International Review of Financial Analysis 71 (2020) 101546

Contents lists available at ScienceDirect

International Review of Financial Analysis

journal homepage: www.elsevier.com/locate/irfa

Predicting stock returns in the presence of COVID-19 pandemic: The role of health news

Afees A. Salisu[a,b,*], Xuan Vinh Vo[b]

[a] Centre for Econometric & Allied Research, University of Ibadan, Ibadan, Nigeria
[b] Institute of Business Research, University of Economics Ho Chi Minh City, Viet Nam

ARTICLE INFO

Keywords:
Health news
COVID-19
Stock returns
Predictability

ABSTRACT

This study derives its motivation from the current global pandemic, COVID-19, to evaluate the relevance of health-news trends in the predictability of stock returns. We demonstrate this by using data covering top-20 worst-hit countries, distinctly in terms of reported cases and deaths. The results reveal that the model that incorporates health-news index outperforms the benchmark historical average model, indicating the significance of health news searches as a good predictor of stock returns since the emergence of the pandemic. We also find that accounting for "asymmetry" effect, adjusting for macroeconomic factors and incorporating financial news improve the forecast performance of the health news-based model. These results are consistently robust to data sample (both for the in-sample and out-of-sample forecast periods), outliers and heterogeneity.

1. Introduction

Theoretical evidence backed by the growing literature shows that news in general cannot be ignored when predicting the movements in economic/financial variables (see Narayan, 2019 for a review of the literature). The "price pressure hypothesis" or "attention theory" (see Barber & Odean, 2008) and "network analysis" (see Nofsinger & Sias, 1999) lend credence to this fact. The "pressure price hypothesis" on the one hand, states that individual investors tend to buy stocks that attract their attention because individual investors do not have enough time or resources to examine thousands of stocks. This often implies that stocks capturing investors' attention (often through news) and searched intensively tend to generate abnormally high returns and trading volume (Takeda & Wakao, 2014). On the other hand, the rationale behind "network analysis" is underscored by the fact that individual or retail investors tend to adopt feedback strategies and rely primarily on stock information to infer value of a stock (Bange, 2000). Therefore, co-attention networks promote information that captures investors' attention (Chen et al., 2010).

Understanding how this relationship works is crucial for certain reasons. First, buying and selling decisions made by individual investors are now more dependent on available news content. Second, the gradual emergence of social media investment platforms which now use crowd wisdom (or wisdom of crowds) and shared information to help users make better decisions (Breitmayer et al., 2019). Meanwhile, how certain news - good or bad (positive or negative) - affect macroeconomic variables especially stock returns remains a subject of debate among researchers. Cohen et al. (2017), Akinchi and Chahrour (2018) and Svensson (1999) citing "bad news principle" argue that only bad news matters in investment decision but Narayan and Bannigidadmath (2015) and Narayan (2019) find that both positive and negative news affect investment decisions. A number of studies have considered variable-specific news such as oil price news and economic news in predicting stock returns (see Calomiris & Mamaysky, 2018; Even-tov, 2017; Liebmann et al., 2016; Nam and Seong, 2018; Narayan, 2019; Narayan & Bannigidadmath, 2015; Shynkevich et al., 2016) while we utilized health news, the choice of which is influenced by the current pandemic.

The outbreak of COVID-19 which triggered crisis in global financial economy is of special interest. Efforts to contain the spread of this disease such as quarantine and restrictions on mobility of labor are slowing down the world economy. Reduction in supply caused by a disrupted global supply chain and a fall in demand have continued to discourage investment and increased risk aversion which is now eroding business and consumer confidence. Commodity prices have nosedived, stock prices are at 10-year record low and still falling (OECD, 2020). The global stock markets continue to sink in the absence of timely policy intervention. Emerging reports from around the world have shown a highly steeped downward sloping trend. Markets in Australia, South Korea and Hong Kong drop by more than 5% daily

* Corresponding author.
E-mail addresses: afees.adebare.salisu@ueh.edu.vn (A.A. Salisu), vinhvx@ueh.edu.vn (X.V. Vo).

https://doi.org/10.1016/j.irfa.2020.101546
Received 19 April 2020; Received in revised form 12 June 2020; Accepted 19 June 2020
Available online 29 June 2020
1057-5219/ © 2020 Elsevier Inc. All rights reserved.

while in China, it is about 3%. Similarly, in the United States, the stock market has faced the same fate. Further aggravated by falling oil prices, investors are hurriedly selling their stocks and share prices are crashing.

With the growing uncertainty in the business arena and no end in sight, the choice of making investment decisions under an extremely dicey condition becomes increasingly inevitable. To avoid the economy going into depression, investment must be sustained. Private investors will need sufficient information to restore their confidence and national government will require advice on the best policy intervention to create an enabling business environment. Knowledge of how stock prices might behave at later dates presents a unique opportunity to stakeholders. This does not only restore market efficiency but also allows investors enough room for strategic planning. Thus, the findings of this study will offer useful insights to investors seeking to maximize returns in the presence of global health crisis.

Studies analyzing the impact of news on return predictability are gradually gaining prominence. The notable ones among them are Buttner and Hayo (2010), Bank et al. (2011), Birz and Lott (2011), Takeda and Wakao (2014), Narayan and Bannigidadmath (2017), Tang and Zhu (2017), Kim et al. (2019), Narayan (2019), Nguyen et al. (2019), Xu et al. (2019), and Ekinci and Bulut (2020), among others. Nonetheless, these studies differ in their choice of news. Majority have used Google searches (see Ekinci & Bulut, 2020; for a review) while a few others have used other news sources such as prints and electronic media (see Narayan, 2019; for a review). Thus, the use of news to predict stock returns is not new and they involve macroeconomic and financial news. What has remained understudied in the literature is the use of health news in return predictability and this constitutes the main contribution of the study. Research in this area becomes crucial given investors' sentiment about the severe consequences of the COVID-19 pandemic on their returns coupled with the need to seek safe investments to minimize the impending high risks and uncertainties associated with pandemic.

In this paper, we utilize health news obtained through Google searches to analyze the predictability of stock returns. The intention is to examine how the news associated with the outbreak of COVID-19 has influenced the trading activities in global stock exchanges particularly those that seem to be worse hit by the pandemic. Since the pandemic is health-related, we hypothesize that related news will be sought by investors when making investment decisions particularly in terms of the severity of the pandemic on the global economy. To the best of our knowledge, this is the first study to incorporate health news in the predictive model for stock returns.[1] To achieve this objective, we consider the following. First, we evaluate the predictability of health news as a potential predictor of stock returns during the pandemic period and beyond. Consequently, we evaluate both the in-sample and out-of-sample forecast performance of the health news-based predictive model for stock returns. This essentially requires comparing the forecast performance of the proposed model with the benchmark model (conventionally described as historical or constant returns model). Third, we further test whether controlling for macro-based predictors will enhance the forecast performance of the proposed model. Fourth, we use dataset that seems global in nature as we cover twenty (20) countries that appear to be worse hit by the COVID-19. Essentially, we use two parameters to identify these countries: the reported cases and deaths associated with the pandemic. Given the countries covered in our analyses with greater impacts on the global economy than other countries of the world put together, it becomes easier to draw meaning generalizations from our research findings. The main findings from our results reveal that incorporating health-related information in the valuation of stocks improves forecast accuracy. Besides, accounting for "asymmetry" effect in terms of good and bad health news and adjusting for macroeconomic factors such as oil price and exchange rate further improves the forecast performance. Several robustness checks are considered to validate the results.

