Out-of- sample stock return predictability of alternative COVID-19 indices

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Abstract[6]

We explore the predictive value of the various indices developed to capture COVID-19 pandemic for daily stock return predictability of 24 Emerging Market economies (based on data availability). We identify eight measures from three classes of COVID-19 indices, namely, the uncertainty due to pandemics and epidemics (*UPE*) index by Baker et al. (2020), the Global Fear Index (*GFI*) by Salisu and Akanni (2020), and the six different indices [COVID index, vaccine index, medical index, travel index, uncertainty index and aggregate COVID-19 sentiment index] by Narayan et al. (2021). We find that, out of the three classes, the *GFI* index consistently offers the best out-of-sample forecast gains followed by the aggregate COVID-19 sentiment index while the UPE index offers the least predictability gains. The outcome generally improves after controlling for oil price but the ranking of forecast performance remains the same and robust to multiple forecast horizons and alternative forecast evaluation methods. We infer that the relative predictive powers of the indices are proportional to the extent to which the indices truly measure the pandemic.

Keywords: COVID-19 Indices, Out-of-sample forecast evaluation, Emerging Markets

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1. Introduction

This study explores the returns predictability of some twenty-four (24) emerging stock markets with a variety of COVID-19 pandemic indices as a contribution to the established nexus between the COVID-19 pandemic and stock markets[7] (see for example, Liu et al., 2020; Salisu & Sikiru, 2020; Salisu & Vo, 2020; Sharma, 2020; Phan & Narayan, 2020; Wang et al., 2021). Theoretically, we can explain the nexus via the investor sentiments thesis (see De Long et al., 1990) which suggests that investor sentiments formed during bullish or bearish conditions can drive stock market fundamentals including returns away from traditional stock market factors. Hence, the low sentiments formed during the COVID-19 pandemic period due to its persistence (given different variants and waves of the pandemic) and its associated uncertainty from health and non-health policy measures to contain it, could be capable of spreading pessimistic expectations in the market. The low sentiments experienced in the worst-hit advanced markets pose the threat to risk contagion into other emerging markets (Salisu & Adediran, 2020; Deng et al., 2021; Rehman et al., 2021; Abuzayed et al., 2021), leading to search for portfolio reallocation benefits.

The empirical motivation for the study rests on studies like Baker at al. (2020), Al-Awadhi et al. (2020), and Zhang et al. (2020) that suggest that the number of reported cases and fatalities from the pandemic are associated with higher stock market risks than previous financial crises in history. There are also evidences that show that the COVID-19 pandemic has negative impacts on stock returns due to closure of businesses and other macroeconomic disruptions (Li et al., 2021; Liu et al., 2021; Zehri, 2021; Rehman et al., 2021; Xu, 2021; Xu, 2022; Samitas et al., 2022). Although in most cases, advanced economies were the most hit by the negative effects of the pandemic on their economies (Salisu, Adediran and Gupta, 2021), there also evidences of risk spillovers to the emerging markets (Li, Zhuang, Wang and Dong, 2021; Abuzayed, Bouri, Al-Fayoumi and Jalkh, 2021); and this necessitates interest in checking the predictability of emerging market stocks via the COVID-19 measures.

Given the foregoing theoretical and empirical attractions, we motivate the contribution of the study on evaluating the out-of-sample stock returns predictability using three alternative COVID-19 indices. First, we employ the Baker et al. (2020) uncertainty index due to pandemics and epidemics (UPE) which covers all kinds of pandemics and epidemics since 1986 including

[7] This connection also captures other financial markets such as foreign exchange market (see Narayan, 2020a, 2020b; Salisu, Lasisi and Olaniran, 2021).

COVID-19. Second, we also utilize the Global Fear Index (GFI) developed by Salisu and Akanni (2020), which unlike the UPE specifically focuses on the COVID-19 pandemic and utilizes information about the reported cases and deaths. Third, we exploit the recently developed COVID-19 sentiment index by Narayan et al. (2021), which covers series of events that are related to COVID-19 such as fatality, vaccine, medical, travel, uncertainty and a composite index comprising the sub-indices.

We achieve the study's objective of evaluating the out-of-sample stock return predictability of alternative COVID-19 indices using three approaches for forecast evaluation; (1) the relative root mean square forecast error, (2) the conventional Clark and West (2001, 2006, 2007) test for evaluating the null of equal predictability between the baseline model and the preferred models that contain the COVID-19 indices as predictors, and (3) the Wild Clark and West approach of Pinchera et al. (2021) which is an extension to the traditional Clark and West as an attempt to correct for the deficiency of the latter by modeling random variables to keep the test statistic from becoming degenerate under the null. Further exercises directed at ensuring that the results are robust involve the inclusion of the international crude oil price as a control variable in the predictive models given extensive literature evidences suggesting its impacts on stock market fundamentals (for example Salisu et al., 2019a,b and relevant papers cited therein). This allows us to compare results for the forecast evaluations with and without the inclusion of additional regressor in the forecast models. We also explore the possibility of using alternative benchmark model by comparing the forecast evaluations between historical average model and autoregressive models (AR(2) and AR(4)) as the alternative baseline models.

