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The COVID-19 pandemic uncertainty, investor sentiment, and global equity markets: Evidence from the time-frequency co-movements

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ABSTRACT

We use daily data of the Google search engine volume index (GSVI) to capture the pandemic uncertainty and examine its effect on stock market activity (return, volatility, and illiquidity) of major world economies while controlling the effect of the Financial and Economic Attitudes Revealed by Search (FEARS) sentiment index. We use a time–frequency based wavelet approach comprising wavelet coherence and phase difference for our empirical assessment. During the early spread of the COVID-19, our results suggest that pandemic uncertainty, and FEARS sentiment strongly co-move, and increased pandemic uncertainty leads to pessimistic investor sentiment. Furthermore, our partial wavelet analysis results indicate a synchronization relationship between pandemic uncertainty and stock market activities across G7 countries and the world market. Our results are robust to the inclusion of alternative pandemic fear measure in the form of equity market volatility infectious disease tracker. The pandemic uncertainty and associated sentiment implications could be one plausible reason for increased volatility and illiquidity in the market, and hence, policymakers should look upon this issue for the financial market stability perspective.

1. Introduction

This paper examines the COVID-19 pandemic information internet-search intensity (Pandemic, hereafter) impact on the stock market returns, volatility, and (il)liquidity of major world economies after controlling the effect of investor sentiment. The coronavirus (COVID-19) pandemic has been acknowledged as a global catastrophe with unprecedented socio-economic consequences. The gravity of the situation was explained by the WHO Director-General as “a unique virus, with unique features. We are in uncharted territory.”

Baker, Bloom, Davis, Kost, Sammon, and Viratyosin (2020), Huynh, Foglia, Nasir, and Angelini (2021), Mishkin and White (2020), Salisu and Akanni (2020), among others, also emphasized that this pandemic spread is indeed different. Amid the COVID-19 spread, analysts have opined that the fallout of the coronavirus pandemic will be a threat to the stability of the world economy. During the spread of the pandemic, the combined effects of three crucial transmission channels related to demand shock, supply shock, and

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1 We use daily data of the Google Search Volume Index (GSVI) to capture pandemic-information searches (“Coronavirus” and “COVID-19”). As the most popular search engine worldwide, Google provides an ideal platform for our cross-country study to measure investor sentiment and examine its price effect (Effenberger et al., 2020; Gao et al., 2018).

2 WHO Director-General’s opening remarks at the media briefing on COVID-19 (2 March 2020).
financial shock have been unprecedented (OECD, 2020; World Bank, 2020a, 2020b). As COVID-19 continues to disseminate every day, policymakers and market participants worldwide are concerned about its profound economic consequences.

Stock market activities have received much attention in the popular financial press and various policy domain discussions. A fast-growing body of recent research suggests that due to the increasing spread of COVID-19, global stock markets have experienced high volatility and lower stock returns (Al-Awadhi, Al-Saifi, Al-Awadhi, & Alhamadi, 2020; Baker et al., 2020; Ramelli & Wagner, 2020; Shaikh & Huyhn, 2021; Sharif, Aloui, & Yarovaya, 2020; Zaremba, Kizys, Aharon, & Demir, 2020; Zhang, Hu, & Ji, 2020). A common consensus that underscores the pandemic’s adverse effects on stock market activity is the economic fallout, heightened policy uncertainty, liquidity concerns, gloomy market sentiment, and looming global financial crisis (Baker et al., 2020; OECD, 2020). There was increasing concern that the stock market looks increasingly dissociated from economic reality (Capelle-Blancard & Desroziers, 2020; Krugman, 2020; Shiller & Malkiel, 2020). For instance, Capelle-Blancard and Desroziers (2020) noted that “since the beginning of the crisis, stock prices seem to be running wild. They first ignored the pandemic, then panicked when Europe became its epicenter. Now, they are behaving as if the containment of half the world’s population will have no economic impact after all.” In other words, the relationship between stock performance has been primarily driven by the oscillation between greed and fear (Krugman, 2020). If speculative bubbles (positive or negative) last long, the objective relation between fundamentals and stock valuations may become suboptimal (Shiller, 2003). The COVID-19 pandemic represents an excellent example of how investor sentiment and difficulty in predicting the severity of the resulting economic disruption can affect stock market activity (Shiller & Malkiel, 2020). One crucial aspect that has been largely ignored is the interrelationship between pandemic information search intensity, investor sentiment, and stock market activity. Our empirical analysis focuses on two research questions. First, whether a time–frequency co-movement relationship exists between the COVID-19 pandemic uncertainty and investor sentiment measured by the Financial and Economic Attitudes Revealed by Search (FEARS) index. Second, whether the COVID-19 pandemic uncertainty influences global stock market behavior after controlling the effects of investor sentiment (FEARS index). The existing recent literature highlights several potential arguments to motivate us for our research questions.

Our first research question identifies the potential relationship between pandemic fear (measured through the internet search volume index information for the COVID-19 and Coronavirus search terms) and investor sentiment. It is essential to understand the relationship between pandemic uncertainty and investor sentiment. The COVID-19-induced investors’ fear appears to be higher in the equity segment for the first time since the market crash of 1987 and the global financial crisis of 2008–2009 (Shaikh & Huyhn, 2021). Moreover, excessive fear could significantly affect investment sentiments and decisions (Costola et al., 2021; Huyhn et al., 2021; Salisu & Akanni, 2020). Fear increases investor pessimism, leading to investors’ overreaction to bad information or news (Su, Liu, & Fang, 2021). Because the full effect of any new information related to the pandemic spread is not immediately apparent to market participants, some participants may vastly underreact (underestimate) or overreact (overestimate) to the arrival of such information in the news (Shiller & Malkiel, 2020). Since there is no fundamental psychological principle that people tend to overreact or underreact (Shiller, 2003), the short-term implications of sentiment-induced mispricing on the market during COVID-19 cannot be ruled out completely. Behavioral finance suggests that investors’ psychological biases could be more pronounced when there is more significant uncertainty (Donadelli, Kizys, & Riedel, 2017; Garcia, 2013). Accordingly, we hypothesized that the increased pandemic-induced uncertainty (Baker et al., 2020) could have led to pessimistic investor sentiment. Recent studies by Salisu & Akanni, (2020), Vasileiou, (2021), and Smales (2021) suggest that investors are perhaps paying more attention to search information to resolve uncertainty concerning the COVID-19 crisis rather than fundamental information. Given the incomparable economic consequences of COVID-19, it has received large-scale media attention worldwide. Recent empirical evidence also suggests that increased volatility in the equity markets results from overwhelming panic generated by coronavirus-related news (Biktimirov, Sokolyk, & Ayanso, 2021; Haroon & Rizvi, 2020; Zaremba et al., 2020). A related research strand on information flow and demand suggests that high media pessimism predicts financial market behavior with increasing volatility and lower return (Garcia, 2013; Tetlock, 2007). Thus, it is reasonable to argue that the COVID-19 pandemic uncertainty could have crucial implications for investor sentiment, and these two are independent information variables. However, limited empirical evidence exists that examines the time-varying relationship between the information transmission channel of pandemic information demand (Pandemic uncertainty or pandemic attention) and investor sentiment. The second important aspect is the lack of sufficient empirical evidence on the COVID-19 impact on aggregate stock market behavior, i.e., stock return, volatility, and market illiquidity. Existing research majorly focuses on the stock return, and volatility aspects (Anastasiou, Ballis, & Drakos, 2022; Costola et al., 2020; Su et al., 2021; Tripathi & Pandey, 2021; Vasileiou, 2021; Wang, Xu, & Sharma, 2021; Zaremba et al., 2020 among others) and the implication of market liquidity has largely been ignored. Moreover, available literature fails to control the effect of prevailing exogenous market sentiment while analyzing the impact of COVID-19 pandemic uncertainty on stock market activity. Our approach first considers the co-movement between FEARS sentiment and pandemic uncertainty. Subsequently, it assesses the independent effects of pandemic uncertainty on stock returns, volatility, and liquidity after removing sentiment impact.

