



Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.



Contents lists available at ScienceDirect

Journal of Economic Behavior and Organization

journal homepage: www.elsevier.com/locate/jebo

Feverish sentiment and global equity markets during the COVID-19 pandemic



Toan Luu Duc Huynh^{a,d,e}, Matteo Foglia^b, Muhammad Ali Nasir^{c,d,*},
Eliana Angelini^b

^aWHU – Otto Beisheim School of Management (Germany), Chair of Behavioral Finance

^bDepartment of Economics “G.D’Annunzio” University of Chieti-Pescara (Italy)

^cUniversity of Huddersfield (United Kingdom)

^dUniversity of Economics Ho Chi Minh City (Vietnam), School of Banking

^eIPAG Business School (France)

ARTICLE INFO

Article history:

Received 8 March 2021

Revised 27 May 2021

Accepted 2 June 2021

Available online 19 June 2021

JEL classification:

G02

G21

D12

D14

Keywords:

COVID-19

Investor sentiment

Feverish sentiment index

Equity indices

ABSTRACT

This paper proposes a new approach to estimating investor sentiments and their implications for the global financial markets. Contextualising the COVID-19 pandemic, we draw on the six behavioural indicators (media coverage, fake news, panic, sentiment, media hype and infodemic) of the 17 largest economies and data from 1st January 2020 to 3rd February 2021. Our key findings, obtained using a time-varying parameter-vector auto-regression (TVP-VAR) model, indicate the total and net connectedness for the new index, entitled ‘feverish sentiment’. This index provides us insight into economies that send or receive the sentiment shocks. The construction of the network structures indicates that the United Kingdom, China, the United States and Germany became the epicentres of the sentimental shocks that were transmitted to other economies. Furthermore, we also explore the predictive power of the newly constructed index on stock returns and volatility. It turns out that investor sentiment positively (negatively) predicts the stock volatility (return) at the onset of COVID-19. This is the first study of its kind to assess international feverish sentiments by proposing a novel approach and its impacts on the equity market. Based on empirical findings, the study also offers some policy directions to mitigate the fear and panic during the pandemic.

© 2021 Elsevier B.V. All rights reserved.

1. Introduction

“The only thing we have to fear is fear itself”

Franklin D Roosevelt

The United States President

During the times when the global economy was passing through its worst, and the Great Depression of the 1930s was at its peak, US President Franklin D Roosevelt (FDR) attempted to console the public in his 1933 inaugural address by

* Corresponding author.

E-mail addresses: toan.huynh@whu.edu, toanhd@ueh.edu.vn, t.huynh@ipag.fr (T.L.D. Huynh), matteo.foglia@unich.it (M. Foglia), m.a.nasir@hud.ac.uk (M.A. Nasir), eliana.angelini@unich.it (E. Angelini).

emphasising the importance of combatting fear. He argued that pessimism and fear completely paralyse efforts to revive the economy. Decades later, in the times of COVID-19, the world has not only experienced a health crisis, but has also faced unprecedented economic losses as the consequence of the pandemic. Investors and market participants are bound to be worried about the economic resiliency as long as this deadly virus lasts. To contain the spread of the virus, or at least limit it, many governments have adopted social distancing policies that have necessitated the temporary closures of businesses and restrictions on social events. The cessation of socio-economic activities, accompanied by a health crisis, has sent a signal of the forthcoming recession that has caused people to fear. Unlike the previous public health crisis (such as H1N1 and Ebola), COVID-19 has been observed to have a significant negative impact on stock markets (Schell et al., 2020). All major and developing stock markets have fallen as the COVID-19 health and financial contagion has spread. Contextualising them in terms of the fear perspective that motivates this study, we examine the implications of fear, and specifically the fear associated with COVID-19 for the financial markets.

While rational asset pricing represents a positive relationship between expected return and risk (Merton, 1980), the behavioural theory in finance adds an additional concept of predictive power to noise trader sentiment and its effect, which persists in financial markets for tactical asset allocation (De Long et al., 1990a; Fisher and Statman, 2000). The theoretical concept provides empirical evidence that investors' sentiment can influence financial assets' prices under two assumptions: (i) the predominant role of sentiment (noise) traders in assets' movements, and (ii) the limitation of arbitrage regarding transaction costs. However, recent studies (Baker and Wurgler, 2006; Kumar and Lee, 2006; Tetlock, 2007; Edmans et al., 2007; Da et al., 2011; Stambaugh et al., 2012; Siganos et al., 2014; Da et al., 2015; Huang et al., 2015) depart from the conventional wisdom and contribute to the subject by providing strong evidence that the investors' sentiment has an impact on stock returns. One of the noteworthy aspects of the behavioural finance literature is the focus on both the sentiments and the causal relationship between investor sentiment and stock returns. Notwithstanding the diversified approaches in estimating sentiment, examining the different economic contexts may appear to be a tedious exercise for researchers, though the ontological benefits of a comprehensive empirical approach cannot be overstated. Obviously, the current situation, and particularly the COVID-19 pandemic, is a unique and unprecedented event, offering numerous actual experiments related to investors' decision-making based on a wide range of information. Therefore, adding to the existing strand of the empirical literature, our study aims to construct cross-country sentiment indices for this context by aggregating different component indicators, including fake news, media coverage, and fear sentiment. The paper will take into account COVID-19 as a potential source for sentiment deviation, which might influence the financial markets.

This paper contributes to the literature in four main respects. First, drawing on a wide range of sentiment indices regarding the coronavirus, such as media coverage, fake news, panic, sentiment, media hype and infodemics, we construct the *Feverish Sentiment Index* at the country level by using principal component analysis (PCA) with 17 new indicators. To validate our approach, we estimate the feverish sentiment connectedness of the largest economies in terms of static and dynamic spillovers. It is noteworthy that these aforementioned approaches not only help us create a representative index to capture what public sentiment looks like, but also enable us to identify the senders and recipients of sentiment shocks during the pandemic. Second, after controlling for various factors in several regression models, we find that the feverish sentiment has strong predictive power for global equity returns. In particular, the higher the feverish sentiment, the lower the global stock return. This suggests how our index can predict the negative returns at the onset of the COVID-19 outbreak, which offers a new predictive factor for the global financial market. Third, we calculate the different hedging ratios, including the feverish sentiment and CBOE volatility index (CBOE VIX), to figure out the optimal investing strategies while accounting for the panic and fear during the pandemic. Therefore, our third contribution also sheds new light on the investing strategies through which investors, financial institutions, policymakers can mitigate the potential risks. Last, we check robustness by exploring the relationship between the regional indicators (return and volatility) and our newly constructed index. Interestingly and more importantly, our sentiment index can negatively (positively) predict the equity returns (volatility) on different continents such as Asia, Africa, Europe, Latin America and North America. Accordingly, this paper aims to answer four questions: (1) How do the sentiments across countries interconnect at the onset of the COVID-19 pandemic?; (2) How does the feverish sentiment influence the global equity market?; (3) What portfolio strategy can be used to tackle the potential risk resulting from the 'panicky feelings' during COVID-19?; and (4) Are there heterogeneous regional effects of feverish sentiment?

"What could the mechanism of sentiment in the financial markets be" This is the main question that behavioural finance attempts to answer to explain investors' sentiment changes. It has been formulated in terms of irrational traders having distorted beliefs regarding market expectations. Therefore, these behaviours might create mispricing in the financial markets. At the same time, they could mitigate arbitrage opportunities. This paper also looks at the strand of literature in behavioural finance in which a significant amount of theoretical work emphasises the existence of investor sentiment in economics models (see De Long et al., 1990a; 1990b; Barberis et al., 1998; Baker and Wurgler, 2007; Dumas et al., 2009). These theoretical frameworks stem from Keynes (1937)' concrete ideas about 'animal spirits' and asset prices. Although a number of empirical studies have been conducted so far to explain how investors' sentiments link to the financial markets, this paper aims to fill a huge gap in the context of the contemporary global landscape – the COVID-19 outbreak. While recent studies have looked at the impacts of the COVID-19 situation on the different types of financial assets, this paper highlights the mechanisms of sending and receiving the fear sentiment during the pandemic. In doing so, it not only contributes to the literature in behavioural finance, but also incorporates the unprecedented event as the exogenous shock (Tausch and Zumbuehl, 2018; Baker et al., 2020a; 2020b; Didier et al., 2021; Caggiano et al., 2020; Spatt, 2020). With few exceptions, studies have used

the separate or individual indicator of investor sentiment as the conditioning variable to predict asset pricing (or volatility) in COVID-19. Our focus, meanwhile, is on the interrelation between different types of 'feverish sentiment' across countries and at the global (and regional) levels.

The paper is divided into five sections. A critical review of literature on the linkage between investor sentiment and financial decisions, the mechanism, and the contemporaneous study of COVID-19 sentiment is presented in [Section 2](#). Our methodology explained in [Section 3](#). Details on the dataset and 'feverish sentiment index' construction are provided in [Section 4](#), while analysis and presentation of findings are offered in [Section 5](#). Conclusions and policy implications are highlighted in [Section 6](#).

2. Literature review

2.1. Investor sentiment and financial decisions

In this section, we critically review the literature about how investors make financial decisions based on sentiments. Before being more specific, we acknowledge the basic theoretical framework in psychological economics, which reveals that humans make their decisions based on emotions ([Elster, 1998](#); [Loewenstein, 2000](#)) as well as preferences ([Zajonc, 1980](#); [Romer, 2000](#); [Lucey and Dowling, 2005](#)), risk and heuristics ([Finucane et al., 2000](#); [Nasir, 2020](#)). Accordingly, the economic human will make the traditional decision to calculate the weight of costs and benefits representing the best risk-benefit trade-off. However, the economic human does not always behave rationally; his decisions are affected by feelings. For example, the role of regret and looking-back thinking on rational choice has shaped the Regret Theory in economics ([Loomes and Sugden, 1982](#)). In the same vein, using the investors' emotions as well as empirics, the study by [Benartzi and Thaler \(1995\)](#) has explained the equity premium puzzle, which was first introduced by [Mehra and Prescott \(1985\)](#).

Recently, the studies focusing on investor sentiments have contributed to the financial literature. Notably, [Kaplanski and Levy \(2010\)](#) found the linkage between anxiety and negative sentiment in cases of aviation disaster and stock returns. Such a disaster is an extreme event that influences investors' behaviours, because [Lee et al. \(1991\)](#) indicated that people are not entirely rational when they feel anxiety. Thus, when aviation incidents happen, investors react irrationally to the 'bad news'. However, their behaviour will become normal just after two days, which is called "*the reversal effects*". Although we pick an extreme event (aeroplane crash) as the typical example, everyday things could also drive the investors' mood and sentiment, and thus impact the financial markets. In particular, [Hirshleifer et al. \(2020\)](#) contributed empirical evidence that mood seasonality could predict stock returns, suggesting that higher mood parameters could subsequently prompt higher returns. The same strand of literature confirms that this effect is stronger in advanced countries ([Li et al., 2018](#)), and also applies to government premiums ([Zaremba, 2019](#)). Interestingly, 'investor sentiment' can be found in households' Google search terms, as demonstrated in [Gao et al. \(2020\)](#). They highlighted that investor sentiment, proxied by sports outcome, becomes a contrarian predictor of country-level market returns. The weather, which may seemingly be irrelevant to financial markets, has predictive power through investor sentiment, as shown by [Cortés et al. \(2016\)](#). Their study used the local sunshine to capture the feelings of investors, who changed their risk tolerance and subjective judgment under the influence of weather conditions.

2.2. The theoretical mechanism of investor sentiment and financial decision making

Sentiments about the COVID-19 pandemic also have implications for the financial markets. Both [Haroon and Rizvi \(2020\)](#) and [Sun et al. \(2021\)](#) confirmed that investors behave irrationally at the onset of a pandemic. Their findings are in line with the empirical findings reported by [Kaplanski and Levy \(2010\)](#), which explain the mechanism of how public health crises might influence investment decisions. We present a main hypothesis that the large-scale COVID-19 pandemic provokes investor sentiment, and particularly a rise in fear and anxiety, which in turn negatively impacts stock prices. Accordingly, we observe that the media coverage ([Ambros et al., 2020](#)) which spreads information about the pandemic, generating fear and anxiety and even conveying fake news ([Brigida and Pratt, 2017](#)), increases the level of pessimistic attitudes towards investment decisions ([Da et al., 2015](#)). We structure the mechanism of sentiment and equity markets in three main pillars, which are relevant to our indicators:

Media coverage, media hype and information about COVID-19. It is intuitive to claim that the role of media (newspaper information, discussions on social media and other information channels) will shape and drive investors' decisions. To be more specific, [Marty et al. \(2020\)](#) collected 276 research papers that had the common theme of news media and financial markets. This comprehensive study showed that media, news and information are inextricable properties of financial markets and investors' decision-making. However, interestingly, [Fang and Peress \(2009\)](#) claimed that stocks with lower media coverage earned higher returns after controlling for a rigorous set of variables. The study by [Solomon et al. \(2014\)](#) reported that the investors' use of media coverage is likely to have a high association with chasing the past returns instead of facilitating the process of making new investments. Overall, the role of media coverage in the financial markets, and particularly in provoking irrational financial decisions, is one of the ubiquitous features of investor sentiments. Although there is empirical evidence that media coverage could predict the stock returns at the onset of the COVID-19 pandemic ([Haroon and Rizvi, 2020](#)), the relevant study only looked at the initial stage, without evaluating the connectedness of news in different markets. Although the study by [Fang and Peress \(2009\)](#) evaluated the cross-country effects, there is considerable space for

us to aggregate different dimensions of media coverage in COVID-19 and test whether the different countries share or send media information regarding this deadly disease or not. Further investigation of the stock market will follow thereafter.