In the end, we find that the emerging stock returns' predictive models that include the alternative COVID-19 indices outperform the historical average and the other alternative benchmark models with or without the inclusion of a control variable. Among the models with the COVID-19 pandemic indices, the Global Fear Index (GFI) index of Salisu and Akanni (2020) offers the best fit followed by the Narayan et al. (2021) index, and the Baker et al. (2020) in the least category. These findings hold in the face of alternative robustness checks. Intuitively, the relative predictive powers of the indices can be attributed to the extent to which the data employed in each of the indices truly gauge the effect of the pandemic. For instance, the Salisu and Akanni (2020)'s index is computed from data (number of cases and deaths) that are directly related to the pandemic. Among the remaining two indices (Baker et al. (2020) and Narayan et al. (2021)), the latter which has the better predictive power of the two appear to cover more items linked to the pandemic (medical, vaccine, travel restrictions, among others) unlike the UPE which has the least predictive power.

Following this section, we present the methodology consisting of data, estimation, and forecast evaluation measures in Section 2. We follow this up with the predictability and forecast evaluation results in Section 3, and .the conclusion comes in Section 4.

2. Data and Methodology

The study requires two classes of data; the stock prices of the emerging markets under consideration and the alternative COVID-19 indices. The study utilizes daily stock price data from December 31, 2019 to April 28, 2021 covering emerging markets and alternative indices for the COVID-19 pandemic.[8] The stock indices considered comprise 24 Emerging Market economies. The classification of the emerging stock markets is based on the Morgan Stanley Capital International (MSCI) country classification (see https://www.msci.com/market-classification). The countries considered are as follows: six from the Americas including Argentina, Brazil, Chile, Colombia, Mexico and Peru; eleven countries from Europe, Middle East and Africa: Czech Republic, Egypt, Greece, Hungary, Poland, Qatar, Russia, Saudi Arabia, South Africa, Turkey and United Arab Emirates; and seven countries from Asia: China, India, Korea, Pakistan, Philippines, Taiwan, and Thailand. The daily stock index data is obtained from the www.investing.com historical data archive (see https://www.investing.com/).

As regards the alternative indices for the COVID-19 pandemic, we consider those indices developed by Baker et al. (2020), Salisu and Akanni (2020), and Narayan et al. (2021) and are described in turn. The theoretical motivation for the consideration of the COVID-19 indexes has been argued from the consequences of the fear and uncertainty associated with the COVID-19 pandemic on the investor sentiments in the stock market.

Baker et al. (2020) provide this first widely accessible index for the pandemic described as uncertainty due to pandemic and epidemic (*UPE*) and can be obtained at http://policyuncertainty.com/infectious_EMV.html. To construct the EMV-ID, Baker et al. (2020) utilize four sets of terms namely, (i) E: economic, economy, financial; (ii) M: "stock market",

[8] The start date for the data scope is informed by the discovery of the COVID-19 virus while the end data is given by the end date of the available COVID-19 indices.

equity, equities, "Standard and Poors"; (iii) V: volatility, volatile, uncertain, uncertainty, risk, risky; (iv) ID: epidemic, pandemic, virus, flu, disease, coronavirus, MERS, SARS, Ebola, H5N1, H1N1. Tracing across approximately 3,000 U.S. newspapers, the authors obtain daily counts of newspaper articles that contain at least one term in each of E, M, V, and ID. The authors scale the raw EMV-ID data which is the volume of counts of all articles in the same day and thereafter multiplicatively rescale the resulting series to match the level of the stock market volatility index VIX by using the overall equity market volatility (EMV) index, and finally scaling the EMV-ID index to reflect the ratio of the EMV-ID articles to total EMV articles.

We also consider the COVID-19 Global Fear Index (*GFI*) developed by Salisu and Akanni (2020) which seeks to measure daily concerns and fear on the spread and severity of the COVID-19 since the declaration of the disease as a pandemic. The *GFI* data[9] rely on the official reports of COVID-19 cases and deaths across the globe to construct a composite index of two factors; Reported Cases and Reported Deaths. The ensuing index obtained from the two factors are put on a scale of 0 to 100, indicating no fear to extreme fear/panic due to the pandemic. Thereafter, the authors account for 'incubation period expectation' in daily reported cases and deaths in constructing the index. The value of the index at 50 is considered neutral, while values higher than 50 indicate greater fear associated to the pandemic than usual. The data is available upon request at the daily frequency from February 2020.