The remainder of this study is organized as follows: Section 2 describes the data with some preliminary statistics and discussions on the behavior of relevant variables; the empirical methodology is detailed in Section 3; Section 4 discusses the findings of the study; and Section 5 concludes the paper.

2. Data and preliminary analyses

Our datasets consist of stock prices (in USD) of the 20 worst-hit countries by the pandemic and corresponding volumes of searches relating to health news. Table 1 shows the list of these countries with the most reported cases and reported deaths of COVID-19 as of 30th of March 2020, as pulled from the website (www.cdc.gov) of the Centre for Disease Control and Prevention (CDC). The list shows the rank of individual countries according to the number of cases and deaths reported respectively. The stock index data for each of the country was obtained from www.investing.com historical data archive.[2] The keyword "health news" was to capture health-related news in order to accommodate all forms of health news searches during the considered period either directly related to COVID-19 or otherwise. The corresponding search volumes using keyword "health news" were obtained from Google trends (https://trends.google.com/trends/explore). Although that data is available in different time frequencies, the daily frequency is preferred and extracted on the 30th of March 2020 starting from 1st of January 2020. The general restriction of the start date to 1st of January 2020 is as a result of data availability as Google trends allows for daily frequencies for data spanning a 90-day period or less.

Table 2 illustrates the descriptive analysis of countries' stock returns and evaluates its relationship with health-related news. The table summarizes the mean and standard deviation of stock returns across all the countries as well as the behavior of stock returns when health-news searches increase or decline. The reported average values in Column I of Table 2 represent the average stock returns across all the countries at the average health-related news searches over the period under consideration, January 01 to March 30. However, Columns II & III report average country stock returns and its standard deviation when the health-news index is below and above its average value, respectively.

It is evident from the table that all of the 20 COVID-19 worst hit countries both in terms of reported cases and deaths experienced a decline in their stock returns with all of them recording negative stock returns during this period with the exception of Australia. The positive returns seen in Australia was expectedly so because the country had suffered economic crises since before the announcement of COVID-19 with the incidences of wild fire disrupting economic activities around the country. The announcement period coincided with the halt of the crisis, when economy had just begun to recover. The United States and Italy despite being most hit with the highest recorded cases and deaths respectively experienced a modest negative stock return. The analyses in Table 2 further show that as the health-related news search increases, stock returns decline across all the countries considered. On the other hand, when health news search declines, stock returns across these countries are above their averages.

These findings have vast implications for the global economy. One, it implies that investment returns during this period will largely depend on the extent of reportage and global discourse surrounding COVID-19,

[1] The only exception is the study of Narayan (2019) however it differs from this study in terms of the choice of news. The former utilizes oil price news while we focus on health-related news.

[2] The platform provides real-time data, quotes, charts, financial tools, breaking news and analysis across 250 exchanges around the world in 44 language editions. With more than 46 million monthly users, and over 400 million sessions, the platform is one of the top three global financial websites according to both Similar Web and Alexa.

Table 1
List of countries with high incidence of COVID-19 Cases and Deaths.

Rank	List of countries with high cases	Actual cases reported	List of countries with high deaths	Actual death reported
1	United States	143,025	Italy	10,781
2	Italy	99,689	Spain	6820
3	China	82,463	China	3311
4	Spain	78,797	France	2606
5	Germany	57,298	United States	2509
6	France	40,174	United Kingdom	1228
7	United Kingdom	19,522	Netherlands	771
8	Switzerland	14,274	Germany	455
9	Netherlands	10,866	Belgium	431
10	Belgium	10,836	Switzerland	257
11	South Korea	9661	South Korea	158
12	Turkey	9217	Brazil	136
13	Austria	8813	Turkey	131
14	Canada	6255	Portugal	119
15	Portugal	5962	Indonesia	114
16	Brazil	4256	Sweden	110
17	Israel	4247	Austria	86
18	Norway	4102	Denmark	72
19	Australia	4093	Philippines	71
20	Sweden	3700	Canada	60

Note: Although, Iran has high incidence of reported COVID-19 cases and deaths, it was omitted from this list because of the unavailability of the country's stock data. The figure represents what it was as of 30th of March 2020 when it was retrieved from the website of CDC.

investors would be very cautious to observe the trend of the pandemic before committing their wealth. For this reason, there is likely going to be absence of any serious investment while news of COVID-19 gathers momentum. If cases of infection continue, the global economy will plunge into an inevitable recession. Two, it also connotes that countries that heal fast from the pandemic will likewise achieve quicker economic recovery than those that heal later.

Fig. 1 is an illustration of the relationship between stock returns and changes in health news since the announcement of COVID-19. The graphical illustration reveals some co-movements between the two series for all the countries with health news being more volatile. The earlier part of the period of COVID-19 announcement witnessed a minimal fluctuation while an increased fluctuation was recorded in the later part of the period. The graph shows that stock returns did not respond immediately to increased fluctuation in health news and only started responding until about the 3rd month of its announcement. This maybe because of the gradual spread of the disease with only few cases reported in Europe and America at those times.

3. Methodology

We construct a predictive model to evaluate the evident relationship between health-related news and stock returns of the worst-hit countries by the COVID-19 pandemic. In line with the study objectives, the predictive power is compared with other plausible forecast models for stock returns. The short-time span since the emergence of the pandemic informs our choice of panel data forecasting approach. By pooling the stock returns series for the 20 most affected countries in terms of cases and deaths, the likely problem of insufficient observations for a country-by-country analysis is circumvented[3] (see Gavin & Theodorou, 2005; Rapach & Wohar, 2004). A generic specification for a typical panel data regression model can be expressed as[4]:

$$r_i = \alpha i_T + X_i\beta_i + e_i = Z_i\gamma_i + e_i;\ i = 1, 2, 3, \ldots, N \quad (1)$$

