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In this study, we examine the response of emerging stock markets due to the uncertainty of pandemics and epidemics (UPE), including the COVID-19 pandemic. We demonstrate this by evaluating the stock return predictability of 24 emerging market stocks using the new datasets on uncertainty due to pandemics as well as the global fear index for the COVID-19 pandemic. We partition the data sample into periods before and after the announcement of the COVID-19 pandemic and employ panel data techniques that account for salient features of both the series and predictive model. We found that emerging stock markets are more vulnerable to UPE than developed market stocks. Put differently, developed stock markets provide a better hedge against UPE than emerging stock markets. We also find that incorporating the UPE indicator in the valuation of stocks, particularly during pandemics, is crucial for investment decisions.

1. Introduction

Research on pandemics is a worthwhile venture at this time due to ongoing risks posed by the COVID-19 disease globally. Before COVID-19, there were previous pandemics and epidemics that impacted the global economy, such as the 1957 and 1958 H2N2 virus, the 1968 H3N2 virus, the 2009 and 2010 Swine Flu, the 2014–2016 Ebola virus, the 2012 MERS virus, and, at the height of them, the 1918 H1N1 virus pandemic. The COVID-19 pandemic bears striking semblance with the 1918 pandemic in terms of biological features (both are respiratory diseases spread through contacts and droplets); coverage of transmission (the 1918 influenza spread to about one-third of the global populace while COVID-19 has recorded close to nine million confirmed cases worldwide in just about six months); and health response (quarantine, isolation, use of disinfectants, calls for better hygiene, and restrictions on travels and gatherings).

The economic consequences revealed by the novel coronavirus (COVID-19) pandemic have brought to the fore the need to better understand pandemics and how they affect economic activities including the stock market. The theoretical basis for studying the pandemics–stocks nexus lies in the

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argument that stock prices, returns and volatility respond to news and macroeconomic conditions that shape investors’ sentiments about the level of uncertainty in financial markets (see Haroon & Rizvi, 2020a, 2020b; Narayan, 2019, 2020; Salisu, Ogbonna, & Adediran, 2020, among others). During pandemics, like during wars, natural disasters and financial crises, the level of uncertainty in the markets is exceptionally high, and so is the level of risk aversion among investors (see Eichenbaum et al., 2020; Haroon & Rizvi, 2020b; Ma et al., 2020; Qadan, 2019; Salisu & Akanni, 2020).

The effect of the COVID-19 pandemic on stock market performance has been widely investigated (see Ashraf, 2020; bib_Akhtaruzzaman_et_al_2020Akhtaruzzaman et al., 2020; Al-Awadhi et al., 2020; Ali et al., 2020; Baig et al., 2020; Gu et al., 2020; Haroon & Rizvi, 2020a, 2020b; He et al., 2020; Mishra et al., 2020; Phan & Narayan, 2020; Salisu & Sikiru, 2020; Salisu & Vo, 2020; Salisu, Ebuh, & Usman, 2020b; Topcu & Gulal, 2020; Zaremba et al., 2020; Zhang et al., 2020). While the majority of these studies examined the effect of COVID-19 on stock market performance from the perspective of global trading, pooling developed and emerging stock markets (see Ashraf, 2020; Ali et al., 2020; Haroon & Rizvi, 2020a, 2020b; Phan & Narayan, 2020; Salisu & Vo, 2020; Salisu, Ebuh, & Usman, 2020b; Zaremba et al., 2020; Zhang et al., 2020), a few others focused on developed stock markets (see Akhtaruzzaman et al., 2020; Baig et al., 2020).

The studies on emerging stock markets, such as Al-Awadhi et al. (2020), Gu et al. (2020), He et al. (2020) and Mishra et al. (2020), only consider the stock performance of firms in China or India, thus precluding empirical evidence on the effect of COVID-19 on the stock market performance of emerging economies. Limited studies on groups of emerging economies include Haroon and Rizvi (2020a) and Topcu and Gulal (2020). While Haroon and Rizvi (2020a) find that the increasing number of confirmed coronavirus cases deteriorates the liquidity condition of emerging stock markets, Topcu and Gulal (2020) conclude that the negative impact of COVID-19 on emerging stock markets has gradually fallen and had begun to taper off by mid-April 2020. Meanwhile, unlike most of the existing studies that focus essentially on the impacts of the COVID-19 pandemic, we consider a broader scope that covers various pandemics and epidemics and thus provide an in-depth understanding of the economic impacts of these infectious diseases in general and COVID-19 in particular. A broader understanding of pandemics has both policy and investment implications.