Fake news. There is not much work on the direct relationship between fake news and financial markets in the extant literature. However, [Brigida and Pratt \(2017\)](#) conducted a study regarding the stock and option market reactions surrounding the timing of fake news releases. Fake news is becoming a concern that many economists are paying attention to, examining it in relation to the US presidential election ([Allcott and Gentzkow, 2017](#)) or the COVID-19 pandemic ([Hartley and Vu, 2020](#)), for example. Using a machine learning approach to cluster the fake news in the US market, the study by [Clarke et al. \(2020\)](#) found that equity price reaction to fake news is discounted when compared with legitimate news articles. Currently, fake news in COVID-19 is a determinant of risk perception as well as risk-taking behaviour ([Huynh et al., 2020](#); [Apuke and Omar, 2021](#)); therefore, adding this component to our Feverish Sentiment Index is an intuitive way to capture investors' behaviours.

Panic and fear feelings. From the psychological perspective, media coverage of traumatic events, especially in disaster, generates increasing anxiety levels ([Collimore et al., 2008](#)). This is an indirect channel through which the media can influence the investors' feelings. Fear and anxiety are associated with perceived risk among investors. The framework of [Slovic \(1987\)](#) revealed that risk could be perceived through uncontrollable, catastrophic or even fatal events. Undoubtedly, the COVID-19 pandemic has been causing fear, anxiety and pessimistic feelings (even negative sentiment) among people. One strand of the literature confirmed that people tend to take less risk when they think more about it ([Hanoch, 2002](#); [Mehra and Prescott, 1985](#)). [Lerner et al. \(2004\)](#) reported that economic decisions could be driven by fear and anger. Therefore, we decided to choose panic and fear as the relevant components to construct the Feverish Sentiment Index for the COVID-19 pandemic.

To sum up, not only media coverage of and information about COVID-19, but also other relevant factors, such as fake news and panic and fear feelings, could contribute to investors' behaviour. While the literature reckons that changes in investor sentiment might lead to risk perception and risk-taking behaviour, the phenomenon has not been examined during the pandemic. The extant literature helps us identify the research gaps where investor sentiment, particularly how feverish feelings about deadly disease could affect stock prices. More importantly, this study will bridge the gap by constructing an index entitled 'feverish sentiment' to cover the wide range of investor sentiment in the global context. We also want to look at how this index varies and sends the relevant information across the globe before testing its impacts on the stock market. In the following subsection, we will address the contemporary studies regarding the financial markets during the coronavirus pandemic.

2.3. The COVID-19 impacts and financial markets from a sentiment perspective

In this section, we would like to acknowledge the current literature in financial studies about the impact of investor sentiment on the financial markets. By doing that, we will reflect on the idiosyncrasy of our study and how it stands apart from the existing empirical evidence on the linkage between COVID-19 sentiment and financial markets, particularly in relation to equity assets, as shown in [Table 1](#).

After reviewing the literature on investor sentiment and financial markets during the COVID-19 pandemic, we summarise our differences and the novelty of our research design, which is distinguished from those of previous studies. First, while the majority of studies focus on a single country, regional area, or specific market (Bitcoin, for example), this study approaches the largest scale of countries (the 17 largest economies). Using only G-20 countries takes into account Google search terms, whereas the cross-country analysis of 20 economies by six investor sentiments (media news index, fake news, and so forth) touches six countries. Therefore, our study is the first that employs all six indicators for investor sentiment, covering the largest sample set of economies. Second, it is noticeable that the existing studies have mainly proxied the investor sentiment with search terms in Google. However, there is a limited number of papers that highlight the different sentimental indices from Ravenpack. Additionally, there is no other study that aggregates these indicators by using principal component analysis (PCA) to obtain the new index, here entitled the Feverish Sentiment Index, to see how investor sentiment varies from country to country during the pandemic. Therefore, our study fills this gap by using the advanced approach TVP-VAR model. Third, this paper summarises and describes the sending and receiving process of sentiment shocks during COVID-19, while the current empirical studies do not indicate this phenomenon. Furthermore, our sketch of the network define which country could be the epicentre for transmitting investor sentiment shocks at the global level. Finally, to our best knowledge, the current literature does not examine the hedging ratios to see how expensive the hedging cost is during the pandemic. Our study, on the other hand, not only contributes to the predictive factor on stock returns after accounting for the relevant factors, but also examines whether reversal effects in behavioural finance exist or not. More importantly, apart from addressing stock returns, as the extant literature does, our paper emphasises the effects of investor sentiment on the volatility of in-depth perspectives. In the following section, we will explain our main methodology, dataset, and the construction of our indices, as well as the presentation of the impacts of investor sentiment on the equity market.

3. Empirical strategy

In this section, we discuss the set of approaches used to derive our empirical findings. First, we build a Feverish Sentiment Index for 17 countries by PCA analysis. PCA allows us to aggregate all the information from several measures (fake

Table 1

A chronological summary of the literature on COVID-19 and financial markets.

Study	Data, methodology and research scope	Main findings
Haroon and Rizvi (2020)	EGARCH model was employed for 23 sectoral indices for the US from Dow Jones from 1 January 2020 till 30 April 2020.	A strongly positive relationship between news coverage and market volatility. However, price volatility had little and moderate effects.
Chen et al. (2020)	Hourly Google search queries on coronavirus-related words were proxied for the sentiment from 15 January 2020 to 24 April 2020. In addition, the Vector Auto-Regression (VARs) was employed with the Bitcoin market.	This study found that an increase in fear of coronavirus is likely to negatively predict the Bitcoin returns and higher trading volume. Furthermore, it indicates that investors perceive Bitcoin as a conventional financial asset rather than a safe-haven asset during market distress.
Buckman et al. (2020)	A brief policy note with the newly developed Daily News Sentiment Index that provides real-time data from 1980 to 2021 was released.	This study found the in-line results of news sentiment and the COVID-19 news coverage. A high correlation with consumer sentiment was found.
Sun et al. (2021)	Coronavirus-related news for 14 events (CRNs) and economic-related announcements for 10 events (ERAs) was used for China, Hongkong, Korea, Japan, and the U.S, from December 2019 to February 2020. Furthermore, the event-study approach and regressions of three-factor models were taken to examine the relationship between this sentiment and stock performance in medical portfolios.	Both indices do not cause irrational behaviours in medical portfolios but they exhibit the positive relationship with five markets' medical portfolios. This study also found stronger effects on institutional investors than individual ones.
Valle-Cruz et al. (2021)	The Twitter data (the content of COVID-19) and important worldwide financial indices were used to examine whether they exhibit the relationship or not. This study used the fundamental and technical financial analysis combined with a lexicon-based approach on financial Twitter accounts. There are two sub-periods (for H1N1: June to July 2009; COVID-19: January to May 2020) for this research.	The market reacted after 0 to 10 days for coronavirus tweets and 0 to 15 for the H1N1 posts. The data source of The New York Times, Bloomberg, CNN News and Investing.com exhibits a high correlation between investor sentiments and equity market behaviour.
Sun et al. (2021)	The sentiment index, retrieved from GubaSenti established by the International Institute of Big Data in Finance for the investor sentiment, was measured by analysing the textual meaning on the largest media platform in China. An event study and regression to define whether sentiment impacts the abnormal returns or not. The Data frame covers the period from 25 July 2019 to 31 March 2020 with 71 industries in China.	Comparing the usual circumstance, the effects of investor sentiment is stronger in the pandemic period. Furthermore, firms having high PB, PE and CMV, low net asset, and low institutional shareholding are more pronounced to the impacts of investor sentiment on stock returns.
Lyócsa et al. (2020); Lyócsa and Molnár (2020)	Google search terms were used to measure the fear and panic feelings of investors over the period from December 2, 2019 to April 30, 2020. This study employs a simplified version of the heterogeneous autoregressive (HAR) model for 10 stock market indices.	This study indicates that this investor sentiment index can be a predictive factor in stock price variation around the world.
Fassas (2020)	Using variance risk premium analysis to measure risk-aversion behaviour, this paper aims to calculate the willingness-to-pay of market participants to hedge the variation before and after COVID-19. The data period stretches from April 2011 until May 2020 in three advanced economies and the methodology is TVP-VAR methodology to capture the connectedness.	This study found that the COVID-19 strengthened the risk-aversion connectedness among these markets.
Smales (2021)	The extended study of Google search terms as proxies for 'investor attention' in G7 and G20 economies from January 2020 to June 2021. This paper also used the robustness check with the 'FEARS' index by Da et al. (2015) to see how this attention influences the stock markets.	There is an association between GSV (Google Search Volume) and the financial market returns. This effect is more pronounced to volatility and weaker effect in the government bond yields, where the institutional investors mostly participate in. The retail investors paid more attention to the FEARS terms.
Mazumder and Saha (2021)	This study proxies the fear by constructing the equally weighted index of both newly infected cases and deaths over the period from January-2019 to July-2020. The set of IPO firms' characteristics were employed for regression to see how the IPO firms perform during the COVID-19 pandemic.	The IPO firms exhibited higher returns in 2020; however, they decrease when increasing fears. Compared to the existing firms, the IPO companies are more sensitive to COVID-19 shocks.
Cepoi (2020)	Using six indicators (The panic Index, The Media Hype Index, The Fake News Index, Country Sentiment Index, The Contagion Index, media coverage Index) for panel data over the period 3 February 2020 to 17 April 2020 in six countries, this study explores the asymmetric relationship between news and stock returns.	There are heterogeneous effects of news on different types of markets (inferior, superior, and middle class). Furthermore, gold is not the 'safe-haven' asset during the COVID-19 pandemic.
Salisu and Akanni (2020)	The global fear index (GFI) for the COVID-19 pandemic was constructed by reported cases and death cases for OECD and BRICS countries since the COVID-19 outbreak.	This study found that GFI has predictive power on stock returns. Furthermore, the "asymmetric" effects of macro (common) factors improve the quality of forecasting power.

(continued on next page)

Table 1 (continued)

Study	Data, methodology and research scope	Main findings
Xu et al. (2020)	This study constructed the new sentiment index with more accurate and critical news than state-controlled media from the study of You et al. (2018) for the period from 1 January 2019 and 30 August 2020. The methodology in this study is the regression to see how this news index influences the stock returns in China.	The public attention (infection scale), as well as this news, play an important role in stock market response to firm-specific information. Particularly, the Chinese stock markets are more sensitive to firm-specific information after the COVID-19 outbreak.
Smales (2020)	Google search terms were used to construct the investor sentiment across 11 industries in the US market from 31 December 2019 to 31 May 2020. The authors constructed the regression to examine whether the investor's attention negatively influenced stock returns.	The author documented the heterogeneous effects of investors' attention on the stock returns (for example, consumer staples, healthcare and IT having better performance in COVID-19 and gaining more attention).
Aloui et al. (2021)	By using the high-frequency domain, this paper draws the data from October 7, 2005 to September 25, 2020 with the methodology of the continuous wavelet transform. This paper also takes into account the American Association of Individual Investors (AAII), St. Louis Fed Financial Stress Index (FSI) and the volatility index (VIX) for constructing the investor sentiment.	This paper contributes empirical evidence that the investor sentiment links to Islamic stocks and bonds over timescales and investment horizons.
Salisu and Vo (2020)	Using the dataset of 20 countries with keywords in Google searching terms "health news" in the period of 30th of March 2020 starting from 1st of January 2020, this paper explores the role of sentiment index, proxied by the attention to "health news" on equity markets. This study also uses a variety of methodologies such as pool regression and the forecast evaluation of the predictor.	The newly constructed index has significant predictive power on stock return. The asymmetric effects improve the quality of prediction. The results hold robust for in-sample, out-sample, outliers and heterogeneity.

news, media coverage, panic sentiment) into a single index. Second, to compute the Feverish Connectedness measure, we apply the time-varying parameter vector autoregressive framework (TVP-VAR) proposed by Antonakakis et al. (2020). This methodology improves on the one provided by Diebold and Yilmaz (2012) because it overcomes the disadvantages of the rolling-window connection approach. The TVP-VAR model provides more robust parameter estimates than the rolling-window VAR model (Antonakakis et al., 2020). Moreover, this model allows researchers to study the dynamics of connection between short time-series, such as the COVID-19 crisis era analysed in this study. Third, to examine the implications of our results in terms of risk management, we calculate optimal hedge ratios in the current period of uncertainty, i.e. portfolio weights. Finally, in order to test the relationship between feverish connectedness sentiment and financial markets, we employ a regression analysis.