We further consider the recent COVID-19 index proposed by Narayan et al. (2021). The Narayan et al. (2021) index involves six indices relating to COVID-19 pandemic that cover other aspects of the COVID-19 pandemic other than those related to the number of cases and deaths recorded as employed in the index in Salisu and Akanni (2020). These indices utilize more than 300 keywords related to vaccines, medicals, travel, and uncertainty, among others in 45 major newspapers. Thus, the study constructs six indices: COVID index, vaccine index, medical index, travel index, uncertainty index and aggregate COVID-19 sentiment index. For each of the 45 newspapers, the authors retrieve daily news articles published between December 31, 2019, and to April 28, 2021 from the ProQuest database.

[9] The GFI data can be obtained from https://www.researchgate.net/publication/350947756_COVID-19_Global_Fear_Index_Data_Update_16042021.

For the forecasting exercise, we begin our analyses with the historical average (constant return) model which ignores the COVID-19 indices:[10]

$$r_{i,t+h} = \alpha + e_{1i,t+h};\ t = 1,2,3,...,T;\ i = 1,2,3,...,N; \tag{1}$$

where r_{it} denotes stock returns computed as log returns; α is a constant parameter; e_{it} is the error term while the out-of-sample forecast horizon is defined as $h = 10, 20, 30$. We use the 50:50 data split and estimate the model using data up to and including day t, use the day-t estimates recursively to compute a dynamic forecast for period $t + h$.

For robustness, we consider the autoregressive (AR) models as alternative benchmark models as follows:

$$r_{i,t+h} = \alpha + \sum_j^2 b_j r_{i,t-j+h} + e_{2i,t+h};\ t = 1,2,3,...,T;\ i = 1,2,3,...,N \tag{2}$$

$$r_{i,t+h} = \alpha + \sum_j^4 b_j r_{i,t-j+h} + e_{3i,t+h};\ t = 1,2,3,...,T;\ i = 1,2,3,...,N \tag{3}$$

where Equation (2) and (3) are AR(2) and AR(4) models, $r_{i,t-j}$ are the lagged terms, b_j are the autoregressive parameters, and the rest of the models are as previously defined.

We specify the predictive model for the study as the COVID-19 index-based forecast model given as follows:

$$r_{i,t+h} = \alpha + \sum_{k=1}^{5} \delta_{i,k} Covid_{i,t-k+h} + e_{4i,t+h} \tag{4}$$

$$e_{4it} = \lambda_i f_t + u_{it} \qquad [5]$$

where $Covid_{it}$ denotes either of the aforementioned COVID-19 indices (Baker et al., 2020 index, Salisu and Akanni 2020 index, and the Narayan et al., 2021 index), all measured as fist difference of its natural logs. Note that the regression disturbance term is further decomposed into unobserved common factor loading (f_t) and heterogeneous factor loading (λ_i) while u_{it} is the remainder disturbance term. Note that we allow for up to five lags given the daily frequency used and also to capture more inherent dynamics in the predictability analysis (see also, Zhang et al., 2017; Salisu

[10] The historical average is used as a baseline model here since it is an equivalent version of a random walk model for logged stock prices (see Bannigidadmath & Narayan, 2015; Narayan & Gupta, 2015; Phan et al., 2015; Narayan et al., 2016; Devpura et al., 2018; Salisu et al., 2019a,b; Salisu and Akanni, 2020).

and Akanni, 2020, among others).[11] In terms of the estimation procedure, we employ the heterogenous panel data techniques of Chudik and Pesaran, (2015), Chudik et al. (2016) and Westerlund et al. (2016) which simultaneously capture both the unobserved common factor loading (f_t) and heterogeneous factor loading (λ_i) in the estimation process thereby circumventing any inherent bias associated with the omission of other predictors.

We also account for another important global factor (that is, the international crude oil price) as a control variable in the COVID-based predictive models. The rationale for the inclusion of oil price as a control variable is due to its close connection with stock market fundamentals through the former's impact on the firms' cash flow (see Narayan and Gupta, 2015; Smyth and Narayan, 2018; Salisu et al., 2019a, 2019b, among others). This allows us to report results for the predictability of the emerging markets' stock returns given alternative COVID-19 indices with and without the control variable. The focus is on the predictive content of the predictor series, rather than the control variable. On the basis of the foregoing, we extend (4) as follows:

$$r_{i,t+h} = \alpha + \sum_{k=1}^{5} \delta_k Covid_{i,t-k+h} + \sum_{j=1}^{5} \gamma_j Oil_{i,t-j+h} + e_{5i,t+h} \tag{6}$$

where Oil_{it} is a measure of global factor/risk which is linked to stocks from the cash-flow channel and is computed as log returns of its price, and the rest of the components have been previously defined.

