Constructing a global fear index for the COVID-19 pandemic

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Abstract

This paper offers two main innovations. First, we construct a global fear index (GFI) for the COVID-19 pandemic to support economic, financial and policy analyses in this area. Second, we demonstrate the application of the index to stock return predictability using OECD data. The panel data predictability results reveal the significance of the index as a good predictor of stock returns during the pandemic. Also, we find that accounting for "asymmetry" effect and macro (common) factors improves the forecast performance of the GFI-based predictive model for stock returns. With regular updates and improvements of the index, several empirical analyses can be extended to other macroeconomic fundamentals in future research.

Keywords: COVID-19; Global Fear Index; OECD Stock prices; Panel data analyses; Predictability

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1. Introduction

The interest to construct a global fear index for the novel coronavirus (COVID-19) is motivated by two factors. First, while viruses generally can infect people, the rate of infection of COVID-19 is unprecedented as it is found to be more infectious than other coronaviruses such as SARS [Severe Acute Respiratory Syndrome] and MERS-CoV [Middle East Respiratory Syndrome - Coronavirus] (WHO, 2020). Second, only COVID-19 outbreak among the class of coronaviruses was declared a global pandemic in less than three months of its emergence and therefore its impact on the global economy is more likely to be severe than other coronaviruses. The increasing number of reported cases and deaths associated with the COVID-19 pandemic has engendered palpable fear among investors due to its threat to the health and livelihood of the people as well as the global economic activity.[1] In fact, the action to lockdown the global economy was informed by the rising cases of infected persons and related deaths, therefore, using these numbers to construct the level of fear associated with the novel virus is justified. This is the main contribution of the study and there is none to the best of our knowledge that has utilized the same parameters to analyse the panic associated with the pandemic.

Information about the fear index is important for a number of reasons. First, policy makers are confronted with the choice between containing the virus and sustaining the economy. Information about the extent of the panic associated with COVID-19 and its impact on the economy (say financial market and real economic activity) will offer useful insights into how much sacrifice the economy will have to endure to contain the virus. The use of our index to predict macroeconomic indices is also demonstrated in this study with special focus on stock returns. [2] Thus, the fear index can also help in analysing how much of distortions in the market can be attributed to the pandemic.

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[1] Between February and March 2020 when the virus spread much rapidly and was declared a global pandemic (See WHO, 2020), the US stock prices fell by 32 percent, the UK's by 27.9 percent and the Italy's by 39.3 percent. Emerging stock markets have also not been spared with the stock prices of Brazil declining by 40.5 percent, Russia's by 24.2 percent and China's by 10.1 percent. Some analysts have attributed the fall in stock prices to investors' panic, as many investors sold out of fear. See also World Economic Forum (https://www.weforum.org/agenda/2020/03/stock-market-volatility-coronavirus/).

[2] A number studies have also investigated the connection between the COVID-19 pandemic and the energy sector (see Apergis & Apergis, 2020; Fu & Shen, 2020; Gil-Alana & Monge, 2020; Liu, Wang & Lee, 2020; Narayan, 2020; and Qin, Zhang, & Su, 2020).

Second, in addition to the impact assessment of the panic on the economy, we also demonstrate how the fear index can be used to project the future path of relevant macroeconomic series such as stock returns. This information is crucial for determining how long it will take the impact of this fear to fizzle e out over time. Investors seeking to maximize returns will find this information useful particularly in terms of portfolio diversification and hedging strategy.

Additionally, analysing the effect of fear on stock market performance is not new in the literature and some of them have relied on the use of media generated panic (see Westerhoff, 2004; Gradinaru, 2014; Economou et al., 2018; Badshah et al., 2018; Narayan, 2019; Haroon & Rizvi, 2020). We also argue that the number of COVID-19 reported cases and deaths constitute an integral part of media report during the pandemic and therefore we hypothesize that the level of panic will increase as these numbers increase and by extension stock returns will decline. This is well demonstrated under the section for descriptive analyses of our proposed COVID-19 fear index. An alternative measure of fear is the one that relies on the implied volatility index (see Shaik and Padhi, 2015; Bouri et al., 2018) and prominent among them is the one introduced by the Chicago Board Options Exchange (CBOE) in 1993 and further modified in 2003 by Shaik and Padhi (2015). Unlike the CBOE index which is limited to the US rather than global and only captures uncertainty due to the stock market (Bouri et al., 2018), one of the strengths of our proposed fear index lies in its coverage as all the countries and by extension regions and territories in the world are considered in the construction of the index. This makes it possible to link the panic to any relevant macroeconomic fundamental or market (financial market, real estate market, commodity market or foreign exchange market, among others) and by extension its response to the panic can easily be evaluated using the newly proposed index. In other words, while the original fear index and its current extensions have played important role in explaining and predicting changes in stock market performance, their inability to capture the recent source of fear associated with COVID-19 suggests that their application may be inefficient. Thus, this study contributes to the literature by developing and applying an alternative fear index that incorporates the COVID-19 parameters which have remained the barometer for actions/decisions taken at all levels, household, business and government.

In order to promote wider acceptability of the newly constructed fear index, we assess its predictive power in the forecast of the OECD stock markets (as developed markets) and BRICS stock markets (as emerging markets)[3]. Apparently, OECD countries have the most developed stock markets in the world and BRICS have the most advanced emerging stock markets (see Mensi et al. 2017). Relevant studies on the predictability of stocks with fear index include Bouri et al. (2018) and Zhu et al. (2019), with both finding that fear index is a good predictor of stock market performance. Our study however differs from Bouri et al. (2018) and Zhu et al. (2019) as it applies the newly developed index with COVID-19 effect. It also covers a group of developed and emerging markets as against Bouri et al. (2018) which only cover emerging markets of BRICS and Zhu et al. (2019), focusing on the US stock market.

Another contribution of this study is in the area of methodology drawn from panel data forecasting techniques. This is rather different from the GARCH-MIDAS method employed in Zhu et al. (2019) and the Bayesian Graphical Structural VAR model utilised in Bouri et al. (2018). Our choice model is considered suitable based on its ability to deal with short time period occasioned by the period between the outbreak of the COVID-19 pandemic and the period of writing this paper. In addition, the use of panel data forecast rather than pooling of individual forecasts of different markets with small T would tend to generate better results (see Baltagi, 2013; Westerlund and Narayan, 2016; Westerlund et al. (2016); for some discussions on panel data forecasting with short T).[4] For completeness and in the spirit of Westerlund et al. (2016), we allow for common factors such as global stock market volatility and commodity price volatility in the predictability of stock returns. The computational advantages of accounting for these factors are well documented in Westerlund et al. (2016). Notwithstanding the short T dimension of our panel data, we also offer some forecast evaluations to complement the predictability results. For robustness, we also compare the forecast performance of our proposed global fear index (GFI) for the COVID-19 pandemic with the existing fear index that is limited to the stock market. Overall, we find that

[3] Notably, OECD denotes Organization for Economic Cooperation and Development while BRICS is the acronym for Brazil, Russia, India, China and South Africa.