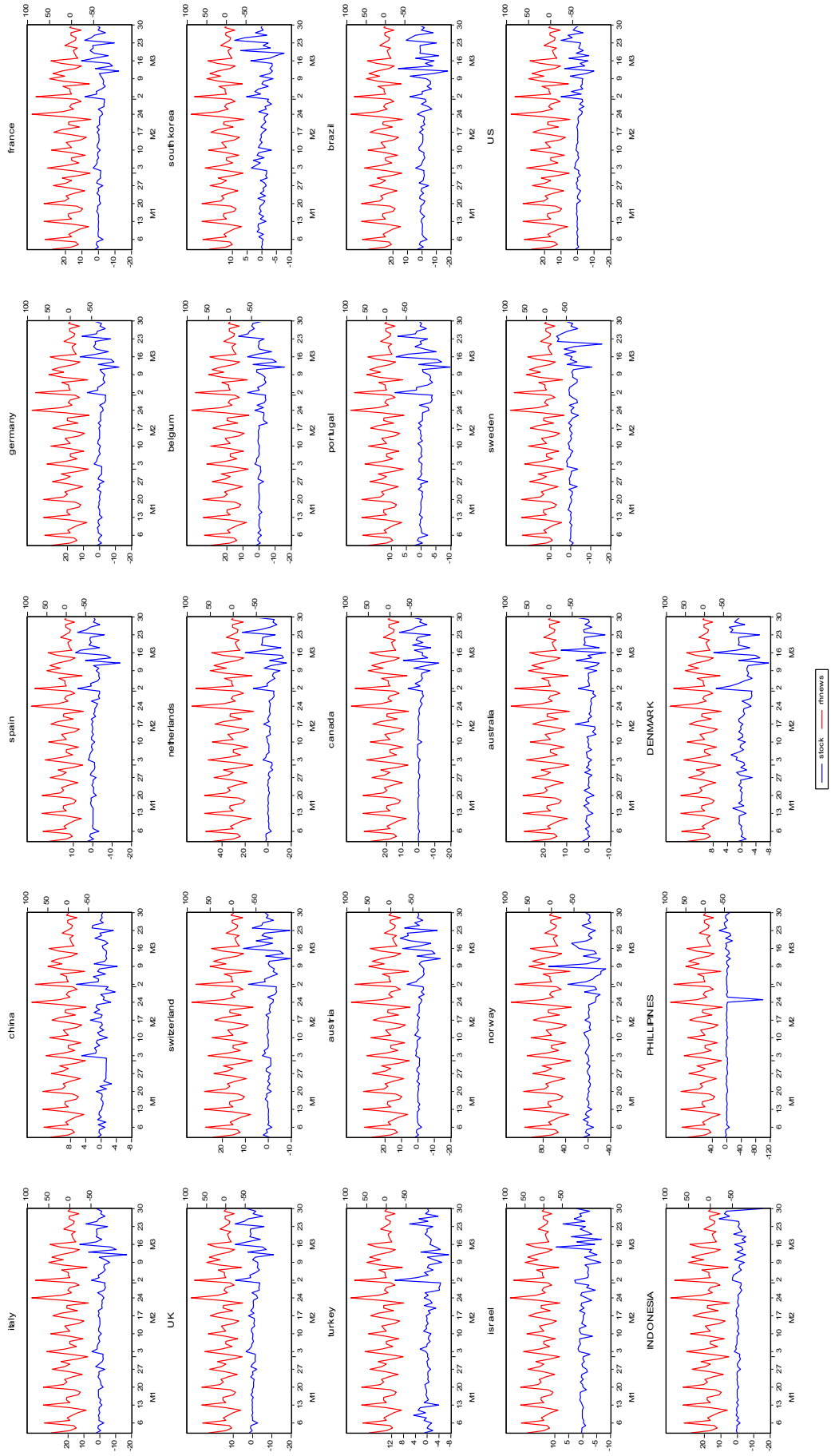
Table 2
Summary statistics for country-specific, global and panel/group-specific variables.

Country		I	II	III
US	Mean	−0.27512	−0.14457	−0.51975
	Std. dev	2.923692	2.613209	3.204853
Italy	Mean	−0.30259	0.203158	−1.0147
	Std. dev	3.465439	2.689175	4.219403
China	Mean	−0.1081	−0.12773	−0.10306
	Std. dev	1.586513	1.179297	1.938712
Spain	Mean	−0.34301	0.095484	−0.96711
	Std. dev	3.062492	2.516457	3.601903
Germany	Mean	−0.27908	0.058186	−0.77646
	Std. dev	3.213911	2.705106	3.678072
France	Mean	−0.28733	0.114451	−0.8722
	Std. dev	3.20983	2.600414	3.785131
UK	Mean	−0.2919	0.000219	−0.72472
	Std. dev	2.853447	2.310346	3.339457
Switzerland	Mean	−0.11165	0.183638	−0.54206
	Std. dev	2.81563	2.160601	3.380111
Netherlands	Mean	−0.45606	−0.11641	−1.16842
	Std. dev	5.535767	5.132157	5.722084
Belgium	Mean	−0.38496	−0.31019	−0.61429
	Std. dev	3.592772	3.37214	3.95359
South Korea	Mean	−0.22093	−0.08243	−0.45071
	Std. dev	2.407475	2.685201	1.986428
Turkey	Mean	−0.27049	−0.02928	−0.59013
	Std. dev	2.331936	1.970248	2.630663
Austria	Mean	−0.45913	0.027861	−1.14705
	Std. dev	3.554242	3.126525	4.008587
Canada	Mean	−0.25422	0.373664	−1.07008
	std. dev	3.07014	2.940587	3.05896
Portugal	mean	−0.25613	−0.04976	−0.58427
	Std. dev	2.5756	2.194417	2.934657
Brazil	Mean	−0.64923	−0.12335	−1.47166
	Std. dev	4.467976	4.052283	4.922037
Sweden	Mean	−0.20767	−0.2272	−0.2761
	Std. dev	2.820559	3.224356	2.524903
Israel	Mean	−0.26765	−0.13891	−0.46261
	Std. dev	2.325098	2.108259	2.531108
Norway	Mean	−0.86409	−1.58061	−3.89979
	Std. dev	12.49835	6.631607	9.702619
Australia	Mean	0.044237	0.426341	−0.51504
	Std. dev	2.686867	2.609828	2.643399
Indonesia	Mean	−0.35459	−0.71135	−0.03043
	Std. dev	2.834217	3.06215	2.621795
Denmark	Mean	−0.04997	0.186669	−0.37901
	Std. dev	2.14059	1.561275	2.619893
Philippines	Mean	−1.40331	−0.43422	−0.31947
	Std. dev	11.33804	3.778193	4.53154

Note: The average stock returns are presented in percentages. Column I depicts the average stock returns and its corresponding standard deviation at the overall mean of health-related news search; Column II indicates the average stock returns and its standard deviation when the health news index is above its overall mean, while Column III considers the same requirements when the news index is below its average value.