The forecast evaluation of (4) and (6) relative to (1) is carried out using the relative root mean square forecast error (relative RMSFE) and Clark and West (2007) test. The relative RMSFE is computed as the ratio of RMSFE of the COVID-19 index-based models to that of the benchmark

[11] Although, there are traditional predictors of stock returns, however, these factors are not considered in this paper for a number of reasons. First, the period for the predictability analysis is limited to the COVID-19 pandemic period and we use daily data for relevant variables in the predictive model. Since the pandemic indices used in this study only start from year 2020, the traditional factors with the highest frequency being monthly can only guarantee 20 (monthly) data points in order to align with the available data scope for the daily pandemic indices. This certainly will not offer meaningful outcomes. Second, should we use the data anyway, this will completely change the focus of the study on comparing the predictability of alternative COVID-19 pandemic indices. Third, the literature is already replete with studies involving the traditional predictors of stock return predictability (see Narayan and Bannigidadmath, 2015; Phan et al., 2015; Narayan et al., 2016) and we do not intend to repeat the exercise in our study. Rather, we isolate the COVID-19 effect in the return predictability following the studies of Narayan and Sharma (2014) and Narayan and Gupta (2015) which also isolated the role of oil price ain return predictability. Fourth, we employ the heterogenous panel data techniques of Chudik and Pesaran, (2015), Chudik et al. (2016) and Westerlund et al. (2016) which simultaneously capture both the unobserved common factor loading and heterogeneous factor loading in the estimation process, thereby circumventing any inherent bias associated with the omission of other predictors.

(historical average) model, such that a value less (greater) than one is considered to indicate superior (inferior) performance of the former over the latter. Further, the Clark and West (2007) approach is used to evaluate the null hypothesis of equal predictability between the COVID-19-based predictive models and the baseline models (Eq. (1), (2) or (3)). The null hypothesis of equal predictive performance (that is, having a zero CW coefficient) is rejected if the t-statistic is greater than +1.282 (for a one sided 0.10 test), +1.645 (for a one sided 0.05 test), and +2.00 (for a one sided 0.01 test) (see for technical details, Clark and West, 2007).

We employ the Wild Clark and West approach of Pinchera et al. (2021) (WCW) that build on the idea that the traditional Clark and West (2007) (CW) degenerates under the null: [($e_{1i,t+h} = e_{4i,t+h}$), ($e_{2i,t+h} = e_{4i,t+h}$), ($e_{3i,t+h} = e_{4i,t+h}$)] without control and [($e_{1i,t+h} = e_{6i,t+h}$), ($e_{2i,t+h} = e_{6i,t+h}$), ($e_{3i,t+h} = e_{6i,t+h}$)] with control variable. In its modification,[12] the WCW attempts to correct for the deficiency of the CW by modeling random variables to keep the test statistic from becoming degenerate in the test of equal predictability [($e_{1i,t+h} - e_{4i,t+h} = 0$), ($e_{2i,t+h} - e_{4i,t+h} = 0$), ($e_{3i,t+h} - e_{4i,t+h} = 0$)] without control and [($e_{1i,t+h} - e_{6i,t+h} = 0$), ($e_{2i,t+h} - e_{6i,t+h} = 0$), ($e_{3i,t+h} - e_{6i,t+h} = 0$)] with control variable. The Wild Clark and West test statistic is specified as:

$$\sqrt{k-1}\, k^{-1} \sum \hat{e}_{1,t+h} \left(e_{1,t+h} - \phi_t e_{4,t+h} \right) \Big/ \sqrt{\hat{s}_{ff}} \tag{7a}$$

$$\sqrt{k-1}\, k^{-1} \sum \hat{e}_{1,t+h} \left(e_{1,t+h} - \phi_t e_{5,t+h} \right) \Big/ \sqrt{\hat{s}_{ff}} \tag{7b}$$

where ϕ_t represent the independent random variables introduced to remove uncertainty, $e_{1,t+h}$ and $e_{2,t+h}$ are zero-mean martingale differenced processes for the benchmark model and the choice predictive model (that could be Eq. (4) or (6)), k is the number of forecasts, $\hat{s}_{ff}$ is the estimated variance of $e_{1,t+h}\left(e_{1,t+h} - \phi_t e_{4,t+h}\right)$ or $e_{1,t+h}\left(e_{1,t+h} - \phi_t e_{6,t+h}\right)$.

Based on the statement of the null, we evaluate the differences in the forecast performances between the COVID-19 index-based model and the benchmark (historical average and AR models) model on one hand and the COVID-19 index-based model with control variables and the benchmark model on the other hand. Like the CW test, the null hypothesis of a zero coefficient for

[12] Simulations conducted by Pinchera et al. (2021) show that the WCW is asymptotically normal and it is well-sized compared to the CW by keeping the distribution of the test statistic around zero mean and removing autocorrelation from the structure.

either of the WCW test statistic is evaluated at 10%, 5%, and 1% significance as follows: +1.282 (for a one sided 0.10 test), +1.645 (for a one sided 0.05 test), and +2.00 (for a one sided 0.01 test) (see Clark and West, 2007).

