Feverish sentiment and global equity market during COVID-19 Pandemic

Abstract

This paper proposes a new approach to the estimation of investor sentiments and their implications for the global financial markets. Contextualising on the COVID-19 pandemic, we drew 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. Employing a Time-varying Parameter-Vector Auto-regression (TVP-VAR) model, the key findings indicate the total and net connectedness for the new index, entitled 'feverish sentiment' providing us insight into economies that send or receive the sentiment shocks. The construction of network structures indicates that the United Kingdom, China, the United States, and Germany became the epicentres of the sentimental shocks that were transmitted to the 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) on the onset of COVID-19. This is the first study of its kind to assess the 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 implications to mitigate the fear and panic during the Pandemic.

JEL Classification: G02; G21; D12; D14

Keywords: COVID-19; investor sentiment; feverish sentiment index; equity indices.

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 emphasising the importance of combating the fear. He argued that pessimism and fear completely paralyse the efforts to revive the economy. Decades later, in the times of COVID-19, the world has not only experienced a health crisis but also faced unprecedented economic and financial losses as the consequence of the pandemic. In the pandemic outbreak, loss of health is not the only thing that people fear. The investors and market participants are bound to be worried about the economic resiliency until this deadly virus lasts. To contain the spread of the virus or at least limit it, many governments adopted the policies of social distancing that enforced the temporary closure of business activities and restrictions of social events. The cease of the socio-economic activities accompanied by a health crisis sent a signal of the forthcoming recession that caused people to fear. Differing from the previous public health crisis, the COVID-19 is observed to have a more significant negative impact on stock markets (Schell et al., 2020). All major and developing stock markets fell as the COVID-19 health and financial contagion spread. Contextualising on the fear perspective that motivates this study, we examine the implications of fear for the financial markets, specifically, the fear associated with the COVID-19.

While the rational asset pricing represents a positive relationship between expected return and risk (Merton, 1980), the behavioural theory in finance puts an additional concept of predictive power on noise trader sentiment and its effect that persists in financial markets for tactical asset allocation (De Long et al., 1990; Fisher and Statman, 2000). The theoretical concept provides empirical evidence that investors' sentiment can influence the 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, the 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 in the behavioural finance literature is the focus on both the sentiments as well as their causal relationship between investor sentiment and stock returns. Notwithstanding the diversified approaches in estimating sentiment, the different economic context may appear to be a tedious exercise for researchers, though the ontological benefits of comprehensiveness of an empirical approach cannot be overstated. Concomitantly, adding to the existing strand of the empirical literature, our study aims to construct the cross-country sentiment indices in the specific context, especially the COVID-19 pandemic, and by aggregating different component indicators, including fake news, media coverage, and fear sentiment. Obviously, the current situation, particularly the COVID-19 outbreak, becomes a unique and unprecedented event, having voluminous actual experiments for investors' decision-making based on a wide range of information, namely fake news, media coverage, panic sentiment. Therefore, this paper will take into account the COVID-19 as the potential source for sentiment deviation, which might influence the financial markets.

This paper contributes to the literature in three main aspects. First, drawing on a wide range of sentiment indices regarding coronavirus such as media coverage, fake news, panic, sentiment, media hype, and infodemic, we constructed the *Feverish Sentiment Index* at the country-level by using Principal component analysis (PCA) with 17 new indicators. To validate our approach, we estimated the feverish sentiment connectedness of these largest economies in terms of static and dynamic spillovers. It is noteworthy that these aforementioned approaches help us not only in having the representative index to capture how the 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 found 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. It implies how our feverish index can predict the negative returns on the onset of the COVID-19 pandemic, which offers a new predictive factor for the global financial market. Third, we also calculated 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.

The paper proceeds in five sections: a critical review of literature on the linkage between investor sentiment and financial decision, the mechanism, and the contemporaneous study of COVID-19 sentiment is discussed in Section 2, the methodology is the Section 3, details on the dataset and 'feverish sentiment index' construction in Section 4, analysis and presentation of findings in Section 5, and conclusion and policy implications in Section 6.