[3] There are two approaches for forecasting stock returns using pooled data; (i) forecasting for the individual countries of the same variable and combining their forecasts to produce a single forecast, and (ii) pooling countries' stock returns data into panel and forecasting. For the former, it has been shown to increase forecast accuracy (see Bates & Granger, 1969; Diebold & Lopez, 1996; Newbold & Harvey, 2002; Stock & Watson, 2004, 2006; Timmermann, 2006; Westerlund & Basher, 2007), there are also inherent instabilities and estimation errors particularly in the combination weights when multiple forecasts of the same variable are combined (see Timmermann, 2006; Westerlund & Basher, 2007). On the other hand, the panel data approach involves the use of panel data procedures and the estimates may eliminate certain biases that may plague country by country estimates.

[4] Previous studies that have examined stock return predictability using historical average as the baseline model include Bannigidadmath and Narayan (2015), Narayan and Gupta (2015), Phan et al. (2015), Narayan et al. (2016), Devpura et al. (2018), Salisu, Adekunle, Alimi, and Emmanuel, 2019, Salisu, Isah, and Akanni, (2019), Salisu, Isah, and Raheem, (2019), Salisu, Raheem, and Ndako, (2019), and Salisu, Swaray, and Oloko, (2019).



Note: stock and hnews denote stock returns and changes in health news search respectively.

Fig. 1. Cross-country stock returns and health news.
Note: stock and hnews denote stock returns and changes in health news search respectively.

where for every i with T time series dimension, r_i is $(T \times 1)$ vector of stock returns computed as log returns $(100 * \log(p_t/p_{t-1}))$; $Z_i = [i_T, X_i]$; X_i is $(T \times K)$; $\gamma_i' = (\alpha_i, \beta_i')$; i_T is a vector of ones of dimension T; and e_i is $(T \times 1)$. The panel data model in matrix form is specified this way to be able to isolate the slope coefficient for each country i without loss of generality (see Baltagi, 2013 for some computational details). In the empirical literature, some studies have favoured the choice of homogenous panels (see Baltagi et al., 2000; Baltagi & Griffin, 1997; Driver et al., 2004). Baltagi et al. (2000) in particular find that homogeneous panel data estimators beat the heterogeneous and shrinkage type estimators in RMSE performance for out-of-sample forecasts and a further complement from Driver et al. (2004) shows that pooled homogeneous estimators outperform their heterogeneous counterparts in out-of-sample forecasts as well. Another strand of empirical literature favours the heterogeneous panel models (see for example, Pesaran & Smith, 1995; Robertson & Symons, 1992). The analyses using heterogenous panel can be done based each country's time series regression, or employing various estimation methods described in the earlier papers (see Baltagi, 2008; Maddala et al., 1997; Pesaran & Smith, 1995; Reese & Westerlund, 2016; Robertson & Symons, 1992; Salisu & Isah, 2017; Salisu & Ndako, 2018). However, the homogeneous panel model is parsimonious (particularly with short T which is the case here) compared to the more parameter-consuming heterogeneous estimators. Besides, it conforms with "keep it simple" principle advocated by Baltagi et al. (2002) and Clements and Hendry (2002), among others.

Consequently, we employ the homogenous panels given the short T dimension of our data. We begin our analyses with the baseline model involving the constant return (historical average) model which ignores any potential predictor of stock and is specified as[5]:

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

where r_{it} denotes stock returns; $\alpha$is a constant parameter; and e_{it} is the error term. We augment the historical average model with the health-news predictor by theoretically relying on the Investor Recognition hypothesis (Merton, 1987). The Investor Recognition hypothesis assumes incomplete market information and investors are not aware of all information about the securities in a market. Therefore, emotions and sentiments based on available information and news influence their decision by selecting only familiar stocks in constructing portfolios (see also Adachi et al., 2017; Aouadi et al., 2013; Bank et al., 2011; Bodnaruk & Ostberg, 2009; Da et al., 2011; Jacobs & Hillert, 2016; Joseph et al., 2011; Preis et al., 2013; Zhu & Jiang, 2018). The health-news predictability model of stock returns is given as:

$$r_{it} = \alpha + \delta hn_{i,t-1} + e_{it} \tag{3}$$

where hn_{it} denotes the health news index expressed in natural logs. The health news index is a measure of investors' awareness and emotions. We also explore an important feature of daily stock returns, the day-of-the-week effect (see Zhang et al., 2017 for a review of the literature). To account for this important feature while also avoiding parameter proliferation in the estimable model, we employ a three-step procedure. First, we regress the return series on dummy variables constructed for the five days of the week, that is, $r_{it} = \theta + \sum_{j=1}^{4} \gamma_j D_{jit} + \upsilon_{it}$ where $D_j = 1$ for each j and zero otherwise. Note that $j = 1, 2, 3, 4$ respectively denotes Monday, Tuesday, Wednesday and Thursday while Friday is the reference day. In the second step, we derive the "day-of-the-week adjusted returns" (denoted as $r_{it}{}^d$) and estimated as $r_{it}^d = r_{it} - \left(\hat{\theta} + \sum_{j=1}^{4} \hat{\gamma}_j D_{jit}\right)$ or simply $r_{it}^d = \hat{\upsilon}_{it}$. The third step involves substituting the day-of-the-week adjusted stock returns series in the health-news predictability model in Eq. (3). Thus, Eq. (3) is modified to become:

$$r_{it}^{adj} = \alpha + \delta hn_{i,t-1} + e_{it} \tag{4}$$

where $r_{it}{}^{adj}$ denotes day-of-the-week adjusted stock returns. A prominent feature when dealing with the predictability of stock returns is to test for possible asymmetry in the predictors, where their positive and negative changes are assumed and have in most case being found to have distinct effects on stock returns (see for example, Narayan, 2019; Narayan & Gupta, 2015; Salisu et al., 2019). Hypothetically, a negative asymmetry is expected to impact positively on stock returns, while on the other hand, positive asymmetry, which implies increase in the health-related news search is expected to have a negative impact on stock returns. To account for asymmetry, we follow the Shin et al. (2014) procedure by decomposing the health news indicator into negative and positive changes which are computed as the partial sums defined by $hn_t{}^- = \Sigma_{j=1}{}^t \Delta hn_j{}^- = \Sigma_{j=1}{}^t \min(\Delta hn_j, 0)$ and $hn_t{}^+ = \Sigma_{j=1}{}^t \Delta hn_j{}^+ = \Sigma_{j=1}{}^t \max(\Delta hn_j, 0)$ for negative and positive partial sums of health news respectively. The predictive model that accounts for these asymmetries can be re-specified as:

$$r_{it}^{adj} = \alpha + \beta_1^+ hn_{i,t-1}^+ + \beta_2^- hn_{i,t-1}^- + e_{it} \tag{5}$$