3.1. Investor sentiment connectedness

To capture the feverish COVID-19 sentiment and analyse the transmission mechanism among countries, we use the TVP-VAR model proposed by Antonakakis et al. (2020). This framework extends the network connectedness model of Diebold and Yilmaz (2014), and it has two main advantages. First, it avoids losing observations by setting a rolling window size. Second, it is not sensitive to outliers (Antonakakis et al., 2020; Korobilis and Yilmaz, 2018). Therefore, the TVP-VAR model is helpful in the context of our analysis, i.e. with a short time horizon.

The model is given by:

$$Y_t = \beta_t Y_{t-1} + \varepsilon_t \tag{1}$$

$$vec(\beta_t) = vec(\beta_{t-1}) + v_t \tag{2}$$

where Y_t is a $N \times 1$ vector of endogenous variables at time t , β_t is a $N \times N$ time-varying coefficient matrix, while $\varepsilon_t \sim (0, S_t)$ and $v_t \sim N(0, R_t)$ are $N \times 1$ vectors of the error terms. S_t and R_t are the time-varying variance-covariance matrices. In order to calculate the H -step-ahead generalized forecast error variance decomposition (GFEVD; Koop et al., 1996; Pesaran and Shin, 1998), we transform the estimated TVP-VAR model into a TVP-VMA process, i.e.: $Y_t = \sum_{i=1}^p \beta_{it} Y_{t-i} + \varepsilon_t = \sum_{j=0}^{\infty} A_{jt} \varepsilon_{t-j}$. Therefore, the GFEVD is given by:

$$\phi_{ij,t}^g(H) = \frac{S_{ii,t}^{-1} \sum_{t=1}^{H-1} (e_i' A_t S_t e_j)^2}{\sum_{j=1}^k \sum_{t=1}^{H-1} (e_i' A_t S_t A_t' e_i)} \tag{3}$$

where H stands for the forecast horizon, S_{ii} is the standard deviation of error term, e_i is a $N \times 1$ selection vector, i.e., equal to 1 for element i and 0 otherwise. Since the sum of elements in each row of the variances decomposition matrix is not equal to one, each element of H -step-ahead matrix is normalised by dividing by the row sum as:

$$\tilde{\phi}_{ij,t}^g(H) = \frac{\phi_{ij,t}^g(H)}{\sum_{j=1}^k \phi_{ij,t}^g(H)} \tag{4}$$

Based on GFEVD estimation, we can derive different connectedness measures: the Total Connectedness Index (TCI) and three measures of directional connectedness (*from-connectedness*, *to-connectedness* and *net-connectedness*). The Total Connectedness Index (TCI) is defined as follows:

$$C_t^g(H) = \frac{\sum_{ij=1, i \neq j}^N \tilde{\phi}_{ij,t}(H)}{\sum_{ij=1}^N \tilde{\phi}_{ij,t}(H)} \times 100 \tag{5}$$

The *to-connectedness* that measures how much of a shock of variable (country) i is transmitted to all other variables (countries) j is given by:

$$C_{i \rightarrow j,t}^g(H) = \frac{\sum_{j=1, j \neq i}^N \tilde{\phi}_{ji,t}(H)}{\sum_{ij=1}^N \tilde{\phi}_{ji,t}(H)} \times 100 \tag{6}$$

The *from-connectedness*, which measures how much variable i (country) is receiving from shocks in all other variables (countries) j , can be measured as:

$$C_{i \leftarrow j,t}^g(H) = \frac{\sum_{j=1, j \neq i}^N \tilde{\phi}_{ij,t}(H)}{\sum_{ij=1}^N \tilde{\phi}_{ij,t}(H)} \times 100 \tag{7}$$

Finally, we can calculate the *net-connectedness* as the difference between *to-connectedness* and *from-connectedness*:

$$C_{i,t}^g = C_{i \rightarrow j,t}^g(H) - C_{i \leftarrow j,t}^g(H) \tag{8}$$

We can consider a variable (country) as a net transmitter when $C_{i,t}^g > 0$, while we can call a net receiver the variable (country) when $C_{i,t}^g < 0$.

3.2. Hedging strategies with sentiment

To compute the hedging strategy analysis, we use the Dynamic Conditional Correlation (DCC) model developed by Engle (2002). This model allows us to estimate the conditional (co)variances, which are practical to use in implementing portfolio strategies. In particular, following Kroner and Sultan (1993), we can compute the hedge ratios as follows:

$$\beta_{ij,t} = \frac{h_{ij,t}}{h_{ii,t}} \tag{9}$$

where $h_{ij,t}$ and $h_{jj,t}$ are the conditional covariance of i and j , while $h_{ii,t}$ is the conditional variance of i .

Next, following Kroner and Ng (1998), we calculate the optimal portfolio weights for Feverish and common market stock, i.e.

$$w_{ji,t} = \frac{h_{ii,t} - h_{ij,t}}{h_{jj,t} - 2h_{ij,t} + h_{ii,t}} \tag{10}$$

with

$$w_{ji,t} = \begin{cases} 0, & \text{if } w_{ji,t} < 0 \\ w_{ji,t}, & \text{if } 0 \leq w_{ji,t} \leq 1 \\ 1, & \text{if } w_{ji,t} > 1 \end{cases} \tag{11}$$

where $w_{ji,t}$ is the weight of stock market return in a 1\$ portfolio of market return and feverish indexes at time t .

3.3. Model specifications of investor sentiment and equity returns

We employ a regression analysis to verify the relationship between total feverish connectedness sentiment and stock market return and volatility. The goal is to analyse the effect of investor sentiment proxied by the feverish COVID-19 connectedness index on common stock market return/volatility. Hence,

$$SMR_t = \beta_0 + \beta_{1,t} \Delta TCI_t + \beta_{2,t} \Delta M_t \tag{12}$$

$$SMV_t = \beta_0 + \beta_{1,t} \Delta TCI_t + \beta_{2,t} \Delta M_t \tag{13}$$

where ΔTCI_t is the return of Total Connectedness Index of feverishness, M_t is a matrix of control variables, while SMR_t and SMV_t are the common stock market return and volatility, respectively¹

¹ We use the FTSE All-World as a proxy of the common stock market. We also used MSCI WORLD as a stock market proxy. The results are qualitatively the same. Market volatility is calculated as the absolute value of stock returns. For completeness, we have also estimated the volatility with the GARCH (1,1) model. The results are qualitatively the same. The list of control variables is calculated as the return for the iBoxx bond index, the gold prices, and the crude oil WTI prices.

Table 2

The summary of each sentimental index component.

Variables	Description	References
Media Coverage	Media Coverage, which measures the percentage of all news sources covering the topic of the novel coronavirus, has a range between 0 and 100.	Cepoi (2020); Haroon and Rizvi (2020)
Fake News	Fake News, which calculates the level of media chatter about the novel virus that makes reference to misinformation or fake news alongside COVID-19, ranges between 0 and 100.	Cepoi (2020)
Panic	The Coronavirus Panic Index, which gauges the level of news chatter that makes reference to panic or hysteria and coronavirus, exhibits the range from 0 to 100.	Cepoi (2020); Haroon and Rizvi (2020)
Sentiment	The Coronavirus Sentiment Index measuring the level of sentiment across all entities mentioned in the news alongside the coronavirus has a range between -100 and 100. To be more precise, a value of 100 is the most positive sentiment(-100 is the most negative) and 0 is neutral.	Cepoi (2020); Haroon and Rizvi (2020); Smales (2014)
Media Hype	The Coronavirus Media Hype Index is the percentage of news talking about the novel coronavirus. Regarding the scale, values range between 0 and 100.	Cepoi (2020)
Infodemic	The Coronavirus Infodemic Index calculateing the percentage of all entities that are linked to coronavirus has a range between 0 and 100.	Cepoi (2020)

Source: Ravenpack

4. Data and feverish sentiment index construction

To measure the feverish sentiment related to COVID-19, we draw on the work of Rognone et al. (2020), Haroon and Rizvi (2020), Cepoi (2020) and Aggarwal et al. (2021), and we use the RavenPack database. RavenPack (<https://coronavirus.ravenpack.com>) provides media data related to COVID-19 issues. We consider six indexes - i.e. the panic index, the media hype, the fake news, the media coverage, the infodemic measure and the sentiment index - for 17 countries: US, Germany, France, Italy, Spain, the UK, China, South Africa, Australia, Japan, India, Russia, South Korea, Turkey, Argentina, Brazil and Indonesia. These countries are listed as the G-20's largest economies. The sample runs from 1 January 2020 (first data available) to 3 February 2021 (286 observations). Table 2 shows a brief definition of the six indexes.²

To have one measure of for coronavirus-related panic for each country, we build a Feverish Sentiment Index by using Principal Component Analysis (PCA).³ This method allows us to isolate the common component of all indicators and then aggregate the existing information into a single composite index. All variables are standardised (mean zero and variance one) to ensure that PCA analysis is not influenced by the scale of units and the size of each measure. We change the Coronavirus Sentiment Index sign to ensure that all measures affect the index in the same direction. To build the Feverish Sentiment Index, we select the first component, which explains about 90% of the total variance for each of the countries. Intuitively, the high values of the Feverish Sentiment Index imply high levels of fear that has implications for financial uncertainty. Thereafter, we test the following hypothesis:

H_0 : Feverish Sentiment Index implies financial market dynamics.

In order to apply the TVP-VAR model, we calculate the daily changes for each index as follows:

$$\Delta \text{Feverish}_{i,t} = \text{Feverish}_{i,t} - \text{Feverish}_{i,t-1} \quad (14)$$

where i is the country while t denotes the day.

In Table 3 we report the summary statistics of the Feverish Sentiment Indexes for all 17 countries. The mean Feverish Sentiment Index change across all the countries is positive. This suggests an overall average rise in feverish sentiment. The standard deviation shows that Turkey and Indonesia recorded the highest variability in feverishness, while the US has the least standard deviation, indicating the comparative stability and resilience of the US economy. The augmented Dickey-Fuller (ADF) test shows all feverish series are stationary, and they can be further used for TVP-VAR modelling.

5. Empirical results

5.1. The feverish connectedness

Table 4 shows the static connectedness obtained based on the TVP-VAR framework. This table presents an overview of the feverish transmission mechanism. The average TCI indicates high co-movement among Feverish Indexes (67.98), suggesting how much the system is integrated. Focusing on to-connectedness, we can see that each country's contribution to the feverish system ranges from 11.28% (Indonesia) to 127.87% (UK). In contrast, the measure of from-connectedness changes more evenly, from 33.14% (Indonesia) to 83.29% (UK), highlighting how the feverish shocks emitted by a country can be

² For the sake of brevity, we do not include descriptive statistics of indexes. However, they are available upon request.

³ Due to space limitations, we do not report the methodological aspects and results of the PCA model. However, they are available on request.

Table 3
Summary of descriptive statistics.

Country	Min	Max	Median	Mean	Std.Dev	ADF
United States (US)	-2.027	2.642	-0.003	0.018	0.561	-5.524***
Germany (DE)	-2.604	2.084	0.013	0.022	0.652	-6.736***
France (FRA)	-2.828	2.995	0.007	0.019	0.714	-6.658***
Italy (ITA)	-2.241	4.015	-0.006	0.015	0.732	-7.051***
Spain (SP)	-2.838	3.246	0.001	0.018	0.709	-7.520***
UK	-3.207	3.274	0.003	0.020	0.647	-6.258***
China (CH)	-3.798	3.683	-0.007	0.023	0.829	-5.757***
South Africa (S_A)	-2.726	3.737	0.014	0.020	0.651	-7.204***
Australia (AU)	-1.666	2.189	0.000	0.022	0.674	-6.040***
Japan (JP)	-2.622	2.108	0.035	0.024	0.711	-7.389***
India (IN)	-4.019	4.205	-0.002	0.016	0.668	-7.529***
Russia (RUS)	-2.181	2.412	0.000	0.019	0.748	-7.276***
South Korea (S_K)	-2.742	3.253	0.012	0.017	0.785	-6.216***
Turkey (TURK)	-4.185	3.902	0.000	0.012	1.004	-7.934***
Argentina (ARG)	-2.863	3.511	0.008	0.018	0.919	-8.442***
Brazil (BRA)	-2.942	4.768	0.020	0.020	0.767	-8.117***
Indonesia (INDO)	-4.323	3.827	0.074	0.020	0.999	-7.874***

Notes: The total observations are 4,862. ADF represents the Augmented Dickey-Fuller for the stationary test.

Table 4
Static feverish connectedness.