In reaction to the COVID-19 pandemic, the global financial markets dominated by advanced economies have been shown to generate increased fear-induced market risks (see Ali et al., 2020; Baker et al., 2020; Okorie & Lin, 2020; Salisu & Akanni, 2020), leading to likely investment losses during the spread as investors tended to engage in panic stock selling (see Phan & Narayan, 2020; Shen et al., 2020; among others). Can this conclusion be extended to all pandemics and epidemics? This is the main research question this study seeks to answer. In addition, we focus on emerging stock markets, which seem to have been understudied during the COVID-19 pandemic compared to their developed counterparts. The integration of both categories of stock markets (developed and emerging) usually constitutes the basis for determining the hedging potential of stock markets (see Jin et al., 2020, for a review). A study similar to this one was undertaken by Haroon and Rizvi (2020a) and Topcu and Gulal (2020); however, these studies differ in terms of the scope of pandemics, measures of uncertainty, methodology and analyses. We also examine the role of government policy interventions during the COVID-19 pandemic (see Ashraf, 2020).

Overall, we offer the following contributions to the literature: First, we utilise data that captures uncertainty due to UPE, including those associated with Severe Acute Respiratory Syndrome, Ebola virus, Middle East Respiratory Syndrome, Zika virus, and COVID-19 (see Baker et al., 2020), to examine the hedging effectiveness or vulnerability of emerging stock markets to pandemics. In other words, we employ UPE to assess whether emerging stocks can serve as a good hedge to uncertainty due to pandemics. Second, in addition to examining the hedging effectiveness or vulnerability of emerging stock markets to pandemics, we also test whether the information about the uncertainties can be exploited to produce better [in-sample and out-of-sample] forecast results for stock returns of emerging markets above the model with no predictor (historical average). Studies have shown that such information may be useful for forecasting purpose (see Salisu & Adediran, 2020; Salisu & Akanni, 2020; Salisu & Vo, 2020).

Third, we consider a newly constructed global fear index for the COVID-19 pandemic (see Salisu & Akanni, 2020) as a form of additional analysis to complement the results obtained for the same period using the UPE data. The intention here is to test whether the outcome is sensitive to the measure of pandemics. The global fear index has been assessed to produce better forecast outcomes for stock returns than the historical average (see Salisu & Akanni, 2020). Finally, we extend the analyses to cover the developed stock markets in order to test whether the response of the stock market to pandemics is influenced by the level of integration or development of the market. For instance, there is evidence of a differing response of emerging and developed countries to the hedging effectiveness of global sectoral stocks such as Global Energy, Financials, Industrials, and Technologies ETFs (see Jin et al., 2020). Overall, the results reveal that emerging stock markets offer less protection to investors against uncertainty due to pandemics and epidemics relative to developed stock markets. In addition, exploiting the information contained in the uncertainty data can improve stock return forecasts and outperform a restrictive model that ignores it. The results leading to this conclusion are robust to alternative measures of pandemics, particularly the COVID-19 pandemic.

We pursue the objectives of the study in the rest of the paper as follows. Section 2 presents the methodology, Section 3 discusses the data and preliminary results, and Section 4 discusses the predictability results. Conclusions are offered in Section 5.
2. Methodology

Our empirical model hinges on the international portfolio diversification theory, which has demonstrated that portfolio diversification in emerging economies could provide investors in developed market economies with a lower risk for a given level of expected return (Moosa & Ramiah, 2014; Al Nasser & Hajilee, 2016; Chen, 2018; Prasad et al., 2018; Dong & Yoon, 2019). We therefore test whether the emerging stocks provide effective hedge against pandemics, including the COVID-19 pandemic. To achieve this objective, we consider the following. First, we formulate a predictive model that incorporates the uncertainty index for UPE as the only predictor. Second, we test whether the results are robust to additional (control) variables such as oil prices (a good proxy for the global factor) (see Phan et al., 2015; Salisu et al., 2019) and emerging market stock market volatility (a good proxy for financial uncertainty) (see Salisu & Akanni, 2020; Salisu & Vo, 2020). Third, we evaluate the predictive power of the uncertainty index both for in-sample and out-of-sample periods by comparing its forecast performance with a benchmark model that ignores uncertainty in the valuation of stocks. Lastly, we replicate all the analyses for the developed stock markets as a form of additional analysis while we also consider an alternative measure of index for pandemics, focusing on COVID-19 for robustness.