Our sample consisted of G7 countries and an overall measure of the world market. Existing research highlights that the empirical analysis of information in Google’s relative search volume index can help measure public attention on the global epidemic and its spread (Effenberger et al., 2020; Ginsberg et al., 2009) and household sentiment (Da, Engelberg, & Gao, 2015). A rise in the number of internet searches during the COVID-19 crisis induced a faster rate of information flow into financial markets (Costola, Iacopini, & Santagiustina, 2021; Smales, 2021; Tripathi & Pandey, 2021), enhancing the fear of the pandemic (Su et al., 2021) and therefore, a higher search volume index of pandemic information can be interpreted as a measure of coronavirus-related uncertainty and perceived risk (Chundakkadan & Nedumparambil, 2021; Szczypinski, Charteris, Bwanya, & Brzeszczynski, 2022; Wang et al., 2021). We use daily data of the GSVI to capture COVID-19 pandemic information demand and investor FEARS sentiment index. Our empirical design considers the wavelet-based time-frequency analysis. We utilized a time–frequency-based approach comprising wavelet coherence...
and partial wavelet analysis for our empirical assessment. This empirical approach enabled us to study the interdependence of pandemic information demand, sentiment, and stock market behavior to better understand the possible interrelationship (Rubbani, Khalid, & Samitas, 2021a, 2021b). We examine the co-movements and the lead-lag relationship between the Pandemic uncertainty and FEARS sentiment index using wavelet coherence and phase difference approach. While investigating the effects of pandemic uncertainty on stock market behavior, we resorted to controlling FEARS sentiment effects using partial wavelet coherency analysis. The use of partial wavelet coherency allows us to examine the scale-specific and localized relationship between the pandemic uncertainty and stock market activity (return, volatility, and liquidity) after eliminating the influence of common dependence between exogenous market sentiment and pandemic uncertainty. Our robustness test uses the newly constructed Equity Market Volatility Infectious Disease Tracker or EMV (Baker, Bloom, Davis, & Kost, 2019, 2020) as an alternative proxy for the pandemic fear sentiment. The application of wavelet analysis combines the advantage of drawing inference from the time series data by focusing on the time-varying relationship between both time and frequency domains (Al-Yahyaee, Rehman, Mensi, & Al-Jarrah, 2019; Dash, Maitra, Debata, & Mahakud, 2019; Rubbaniy et al., 2021a, 2021b; Sharif et al., 2020). The time–frequency-based wavelet analysis helps to accommodate these two domains within a unified framework (Crowley, 2007; Dash & Maitra, 2019; Mensi, Rehman, Al-Yahyaee, Al-Jarrah, & Kang, 2019; Ramsey, 2002; Sharif et al., 2020).

Our time–frequency co-movement results suggest that the FEARS sentiment and Pandemic indexes are positively correlated. Results indicate that pandemic spread leads to pessimistic investor sentiment. On 1 March 2020, this strong coherence intensified after COVID-19 was declared a global pandemic. Our partial wavelet analysis results show signs of a synchronization relationship across G7 countries and the world market between pandemic uncertainty and stock market activities (after controlling for FEARS sentiment). Our results are robust to the use of alternative measure of pandemic fear sentiment.

This study extends the rapidly growing body of research on the impact of COVID-19 on the stock market behavior. Our study also provides some initial evidence on the pandemic induced uncertainty and stock market liquidity. Existing literature majorly focused on the return and volatility dimensions of the stock market behavior, and the trading or liquidity aspect of the market has been largely ignored. To the best of our knowledge, no known study focuses on the stock market’s return, volatility, and liquidity effect amid the pandemic spread. Our findings contribute to the ongoing discussion between the co-movements of pandemic induced uncertainty and investor sentiment. Existing literature majorly focuses on the COVID-19 investor attention or pandemic uncertainty measures derived from the search volume information on the stock market without accounting for the exogenous sentiment effect in the market. There has been a limited examination of the impact of pandemic-information search on investor sentiment and its effect on stock markets activity. Our empirical approach also brings novelty with the use of wavelet-based time–frequency analysis. The wavelet-based approach helps to accommodate different investment horizons and understand the relationship between pandemic attention, sentiment, and stock market behavior in various time–frequency domains. Markets are composed of multiple agents operating in each moment at different time scales (short- and long-term). It is essential to accommodate both the time and frequency domains within a unified framework to simultaneously assess how our variables were related at different frequencies and how such a relationship has evolved. This approach provides a scope to explore the relationship across different frequencies of sentiment variations, which is essential for investors considering different investment opportunities (e.g., daily -movements for short-term investors) and for policymakers looking at the broader aspect of the financial market stability. This paper also extends the related strand of literature on the implications of internet search-based market participants’ expectation measures of financial market behavior.

The remainder of this paper is structured as follows. Section 2 provides a brief overview of related literature. Section 3 presents data and variables. Section 4 discusses our empirical approach. Section 5 outlines our main empirical results and robustness tests. Lastly, section 6 concludes the paper.

2. Review of related literature

The coronavirus (COVID-19) outbreak in early 2020 has posed adverse economic consequences on the global economy and financial markets worldwide (Contessi & De Pace, 2021; OECD, 2020; World Bank, 2020a, 2020b). As Shaikh and Huynh (2021) cogently describe the unique pandemic effect, “the COVID19 is an uncontained epidemic; just wait and watch!” The disruptive effect of the pandemic shock and the international health crisis on financial markets is well documented in the recent strand of literature. Amid the pandemic spread, the stock market behavior worldwide has drawn considerable attention. The January-May 2020 market crash does not account for the bursting of the asset price bubble. Instead, the market crash occurs for the first time in economic history when fundamentals are strong and there is a panic selling. Baker et al. (2020) highlight that the unprecedented U.S. stock market volatility during the first quarter of 2020 surpasses the Great Depression, the Great Financial Crisis (GFC), and the Spanish Flu pandemic.

This section presents a brief review of recent literature that examines the implication of COVID-19 associated uncertainty and fear on the global equity market. The inimitable effect of the COVID-19 pandemic outbreak on the global financial system can be characterized as a decline in liquidity, increase in volatility, lower return, and cross-market or cross-asset economic shock spillover (Al Guindy, 2021; Baker et al., 2020; Contessi & De Pace, 2021; Huynh et al., 2021; Paule-Vianez, Orden-Cruz, & Escamilla-Solano, 2021; Rubbaniy et al., 2021; Shaikh & Huynh, 2021; Xu, Chen, Zhang, & Zhao, 2021; Zaremba et al., 2020; Zhang, Ding, & Li, 2021, among others). Although the empirical research question remains focused on COVID-19 and stock market behavior, the approach to measuring COVID-19’s impact varies considerably. For example, existing literature documents operationalization of Global COVID-19 fear index (Al-Awadhi et al., 2020; Mazumder & Saha, 2021; Rubbaniy et al., 2021; Salisu & Akanni, 2020; Salisu, Ebuh, & Usman, 2020a; Zhang et al., 2021) measured from the daily death and confirmed cases, Feverish sentiment (Huynh et al., 2021), pandemic anxiety indexes (Yu, Xiao, & Liu, 2021), the COVID19- positive sentiment index (Anastasiou et al., 2022), Equity Market Volatility Infectious Disease Tracker (EMV) (Al Rababa’a, Alomari, Mensi, Matar, & Saidat, 2021; Bai, Wei, Wei, Li, & Zhang, 2021; Baker et al., 2020; Bouri, Gkillas, Gupta,
Table 1
Overview of recent literature: COVID-19 pandemic and financial markets.