where $\beta_1{}^+$ and $\beta_1{}^-$ are respectively the coefficients of the positive and negative asymmetry parameters. Lastly, the Arbitrage Pricing Theory provides the theoretical premise for incorporating systemic or macroeconomic risks in the predictability of stock returns. Therefore, we also account for some other important factors that can influence stock returns. Some of the prominent macro-related fundamentals considered in the empirical literature include earnings expectations and interest rates, in addition to global factors such as exchange rates and crude oil prices (see also Bannigidadmath & Narayan, 2015; Chen et al., 1986; Devpura et al., 2018; Narayan et al., 2016; Rossi, 2013; Salisu, Adekunle, Alimi, and Emmanuel, 2019; Salisu, Isah, and Akanni, 2019; Salisu, Isah, and Raheem, 2019; Salisu, Raheem, and Ndako, 2019; Salisu, Swaray, and Oloko, 2019). Due to data limitation however, given the fact that our focus is on the COVID-19 period, our macro-related variables are limited to those that are available at a high frequency namely exchange rate and crude oil prices. On this basis, the single predictor model is extended to become:

$$r_{it}^{adj} = \alpha + \delta hn_{i,t-1} + Z_{it}'\phi + e_{it} \tag{6}$$

where Z_{it}' is $(1 \times K)$ vector of additional (macroeconomic) variables, and ϕ is $(K \times 1)$ vector of parameters for the additional K regressors.[6] To circumvent having so many parameters in the predictive model and in the spirit of Westerlund et al. (2016), we adopt the same procedure followed in the computation of the day-of-the-week-adjusted stock returns. In other words, we regress the return series on the selected macro variables,[7] that is, $r_{it} = \vartheta + Z_{it}'\phi + u_{it}$ and thereafter, the macro-adjusted returns series is regressed on the health news predictor. Ideally, the choice of the return series will be determined by the relative forecast performance of r_{it} and $r_{it}{}^d$ from the single-predictor case.

[5] This is not the first study to examine stock return predictability using historical average as the baseline model (see Bannigidadmath & Narayan, 2015; Devpura et al., 2018; Narayan et al., 2016; Narayan & Gupta, 2015; Phan et al., 2015; Salisu, Adekunle, Alimi, and Emmanuel, 2019; Salisu, Isah, and Akanni, 2019; Salisu, Isah, and Raheem, 2019; Salisu, Raheem, and Ndako, 2019; Salisu, Swaray, and Oloko, 2019). What is however new is the use of panel data (i.e. pooling of countries) to achieve the same objective while also accounting for some level heterogeneity in the cross-sections.

[6] This idea is also technically motivated by the work of Westerlund et al. (2016) which provides some technical details and computational procedure on how to incorporate common factors in the predictability of stock returns. The approach followed in the estimation of this model is similar in spirit to that of Westerlund et al. (2016). One major attraction to this approach is that it does not require integration property of the common factors used in the predictive model.

[7] The macroeconomic variables considered include global crude oil prices and country's domestic currency exchange rates against the US Dollar.

Finally, the forecast evaluation of the predictor is rendered using two pair-wise forecast measures, namely Campbell & Thompson, 2008 and Clark & West, 2007 tests.[8] These measures are particularly useful when dealing with nested predictive models. The (Campbell & Thompson, 2008) test is specified as:

$$CT = 1 - (\widehat{MSE}_u / \widehat{MSE}_r) \tag{7}$$

where $\widehat{MSE}_u$ is the mean squared error obtained from the unrestricted model, in this case the health news-based predictor (Eq. (3)) and $\widehat{MSE}_r$ is the mean squared error obtained from the restricted model (for example, the historical average or constant return model, Eq. (2)). Consequently, Eq. (3) outperforms Eq. (2) if $CT > 0$ and vice versa. The Clark and West (2007) test on the other hand is used to establish the statistical significance of the forecast evaluation procedure in the Campbell and Thompson (2008). For a forecast horizon h, the Clark and West (2007) test is specified as:

$$\widehat{f}_{t+h} = \widehat{MSE}_r - (\widehat{MSE}_u - adj) \tag{8}$$

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

For additional results, first we extend the evaluation of the health-news predictability model by investigating the relevance of financial news in the health new predictability of stock returns. The foremost indicator of measuring investors' sentiments in the global stock markets is the stock market volatility index (VIX) compiled by the Chicago Board Options Exchange (CBOE) (for additional literature, see Balcilar & Demirer, 2015; Psaradellis & Sermpinis, 2016; Taylor, 2019; Wang, 2019; Zhu et al., 2019; Yun, 2020). The VIX series is considered as a leading barometer of market volatility relating to listed options and it has been found to have larger in-sample predictability performance on stock markets (Wang, 2019; Yun, 2020; Zhu et al., 2019). Thus, for robustness, we evaluate the forecast performance of the combined news indices, i.e. VIX, an indicator of financial market news, and the health-news index, in the stock returns predictability of top-20 COVID-19 affected countries. The objective here is to see if including the two news indices will produce better forecast accuracy for stock returns relative to the benchmark model as well as the single-predictor health-based model.

The second aspect of the additional results involves accounting for any inherent heterogeneity across the stock returns of the selected countries.[9] We apply the heterogeneous panel model approach suggested by Chudik and Pesaran (2015) and Chudik et al. (2016) which have been demonstrated to account for unobserved common factors among cross sections (see also Ditzen, 2018; Westerlund et al., 2016). The predictive panel data model for stock returns[10] where the health-related news index is the only predictor as specified in Eq. (3) above is re-written as[11]:

$$r_{it} = \alpha + \delta hn_{i,t-1} + e_{it} \tag{9}$$

$$e_{it} = \lambda_i f_t + u_{it} \tag{2}$$

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

where α_i and δ_i in Eq. (9) respectively represent the heterogenous 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 (λ_i) and the remainder error term (u_{it}). Thus, in addition to allowing for heterogeneity in the predictability, it also incorporates unobserved common factors for the countries' stock returns. The predictability performance of the stock returns model using the panel heterogenous estimator is evaluated and compared with the historical average model using both the CT and CW tests.

4. Results and discussion

We evaluate the health news predictability of stock returns since the emergence of COVID-19 by evaluating the stock returns behavior of top 20 most affected countries. We rely on official daily information on the number of reported cases and deaths in the selection of these countries. By pooling countries based on the number of reported cases and deaths, we evaluate the veracity of health-news predictability of stock returns. The four variant models estimated and compared with the historical average (constant returns) model as discussed in the methodology section include: (i) the single factor health-news predictability model (Eq. (3) denoted as MD1); (ii) predictability model with day-of-the-week adjusted stock returns series (Eq. (4) denoted as MD2); (iii) asymmetry heath-news predictability model (Eq. (5) denoted as MD3), and (iv) health news predictability model with macro-adjusted stock returns (Eq. (6) denoted as MD4). As discussed in the methodology section, each model from the historical average model (Eq. (2)) to the macro-adjusted model (MD4) is specified to account for different fundamentals and their relative forecast performance is evaluated. The predictability results for the four models are summarized in Table 3 and we find that the estimated coefficients for almost all the models are correctly signed and statistically significant following the a priori expectation both across top-cases and top deaths reporting countries. However, while the coefficient of the positive asymmetry is negative, which conforms with the expected sign and statistically significant, the coefficient of the negative asymmetry is also negative over the period under consideration. By implication, regardless of the movements in health news, its impact on stock returns is negative during the pandemic, although, increased searches for health news have greater adverse effects on stock returns. Furthermore, the stock returns predictability estimates after controlling for macroeconomic variables are summarized in the MD4 column of Table 3. The estimated coefficient of health-news is also negative and statistically significant conforming with the a priori expectation.