From the foregoing, we construct the following predictive model for stock returns that accommodates any inherent heterogeneity and unobserved common factors among the cross-sections in addition to the predictor series (see Chudik et al., 2016; Chudik & Hashem Pesaran, 2015; Ditzen, 2018; Westerlund et al., 2016):

\[ r_i = \alpha_i + \sum_{j=1}^{5} \beta_{ij} UPE_{i,t-j} + Z_{it} \phi_i + \epsilon_{it} \]

\[ \epsilon_{it} = \lambda_j c_i + u_{it} \]

\[ i = 1, 2, \ldots, N; \quad t = 1, 2, \ldots, T. \]

where \( r_i \) denotes stock returns computed as log returns, given as \( 100 \log(S_{it}/S_{it-1}) \) with \( S_{it} \) defined as the stock index data for country \( i \) at period \( t \); \( UPE_{i,t-j} \) represents uncertainty due to pandemics and epidemics; \( Z_{it} \) is a vector of control variables; \( \alpha_i \) and \( \beta_{ij} \) represent the heterogeneous intercept and slope coefficients, respectively, which are allowed to vary across the units; \( \phi_i \) is a vector of corresponding parameters for the control variables with similar features as \( \alpha_i \) and \( \beta_{ij} \); and \( \epsilon_{it} \) is the composite error term comprising an unobserved common factor loading \( (c_i) \), accompanied by 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 stocks. For the predictability of UPE, we allow up to five lags given in a 5-day daily data frequency, in which stock return is expected to exhibit day-of-the-week effect (see also Salisu & Akanni, 2020; Salisu & Vo, 2020; Zhang et al., 2017). Thus, the hedging potential of emerging markets against risk associated with pandemics is evaluated using the Wald test for joint significance \( \sum_{j=1}^{5} \beta_j = 0 \). The considered markets are likely to at least retain the value of their returns, on the average, in the face of pandemics, if \( \sum_{j=1}^{5} \beta_j \) is positive and statistically significant; otherwise, they are more likely to be vulnerable.

As noted earlier, we test whether the inclusion of uncertainty information in the predictive model of stock returns will enhance its forecast outcome. This is achieved by comparing the forecast performance of the unrestricted model (equation (1)) with the restricted model (which is the historical average or, in this case, the constant return model). The constant return model ignores any potential predictor of stock returns and has been widely used in empirical research as the baseline model when evaluating stock return predictability (see Bannigidadmath & Narayan, 2015; Devpura et al., 2018; Narayan et al., 2016; Narayan & Gupta, 2015; Phan et al., 2015; Salisu et al., 2019). The constant returns model could be specified as

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

We employ both the single root mean square error (RMSE) and pairwise Clark and West (CW) test (2007) forecast measures to evaluate the forecasts. While a lower RMSE value is preferred between two competing models, the CW test involves testing whether the difference in the forecast errors of two nested models is statistically significant. For a forecast horizon \( h \), the CW test is specified as

\[ \hat{f}_{t+h} = \text{MSE}_{t} - (\text{MSE}_{t} - \text{adj}) \]

where \( \hat{f}_{t+h} \) is the forecast horizon, \( \text{MSE}_{t} \), and \( \text{MSE}_{t} \) denote the mean squared errors of the restricted and unrestricted predictive models, respectively; and they are computed as \( P^{-1} \sum (\hat{r}_{i,t+h} - \hat{r}_{i,t+h})^2 \) and \( P^{-1} \sum (\hat{r}_{i,t+h} - \hat{r}_{i,t+h})^2 \), respectively. The term is included to adjust for noise in the unrestricted model and it is defined by \( P^{-1} \sum (\hat{r}_{i,t+h} - \hat{r}_{i,t+h})^2 \). \( P \) is the amount of predictions in which the averages are computed. Lastly, the statistical significance of regressing \( \hat{f}_{t+h} \) on a constant confirms the CT test. 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 & West, 2007). In terms of data split for the forecast analyses, we adopt a 50:50 data split for the in-sample and
out-of-sample forecast evaluations involving the full sample. Three out-of-sample forecast horizons, namely 10-day, 20-day and 30-day ahead forecast horizons, are considered. However, for the COVID-19 sample, we adopt a 75:25 data split due to data limitations.