3. The Results

We proceed with the out-of-sample predictability analysis of emerging stock returns given the predictive models with alternative COVID-19 indices by relying on three approaches to comparing forecast performance between the alternative baseline models (historical average and autoregressive models) and the COVID-19-based predictive models. The first approach is the relative root mean square forecast error (i.e. relative RMSFE) (see Table 1), which is computed as the ratio of RMSFE of the COVID-19 index-based models in relation to that of the historical average or the autoregressive model used as the benchmark model. The interpretation of the relative RMSFE is such that a value less (greater) than one is considered to indicate superior (inferior) performance of the COVID-19 index-based model over the benchmark model. The second approach, the conventional Clark and West (2006, 2007) is a formal statistical test for evaluating the null hypothesis of equal predictability between the benchmark model and the COVID-19 index-based predictive models (see Table 2 and Table A1) in the appendix. The third approach, the Wild Clark and West approach (Pinchera et al., 2021) improves on the conventional Clark and West test by keeping the Clark and West statistic from becoming degenerate under the null (see Table A2 in the appendix to the paper).

In order to ensure that the findings are robust, we compare the out-of-sample predictability results for three alternative proxies for measuring the COVID-19 pandemic: the UPE index of Baker et al. (2020), the Global Fear Index (GFI) index of Salisu and Akanni (2020), and the Narayan et al. (2021) COVID-19 sentiment index. We also compare the forecasts by controlling for oil price as a measure of global risk that matter in driving stock market fundamentals. The results for the aforementioned are contained in Tables 1&2 and Tables A1 & A2. We also explore the possibility of using alternative benchmark model by comparing the forecast evaluations between historical average model and autoregressive models (AR(2) and AR(4)) as the alternative baseline models (see the results in Tables A3 and A4 for AR(2) and AR(4) respectively).

We present two tables to illustrate the forecast performance of the various indices analysed where Tables 1 and 2 depict the relative root mean square forecast error statistics and the results of the Clark and West (2007) test respectively. The Table A1 in the appendix shows the root mean square error (RMSE) statistics used to compute the relative RMSFE statistics in Table 1. All the result tables are partitioned into two to differentiate the model that excludes the control variable (oil price) from the model that accommodates it. In Table 1, we use the boldface to indicate the COVID-19-based model for stock returns that outperforms the benchmark (historical average) judging by the relative RMSFE statistics. Green colour highlights the best model among the COVID-19 related indices. The results show that majority of the COVID-19-based models outshine the benchmark model at the different out-of-sample forecast horizons.

The results of the relative RMSFE statistics show that the Global Fear Index (*GFI*) index of Salisu and Akanni (2020) offers the highest out-of-sample gains followed by the aggregate COVID [A_COVID] index of Narayan et al. (2021) while the UPE index has the least predictive value for the out-of-sample predictability of stock returns, among the three classes of the COVID-19 indices. Further, we find significant improvements in the predictability of all the indices after controlling for oil price (see Model 6 on Table 1) as they all outperform the benchmark model at all the forecast horizons while the ranking of the indices remains unchanged with the *GFI* and the Aggregate COVID index retaining the first and second positions respectively. This outcome further highlights the significance of controlling for oil price on the one hand and its strong connection with stock returns on the hand (see Smyth and Narayan, 2018) to the extent that the outcome may be biased if this important (additional) predictor is ignored in the predictability analysis of stock returns.

The results obtained from Clark and West (2007) as depicted in Table 2 further corroborate the predictability of the COVID-19 related indices for stock returns as shown in the relative RMSFE where all the *t* statistics are statistically significant indicating the superiority of the predictive model that includes the indices over the benchmark model. In alignment with the performance results as presented earlier, all the indices outperform the benchmark model across the sub-samples for Models 4 and 5 at 1% level of significance (see Table 2). In addition to these, the results of the Wild Clark and West (Pincheira, Hardy and Muñoz, 2021) test lead to the same conclusion as the conventional CW test where all the WCW coefficients in Table A2 are statistically significant at 1% significance level, indicating the superiority of the COVID-19-based models over the benchmark. In other words, regardless of the relative performance of the alternative indices, they offer significantly higher out-of-sample forecast gains over the benchmark model. The results are also consistent even when we vary the benchmark model and adopt the AR(2) and AR(4) models in place of the historical average model in Table A3 and Table A4 respectively.