| Articles                          | COVID-19 Measure                          | Market                      | Approach            | Findings                                                                 |
|----------------------------------|-------------------------------------------|-----------------------------|---------------------|--------------------------------------------------------------------------|
| Szczygieński et al. (2022)       | Pandemic uncertainty: Google search query | Equity market: 68 industries | Panel regression    | The COVID-19 related uncertainty is associated with higher level of volatility |
| Anastasiou et al. (2022)         | Positive sentiment index (COVID19+)       | G20 stock markets          | Panel-GARCH         | COVID19+ affects investor sentiment by increasing stock return          |
| Bai et al. (2021)                | Infectious Disease Equity Market Volatility Tracker (EMV-ID) | The US, China, UK, and Japan | GARCH-MIDAS         | Infectious disease pandemic (EMV-ID) impacts market volatility          |
| Huynh et al. (2021)              | Feverish sentiment: RavenPack database    | G-20 countries equity market | TVP-VAR model       | Investor sentiment positively (negatively) predicts the stock volatility (return) |
| Al Rababa’a et al. (2021)        | Infectious diseases equity market volatility (EMV) index | Gold, oil, and US dollar | Quantile regression model | The infectious diseases EMV index affects gold, oil, and US dollar returns. |
| Liu et al. (2021)                | Fear sentiment: Baidu search volume Index | China stock market          | Time series model   | Fear sentiment exacerbates crash risk                                    |
| Smales (2021)                    | Investor attention: Google search query   | G20 countries               | EGARCH              | Investor attention negatively influences global stock returns.         |
| Costola et al. (2021)            | Public concern: Google search query       | Equity market               | Regression          | Search query volumes predicts equity market returns.                    |
| Rubbaniy et al. (2021a)          | Global COVID-19 fear index                | Commodity markets           | Wavelet analysis    | Soft commodities show safe-haven behavior                               |
| Chundakkadan and Nedumparambil (2021) | Investor attention: Google search query     | 59 countries equity market | Panel data model    | Pandemic and the resultant sentiment-driven trade increases volatility in the market. |
| Subramaniam and Chakraborty (2021) | COVID-19 fear index: Google search query | Equity market               | Regression          | Negative association between COVID-19 fear and stock returns            |
| Wang et al. (2021)               | Expected and unexpected investor attention | U.S. stock market           | Regression          | Unexpected attention to COVID-19 is noisy                                 |
| Goel and Dash (2021)             | Pandemic intensity: Google search query    | 53 countries equity market  | Panel data model    | Pandemic search intensity has a negative effect on equity market return  |
| Tripathi and Pandey (2021)       | Investor attention: Google search query    | 25 equity market            | Panel data model    | Information from non-systematic sources contributed to the price decline |
| Su et al. (2021)                 | Pandemic-induced fear (PIF)               | China stock market          | Regression          | Investors’ internet search behaviors heighten the fear of the pandemic   |
| Mazumder and Saha (2021)         | Fear index: reported cases and deaths      | US Stock Market             | Regression          | IPO returns are sensitive to the fear of the pandemic                   |
| Sun et al. (2021)                | Coronavirus-related news (CRNs)           | Equity market               | Event study         | Covid-19 is negatively associated with investor sentiment               |
| Yu et al. (2021)                 | Pandemic anxiety indexes                  | BRICS and G7 countries     | Regression          | Time varying relationship: stock returns and the epidemic anxiety indexes |
| Rubbaniy et al. (2021b)          | Global COVID-19 fear index                | Cryptocurrency              | Wavelet analysis    | Safe haven properties of cryptocurrencies are not plausible             |
| Zhang et al. (2021)              | COVID-19 pandemic: death rate             | 36 countries equity market | Panel regression    | Significant negative impact on economic sentiment                       |
| Paule-Vianez et al. (2021)       | COVID-induced fear: Google search query   | G7 countries bond market    | Regression          | COVID-induced fear was associated with an increase in country risk perception |
| Xu et al. (2021)                 | Pandemic attention: Baidu search index     | China stock market          | Panel regression    | The stock market response to firm-specific information is decelerated    |
| Al Guindy (2021)                 | COVID-19 Twitter intensity                | US Stock Market             | Regression          | Increase in Twitter COVID-19 intensity corresponds to negative market returns |
| Harjoto et al. (2021)            | Pandemic transmission speed               | 78 countries equity market  | Panel regression    | Stock markets react negatively to the COVID-19 infection and death cases |
| Vasileiou (2021)                 | Coronavirus Fear Index (CFI): Google      | US stock market             | Regression          | Market inefficiency exists during the pandemic spread.                  |
| Smales (2020)                    | Investor attention: Google search query   | S&P500 composite index      | Regression          | Heightened investor attention negatively influenced US stock returns    |
| Chen et al. (2020)               | Fear sentiment: Google search query        | Cryptocurrency              | VAR models          | Market volatility has been exacerbated by fear sentiment                |
| Biktimirov et al. (2020)         | Media sentiment/coverage intensity        | Equity market               | Regression          | The sentiment scores are generally negative                             |
| Salisu et al. (2020a)            | Global fear index (GFI)                   | Commodity markets           | Panel data model    | Positive relationship between commodity price and GFI                    |
| Salisu et al. (2020b)            | Equity Market Volatility                  | 24 emerging market stocks   | Panel regression    | Emerging stock markets are more vulnerable than developed market stocks   |
| Salisu and Akanni (2020)         | Global COVID-19 fear index (GFI)          | Equity markets              | Panel regression    | Inverse relationship between stock prices and the fear index             |
| Lyóca et al. (2020)              | Fear of the coronavirus: search query     | 10 Global equity markets    | Regression          | Excess search volume predicts price variation                            |
| Bouri et al. (2021)              | Equity Market Volatility                  | Energy market               | EGARCH              | EMV helps to predict the forecast accuracy.                              |
selective attention-grabbing information, it results in temporary price pressure (Da et al., 2015). Existing literature have highlighted attention to a limited set of information (Smales, 2021). This argument postulates that when investor investment decisions focus on 2008). Given that the potential investment universe is vast, with a binding constraint of cognitive capability, investors selectively pay the fear associated with household FEARS during the COVID-19 crisis. Behavioral finance literature provides two competing theories for investor attention exuberated the pessimistic sentiment in the market. On the other hand, due to the prevailing pessimistic sentiment attributable to the potential investment universe is vast, with a binding constraint of cognitive capability, investors selectively pay attention to pandemic information is not a comprehensive view of the market sentiment. In the COVID-19 pandemic, fear, anxiety, and increased intensity of anxiety (worry), stress, fear, and sadness (Arora et al., 2020; Aslam, Awan, Syed, Kashif, & Nedumparambil, 2020). The persistent flow of COVID-19 spread information with increasing infection and death cases, perceived vulnerability may generate a negative sentiment, reduce the performance of stock markets, and therefore, the fear associated with “coronaphobia” (Asmundson & Taylor, 2020). Consequently, the fear characterized by coronaphobia may generate a negative sentiment, reduce the performance of stock markets, and therefore, investors may resort to rebalancing their portfolio asset allocation (Aslam et al., 2020; Capelle-Blancard & Desroziers, 2020; Chun & Nedumparambil, 2021; Liu et al., 2021; Smales, 2020; Su et al., 2021; Vasileiou, 2021; Wang et al., 2021). The abovementioned discussion highlights certain essential limitations in the existing literature, which fails to control the effect of investor sentiment while examining the implication of pandemic uncertainty in the stock market. The Covid-19 pandemic fear or uncertainty or pandemic attention measured through the internet search intensity may not be a complete source of investor sentiment characterization. Investor attention-related sentiment measures (like FEARS) and pandemic fear or uncertainty measures are no different. It is equally likely that both may exist in the market simultaneously and feed on each other during market turbulence. Therefore, ignoring the effect of FEARS sentiment in the model prediction of pandemic uncertainty on stock prices may not reveal an accurate picture. We offer answers to the following two research questions based on the preceding arguments. First, whether there exists a co-movements and lead-lag relationship between the FEARS sentiment and Pandemic uncertainty across the major world economies. Second, whether the Pandemic uncertainty impacts the four broad aspects of stock market behavior, i.e., return, volatility, liquidity, and illiquidity, after controlling the effect of FEARS sentiment. Fig. 1 provides a theoretical framework on the relationship between Pandemic uncertainty, investor FEARS sentiment, and stock market behavior concerning our two research questions. Our findings help to shed more insights on the COVID-19 impact on the financial market after controlling for the effect of investor sentiment. Furthermore, the available literature emphasizes either the stock market return or volatility. To the best of our knowledge, no known study focuses on the stock market’s return, volatility, and (il)liquidity effect amid the pandemic spread. Our paper also brings novelty in the empirical design by using wavelet-based time–frequency analysis. The benefit of the wavelet methods (WTC) is their ability to unite both the time domain (e.g., consideration of changes in time-period of a variable at a specified frequency) and the frequency domain (e.g., change in frequency of a variable but not periods) aspect of time-series data (Al-Yahyaee et al., 2019; Dash & S.R. Dash and D. Maitra
This approach effectively examines the co-movements between financial variables over time and under different frequencies (high, medium, and low) (Al-Yahyae et al., 2019; Crowley, 2007; Mensi et al., 2019; Rubbaniy et al., 2021a, 2021b; Sharif et al., 2021).

3. Data and variables

This study uses the daily data over a sample period of January 2020 till May 2020 (138 daily observations), when several European countries and the USA became epicenters of the COVID-19 pandemic. Similar sample selection criteria were also employed by Contessi and De Pace (2021), Salisu et al. (2020), and Smales (2021), among others.