[4] A number of studies (see Narayan and Liu, 2018 for a review) have suggested the use of GARCH models for forecasting stock returns, we however differ based on the time series dimension required for GARCH modelling and forecasting. The forecasts from GARCH models are found to be less optimal when confronted with small samples (see Shumway & Stoffer, 2000; Ng & Lam, 2006) and the same problem is evident even with panel GARCH models (see Pakel et al., 2011).

the proposed index offers better predictability than the benchmark model (historical average or constant returns model). Similarly, an extended GFI-based model that accounts for "asymmetry" effect and macro factors further enhances the predictability of the index. Finally, the GFI is a better predictor of fear/panic in the stock market than the existing fear index. Our results offer meaningful generalizations about the behavior of the GFI given the coverage of the data scope (OECD and the BRICS emerging economies) which is a reasonable proxy for the global stock markets.

The remainder of the paper is structured as follows: Section 2 provides the procedures for the construction of fear index. Section 3 presents the trend and description of the fear index. Section 4 shows the empirical application of the global fear index in stock market predictability. It also presents and discusses the results. Section 5 concludes the paper.

2. Construction of the global fear index

The World Health Organisation (WHO) on March 11, 2020, noting the number of reported cases for preceding two weeks, declared COVID-19 as a global health pandemic.[5] The tragic health consequences of COVID-19 and the expectation of increase in number of cases pose some economic uncertainties and disruptions that came at a significant cost to the global economy. The global fear index (GFI) seeks to measure daily concerns and emotions on the spread and severity of COVID-19 since the pandemic declaration. Excessive fear could have significant implications on investment sentiments and decisions, and as such affecting prices such as stocks and oil prices. Relying on the official reports of COVID-19 cases and deaths globally[6], the GFI is a composite index of two factors; Reported Cases and Reported Deaths, on a scale of zero to 100, respectively indicating absence and presence of extreme fear/panic. We considered the incubation period expectation and daily reported cases and deaths in constructing the index. By incubation period expectation, we meant the time-expectations between catching the virus and emergence of symptoms of the disease (WHO, 2020).

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[5] See (WHO, 2020): "WHO Director-General's opening remarks at the media briefing on COVID-19 - 11 March 2020" at: https://www.who.int/dg/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020.

[6] Daily data on official COVID-19 cases and deaths, based on reports from health authorities worldwide, is collected from the European Centre for Disease Prevention and Control (ECDC) Epidemic Intelligence and it is available up-to-date at https://www.ecdc.europa.eu/en/geographical-distribution-2019-ncov-cases

i. Reported Cases Index (RCI)

It measures how far expectations from reported cases in a 14-day period ahead veered from the present reported case. Most estimates of the incubation period for COVID-19 range from 1-14 days (WHO, 2020). Therefore, the choice of 14-day expectations represents the highest number of incubation days as defined by the WHO. The RCI is computed as:

$$RCI_t = \left(\frac{\sum_i^N c_{i,t}}{\sum_i^N \left(c_{i,t} + c_{i,t-14} \right)} \right) \times 100\,; \qquad [1]$$

$$i = 1,2,\ldots,N;\ \ t = 1,2,\ldots,T.$$

where RCI_t denotes the Reported Cases Index computed for period t; $\sum_i^N c_{i,t}$ is the total number of COVID-19 reported cases at time t for all the countries in the world, $i = 1,2,\ldots,N$ where N is the total number of cross-sections captured in the index; $c_{i,t-14}$ is the number of COVID-19 reported cases for each cross-section at the beginning of the incubation period, which is represented as the preceding 14th day. The multiplication by 100 provides the index on a scale of 0 to 100 with the highest value representing the highest level of fear during the pandemic and decreases as the index tends towards 0.

ii. Reported Death Index (RDI)

Similar to the Reported Cases Index, the Reported Death Index mirrors the reported cases by relating the number of daily reported deaths to expectations from reported number of deaths in a 14-day period ahead in line with the assumption for RCI based on WHO declaration. The index is computed as:

$$RDI_t = \left(\frac{\sum_i^N d_{i,t}}{\sum_i^N \left(d_{i,t} + d_{i,t-14} \right)} \right) \times 100 \qquad [2]$$

where RDI_t denotes the Report Death Index; $\sum_i^N d_{i,t}$ is the total number of COVID-19 reported deaths at time t for all countries, denoted as N; $d_{i,t-14}$ is the number of COVID-19 reported deaths at the beginning of the incubation period, $t-14$. The index is also given on a scale between 0 and 100 where the highest value signifies the highest level of fear due to the pandemic.

iii. Global Fear (Composite) Index [GFI]

The construct of the GFI pulls the two indexes together with equal weights assigned to obtain the composite index. The composite index (GFI_t) is given as:

$$GFI_t = \left[0.5\left(RCI_t + RDI_t\right)\right] \qquad [3]$$

As expressed in [3], the global fear index utilizes all the available data for both reported cases and deaths and therefore may be more representative in capturing the severity of fear due to the pandemic. Like the RCI and RDI, the global fear index is also given on a scale of 0 to100 where 50 signifies moderate level of fear and increases as the index tends towards 100.

2.1 Descriptive statistics using the constructed GFI data[7]

We render some descriptive statistics for the constructed GFI data obtained and thereafter evaluate its relationship with the stock returns of OECD and BRICS countries[8]. The start and end periods for data collection used in constructing the GFI is informed by the data availability and start period of COVID-19. However, to avoid the problem of zero weights, especially in the number of deaths[9] declared as well as to account for the incubation period, the start period is selected as 14-days after the recorded number of deaths exceeded10. This date which forms the start period of our analysis coincides with the 10th of February, 2020.

[7] We hope to publish the indices in the Data-in-Brief journal in order to make it publicly accessible. In the meantime, the data can be made available on request.

[8] The Organisation for Economic Co-operation and Development (OECD) countries comprise Austria, Australia, Belgium, Mexico, Canada, Chile, Czech Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, South Korea, Latvia, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom and United States. The BRICS are Brazil, Russia, India, China and South Africa. The daily data of stock price indices for each of the countries was collected from the Federal Reserve Bank of St. Louis database.

[9] Although the first case of COVID-19 was reported on 31 December 2019. The first COVID-19 related death was reported on 11 January 2020. The preceding days are intermitted with both new cases and deaths reported as well as absence of occurrence. However, since 20 January 2020, there have been consistent reports on new cases and death globally. Hence and in order to account for the incubation period, 14-days after is selected as the start period for the index computation and this coincides with February 11, 2020.

The summary of the mean, standard deviation and relative standard deviation is presented in Table 1. Unlike the coefficient of variation that is commonly used, which divides the standard deviation by the mean, the relative standard deviation is the absolute value of the coefficient of variation. If the mean is negative, the coefficient of variation will be negative while the relative standard deviation used here will always be positive. Hence, the preference for the latter for evaluating the series variability. The average stock returns across most of the countries considered are negative over the period under consideration. This indicates an overall average decline in stock returns across the countries. On the stock return variability, the relative standard deviation statistics show that Latvia records the highest stock return variability over the period under consideration while Spain has the least variability. However, for the pool of countries, the average stock returns is given as -0.2639 percent with a relative standard deviation of 5.29 percent. Overall, the rate of change in GFI is more volatile compared to the variation in the stock returns across all the countries, as measured by the relative standard deviation given as 15.12 percent.