2 Literature Review

2.1 Investor sentiment and financial decision

In this section, we critically reviewed the literature about how investors make financial decisions based on sentiments. Before going to be more specific, we acknowledge the basic theoretical framework in psychological economics which reveals that humans make their decisions based on emotion (Elster, 1998; Loewenstein, 2000), feelings 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 from the calculation of the weight of cost and benefit, representing the best risk-benefit trade-off. However, the economic human does not always behave rationally but his decision is impacted by emotions. For example, the role of regret and looking-back thinking on rational choice shaped the Regret Theory in economics (Loomes and Sugden, 1982). In the same vein, using the investors' emotion as well as the empirics, the study of Benartzi and Thaler (1995) explained the equity premium puzzle, which was first introduced by Mehra and Prescott (1985).

Recently, the studies focusing on investor sentiment's have contributed to the financial literature. More noticeably, Kaplanski and Levy (2010) found the linkage between anxiety as well as negative sentiment in aviation disaster and stock returns. It is an extreme event that influences the investors' behaviours because Lee et al. (1991) indicated that people are not fully rational under the anxiety feeling. Thus, when aviation incidents happen, investors react irrationally with the "bad news". However, their behaviour will become normal just after two days, which is called *"the reversal effects"*. Although we pick the extreme event (aeroplane crash) as the typical example, the usual and normal things could drive the investors' mood and sentiment, which impacts the financial markets. In particular, Hirshleifer et al. (2020) contribute empirical evidence that mood seasonality could predict stock returns, representing that higher mood parameter could subsequently earn higher returns. The same strand of literature confirms the stronger effect in advanced countries (Li et al., 2018) and it has valid results on government premium (Zaremba, 2019). Interestingly, the investors' sentiment can be found in Google household's searching terms as in Gao et al. (2020). They highlighted that investors 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 the investors' sentiment as shown by Cortés et al. (2016). Their study used the local sunshine to capture the feelings of investors, who change their risk tolerance and subjective judgment under the influence of weather conditions.

2.2 The theoretical mechanism of investor sentiment and financial decision making

The sentiments about the COVID-19 pandemic also have implications for the financial markets. On this aspect, Haroon and Rizvi (2020) and Sun et al. (2021) confirmed that the 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 explained the mechanism of how public health crises might influence investment decisions. We hypothesize the main statement that the large-scale COVID-19 pandemic provokes investors' sentiment, particularly a rise in fear and anxiety, which in turn negatively impacts stock prices. Accordingly, we observed that the media coverage (Ambros et al., 2020), which spreads the information about pandemic generating fear and anxiety, even conveying the fake news (Brigida and Pratt, 2017), increases the level of pessimistic attitudes towards the investment decisions (Da et al., 2015). We will 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, the discussion on social media, as well as the other information channels) will shape and drive the investors' decision. To be more specific, Marty et al. (2020) collected 276 research papers that have the common theme of news media and financial markets. This comprehensive study admits that media, news and information are inextricable properties of financial markets and investors' decision-making. However, interestingly, Fang and Peress (2009) claimed that the stock with lower media coverage earned a higher return after controlling a rigorous set of variables. The study by Solomon et al. (2014) reported that the investors are likely to use the media coverage information with the high association with chasing the past returns instead of facilitating the process of putting in new investment. Overall, the role of media coverage in the financial markets, particularly provoking irrational financial decision, is one of the ubiquitous features of investor sentiments. Although there is empirical evidence that media coverage could predict the stock returns on the onset of the COVID-19 pandemic (Haroon and Rizvi, 2020), their study only looks at the initial stage without any connectedness of news in different markets. Although the study of 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 the media information regarding this deadly disease or not. Thereafter, further investigation of the stock market will follow.

- **Fake news:** There is not much 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 time of releasing fake news. Fake news is becoming a concern that many economists are paying attention to; for example, the US Presidential election (Allcott and Gentzkow, 2017) or the COVID-19 pandemic (Hartley and Vu, 2020). 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 comparing 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 is intuitive to capture the investors' behaviours.

