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Full length article

The COVID-19 global fear index and the predictability of commodity price returns

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ABSTRACT

In this paper, we subject the global fear index (GFI) for the COVID-19 pandemic to empirical scrutiny by examining its predictive power in the predictability of commodity price returns during the pandemic. One of the attractions to the 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. Our results show evidence of a positive relationship between commodity price returns and the global fear index, confirming that commodity returns increase as COVID-19 related fear rises. By way of extension, we further establish that commodity market offers better safe-haven properties than the stock market given the negative association between GFI and the latter. Finally, the GFI series improves the forecast accuracy of the predictive model for commodity price returns and its forecast outcome outperforms the historical average (constant returns) model both for the in-sample and out-of-sample forecasts. Our results are robust to alternative measures of pandemic.

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1. Introduction

The coronavirus (COVID-19) outbreak was first reported on the 31st December, 2019 in Wuhan, Hubei province in China. Three months later, it has generated into a pandemic outbreak and has posed adverse consequences on the global economy. Business activities are most affected by this shock. For instance, there is a wide disruption in the global supply chains, weaker demand for goods and services, significant decline in tourism and business travels, lower consumer and business confidence, increase in the rate of risk aversion in the financial system and fall in equity prices, among others. Human normal routines are not spared, as virtually all countries have put in place some forms of restrictions on movements.1 It is safe to assert that the world is experiencing a global crisis, something different to what we are used to such as the financial, debt, and currency crises. Historically, global crises have attendant effect on global variables, such as commodity prices. For instance, Sanderson et al. (2015) note that commodity prices have fallen to their lowest level since the financial crisis and – by at least one measure – to the lowest this century. Also, Zhang and Broadstock (2019) documented a dramatic change in the nature of connectedness in global commodity prices following the 2008 global financial crisis. They show that co-dependence in price-changes among seven major commodity classes goes from a pre-crisis average of 14.82% to a strikingly larger average of 47.87% in the period following the crisis, and which has endured until now.

Thus, as COVID-19 has been declared to be pandemic, its impact is expected to transcend a single country, region or continent. In other words, it is expected to affect the global demand and supply of goods and services, chief among which are commodity prices and stock prices. Since the outbreak of the pandemic, oil prices seem to have declined significantly2 while stock, such as the EOG Resources stock which is oil-related, has dropped by 50%. The importance of accurate prediction of commodity prices in times of crisis cannot be overemphasized and can be explained based on the two reasons. First, Zhang and Broadstock (2019) showed that there is high connectedness between commodity markets and other markets. Relatedly, the

1 Most countries in the world are currently under lockdown. However, the intensity vary across countries. For instance, while Spain, Italy, France, India have announced restriction of movement to only essential needs (purchase of foods, medicines and hospital visits), other countries are more liberal. Schools have closed, while tertiary institutions have migrated to virtual learning/teaching. The only businesses allowed to open are those classified as essential. However, it is anticipated that towards the turn of summer, countries would begin to ease these restrictions as they prepare to restart the economy.

2 To fact, crude oil futures prices nosedived and plunged below zero for the first time in the second half of April, 2020.
concept of commodity financialization has raised interest among academicians and policymakers to the extent that commodity is now considered as a core asset classification by financial investors (Cheng and Xiong, 2014; Zhang et al., 2017). This has also led to an increase in speculative activities (Hamilton and Wu, 2014). The same argument goes for commodity currency (Chen and Rogoff, 2003). Hence, the inability to accurately predict commodity prices might lead to commodity price crash and thus spillover to other markets, which can further exacerbate the intensity of the already existing crisis. However, taking this information on board helps investors make decisions about portfolio adjustments and asset pricing. It also helps academicians develop models that will enhance forecasting.

Secondly, evidences have shown that some of the post-crisis consequences are the high volatility and reversal in commodity prices and uncertainty in financial markets (Antonakakis et al., 2017). No doubt, at the moment, there has been a reversal in the prices of some commodities. The stability can be explained under the guise of lower demand attributed to the “global lockdown” policies set by government. The benefit of accurate prediction in bear times is of utmost importance to both investors and policymakers. Starting with the investors, studies have shown that the inclusion of commodity assets in the portfolios of investors is able to hedge against risk, thus offering higher returns, especially when the market is in bear mode (Öztek and Ocal, 2017; Zhang et al., 2017; Ait-Yousef, 2019; Salisu et al., 2020) show the relationship between stock markets and agricultural commodity is significant during turbulent times, such as the 2008 financial crisis.