Next, we examine the forecast performance of each of the contending models, which include the historical average model and the various health-news predictability models. The forecast performance is evaluated for the in-sample and out-of-sample forecast horizons using the two pair-wise forecast measures: Campbell and Thompson (2008) and Clark and West (2007) tests. The CT statistic compares the Mean Square Error (MSE) or Root Mean Square Error (RMSE), a measure of the deviation of the forecast from the actual, for the contending models and a model (whose RMSE is the numerator) is said to perform better relative to another model (whose RMSE is the denominator) when the CT statistic is positive, otherwise (i.e., if the CT statistic is negative), it does not. The CW test on the other hand provides the formal procedure for ascertaining the statistical significance of the difference in the observed forecast errors. A positive and significant value of the constant parameter in the CW test regression indicates better forecast performance of the model with the adjusted-MSE relative to the one without adjustment (see the Methodology section for details). The CT and CW test results are summarized in Table 4.

[8] Given the nature of our time series dimension, the forecast evaluation is limited to the in-sample and a single out-of-sample forecast evaluation with one-week ahead period for brevity.

[9] We thank the Anonymous reviewer for suggesting this additional robustness analysis.

[10] he model also helps to resolve any inherent nonstationarity in the series, can also accommodate mixed order of integration and is useful in the estimation of long run and short run dynamics including the speed of adjustment.

[11] 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.

Table 3
Stock returns predictability results.

Coefficients	MD1	MD2	MD3	MD4
Cases				
$hn_{i,\ t-1}$	−3.1265***	−3.0488***		−3.3164***
	(0.2627)	(0.2628)		(0.2765)
$hn_{i,\ t-1}{}^{+}$			−2.3602***	
			(0.3427)	
$hn_{i,\ t-1}{}^{-}$			−1.8250	
			(0.4724)	
Deaths				
$hn_{i,\ t-1}$	−2.5913***	−2.5157***		−2.6254***
	(0.1999)	(0.1984)		(0.2047)
$hn_{i,\ t-1}{}^{+}$			−2.1412***	
			(0.2593)	
$hn_{i,\ t-1}{}^{-}$			−1.8497***	
			(0.3575)	

Note: The upper pane of the table summarizes the predictability results for the top-20 countries in terms of COVID-19 reported cases, while the lower pane summarizes the results for the top-20 countries with COVID-19 related deaths. MD1 indicates the single-predictor model with health news as the only predictor; MD2 is the single predictor model with day-of-the-week adjusted stock returns series; MD3 is the heath-news predictor model with "asymmetry" effect; and MD4 is the predictability model with macro-adjusted stock returns series. $hn_{i,\ t-1}$, $hn_{i,\ t-1}{}^{+}$ and $hn_{i,\ t-1}{}^{-}$ are respectively the coefficients of one period-lag of symmetric, positive and negative health news effects. Standard errors are reported in parentheses.
*** Indicates statistical significance at 1% level.

Table 4
In-sample and out-of-sample forecast evaluation.

	In-sample		Out-of-sample	
	C-T stat	Clark & West	C-T stat	Clark & West
Cases				
MD1 vs CR	0.0671	1.5869*** (0.2503)	0.0819	3.8387*** (0.6297)
MD2 vs MD1	0.0020	0.4360*** (0.1582)	0.0278	0.9358*** (0.1718)
MD3 vs CR	0.0796	1.5193*** (0.1910)	0.1081	3.0375*** (0.4316)
MD3 vs MD1	0.0133	0.6328*** (0.1804)	0.0285	1.1650*** (0.1895)
MD4 vs CR	0.0742	1.5385*** (0.2182)	0.1004	3.5363*** (0.5529)
MD4 vs MD1	0.0077	0.5238*** (0.1842)	0.0201	0.8641*** (0.2076)
Deaths				
MD1 vs CR	0.0777	1.0911*** (0.1793)	0.0963	2.9146*** (0.4824)
MD2 vs MD1	0.0138	0.3327*** (0.1196)	0.0393	0.7596*** (0/1358)
MD3 vs CR	0.1169	1.0869*** (0.1296)	0.1257	2.4249*** (0.3579)
MD3 vs MD1	0.0425	0.5219*** (0.1545)	0.0325	0.7835*** (0.1613)
MD4 vs CR	0.1133	1.0953*** (0.1438)	0.1232	2.6784*** (0.4185)
MD4 vs MD1	0.0386	0.4542*** (0.1605)	0.0298	0.6610*** (0.1836)

Note: CR is the historical average model, MD1 indicates the single-predictor model with health news as the predictor; MD2 is the single predictor model with day-of-the-week adjusted stock returns series; MD3 is the heath-news predictor model with "asymmetry" effect; and MD4 is the predictability model with macro-adjusted stock returns series. Forecast performance of the variant models (MD2 to MD4) is evaluated and compared with the performance of the historical average as well as the single predictor model (MD1). Standard errors are reported in parentheses and *** indicates statistical significance at 1% level. The C-T stat indicates the Campbell and Thompson (2008) test statistics.

The positive values for the CT statistics and CW coefficients, as well as the statistical significance of the latter, both for in-sample and out-of-sample data samples, indicate the outperformance of the models over the historical average predictor. By implication, the results establish that: (i) the single-predictor model of stock returns with health-news index as the predictor outperforms the historical average (constant returns) model; (ii) adjusting stock returns series for day-of-the-week effect is relevant and improves the forecast performance of the single predictor; (iii) asymmetry in health-news searches is important in the predictability of stock returns, although increased searches for health news have greater depressing effect on stock returns; and, (iv) controlling for macroeconomic variables improves the forecasting performance of stock returns predictability.

Table 5
Combined health-news and VIX predictability results and forecast evaluation – top-20 countries with reported COVID-19 cases.