The intuition behind the *GFI* as the most significant implies that stock returns tend to react more to the COVID-19-induced fear emanating from number of deaths and reported cases than measures that focus on travel restrictions and availability of vaccines, among others. This outcome is reinforced in a similar study conducted by Caldara and Iacoviello (2019) on the responsiveness of stock market and trading activities in the US to an actual occurrence of geopolitical risk (GPRA) and the threats that result from geopolitical risks (GPRT) such as fear of war and terrorism and they find that GPRT has more adverse effects on the US stock market than the actual occurrence (GPRA). Furthermore, we could argue that the relative predictive powers of the three indices is due to the extent to which the indices truly measure the pandemic. For instance, the Salisu and Akanni (2020)'s index is computed from data (number of cases and deaths) that can be directly linked to the pandemic. In second position, the Narayan et al. (2021)) index appears to cover more items linked to the pandemic (medical, vaccine, travel restrictions, among others) than the (Baker et al. (2020) index in the third position.

The results inform a number of implications for policy and investment decisions in the emerging markets. For instance, the findings suggest the exposure of the emerging stock markets to the COVID-19 pandemic risks; the sentiment, panic, fear, and uncertainty brought to bear by the pandemic. The COVID-19 pandemic represents period of low investors' sentiments in the stock markets where the number of pessimistic investors increase in the market and this leads to undervaluation of stocks (i.e. mispricing of stocks). This suggests the need for portfolio diversification strategies for investors in the emerging markets during the pandemic and similar occurrences where financial risks are exceptionally high and investors' sentiments are low for instance during financial crisis periods and geopolitical tensions (e.g. the ongoing Russia/Ukraine war that has led to plunges in the major global stock indices). There may also be need for the emerging economies to learn from the conventional and unconventional policies instituted by the advanced economies to speed up economic recovery in their economies in the wake of the pandemic.

4. Conclusion

The COVID-19 pandemic has received a great deal of attention in the literature with several studies searching for proxies to measure it and to quantify its impact on macroeconomic variables including stock market fundamentals like stock price, returns, or volatility. The theoretical linkage between the COVID-19 pandemic and stock market fundamentals have been argued from the fear and uncertainty associated with the former in terms of casualties, deaths, mutation of the virus, isolation and social restriction measures, leading to disruption in economic activities. The period represents the condition when the market sentiment is low due to heightened risk levels in financial markets of countries worst-hit by the pandemic and empirical evidences abound of risk spillover to other (emerging) markets. The present study makes contribution among group of studies that developed indices for measuring the pandemic such as the uncertainty due to pandemics and epidemics (UPE) index by Baker et al. (2020), the Global Fear Index (*GFI*) by Salisu and Akanni (2020), and the six different indices [COVID index, vaccine index, medical index, travel index, uncertainty index and aggregate COVID-19 sentiment index] by Narayan et al. (2021).

In this study, we compare the predictive values of these indices for stock return predictability using daily stock returns of 24 emerging market economies with focus on out-of-sample predictability as the in-sample predictability may be less informative about the forecasting ability of the predictive models. Thus, we construct a predictive model where the COVID-19-related indices are individually and independently incorporated as predictors and the out-of-sample forecast evaluation are conducted over multiple forecast horizons and various forecast evaluation methods (the relative root mean square forecast error, the conventional Clark and West (2006, 2007) test, and the Wild Clark and West approach of Pinchera et al. (2021)). In all, we find that all the COVID-19 indices outperform the various benchmark models (historical average and autoregressive models). Among the indices, the *GFI* index (which captures the inherent fear associated with the pandemic) consistently offers the highest out-of-sample forecast gains followed by aggregate COVID-19 sentiment index, and the UPE offers the least gains. We find similar results with or without controlling for oil price as a measure of global risk, amid other efforts at robustness.

The findings suggest the exposure of the emerging stock markets to the COVID-19 pandemic; the panic, fear and uncertainty caused by it. The findings corroborates some of the earlier results that suggest risk contagion from advanced to emerging markets during the pandemic.

The foregoing suggest the need for portfolio diversification strategies for investors during similar occurrences when financial risks are exceptionally high and investors' sentiments are low such as during pandemic, financial crisis, geopolitical tensions (like the ongoing Russian invasion of Ukraine). Other studies could build on our results and extend the analysis to other financial markets such as the foreign exchange market, bond market and money market for more insightful outcomes.

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Table 1: Out-of-Sample Relative Root Mean Square Forecast Error

The Constant returns [Historical average (HA)] model serves as a benchmark and its entries are the values of Mean Square Forecast Errors (MSFEs) for each forecast horizon. Entries for each subsequent models based on COVID-19 related indices are MSFEs relative to the values of the HA benchmark. MSFEs lower than one signify improvement relative to the benchmark and vice-versa for values higher than one. Boldface indicates improvements relative to HA forecast. Green indicates the best model among the COVID-19 related models. A_COVID Index is the aggregate of the five COVID-19 indices of Narayan et al. (2021); UPE is the Uncertainty due to Pandemics and Epidemics of Baker et al. (2020) while *GFI* is the Global Fear Index of Salisu and Akanni (2020).

