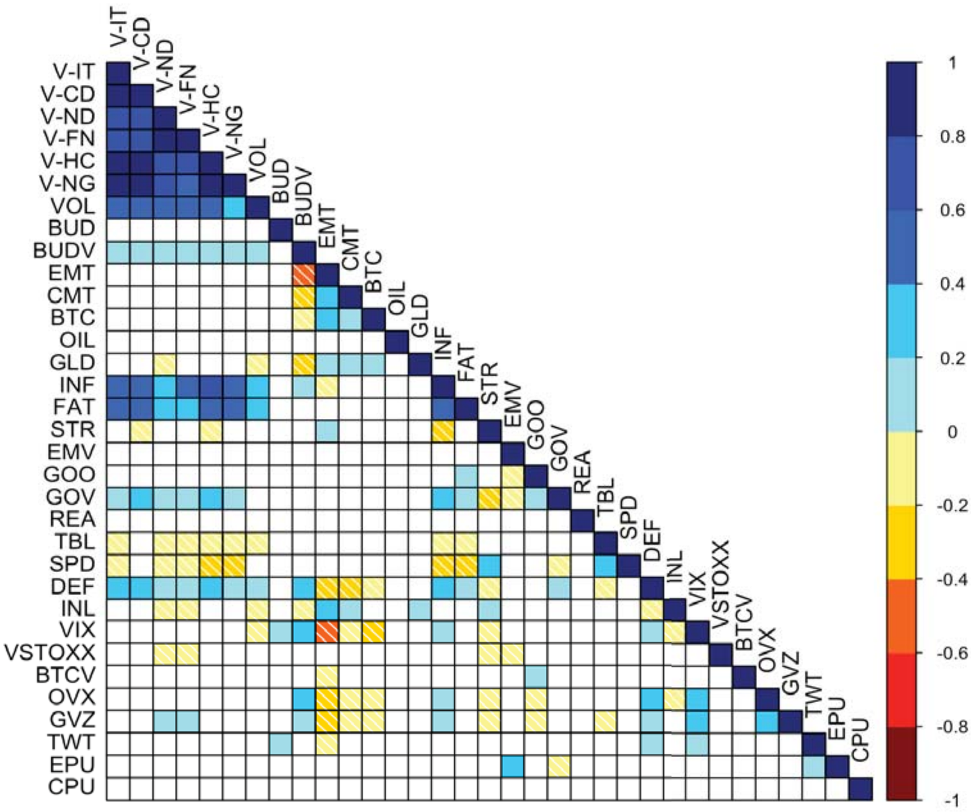

Fig. 2. A heatmap representation of pairwise correlations.

Note: “V-” represents a sector-specific index volatility. For example, “V-ND” and V-NG” denote return volatilities of Industrials and Energy sectors, respectively.

4. Econometric methodology

The econometrics and statistics literature proposes a wide variety of methodologies devised to single out the most powerful covariates in a regression model analysis. The LASSO method and its more enhanced versions hold significance as vital tools for selecting features or variables, addressing challenges in parameter interpretation, forecasting accuracy, as well as managing computational complexities within a specific model (Simon et al., 2013). We define the response variable, , as the vector standing for the conditional volatility of the sectoral index, and as the vector comprising potential volatility determinants. The linear model denoting the linkage between and is formulated as:

where are the parameter coefficient estimates of the regression model and are the disturbance terms. Standardizing variables before applying LASSO ensures that the regularization process focuses on the variables' relative importance in predicting the response variable, allowing for a fair and interpretable comparison between them (Simon et al., 2013). The intercept term in Eq. (7) is omitted due to the standardization applied to all variables. Tibshirani (1996) maintains that the LASSO method is premised on a penalty function to produce a sparse solution for the convex optimization problem:

where stands for the penalty. This penalty term is a crucial component of the LASSO method as it encourages sparsity in the model by shrinking coefficients towards zero and promoting variable selection. The parameter acts as a tuning parameter that controls the strength of the penalty applied to the estimated coefficients Tibshirani (1996) indicates that a larger value results in more aggressive shrinkage, potentially leading to more coefficients being pushed to zero, thereby promoting sparsity. Conversely, a smaller value reduces the penalty, allowing more coefficients to retain non-zero values.