Coefficients		HN &VIX-predictor model
$hn_{i,\ t-1}$		−1.4411***
		(0.4754)
$vix_{i,\ t-1}$		−1.4644***
		(0.3621)
Forecast evaluation	**VIX model vs historical average**	**HN &VIX model vs HN**
In-sample		
C-T stat	0.0810	−0.0075
Clark & West	2.3769***	0.0010
	(0.3723)	(0.0634)
Out-of-sample		
C-T stat	0.0134	0.0920
Clark & West	6.2320***	3.5413***
	(1.1938)	(0.7999)

Note: $hn_{i,\ t-1}$and $vix_{i,\ t-1}$ are the coefficients of health-news and stock market volatility index predictors respectively. The C-T stat indicates the Campbell and Thompson (2008) test statistics.
*** Indicates statistical significance at 1% level.

4.1. Additional results

As discussed in the methodology section, our first additional results involve evaluating the forecast performance of the stock returns predictability by introducing financial news captured with the VIX data into the health news model. The predictability results are presented in Tables 5 and 6 for top-20 countries with reported COVID-19 cases and reported deaths respectively. In line with the previous analyses, we also evaluate the forecast performance of the VIX-augmented health news model relative to the historical average as well as the single predictor health news model (MD1).

The estimated predictability regression when VIX is combined with

Table 6
Combined health-news and VIX predictability results and forecast evaluation – top-20 countries with reported COVID-19 deaths.

Coefficients		HN &VIX-predictor model
$hn_{i,\ t-1}$		−1.2327***
		(0.3585)
$vix_{i,\ t-1}$		−1.1687***
		(0.2733)
Forecast evaluation	**VIX model vs historical average**	**HN &VIX model vs HN**
In-sample		
C-T stat	0.1053	−0.0137
Clark & West	1.6604***	−0.0272
	(0.2920)	(0.0470)
Out-of-sample		
C-T stat	0.0550	0.0739
Clark & West	4.9528***	2.2112***
	(0.9434)	(0.5851)

Note: $hn_{i,\ t-1}$and $vix_{i,\ t-1}$are the coefficients of health-news and stock market volatility index predictors. Both models are estimated using the day-of-the-week adjusted stock returns; C-T stat indicates the Campbell and Thompson (2008) test statistics while C-W test is the Clark and West (2007) test. Both tests evaluate the forecast performance of the historical average model and the HN and VIX predictor models.
*** Indicate statistical significance at 1% level.

Table 7
Health-news predictability results and forecast evaluation using heterogenous panel estimator.

Coefficients	Top reported cases	Top reported deaths
$hn_{i,\ t-1}$	−3.1265*** (0.5106)	−2.5901*** (0.2804)
Forecast evaluation	**HN model vs historical average**	**HN model vs historical average**
In-sample		
C-T stat	0.0927	0.0863
Clark & West	2.3693*** (0.5293)	1.3211*** (0.2623)
Out-of-sample		
C-T stat	0.0881	0.1046
Clark & West	5.0126*** (1.1415)	3.3366*** (0.6890)

Note: $hn_{i,\ t-1}$indicate the coefficient of health-news predictor. The C-T stat indicates the Campbell and Thompson (2008) test statistics. For the two categories of countries, i.e. top reporting COVID-19 cases and deaths, the tests evaluate the forecast performance of the historical average model against the HN predictor model.

*** Indicates statistical significance at 1%, level.

the health news index shows that both coefficients of one-period lagged health news and VIX are negative and statistically significant. For the forecast performance, the results show that the VIX-augmented model outperforms the historical average model both for the in-sample and out-of-sample data partition. Similarly, the model that accommodates both news indices (health and financial news) perform better than the one with health news only, although the forecast accuracy is relatively equal for the in-sample period. This appears to mirror reality as rational investors seek for all the available information that will strengthen their understanding of the market risks.

The second additional results involve estimating the health news predictability model of stock returns using the heterogeneous panel model approach in order to account for unobserved common factors among the cross sections. The results are summarized in Table 7. The coefficients conform with our a priori expectation that stock returns responds negatively to increasing health-news searches and it is in tune with earlier results using the homogenous panel estimator. Further, the in-sample and out-of-sample forecast performance evaluation further confirms that using health news as a predictor in stock returns predictability will outperform the historical average model, using both the Campbell and Thompson (2008) and Clark and West (2007) tests.

Lastly, we account for the possible influence of extreme observations or outliers in the predictability models. The empirical literature have established that having some units that are far away from the behavior of other observations in the sample could impact estimated results (see Bramati & Croux, 2007; Verardi & Croux, 2009; Verardi & Wagner, 2011). Therefore, as an additional robustness test to check for the presence and influence of possible outliers in the dataset, we re-estimated the health-news predictability model of stock returns using robust-to-outliers panel estimator. We employed the robust least squares procedure which addresses both the potential outliers in the predictor and predicted variables and the results are summarized in Table A1 in the Appendix. We find that the estimated predictability results and the forecast performance are consistent after accounting for outliers. Although the magnitude of impact of health news on stock returns declined after adjusting for outliers, the sign is still negative and statistically significant (see Table A1). In addition, both the forecast measures confirm that the single predictor health news model outperforms the historical average. By implication, predicting stock returns using health news index consistently outperforms the benchmark model regardless of the underlying assumptions for the parameter estimates.

5. Conclusion

This study derives its motivation from the current global pandemic, COVID-19, to explore the significance of health news Google searches in predicting stock returns. Our analyses cover top-20 most affected countries during the pandemic in terms of reported cases and deaths. The empirical literature is replete with studies on how news and information trends can predict economic and financial variables (see Calomiris & Mamaysky, 2018; Even-tov, 2017; Liebmann et al., 2016; Nam & Seong, 2018; Narayan, 2019; Narayan & Bannigidadmath, 2015; Salisu et al., 2020a, 2020b; Shynkevich et al., 2016). However, the role of health news in the return predictability is less understudied, this is the main contribution of the study. Given the limited time dimension of available data since the emergence of the novel coronavirus, we employ panel data forecasting approach to evaluate the performance of health-news for stock return predictability. Alternative variants of the health news-based models are considered for robustness. We account for an important feature of the stock returns series, the day-of-the-week effects as well as the "asymmetry" effect and macro-common factors in the health-news predictive model for stock returns. We find that health-news has a negative and statistically significant effect on stock returns, indicating that returns decline as more information is sought on health issues since the pandemic outbreak. While the single predictor model consistently outperforms the historical average model both for in-sample and out-of-sample, accounting for daily effects and controlling for other macroeconomic variables and "asymmetry" effect improves the forecast accuracy of health news.

On the implication of findings, rational investors seeking to maximize returns may need to evaluate the extent of uncertainty associated with infectious diseases before taking any investment decision in the stock market and perhaps other financial markets. By way of suggestion for future research, extending the analyses to other financial market such as the commodity, foreign exchange, bond and money markets would offer more insightful outcomes.

Appendix A

Table A1
Health-news predictability results and forecast evaluation using panel robust least squares estimator.