	HA	A_COVID Index	Medical Index	Travel Index	Uncertainty Index	Vaccine Index	COVID Index	UPE	*GFI*
					Without Control [Model 4]				
h=10	0.0301	**0.9668**	**0.9934**	**0.9668**	**0.9767**	1.0100	**0.9535**	**0.9900**	**0.9302**
h=20	0.0292	**0.9795**	1.0034	**0.9726**	**0.9897**	1.0103	**0.9623**	1.0034	**0.9315**
h=30	0.0287	**0.9791**	1.0000	**0.9686**	1.0035	1.0174	**0.9652**	**0.9965**	**0.9303**
					With Control [Model 6]				
h=10	0.0301	**0.9435**	**0.9701**	**0.9369**	**0.9535**	**0.9801**	**0.9302**	**0.9668**	**0.9037**
h=20	0.0292	**0.9589**	**0.9795**	**0.9418**	**0.9726**	**0.9829**	**0.9418**	**0.9795**	**0.9075**
h=30	0.0287	**0.9617**	**0.9756**	**0.9408**	**0.9826**	**0.9895**	**0.9443**	**0.9756**	**0.9059**

Table 2: Out-of-Sample Clark and West (2007) test

The Clark and West (2007) test measures the significance of the difference between the forecast errors of each of the COVID-19 index-based models and HA benchmark model. The null hypothesis of a zero coefficient is rejected if this statistic is greater than +1.282 (for a one sided 0.10 test), +1.645 (for a one sided 0.05 test) and +2.00 for 0.01 test (for a one sided 0.01 test) (see Clark and West, 2007). The values presented are the Clark and West t-statistics. 'a' indicates statistical significance at 1% level. A_COVID Index is the aggregate the five COVID-19 indices of Narayan et al. (2021); UPE is the Uncertainty due to Pandemics and Epidemics of Baker et al. (2020) while *GFI* is the Global Fear Index of Salisu and Akanni (2020).

	A_COVID Index	Medical Index	Travel Index	Uncertainty Index	Vaccine Index	COVID Index	UPE	*GFI*
				Without Control [Model 4]				
h=10	10.03[a]	9.94[a]	10.54[a]	7.92[a]	7.83[a]	9.96[a]	8.39[a]	5.50[a]
h=20	9.84[a]	9.30[a]	10.68[a]	7.79[a]	7.49[a]	9.65[a]	8.05[a]	5.53[a]
h=30	10.18[a]	9.37[a]	11.17[a]	7.41[a]	7.18[a]	9.82[a]	8.71[a]	5.57[a]
				With Control [Model 6]				
h=10	10.15[a]	9.63[a]	10.46[a]	8.59[a]	9.10[a]	10.20[a]	8.68[a]	6.63[a]
h=20	10.04[a]	9.35[a]	10.59[a]	8.48[a]	8.90[a]	9.95[a]	8.55[a]	6.66[a]
h=30	10.31[a]	9.43[a]	11.00[a]	8.23[a]	8.84[a]	10.09[a]	9.05[a]	6.71[a]

Appendix

Table A1: Out-of-Sample Root Mean Square Forecast Errors

We report the Root Mean Square Forecast Errors (RMSFEs) for both the benchmark [Historical average (HA)] model and models with COVID-19 related indices. Lower RMSFEs indicate improvement relative to the rest of the models including the HA. Boldface indicates the best model among the COVID-19 related and HA models. A_COVID Index is the aggregate of the five COVID-19 indices of Narayan et al. (2021); UPE is the Uncertainty due to Pandemics and Epidemics of Baker et al. (2020) while *GFI* is the Global Fear Index of Salisu and Akanni (2020).

	HA	A_COVID Index	Medical Index	Travel Index	Uncertainty Index	Vaccine Index	COVID Index	UPE	*GFI*
					Without Control [Model 4]				
h=10	0.0301	0.0291	0.0299	0.0291	0.0294	0.0304	0.0287	0.0298	**0.0280**
h=20	0.0292	0.0286	0.0293	0.0284	0.0289	0.0295	0.0281	0.0293	**0.0272**
h=30	0.0287	0.0281	0.0287	0.0278	0.0288	0.0292	0.0277	0.0286	**0.0267**
					Without Control [Model 6]				
h=10	0.0301	0.0284	0.0292	0.0282	0.0287	0.0295	0.0280	0.0291	**0.0272**
h=20	0.0292	0.0280	0.0286	0.0275	0.0284	0.0287	0.0275	0.0286	**0.0265**
h=30	0.0287	0.0276	0.0280	0.0270	0.0282	0.0284	0.0271	0.0280	**0.0260**