- **Panic and fear feelings:** From the psychological perspective, the media coverage of traumatic events, especially in disaster, generates increasing anxiety level (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 can be perceived through uncontrollable, catastrophic even fatal events. Undoubtedly, the COVID-19 pandemic has been causing fear, anxiety, and pessimistic feelings (even negative sentiment) among the people. The strand of the literature confirmed that people tend to take less risk when they think more about risk (Hanoch, 2002; Mehra and Prescott, 1985). Lerner et al. (2004) reported that economic decisions can be driven by fear and anger. Therefore, we decided to choose panic and fear as the relevant components to construct the Feverish Sentiment for the COVID-19 pandemic.

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

2.3 The COVID-19 impacts and financial markets in 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 equity assets in Table 1.

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 over the period 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 which are 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 analyzing 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 the method of variance risk premium 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 exhibit 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.
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.

After reviewing the literature on investor sentiment and financial markets during the COVID-19, we summarize our differences and novelty of research design, which are distinguished from the previous studies.

- While the majority of studies focus on the single country, regional area, or specific market (for example Bitcoin), this study approaches the largest scale of countries (17 largest economies). The only G-20 countries take into account Google searching terms whereas the cross-country analysis of 20 economies of six investor sentiment (by media news index, fake news, and so forth) touches six countries. Therefore, our study is the first study that employs all six indicators for investor sentiment covering the largest sample set of economies.

- It is noticeable that the studies mainly proxied the investor sentiment with search terms in Google. However, there is a limited number of papers that highlights the different sentimental indices from Ravenpack. Additionally, there is no study which aggregates these indicators by using Principal Component Analysis (PCA) to obtain the new index, entitled 'Feverish 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.

- This paper summarizes and describes the sending and receiving process of sentiment shocks during COVID-19 while the current empirical studies do not indicate this phenomenon. Furthermore, the draw of the network will define which country could be the epicentre for transmitting investor sentiment shocks at the global level.

- Finally, to our best knowledge, the current literature did not examine the hedging ratios to see how expensive the hedging cost is during the pandemic. Concomitantly, our study does not only contribute to the predictive factor on stock returns after accounting for the relevant factors but also examine whether reversal effects in behavioural finance exist or not. More importantly, apart from the stock returns as the extant literature did, our paper emphasizes the effects of investor sentiment on the volatility for having in-depth perspectives.

In the following section, we will explain our main methodology, dataset, how to construct the indices as well as the presentation of the impacts of investor sentiment on the equity market.

3 Methodologies

In this section, we overview the methodologies used to derive our empirical findings: the TVP-VAR model, the hedging analysis, and the model specifications.

3.1 Investor sentiment connectedness

To capture the Feverish COVID-19 Sentiment and to 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 Yılmaz (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 useful in the context of our analysis, i.e., with a short time horizon.

The model is given by:

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

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

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 $\nu_t \sim N(0, R_t)$ 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:

$$\phi^g_{ij,t}(H) = \frac{S^{-1}_{ii,t} \sum_{t=1}^{H-1} (e'_i A_t S_t e_j)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} (e'_i A_t S_t A'_t e_i)} \tag{3}$$

where H stands for the forecast horizon, S_{ii} is the 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:

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

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

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

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:

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

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

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

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

$$C^{g}_{i,t} = C^{g}_{i\to j,t}(H) - C^{g}_{i\leftarrow j,t}(H) \tag{8}$$

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

3.2 Hedging strategies with sentiment

To compute the hedging strategy analysis, we use the Dynamic Conditional Correlation (DCC) model of Engle (2002). This model allows us to estimate the conditional (co)variances, useful to implement 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$ dollar portfolio of market return and feverish at time t.

3.3 Model specifications of investor sentiment and equity returns

To verify the relationship between total Feverish connectedness sentiment and stock market return and volatility, we will extend the analysis further to regression. 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 Feverish, M_t is a matrix of control variables, while SMR_t and SMV_t are the common stock market return and volatility, respectively[1].

4 Data and 'Feverish index' construction

To measure the COVID-19 Feverish sentiment, 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 sentiment index for 17 countries: US, Germany, France, Italy, Spain, the UK, China, South Africa, Australia, Japan, India, Russia, South Korea, Turkey, Argentina, Brazil, Indonesia. These countries are listed as the G-20 largest economies in the world. 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].

[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 and 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.