Table 1: Summary statistics

Note: Like the stock returns, the GFI* is computed as the rate of change in the index in order to allow for easy comparison between the two indices. The R.Std is the relative standard deviation statistic. It slightly differs from the commonly used coefficient of variation which is computed as the standard deviation divided by the mean. Here, we divide the standard deviation by the absolute value of the mean expressed in percentage (%). If the mean is negative, the coefficient of variation will be negative while the relative standard deviation used here will always be positive.

Country	Mean	Std. Deviation	R.Std (%)	Country	Mean	Std. Deviation	R.Std (%)
Stock Returns							
Australia	-0.4266	3.3653	*7.89*	Japan	-0.2848	2.6480	*9.30*
Austria	-0.6015	4.0952	*6.81*	Korea	-0.1980	2.9415	*14.86*
Belgium	-0.5005	3.5606	*7.11*	Latvia	-0.0817	3.1555	*38.63*
Brazil	2.5175	24.0264	*9.54*	Mexico	-0.3495	2.4087	*6.89*
Canada	-0.3259	4.1869	*12.85*	Netherland	-0.3302	3.0817	*9.33*
Chile	-0.2537	3.7907	*14.94*	New Zealand	-0.2081	2.8820	*13.85*
China	-0.0425	1.4419	*33.89*	Norway	-0.2706	2.9077	*10.75*
Czech	-0.4303	2.7726	*6.44*	Poland	-0.3932	3.1957	*8.13*
Denmark	-0.1459	2.1631	*14.83*	Portugal	-0.3739	2.8490	*7.62*
Finland	-0.3633	2.9905	*8.23*	Russia	-0.2579	2.9266	*11.35*
France	-0.4900	3.4540	*7.05*	Slovakia	-0.1227	0.9885	*8.06*
Germany	-0.3875	3.4557	*8.92*	Slovenia	-0.3516	2.4901	*7.08*
Greece	-0.6478	4.8145	*7.43*	South Africa	-0.2172	3.3776	*15.55*
Hungary	-0.4212	3.3666	*7.99*	Spain	-0.6323	3.4680	*5.48*
Iceland	-0.2043	2.2822	*11.17*	Sweden	-0.2918	2.9643	*10.16*
India	-0.3483	3.8551	*11.07*	Switzerland	-0.2441	2.6636	*10.91*
Ireland	-0.4142	3.3819	*8.17*	Turkey	-0.2810	2.5230	*8.98*
Israel	-0.3281	2.8955	*8.82*	UK	-0.4154	3.1669	*7.62*
Italy	-0.5821	3.9523	*6.79*	USA	-0.3294	4.3710	*13.27*
Australia	-0.4266	3.3653	*7.89*				
Panel	-0.2639	4.9892	5.29	GFI*	5.7626	38.1087	15.12

Following the descriptive analysis of the series, we conduct some scenario analyses of the relationship between the GFI and the stock returns across OECD and BRICS countries. We evaluate the behaviour of stock returns to when the GFI increases or declines. Table 2 summarises the average stock returns across the thirty-eight countries, at the average change in GFI, as well as below and above its average. The reported average values in column II of the Table represent the average stock returns across all the countries at GFI values above the overall average change of 8.49 as earlier depicted in the lower pane of Table 1, while column III reports stock returns when the GFI is below the average change. It is evident from the analyses that as the change in GFI increases, stock returns decline across most of the countries considered. On the other hand, when the change in GFI declines, stock returns across the countries are above their averages.

Table 2: Scenario analyses

Note: the average values reported in each column indicate the average stock returns for each of the countries for three different scenarios over the period considered. The first scenario is the Mean which depicts the average stock returns at the overall average change in the global fear index (GFI). Above indicates the average returns when the changes in GFI is above its overall average, while Below connote the average stock returns when the GFI changes below its average value.

Country	Mean	Above	Below	Country	Mean	Above	Below
Column	**I**	**II**	**III**		**I**	**II**	**III**
Stock Prices							
Australia	-0.4266	-0.3575	-0.4542	Japan	-0.2848	0.0410	-0.4152
Austria	-0.6015	-0.7188	-0.5545	Korea	-0.1980	-0.0162	-0.2707
Belgium	-0.5005	-0.6387	-0.4453	Latvia	-0.0817	0.1746	-0.1842
Brazil	2.5175	10.1602	-0.5396	Mexico	-0.3495	-0.2398	-0.3933
Canada	-0.3259	-1.1296	-0.0045	Netherlands	-0.3302	-0.5486	-0.2428
Chile	-0.2537	-0.5240	-0.1456	New Zealand	-0.2081	0.3266	-0.4220
China	-0.0425	-0.0434	-0.0422	Norway	-0.2706	-0.6942	-0.1011
Czech	-0.4303	-0.4086	-0.4390	Poland	-0.3932	-0.9810	-0.1580
Denmark	-0.1459	-0.1848	-0.1303	Portugal	-0.3739	-0.5384	-0.3081
Finland	-0.3633	-0.5222	-0.2998	Russia	-0.2579	-0.5535	-0.1397
France	-0.4900	-0.4378	-0.5108	Slovakia	-0.1227	0.2734	-0.2811
Germany	-0.3875	-0.3943	-0.3848	Slovenia	-0.3516	-0.0268	-0.4815
Greece	-0.6478	-1.2160	-0.4205	South Africa	-0.2172	-0.3044	-0.1823
Hungary	-0.4212	-0.6983	-0.3103	Spain	-0.6323	-0.6523	-0.6243
Iceland	-0.2043	-0.2943	-0.1683	Sweden	-0.2918	-0.4162	-0.2420
India	-0.3483	0.1291	-0.5393	Switzerland	-0.2441	-0.4840	-0.1481
Ireland	-0.4142	-0.3903	-0.4237	Turkey	-0.2810	-0.0349	-0.3794
Israel	-0.3281	-0.6339	-0.2058	UK	-0.4154	-0.6906	-0.3054
Italy	-0.5821	-0.4276	-0.6439	USA	-0.3294	-0.5893	-0.2254

In line with the standard practice in the literature, we also render some graphical illustrations of the GFI and stock prices across the countries considered (see Fig. 1). We used the level series for both indices to be able to trace any potential or existing co-movement between the two of them.

The graphical representations highlight the co-movements between our constructed GFI index and stock prices for the selected countries. The graphs show an inverse relationship between stock prices and the fear index, which is similar to findings from the scenario analyses.

3.1 Additional descriptive analysis

In addition to the global fear index computed and discussed above, we extend the analysis to evaluate the index across COVID-19 most affected countries across the globe. We concentrate mainly on countries with the highest reported cases. Table 3 summarises the cumulative reported cases for the ten countries with the highest reported cases as well as their average weekly GFI since the announcement of COVID-19 as a pandemic by the WHO. The last column labelled "Average" in Table 3 indicates the average GF index across the period considered between March 11, when COVID-19 was declared pandemic and April 30, 2020, selected based on most recent and latest available data on COVID-19.