3.1. Stock market data

Our sample focuses on a worldwide measure and G7 country specific variables (Canada, France, Germany, Italy, Japan, the UK, and the USA). Our sample countries were affected by the COVID-19 at different stages of pandemic spread. The rationale behind G7 country selection was based on their significance in global economic activities and financial markets. We measured G7 country and world market daily stock market activities using four proxies: stock return, time-varying volatility using generalized autoregressive conditional heteroskedastic (GARCH) processes, the Amihud (2002) illiquidity measure, and turnover as a liquidity measure. We considered the S&P TSX composite, CAC 40, DAX 30, FTSE Italia All-Share, NIKKEI, FTSE 100, Nasdaq 100, and S&P Global 100 benchmarking market index for Canada, France, Germany, Italy, Japan, the UK, the USA, and the world market, respectively. We collected our stock market data from the Thomson Reuters database.

3.2. The COVID-19 uncertainty

Following Da et al. (2015) and Effenberger et al. (2020), we utilized the GSVI as a proxy for attention search. In order to create a Pandemic search intensity variable, we used two search terms, i.e., “Coronavirus” and “COVID-19”, by restricting our search geography to different countries around the world. The final Pandemic index is a simple average of the standardized search intensity of two search terms (Coronavirus and COVID-19). However, we do not make any country specific language translation for the words “Coronavirus” and “COVID-19” as they are considered as synonym of a global pandemic (Chundakkadan & Nedumparambil, 2021; Costola et al., 2021; Liu et al., 2021; Smales, 2021; Subramaniam & Chakraborty, 2021). Searching for information about a particular subject clearly shows that one is paying attention to that subject (Smales, 2021). Moreover, the World Health Organization (WHO) official announcement of disease outbreak news (30 Jan 2020) considers the novel coronavirus (COVID-19) outbreak as a public health emergency of international concern (PHEIC), irrespective of any global, regional, and country-level differentiation.

Existing literature highlight that stock market volatility amid the pandemic spread is subject to good or bad news and even responses to fake news and policy changes (Shaikh & Huynh, 2021). However, our measure of pandemic uncertainty is different from the news-based uncertainty measure (Sun et al., 2021) and follows the search volume-based measure of pandemic uncertainty (Chundakkadan & Nedumparambil, 2021; Costola et al., 2021; Liu et al., 2021; Su et al., 2021; Smales, 2021; Vasileiou, 2021).

Fig. 1. Framework of pandemic uncertainty, investor sentiment, and stock market behaviour.

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3 Google Trends (https://www.google.com/trends/) provides the search volume index of any search item across various countries, in different languages, and during specific period starting from 2004.
3.3. Sentiment indicator

Our analysis employs sentiment indicator measured by the Financial and Economic Attitudes Revealed by Search (FEARS). To construct FEARS sentiment index, our approach closely follows Da et al. (2015). For better consistency, our search keywords remained unchanged irrespective of the country selection. Consistent with Gao, Ren, and Zhang (2020), our search terms closely follow the same primitive word list suggested by Da et al. (2015), however, with reference to a specific country our search terms have been translated into the country specific language (e.g., French, Italian, Japanese language for France, Italy, and Japan respectively). For our sample countries like the world market, Canada, the UK, and the USA we use the English language for the exact primitive word list suggested by Da et al. (2015), Goel and Dash (2021), and Burggraf et al. (2021).

Along with internet search intensity-based FEARS sentiment measure, we also use the newly constructed Equity Market Volatility Infectious Disease Tracker (EMV) developed by Baker et al. (2019, 2020) as an alternative pandemic sentiment indicator. The EMV is a newspaper text analysis-based equity market volatility tracker that moves with the VIX and with the realized volatility of returns on the S&P 500. Similar approach has been used by Al Rababa’a et al. (2021), Bai et al. (2021), Bouri et al. (2021), Salisu et al. (2020b) as the measure of pandemics fear.

Fig. 2 displays a consistent co-movement between the FEARS and Pandemic time series across all the panels, suggesting the impacts of the COVID-19 pandemic on the sentiment towards the FEARS sentiment index is pervasive. The time series co-movement of the FEARS and Pandemic search volume supports the notion that the pandemic has potential deterrent effects on economic activities. Besides, we also examine the pair-wise rolling window correlation (R_Corr.) for a 20-day window between FEARS sentiment and Pandemic indexes of each country in the sample. We observed a high degree of correlation between coronavirus-information searches and the FEARS sentiment indexes. The strength of the relationship is higher for the USA, UK, Canada, and Japan. We notice that the correlation has intensified to 50% at the end of March. In our sample, Italy shows a sharp jump in the correlation at the end of April. The results exhibit the contagion effects of a Pandemic on the FEARS sentiment.

Table 2 presents the descriptive statistics of all the variables. We use Augmented Dickey–Fuller unit root tests (Panel B of Table 2) to check the stationarity of the data. Panel (A) of Table 2 suggests a negative mean return for all the G-7 markets during our sample period. This is consistent with the extreme market downfall in the global equity markets during the early spread of COVID-19. There is heightened market uncertainty measured by return volatility for markets like Canada, Germany, Italy, and the USA. The global stock markets continue to exhibit a high degree of volatility, with a cumulative loss of 12.35% between January and May 2020 and a more than $9 trillion loss since the outbreak of COVID-19 (Salisu et al., 2020). Our Pandemic sentiment measure found to be consistently negative across the G-7 markets. The prevailing high level of pessimism in the global market during the COVID-19 pandemic spread is consistent with the notion that due to heightened economic uncertainty amid pandemic spread (Baker et al., 2020), investors may prefer to pay more attention to search information concerning the COVID-19 crisis to resolve uncertainty (Salisu & Akanni, 2020; Smales, 2021; Vasileiou, 2021).

4. Empirical approach

In this paper, we use an empirical framework based on a wavelet approach. We investigate co-movement between the FEARS sentiment and Pandemic sentiment measures using the Wavelet Coherence (WTC) Analysis. To conduct our empirical analysis, we considered three wavelet methods, namely Wavelet Coherence Analysis (WCA), The Wavelet Phase Angle (WPA), and Partial Wavelet Coherence Analysis (PWCA). The WTC and the wavelet phase angle offer the benefits of testing the multi-time horizon co-movement of two indexes. The wavelet approach allows us to study the co-movements between sentiment and stock market behavior over time and under high, medium, and low frequencies (Crowley, 2007; Ramsey, 2002) and could be helpful for both short and long-term investors (Aguirar-Conraria et al., 2008; Mensi et al., 2020; Dash & Maitra, 2019; Mensi et al., 2019). Since, managing portfolio risk requires a strategic approach encompassing the time and frequency domain relationship between economic or financial indicators (e.g., sentiment and volatility of the market) it is useful for designing appropriate investment strategies. In this section, we briefly discuss the wavelet approach adopted to address our research questions.

4.1. Wavelet coherence analysis (WCA)

Wavelet coherence measures the strength of association between two time series. It gives a local correlation over time as well as across frequencies. In order to estimate wavelet coherence, each time series has to be transformed into a continuous wavelet. The continuous wavelet transform is defined as the convolution of the $p_i$ is expressed as:

$$W_p(\tau, s) = \int_{-\infty}^{\infty} p(t) \frac{1}{\sqrt{s}} \psi^* \left( \frac{t-\tau}{s} \right) dt$$

(1)

where $\tau$ and $s$ is the time position controlling its location and scale controlling the width of the wavelet, respectively. $1/\sqrt{s}$ normalizes the wavelet transforms to make them comparable across scales and time series. A measurement of the amplitude of a specific time series or variance of the time series at each time and each scale can be achieved by following the wavelet power spectrum (WPS) $WPS_p(\tau, s)$.

4 Detail information is available at: https://www.policyuncertainty.com/infectious_EMV.html (see Baker et al., 2019, 2020 for details).
Similar to time series $p_t, q_t$ can also be transformed into a continuous wavelet.