3. Data description and preliminary analyses

We collected the daily data of major stock indices of 24 emerging market economies based on the Morgan Stanley Capital International (MSCI) country classification. The countries include Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Mexico, Pakistan, Peru, Philippines, Poland, Qatar, Russia, South Africa, Taiwan, Thailand, Turkey and United Arab Emirates. For completeness and comparison, the responsiveness to uncertainty of the stock returns due to UPE of 21 developed economies is also considered. These countries are Australia, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the United Kingdom (UK) and the United States of America (USA).

The stock index data for each country was obtained from www.investing.com, historical data archive. In addition, we collected the newspaper-based Equity Market Volatility Infectious Disease Tracker (EMV) from the Federal Reserve Bank of St. Louis database (available at https://fred.stlouisfed.org/series/INFECTDISEMVMTRACKD). The EMV index documents and quantifies increases in economic uncertainty, and it is constructed by Baker et al. (2019). To construct the index, the authors identify three indicators: stock market volatility, newspaper-based economic uncertainty, and subjective uncertainty in business expectation surveys that provide real-time, forward-looking uncertainty measures. The following three steps are involved in the construction of the Baker et al.’s (2019) newspaper-based EMV tracker for measuring uncertainty due to UPE. In the first step, calculate the monthly fraction of articles in 11 major US newspapers that contain (a) terms related to the economy, (b) terms related to equity markets and (c) terms related to market volatility. In the second step, identify the subset of EMV articles that contain one or more terms related to COVID-19 or other infectious diseases (such as epidemic, pandemic, virus, flu, disease, coronavirus, MERS, SARS, Ebola, H5N1 or H1N1). In the third step, the fraction of EMV articles that contain one of these terms is multiplied by the EMV tracker to yield Infectious Disease EMV tracker (see Baker et al., 2019, for details). This was used as the measure of uncertainty due to UPE in this study.

The data sample start period was selected to ensure a balanced panel data set across the cross-section of countries. Therefore, the sample ranges between May 10, 2016 and June 17, 2020, which gives a total of 1058 observations. However, as previously mentioned, we perform distinct analyses before and after the emergence of the COVID-19 pandemic. Hence, the data is portioned into two periods: pre- and post-COVID-19. The pre-COVID-19 period ranges between May 2016 and December 2019, while post-COVID-19 covers the period of January to July 2020 based on data availability.

The summary statistics presented in Table 1 show the mean and the standard deviation of equity market volatility, the stock returns of emerging and developed economies under the full sample, and before and after the emergence of the COVID-19 pandemic. The results indicate average negative return on emerging stock markets across all periods, while positive average returns were observed on developed stock markets over the full sample and before the COVID-19 pandemic. After the emergence of COVID-19, the results show that negative returns on emerging stock markets increased, and the average stock returns of developed stock markets became negative. This is indicative of the high adverse effect of the COVID-19 pandemic on both the emerging and developed stock markets. The results also confirm an important corporate finance hypothesis, which states that the higher the risk, the higher the returns (see Salisu & Oloko, 2015). This is apparent as the developed stock markets with relatively higher returns have a higher standard deviation, which indicates that the developed markets are relatively riskier compared to the emerging stock markets. Evidence of the higher risk of developed stock markets was displayed during the COVID-19 pandemic, as the results show that on the average, stock returns of developed stock markets fell with a higher magnitude (−0.12%) compared to that of the emerging stock markets (−0.06%).

More so, the result of EMV for infectious diseases (Table 1) shows a drastic increase in the level of uncertainty after the outbreak of COVID-19. This implies that the outbreak has a significant impact on the confidence of investors, making them risk averse and thereby increasing stock market uncertainty and discouraging investment (Salisu & Vo, 2020). Table 2 illustrates how the stock returns of emerging and developed stock markets behave under different level of uncertainties. With reference to emerging stock markets, the result suggests that in the period of tranquillity (when the EMV is low, below its mean), the average stock returns are positive but lower than those of the developed countries before the outbreak of COVID-19. With an increase in EMV after COVID-19 had been declared a pandemic (where EMV increases, higher than its average), the average stock returns for both emerging and developed markets were negative, but the negative effect was weaker for emerging stock markets than for developed stock markets. This is consistent with the earlier result (discussed in Table 1). This result can also be echoed from the empirical results for individual countries as seen in appendices A and B.