Some studies have argued to account for the extreme periods when modelling financial series (Andersen et al., 2007). We take a more radical, but similar approach. Specifically, we hypothesize that focusing solely on the extreme periods will reveal the true relationship among the series in the model. Whereas, combining bear and bull periods while modelling will distort some inherent information present in the data. Another justification for the sole reliance on the bear period is due to the current “lockdown” restrictions in most countries of the world. Hence, it could be subtly argued that financial and economic series are inoperative.

Based on the foregoing, we offer the following innovations to the existing literature on the predictability of commodity prices. First, we construct a predictive model for commodity prices that accounts for the impact of the COVID-19 pandemic. This is a major contribution to the literature as forecasting economic and financial series during crisis is usually a daunting task for economic, financial and policy analysts. To the best of our knowledge, we are not aware of similar studies that had conducted similar exercise, especially during the recent crisis period. To achieve this objective, we select twenty-four (24) commodities covering precious metals, agriculture and industrial inputs that are allowed to trade during the period of the pandemic. Second, we utilize the global fear index (GFI) constructed by Salisu and Akanni (2020) to capture the fear/panic associated with the pandemic. One of the strengths of the index lies in its coverage as all the countries and by extension regions and continents in the world are considered in the construction of the index. Third, we test the predictive power of GFI in the predictability of commodity prices. Several plausible scenarios are rendered to validate our results. Fourth, we made a safe-haven comparison analyses between commodity prices and stock markets in order to examine the best investment options for policymakers and investors.

The recency of COVID-19 has led to the emergence of studies that had examined how the pandemic has impacted the commodity market. For instance, Sharif et al. (2020) used a time-frequency domain to examine the relationship between COVID-19 and oil price. Some studies have verified whether gold still possesses its hedging and safe haven features during this pandemic (Conlon and McGee, 2020; Corbet et al., 2020; Yarovaya et al., 2020). Salisu et al. (2020a) use a panel VAR model to show that both oil and stock markets may experience greater initial and prolonged impacts of own and cross shocks during the pandemic than the period before it. Wang et al. (2020) examine the impact of COVID-19 on the cross-correlations between crude oil and agricultural futures markets. Aloui et al. (2020) assess the impact of COVID-19 shocks on the energy futures markets, particularly on crude oil and natural gas S&P GS Indexes. A glimpse of our results suggests a high predictive power of the GFI in the predictability of commodity price returns. The inclusion of the index further improves the predictive model for commodity price returns and more specifically, its forecast outcome outperforms the historical average (constant returns) model. Further results suggest that commodity market appears to offer better safe-haven properties than the stock market during the pandemic.

The rest of the study is structured as follows: Section 2 provides the methodology; the results are presented and discussed in Section 3 while Section 4 concludes.

2. Methodology

We formulate a predictive model for commodity price returns where the global fear index serves as a predictor. The underlying intuition is that as the panic associated with the pandemic becomes severe (implying an increase in the index), the global economic activity reduces, which would lower trading in the commodity market and by extension returns. Since our focus is on the COVID-19 period and given the need to consider a long range of data sample, we utilize panel data where the various commodities are pooled over the available data period for COVID-19. In order to account for any inherent heterogeneity in the selected commodities, we favour the heterogeneous panel models (see for example, Robertson and Symons, 1992; Pesaran and Smith, 1995). The analyses using heterogeneous panel can be done using each commodity’s time series regression, or using various estimation methods described in the earlier papers (see Baltagi, 2008; Eberhardt, 2012; Chudik and Pesaran, 2015; Chudik et al., 2016; Westerlund and Narayan, 2016; Salisu and Isah, 2017; Ditzen, 2018; Salisu and Ndako, 2018). Notwithstanding the inherent heterogeneity in the commodities, a number of studies have also demonstrated the need to account for unobserved common factors (see Chudik and Pesaran, 2015; Chudik et al., 2016). In other words, regardless of the specificities of these commodities, they may be driven by some unobserved common factors. Thus, following the studies of Chudik and Pesaran (2015), Chudik et al. (2016), and Ditzen (2018), we construct a predictive panel data model for commodity price returns where the GFI

3 On the 26th March, 2020, the UK government suspended the housing and property market in the country. It was announced that this suspension will, at least, last during the stay-at-home order.