A number of thought-provoking information emanate from the weekly distribution of the index and the analysis rendered. Recall that the construction GF index takes into consideration incubation expectations, which implies the reported cases and deaths 14 days earlier which marks the beginning of incubation period, by implication, when the number of current daily cases and/or deaths reported falls below the reported cases and deaths 14 days earlier, the current GF index tends to be lower than the previous index.

The analysis summarised in Table 3 shows that while the United States has the highest number of cumulative reported cases and deaths, its GF index between March 11 and April 30 ranks behind Russia (87.5). Lastly, China has the lowest GF index among the top-ten COVID-19 cases reporting countries over the period considered. This is expected as the number of reported cases and deaths has been declining for China in the post-pandemic declaration of COVID-19 by the WHO, while other the other countries witnessed increase in daily reported COVID-19 cases.

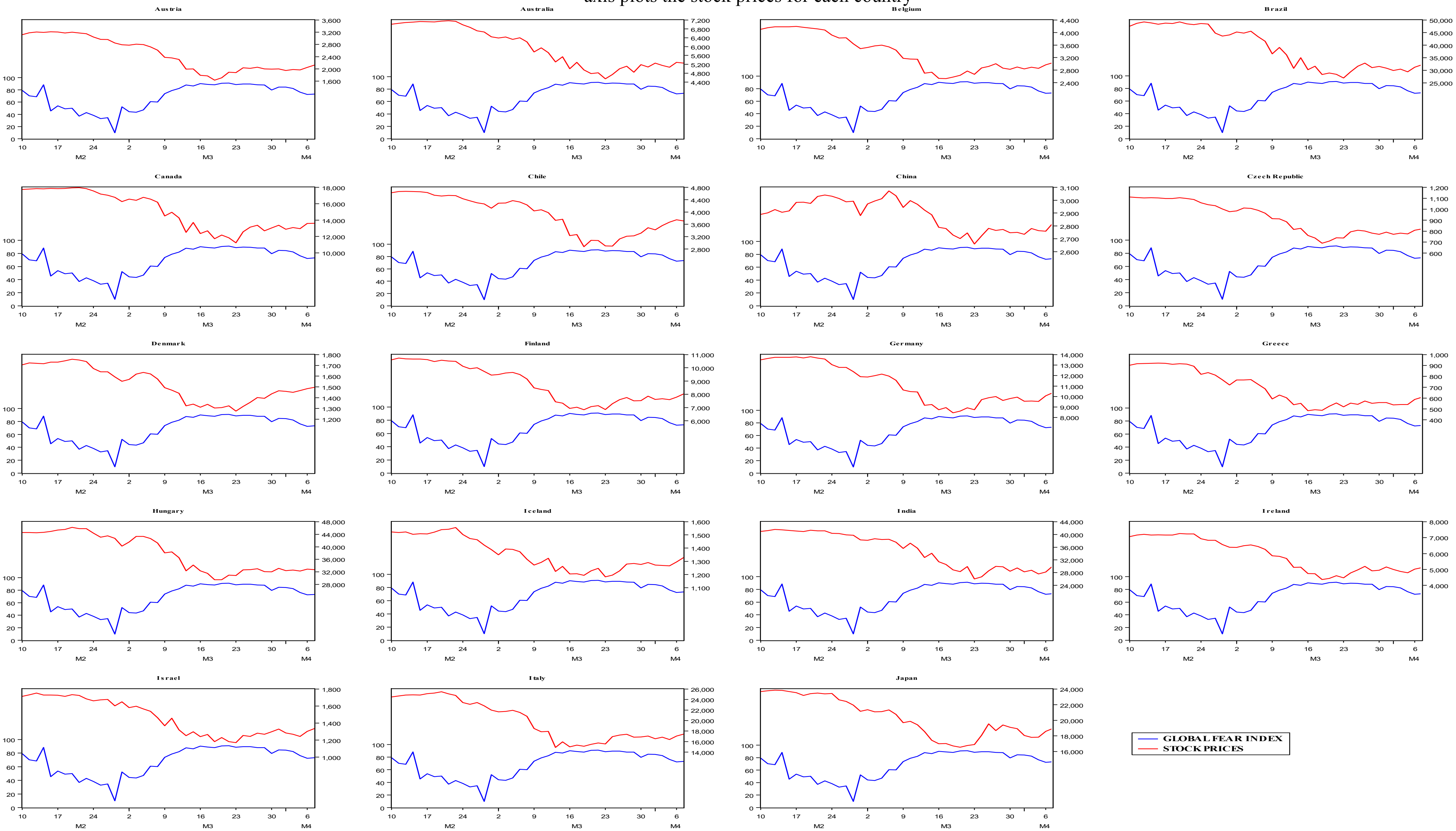
Table 3: Fear Index for Top Ten Cases Reporting Countries

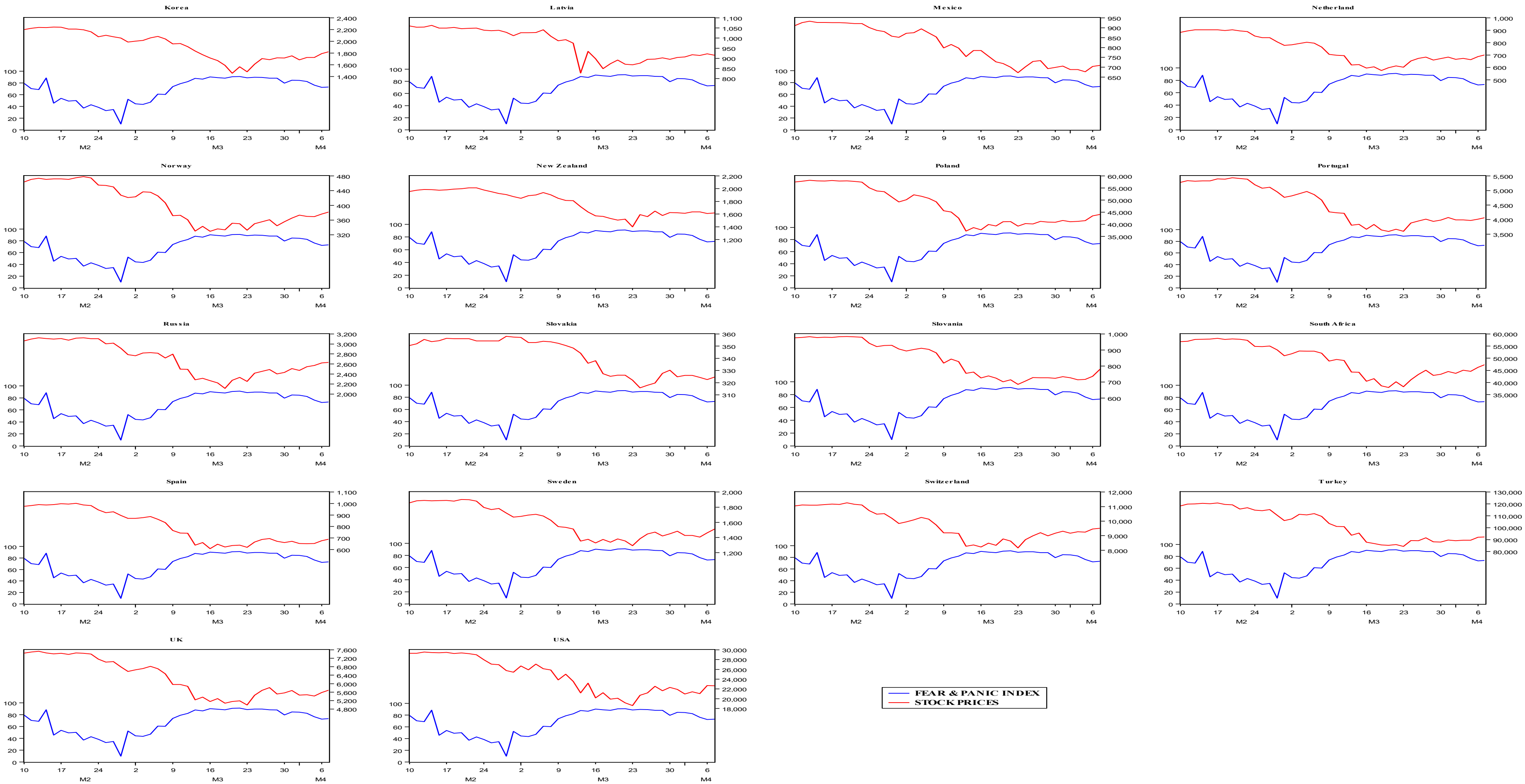
Note: Average indicates the average GF index across the eight-weeks period considered between March 11 and April 30, 2020. W1 indicates the first two weeks that follow the announcement by WHO that COVID-19 is a global pandemic; W2, W3 and W4 are respectively the successive two-weeks periods that followed W1; Cases indicate the cumulative number of reported cases for each of the country; while deaths is the total number of deaths recorded as at 30th April 2020.