	US	DE	FR	IT	SP	UK	CH	SA	AU	JP	ID	RU	SK	TUK	ARG	BRA	INDO	FROM
US	21.1	7.4	7.41	5.92	4.51	11.18	8.47	3.62	4.84	2.21	5.06	6.21	3.22	1.84	2.23	3.94	0.87	78.93
DE	7.74	20.54	7.48	7.28	4.67	10.71	6.71	1.46	2.59	3.16	7.43	7.22	2.28	2.52	3.92	3.44	0.86	79.47
FR	8.7	9.26	22.68	8.49	5.07	9.14	9.07	1.81	2.65	5.13	3.6	3.59	2.29	3.29	1.51	3.38	0.36	77.32
IT	5.85	8.99	7.75	22.42	5.78	8.86	8.89	1.72	1.99	2.79	5.91	3.65	4.16	2.79	2.73	5.58	0.16	77.58
SP	6.25	6.94	5.89	6.28	27.99	9.4	6.55	2.89	2.74	0.72	9.15	1.71	2.7	0.91	3.92	5.63	0.32	72.01
UK	9.43	8.98	6.94	6.92	6.73	16.7	9.12	3.19	4.13	1.79	8.05	4.64	2.98	0.94	2.14	6.78	0.55	83.29
CH	8.69	6.59	7.72	8.92	5.21	10.64	19.1	2.78	2.98	3.38	6.6	4.54	4.05	1.27	1.42	5.76	0.34	80.89
SA	7.19	3.25	3.52	3.51	4.19	8.06	5.28	36.09	5.4	0.48	6.7	4.61	1.83	1.02	2.8	4.74	1.34	63.92
AU	8.34	4.45	4.08	3.01	3.39	8.58	4.76	5.06	32.9	2.02	4.65	3.74	6.29	0.57	2.3	3.48	2.39	67.1
JP	4.27	7.48	10.52	5.44	0.96	3.91	7.68	0.58	2.13	40.27	0.96	3.59	4.43	5.63	0.6	1.12	0.46	59.73
ID	5.49	8.97	2.98	5.84	7.85	10.62	7.96	3.78	3.07	0.89	23.3	5.36	1.87	0.1	2.65	9.12	0.13	76.69
RU	8.48	8.88	3.64	4.84	1.41	7.78	7.4	3.53	3.02	1.82	6.88	31.1	2.11	2.21	2.56	3.94	0.45	68.93
SK	6.12	3.8	3.15	7.08	3.87	6.61	8.53	2.81	5.84	3.59	3.25	2.89	35.4	0.72	1.61	3.87	0.86	64.59
TURK	4.61	4.62	7.1	4.57	1.38	2.26	4.23	1.95	1.12	4.25	0.2	4.55	0.92	54.6	2.8	0.1	0.73	45.4
ARG	4.47	6.7	2.66	4.35	4.12	5.13	2.77	3.16	2.82	0.8	3.58	4.21	2.07	1.72	48.07	2.62	0.76	51.93
BRA	5.35	6.24	3.66	6.83	6.98	10.82	8.14	3.16	2.87	1.49	9.56	3.12	3.34	0.05	2.52	25.2	0.7	74.82
INDO	4.17	2.94	2.04	1.48	0.47	4.18	2.16	3.4	4.26	1.12	0.9	0.96	1.91	0.27	0.84	2.06	66.86	33.14
TO	105.2	105.48	86.54	90.76	66.57	127.9	107.7	44.89	52.43	35.63	82.47	64.58	46.44	25.84	36.55	65.56	11.28	1155.7
ALL	126.2	126.02	109.21	113.18	94.56	144.6	126.8	80.97	85.33	75.9	105.8	95.65	81.85	80.44	84.62	90.74	78.13	TCI
NET	26.22	26.02	9.21	13.18	-5.44	44.58	26.82	-19.03	-14.7	-24.1	5.78	-4.35	-18.2	-19.6	-15.38	-9.27	-21.87	67.98

Notes: Variance decompositions are based on a TVP-VAR with the lag length of order 1 (BIC) and a 10-step-ahead forecast.

small (11.28%) or strong (127.87%), but are relatively evenly distributed across countries. The table demonstrates that the main transmitters of shock are the UK, China, US, and Germany, while Japan, Turkey, S. Africa and S.Korea are the main net receivers.

Fig. 1 the net pairwise directional connection for the 17 countries. In the network, each country is the node, and the pairwise dependence between the two countries is the edge. The larger the size of the arrow, the greater the connection between these countries. The figure easily helps reveal the direction and path of information spillover between various countries. Several important findings emerge from this analysis. First, the UK is the largest epicentre and issuer of net feverish shocks, followed by the US and China. As could be expected, the countries initially most affected by COVID-19 emit the most feverishness. The case of Spain is notable, as unlike the rest of the European countries, the country receives fear shocks. This suggests that Spain receives more media stress than it emits. This result could be explained by the role played by the Spanish Ministry of Health in transmitting information about the pandemic. In fact, [de Las Heras-Pedrosa et al. \(2020\)](#) have shown how the Ministry of Health has always wanted to convey messages of a positive and confident nature to the Spanish people.

To analyse specific events that affect the connectedness over time, we plot in Fig. 2 the dynamic of TCI. As we can see, the index varies during the period, assuming values between 56% and 77%. Fig. 2 shows a pronounced connection around mid-March, which coincides with the declaration of the global pandemic by the World Health Organization (March 11, 2020). The connection is persistent since March 2020, reflecting the serious epidemiological situation. The index shows a gradual decrease since late summer, recording its lowest value (about 56%). In fact, after some government responses to the

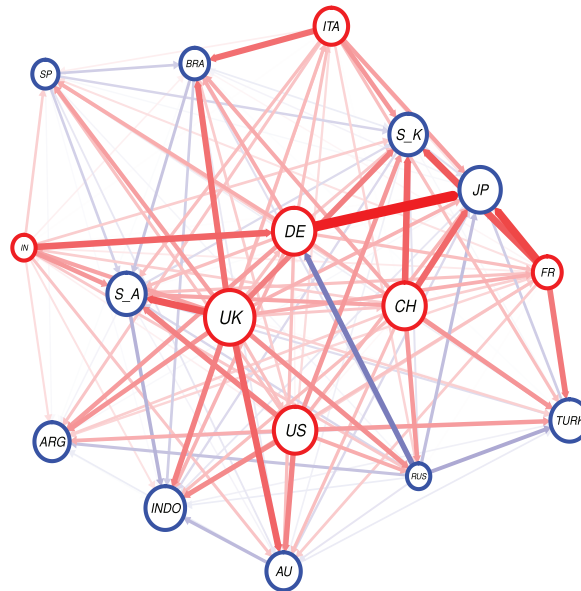


Fig. 1. Network of Net Feverish pairwise Notes: The size of the node shows the degree of the net-pairwise connectedness. The colour of the node indicates whether a country is a net transmitter (red) or net receivers (blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

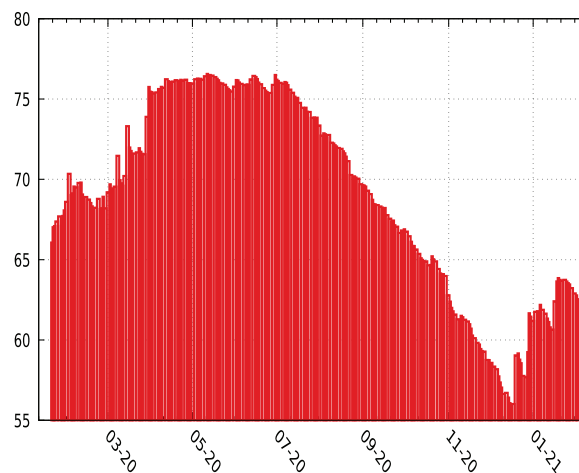


Fig. 2. Total feverish spillover.

COVID-19, the panic feelings decrease, then increase slightly at the beginning of 2021 (second waves). To sum up, during the COVID-19 outbreak, the dynamic total connectedness index changes as a combination of factors, including (i) global pandemic announcement (March), (ii) instability in financial and oil markets (April), and (iii) COVID-19 variants (September to date).

Fig. 3 displays the net spillover feverish dynamics. Positive values indicate when a country is a net transmitter, while negative values mean that the country is a net recipient from others. The figure shows how the US, Germany, France, the UK and China assume a net transmitting role. On the other hand, Spain, South Africa, Japan, Russia, South Korea, Turkey, Argentina, Brazil and Indonesia are the persistent recipients of the shocks from their counterparts. According to Table 4, the countries initially most affected by the pandemic are those that emit more feverishness (excluding Spain) to other countries than they receive. As we can see, the net spillover becomes more pronounced during the COVID-19 pandemic announcement. After China, the pandemic broke out in Europe, creating high uncertainty in all markets (Janiak et al., 2021). As a matter of fact, during this period, the stock markets suffered a great drop (Ashraf, 2020; Seven and Yilmaz, 2021; Corbet et al., 2021), reacting to the bad news about the recent health crisis. After the announcement of the global pandemic, the whole world changed its perception of the risk of pandemics like the coronavirus. This led to higher levels of transmission of negative shocks. Reduced confidence with increased panic increased the fallout from bad news.

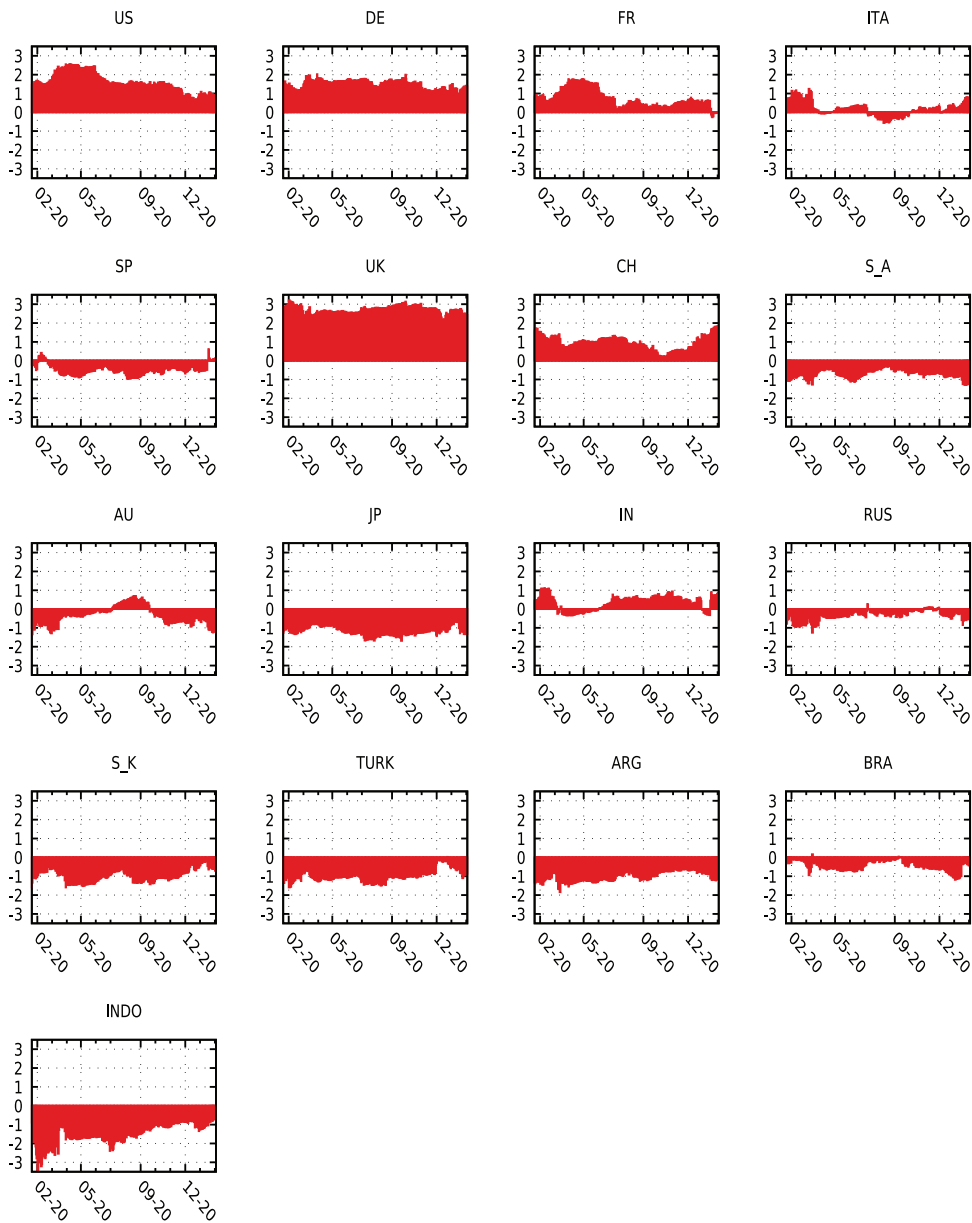


Fig. 3. NET feverish spillover.