4. Main results

Having highlighted some descriptive statistics for relevant variables, we proceed to the empirical section which involves
predictability and forecast performance analysis. We first examined the sole effect of the predictor: in this case, uncertainty due to pandemics and epidemics - UPE (i.e., model without control). Our results show that, overall, emerging stock markets are more vulnerable to health risks than developed stock markets. By implication, this means that health risks impacted negatively more on emerging stock markets than on developed stock markets. This result also suggests that both markets showed a certain level of tolerance to health risk during the COVID-19 outbreak, with developed markets showing a significantly higher level of tolerance. This result is corroborated by Su et al. (2019) and Qadan, 2019. The relatively lower resilience of emerging stock markets during the COVID-19 pandemic suggests that investment in emerging stock markets is not a suitable safe-haven option for potential investors (see Dutta et al., 2020; Ji et al., 2020). In other words, risk-averse investors in emerging stock markets will need to shun domestic asset sentiment and diversify their investment portfolio with assets that are more resilient to pandemics and epidemics, such as gold. Evidently, Dutta et al. (2020) noted that gold serves better than bitcoin as a safe-haven asset. This was also supported by Ji et al. (2020), who found that gold and soybean futures possess strong safe-haven roles. The result may also suggest that developed stock markets provide a better hedge against UPE than emerging stock markets (see Conlon & McGee, 2020).

The inclusion of some control variables, in this case financial risk, increases the overall vulnerability in both markets—although developed market stock was more vulnerable during the COVID-19 period. A plausible explanation for this is because developed economies had high incidences of the coronavirus disease, and non-pharmaceutical interventions (NPI) such as lock down and social distancing were more adhered to in developed economies than in emerging economies. It is also noteworthy to mention that by the time COVID-19 was ravaging America and Europe, home to most developed economies, China, the primary epicentre of the disease and place of outbreak, was already recovering.

We also evaluated the forecast power of the uncertainty indicator; therefore, we partitioned the data sample into in-sample and out-of-sample periods using the 75:25 data split, respectively. These results are presented in Table 4. Forecast evaluation is based on the CW test, and the decision rule is that a positive and significant value of the constant parameter in the test equation shows that our model’s performance outperforms the benchmark model (i.e. historical average). An overview of the table shows that our proposed model, with or without control variables, provides better forecasting results in contrast to the benchmark model. The significance of the CW test is higher during the COVID-19 period.

Table 3: Predictability results for pandemics and stock returns.

|       | Emerging Markets | Developed Markets |
|-------|------------------|-------------------|
|       | Pre-COVID        | COVID             |
|       | Full             | Emerging          | Developed |
| Full  | Without Control  | (18.46)           | (0.55) |
|       | –0.0034          | (0.21)            | (54.43) |
|       | (0.15)           | (0.53)            |        |
|       | With Control     | –0.0053           | –0.0932 |
|       | 0.0043           | (0.34)            | (16.15) |
|       | (5.57)           | (0.53)            | (54.43) |

Table 2: Scenario analysis of stock returns in different periods.

|       | Emerging Markets | Developed Markets |
|-------|------------------|-------------------|
|       | Below            | Above             |
|       | Below            | Above             |
|       | Before           | After             |
|       | Full             | Before            | After |
|       | Emerging Markets | Developed Markets |
|       | Before           | After             |
|       | Full             | Before            | After |
|       | Without Control  | (0.003467)        | (0.01359) |
|       | (0.01529)        | (0.165179)        | (0.320791) |
|       | (0.074153)       | (0.075859)        | (0.074153) |
|       | (0.11168)        | (0.151484)        | (0.11168) |
|       | (0.00261)        | (0.00431)         | (0.00261) |
|       | (0.080121)       | (0.00431)         | (0.080121) |
|       | (0.66118)        | (0.66118)         | (0.66118) |

Note: Below represents the values of stock returns when EMV is below its mean, and above is the value of stock returns when EMV values are above the mean. SD represents standard deviation.