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

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

To have one measure, for each country, for coronavirus-related panic, we build a Feverish Sentiment Index by using the Principal Component Analysis (PCA)[3]. This method allows us to isolate the common component to all indicators, then it helps us aggregate the existing information to a single composite index. All variables are standardized (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 changed the sign of the Coronavirus Sentiment Index, to ensure that all measures affect the index in the same direction. To build the Feverish Sentiment Indexes, we selected the first component, which explains for each of the countries, about 90% of the total variance. 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 calculated the daily changes for each index as follows:

$$\Delta Feverish_{i,t} = Feverish_{i,t} - Feverish_{i,t-1} \tag{14}$$

where i is the country while t denotes the day.

In Table 3 we report the summary statistics of Feverish 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 feverish variability, 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).

[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.

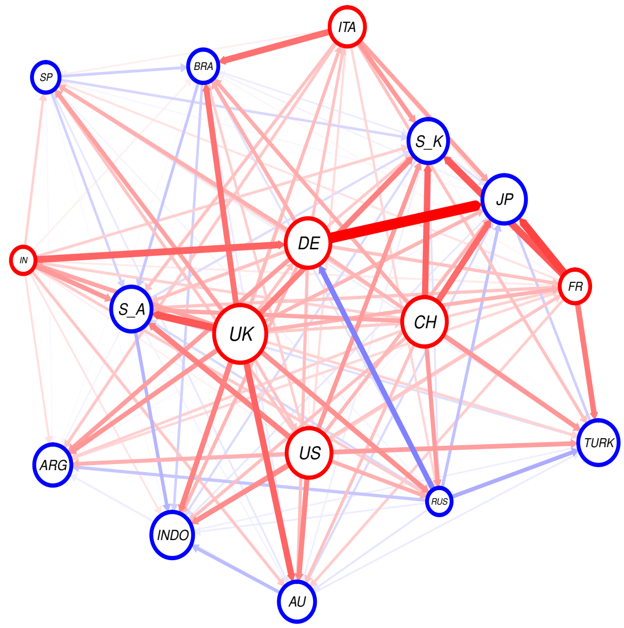
In contrast, the measure of from-connectedness changes more evenly, from 33.14% (Indonesia) to 83.29% (UK), highlighting how the feverish shocks emitted by a country can be small (11.28%) or strong (127.87%) but are relatively evenly distributed across countries. The table points out that the main transmitters of shock are the UK, China, US, and Germany, while Japan, Turkey, S. Africa and S. Korea are the main net receivers.

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.

Figure 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).

Figure 4 shows 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 most affected initially by COVID-19 are those that emit the most feverish. Particularly is the case of Spain, which contrary to the rest of the European countries, 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 Spain Ministry of Health in transmitting information about the pandemic. In fact, de Las Heras-Pedrosa et al. (2020) show 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 Figure 2 the dynamic of TCI. As we can see, the index varies during the period assuming values between 56% and 77%. The Figure shows a pronounced connection around mid-March, which coincides with the declaration of the global pandemic by the World Health Organization (March 11, 2020). Since March 2020, the connection is persistent, reflecting the serious epidemiological situation. Since late summer, the index shows a gradual decrease, recording its lowest value (about 56%). In fact, after some government responses to the COVID-19, the panic feelings decrease and slightly increase 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), iii) COVID-19 variants (September - to date).