	COVID-19 Reported		**Fear Index**				
Country	**Cases**	**Deaths**	**W1**	**W2**	**W3**	**W4**	**Average**
United States	1,039,909	60,966	92.81	92.68	66.69	47.88	77.37
Spain	211,291	24,090	97.87	81.20	38.50	27.84	64.64
Italy	203,591	27,682	90.89	61.70	41.78	40.73	60.54
United Kingdom	165,221	22,473	96.48	91.67	66.77	45.30	77.22
Germany	159,119	6,288	96.56	82.97	52.81	40.18	70.87
France	128,442	24,087	95.38	83.02	50.94	31.64	68.54
Turkey	117,589	3,081	-	95.43	71.63	46.04	72.55
Russia	99,399	972	94.08	92.91	88.14	77.11	87.50
Iran	93,657	5,957	80.71	59.75	39.89	40.45	56.98
China	83,944	4,637	25.17	46.45	34.34	7.97	31.85

Fig. 1: Trends in Stock prices and the Global Fear Index (GFI) for the COVID-19 pandemic

Note: Each graph plots stock prices against the fear index; the left axis depicts the global fear index while the right axis plots the stock prices for each country




Korea
Latvia
Mexico
Netherland
Norway
New Zealand
Poland
Portugal
Russia
Slovakia
Slovania
South Africa
Spain
Sweden
Switzerland
Turkey
UK
USA
FEAR & PANIC INDEX
STOCK PRICES

3. Some empirical applications of the global fear index for COVID-19

The evident relationship between the constructed index and stock prices provides a strong motivation to probe further into the predictive power of the formulated index. Thus, we construct a predictive model for the stock returns of the OECD and BRICS stock markets where the GFI is used as a predictor and its predictive power is comparatively evaluated with other plausible forecast models for stock returns. The considered stock markets are good representations of the global stock market and by extension results obtained offer reasonable generalizations for other stock markets (Christou & Gupta, 2019). In addition, pooling the stock markets helps to circumvent the problem of insufficient observations that may plague country-specific analyses.[10] Given the short time span of the available data for COVID-19, we employ homogenous panel data procedures[11].

Consequently, the predictive models constructed in this paper for the return predictability are structured in panel form. We begin our analyses with the historical average (constant return) model which ignores any potential predictor of stock and is specified as:[12]

$$r_{it} = \alpha + e_{it};\ t = 1,2,3,\ldots,T;\ i = 1,2,3,\ldots,N\ ; \qquad [2]$$

where r_{it} denotes stock returns computed as log returns; α is a constant parameter; and e_{it} is the error term. Premised on the Investor Recognition hypothesis (see Merton, 1987), we construct a single predictor model using the Global Fear index as a regressor. The Investor Recognition hypothesis, by assuming incomplete market information, suggests that investors are not aware of all securities in a market and therefore they prefer to choose familiar stocks in constructing portfolios (for relevant literature see Bodnaruk & Ostberg, 2009; Bank et al., 2011; Joseph et al., 2011; Da et al., 2011; Preis et al., 2013; Aouadi et al. 2013; Jacobs & Hillert, 2016; Adachi et al. 2017; Zhu & Jiang, 2018). The single predictor model is given as:

[10] Some of the advantages of using panel data over cross-section as well as time series data in estimation and testing has been well documented in Hsiao (2003), Baltagi (2008a,b) and Baltagi (2013), among others.
[11] See Baltagi (2013) and papers cited therein for computational advantages of using homogenous panel data approach when forecasting with short T.
[12] This is not the first study to examine stock return predictability using historical average as the baseline model (see Bannigidadmath & Narayan, 2015; Narayan & Gupta, 2015; Phan et al., 2015; Narayan et al., 2016; Devpura et al., 2018; Salisu et al., 2019a,b,c,d,&e). What is however new is the use of panel data (i.e. pooling of countries) to achieve the same objective albeit with a different predictor.

$$r_{it} = \alpha + \sum_{k=1}^{5} \delta_k gfi_{i,t-k} + e_{it} \qquad [3]$$

where gfi_{it} denotes the constructed Global Fear index expressed in natural logs, a measure of investors' emotion and attention. Note that we allow for up to five lags given the underlying frequency for our analysis which is daily and therefore the proximity of the data points can be exploited to account for more dynamics in the predictive model. Thus, in addition to the behavior of the individual parameters, testing for the overall sign and significance of these parameters jointly is crucial to arrive at a distinct conclusion on the predictability of GFI on stock returns. The testable null hypothesis of no predictability can therefore be expressed as $H_0 : \sum_{k=1}^{5} \hat{\delta} = 0$ against the alternative hypothesis of $H_0 : \sum_{k=1}^{5} \hat{\delta} \neq 0$. One important feature of daily stock returns is that they tend to exhibit day-of-the-week effect (see Zhang et al., 2017 for a review of the literature). To account for this feature and at the same time prevent parameter proliferation, we follow a three-step procedure. First, we regress the return series on dummy variables constructed for the five days of the week, that is, $r_{it} = \theta + \sum_{j=1}^{4} \gamma_j D_{jit} + \upsilon_{it}$ where $D_j = 1$ for each j and zero otherwise. Note that $j = 1,2,3,4$ respectively denotes Monday, Tuesday, Wednesday and Thursday while Friday is the reference day. The second step requires determining the day-of-the-week adjusted returns (r_{it}^d) which can be estimated as $r_{it}^d = r_{it} - \left(\hat{\theta} + \sum_{j=1}^{4} \hat{\gamma}_j D_{jit} \right)$ or simply $r_{it}^d = \hat{\upsilon}_{it}$. The third step involves regressing the latter on the GFI predictor series, that is,