Note: EMV denotes equity market valuation for infectious diseases; before and after denotes periods before and after the announcement of COVID-19 as a world pandemic, respectively; and full is the combination of both periods.
In the introduction section, we extend the predictability analysis for the post COVID-19 period using a newly constructed global fear and panic index ($gfi$) constructed with the number of daily cases and deaths for COVID-19 (see Salisu & Akanni, 2020). The stock returns predictability is re-estimated using the global fear index; thereafter, the forecast performance is evaluated and compared with both the baseline constant returns of emerging and developed stock markets. Government responses to the COVID-19 pandemic were quantified using Oxford COVID-19 Government Response Tracker from OXCGRT database (see also Hale et al., 2020). The OXCGRT computation outperforms the infectious disease equity market volatility index.

In addition, following Ashraf (2020), we examine the effect of government responses to the COVID-19 pandemic on stock returns of emerging and developed stock markets. Government responses to the COVID-19 pandemic were quantified using Oxford COVID-19 Government Response Tracker from OXCGRT database (see also Hale et al., 2020). The OXCGRT

### Table 4

| Model 1 vs Model 2 | Model 1 vs Model 3 |
|--------------------|--------------------|
| Full               | 0.6898* [2.91]     | 3.7253* [4.88] |
| Pre-COVID          | 0.8245* [3.25]     | 5.3944* [5.26] |
| COVID              | 5.6816* [3.70]     | 12.2068* [5.48] |
| Out-of-Sample Forecast Evaluation [h = 10] | 0.7151* [4.25] | 2.7060* [3.86] |
| Full               | 0.6459* [2.74]     | 3.6770* [4.72] |
| Pre-COVID          | 0.8050* [3.22]     | 5.3402* [5.29] |
| COVID [h = 5]      | 5.3053* [3.60]     | 11.4209* [3.89] |
| Out-of-Sample Forecast Evaluation [h = 20] | 0.6784* [4.15] | 2.5510* [3.73] |
| Full               | 0.6195* [2.65]     | 3.6235* [4.80] |
| Pre-COVID          | 0.7846* [3.18]     | 5.3592* [5.34] |
| COVID [h = 10]     | 5.2463* [3.73]     | 11.8254* [3.82] |
| Out-of-Sample Forecast Evaluation [h = 30] | 0.8203* [4.29] | 3.0598* [3.69] |
| Full               | 0.5360* [2.57]     | 3.6182* [4.84] |
| Pre-COVID          | 0.7640* [3.12]     | 5.3593* [5.41] |
| COVID [h = 20]     | 4.7652* [3.68]     | 14.1160* [4.07] |

Model 1 is the Historical Average model; Model 2 is the model without control; Model 3 is the model with control. The Clark and West test measures the significance of the difference of the forecast errors of two competing models. 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 & West, 2007). Values in square brackets [ ] are for t-statistics; a, b and c indicate statistical significance at 1%, 5% and 10% levels, respectively. Also, out-of-sample forecast evaluations during COVID-19 are $h = 5, 10$ and 20, due to small sample size.

4.1. Additional results

In line with the study’s second contribution, as discussed in the introduction section, we extend the predictability analysis for the post COVID-19 period using a newly constructed global fear and panic index ($gfi$) constructed with the number of daily cases and deaths for COVID-19 (see Salisu & Akanni, 2020). The stock returns predictability is re-estimated using the global fear index; thereafter, the forecast performance is evaluated and compared with both the baseline constant returns and $emv$-based predictability models. The predictability and forecast evaluation results are summarised in Table 5. The estimated stock returns predictability regression for the global fear index shows that the coefficient of one-period lagged for $gfi$ is negative and statistically significant. Furthermore, the forecast performance results show that the $gfi$-based model outperforms both the historical average and $emv$-based model for the in-sample and out-of-sample data partitions for the three forecast horizons. By implication, while both the infectious disease and global fear index stock returns predictability models perform better than the historical average model, the global fear index—which combines both the reported cases and deaths due to COVID-19—in its period than the pre-COVID-19 period for both markets, which implies that inclusion of health and financial risks is crucial when forecasting stock returns during the COVID-19 pandemic. The results of the out-of-sample forecast are similar to the in-sample forecast; however, inclusion of financial risk may not be as crucial in the emerging market as it is in the developed market, Table 3.