To further investigate the dynamic of net feverishness, following Wang et al. (2018), we display the ranking based on net connectedness of 17 countries in Fig. 4. The colours of the heatmap range from yellow to blue, indicating the ranking from the first (largest feverishness emitter) to the last (largest feverishness receiver). As we can see, the UK, China, the United States and Germany are the epicentres of sentiment shock spillover throughout the period. This result highlights the key role played by big economies in the transmission of sentiment worldwide (Rehman et al., 2017; Audrino and Teterova, 2019; Croitorov et al., 2020).

5.2. Hedging strategies

In this section, through the hedge ratio, we estimate the optimal portfolio weights for risk management. We use the DCC model for this purpose (Engle, 2002). The hedge ratio (HR) between two assets can be described as a long position in one asset (FTSE all World) that can be hedged with a short position in the other asset (Feverish Sentiment Index). We use the hedge ratio to calculate optimal weights for FTSE and feverish investments that minimise risk without reducing expected return.

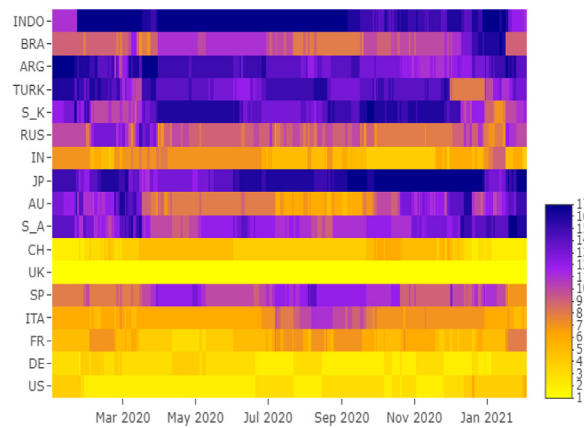


Fig. 4. Feverish ranking. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 5
Optimal Portfolio weights (FTSE/Feverish) summary statistics.

Optimal weights	$w_{j,i,y}$	Std.Dev.	5%	95%	HE
FTSE/US Feverish	0.83	0.11	0.6	0.94	0.29***
FTSE/DE Feverish	0.86	0.12	0.6	0.97	0.36***
FTSE/FRA Feverish	0.88	0.09	0.7	0.96	0.29***
FTSE/ITA Feverish	0.88	0.12	0.7	0.95	0.35***
FTSE/SP Feverish	0.88	0.13	0.6	0.96	0.35***
FTSE/UK Feverish	0.85	0.11	0.6	0.97	0.36***
FTSE/CH Feverish	0.93	0.08	0.7	0.98	0.26**
FTSE/S_A Feverish	0.86	0.13	0.6	0.98	0.34***
FTSE/AU Feverish	0.89	0.12	0.6	0.97	0.18
FTSE/JP Feverish	0.88	0.14	0.7	0.96	0.35***
FTSE/IN Feverish	0.88	0.12	0.6	0.97	0.27**
FTSE/RUS Feverish	0.89	0.11	0.7	0.98	0.24**
FTSE/S_K Feverish	0.92	0.09	0.7	0.98	0.32***
FTSE/TURK Feverish	0.92	0.08	0.8	0.98	0.35***
FTSE/ARG Feverish	0.92	0.08	0.8	0.98	0.30***
FTSE/BRA Feverish	0.93	0.1	0.7	0.99	0.25**
FTSE/INDO Feverish	0.93	0.07	0.8	0.99	0.33***

Notes: * < 0.1; ** < 0.05; *** < 0.01. Hedging Effectiveness (HE) is computed as $1 - (Var(H)/Var(U))$. $Var(H)$ and $Var(U)$ are the variance of the hedged and unhedged positions, respectively.

Table 5 shows the summary statistics of optimal portfolio weights. In general, we observe that investors should, on average, hold higher weights in the stock market relative to uncertainty. Portfolio weights range from 0.83 (FTSE/US) to 0.93 (FTSE/INDO). This means that, for a dollar portfolio, 0.83 cents on the dollar should be invested in the equity market, and the remaining 17 cents should be invested in the US uncertainty or VIX. Optimal hedge ratios vary slightly between countries. Hedge effectiveness ratios indicate that risk reduction ranges from 18% to 36%. The highest hedge effectiveness is obtained between the FTSE and the French Feverish Sentiment Index. Moreover, the hedge effectiveness statistics are almost all statistically significant at the 1% level (except in Australia). This result is perfectly confirmed in Table 6, where the portfolio is constructed with VIX, i.e. a proxy for investors' sentiment or fear (Shaikh and Padhi, 2015; Smales, 2017), and domestic financial markets. As we can see, on average, the two indices indicate the same optimal portfolio composition.

In Fig. 5, we plot the time-varying portfolio weights for the FTSE/Feverish and Market/VIX portfolios, respectively. Specifically, the red line is the time-varying portfolio weight for a portfolio composed of the global equity market (FTSE all World) and the feverishness indices for each country, while the blue line is the time-varying portfolio weight for the portfolio composed with the national stock market (e.g. S&P 500 for the US) and the VIX.

The graphical evidence is consistent with the results reported in Table 5 and 6. The dynamics of the indices are quite similar, and show a significant reduction after the announcement of the global epidemic (March). However, we can note that during periods of high volatility such as today's, the optimal weights tend to be zero, i.e. zero-dollar investments on uncertainty. In general, the evidence supports the view that the portfolio weights are relatively constant over time, highlighting the significant uncertainty throughout the period of analysis. In fact, we can observe that they do not change significantly in earlier periods and during the acute phase of the COVID-19 era. Moreover, the results show that the optimal weights do not vary much from one financial market to another, providing evidence that the pandemic affected countries indiscriminately.

Table 6
Optimal Portfolio weights (Market/VIX) summary statistics.

Optimal weights	$w_{ji, y}$	Std.Dev.	5%	95%	HE
US/VIX	0.87	0.06	0.7	0.92	0.76***
DE/VIX	0.88	0.05	0.8	0.93	0.42***
FR/VIX	0.89	0.05	0.8	0.94	0.41***
ITA/VIX	0.88	0.05	0.8	0.93	0.46***
SP/VIX	0.89	0.05	0.8	0.94	0.41***
UK/VIX	0.91	0.04	0.8	0.94	0.39***
CH/VIX	0.97	0.01	0.9	0.99	0.04
S_A/VIX	0.91	0.03	0.8	0.95	0.18*
AU/VIX	0.95	0.03	0.9	0.98	0.22**
JP/VIX	0.95	0.03	0.9	0.98	0.08
IN/VIX	0.92	0.06	0.8	0.96	0.23**
RUS/VIX	0.93	0.03	0.9	0.96	0.25**
S_K/VIX	0.94	0.04	0.9	0.97	0.15
TURK/VIX	0.91	0.03	0.9	0.95	0.31***
ARG/VIX	0.83	0.06	0.7	0.91	0.35***
BRA/VIX	0.88	0.05	0.7	0.93	0.60***
INDO/VIX	0.95	0.04	0.9	0.98	0.13

Notes: * < 0.1; ** < 0.05; *** < 0.01. Hedging Effectiveness (HE) is computed as $1 - (Var(H)/Var(U))$. $Var(H)$ and $Var(U)$ are the variance of the hedged and unhedged positions, respectively.

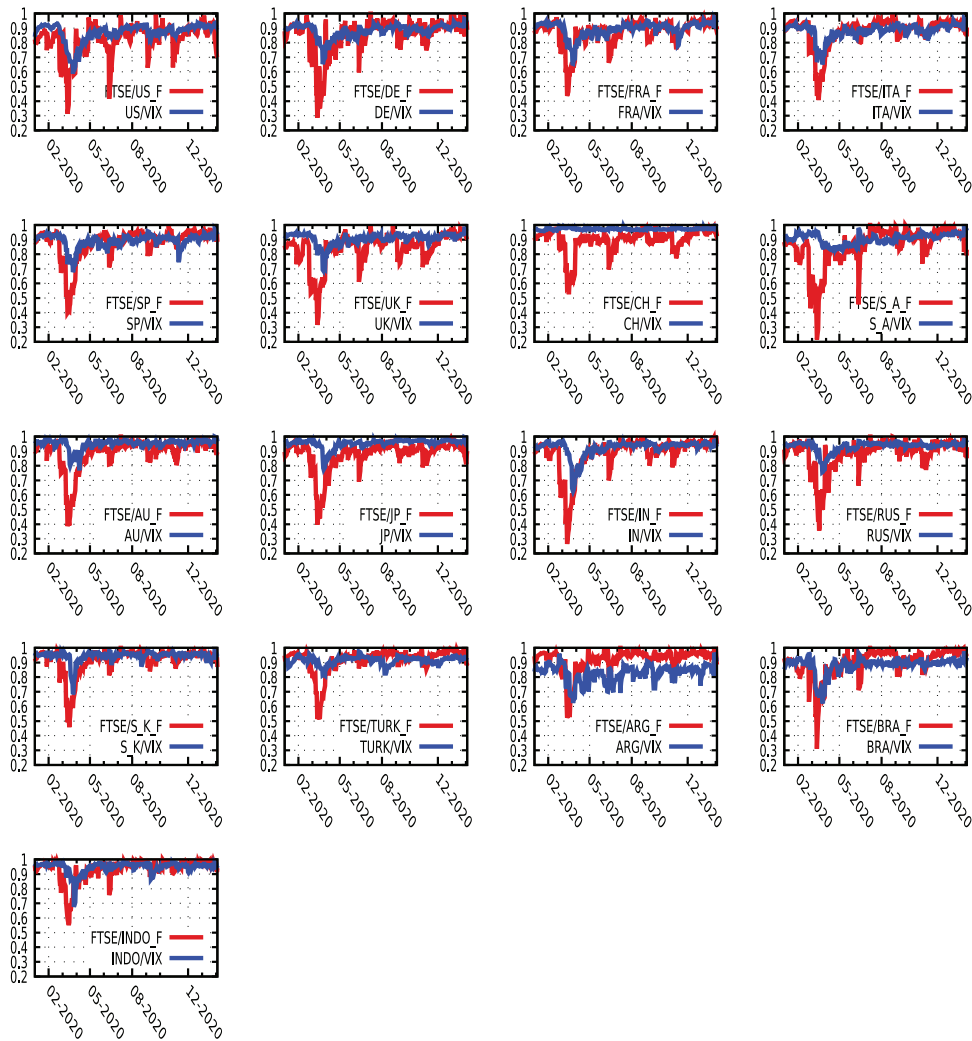


Fig. 5. Time-varying portfolio weights. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 7
The sequential lagged terms of feverish and its predictive power on stock market return.

Variables	The dependent variable is the FTSE All-World return							
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
ΔTF Connectedness	-0.417*** [-0.128]	-0.364*** [-0.119]	-0.430*** [-0.129]	-0.378*** [-0.12]	-0.435*** [-0.131]	-0.371*** [-0.125]	-0.441*** [-0.129]	-0.379*** [-0.121]
ΔTF Connectedness _(t-1)			0.118 [-0.129]	0.124 [-0.12]	0.126 [0.131]	0.116 [-0.121]	0.105 [-0.131]	0.098 [-0.121]
ΔTF Connectedness _(t-2)					-0.06 [-0.131]	0.07 [-0.123]	-0.027 [-0.131]	0.096 [-0.122]
ΔTF Connectedness _(t-3)							-0.289** [-0.13]	-0.243** [-0.121]
Constant	0.001 [-0.001]	0.001 [-0.001]	0.001 [-0.001]	0.001 [-0.001]	0.001 [-0.001]	0.001 [-0.001]	0.001 [-0.001]	0.001 [-0.001]
Control variables	NO	YES	NO	YES	NO	YES	NO	YES
R-squared	0.04	0.18	0.04	0.18	0.04	0.19	0.05	0.20

Notes: *, **, and *** indicate 10%, 5%, and 1% significance level. Standard errors are reported in parentheses. Model (1), (3), (5) and (7) report the baseline model without any control variables while the remaining models included the other determinants to reduce the omitted factors. We use the FTSE All-World as a proxy of the common stock market. We also used MSCI-World as a stock market proxy. The results are qualitatively the same. Δ denotes the change (first-difference) of TCI Fear index. The list of control variables is calculated as the return for the iBoxx bond index, the gold prices, and the crude oil WTI prices.

Table 8
The sequential lagged terms of feverish and its predictive power on stock market volatility.