In the next step, wavelet coherence is calculated by taking the ratio of the cross-spectrum to the product of the spectrum of two signals or time series. The wavelet coherence of two time series $p_t$ and $q_t$ is given as:

$$R^2_{pq}(\tau, s) = \frac{|S(s^{-1}W_{pq}(\tau, s))|^2}{S(s^{-1}|W_p(\tau, s)|^2)S(s^{-1}|W_q(\tau, s)|^2)}$$

(2)
where $S$ represents smoothing operator both over time and scale, with $0 \leq R^2(\tau, s) \leq 1$. A high (low) $R^2$ value suggests higher (lower) co-movement between two series. The co-movement between two time series over time and frequencies or scales is denoted by the contour plot. The level of co-movement is determined by the contour plot color. A yellow (blue) color denotes strong (weak) co-movement between two time series. The co-movement between two time series over time and frequencies or scales is denoted by the contour plot. The level of co-movement is determined by the contour plot color. A yellow (blue) color denotes strong (weak) co-movement between two time series.

4.2. The wavelet phase angle (WPA)

The phase difference indicates delays of the oscillations of two time series as a function of time and scale. The wavelet phase difference can be estimated as:

$$\phi_{\mu}(\tau, s) = \tan^{-1}\left(\frac{\Re(W_{\mu}(\tau, s))}{\Im(W_{\mu}(\tau, s))}\right)$$  \hspace{1cm} (3)

where $\Re$ and $\Im$ is an imaginary and real operator, respectively. The phase relationship between two time series is given by the wavelet phase angle. The circular phase is calculated to quantify the phase relationship, with statistical significance greater than 5% plus within the COI. Black arrows refer to phase differences. A phase difference of zero, denoted by arrows pointed to the right, suggests that time-series co-move at the specified frequency. In contrast, arrows directed to the left signify that the two series are negatively correlated and anti-phase. If arrows are directed towards $[0, n/2]$, then series are in phase, and $y$ leads $x$ (if $x$ and $y$ are the first and second time series in order); if arrows are pointed towards $[-n/2, 0]$, then $x$ leads $y$ negatively. If arrows show the direction towards $[n/2, n]$, then $x$ leads $y$ positively; arrows towards the direction of $[-n, -n/2]$ show that $y$ leads $x$ negatively. Monte Carlo simulations are used to test the statistical significance of coherence.

4.3. Partial wavelet coherence analysis (PWCA)

The PWCA enables the user to consider three time-series. Let us denote the three time-series as: $X_n$, $Y_1$, and $Y_2$, and let their wavelet transformation be: $WL_{X_n}^S(S)$, $WL_{Y_1}^S(S)$ and $WL_{Y_2}^S(S)$ respectively. Thus, the squared PWC may be defined as:

Table 2
Descriptive statistics.

| Countries | FEARS | Pandemic | Return | Volatility | Liquidity | Illiquidity |
|-----------|-------|----------|--------|------------|-----------|------------|
| Countries | Mean  | Stdev    | Mean   | Stdev      | Mean      | Stdev      |
| World     | 0.001 | 0.497    | -0.007 | 2.906      | -0.049    | 2.630      |
| Canada    | 0.005 | 0.302    | -0.001 | 0.986      | -0.113    | 3.215      |
| France    | 0.001 | 0.279    | -0.001 | 0.989      | -0.274    | 2.789      |
| Germany   | -0.001 | 0.256  | -0.001 | 0.989      | -0.164    | 2.821      |
| Italy     | -0.001 | 0.278  | -0.001 | 0.986      | -0.286    | 2.952      |
| Japan     | -0.001 | 0.278  | -0.003 | 0.983      | -0.140    | 2.193      |
| UK        | 0.001  | 0.328    | -0.001 | 0.987      | -0.211    | 2.536      |
| USA       | -0.001 | 0.387  | -0.001 | 0.989      | 0.062     | 3.246      |

Panel (B) Augmented Dickey–Fuller test (ADF) Unit Root Tests

| Countries | ADF | P-value | ADF | P-value | ADF | P-value | ADF | P-value | ADF | P-value |
|-----------|-----|---------|-----|---------|-----|---------|-----|---------|-----|---------|
| World     | -12.53 | (0.00) | -2.64 | (0.08) | -13.31 | (0.00) | -3.57 | (0.09) | -3.40 | (0.00) |
| Canada    | -13.69 | (0.00) | -3.87 | (0.02) | -13.07 | (0.00) | -5.52 | (0.00) | -3.47 | (0.00) |
| France    | -18.58 | (0.00) | -3.87 | (0.02) | -9.51  | (0.00) | -3.92 | (0.00) | -2.72 | (0.00) |
| Germany   | -17.35 | (0.00) | -3.87 | (0.02) | -9.26  | (0.00) | -4.21 | (0.01) | -2.84 | (0.00) |
| Italy     | -19.06 | (0.00) | -3.80 | (0.00) | -10.69 | (0.00) | -3.84 | (0.01) | -3.45 | (0.00) |
| Japan     | -14.81 | (0.00) | -3.86 | (0.00) | -8.12  | (0.00) | -1.98 | (0.09) | -2.44 | (0.00) |
| UK        | -14.18 | (0.00) | -3.87 | (0.00) | -9.64  | (0.00) | -4.30 | (0.01) | -3.11 | (0.00) |
| USA       | -13.78 | (0.00) | -3.87 | (0.00) | -15.97 | (0.00) | -2.45 | (0.09) | -2.47 | (0.00) |

Notes: This table reports the descriptive statistics and unit root test results of all variables for the World stock market and the G7 countries. Pandemic is the Google search intensity index of COVID-19 pandemic. FEARS is the sentiment index constructed using the Google search volume intensity index (Da et al., 2015). We consider SandP TSE composite, CAC 40, DAX 30, FTSE Italia All Share, Nikkei, FTSE 100, Nasdaq 100, and SandP Global 100 as benchmarking market index for the Canada, France, Germany, Italy, Japan, UK, USA, and the World market. Volatility is measured through the GARCH estimation. Liquidity is measured as turnover, and illiquidity is measured through the Amihud (2002) price impact measure. The sample period is from 02 January 2020 till 18 May 2020 (138 daily observations).
\[
(Rc_{XY1_n}^{XY2})^2 = \frac{|Rc_{XY1_n}^{XY2} - Rc_{XY1_n}^{XY2}|^2}{(1 - (Rc_{XY1_n}^{XY2})'(1 - (Rc_{XY1_n}^{XY2})')}
\]

\[
(Rc_{XY2_n}^{XY1})^2 = \frac{|Rc_{XY2_n}^{XY1} - Rc_{XY2_n}^{XY1}|^2}{(1 - (Rc_{XY2_n}^{XY1})'(1 - (Rc_{XY2_n}^{XY1})')}
\]

Fig. 3. Wavelet coherency: pandemic uncertainty and FEARS sentiment. Notes: This figure presents the wavelet coherency test results between Pandemic Uncertainty and FEARS sentiment for G7 countries and the world market. The horizontal and vertical axis represents time in months and the period, respectively. The colors range from deep blue (low coherence/no correlation) to deep yellow (high coherence/perfect correlation). The area within the black contours indicates coherency significance at 5% level. If arrows pointed toward the right (left) indicates both Pandemic and FEARS are in-phase (out-of-phase).
5. Results discussion

5.1. Time-frequency co-movement between FEARS sentiment and pandemic uncertainty

Fig. 3 examines the co-movements between the FEARS sentiment and Pandemic uncertainty by employing wavelet coherence and phase difference approaches. The strength of coherence ranges from yellow (strong) to blue (weak). The horizontal (vertical) axis shows time (frequency). The frequency numbers denote the number of days. The black contours in the figure suggest significant coherent regions at a 5 percent level of significance. The outer solid line of the cone indicates the cone of influence. We notice that the COVID-19 pandemic has a high impact on the FEARS sentiment starting from 21 January until 30 April across all frequency bands at the world level. Our evidence also coincides with two significant events around that time and of important implications for the world economy. First, on 21 January, the first travel-related case in the USA was confirmed in Washington state. Second, the WHO experts conducted a brief field visit to Wuhan, China, on 21 January 2020; on 22 January 2020, preliminary evidence of human-to-human transmission in Wuhan, China, was confirmed by the WHO. Finally, on 30 January 2020, WHO Director-General recommended that the COVID-19 outbreak constituted an International Public Health Emergency. Countries such as the US, UK, Canada, and Japan show higher Pandemic impacts on FEARS sentiment. Effenberger et al. (2020) and Sun et al. (2021) confirmed that the worldwide public interest COVID-19 reached its first peak at the end of January when the numbers of newly infected patients started to increase exponentially in China. The strong coherence across all bands indicates the contagion effects between pandemic and market sentiment; however, more meaningful coherence is present at the scale between 16 and 32 days, i.e., the medium term. The magnitude of co-movements increased after 01 March, which overlaps with the periods: i) beginning of health crisis in most countries worldwide; ii) implementation of strict rules regarding social distancing and quarantine; and iii) moderate to intense economic lockdown across countries. Besides, France, Germany, and Italy also show coherence between the pandemic and FEARS sentiment. These three countries reveal the significant contagion effects of the pandemic from 21 March to 10 April at the frequency band of 4–8 days.