Figure 2. Total Feverish Spillover

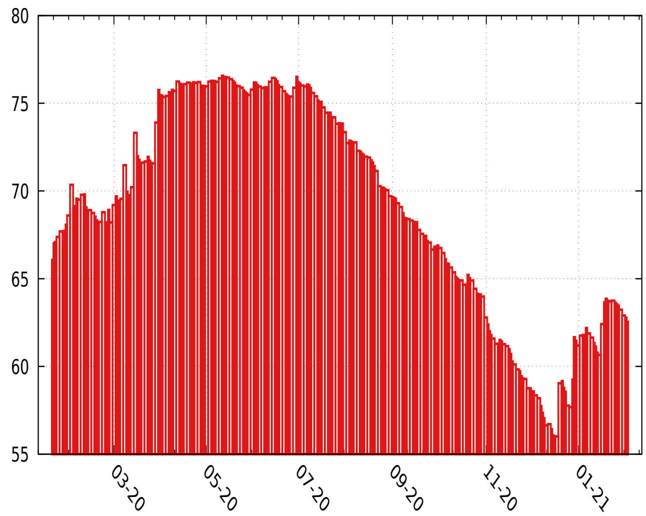
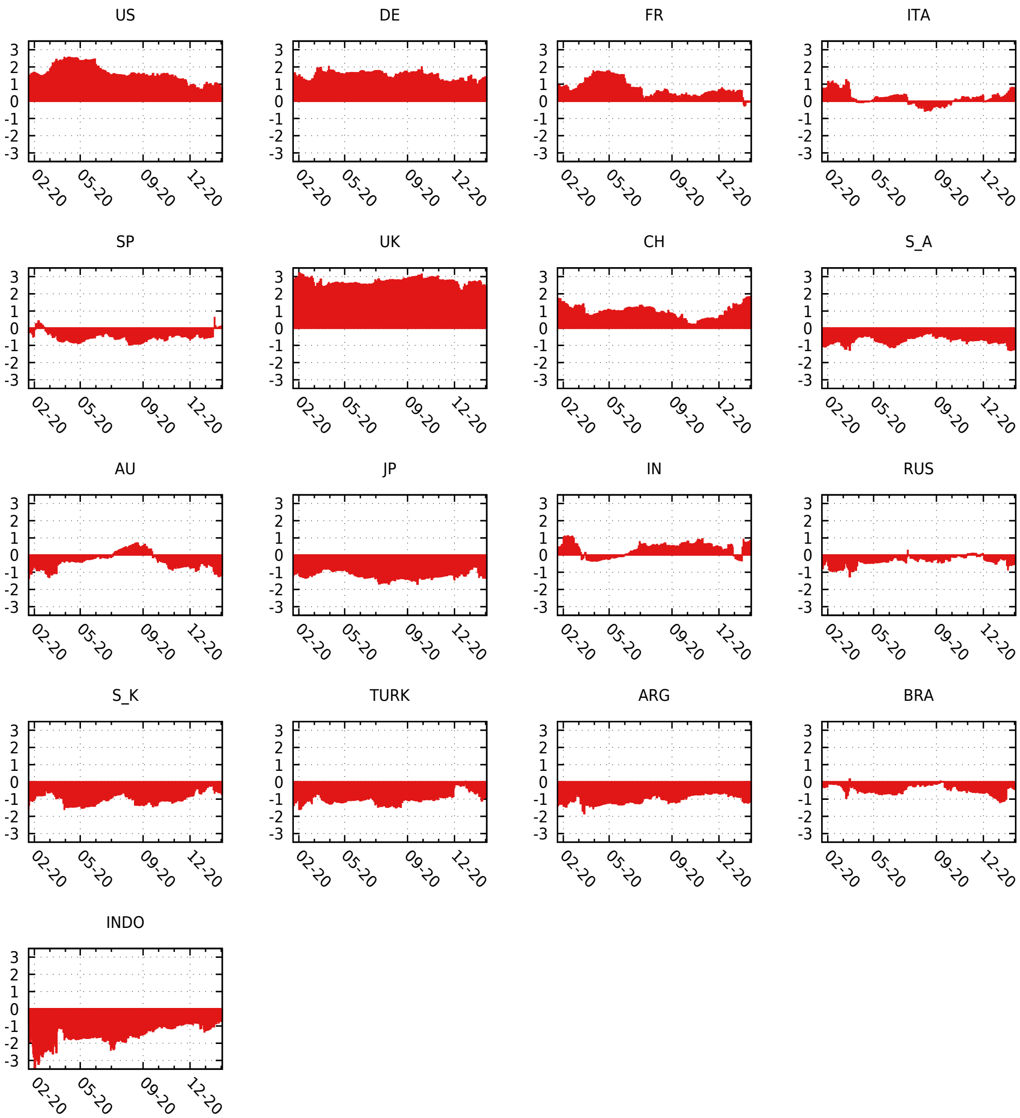


Figure 3 displays the net-spillovers Feverish dynamics. Positive values indicate when a country is a net-transmitting, while negative values mean that the country is a net-recipient from others. The figure shows how the US, Germany, France, UK, China assumes a net-transmitting role. On the other hand, 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 most affected initially by the pandemic are those that emit more feverish (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 Yılmaz, 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 towards pandemic like the Coronavirus. This led to higher levels of transmission of negative shocks. Reduced confidence with increased panic increased the fallout from bad news.