Variables	The dependent variable is the FTSE All-World volatility							
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
ΔTF Connectedness	0.301*** [-0.102]	0.235*** [-0.095]	0.288*** [-0.1]	0.224** [-0.092]	0.298*** [-0.1]	0.224*** [-0.093]	0.298*** [-0.1]	0.223*** [-0.093]
ΔTF Connectedness _(t-1)			0.118 [-0.129]	0.035 [-0.091]	0.03 [-0.101]	0.034 [-0.092]	0.032 [-0.101]	0.031 [-0.093]
ΔTF Connectedness _(t-2)					0.133 [-0.1]	0.001 [-0.062]	0.131 [-0.101]	0.012 [-0.094]
ΔTF Connectedness _(t-3)							0.02 [-0.01]	-0.042 [-0.093]
Constant	0.010*** [0]	0.011*** [0]	0.010*** [-0.001]	0.010*** [0]	0.010*** [0]	0.010*** [0]	0.010*** [0]	0.010*** [0]
Control variables	NO	YES	NO	YES	NO	YES	NO	YES
R-squared	0.03	0.19	0.03	0.19	0.03	0.19	0.04	0.20

Notes: *, **, and *** indicate 10%, 5%, and 1% significance level. Standard errors are reported in parentheses. Model (1), (3), (5) and (7) report the baseline model without any control variables while the remaining models included the other determinants to reduce the omitted factors. We use the FTSE All-World as a proxy of the common stock market. We also used MSCI World as a stock market proxy. The results are qualitatively the same. Market volatility is calculated as the absolute value of stock returns. For completeness, we have also estimated the volatility with the GARCH (1,1) model and the results are qualitatively the same. Δ denotes the change (first-difference) of TCI Fear index. The list of control variables is calculated as the return for the iBoxx bond index, the gold prices, and the crude oil WTI prices.

5.3. Feverishness and the stock market

In this section, we aim to study the effects of investor sentiment proxied by the Feverish COVID-19 Connectedness Index on the stock market. For this purpose, we estimated the OLS regression to examine the stock market’s response to the TCI. Our main hypothesis is that the total network connection measure is informative for stock market performance. **Tables 7 and 8** present the regression results. As we can see, the Feverish coefficient exhibits a significance level of 0.1%. The results are statistically significant in the bivariate case (Model 1, 3, 5, 7) and after controlling for other assets (Model 2, 4, 6, 8). Therefore, the estimates provide evidence of a significant negative (positive) effect of the change in the feverish connections on stock market returns (volatility). The finding is in line with the literature (Siganos et al., 2014; Helseth et al., 2020; Lyócsa et al., 2020; Lyócsa and Molnár, 2020; Haroon and Rizvi, 2020; Cepoi, 2020; Aggarwal et al., 2021), that has focused on the key role of sentiment index in financial markets dynamics. These results suggest investors should consider the implications of feverish shocks in their portfolio choices.

When it comes to the ‘reversal effects’, we find that the feverish sentiment coefficients in the contemporaneous and three-lagged terms are negatively correlated to the stock market returns. The results hold robust across eight models without any changes in signs. However, the one-period lagged term has positive coefficients. Furthermore, the two-period lagged terms have negative coefficients. This implies that the ‘feverish sentiment’ shows the ‘reversal effects’. Although these coefficients (one-period lag and two-period lag) are insignificant, we also observe the ‘reversal effect’ where the investors tend to overreact to panic and fear feelings, as proxied by the feverish sentiment. Afterwards, the investors recover their feelings by reacting in the opposite way to what they did before.

Table 9
Feverish Connectedness and Regional stock market returns.

Variables	Stock market Returns									
	Africa		Asia		Europe		Latin America		North America	
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)	Model (10)
Δ TF Connectedness	-0.344** [0.138]	-0.289*** [0.123]	-0.192** [0.096]	-0.141* [0.085]	-0.341*** [0.129]	-0.298** [0.125]	-0.736*** [0.214]	-0.625*** [0.200]	-0.519*** [0.155]	-0.477*** [0.159]
Constant	0.001 [0.001]	0.001 [0.001]	0.001 [0.001]	0.001 [0.001]	-0.001 [0.001]	-0.001 [0.001]	-0.001 [0.001]	-0.001 [0.001]	0.001 [0.001]	0.001 [0.001]
Control variables	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
R-squared	0.02	0.24	0.01	0.23	0.02	0.11	0.04	0.18	0.04	0.14

Notes: *, **, and *** indicate 10%, 5%, and 1% significance level. Standard errors are reported in parentheses. Model (1), (3), (5), (7) and (9) report the baseline model without any control variables while the remaining models included the other determinants to reduce the omitted factors. As regional indexes we use: FTSE/JSE Top 40, FTSE Asia Pacific, FTSE Euro 100, FTSE Latin America and FTSE North America. Δ denotes the change (first-difference) of TCI Fear index. The list of control variables is calculated as the return for the iBoxx bond index, the gold prices, and the crude oil WTI prices.

Table 10
Feverish connectedness and regional stock market volatility.

Variables	Stock market Volatility									
	Africa		Asia		Europe		Latin America		North America	
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)	Model (10)
Δ TF Connectedness	0.024*** [0.007]	0.018*** [0.006]	0.005* [0.002]	0.003* [0.001]	0.014* [0.008]	0.008* [0.005]	0.084*** [0.019]	0.068*** [0.016]	0.052*** [0.010]	0.043*** [0.009]
Constant	0.001*** [0.000]	0.001*** [0.000]	0.001*** [0.000]	0.001*** [0.000]	0.001*** [0.000]	0.001*** [0.000]	0.001*** [0.000]	0.001*** [0.000]	0.001*** [0.000]	0.001*** [0.000]
Control variables	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
R-squared	0.03	0.25	0.01	0.13	0.01	0.17	0.06	0.39	0.08	0.31

Notes: *, **, and *** indicate 10%, 5%, and 1% significance level. Standard errors are reported in parentheses. Model (1), (3), (5), (7) and (9) report the baseline model without any control variables while the remaining models included the other determinants to reduce the omitted factors. As regional indexes we use: FTSE/JSE Top 40, FTSE Asia Pacific, FTSE Euro 100, FTSE Latin America and FTSE North America. Market volatility is calculated as the absolute value of stock returns. Δ denotes the change (first-difference) of TCI Fear index. The list of control variables is calculated as the return for the iBoxx bond index, the gold prices, and the crude oil WTI prices.

Our study is also consistent with the literature that suggests investor sentiment, particularly fear and uncertainty, provokes volatility (Brown, 1999; Kumar and Lee, 2006; Siganos et al., 2014; Kumari and Mahakud, 2015; Hamid and Heiden, 2015; Behrendt and Schmidt, 2018; Nasir and Morgan, 2018; Jiao et al., 2020). The key findings indicate that the negative attitudes towards the COVID-19 situation are associated with market volatility. Therefore, this phenomenon might be explained by the proposition that the noise traders' pessimism would shake the market up.

5.3.1. Feverishness and regional stock markets

To evaluate the impact of the Total Feverish Connectedness Index on financial markets, we now focus our analysis on regional stock indexes. Indeed, awareness of the relationship between COVID feverishness and regional equity markets is important for policymakers seeking to make timely targeted intervention in a specific financial market, as well as for investors seeking to make rational investment choices. We use the daily returns (and volatility) of stock market indices from five different geographic regions. More specifically, we use the FTSE Asia Pacific (Asia stock market), the FTSE/JSE Top 40 (Africa stock market), the FTSE Euro 100 (European stock market), the FTSE Latin America (Latin America stock market) and the FTSE North America (North America stock market).

Tables 9 and 10 summarise the estimation results for stock market returns and volatility, respectively. In this case, the findings support our hypothesis, namely that the Feverish Sentiment Index has an impact on financial markets dynamics.

The results in Table 9 indicate that returns for all regions are negatively (significantly) affected by the Feverish Sentiment Index, while Table 10 shows the positive and significant impact of the index on volatility. The results of the analysis are fully consistent with Janiak et al. (2021), who have found that regional stock markets are negatively affected by COVID-19 related uncertainty.

5.4. Robustness check

The findings are verified by applying a Panel Pooled model. Specifically, we analyse the relationship between each country's fear index and its benchmark national stock market⁴ The choice to apply a Panel Pooled model is based on the F-test⁵,

⁴ Please see Table A.1 in Appendix, for the list of country-specific stock indexes.

⁵ Joint significance of differing group means: $F(16, 4827) = 0.204$ with p -value 0.999.

Table 11
Robustness check.

Variables	Market Returns		Market Volatility	
	Model (1)	Model (2)	Model (3)	Model (4)
Δ Feverish	-0.027*** [-0.002]	-0.018*** [-0.003]	0.010*** [-0.002]	0.004* [-0.002]
Constant	0.001 [-0.002]	0.001 [-0.002]	0.012*** [0]	0.012*** [-0.002]
Control variables	NO	YES	NO	YES
Observations	4845	4845	4845	4845
R-squared	0.011	0.124	0.002	0.112

Notes: *, **, and *** indicate 10%, 5%, and 1% significance level. Standard errors are reported in parentheses. Model (1) and (3) report the baseline model without any control variables while the remaining models included the other determinants to reduce the omitted factors. Market volatility is calculated as the absolute value of stock returns. For completeness, we have also estimated the volatility with the GARCH(1,1) model and the results are qualitatively the same. Δ denotes the change (first difference) of Fear indexes. The list of control variables is calculated as the return for the iBoxx bond index, the gold prices, and the crude oil WTI prices

Table 12
Endogeneity estimation results (Market returns).

Variables	Market returns					
	OLS		Fixed Effects		System GMM	
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Market returns _(t-1)					-0.056 [0.156]	-0.251** [0.125]
Market returns _(t-2)					-0.045 [0.103]	-0.094 [0.087]
Δ Feverish	-0.041*** [0.003]	-0.019*** [0.003]	-0.042*** [0.003]	-0.019*** [0.003]	-0.071*** [0.011]	-0.026* [0.015]
Constant	0.001*** [0.000]	0.001 [0.001]	0.001 [0.001]	0.001 [0.001]	0.001*** [0.000]	0.001* [0.000]
Control variables	NO	YES	NO	YES	NO	YES
Observation	969	969	969	969	952	952
R-squared	0.11	0.27	0.12	0.28		
AR (1)					-2.515**	-2.346*
AR (2)					0.412	-0.027
Sargan test					15.27	13.65

Notes: Columns 2–3 report results based on OLS estimation, columns 4–5 report results based on the Fixed effects model, while columns 6–7 report estimation based on System GMM model. Sargan is a test of the over-identifying restrictions, while AR (1) and AR (2) are the Arellano-Bond tests for first-order and second-order correlation, respectively. *, **, and *** indicate 10%, 5%, and 1% significance level. Standard errors are reported in parentheses. Model (1), (3) and (5) report the baseline model without any control variables while the remaining models included the other determinants to reduce the omitted factors. Δ denotes the change (first difference) of Fear indexes. The list of control variables is calculated as the return for the iBoxx bond index, the gold prices, and the crude oil WTI prices.

which suggests that we adopt the Pooled model at the expense of the Panel Fixed or Random effect. Table 11 summarises the results of the regression. The results are perfectly in line with our expectations. An increase in fear has a negative effect on stock returns and a positive effect on volatility.

5.4.1. Endogeneity check

In this section, we apply the step-by-step procedure proposed by Ullah et al. (2018) to check the endogeneity issues in our model. The steps are:

1. Estimation of the OLS regression. We run an OLS analysis to study the relationship between stock market returns (volatility) and feverish measures.⁶
2. Detection of endogeneity bias through Durbin-Wu-Hausman test. The test is statistically significant (please see Table A-2 in Appendix); the explanatory variable is correlated with the residuals. Therefore, we proceed with step 3.
3. Controlling for unobservable heterogeneity by estimating the fixed effects model.
4. Overcoming the endogeneity issues by employing the two-step system generalised method of moments (GMM), i.e. the dynamic panel model. Following Wintoki et al. (2012) and Ullah et al. (2018), we use two lags of the dependent variables.

⁶ To apply this procedure, we transform the data from daily to weekly. The transformation occurs because the software cannot allocate the amount of memory necessary to estimate the dynamic GMM model with daily data.

Table 13
Endogeneity estimation results (Volatility returns).

Variables	Market Volatility					
	OLS		Fixed Effects		System GMM	
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Volatility _(t-1)					0.187*** [0.037]	0.056 [0.078]
Volatility _(t-1)					0.007 [0.039]	0.018 [0.046]
Δ Feverish	0.001*** [0.000]	0.001*** [0.000]	0.001*** [0.000]	0.001*** [0.000]	0.003* [0.001]	0.003* [0.001]
Constant	0.001*** [0.000]	0.001*** [0.000]	0.001*** [0.000]	0.001*** [0.000]	0.001*** [0.000]	0.001*** [0.000]
Control variables	NO	YES	NO	YES	NO	YES
Observation	969	969	969	969	952	952
R-squared	0.02	0.27	0.04	0.30		
AR (1)					-2.299**	-2.308**
AR (2)					0.876	0.247
Sargan test					12.61	12.38

Notes: Columns 2–3 report results based on OLS estimation, columns 4–5 report results based on the Fixed effects model, while columns 6–7 report estimation based on System GMM model. Sargan is a test of the over-identifying restrictions, while AR (1) and AR (2) are the Arellano-Bond tests for first-order and second-order correlation, respectively. *, **, and *** indicate 10%, 5%, and 1% significance level. Standard errors are reported in parentheses. Model (1), (3) and (5) report the baseline model without any control variables while the remaining models included the other determinants to reduce the omitted factors. Market volatility is calculated as the absolute value of stock returns. For completeness, we have also estimated the volatility with the GARCH(1,1) model and the results are qualitatively the same. Δ denotes the change (first difference) of Fear indexes. The list of control variables is calculated as the return for the iBoxx bond index, the gold prices, and the crude oil WTI prices

5. Finally, we check if the instruments are exogenous. According to [Arellano and Bond \(1991\)](#), three additional conditions should be met to avoid model misspecification: significant serial correlation AR(1), lack of serial correlation AR(2) and rejection of Sargan test statistic.