$$r_{it}^d = \alpha + \sum_{k=1}^{5} \delta_k gfi_{i,t-k} + e_{it}. \qquad [4]$$

We also test for possible asymmetry in the GFI series where positive and negative changes in the index are assumed to have distinct effects on stock returns. This idea is prominent when dealing with the predictability of stock returns (see for example, Narayan & Gupta, 2015; Narayan, 2019; Salisu et al., 2019d). Hypothetically, a decline in the GFI (negative asymmetry) is expected to impact positively on stock returns, while on the other hand, positive asymmetry, which implies increase in the COVID-19 GFI is expected to have a negative impact. The predictive model can be specified as $r_{it} = \alpha + \beta D_{1,it-1} + \rho \Delta gfi_{it-1} + \psi \Delta gfi^{*}_{it-1} + e_{it}$ where $D_{1,it} = 1$ if $\Delta gfi_{it} > 0$ and zero otherwise; $\Delta gfi^{*}_{it} = D_{1,it} * \Delta gfi_{it}$ [13]. Therefore, the impact of positive changes in GFI on stock returns can be estimated as $(\rho + \psi)$ (i.e. evaluated at $D_{1,it} = 1$) while it is ρ for negative asymmetry (i.e. evaluated at $D_{1,it} = 0$). The differential slope coefficient between the two asymmetries is measured as ψ and its statistical significance implies the presence of asymmetry, otherwise, the positive and negative "asymmetry" effects are assumed identical.

For completeness, we also account for some other important factors that can influence stock returns (see also Bannigidadmath and Narayan, 2015; Narayan et al., 2016; Devpura et al., 2018; Salisu et al., 2019a,b,c,d,&e). The Arbitrage Pricing Theory offers the theoretical basis for incorporating systemic or macroeconomic risks in the predictability of stock returns. On this basis, we extend the single predictor model as:

$$r_{it} = \alpha + \sum_{k=1}^{5} \delta_k gfi_{i,t-k} + Z_{it}{}' \phi + e_{it} \qquad [5]$$

where $Z_{it}{}'$ is $(1 \times K)$ vector of additional (macroeconomic) variables, and ϕ is $(K \times 1)$ vector of parameters for the additional K regressors.[14] Again, to circumvent having so many parameters in the predictive model and in the spirit of Westerlund et al. (2016), we adopt the same procedure followed in the computation of the day-of-the-week-adjusted stock returns. In other words, we regress the return series on the selected macro variables, that is, $r_{it} = \vartheta + Z_{it}{}' \phi + u_{it}$ and thereafter, the macro-adjusted returns series is regressed on the GFI predictor. Ideally, the choice of the return series will be determined by the relative forecast performance of r_{it} and r^{d}_{it} from the single-predictor case.

[13] This approach is similar in spirit to that of Shin et al. (2014), however, we favour the one used in this paper due to its simplicity and easy replication of results.
[14] This idea is also technically motivated by the work of Westerlund et al. (2016) which provides some technical details and computational procedures on how to incorporate common factors in the predictability of stock returns. The approach followed in the estimation of this model is similar in spirit to that of Westerlund et al. (2016). One major attraction to this approach is that it does not require integration property of the common factors used in the predictive model.

Finally, the forecast evaluation of the predictor is rendered for both in-sample and out-of-sample periods. Since there is no formal procedure of splitting the data for this purpose[15], we consider 75% and 25% split for the in-sample and out-of-sample periods respectively. This choice is informed by the need to have sufficient observations that will allow for meaningful regression analyses from which the forecasts will be obtained. For robustness purpose, we also consider multiple out-of-sample forecast horizons - 5-day, 10-day and 15-day ahead forecasts. We adopt two pair-wise forecast measures, namely Campbell-Thompson (CT, 2008) and Clark and West (CW, 2007) tests for the forecast evaluation. These measures are particularly useful when dealing with nested predictive models. The (CT, 2008) test is specified as:

$$CT = 1 - (M\hat{S}E_u \ / \ M\hat{S}E_r) \qquad [6]$$

where $M\hat{S}E_u$ is the mean squared error obtained from the unrestricted model, in this case the GFI-based model (equation [3]) and $M\hat{S}E_r$ is the mean squared error obtained from the restricted model (for example, the historical average or constant return model, equation [2]). In this case, equation [3] outperforms equation [2] if $CT > 0$ and vice versa. The CW (2007) test on the other hand is used to establish the statistical significance of the forecast evaluation procedure in the CT (2008). For a forecast horizon h, the CW (2007) test is specified as:

$$\hat{f}_{t+h} = M\hat{S}E_r - (M\hat{S}E_u - adj) \qquad [7]$$

where $\hat{f}_{t+h}$ is the forecast horizon; $M\hat{S}E_r$ and $M\hat{S}E_u$ respectively are the squared errors of restricted and unrestricted predictive models and they are respectively computed as: $P^{-1}\sum\left(r_{i,t+h} - \hat{r}_{ri,t+h}\right)^2$ and $P^{-1}\sum\left(r_{i,t+h} - \hat{r}_{ui,t+h}\right)^2$. The term *adj* is included to adjust for noise in the unrestricted model and it is defined by $P^{-1}\sum\left(\hat{r}_{ri,t+h} - \hat{r}_{ui,t+h}\right)^2$; P is the amount of predictions that the averages are computed. Lastly, the statistical significance of regressing $\hat{f}_{t+h}$ on a constant confirms the CT test.

[15] Notwithstanding, researchers have adopted 50:50; 25:75 and 75:25 splits for the in-sample and out-of-sample periods where the first argument in each split is for the in-sample while the second argument is for the out-of-sample (see also Narayan & Gupta, 2015). However, the first and second options (i.e. 50:50 and 25:75) may be used if the period is sufficiently large to accommodate regression analyses while the last option (i.e. 75:25) may be preferred for a small sample.

4.1 The results of the empirical application of COVID-19 Global Fear Index

We demonstrate the empirical application of the global fear index (GFI) by evaluating its predictability of stock returns across OECD and BRICS countries. We estimate a single factor predictive model with the GFI as the predictor, and compared the forecast performance with the historical average model. We further extend the estimation to account for day-of-the-week effects by adjusting the stock returns series for possible day-of-the-week anomalies. The predictability results are summarized in Table 4 and the estimated coefficients show that the predictors are correctly signed and statistically significant. The joint coefficient of the GFI lags, after controlling for the day-of-the-week effects, is also negative and significant. By implication, the estimated predictabilities confirm that the COVID-19 GFI poses a negative impact on stock returns. More importantly, we find that accounting for other salient features of the stock return series such as the day-of-the-week effect improves the predictability results. This is in line with the extended predictive model previously specified in equation [4] which assumes a role for these effects in the predictability of stock returns. This outcome also validates our findings from the descriptive statistics rendered in the immediate preceding section where an inverse relationship between the two series is also observed.