4 In the UK, a three months moratorium has been placed on private loans and mortgages in March, 2020 and has been further extended by another quarter. The Reserve Bank of Australia announced short term funding for the banking system. Financial regulators in China pledge to enhance liquidity support for the market, increasing credit support and extending repayment period for enterprises. Bank of Japan to provide loans against corporate debt and 0% interest rate. The European Commission provides guarantees, to member countries, to ensure banks keep providing loans to the customers who need them.

5 In addition to the suitability of the model for long T, it also helps resolve any inherent nonstationarity which is a suspect when dealing with long T. It also accommodates mixed order of integration and facilitates the estimation of long run and short run dynamics including the speed of adjustment.
series is the only predictor$^6$:

$$r_{it} = \alpha_i + \sum_{k=1}^{5} \delta_k g_{t-k} + e_{it},$$

(1)

$$e_{it} = \lambda_i f_t + u_{it}$$

(2)

where $r_{it}$ denotes commodity price returns computed as log return i.e. $100\times\log(C_t/C_{t-1})$ with $C_t$ being the commodity price data for commodity $i$ at period $t$; $g_{t-k}$ is the natural logarithm of the global fear index data; $\alpha_i$ and $\delta_k$ represent the heterogeneous intercept and slope coefficients which are allowed to vary across the units; and $e_{it}$ is the error term. Note that $e_{it}$ is a composite error term comprising an unobserved common factor loading ($f_t$) accompanied with a heterogeneous factor loading ($\lambda_i$) and the remainder error term ($u_{it}$). Thus, in addition to allowing for heterogeneity in the predictability, we also incorporate unobserved common factors for the selected commodities.

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 behaviour 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 the return series. The testable null hypothesis of no predictability can therefore be expressed as $H_0: \sum_{k=1}^{5} \delta_k = 0$ against the alternative hypothesis of $H_0: \sum_{k=1}^{5} \delta_k \neq 0$. For the purpose of estimation, we follow the procedure of Chudik and Pesaran (2015) by allowing for common-correlated effects (CCE) in the evaluation of the return predictability of the GFI series. Some of the computational advantages of allowing for the CCE in return predictability and the estimation procedure are also well documented in Ditzen (2018, 2019).

Also, we reformulate Eq. (1) to include an observed common factor motivated by the Arbitrage Pricing Theory which allows for the inclusion of systemic or macroeconomic risks in the predictability of returns. Consequently, we consider an index, the VIX (volatility) index, a prominent measure of systemic risk and possibly macroeconomic risk. There are variants of the VIX index for different markets thus allowing us to narrow the systemic risk to commodity market. On this basis, the single predictor model in (1) is extended to become:

$$r_{it} = \alpha_i + \sum_{k=1}^{5} \delta_k g_{t-k} + \phi_i z_{it} + e_{it},$$

(3)

where $z_{it}$ is a measure of systemic risk, and $\phi_i$ is the corresponding coefficient for each cross-section while Eq. (2) remains the same. As a result, we are able to capture both observed and unobserved common factors in Eq. (3). We favour an approach that allows us to use the risk-adjusted returns rather than estimating the direct impact of the systemic risk on returns. This also helps circumvent any potential endogeneity bias that may result from the correlation between the two predictors. Therefore, we first regress the return series on $z$, that is, $r_{it} = \theta + \phi_i z_{it} + u_{it}$ and thereafter, the risk-adjusted returns series defined as $r^*_{it}$ is regressed on the GFI predictor also in the presence of CCE.