### Table 5

| Coefficients | GFI-predictor model |
|--------------|----------------------|
| $gfi_{t-1}$  | $-0.0030^{***}$       |
|              | (0.0003)              |

**Forecast evaluation**

| In-sample | GFI model vs historical average | GFI vs EMV model |
|-----------|---------------------------------|------------------|
| C-T stat  | 0.1205                          | 0.1431           |
| Clark & West | 0.0129***                   | 0.0146***       |
|              | (0.0008)                      | (0.0009)         |

| Out-of-sample | GFI model vs historical average | GFI vs EMV model |
|--------------|---------------------------------|------------------|
| $h = 1$ C-T stat | 0.1522                          | 0.2300           |
| Clark & West | 0.0094***                      | 0.0122***       |
|              | (0.0006)                      | (0.0007)         |
| $h = 2$ C-T stat | 0.1454                          | 0.2254           |
| Clark & West | 0.0087                          | 0.0116***       |
|              | (0.0006)                      | (0.0007)         |
| $h = 3$ C-T stat | 0.1389                          | 0.2076           |
| Clark & West | 0.0081***                      | 0.0100***       |
|              | (0.0005)                      | (0.0006)         |

Note: $gfi_{t-1}$ is the coefficient of global fear index predictor. EMV indicates the infectious disease index. The C-T stat indicates the Campbell-Thompson (2008) test statistics. *** indicates statistical significance at 1% level.
government response index comprised three main indexes: the stringency index, containment and health index, and economic support index. The effect of government responses to the COVID-19 pandemic is presented in Table 6. Markedly, the results show that accounting for government responses does not significantly impact the relationship between UPE and emerging stock markets. However, government responses to the COVID-19 pandemic appear to reduce the impact of UPE on the developed stock markets. This suggests that developed economies respond more positively to government responses than emerging economies, and better performance of developed economies respond more positively to government responses while ‘c’ indicate statistical significance at 1%, 5% and 10% levels, respectively.

5. Conclusion

This study attempts to contribute to the growing literature on the role of pandemics in the valuation of emerging market stocks. Following the proposition of the international portfolio diversification theory, we demonstrate whether harnessing information contained in the uncertainty of infectious diseases could help investors make decisions that will lower risks in the presence of pandemics. For the purpose of making meaningful generalizations, we collected daily data on 24 emerging stock markets; and for completeness and comparison, we gathered similar data on 21 developed stock markets. Thereafter, we partitioned our data into three sub-samples: full sample and periods before and after the emergence of the COVID-19 pandemic.

Empirical evidence from this study suggests that uncertainty due to UPE impacted negatively more on emerging market stocks than on developed market stocks. More importantly, we found that the negative relationship between pandemics and stock returns is more pronounced during the COVID-19 pandemic. This result is robust to alternative measures of the COVID-19 pandemic and is consistent across in-sample and out-of-sample forecast periods. The relatively lower resilience of emerging stock markets during the COVID-19 pandemic suggests that investment in emerging stock markets is not a good safe-haven option for potential investors (see Dutta et al., 2020; Ji et al., 2020). This also suggests that the developed stock markets provide a better hedge against UPE than the emerging stock markets. Accounting for the role of government policies due to the COVID-19 pandemic, our results suggest that government policies have no significant influence on the effect of uncertainty due to UPE on the stock returns of emerging markets.

Appendix.

Table 6: Government response and stock returns during COVID-19 pandemic.

| Government Response | Without Control | With Control |
|---------------------|----------------|-------------|
|                     | Emerging       | Developed   | Emerging | Developed |
|                     | 0.0143a(37.36) | 0.0168(253.66) | 0.0143(30.14) | 0.0143(267.02) |

Note: “Without Control” implies the model with the predictor of interest only [i.e. government response] while “With Control” is an extension of the original model to include relevant control variables. Irrespective of the model, the coefficient reported under each category [i.e., Emerging and Developed stock models] is the sum of the coefficients of the five lags whose significance is jointly evaluated using the Wald test for coefficient restriction. As such, the values in parentheses ( ) are the F statistics for the joint coefficients; ‘a’, ‘b’ and ‘c’ indicate statistical significance at 1%, 5% and 10% levels, respectively.