Table 4: GFI Predictability of Stock Return

Note**:** Model 1 is the COVID-19 GFI predictability model of stock returns while in Model 2, the stock returns series is adjusted for the day-of-the-week effect; GFI_{t-j} is the sum of the lags of coefficients of global fear index where *t* period and *j* is the number of lags and it equals 1 to 5; The sign and significance of joint coefficient is evaluated using the Wald test for coefficient restriction; Standard errors are presented in parentheses while the t-statistics are in squared brackets. The asterisk ** & * indicate statistical significance at 5% and 10% levels respectively.

Coefficients	Model 1	Model 2
GFI_{t-j}	-1.3954*	-1.5378**
	(0.7636)	(0.7563)
	[-1.8275]	[-2.0332]

The forecast evaluation of the predictive models using both the in-sample and out-of-sample data periods is also carried out and the results are summarized in Table 5. The in-sample predictability evaluation, as described in the methodology section, is performed using 75% of the entire data sample for the in-sample forecasts and the balance for the out-of-sample forecasts. For robustness, we consider multiple out-of-sample forecast horizons using 5-day, 10-day and 15-day ahead forecasts. For the predictability models evaluated, first we compare the performance of the single predictor with the GFI model (Model 1) with that of the historical average. Second, we compare the predictability performance between the model that accounts for day-of-the-week effects (i.e. Model 2) and the model that ignores the same (i.e. Model 1). The criteria for interpreting the forecast measures have been previously discussed. Based on the two forecast measures, the obtained results, both in-sample and out-of-sample forecast horizons, indicate that: (i) the GFI predictability model for stock returns outperforms the historical average, and (ii) the stock return model that adjusts for day-of-the-week effects also outperforms the model that ignores the same. Thus, controlling for the day-of-the-week effects is imperative in stock return predictability (see also Boubaker, Essaddam, Nguyen, & Saadi, 2017; Zhang, Lai, & Lin, 2017).

Table 5: In-sample and out-of-sample forecast evaluation

Note: Model 1 is the COVID-19 GFI predictability model of stock returns while in Model 2, the stock returns series is adjusted for the day-of-the-week effect. The C-T stat denotes the Campbell-Thompson (2008) test while the C-W test is the Clark and West (2007) test. ***, ** & * indicate statistical significance at 1%, 5% & 10% levels respectively.

Forecast evaluation	**Model 1 Vs Historical average**	**Model 2 Vs Model 1**
In-sample		
CT statistic	0.1973	0.0484
CW test	0.8157***	1.5148***
	(0.2849)	(0.2977)
h=1		
CT statistic	0.2063	0.0414
CW test	0.7917***	1.0436***
	(0.2037)	(0.2183)
h=2		
CT statistic	0.2221	0.0369
CW test	1.0945***	0.8128***
	(0.1721)	(0.1664)
h=3		
CT statistic	0.2244	0.0084
CW test	1.0796***	0.2185
	(0.1472)	(0.1501)

We further extend the analysis by accounting for the impact of asymmetries in the GFI predictability of stock returns. Hypothetically, it is expected that the decline in the COVID-19 GFI (negative asymmetry) would have a positive impact on stock returns, while the reverse would be the case for positive asymmetry. The results are summarized in Table 6 as Model 3 and we find that positive asymmetry has a negative sign and statistically significant, while on the other hand the negative asymmetry has a positive coefficient as hypothesized. In other words, any increase in the COVID-19 GFI will impact stock returns negatively, while a decline in the index improves stock returns across the countries under consideration, on average. The statistical significance of the differential slope coefficient between the two asymmetries is reported in the lower pane of the

Table and its statistical significance further implies the presence of asymmetry. Consequently, positive and negative changes in the GFI will not have identical impact on stock returns.

Furthermore, the predictability estimates after controlling for macroeconomic variables show that the estimated Wald test for the joint coefficient of the five-period lagged GFI is negative and statistically significant conforming with the a priori expectation.

Table 6: Macroeconomic-adjusted and asymmetric stock returns predictability results

Note: Model 3 is the asymmetry GFI predictability model and Model 4 controls for macroeconomic volatility effects. GFI is the sum of the coefficients on the five-lag global fear index; GFI^P and GFI^N are respectively the positive and negative asymmetries of GFI. The asymmetry test reported is the coefficient of the differential slope coefficient and its statistical significance implies the presence of asymmetry. The reported standard error and t-stats, respectively in parentheses and squared brackets, are computed using the Wald test for coefficient restriction. The asterisks ***, ** and * respectively indicate statistical significance at 1%, 5% and 10% levels.

Coefficients	Model 3	Model 4
GFI		-1.4992***
		(0.7738)
		[-1.9375]
GFI^P	-0.7999**	
	(0.4003)	
	[-1.9982]	
GFI^N	0.3096	
	(0.1327)	
	[4.7081]	
Asymmetry test	-1.1096**	

The evaluation of forecast performance for Models 3 and 4 is summarized in Table 7. The two models are respectively compared with the historical average and the baseline GFI predictability models. The results show positive CT statistics and statistically significant CW test statistics for both the in-sample and out-of-sample periods across the multiple forecast horizons [i.e. at 5-day, 10-day and 15-day ahead forecasts]. These results further imply that: (i) accounting for asymmetry in the forecast analyses is encourages as its forecasting power outperforms the model that ignores the same including the historical average, and (ii) controlling for macroeconomic variables such as stock and commodity markets volatilities, improves the forecasting performance of stock returns predictability.

Table 7: Forecast evaluation for macroeconomic-adjusted and asymmetric stock returns models

Note**:** Model 3 is the asymmetry GFI predictability model and Model 4 controls for macroeconomic volatility effects. The C-T stat denotes the Campbell-Thompson (2008) test while the C-W test is the Clark and West (2007) test. ***, ** & * indicate statistical significance at 1%, 5% & 10% levels respectively.

Forecast evaluation	**Model 3 Vs Historical average**	**Model 3 Vs Model 1**	**Model 4 Vs Historical average**	**Model 4 Vs Model 1**
In-sample				
C-T stat	0.1629	0.0411	0.2481	0.0633
C-W test	1.9597***	1.4239***	2.5867***	1.9682***
	(0.3468)	(0.3489)	(0.4442)	(0.3668)
h =1				
C-T stat	0.1634	0.0536	0.2456	0.0496
C-W test	1.6763***	1.0233***	1.8682***	1.2154***
	(0.2644)	(0.2535)	(0.3123)	(0.2643)
h= 2				
C-T stat	0.1643	0.0691	0.2562	0.0439
C-W test	1.5167***	0.7442***	1.8437***	0.9509***
	(0.2155)	(0.1952)	(0.2526)	(0.2026)
h = 3				
C-T stat	0.1413	0.0967	0.2147	-0.0125
C-W test	0.7906***	0.0808***	0.6798***	-1381
	(0.1977)	(0.1760)	(0.2536)	(0.2077)