Furthermore, we examined the lead-lag relationship between the Pandemic uncertainty and FEARS sentiment indexes. In Fig. 3, the arrows pointing to the right (→) and left (←) indicate that the first and second series are in-phase and out-of-phase, respectively. The in-phase or out-of-phase relationship shows whether the two are positively or negatively co-moving. The upwards (downwards) ([↑(↓)]) arrows indicate that the FEARS sentiment is leading (lagging). The right up (↗) and left down (↙) arrows suggest the FEARS sentiment is lagging. We notice that both the FEARS sentiment and Pandemic uncertainty are positively correlated as the arrows are directed to the right. The FEARS sentiment is led by pandemic conditions of the country and world. In a nutshell, we observe a strong positive relationship between the FEARS sentiment and Pandemic due to COVID-19. The world majors like the US, UK, Canada, and Japan show stronger co-movements between the two series. The strong coherence intensified after 01 March, when the spread of COVID-19 has substantially increased across the world. Effenberger et al. (2020) also supports the view that worldwide interest peaked in mid-March 2020, shortly after COVID-19 was declared a pandemic. Consistent with our observation, Effenberger et al. (2020) note that the highest search volume index for the pandemic peaked during mid of March, which is in line with rigorous policies by the government regarding the rapid spread. The results corroborate the findings of Ramelli and Wagner (2020) that the extreme event like COVID-19 is likely to have a significant effect on economic uncertainty, and thus on the investor sentiment. Therefore, the impacts stemming from economic uncertainty, sentiment, and financial markets are difficult to ascertain (Rush, 2020; Stirling, Curran, & Bosley, 2020). The increase in economic uncertainty may be due to a fall in global trade, stock price reactions to COVID-19, the decline of credit lines, and bond-floating activities during the pandemic crisis (2020b; Baker et al., 2020; Huyhn et al., 2021; OECD, 2020; Shaikh & Huyhn, 2021; World Bank, 2020). Our results also support the arguments of Bloom, Daniel, and Sevilla (2018) and Fan, Jamison, and Summers (2018) toward the deterrent impact of pandemic events on increasing economic and policy uncertainty. Overall, our results reveal that the COVID-19 pandemic represents a menacing risk that is stirring up feverish behavior in investors worldwide (Capelle-Blancard & Desroziers, 2020; Ramelli & Wagner, 2020; Subramaniam & Chakraborty, 2021; Wang et al., 2021; Zhang et al., 2021). The potential impact of pandemic search intensity on investor sentiment could be due to the availability cascade effect observed by Kahneman (2011). An availability cascade effect (Kahneman, 2011) is a self-sustaining chain of events that could be due to the emotional reaction by investors due to the excessive media coverage of pandemic spread (Capelle-Blancard & Desroziers, 2020; Huyhn et al., 2021; Krugman, 2020; Shiller & Malkiel, 2020; Sun et al., 2021; Tripathi & Pandey, 2021). Similarly, analyses of sentiments and emotions evoked by news headlines regarding the coronavirus disease outbreak revealed that the news headlines had high emotional scores with negative polarity (Aslam et al., 2020).

5.2. Partial wavelet coherency analysis

Fig. 4 reveals the PWCA between stock market variables (return, volatility, liquidity, and illiquidity) of G7 countries and Pandemic uncertainty after controlling the FEARS sentiment. Since Pandemic uncertainty and FEARS sentiment can have significant correlations due to heightened concern of economic uncertainty, any effects of the FEARS sentiment must be controlled to examine the co-

\footnote{The frequencies are between scale one, followed by 4, 8, 16, and 32 days.}

\footnote{Per Coronavirus disease 2019 (COVID-19) Situation Report – 41 published by the WHO on 1 March 2020, there were 87,137 confirmed global cases; the report suggested a “very high” category risk assessment by the WHO.}
movements between stock market variables and Pandemic intensity. In a more illustrative way, phycologists described that “when it comes to making decisions that involve risks, we humans can be irrational in quite systematic ways. When we see actual death tolls climbing daily, as we do with the coronavirus—another factor besides our sensitivity to losses comes into play: fear.” As previously mentioned, PWCA squared helps to detect the correlation between two time series, $y(t)$ and $x_1(t)$, after controlling for the effect of $x_2(t)$.

For example, in Fig. 4, columns 1, 2, 3, and 4 represent the co-movements of Pandemic uncertainty with stock returns, volatility, liquidity, and illiquidity, respectively, after controlling the effect of FEAR sentiment. Fig. 4 reveals that the pandemic co-movements with the stock market returns of the world and all G7 markets. Except for the UK, we notice a strong co-movement for all other stock markets. We documented that the relationship between pandemic and stock returns (after controlling for FERAS sentiment) shows signs of synchronization across countries. Moreover, our results indicate a strong co-movement at the lower frequency scale of 8–16 days. However, the partial coherence peaked between February to March 2020 in Canada, France, Italy, and Japan. During peak periods, the coherence extends to higher frequencies (4–8 days) for Canada, Italy, Japan, and the world.

Our results for the Pandemic intensity and stock return behavior are consistent with the findings of Al-Awadhi et al. (2020), Ramelli and Wagner (2020), and Zhang et al. (2020). A similar co-movement pattern can be observed between pandemic and stock return volatility for France, Italy, and Japan. Interestingly, unlike stock returns, the volatility co-movement with Pandemic intensity is not strongly apparent. Our results are consistent with the notion that the prolongation of the coronavirus pandemic and associated stringent policy responses are important sources of financial market volatility (Zaremba et al., 2020). In Fig. 4, the third and fourth columns show that liquidity and illiquidity were affected due to the world pandemic. Countries that strongly display the effects of pandemic fear on (il)liquidity include the UK, Canada, France, Italy, and Japan. Very short-term (il)liquidity, up to a week, was influenced by Pandemic intensities in the UK, France, Germany, Italy, and Japan. However, in Canada, France, and Japan, the (il)

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7 DeSteno, D. (2020). How fear distorts our thinking about the Coronavirus. The New York Times. https://www.nytimes.com/2020/02/11/opinion/international-world/coronavirus-fear.html.
liquidity shows strong concern due to the pandemic for the frequency of 8–16 days, equivalent to a period between a week to a fortnight. Our results are consistent with Dash et al. (2019) findings, which suggest that increasing concern over policy uncertainty could deteriorate market liquidity for countries such as Canada, France, Germany, and the USA.

5.3. Robustness tests

In this section we carry out additional robustness test using the Equity Market Volatility Infectious Disease Tracker (EMV) (Baker et al., 2019, 2020) as an additional pandemic fear sentiment indicator. Since VIX or volatility index is popularly used in the behavioral asset pricing tests as a proxy for the pessimistic sentiment, consistent with the argument of Al Rababa’a et al. (2021), Bai et al. (2021), Bouri et al. (2021), and Salisu et al. (2020b) we resort to the operationalization of EMV as an alternative measure of pandemic fear sentiment. The robustness test focusses on the partial wavelet coherence test between pandemic uncertainty and stock market activity of our sample countries after controlling the effects of EMV pandemic fear sentiment index. The reason for the choice of alternative pandemic fear sentiment measure follows the argument that in times of crisis, FEARS sentiment index might not be very effective in catheterizing investor sentiment as pandemic effect will be more dominant. Since Pandemic uncertainty and FEARS sentiment may feed each other during the market turmoil and heightened economic concern amid the pandemic spread, it is reasonable to reexamine our previous findings in the presence of alternative pandemic fear sentiment.

Fig. 5 presents the PWCA between G7 countries stock market return, volatility, and (il)liquidity, and Pandemic uncertainty after controlling the effect of EMV or pandemic fear sentiment. Fig. 5 shows that the pandemic co-movements with the stock market returns of the world and all G7 markets after controlling the effects equity market volatility due to infectious disease (EMV). Our results indicate a strong co-movement at the lower frequency scale of 8–16 days. Similar to Fig. 4, the partial coherence peaked between February to March 2020 in Canada, France, Italy, and UK. We do not notice a significant co-movement between stock market volatility and pandemic uncertainty; however, illiquidity shows relatively higher coherency with pandemic uncertainty compared to liquidity. Taken together, our results are robust to the inclusion of alternative pandemic sentiment measure as EMV and co-movements between Pandemic uncertainty and stock market variables (return, volatility, and (il)liquidity) is consistently visible.