Appendix A: Summary statistics for stock returns by country

| Country  | Before | After | Full |
|----------|--------|-------|------|
| Argentina | mean 0.001529 | −0.00332 | 0.002655 |
|          | Sd 0.02976 | 0.051435 | 0.043194 |
| Brazil   | mean 0.00129 | −0.00093 | −0.00028 |
|          | Sd 0.03051 | 0.051028 | 0.0405 |
| Chile    | mean 0.002082 | −0.00049 | 0.001979 |
|          | Sd 0.066128 | 0.03362 | 0.035172 |
| China    | mean 0.000303 | −0.00072 | 0.000413 |
|          | Sd 0.021298 | 0.013649 | 0.012427 |
| Colombia | mean 0.000654 | 0.00425 | 0.001931 |
|          | Sd 0.035883 | 0.098628 | 0.081231 |
| Czech    | mean 0.000733 | −0.00212 | 0.001249 |
|          | Sd 0.038384 | 0.027752 | 0.036271 |
| Egypt    | mean 0.007159 | 0.026183 | 0.048128 |
|          | Sd 0.427962 | 0.20664 | 0.282308 |
| Greece   | mean 0.001578 | 0.001566 | −0.00192 |
|          | Sd 0.049482 | 0.059592 | 0.047601 |
| Hungary  | mean 0.003641 | 0.002692 | 0.006518 |
|          | Sd 0.088508 | 0.049462 | 0.093678 |
| India    | mean 0.005024 | −0.00678 | 0.001487 |
|          | Sd 0.098353 | 0.083541 | 0.096792 |
| Indonesia| mean 0.001941 | −0.00169 | 0.0016 |
|          | Sd 0.063224 | 0.039395 | 0.044159 |
| Korea    | mean 0.000705 | −0.00166 | 0.001845 |
|          | Sd 0.038015 | 0.03179 | 0.029508 |
| Mexico   | mean 5.02E-05 | 0.005403 | 0.000898 |
|          | Sd 0.014245 | 0.059441 | 0.051141 |
| Pakistan | mean 0.001353 | −0.00137 | −0.00222 |
|          | Sd 0.049642 | 0.040685 | 0.035006 |
| Peru     | mean 0.002912 | −0.00445 | −0.00993 |
|          | Sd 0.072578 | 0.025348 | 0.021592 |
| Philippines | mean 0.000318 | 0.005772 | 0.00225 |
|          | Sd 0.023875 | 0.093915 | 0.076176 |
| Poland   | mean 0.001311 | −0.00362 | 0.000176 |
|          | Sd 0.051943 | 0.034823 | 0.036373 |
| Qatar    | mean 0.001517 | −0.00168 | 0.001921 |
|          | Sd 0.054474 | 0.084558 | 0.069675 |
| Russia   | mean 0.001064 | 0.008205 | 0.004099 |
|          | Sd 0.046307 | 0.103784 | 0.095015 |
| Taiwan   | mean 0.00232 | 0.002002 | 0.004313 |
|          | Sd 0.062172 | 0.088865 | 0.069446 |
| Thailand | mean 0.001319 | −0.00043 | 0.003467 |
|          | Sd 0.051738 | 0.050655 | 0.048728 |
| Turkey   | mean 0.001381 | 0.002311 | 2.44E-05 |
|          | Sd 0.045908 | 0.090365 | 0.070981 |
| UAE      | mean 0.001843 | −0.00296 | 0.002762 |
|          | Sd 0.058527 | 0.076306 | 0.073828 |
| South Africa | mean 0.000357 | −6.72E-05 | −0.00069 |
|          | Sd 0.022174 | 0.032579 | 0.027954 |
Appendix B: Scenario analysis of stock returns in different periods by countries

| Country     | Before | After | Full  | Country     | Before | After | Full  |
|-------------|--------|-------|-------|-------------|--------|-------|-------|
| Argentina   | 0.001061 | 0.004831 | 0.001305 | Mexico      | −1.43E-05 | −0.00442 | 3.84E-05 |
| Brazil      | 0.00764 | 0.00126 | 0.001189 | Pakistan    | 0.000267 | −0.00041 | 0.001503 |
| Chile       | 0.00351 | −0.00187 | 0.001922 | Peru        | 0.001417 | 0.001618 | 0.0028  |
| China       | 0.000432 | 0.003349 | 0.000642 | Poland      | 0.000728 | −0.00022 | 0.00125  |
| Colombia    | 0.001166 | −0.00484 | 0.000642 | above mean  | 0.000351 | 0.001229 | 0.00176  |
| Czech Rep.  | 0.001764 | −0.00057 | 0.00072 | Qatar       | 0.002108 | 0.003947 | 0.00143  |
| Egypt       | 0.008108 | 0.004519 | 0.007569 | Russia      | 0.002089 | 0.013299 | 0.001919 |
| Greece      | 0.000254 | −0.00122 | 0.001249 | above mean  | 0.000363 | −0.00168 | 0.001921 |

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