A limitation of the LASSO method is that, in cases of high multicollinearity, it may struggle to handle correlated predictors efficiently, potentially leading to instability and arbitrary selection among strongly correlated variables. Zou and Hastie (2005) show that if a model's predictors display significant multicollinearity, the LASSO method can encounter instability in its solution paths. In such scenarios, the LASSO often chooses a random variable from closely correlated groups. To tackle this challenge, Zou and Hastie (2005) introduce the elastic net technique. This method handles highly correlated variables by employing a "grouped selection" strategy and merges LASSO-style shrinkage with automatic feature selection. Besides the norm penalty, elastic net regularization employs the norm penalty, which penalizes the sum of squared coefficients. It is expressed as follows:

In Equation (7), we make the assumption that . However, the exogeneity assumption is at a higher risk of being breached in time-series regression models that include a large number of regressors, as is the case in our situation. Unless adequately addressed, such endogeneity issue can introduce bias into the model's parameter estimates and result in incorrect inferences. To mitigate the risk of endogeneity, we deploy a two-step approach, in line with Chernozhukov et al. (2015a) and Belloni et al. (2016). Initially, as mentioned earlier, we use the elastic net method to identify the most significant factors influencing stock volatility. Subsequently, the variables identified in the first step as robust determinants of volatility (referred to as primary regressors) are included in a cross-fitting partialing-out LASSO instrumental-variables linear regression (POLASSO, hereafter) model. Meanwhile, the remaining variables, which are indeed weak in statistical sense, are utilized as controls. POLASSO treats these control variables as irrelevant, and thus, their corresponding inferential statistics are not presented (Chernozhukov et al., 2015b). The econometric representation of the POLASSO model is given as:

where is the response variable (i.e., sector index volatility), is a vector of endogenous variables and are their respective coefficient estimates of interest. is a -dimensional vector of instruments and is a -dimensional vector of exogenous control variables, from both of which a LASSO-type estimator specifies those incorporated in and those dropped from the final model. In this context, we have , but , which results in endogeneity. The fundamental concept behind this estimation method is based on the orthogonality principle, achieved through partialing out (Belloni et al., 2016). This involves creating orthogonal estimating equations for each . To do so, we employ a post-LASSO estimator to separate the influence of from , , and . The resulting residuals are then utilized to calculate the instrumental variable estimator, , for the parameter . We perform inference on utilizing and heteroscedasticity-robust standard errors. In our empirical analysis, we designate the second and third lags of the main explanatory variables as instrumental variables. Due to the challenges associated with proving that external instrumental variables contain relevant information for the endogenous counterparts while remaining unrelated to the disturbance term, lagged values are introduced as suitable instruments. This is because they provide information about the endogenous regressors and are independent of the disturbance term. In the POLASSO method, tests are conducted for all variables under investigation, whether they are exogenous or endogenous, and LASSO is used to select potential controls and instruments.

5. Empirical evidence

Our analysis includes two primary steps. First, we adopt the elastic-net regularized linear regression to pinpoint the factors that add to the US market sector volatility. Second, the potential for endogeneity among those regressors selected in the first step is addressed using the POLASSO modelling method.