[Tables 12–13](#) show the regression results for stock returns and volatility as the dependent variable, respectively. We find that the relationships between financial markets and feverish sentiment are consistent using OLS, fixed effects and system GMM. In fact, we can note how the Feverish variable is statically significant. The GMM model, including the lagged dependent variable, is useful to control for the three types of endogeneity: unobserved heterogeneity, simultaneity, and dynamic endogeneity ([Ullah et al., 2018; 2020](#)).

The values of the tests (AR[1], AR[2] and Sargan) confirm the validity of the instruments used in our estimation process. In particular, we report Sargan's statistical test, which examines over-identification restrictions. The Sargan test statistics for all models are not significant. Therefore, we are unable to reject the null hypothesis, i.e. the econometric model is valid. Furthermore, we report the Arellano and Bond test for autocorrelation. As can be observed, the assumptions of [Arellano and Bond \(1991\)](#) are met. Thus, all models are free from autocorrelation.

6. Conclusion

In this study, we focused on the investor sentiments by developing and employing a new approach in the form of a comprehensive Feverish Sentiment Index, which includes a wide range of factors such as fake news, media coverage, panic feelings. Using TVP-VAR to examine the sentiment spillover across the 17 largest economies, we explored the network structure of emissions and the reception of fear shocks in underlying countries. Furthermore, we investigated the effectiveness of hedging strategies for investing in the stock markets during the COVID-19 pandemic. Finally, to validate the feverish sentiment, we analysed the predictive power of this index for the stock market returns and volatility. Unlike some previous studies, the subject treatise focused on the role of investor sentiment by drawing on an extended set of components in the 17 largest countries. More noticeably, the feverish sentiment can be seen as a systematic risk factor on the onset of the disease outbreak, which is also priced and manifested in the stock market. By comparisons with previous pandemics such as H1N1 and Ebola, our study also confirms that COVID-19 is an unprecedented event that negatively influences the financial market ([Schell et al., 2020; Baker et al., 2020a](#)). Moreover, our study also offers the new insight that the American markets are likely to suffer more with the high level of feverish sentiment about COVID-19. The incidences of the H1N1 outbreak and financial crisis (2007–2008) were more pronounced in Asian countries ([Peckham, 2013](#)). Similarly, not only the US but also the European stock market exhibited negative reactions to the Great Influenza Pandemic (1918), and the same holds in the case of the COVID-19 pandemic. However, in this era, we can estimate the market sentiment and also offer insights into the linkage between sentiments and market disruption.

The empirical findings lead us to draw inferences, and can be summarised in the following points. First and most importantly, we confirm the persistence of the predictive power of 'feverish sentiment' in explaining the stock returns and volatility. It implies that the higher such sentiment, the higher (lower) market volatility (return). Our findings are intuitive, consistent with the prevailing view of the role of uncertainty in causing financial turbulence. Second, the study contributes to the literature not only in methodological terms, by developing a novel approach to the estimation of investor sentiment, but also by providing insight into its role in the prediction of the stock market behaviour. The findings are consistent with the theoretical framework that investor sentiment might drive the stock returns and volatility, while the study focuses explicitly on capturing the unprecedented event and public health crisis in the form of the COVID-19 outbreak. Although we found the reversal effect, it seems to be rather mild. It can be concluded that investors are likely to overreact to the 'bad news' and readjust their sentiment and resulting stance in the following days. Third, the investor sentiments in 17 countries exhibit strong connectedness. The US, the UK, Germany, China, Italy and France turned out to be the epicentres of sentiment shock transmission. Overarchingly, the subject treatise manifests the importance of appropriate prudential frameworks to tame the fear sentiment that can potentially lead to financial instability. Furthermore, it provides evidence that the hedging cost is relatively low when the pandemic is contained successfully at the beginning of the outbreak, like in Australia. However, hedging loses its effectiveness once the public health crisis intensifies. Our study also has two main implications for investment behaviour. First, after dealing with the endogeneity, we find that COVID-19 feverish sentiment is an exogenous shock affecting the financial markets. Therefore, policymakers should consider public health crisis events, which might induce market volatility as well as market disruption. Second, we find that the US exhibits the highest volatility and lowest return in terms of feverish connectedness. It also makes sense because the US has struggled with reducing the number of infected cases during the pandemic. This phenomenon negatively influences the financial markets; therefore, the policymakers in this area should pay attention to not spreading the "panicky feelings", and more importantly, to containing the virus transmission in the community. Concomitantly, the investors could rely on the heterogeneous effects of continents to construct their investing strategies (for example, arbitrage with the different impacts of equity markets).

As it stands, the pandemic is not over, but future research can be focused on the 'recovery sentiment' to investigate how the investors perceive the optimistic side of the economic recovery and after overcoming the pandemic. However, that will be for those interested in exploring investor sentiments about the prospect of economic recovery post-COVID-19 pandemic. Since this Feverish Sentiment Index was constructed by aggregating the global perspectives with different categories of sentiment, future research can decompose them into country-level to obtain the heterogeneous effects. Furthermore, this index is mainly focused on "panicky feelings", while a brighter world will come with good news, such as vaccination campaigns, re-opening economies, and so forth. Hence, the 'optimistic feeling of post-COVID' will have certain merits. As a final remark, this paper only offers insights about the equity market, while future studies could extend the analysis by investigating how "feverish sentiment" could impact the sovereign bond, cryptocurrency, exchange rate and commodity markets.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Toan Luu Duc Huynh: Conceptualization, Methodology, Investigation, Formal analysis, Writing - original draft, Writing - review & editing. **Matteo Foglia:** Conceptualization, Methodology, Software, Formal analysis, Data curation, Validation, Visualization, Writing - original draft, Writing - review & editing. **Muhammad Ali Nasir:** Conceptualization, Writing - original draft, Writing - review & editing, Project administration, Supervision. **Eliana Angelini:** Supervision, Writing - review & editing.

Acknowledgment

We gratefully acknowledge the Professor Daniel Houser and Professor Daniela Puzzello, the co-editors in chief of Journal of Economic Behavior & Organization. We also thank Professor H. B. Ameer, Professor Z. Ftiti, Professor W. Louhichi and Professor J.L. Prigent (Co-Guest Editors in special issue), and the two anonymous referees for their helpful questions and comments. Any errors and shortcomings remain the authors' responsibility. This research is funded by University of Economics Ho Chi Minh City (Vietnam) for Toan Luu Duc Huynh and Muhammad Ali Nasir (Registered code 2021-03-15-0275).

Appendix

Table A-1

List of country-specific stock indices.

Country	Stock Index	Country	Stock Index
US	S&P 500	JP	NIKKEI 225
DE	DAX 30	IN	S&P BSE
FRA	CAC 40	RUS	MOEX RUSSIA
ITA	FTSE MIB	S_K	KOREA SE COMPOSITE
SP	IBEX 35	TURK	BIST NATIONAL 100
UK	FTSE 100	ARG	S&P MERVAL
CH	SHANGHAI COMPOSITE	BRA	BRAZIL BOVESPA
S_A	JSE	INDO	IDX COMPOSITE
AU	ASX		

Table A-2

Durbin-Wu-Hausman tests for endogeneity.

Model	Test	Statistic	p-value
Stock returns	Durbin-Wu-Hausman χ^2	25.290	0.000
Volatility	Durbin-Wu-Hausman χ^2	11.750	0.000

Notes:Null Hypothesis (H_0): Regressor is Exogenous.

References

- Aggarwal, S., Nawn, S., Dugar, A., 2021. What caused global stock market meltdown during the COVID pandemic–lockdown stringency or investor panic? *Financ. Res. Lett.* 38, 101827.
- Allcott, H., Gentzkow, M., 2017. Social media and fake news in the 2016 election. *J. Econ. Perspect.* 31 (2), 211–236.
- Aloui, C., Shahzad, S.J.H., Hkiri, B., Helal, B.H., Khan, M.A., 2021. On the investors' sentiments and the islamic stock-bond interplay across investments' horizons. *Pac. Basin Financ. J.* 65, 101491.
- Ambros, M., Frenkel, M., Huynh, T.L.D., Kilinc, M., 2020. Covid-19 pandemic news and stock market reaction during the onset of the crisis: evidence from high-frequency data. *Appl. Econ. Lett.* 1–4.
- Antonakakis, N., Chatziantoniou, I., Gabauer, D., 2020. Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *J. Risk Financ. Manag.* 13 (4), 84.
- Apuke, O.D., Omar, B., 2021. Fake news and COVID-19: modelling the predictors of fake news sharing among social media users. *Telemat. Inform.* 56, 101475.
- Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Rev. Econ. Stud.* 58 (2), 277–297.
- Ashraf, B.N., 2020. Stock markets' reaction to COVID-19: cases or fatalities? *Res. Int. Bus. Financ.* 54, 101249.
- Audrino, F., Teterova, A., 2019. Sentiment spillover effects for us and european companies. *J. Bank. Financ.* 106, 542–567.
- Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. *J. Financ.* 61 (4), 1645–1680.
- Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. *J. Econ. Perspect.* 21 (2), 129–152.
- Baker, S.R., Bloom, N., Davis, S.J., Kost, K., Sammon, M., Viratyosin, T., 2020a. The unprecedented stock market reaction to COVID-19. *Rev. Asset Pric. Stud.* 10 (4), 742–758.
- Baker, S.R., Bloom, N., Davis, S.J., Terry, S.J., 2020. Covid-induced economic uncertainty. Technical Report. National Bureau of Economic Research.
- Barberis, N., Shleifer, A., Vishny, R., 1998. A model of investor sentiment. *J. Financ. Econ.* 49 (3), 307–343.
- Behrendt, S., Schmidt, A., 2018. The twitter myth revisited: intraday investor sentiment, twitter activity and individual-level stock return volatility. *J. Bank. Financ.* 96, 355–367.
- Benartzi, S., Thaler, R.H., 1995. Myopic loss aversion and the equity premium puzzle. *Q. J. Econ.* 110 (1), 73–92.
- Brigida, M., Pratt, W.R., 2017. Fake news. *N. Am. J. Econ. Financ.* 42, 564–573.
- Brown, G.W., 1999. Volatility, sentiment, and noise traders. *Financ. Anal. J.* 55 (2), 82–90.
- Buckman, S.R., Shapiro, A.H., Sudhof, M., Wilson, D.J., et al., 2020. News sentiment in the time of COVID-19. *FRBSF Econ. Lett.* 8, 1–05.
- Caggiano, G., Castelnuovo, E., Kima, R., 2020. The global effects of COVID-19-induced uncertainty. *Econ Lett* 194, 109392.
- Cepoi, C.-O., 2020. Asymmetric dependence between stock market returns and news during COVID-19 financial turmoil. *Financ. Res. Lett.*
- Chen, C., Liu, L., Zhao, N., 2020. Fear sentiment, uncertainty, and bitcoin price dynamics: the case of COVID-19. *Emerg. Mark. Financ. Trade* 56 (10), 2298–2309.
- Clarke, J., Chen, H., Du, D., Hu, Y.J., 2020. Fake news, investor attention, and market reaction. *Inf. Syst. Res.* 32 (1), 35–52. doi:10.1287/isre.2019.0910.
- Collimore, K.C., McCabe, R.E., Carleton, R.N., Asmundson, G.J., 2008. Media exposure and dimensions of anxiety sensitivity: differential associations with PTSD symptom clusters. *J. Anxiety Disord.* 22 (6), 1021–1028.
- Corbet, S., Hou, Y.G., Hu, Y., Oxley, L., Xu, D., 2021. Pandemic-related financial market volatility spillovers: evidence from the Chinese COVID-19 epicentre. *Int. Rev. Econ. Financ.* 71, 55–81.
- Cortés, K., Duchin, R., Sosyura, D., 2016. Clouded judgment: the role of sentiment in credit origination. *J. Financ. Econ.* 121 (2), 392–413.
- Croitorov, O., Giovannini, M., Hohberger, S., Ratto, M., Vogel, L., 2020. Financial spillover and global risk in a multi-region model of the world economy. *J. Econ. Behav. Organ.* 177, 185–218.
- Da, Z., Engelberg, J., Gao, P., 2011. In search of attention. *J. Financ.* 66 (5), 1461–1499.
- Da, Z., Engelberg, J., Gao, P., 2015. The sum of all fears investor sentiment and asset prices. *Rev. Financ. Stud.* 28 (1), 1–32.
- De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J., 1990a. Noise trader risk in financial markets. *J. Polit. Econ.* 98 (4), 703–738.
- De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J., 1990b. Positive feedback investment strategies and destabilizing rational speculation. *J. Financ.* 45 (2), 379–395.
- Didier, T., Huneus, F., Larrain, M., Schmukler, S.L., 2021. Financing firms in hibernation during the COVID-19 pandemic. *J. Financ. Stab.* 53, 100837.

- Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: predictive directional measurement of volatility spillovers. *Int. J. Forecast.* 28 (1), 57–66.
- Diebold, F.X., Yilmaz, K., 2014. On the network topology of variance decompositions: measuring the connectedness of financial firms. *J. Econom.* 182 (1), 119–134.
- Dumas, B., Kurshev, A., Uppal, R., 2009. Equilibrium portfolio strategies in the presence of sentiment risk and excess volatility. *J. Financ.* 64 (2), 579–629.
- Edmans, A., Garcia, D., Norli, Ø., 2007. Sports sentiment and stock returns. *J. Financ.* 62 (4), 1967–1998.
- Elster, J., 1998. Emotions and economic theory. *J. Econ. Lit.* 36 (1), 47–74.
- Engle, R., 2002. Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *J. Bus. Econ. Stat.* 20 (3), 339–350.
- Fang, L., Peress, J., 2009. Media coverage and the cross-section of stock returns. *J. Financ.* 64 (5), 2023–2052.
- Fassas, A.P., 2020. Risk aversion connectedness in developed and emerging equity markets before and after the COVID-19 pandemic. *Heliyon* 6 (12), e05715.
- Finucane, M.L., Alhakami, A., Slovic, P., Johnson, S.M., 2000. The affect heuristic in judgments of risks and benefits. *J. Behav. Decis. Mak.* 13 (1), 1–17.
- Fisher, K.L., Statman, M., 2000. Investor sentiment and stock returns. *Financ. Anal. J.* 56 (2), 16–23.
- Gao, Z., Ren, H., Zhang, B., 2020. Googling investor sentiment around the world. *J. Financ. Quant. Anal.* 55 (2), 549–580.
- Hamid, A., Heiden, M., 2015. Forecasting volatility with empirical similarity and Google trends. *J. Econ. Behav. Organ.* 117, 62–81.
- Hanoch, Y., 2002. "Neither an angel nor an ant": emotion as an aid to bounded rationality. *J. Econ. Psychol.* 23 (1), 1–25.
- Haron, O., Rizvi, S.A.R., 2020. Covid-19: media coverage and financial markets behavior—a sectoral inquiry. *J. Behav. Exp. Financ.* 27, 100343.
- Hartley, K., Vu, M.K., 2020. Fighting fake news in the COVID-19 era: policy insights from an equilibrium model. *Policy Sci.* 53 (4), 735–758.
- Helseth, M.A.E., Krakstad, S.O., Molnár, P., Norlin, K.-M., 2020. Can policy and financial risk predict stock markets? *J. Econ. Behav. Organ.* 176, 701–719.
- Hirshleifer, D., Jiang, D., DiGiovanni, Y.M., 2020. Mood beta and seasonalities in stock returns. *J. Financ. Econ.* 137 (1), 272–295.
- Huang, D., Jiang, F., Tu, J., Zhou, G., 2015. Investor sentiment aligned: a powerful predictor of stock returns. *Rev. Financ. Stud.* 28 (3), 791–837.
- Huynh, T.L., et al., 2020. The COVID-19 risk perception: a survey on socioeconomics and media attention. *Econ. Bull.* 40 (1), 758–764.
- Janiak, A., Machado, C., Turén, J., 2021. COVID-19 contagion, economic activity and business reopening protocols. *J. Econ. Behav. Organ.* 182, 264–284.
- Jiao, P., Veiga, A., Walther, A., 2020. Social media, news media and the stock market. *J. Econ. Behav. Organ.* 176, 63–90.
- Kaplanski, G., Levy, H., 2010. Sentiment and stock prices: the case of aviation disasters. *J. Financ. Econ.* 95 (2), 174–201.
- Keynes, J.M., 1937. The general theory of employment. *Q. J. Econ.* 51 (2), 209–223.
- Koop, G., Pesaran, M.H., Potter, S.M., 1996. Impulse response analysis in nonlinear multivariate models. *J. Econom.* 74 (1), 119–147.
- Korobilis, D., Yilmaz, K., 2018. Measuring dynamic connectedness with large Bayesian var models. Available at SSRN 3099725.
- Kroner, K., Ng, V., 1998. Modeling asymmetric movement of asset prices. *Rev. Financ. Stud.* 11, 844–871.
- Kroner, K.F., Sultan, J., 1993. Time-varying distributions and dynamic hedging with foreign currency futures. *J. Financ. Quant. Anal.* 535–551.
- Kumar, A., Lee, C.M., 2006. Retail investor sentiment and return comovements. *J. Financ.* 61 (5), 2451–2486.
- Kumari, J., Mahakud, J., 2015. Does investor sentiment predict the asset volatility? Evidence from emerging stock market india. *J. Behav. Exp. Financ.* 8, 25–39.
- de Las Heras-Pedrosa, C., Sánchez-Núñez, P., Peláez, J.I., 2020. Sentiment analysis and emotion understanding during the COVID-19 pandemic in Spain and its impact on digital ecosystems. *Int. J. Environ. Res. Public Health* 17 (15), 5542.
- Lee, C.M., Shleifer, A., Thaler, R.H., 1991. Investor sentiment and the closed-end fund puzzle. *J. Financ.* 46 (1), 75–109.
- Lerner, J.S., Small, D.A., Loewenstein, G., 2004. Heart strings and purse strings: carryover effects of emotions on economic decisions. *Psychol. Sci.* 15 (5), 337–341.
- Li, F., Zhang, H., Zheng, D., 2018. Seasonality in the cross section of stock returns: advanced markets versus emerging markets. *J. Empir. Financ.* 49, 263–281.
- Loewenstein, G., 2000. Emotions in economic theory and economic behavior. *Am. Econ. Rev.* 90 (2), 426–432.
- Loomes, G., Sugden, R., 1982. Regret theory: an alternative theory of rational choice under uncertainty. *Econ. J.* 92 (368), 805–824.
- Lucey, B.M., Dowling, M., 2005. The role of feelings in investor decision-making. *J. Econ. Surv.* 19 (2), 211–237.
- Lyócsa, Š., Baumöhl, E., Výrost, T., Molnár, P., 2020. Fear of the coronavirus and the stock markets. *Financ. Res. Lett.* 36, 101735.
- Lyócsa, Š., Molnár, P., 2020. Stock market oscillations during the corona crash: the role of fear and uncertainty. *Financ. Res. Lett.* 36, 101707.
- Marty, T., Vanstone, B., Hahn, T., 2020. News media analytics in finance: a survey. *Account. Financ.* 60 (2), 1385–1434.
- Mazumder, S., Saha, P., 2021. COVID-19: fear of pandemic and short-term ipo performance. *Financ. Res. Lett.* 101977.
- Mehra, R., Prescott, E.C., 1985. The equity premium: a puzzle. *J. Monet. Econ.* 15 (2), 145–161.
- Merton, R.C., 1980. On estimating the expected return on the market: an exploratory investigation. *J. Financ. Econ.* 8 (4), 323–361.
- Nasir, M.A., 2020. Forecasting inflation under uncertainty: the forgotten dog and the frisbee. *Technol. Forecast. Soc. Change* 158, 120172.
- Nasir, M.A., Morgan, J., 2018. Pre-brexite: the eu referendum as an illustration of the effects of uncertainty on the sterling exchange rate. *J. Econ. Stud.* 45 (5), 910–921.
- Peckham, R., 2013. Economies of contagion: financial crisis and pandemic. *Econ. Soc.* 42 (2), 226–248.
- Pesaran, H.H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. *Econ. Lett.* 58 (1), 17–29.
- Rehman, M.Z.U., ul Abidin, Z., Rizwan, F., Abbas, Z., Baig, S.A., 2017. How investor sentiments spillover from developed countries to developing countries? *Cogent Econ. Financ.* 5 (1), 1309096.
- Rognone, L., Hyde, S., Zhang, S.S., 2020. News sentiment in the cryptocurrency market: an empirical comparison with forex. *Int. Rev. Financ. Anal.* 69, 101462.
- Romer, P.M., 2000. Thinking and feeling. *Am. Econ. Rev.* 90 (2), 439–443.
- Salisu, A.A., Akanni, L.O., 2020. Constructing a global fear index for the COVID-19 pandemic. *Emerg. Mark. Financ. Trade* 56 (10), 2310–2331.
- Salisu, A.A., Vo, X.V., 2020. Predicting stock returns in the presence of COVID-19 pandemic: the role of health news. *Int. Rev. Financ. Anal.* 71, 101546.
- Schell, D., Wang, M., Huynh, T.L.D., 2020. This time is indeed different: a study on global market reactions to public health crisis. *J. Behav. Exp. Financ.* 27, 100349.
- Seven, Ü., Yılmaz, F., 2021. World equity markets and COVID-19: immediate response and recovery prospects. *Res. Int. Bus. Financ.* 56, 101349.
- Shaikh, I., Padhi, P., 2015. The implied volatility index: is 'investor fear gauge' or 'forward-looking'? *Borsa Istanbul Rev.* 15 (1), 44–52.
- Siganos, A., Vagenas-Nanos, E., Verwijmeren, P., 2014. Facebook's daily sentiment and international stock markets. *J. Econ. Behav. Organ.* 107, 730–743.
- Slovic, P., 1987. Perception of risk. *Science* 236 (4799), 280–285.
- Smales, L.A., 2014. News sentiment and the investor fear gauge. *Financ. Res. Lett.* 11 (2), 122–130.
- Smales, L.A., 2017. The importance of fear: investor sentiment and stock market returns. *Appl. Econ.* 49 (34), 3395–3421. doi:10.1080/00036846.2016.1259754.
- Smales, L.A., 2020. Investor attention and the response of US stock market sectors to the COVID-19 crisis. *Rev. Behav. Financ.* 13 (1), 20–23. doi:10.1108/RBF-06-2020-0138.
- Smales, L.A., 2021. Investor attention and global market returns during the COVID-19 crisis. *Int. Rev. Financ. Anal.* 73, 101616.
- Solomon, D.H., Soltes, E., Sosyura, D., 2014. Winners in the spotlight: media coverage of fund holdings as a driver of flows. *J. Financ. Econ.* 113 (1), 53–72.
- Spatt, C.S., 2020. A tale of two crises: the 2008 mortgage meltdown and the 2020 COVID-19 crisis. *Rev. Asset Pric. Stud.* 10 (4), 759–790.
- Stambaugh, R.F., Yu, J., Yuan, Y., 2012. The short of it: investor sentiment and anomalies. *J. Financ. Econ.* 104 (2), 288–302.
- Sun, Y., Bao, Q., Lu, Z., 2021. Coronavirus (COVID-19) outbreak, investor sentiment, and medical portfolio: evidence from China, Hong Kong, Korea, Japan, and US. *Pac. Basin Financ. J.* 65, 101463.
- Tausch, F., Zumbuehl, M., 2018. Stability of risk attitudes and media coverage of economic news. *J. Econ. Behav. Organ.* 150, 295–310.
- Tetlock, P.C., 2007. Giving content to investor sentiment: the role of media in the stock market. *J. Financ.* 62 (3), 1139–1168.

- Ullah, S., Akhtar, P., Zaefarian, G., 2018. Dealing with endogeneity bias: the generalized method of moments (gmm) for panel data. *Ind. Mark. Manag.* 71, 69–78.
- Ullah, S., Zaefarian, G., Ullah, F., 2020. How to use instrumental variables in addressing endogeneity? A step-by-step procedure for non-specialists.
- Valle-Cruz, D., Fernandez-Cortez, V., López-Chau, A., Sandoval-Almazán, R., 2021. Does twitter affect stock market decisions? financial sentiment analysis during pandemics: a comparative study of the h1n1 and the covid-19 periods. *Cognit. Comput.* 1–16.
- Wang, G.-J., Xie, C., Zhao, L., Jiang, Z.-Q., 2018. Volatility connectedness in the Chinese banking system: do state-owned commercial banks contribute more? *J. Int. Financ. Mark. Inst. Money* 57, 205–230.
- Wintoki, M.B., Linck, J.S., Netter, J.M., 2012. Endogeneity and the dynamics of internal corporate governance. *J. Financ. Econ.* 105 (3), 581–606.
- Xu, L., Chen, J., Zhang, X., Zhao, J., 2020. COVID-19, public attention and the stock market. *Account. Financ.*.
- You, J., Zhang, B., Zhang, L., 2018. Who captures the power of the pen? *Rev. Financ. Stud.* 31 (1), 43–96.
- Zajonc, R.B., 1980. Feeling and thinking: preferences need no inferences.. *Am. Psychol.* 35 (2), 151.
- Zaremba, A., 2019. Cross-sectional seasonalities in international government bond returns. *J. Bank. Financ.* 98, 80–94.