Table A2: Out-of-Sample Wild Clark and West test

The "Wild Clark and West (WCW)" test proposed by Pincheira, Hardy and Muñoz (2021) is a simple modification of the ENC-T (Clark and McCracken (2001) and Clark and West (2006, 2007)) core statistic that ensures asymptotic normality. The test introduces an independent random variable that prevents the CW test from becoming degenerate under the null hypothesis of equal predictive accuracy. Since it is a one-sided test like the CW test, the null hypothesis of equal predictability between the restricted and the unrestricted model is rejected if this statistic is greater than +1.282 (for a one sided 0.10 test), +1.645 (for a one sided 0.05 test) and +2.00 for 0.01 test (for a one sided 0.01 test). The values presented are the WCW-statistics. "a" indicate statistical significance at 1% level. A_COVID Index is the aggregate the five COVID-19 indices of Narayan et al. (2021); UPE is the Uncertainty due to Pandemics and Epidemics of Baker et al. (2020) while *GFI* is the Global Fear Index of Salisu and Akanni (2020).

	A_COVID Index	Medical Index	Travel Index	Uncertainty Index	Vaccine Index	COVID Index	UPE	*GFI*
				Without Control [Model 4]				
h=10	2.5494[a]	2.5493[a]	2.5494[a]	2.5494[a]	2.5493[a]	2.5494[a]	2.5493[a]	2.5495[a]
h=20	2.6259[a]	2.6258[a]	2.6259[a]	2.6259[a]	2.6258[a]	2.6259[a]	2.6258[a]	2.6260[a]
h=30	2.7425[a]	2.7425[a]	2.7426[a]	2.7424[a]	2.7424[a]	2.7426[a]	2.7425[a]	2.7427[a]
				With Control [Model 6]				
h=10	2.5495[a]	2.5494[a]	2.5495[a]	2.5494[a]	2.5494[a]	2.5495[a]	2.5494[a]	2.5496[a]
h=20	2.6259[a]	2.6259[a]	2.6260[a]	2.6259[a]	2.6259[a]	2.6260[a]	2.6259[a]	2.6261[a]
h=30	2.7426[a]	2.7425[a]	2.7427[a]	2.7425[a]	2.7425[a]	2.7427[a]	2.7425[a]	2.7428[a]

Table A3: Out-of-Sample Clark and West (2007) test using an alternative benchmark model [AR(2)]

Note: See note to Table 2 except the benchmark model which is now AR(2).

	A_COVID Index	Medical Index	Travel Index	Uncertainty Index	Vaccine Index	COVID Index	UPE	*GFI*
				Without Control [Model 4]				
h=10	9.31[a]	8.37[a]	9.81[a]	7.82[a]	6.47[a]	9.50[a]	7.71[a]	5.44[a]
h=20	9.16[a]	7.95[a]	9.97[a]	7.71[a]	6.31[a]	9.23[a]	7.45[a]	5.49[a]
h=30	9.49[a]	8.03[a]	10.43[a]	7.27[a]	6.12[a]	9.40[a]	8.08[a]	5.53[a]
				With Control [Model 6]				
h=10	9.72[a]	9.09[a]	10.09[a]	8.49[a]	8.75[a]	9.88[a]	8.36[a]	6.58[a]
h=20	9.64[a]	8.86[a]	10.24[a]	8.39[a]	8.61[a]	9.66[a]	8.24[a]	6.62[a]
h=30	9.90[a]	8.95[a]	10.63[a]	8.10[a]	8.54[a]	9.80[a]	8.72[a]	6.67[a]

Table A4: Out-of-Sample Clark and West (2007) test using an alternative benchmark model [AR(4)]

Note: See note to Table 2 except the benchmark model which is now AR(4).

	A_COVID Index	Medical Index	Travel Index	Uncertainty Index	Vaccine Index	COVID Index	UPE	*GFI*
				Without Control [Model 4]				
h=10	9.52[a]	5.52[a]	8.32[a]	8.93[a]	3.35[a]	10.50[a]	6.58[a]	5.47[a]
h=20	9.41[a]	5.37[a]	8.50[a]	8.88[a]	3.38[a]	10.21[a]	6.32[a]	5.55[a]
h=30	9.82[a]	5.63[a]	9.00[a]	8.37[a]	3.46[a]	10.52[a]	6.98[a]	5.47[a]
				With Control [Model 6]				
h=10	10.73[a]	8.68[a]	10.60[a]	10.21[a]	7.80[a]	11.32[a]	8.67[a]	6.58[a]
h=20	10.65[a]	8.50[a]	10.77[a]	10.14[a]	7.75[a]	11.06[a]	8.45[a]	6.65[a]
h=30	10.99[a]	8.74[a]	11.24[a]	9.74[a]	7.75[a]	11.32[a]	9.03[a]	6.74[a]