5.1 Elastic net regression findings

We report the results of the elastic net estimator in Table 2. We observe that only 8 out of 32 factors are demonstrated as robust determinants of the volatility within the information technology sector. This small chosen group of factors implies the sparsest model representation for this sector. In contrast, the elastic net method selects 16 out of 32 factors as sturdy drivers of the volatility within the industrials and financials sectors, resulting in the least parsimonious model representations for both sectors. It is worth mentioning that Google search queries related to coronavirus, the number of positive cases, trading volume, US economic policy uncertainty, the rollout progress of COVID-19 vaccinations, the VIX, and the sudden emergence of the Omicron variant are among the most prevalent drivers of volatility across nearly all sectors. There are factors that affect 3 or 4 sectors, including Google search volume for market sectors, the stringency index of policy responses, the volatility of USD exchange rates, oil prices, the implied volatility of oil, the oil price war, the COVID-19 death rates, term spread, and the US stock market turbulence. Other factors appear to contribute to explaining the volatility in fewer than half of the sectors (i.e., Twitter-based economic uncertainty, European stock market returns, the US presidential elections, contagious disease stock price turbulence, US economic activity, and Euro STOXX volatility). On the flip side, we identify 10 factors (i.e., China's economic uncertainty, implied volatility of gold prices, default spread, implied volatility of Bitcoin prices, expected inflation rates, treasury bill rates, gold prices, stock prices on Chinese exchanges, Bitcoin prices, and USD exchange rates) that seem to have no relevance to the volatility of the US sectoral index.

Regarding their signs, the chosen regressors exhibit the anticipated theoretical signs in most instances. For example, rises in the COVID-19 infection rates and deaths, Google search volume, VIX, trading volume, US economic uncertainty, and term spread typically correlate with heightened sectoral volatility. However, the vaccination campaign's progress in the US and real economic activity seem to diminish volatility. On the other hand, the situation is less consistent for oil prices and European stock returns, since their corresponding coefficients change signs across different sector specifications.

Table 2

Results of the elastic net estimator

Variable	Information Technology	Energy	Industrials	Financials	Healthcare	Consumer Discretionary
Trading volume	0.318		0.305	0.263	0.153	0.240
Broad US dollar index						
Volatility of broad USD index		0.109	0.476	0.407		
European stock market				0.074–		0.023
Chinese stock market						
Bitcoin prices						
Oil prices		0.532	0.261		0.164–	0.350–
Gold prices						
US coronavirus infection cases		0.108	0.139	0.491	0.411	0.018
US coronavirus fatalities				0.032	0.246	0.019
Stringency of US policy responses		0.115		0.127	0.031	0.072
Infectious disease equity market volatility			0.098	0.006		
Google search queries for US market sectors		0.354		0.361	0.052	0.377
Google search queries for coronavirus	0.029	0.072	0.053	0.008	0.063	0.021
US economic activity		0.026–	0.083–			
Relative TB rate						
Term spread	0.071		0.138	0.042		0.063

Default spread						
Inflation expectation rates						
VIX	0.025	0.074	0.062	0.241	0.063	
Euro STOXX 50 volatility						0.079
Implied volatility of Bitcoin						
CBOE oil ETF volatility index		0.386	0.464	0.154		0.166
CBOE gold ETF volatility index						
Twitter-based economic uncertainty		0.055		0.087		
US economic uncertainty	0.047	0.003	0.175	0.035		0.053
China economic uncertainty						
Stock market turmoil	0.011	0.443	0.065	0.094		
Oil price war		0.455	0.304			0.069
US presidential elections			0.002			
COVID-19 vaccinations	0.083−	0.027−	0.068−		0.018−	0.086−
New COVID-19 variant	0.093		0.038	0.049	0.111	0.073
No. of factors chosen	8	14	16	16	10	15

Notes: This table displays outcomes from the elastic net penalized regression for parameter selection. Empty cells indicate variables whose coefficients have been reduced to zero.

5.2 Inferential findings

In the second step, we utilize the POLASSO modelling methodology with a view to tackling potential endogeneity problems. For purposes of parsimony, the variables that the elastic-net algorithm identified as relevant drivers of volatility are those that we are interested in. Table 3 presents the estimation results.