\^ We are thankful to the anonymous reviewer for guiding us in this direction.
Fig. 5. Pandemic uncertainty and stock market behaviour: controlling the effect of Pandemic fear sentiment (EMV). Notes: The yellow area within the patches surrounded by black line indicates the high power significant at 5% level of significance. Monte-Carlo simulation is employed to find whether the patches are significant. We present the color bar on the right side of each figure. The color blue signifies low power and blue, reddish yellow, and yellow indicates high, higher, and highest power, respectively. The greater the density of the colors is, the higher the power of the wavelet. The color bar also indicates the degree of correlations, which range between 0.5 (50%) and 0.9 (90%). Wavelet squared coherency detects the different investment horizons, i.e. short, medium, and long-term across the sample period. The X-axis presents the timeline for each stock market variable and pandemic pair whereas the Y-axis measures scale or frequency.
6. Conclusion

This paper uses daily data from the G7 countries and world equity markets to examine the pandemic uncertainty (measured by search volume index) implications for the stock market behavior. The stock market behavior has been analyzed from the return, volatility, and liquidity aspects. Using wavelet-based time–frequency analysis, this paper focuses on two important research questions. First, whether there exists a co-movements and lead-lag relationship between the FEARS sentiment and Pandemic uncertainty across the major world economies. Second, whether the Pandemic uncertainty impacts the four broad aspects of stock market behavior, i.e., return, volatility, liquidity, and illiquidity, after controlling the effect of FEARS sentiment. Our findings suggest that the rapid spread of the COVID-19 pandemic increased the pessimistic sentiment environment within the world’s major economies. We notice that the COVID-19 pandemic has a high impact on the FEARS sentiment during the early spread of the pandemic (January-March 2020). Results indicate that pandemic spread leads to pessimistic investor sentiment. The macroeconomic expectation hypothesis suggests that stock markets are forward-looking in nature, and hence, market participants’ trading behaviors are directly related to expectations about future economic uncertainty. Our results reveal that, due to heightening economic uncertainty amid COVID-19’s spread (Baker et al., 2020; Huynh et al., 2021; OECD, 2020; Shaikh & Huynh, 2021; Sharif et al., 2020; Wang et al., 2021; World Bank, 2020a, 2020b; Zhang et al., 2020), market participants may resort to the pessimistic considerations regarding future expected cash flow and discount rates, which affects stock market activity. Furthermore, the relationship between the pandemic uncertainty and stock market activities (after controlling for FEARS sentiment) shows signs of synchronization across G7 countries and the world market. The results are robust to alternative measures of pandemic fear sentiment.

Overall, this study highlights that there is a time-varying lead-lag relationship between pandemic uncertainty and the impact of pandemic uncertainty on stock market is persistent even after controlling the effect of investor’s FEARS sentiment. Our findings are having practical implications for the financial market participants and policy makers. Our findings highlight the importance of investor sentiment measures for the financial modeling and asset pricing purpose, and even in the short-horizon trading strategies. Markets are composed of investors operating in each moment at different time scales (short- and long-term). Our findings supported by time–frequency co-movement accommodate both the time and frequency domains within a unified framework to simultaneously assess how sensitive the stock market activity (return, volatility, and liquidity) to pandemic uncertainty at different time horizons. Moreover, pandemic uncertainty matters for the equity markets return, volatility, and trading activities. The pandemic uncertainty and associated sentiment implications could be one plausible reason for increased volatility and illiquidity in the market, and hence, policymakers should look upon this issue for the financial market stability perspective. After the initial spread of the pandemic, there are several policy interventions undertaken by the Government authorities. Given that our sample only accounts for the initial spread of the pandemic, future research could bring more insights on the pandemic uncertainty and stock market activity after the introduction of the policy measures and vaccination drive around the world.

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References

Aguilar-Contraria, L., Azevedo, N., & Soares, M. J. (2008). Using wavelets to decompose the time–frequency effects of monetary policy. *Physica A: Statistical Mechanics and its Applications*, 367(12), 2863–2876.

Al Rababa’a, A. R., Alomari, M., Mensi, W., Matar, A., & Saidat, Z. (2021). Does tracking the infectious diseases impact the gold, oil and US dollar returns and correlation? A quantile regression approach. *Resources Policy*, 74, Article 102311.

Al-Awadhi, A. M., Al-Saifi, K., Al-Awadhi, A., & Alhamadi, S. (2020). Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns. *Journal of Behavioral and Experimental Finance*, 100326.

Al-Yahyaee, K. H., Rehman, M. U., Mensi, W., & Al-Jarrah, I. M. W. (2019). Can uncertainty indices predict Bitcoin prices? A revisited analysis using partial and multivariate wavelet approaches. *The North American Journal of Economics and Finance*, 49, 47–56.

Al Guindy, M. (2021). Fear and hope in financial social networks: Evidence from COVID-19. *Finance Research Letters*, 102271.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, 5(1), 31–56.

Anastasiou, D., Ballis, A., & Drakos, K. (2022). Constructing a positive sentiment index for COVID-19: Evidence from G20 stock markets. *International Review of Financial Analysis*, 102111.

Arora, A., Jha, A. K., Alai, P., & Das, S. S. (2020). Understanding coronaphobia. *Asian Journal of Psychiatry*, 54, Article 102384.

Aslam, F., Awan, T. M., Syed, J. H., Kashif, A., & Parveen, M. (2020). Sentiments and emotions evoked by news headlines of coronavirus disease (COVID-19) outbreak. *Humanities and Social Sciences Communications*, 7(1), 1–9.

Asmundson, G. J., & Taylor, S. (2020). Coronaphobia: Fear and the 2019-nCoV outbreak. *Journal of Anxiety Disorders*, 70, Article 102196.

Bai, L., Wei, Y., Wei, G., Li, X., & Zhang, S. (2021). Infectious disease pandemic and permanent volatility of international stock markets: A long-term perspective. *Finance Research Letters*, 40, Article 101799.

Baker, S. R., Bloom, N., Davis, S. J., & Kost, K. J. (2019). Policy news and stock market volatility, National Bureau of Economic Research (NBER), NBER Working Paper No. w25720.

Baker, S. R., Bloom, N., Davis, S. J., Kost, K. J., Sammon, M. C., and Viratyosin, T. (2020). The unprecedented stock market impact of COVID-19 (Working paper No. w26945).

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The review of financial studies*, 21(2), 785–818.

Biktimirov, E. N., Sokolych, T., & Ayanso, A. (2021). Sentiment and hype of business media topics and stock market returns during the COVID-19 pandemic. *Journal of Behavioral and Experimental Finance*, 31, Article 100542.
Bloom, D. E., Daniel, C., & Sevilla, J. P. (2018). Epidemics and economics: New and resurgent infectious diseases can have far-reaching economic repercussions. *Finance and Development*, 55(2), 46–49.

Bouri, E., Gkillas, K., Gupta, R., & Prierdziuch, C. (2021). Forecasting power of infectious diseases-related uncertainty for gold realized variance. *Finance Research Letters*, Article 101936.

Burggraf, T., Huyhn, T. L. D., Rudolf, M., & Wang, M. (2021). Do FEARS drive bitcoin? *Review of Behavioral Finance*, 13(3), 229–258.

Capelle-Blancard, G., & Desroziers, A. (2020). The stock market is not the economy? Insights from the COVID-19 crisis. *Covid Economics: Vetted and Real-Time Papers, CEPR*.

Chen, C., Liu, L., & Zhao, N. (2020). Fear sentiment, uncertainty, and Bitcoin price dynamics: The case of COVID-19. *Emerging Markets Finance and Trade*, 56(10), 2298–2309.

Chundakkadan, R., & Nedumparambil, E. (2021). In search of COVID-19 and stock market behavior. *Global Finance Journal*, 100639.

Contessi, S., & De Pace, P. (2021). The international spread of COVID-19 stock market collapses. *Finance Research Letters*, Article 101894.

Costola, M., Iacopini, M., & Santagastina, C. R. (2021). Google search volumes and the financial markets during the COVID-19 outbreak. *Finance Research Letters*, 42, Article 101884.