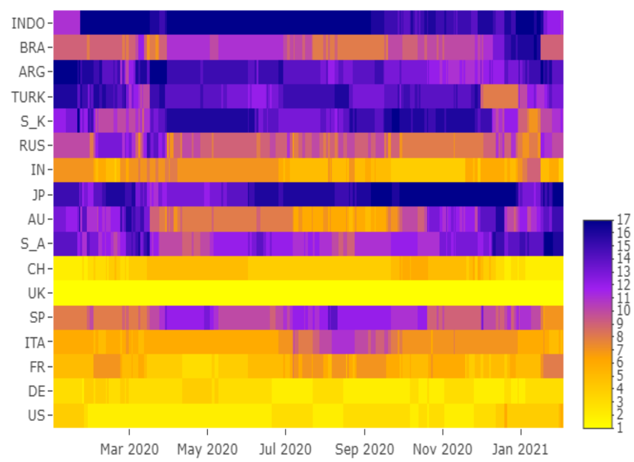
further investigate the dynamic of net feverish, following Wang et al. (2018), in Figure 4 we plot the ranking based on net-connectedness of 17 countries. The colours of the heatmap range from yellow to blue,

Figure 3. NET Feverish Spillover



indicating the ranking from the first (largest feverish emitter) to the last (largest feverish receiver). As we can see, the United Kingdom, China, the United States, and Germany are the epicentres of sentiment shocks spillover over all the period. This result highlights the key role played by big economies in the transmission of sentiment worldwide (Rehman et al., 2017; Audrino and Tetereva, 2019; Croitorov et al., 2020).

Figure 4. Feverish Ranking



5.2 Hedging strategies

In this section, through the hedge ratio, we estimate the optimal portfolio weights for risk management. For this purpose, we used the DCC model (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 index). We used the hedge ratio to calculate optimal weights for FTSE and Feverish investments that minimise risk without reducing expected return.

Table 5 shows the summary statistics of optimal portfolio weights. In general, we observed 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 FTSE and France Feverish. Moreover, the hedge effectiveness statistics are almost all statistically significant at the 1% level (except for Australia). This result 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, the two indices indicate on average the same optimal portfolio composition.

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

Optimal weights	$w_{ji,y}$	**Std.Dev.**	**5%**	**95%**	**HE**
FTSE/US Feverish	0.83	0.1	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	0.1	0.7	0.95	0.35***
FTSE/SP Feverish	0.88	0.1	0.6	0.96	0.35***
FTSE/UK Feverish	0.85	0.11	0.6	0.97	0.36***
FTSE/CH Feverish	0.9	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	0.1	0.6	0.97	0.18
FTSE/JP Feverish	0.88	0.1	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	0.9	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.

In Figure 5, we plotted the time-varying portfolio weights for the FTSE/Feverish and Market/VIX portfolios, respectively. 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.

5.3 Feverish and 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 response of the stock market to the TCI feverish index. Our main hypothesis is that the total network connection measure is informative for stock market performance. Table 7 presents 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