Table 3

Estimation results of POLASSO models

Variable	Information Technology	Energy	Industrials	Financials	Healthcare	Consumer Discretionary
Trading volume	***0.428 (0.065)		**308 .0 (0.134)	***0.509 (0.119)	**0.370 (0.171)	***0.134 (0.028)
Volatility of broad USD index		***0.125 (0.038)	**167 .0 (0.078)	**0.381 (0.180)		
European stock market				0.133− (0.272)		0.303 (0.288)
Oil prices		***0.169 (0.045)	**0.204 (0.095)		0.328− (0.297)	**0.076− (0.037)
US coronavirus infection cases		**0.250 (0.111)	**0.281 (0.129)	0.093 (0.074)	***0.576 (0.158)	*0.142 (0.083)
US coronavirus fatalities				*0.217 (0.116)	**0.462 (0.203)	**0.207 (0.085)
Stringency of US policy responses		*0.089 (0.051)		*0.079 (0.045)	***0.438 (0.130)	*0.064 (0.037)
Infectious disease equity market volatility			0.047 (0.217)	0.172 (0.123)		
Google search queries for US market sectors		***0.216 (0.058)		**0.223 (0.101)	**0.316 (0.145)	***0.461 (0.107)
Google search queries for coronavirus	0.035 (0.312)	0.197 (0.222)	**0.269 (0.115)	*0.213 (0.120)	**0.379 (0.177)	**0.363 (0.172)
US economic activity		0.106− (0.185)	0.385− (0.295)			
Term spread	0.040 (0.112)		0.165 (0.127)	0.106 (0.095)		*0.109 (0.059)
VIX	**0.147 (0.070)	***0.308 (0.032)	***0.189 (0.048)	**0.429 (0.191)	***0.224 (0.066)	

Euro STOXX 50 volatility						0.192 (0.128)
CBOE oil ETF volatility index		**0.430 (0.190)	**0.096 (0.046)	0.039 (0.073)		***0.102 (0.033)
Twitter-based economic uncertainty		0.395 (0.297)		0.480 (0.377)		
US economic uncertainty	**0.183 (0.089)	***0.293 (0.065)	**0.127 (0.058)	***0.246 (0.031)		**0.165 (0.078)
Stock market turmoil	*0.207 (0.109)	0.209 (0.196)	0.054 (0.034)	**0.186 (0.081)		
Oil price war		**0.363 (0.152)	*0.176 (0.096)			0.184 (0.165)
US presidential elections			0.113 (0.087)			
COVID-19 vaccinations	*0.308− (0.172)	0.081− (0.110)	**0.159− (0.075)		***0.374− (0.087)	**0.137− (0.067)
New COVID-19 variant	*0.159 (0.091)		0.086 (0.060)	**0.116 (0.049)	**0.285 (0.143)	0.194 (0.177)
(W-test statistic (p-value	92.430 (0.000)	174.990 (0.000)	70.890 (0.000)	21.250 (0.019)	145.180 (0.000)	181.740 (0.000)

Notes: This table shows estimation results of the POLASSO model for each sector. Heteroskedasticity-robust standard errors are in parentheses. The W-test, known as the Wald test, examines the collective significance of independent variables. It follows an asymptotic distribution under the assumption that all parameters are collectively equal to zero in the null hypothesis. ***, **, and * stand for statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Several conclusions can be extracted from Table 3. First, barring a few commonalities, the factors impacting sectoral volatility show considerable heterogeneity. This outcome is by no means surprising, given the varied nature of industries in the US market. The disparities among US stock sectors arise from their distinct structural compositions, varied operational challenges, divergent historical performance trends, and dissimilar sensitivities to economic and financial uncertainties, all contributing to the likelihood that relevant factors will affect each sector uniquely. Si et al. (2021) find that China's sectoral stock volatilities display dissimilar responses to policy uncertainty shocks. Kanno (2021) demonstrates that the onset of the COVID-19 pandemic has varied impacts on the performance of Japan's key industries.