Finally, we evaluate the forecast performance of the model using two pair-wise forecast measures, namely Campbell-Thompson (CT, 2008) and Clark and West (CW, 2007) tests. These measures are particularly useful when dealing with nested predictive models. The benchmark model for our analysis is the historical average or constant return model specified as:

$$r_{it} = \alpha_i + u_{it}; \quad t = 1, 2, \ldots, T; \quad i = 1, 2, \ldots, N$$

(4)

The CT (2008) test for forecast evaluation is specified as:

$$CT = 1 - \left( \frac{MSE_u}{MSE_{\hat{r}}} \right)$$

(5)

where $MSE_u$ is the mean squared error obtained from the unrestricted model, in this case the GFI-based model (Eq. (1)) and $MSE_{\hat{r}}$ is the mean squared error obtained from the restricted model (for example, the historical average or constant return model, Eq. (4)). In this case, Eq. (1) outperforms Eq. (4) 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:

$$\hat{f}_{t+h} = \hat{MSE}_r - \left( \frac{MSE_{\hat{r}} - adj}{SE_{\hat{r}}} \right)$$

(6)

where $\hat{f}_{t+h}$ is the forecast horizon; $MSE_r$ and $MSE_{\hat{r}}$ respectively are the squared errors of restricted and unrestricted predictive models and they are respectively computed as:

$$P^{-1} \sum (\hat{r}_{i,t+h} - \hat{r}_{t+h})^2$$

and

$$P^{-1} \sum (\hat{r}_{i,t+h} - \hat{r}_{t+h})^2.$$ The term adj is included to adjust for noise in the unrestricted model and it is defined by $P^{-1} \sum (\hat{r}_{i,t+h} - \hat{r}_{t+h})^2; P$ 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.

3. Results and discussion

3.1. Data and preliminary analyses

Our data set consists of commodity prices (in USD) of the 24 major commodities traded globally, commodity-related volatility indexes, including crude oil gold and silver, and the global fear index (GFI).$^8$ Daily price series for each of the commodities were retrieved from www.investing.com historical data while the volatility index data were collected from the Chicago Board of Exchange (CBOE) database (http://www.cboe.com). On the other hand, the GFI series was obtained from Salisu and Akanni (2020).$^9$ The start period was selected to conform with the declaration of the COVID-19 as a global pandemic by the World Health Organisation (WHO).$^{10}$ Hence, the daily data was collected between March 11 and May 18, 2020, spanning 46 observations. Some graphical representations are rendered to highlight the movements between each of the commodity prices and the global fear index (see Fig. 1). The graphical illustration reveals that there

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$^6$ We are grateful to Ditzen (2018, 2019) for providing the relevant codes for the estimation of dynamic panel data models with dynamic common correlated effects.

$^7$ We account for an important feature of price returns which include commodities and stock prices. These prices series tend to exhibit day-of-the-week effect (for a review of literature, see Zhang et al., 2017). In order to account for this feature, we regress the return series on dummy variables constructed for the five days of the week, to obtain the day-of-the-week adjusted returns (See Salisu and Akanni, 2020)

$^8$ The commodities comprise aluminium, cocoa, coffee, copper, corn, cotton, crude oil, gasoline, gold, heating oil, lead, lumber, natural gas, nickel, oats, palladium, platinum, rough rice, silver, soybean, sugar, tin, wheat, and zinc.

$^9$ See the Appendix for the description of the index. The GFI data can be obtained from the Mendeley data cited as Salisu and Akanni (2020). Global Fear Index Data for the COVID-19 Pandemic, Mendeley Data, http://dx.doi.org/10.17632/yhs32p9d7d1.

$^{10}$ 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"
are co-movements in the commodity prices and the global fear index.

Table 1 rendered some descriptive statistics of the commodity price and gfi series. The mean shows that average returns across all the commodities considered is negative over the period under consideration indicating an overall average decline in prices of these commodities. The relative standard deviation shows Natural gas recorded the highest returns variation, which is followed by Oats and Silver. On the other hand, the least variation is recorded for Sugar and Corn over the period considered. The average return for the pool of commodities is also negative, while the average change in the global fear index is about 4.7%.

### 3.2. Main results

Table 2 summarizes the estimated predictability results for the global fear index predictability of commodity price returns. As discussed in the methodology section, we considered two GFI predictability models, the baseline model with a single factor predictive model and the macroeconomic volatility adjusted model. Following the prominent feature of traded stock and commodity prices as documented in empirical literature (see Zhang et al., 2017; Salisu and Akanni, 2020), we adjust the commodity price returns for day-of-the-week effects. The estimated joint coefficient of five-period lag of the global fear index as summarized in Table 2 shows a positive and significant relationship with commodity price returns. In addition, the estimated coefficient after accounting for macroeconomic volatility effect shows a positive and significant impact of global fear index on commodity price returns. These positive results conform with findings in empirical economics and finance literature on the hedging features of commodities including metals such as gold, silver, platinum and palladium (Chen et al., 2014); and agricultural commodities such as coffee and cocoa (see Tule et al., 2019). These studies found that investors exploit the wealth protection features of commodities by holding and spreading their investment portfolios from stocks and bonds especially during crisis, such as the COVID-19 pandemic.