Figure 5. Time-varying portfolio weights

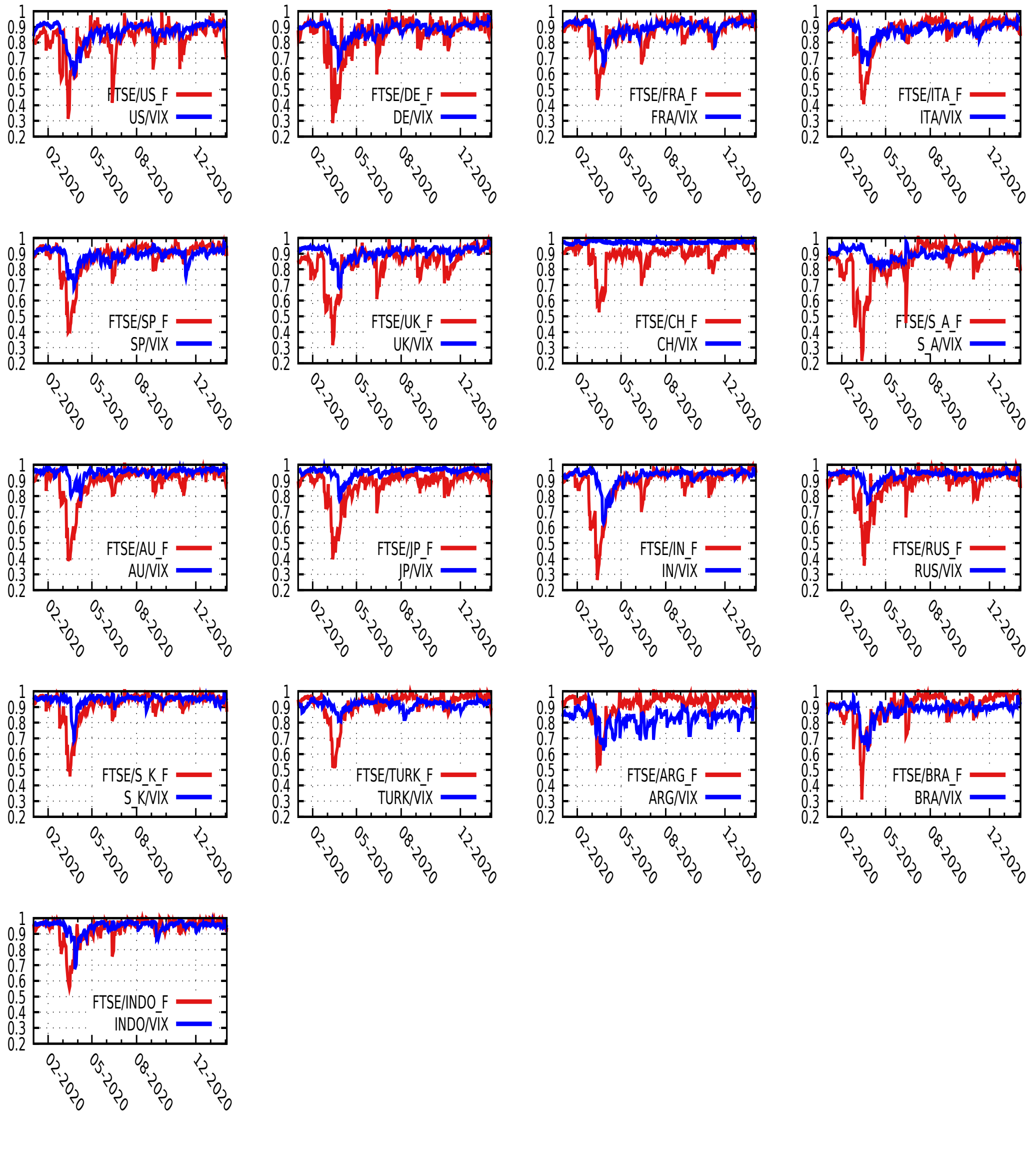


Table 6. Optimal Portfolio weights (Market/VIX) summary statistics

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	0.99	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	0.9	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.

et al., 2021), that has focused on the key role of sentiment index in financial markets dynamics. These results suggest that investors should consider the implications of feverish shocks in their portfolio choices.

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)**
ΔTotal Feverish Connectedness	-0.417***	-0.364***	-0.430***	-0.378***	-0.435***	-0.371***	-0.441***	-0.379***
	[-0.128]	[-0.119]	[-0.129]	[-0.12]	[-0.131]	[-0.125]	[-0.129]	[-0.121]
ΔTotal Feverish Connectedness$_{(t-1)}$			0.118	0.124	0.126	0.116	0.105	0.098
			[-0.129]	[-0.12]	[0.131]	[-0.121]	[-0.131]	[-0.121]
ΔTotal Feverish Connectedness$_{(t-2)}$					-0.06	0.07	-0.027	0.096
					[-0.131]	[-0.123]	[-0.131]	[-0.122]
ΔTotal Feverish Connectedness$_{(t-3)}$							-0.289**	-0.243**
							[-0.13]	[-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. 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.