Second, we observe that the coefficient estimates associated with trading volume, positive cases of coronavirus, stringency of US policy responses, Google search trends of market sectors, Google search volume for coronavirus, VIX, US economic policy uncertainty, and the launch of vaccination programs prove statistically significant at the 0.10 level or better across the majority of sectors (i.e., 4 sectors or more). The corresponding signs are positive, which suggest that positive changes in these explanatory variables are inclined to raise sectoral volatility. For instance, every one-percentage-point increase in the overall trading volume would lead to 0.308, 0.509, and 0.428 percentage-point rises in the volatilities of industrials, financials, and information technology sectors respectively, *ceteris paribus*. Likewise, a one-percentage-point higher in the VIX, all else equal, would result in 0.189, 0.308, and 0.429 percentage points higher in the volatilities of industrials, energy, and financials sectors, respectively. Other covariates (namely, the USD exchange rate fluctuations, oil prices, COVID-19 death rates, implied volatility of oil prices, the 2020 equity market collapse, the 2020 oil price war, and the spread of Omicron variant) demonstrate statistical relevance to volatility at conventional significance levels, though for a range of 3 sectors or less.

Third, the estimated coefficients corresponding to European stock returns, contagious disease stock price turmoil, US economic activity, term spread, Twitter-based economic uncertainty, Euro STOXX volatility, and US presidential elections either are marginally significant or fail to achieve statistical significance at even the 0.10 percent level. Since the overall health of the economy and financial market volatility are closely correlated via a variety of channels and mechanisms (e.g., Christiansen et al., 2012; Engle et al., 2013; Schwert, 1989), the finding that US economic and monetary factors have no demonstrable role in explaining sectoral volatility seems to be rather surprising. Veronesi (1999) proposes an intertemporal, rational expectations equilibrium model that depicts the relationship between stock market volatility and economic uncertainty. He shows that during times of elevated uncertainty, investors are more susceptible to news, which in turn pushes up the volatility of asset prices. Engle et al. (2013) develop a brand-new category of component volatility models and connect them directly to US macroeconomic fundamentals. For European stock markets, Errunza and Hogan (1998) document that macroeconomic information serves to improve the predictability of return volatility. For China, Girardin and Joyeux (2013) and Cai et al. (2017) establish that economic activity indicators are important for understanding and forecasting volatility.

Fourth, although the extent and strength of their effects differ across sectors, pandemic- and health-related variables seem to be a contributing factor to volatility. In particular, the introduction of vaccination programs leads to a decrease in volatility, with the energy sector being the only exception. For example, a one-percentage-point rise in the vaccination rate would be associated with 0.159, 0.308, and 0.374 percentage-point reduction in the volatilities of industrials, information technology, and healthcare sectors respectively, *ceteris paribus.*

Fifth, in terms of the relative impact of independent variables, trading volume, the VIX, and US economic policy uncertainty are the most influential factors in explaining volatility in 5 out of 6 sectors. In contrast, European stock returns, US real economic activity, contagious disease stock price turbulence, and US presidential elections provide the weakest explanatory power.

Finally, the last row of Table 3 shows the statistic, which is significant across sectors at the 0.05 level or better. This implies rejection of the null hypothesis that the estimated coefficients of each model are jointly indistinguishable from zero.

6. Discussion and policy implications

Taken together, our evidence reveals that, apart from some common ones, the factors affecting volatility tend to differ across US equity sectors. Trading volume, stringency of US policy responses, volatility of broad USD exchange rates, Google search for market sectors, positive cases of coronavirus, US economic policy uncertainty, Google search volume for coronavirus, the introduction of mass vaccinations and VIX are the most relevant factors for the majority of sectors. This finding is largely consistent with the results of previous research works, which show that market volatility is associated with trading volume (e.g., Brailsford, 1996; Chen et al., 2001; Ngene and Mungai, 2022), volatility of foreign exchange rates (e.g., Apergis and Rezitis, 2001; Cho et al., 2020; Maghrebi et al., 2006; Sikhosana and Aye, 2018), confirmed cases and deaths of coronavirus (e.g., Bora and Basistha, 2021; Choi and Hung, 2022; Lúcio and Caiado, 2022; Uddin et al., 2021; Xu, 2022), the stringency index of policy responses (e.g., Baig et al., 2021; Bakry et al., 2022; Kheni and Kumar, 2021; Lo et al., 2022; Wang et al., 2021b), Google search trends (e.g., Afkhami et al., 2017; Audrino et al., 2020; Dimpfl and Jank, 2016; Hamid and Heiden, 2015; Xu et al., 2019), VIX (e.g., Bekaert and Hoerova, 2014; Liu et al., 2022; Wang, 2019; Xiao et al., 2021), economic policy uncertainty indicators (e.g., Belcaid and El Ghini, 2019; Li et al., 2020; Liu and Zhang, 2015; Mei et al., 2018; Si et al., 2021), and mass vaccination programs (e.g., Apergis et al., 2022; Demir et al., 2022; Rouatbi et al., 2021). Based on data pertaining to Gulf Cooperation Council (GCC) stock sector indices, Bouri et al. (2023b) find that oil implied volatility has a greater influence on sectoral index returns and volatilities than does geopolitical risk, particularly for consumer discretionary and consumer staples sectors.