Crowley, P. M. (2007). A guide to wavelets for economists. *Journal of Economic Surveys*, 21(2), 207–267.

Da, Z., Engelberg, J., & Gao, P. (2015). The sum of all FEARS investor sentiment and asset prices. *The Review of Financial Studies*, 28(1), 1–32.

Dash, S. R., Maitra, D., Debarata, B., & Mahakud, J. (2019). Economic policy uncertainty and stock market liquidity: Evidence from G7 countries. *International Review of Finance*, 1–16.

Dash, S. R., & Maitra, D. (2019). The relationship between emerging and developed market sentiment: A wavelet-based time-frequency analysis. *Journal of Behavioral Economics and Finance*, 22, 135–150.

Donadelli, M., Kizys, R., & Riedel, M. (2017). Dangerous infectious diseases: Bad news for main street, good news for Wall Street? *Journal of Financial Market, 35*, 84–103.

Effenberger, M., Kronbichler, A., Shin, J. I., Mayer, G., Tilg, H., & Perco, P. (2020). Association of the COVID-19 Pandemic with internet search volumes: A google trends analysis. *International Journal of Infectious Diseases*, 95, 192–197.

Fan, Y., Jiamiong, D. T., & Summers, L. H. (2018). Pandemic risk: How large are the expected losses? *Bulletin of the World Health Organization*, 96(2), 129.

Gao, Z., Ren, H., & Zhang, B. (2020). Googling investor sentiment around the world. *Journal of Financial and Quantitative Analysis*, 55(2), 549–580.

Garcia, D. (2013). Sentiment during recessions. *The Journal of Finance*, 68(3), 1267–1300.

Ginsberg, J., Mohebi, M. H., Patel, R. S., Brammer, L., Smolinski, M. S., & Brilliant, L. (2009). Detecting influenza epidemics using search engine query data. *Nature*, 457(7233), 1012–1014.

Goel, G., & Dash, S. R. (2021). Investor sentiment and government policy intervention: Evidence from COVID-19 spread. *Journal of Financial Economic Policy*, 14(2), 1757–6385.

Haroon, O., & Rizvi, S. A. R. (2020). COVID-19: Media coverage and financial markets behavior—A sectoral inquiry. *Journal of Behavioral and Experimental Finance*, Article 100343.

Huyhn, T. L. D., Foglia, M., Nasir, M. A., & Angelini, E. (2021). Feverish sentiment and global equity markets during the COVID-19 pandemic. *Journal of Economic Behavior & Organization*, 188, 1088–1108.

Kahneman, D. (1973). Attention and effort (Vol. 1063, pp. 218–226). Englewood Cliffs, NJ: Prentice-Hall.

Kahneman, D. (2011). *Thinking, fast and slow*. Macmillan.

Krugman, P. (2020). Crashing economy, rising stocks: What’s going on? The New York Times.

Liu, Z., Huyhn, 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, Article 101419.

Lyócsa, S., Baumohl, E., Výrost, T., & Molnár, P. (2020). Fear of the coronavirus and the stock markets. *Finance Research Letters*, 36, Article 101735.

Maxumder, S., & Saha, P. (2021). COVID-19: Fear of pandemic and short-term IPO performance. *Finance Research Letters*, 43, Article 101977.

Mensi, W., Rehman, M. U., Al-Yahyae, K. H., Al-Jarrah, I. M. W., & Kang, S. H. (2019). Time frequency analysis of the commonalities between Bitcoin and major cryptocurrencies: Portfolio risk management implications. *The North American Journal of Economics and Finance*, 48, 283–294.

Mensi, W., Rehman, M. U., Maitra, D., Al-Yahyae, K. H., & Sensoy, A. (2020). Does bitcoin crypto-move and share risk with Sukuk and world and regional Islamic stock markets Evidence using a time-frequency approach. *Research in International Business and Finance*, 53, Article 101230.

OECD. (2020). *OECD Economic outlook, Volume 2020 Issue 1: Preliminary version*, No. 107, OECD Publishing, Paris, https://doi.org/10.1787/0d1d1e2e-en.

Paule-Vianez, J., Orden-Cruz, C., & Escamilla-Solano, S. (2021). Influence of COVID-induced fear on sovereign bond yield. *Economic Research-Ekonomska Istraživanja*, 1–16.

Ramelli, S., & Wagner, A. F. (2020). Feverish stock price reactions to the novel Coronavirus. *Swiss Finance Institute Research Paper No. 20-12*.

Ramsay, J. B. (2002). Wavelets in economics and finance: Past and future. *Studies in Nonlinear Dynamics and Econometrics*, 6(3), 1–27.

Rubbaniy, G., Khalid, A. A., & Samitas, A. (2021a). Are crypto safe-haven assets during covid-19? Evidence from wavelet coherence analysis. *Emerging Markets Finance and Trade*, 57(6), 1741–1756.

Rubbaniy, G., Khalid, A. A., Syriopoulos, K., & Samitas, A. (2021b). Safe-haven properties of soft commodities during times of COVID-19. *Journal of Commodity Markets*, Article 100223.

Rush, J. (2020). What the coronavirus shock means for Europe’s economies. Bloomberg.com: BloombergQuint.

Salisu, A. A., & Akanni, L. O. (2020). Constructing a global fear index for the COVID-19 pandemic. *Emerging Markets Finance and Trade*, 56(10), 2310–2331.

Salisu, A. A., Elbuluk, G. U., & Usman, N. (2020a). Revisiting oil-stock nexus during COVID-19 pandemic: Some preliminary results. *International Review of Economics and Finance*, 69, 280–294.

Salisu, A. A., Sikiru, A. A., & Vo, X. V. (2020b). Pandemics and the emerging stock markets. *Borsa Istanbul Review*, 20, S40–S48.

Shaikh, I., & Huyhn, T. L. D. (2021). Does disease outbreak news impact equity, commodity and foreign exchange market? Investors’ fear of the COVID-19 pandemic. *Journal of Economic Studies*, Article 101186.

Smale, L. A. (2021). Investor attention and global market returns during the COVID-19 crisis. *International Review of Financial Analysis*, 73, Article 101616.

Smale, L. A. (2020). Investor attention and the response of US stock market sectors to the COVID-19 crisis. *Review of Behavioral Finance*, 13(1), 20–39.

Stirling, C., Curran, E., & Bosley, C. (2020). A global pandemic could cost $1 trillion. BloombergQuint, Bloomberg.com.

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*, Article 101496.

Shiller, R. J. (2000). *A behavioral approach to finance*. *Journal of Economic Perspectives*, 17(1), 83–104.

Shiller, R., & Maltiel, B. (2020). Does Covid-19 prove the stock market is inefficient? *International Review of Financial Analysis*, 62(3), 1159–1168.

Tropp, C., & Gomme, P. (1998). A practical guide to wavelet analysis. *Bulletin of the American Meteorological society*, 79(1), 61–78.

Tripathi, A., & Pandey, A. (2021). Information dissemination across global markets during the spread of the COVID-19 pandemic. *International Review of Economics & Finance*, 74, 103–115.
Vasileiou, E. (2021). Behavioral finance and market efficiency in the time of the COVID-19 pandemic: Does fear drive the market? *International Review of Applied Economics*, 1–18.

Wang, H., Xu, L., & Sharma, S. S. (2021). Does investor attention increase stock market volatility during the COVID-19 pandemic? *Pacific-Basin Finance Journal*, 69, Article 101638.

World Bank. (2020a). The global economic outlook during the COVID-19 pandemic: a changed world. World Bank. (2020b). COVID-19 to Plunge Global Economy into Worst Recession since World War II.

Xu, L., Chen, J., Zhang, X., & Zhao, J. (2021). COVID-19, public attention and the stock market. *Accounting & Finance*, 61(3), 4741–4756.

Yu, X., Xiao, K., & Liu, J. (2021). Dynamic co-movements of COVID-19 pandemic anxieties and stock market returns. *Finance Research Letters*, Article 102219.

Zaremba, A., Kizys, R., Abarom, D. Y., & Demir, E. (2020). Infected markets: Novel coronavirus, government interventions, and stock return volatility around the globe. *Finance Research Letters*, Article 101597.

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, Article 101528.

Zhang, H., Ding, Y., & Li, J. (2021). Impact of the COVID-19 pandemic on economic sentiment: A cross-country study. *Emerging Markets Finance and Trade*, 57(6), 1603–1612.