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 volaility**							
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**	**Model (7)**	**Model (8)**
ΔTotal Feverish Connectedness	0.301***	0.235***	0.288***	0.224**	0.298***	0.224***	0.298***	0.223***
	[-0.102]	[-0.095]	[-0.1]	[-0.092]	[-0.1]	[-0.093]	[-0.1]	[-0.093]
ΔTotal Feverish Connectedness$_{(t-1)}$			0.118	0.035	0.03	0.034	0.032	0.031
			[-0.129]	[-0.091]	[-0.101]	[-0.092]	[-0.101]	[-0.093]
ΔTotal Feverish Connectedness$_{(t-2)}$					0.133	0.001	0.131	0.012
					[-0.1]	[-0.062]	[-0.101]	[-0.094]
ΔTotal Feverish Connectedness$_{(t-3)}$							0.02	-0.042
							[-0.01]	[-0.093]
Constant	0.010***	0.011***	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***
	[0]	[0]	[-0.001]	[0]	[0]	[0]	[0]	[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.

When it comes to the "reversal effects", we found 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 8 models without any changes in signs. However, the one-period lagged term observed the positive coefficients. Furthermore, the two-period lagged terms have negative coefficients. It implies that the 'feverish sentiment' shows the 'reversal effects'. Although these coefficients (one-period lag and two-period lag) are insignificant, we also observed the 'reversal effect' where the investors tend to overreact to the panic and fear feelings, proxied by the feverish sentiment. Afterwards, the investors recovered their feelings by reacting to the opposite side as compared to what they did before.

Our study is also consistent with the literature that suggests that the investor sentiment, particularly fear and uncertainty, provokes volatility (Brown, 1999; Kumar and Lee, 2006; Siganos et al., 2014; Kumari and Mahakud, 2015; Behrendt and Schmidt, 2018; Nasir and Morgan, 2018). 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.

5.4 Robustness check

The findings are verified by applying a Panel Pooled model. Specifically, we analysed the relationship between each country's fear index and its benchmark national stock market[4]. The choice to apply a Panel Pooled model is based on the F-test[5], which suggests that we adopted the Pooled model at the expense of the Panel Fixed or Random effect. Table 9 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.

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 etc. By using TVP-VAR to examine the sentiment spillover across the 17 largest economies, we also explored the network structure of emissions and reception of fear shocks in underlying countries. Furthermore, in this study, we also investigated the hedging strategies where the effectiveness was examined for investing in the stock markets during the COVID-19 pandemic. Finally, to validate the feverish

[4] Please see Table A.1 in Annex, 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 9. Robustness check

Variables	Market Returns		Market Volatility	
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**
Δ Feverish	-0.027***	-0.018***	0.010***	0.004*
	[-0.002]	[-0.003]	[-0.002]	[-0.002]
Constant	0.001	0.001	0.012***	0.012***
	[-0.002]	[-0.002]	[0]	[-0.002]
Control variables	NO	YES	NO	YES
Observations	4,845	4,845	4,845	4,845
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. 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 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

sentiment, we analysed the predictive power of this index for the stock market returns and volatility. Unlike some of the previous studies, the subject treatise focused on the role of investor sentiment by drawing on an extended set of components in the largest 17 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.

The empirical findings lead us to draw inferences and can be summarized in the following points. First and most importantly, we conclude on the persistence of the predictive power of 'Feverish Sentiment' in explaining the stock returns and volatility. It implies that the higher the 'Feverish 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 the methodological aspect by developing a novel approach to the estimation of investor sentiment but also provides 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 it specifically focuses 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 drawn to the conclusion that the investors are likely to overreact to the 'bad news' and readjust the sentiment and resulting stance in the following days. Third, the investor sentiment in 17 countries exhibit strong connectedness, most prominently, the United States, the United Kingdom, Germany, China, Italy, and France turned out to be the epicentres of sentiment shocks 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 also provides evidence that the hedging cost is quite very low when the pandemic is contained successfully at the beginning of the outbreak like in Australia. On the contrary, hedging losses its effectiveness once the crisis exacerbates and the public health crisis intensifies.

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 future research and for those interested to explore the investor's sentiments to the prospect of economic recovery Post-COVID-19 pandemic.

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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		