Surprisingly, on the other hand, several factors, including for example, USD exchange rate changes, gold, US real economic activity, default spread, and Bitcoin are uncorrelated with sectoral volatility. Our findings regarding the insignificance of these factors contrast with the outcomes observed in several earlier studies. For instance, Bouri et al. (2022) show that Bitcoin prices serve as a robust predictor for the volatility observed in US sectoral stock indices. Uzonwanne (2021) finds bidirectional shock transmissions between the S&P 500 market and Bitcoin over the long term. Schwert (1989) finds that stock price swings are correlated with the level of macroeconomic activity. Mnasri and Essaddam (2021) find that US presidential elections seem to amplify the S&P 500 index's volatility. Based on monthly data from China, Si et al. (2021) establish that trade policy uncertainty tends to increase the volatility of telecommunication services, information technology, financials, energy, and utilities sectors. Fang et al. (2020) demonstrate that default spread is among the most robust predictors of the long-term stock volatility in US markets.

The findings also document that trading volume has a paramount role in describing price fluctuations in the vast majority of sectors. Such evidence is in line with some chief liquidity-based theories that underscore the positive link between price volatility and trading volume. More plainly, specifically, liquidity-based theories underline the importance of market liquidity in understanding the relationship between trading volume and price volatility. They emphasize that changes in liquidity conditions can impact the ease of trading and the subsequent price movements, leading to a positive association between trading volume and price volatility. These theories offer insights into the mechanisms through which liquidity considerations can influence market dynamics (e.g., Amihud, 2002; Glosten and Harris, 1988).

By and large, our evidence presents practical implications for investment professionals and policy makers. A thorough understanding of the factors underlying sectoral volatility enables portfolio managers to devise sensible investment decisions, and policy makers to lay down regulations intended to curb excessive volatility. More specifically, the dynamics of trading volume, the USD exchange rate volatility, positive cases of coronavirus, stringency of US policy responses, Google search trends, US economic policy uncertainty, and VIX seem to contain important information about sectoral volatility and, consequently, should be taken account of by thematic fund managers seeking diversification opportunities across sectors. Monitoring the time path of the robust factors serves to provide a general picture of the direction sector-specific volatilities will take in the future, thereby broadening the information set that investors can draw upon to make informed decisions. Investors can modify their expectations for future volatility based on the behavior of the robust explanatory variables as a sign of a sectoral rally or downturn. Furthermore, given the decoupling of sectoral volatilities from the price swings of Bitcoin and gold, both investment options can act as a potential safe-haven asset against US stock market fluctuations. On the other hand, as the coronavirus threat is more likely to last over time, policy makers and stock market regulators should carefully consider effective means that keep the overall market sentiment buoyant in the face of the pandemic-induced adversities. The observed impact of mass vaccination schemes on returns and volatility highlights the favourable outcomes of promoting the public health-financial market nexus. In addition to being crucial for accomplishing national health goals and reducing the pandemic's human cost, the successful rollout of vaccine campaigns is a fundamental key to maintaining an optimistic outlook for the US economy and asset markets, which, in turn, helps to limit extreme price movements. Equally important, given the varying factors driving market volatility, policymakers may need to strengthen macroprudential policies to promote financial stability. Macroprudential policies aim to address systemic risks that can affect the stability of the financial system as a whole. These policies may include setting limits on leverage, improving risk monitoring systems, and enhancing stress testing to identify potential vulnerabilities.