4.2 Additional results

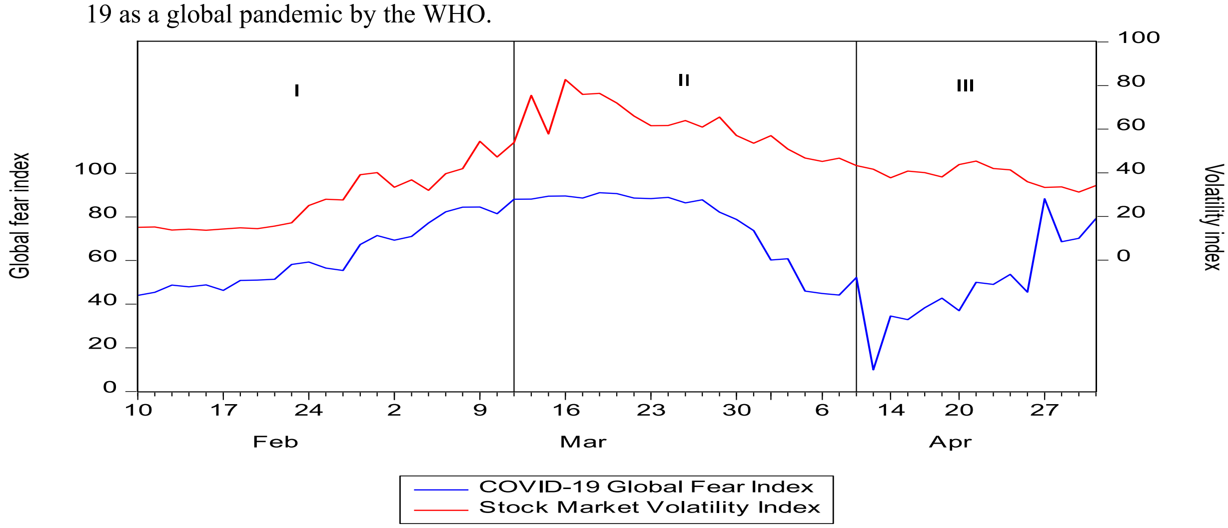
The Chicago Board Options Exchange (CBOE) Volatility Index (VIX) has long been recognized in the empirical literature as a prominent index to measure fear sentiment in global stock markets[16]. Although, similar measures are available and have also been applied in empirical studies, the VIX and its different components are adjudged as leading barometers of investor sentiment and market volatility relating to listed options[17]. One of such alternative measures is the Equity Market Volatility (EMV) which was created based on the text-counts of newspaper articles including several keywords related to the economy and stock market volatility[18]. These alternative volatility indexes are mostly constructed using single or selected country information and are mostly available in monthly frequencies. However, the VIX has also been generally found to understate true volatility, and its estimation errors are found to be considerably enlarged during volatile markets and turbulence periods (Allechi & Niamkey, 1994; Chow, Jiang, & Li, 2014;

[16] See Balcilar & Demirer (2015); Psaradellis & Sermpinis (2016); Taylor (2019); Wang (2019); Zhu, Liu, Wang, Wei, & Wei (2019) and Yun (2020).
[17] See http://www.cboe.com/products/vix-index-volatility/volatility-indexes
[18] Zhu, Liu, Wang, Wei, & Wei (2019) applied the GARCH-MIDAS method to quantify the in-sample explanatory and out-of-sample predictive powers of the EMV and VIX in the US stock markets. The empirical results show that VIX has larger in-sample impacts on US stock market volatility than EMV trackers. However, the out-of-sample volatility predictive performances of EMV trackers are generally superior to VIX across different US stock indices and prediction time horizons.

Bongiovanni, De Vincentiis, & Isaia, 2016). One of such periods could be the current global COVID-19 pandemic with impacts that cut across every facet of human and economic existence. Therefore, our additional analyses involved evaluating the stock return predictability of the constructed Global Fear Index versus the predictability performance of the VIX. Figure 2 depicts the graphical highlight of the co-movements between COVID-19 GFI and the VIX. For illustration purposes, we partitioned the graph into three phases; I, II and III (see Fig. 2). The graphs show a general positive co-movement between the two indexes in the first phase which is the period before the declaration of COVID-19 as a global pandemic by the WHO (correlation coefficient between the two for this period is about 94%). However, the VIX reflects a smooth decline in the second phase than the GFI. Overall the co-movement between GFI and VIX is positive indicated by the correlation coefficient of about 61%.

Fig. 2: Co-movements between Global Fear Index (GFI) for COVID-19 and CBOE Volatility Index (VIX)

Note: The left axis plots the COVID-19 global fear index and the CBOE volatility index is plotted on the right axis. The graph is portioned into three phases; I, II, and III, in order to depict the co-movements between the two indexes before and after the declaration of COVID-19 as a global pandemic by the WHO.



Next, the predictability performance of stock returns using the VIX is evaluated and compared with that of the historical average and the COVID-19 Global Fear index predictor models. The predictability and forecast evaluation results are summarized in Table 8. The estimated VIX predictability regression shows a negative and statistically significant relationship between volatility index and stock returns. The forecast evaluation also reveals that it outperforms the historical average. However, when compared with the GFI-based predictive model, the latter tends to outperform the VIX-based model. This finding further attests to the underperformance of the VIX as a measure of fear during crisis/turbulent period.

Table 8: VIX predictability of stock returns and forecast evaluation

Note: VIX_{t-1} is the one-period lag volatility index. Standard errors and t-stats are respectively reported in parentheses and squared brackets. The C-T stat denotes the Campbell-Thompson (2008) test while the C-W test is the Clark and West (2007) test. ***, ** & * indicate statistical significance at 1%, 5% & 10% levels respectively.

Coefficients	VIX-predictor model
VIX_{t-1}	-0.6799*
	(0.3860)
	[-1.7616]

Forecast evaluation	VIX model Vs Historical average	GFI model Vs VIX model
In-sample		
C-T stat	0.0253	0.2164
Clark & West	2.0418***	1.4040***
	(0.2947)	(0.3653)
Out-of-sample		
C-T stat	0.0307	0.2150
C-W test	1.5921***	1.0853***
	(0.2309)	(0.2514)

5. Conclusion

This study motivates the literature to aid research on the COVID-19 pandemic. This becomes crucial given the need to analyze the potential negative impacts of the pandemic on the global economy whether developed, emerging or developing economies. However, there is no standard measure of COVID-19 in a way that accommodates all the relevant parameters such as reported cases, deaths and recoveries into a single index. This is the main contribution of the study. Thus, a composite index [Global Fear Index (GFI)] that accounts for the mentioned parameters and covers all the countries in the world is constructed. To validate the data, we demonstrate how it can be used to forecast economic and financial series using OECD and BRICS stock returns data. Expectedly, the model that incorporates the index during the pandemic period outperforms benchmark model. In addition, there may be need to account for "asymmetry" effect and macro-common factors in the GFI-based predictive model for stock returns to further improve its forecast performance. Finally, we show that the GFI is a better predictor of fear/panic in the stock market than the existing fear index (technically described as the Chicago Board Options Exchange (CBOE) Volatility Index (VIX)) at least during the pandemic period. We do hope to regularly update the database used for the index to encourage further extension of its application to other macroeconomic fundamentals.

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