Next, we carried out the forecast evaluation of the predictive models by dividing the data into in-sample and out-of-sample periods. For the in-sample predictability evaluation, 75% of the entire data sample is used, while the out-of-sample periods include 7-day and 14-day ahead forecast horizons, for robustness purposes. The forecast performance evaluation is carried out using both the CT (2008) and CW (2007) tests. We evaluate the predictability performance of the baseline single predictor model against the constant returns historical average model. In addition, we also compared the predictability performance of the volatility adjusted model with the historical average model. The results are summarized in Table 3 for both the in-sample and out-of-sample periods. The results show positive values for the CT statistic both in-sample out-of-sample data partitions, while the CW tests also reported statistically significant coefficients. By implication, the global fear index predictability model of commodity price returns performs better than the historical average model. Similarly, accounting for the relevance of commodity related volatilities also outperforms the historical average model, thus confirming the importance of accounting for such effects in commodity returns predictability.

### 3.3. Additional results

For robustness purpose, we conduct two sets of additional analyses. First, we evaluate the robustness of the COVID-19 global fear index as an alternative measure of the pandemic in the predictability commodity price returns. To do this, we employ the Infectious Disease Equity Market Volatility (ID-EMV) data which captures a broad range of pandemics (see Baker et al., 2020). The ID-EMV dataset comprehensively covers epidemics and pandemics that predate the emergence of the COVID-19 some of which include the Severe Acute Respiratory Syndrome, Ebola virus, Middle East Respiratory Syndrome and Zika virus. Hence, it is the most suitable alternative index to measure uncertainties related to fear the COVID-19 health risks. In the same vein as the main results, we evaluate the predictability performance of the single-predictor model, i.e ID-EMV against the gfi-based and historical average models.

The estimated predictability as well as the in-sample and out-of-sample forecast evaluation results are summarized in Table 4. The result shows that the coefficient of lagged infectious disease index is positive and statistically significant. While for the forecast performance, the results show that the EMV-based predictability model outperforms the historical average model both for the in-sample and out-of-sample data partition. However, the
Fig. 1. Co-movement between commodity prices and global fear index.

Table 3
In-sample and out-of-sample forecast evaluation.

|                | Model 1 Vs CR | Model 2 Vs CR |
|----------------|---------------|---------------|
| **In-sample**  |               |               |
| Campbell-Thompson | 0.1033        | 0.7709        |
| Clark & West    | 10.2522*** (2.0859) | 0.2992 (0.7240) |
| **Out-of-sample** |               |               |
| $h = 1$        |               |               |
| Campbell-Thompson | 0.0371        | −0.0002       |
| Clark & West    | 6.2962** (1.8548) | 0.9510** (0.4570) |
| $h = 2$        |               |               |
| Campbell-Thompson | 0.0273        | 0.0116        |
| Clark & West    | 3.1515* (1.6804) | 1.2339*** (0.4186) |

Note: CR is the historical average (constant returns) model; Model 1 indicates the GFI-based single predictor model; Model 2 is for the macro-adjusted stock return series. Forecast performance of the two variant models is evaluated and compared with the performance of the historical average. Standard errors are reported in parentheses and ***, *** & * respectively indicate statistical significance at 1%, 5% & 10% levels, respectively.

The EMV model does not outperform the GFI-based model, given the negative values of the CT statistics.

For the second additional results for robustness, we follow the empirical literature that a vast support for the hedging potential and characteristics of commodities for stock and other financial markets. These hedging characteristics can be said to be more relevant during crisis period. Several factors characterize the desirable features of these commodities, particularly gold and other precious metals, and these include: (i) the intrinsic value of most commodities neither depends on prospective cash flows nor carries a default risk; (ii) precious metals universally acceptable and scarce; (iii) most commodities have relative supply inelasticity and their observed counter-cyclical demand characteristics make them store of value; (iv) their protection attributes and properties are commonly referred to by many investors, individuals and the media (see Arnold and Auer, 2015). Therefore, to further evaluate the hedging features of commodities during the current volatile and turbulent global economy as a result of the COVID-19 pandemic, we extend the analysis to evaluate the global fear index predictability of OECD countries stock returns since the declaration of COVID-19 as a global pandemic by the WHO.