7. Conclusion

In this study, we aim to identify the sturdy factors influencing the volatility of US stock returns within specific major sectors (i.e., Information Technology, Consumer Discretionary, Industrials, Financials, Healthcare, and Energy), under the persistent impact of the COVID-19 pandemic. The paper also examines whether these factors are heterogeneous across sectors. The pool of potential volatility determinants embrace macroeconomic fundamentals (inflation expectation rates, treasury bill interest rates, real economic activity, default spread, term spread), market sectors' exposure to the pandemic (US coronavirus positive cases, death counts, stringency of US policy responses, infectious disease equity market volatility), public attention (Google search queries for COVID-19 and the US equities), financial markets (aggregate trading volume, broad US dollar index, European and Chinese stocks, Bitcoin, gold, and oil), global anxiety and uncertainty (Twitter-based economic uncertainty, policy uncertainty in US and China, forward-looking volatility indices for gold, oil, Bitcoin, and for stock markets of US and Europe), and crucial events (the equity market collapse, the oil price crash, US presidential race, the commencement of COVID-19 vaccination campaign, detection of the first US Omicron infection). To model sectoral volatility, we utilize a Beta-Skew-t-EGARCH model. This GARCH-type framework is robust to outliers and volatility jumps, and serves to split volatility into short-term and long-term components. The empirical analysis includes two primary steps. First, we adopt the elastic-net regularized linear regression to pinpoint factors that add to the US market sector volatility. Second, the potential for endogeneity among those regressors selected in the first step is addressed using the POLASSO modelling method.

Our chief findings are summarized as follows. First, USD exchange rate changes, gold, Bitcoin, European stock returns, treasury bill rates, term spread, and implied volatility of gold are uncorrelated with sectoral volatility. Second, pandemic-induced factors (i.e., COVID-19 positive cases and fatalities, stringency of US policy responses, vaccination campaign rollouts, and the detection of Omicron cases) tend to add to sectoral volatility. Third, trading volume, stringency of US policy responses, volatility of broad USD exchange rates, Google search trends of market sectors, positive cases of coronavirus, US economic policy uncertainty, Google search volume for coronavirus, VIX, and the introduction of vaccination programs are the predominant variables explaining sectoral volatility. Fourth, barring such common determinants, a group of heterogeneous factors appear to be relevant to sectoral volatility. In retrospect, the peculiar conditions of the pandemic had a significant impact on the factors driving US equity market volatility during the COVID-19 period. However, there were also sector-specific risks, industry dynamics, company-specific characteristics, and investor behavior that contributed to dissimilar volatility patterns across sectors. While the aforementioned common factors did arise across the bulk of sectoral indexes, the diversity of factors can be explained by the fact that different businesses within each industry responded to the pandemic in various ways. For instance, companies with strong balance sheets, effective online presence, or essential products/services were often more resilient, than those with weaker counterparts, which frequently experienced financial setbacks or operational disruptions. Company-specific factors, such as earnings reports, supply chain disruptions, or remote work transitions, contributed to volatility at the individual stock level, affecting sectoral indices differently. The progress in vaccine development and treatment options significantly impacted market volatility during the COVID-19 period. Positive news about vaccine efficacy, distribution plans, or treatment breakthroughs often resulted in market rallies, benefiting sectors directly impacted by the pandemic. Conversely, setbacks or concerns related to vaccine distribution, efficacy, or virus variants increased volatility within these sectors. During the pandemic, the emphasis on public health and safety led to higher investments in the healthcare industry and a faster development and distribution of vaccinations, treatments, and medical equipment. The healthcare industry was affected by regulatory changes regarding telehealth and virtual healthcare in a different way than other industries.

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