The estimated stock returns predictability results summarized in the upper pane of Table 5 reported a negative and statistically significant coefficient. The joint coefficient of the five-days lagged coefficient of the global fear index has a negative sign indicating that an adverse effect of COVID-19 on stock returns. contrary
to the positive coefficient reported for commodity price returns predictability, the result for stock returns, as expected, shows that inverse relationship. By implication, as investors’ fear associated with the COVID-19 pandemic increase, stock returns decline, while commodity price returns increase (see Table 2). We further applied the two criteria for evaluating the forecast performance as discussed in the methodology section, that is the C-T (2008) and CW (2007) tests. The in-sample period and two out-of-sample forecast horizons confirm that the global fear index predictability of stock returns outperforms the historical average constant stock returns model.

4. Conclusion

The central theme of this study is to evaluate the predictability of commodity prices during economic and financial crisis, particularly the current unprecedented COVID-19 pandemic. In addition, we evaluate whether investing in commodities during these trying times serves as a good hedge to investors against volatilities and decline witnessed conventional assets, especially equities. We employed the global fear index (GFI) recently constructed by Salisu and Akanni (2020) in a predictive model for 24 major commodity prices. Our results show evidence of positive relationship between commodity price returns and the global fear index, confirming that commodity returns increase as COVID-19 related fear rises. The predictability performance further confirms that the outperformance of the predictive model above the constant return predictor, both in-sample and out-of-sample.

For robustness purpose and in order to further confirm the hedging potential of commodities during crisis, we extend the analysis to evaluate the performance of OECD stocks during the pandemic period. The estimated result report a negative relationship between stock returns and the global fear index with statistically significant forecast performance, in-sample and out-of-sample. Thus, the results support findings in several previous empirical literature that investing in commodity, especially during crisis and turbulent periods, serves as a good hedge against the volatility and declines in stock markets.

Declaration of competing interest

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

Appendix. Description of the Global fear index for the COVID-19 pandemic

The COVID-19 Global Fear Index (GFI) seeks to measure daily concerns and emotions on the spread and severity of COVID-19 since the pandemic declaration. Excessive fears 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 across the globe, the GFI is a composite index of two factors; Reported Cases and Reported Deaths, on a scale of 0 to 100, respectively indicating no fear to extreme fear/panic. An index value of 50 is considered neutral, while anything higher signals more fear than usual. We employed what we referred to as the incubation period expectation in daily reported cases and deaths in constructing the index. The incubation period expectation is defined as the time expectation between when a person could be exposed to the Coronavirus and emergence of symptoms of the disease. According to the World Health Organization (WHO), most estimates of the incubation period for COVID-19 range from 1–14 days (WHO, 2020).

The first component of the COVID-19 Global Fear Index (GFI) is the Reported Cases Index (RCI) which measures how far peoples’ expectations on reported cases in the preceding 14-days period veered from the present day’s reported case. The choice of 14-day expectations represents the highest number of days for COVID-19 incubation period as defined by the WHO. The RCI for a given day is computed as the ratio of COVID-19 reported cases globally on the day under consideration and the sum of reported cases for the current day and reported cases at the start of the incubation period. The ratio is then multiplied by 100 to give the index on a scale between 0 and 100.

The second component is the Reported Deaths Index (RDI) and measures how far peoples’ expectations from reported deaths...
in the preceding 14-days period veered from the present day's reported deaths. The RDI, just as the RCI, is computed as the ratio of COVID-19 related reported deaths across the world and the sum of reported deaths on the day under consideration and the start of its incubation period (14 days ago). The ratio is also multiplied by 100 to give an index between 0 and 100. Finally, the construct of the GFI pulls the two indexers together with equal weights assigned to obtain the composite index. The composite index is given as the simple average of RCI and RDI defined above. The higher the value of GFI, the higher the global fear of the COVID-19 pandemic.

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