Coefficients	Top reported cases	Top reported deaths
$hn_{i,\ t-1}$	−0.7316*** (0.1479)	−0.5247*** (0.1377)
Forecast evaluation	**HN model vs historical average**	**HN model vs historical average**
In-sample		
C-T stat	0.0281	0.0291
Clark & West	0.4086***	0.2415***

(*continued on next page*)

Table A1 (*continued*)

Forecast evaluation	HN model vs historical average	HN model vs historical average
	(0.0657)	(0.0402)
Out-of-sample		
C-T stat	0.0395	0.0371
Clark & West	1.0341***	0.6702***
	(0.1584)	(0.1041)

Note: $hn_{i,\ t-1}$indicate the coefficient of health-news predictor. C-T stat indicates the Campbell and Thompson (2008) test statistics while C-W test is the Clark and West (2007) test. For the two categories of countries, i.e. top reporting COVID-19 cases and deaths, the tests evaluate the forecast performance of the historical average model against the HN predictor models. Both models are estimated using panel robust least squares estimators which accounts for inherent outliers in the predictor and predicted series.

*** Indicate statistical significance at 1%, level.

References

Adachi, Y., Masuda, M., & Takeda, F. (2017). Google search intensity and its relationship to the returns and liquidity of Japanese startup stocks. *Pacific-Basin Finance Journal, 46*, 243–257.

Akinchi, O., & Chahrour, R. (2018). Good news is bad news: Leverage cycles and sudden stops. *Journal of International Economics, 114*, 362–375.

Aouadi, A., Arouri, M., & Teulon, F. (2013). Investor attention and stock market activity: Evidence from France. *Economic Modelling, 35*, 674–681.

Balcilar, M., & Demirer, R. (2015). Effect of global shocks and volatility on herd behavior in an emerging market: Evidence from Borsa Istanbul. *Emerging Markets Finance and Trade, 51*(1), 140–159. https://doi.org/10.1080/1540496X.2015.1011520.

Baltagi, B. H. (2008). *Econometric analysis of panel data.* Chichester: Wiley & Sons.

Baltagi, B. H. (2013). Panel data forecasting. *Handbook of economic forecasting. Vol. 2(B). Handbook of economic forecasting* (pp. 995–1024).

Baltagi, B. H., Bresson, G., & Pirotte, A. (2002). Comparison of forecast performance for homogeneous, heterogeneous and shrinkage estimators: Some empirical evidence from US electricity and natural-gas consumption. *Economics Letters, 76*, 375–382.

Baltagi, B. H., & Griffin, J. M. (1997). Pooled estimators vs. their heterogeneous counterparts in the context of dynamic demand for gasoline. *Journal of Econometrics, 77*, 303–327.

Baltagi, B. H., Griffin, J. M., & Xiong, W. (2000). To pool or not to pool: Homogeneous versus heterogeneous estimators applied to cigarette demand. *Review of Economics and Statistics, 82*, 117–126.

Bange, M. M. (2000). Do the portfolios of small investors reflect positive feedback trading? *The Journal of Financial and Quantitative Analysis, 35*(2), 239. https://doi.org/10.2307/2676192.

Bank, M., Larch, M., & Peter, G. (2011). Google search volume and its influence on liquidity and returns of German stocks. *Financial Markets and Portfolio Management, 25*(3), 239–264.

Bannigidadmath, D., & Narayan, P. (2015). Stock return predictability and determinants of predictability and profits. *Emerg. Market. Rev. 26*, 153–173.

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies, 21*, 785–818.

Bates, J. M., & Granger, C. W. J. (1969). The combination of forecasts. *Operations Research Quarterly, 20*, 451–468.

Birz, G., & Lott, J. R. (2011). The effect of macroeconomic news on stock returns: New evidence from newspaper coverage. *Journal of Banking & Finance, 35*, 2791–2800.

Bodnaruk, A., & Ostberg, P. (2009). Does investor recognition predict returns. *Journal of Financial Economics, 91*(2), 208–226.

Bramati, M. C., & Croux, C. (2007). Robust estimators for the fixed effects panel data model. *The Econometrics Journal, 10*(3), 521–540.

Breitmayer, B., Massari, F., & Pelster, M. (2019). Swarm intelligence? Opinion of the crowd and stock returns. *International Economics and Finance, 64*, 443–464.

Buttner, D., & Hayo, B. (2010). News and correlations of CEEC-3 financial markets. *Economic Modelling, 27*, 915–922.

Calomiris, C. W., & Mamaysky, H. (2018). How news and its context drive risk and returns around the world. *Journal of Financial Economics, 133*, 299–336.

Campbell, J. Y., & Thompson, S. B. (2008). Predicting excess stock returns out of sample: Can anything beat the historical average? *Review of Financial Studies, 21*, 1509–1531.

Chen, N. F., Roll, R., & Ross, S. A. (1986). Economic forces and the Stock market. *Journal of Business, 59*(3), 383–403.

Chen, X., Kim, K., Yao, T., & Yu, T. (2010). On the predictability of Chinese stock. *Pacific-Basin Finance Journal, 18*, 403–425.

Chudik, A., Mohaddes, K., Pesaran, M. H., & Raissi, M. (2016). *Long-run effects in large*.

Chudik, A., & Pesaran, M. H. (2015). *Common correlated effects estimation of heterogeneous*.

Clark, T. E., & West, K. D. (2007). Approximately normal tests for equal predictiveaccuracy in nested models. *Journal of Econometrics, 138*, 291–311.

Clements, M. P., & Hendry, D. F. (2002). Modelling methodology and forecast failure. *The Econometrics Journal, 5*(2), 319–344.

Cohen, L. J., Marcus, A. J., Rezaee, Z., & Tehranian, H. (2017). Waiting for guidance: Disclosure noise, verification delay, and the value relevance of good-news versus bad-news management earnings forecasts. Global finance Journal, doi:10.1016/j.gfj.2018.03.001 countries *Finance Research Letters, 20*, 47–62.

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *The Journal of Finance, 66*(5), 1461–1499.

Devpura, N., Narayan, P. K., & Sharma, S. S. (2018). Is stock return predictability time varying? *J. Int. Financ. Market. Inst. Money, 52*, 152–172.

Diebold, F. X., & Lopez, J. A. (1996). Forecast evaluation and combination. In G. S. Maddala, & C. R. Rao (Eds.). *Handbook of statistics. North-Holland, Amsterdam* (pp. 241–268). (dimension. International Journal of Forecasting 32 (2016) 1162–1177).

Ditzen, J. (2018). Estimating dynamic common correlated effects in Stata. *The Stata Journal, 18*(3), 585–617.

Ditzen, J. (2019). Estimating long run effects in models with cross-sectional dependence using xtdcce2. *CEERP working paper series: 7*.

Driver, C., Imai, K., Temple, P., & Urga, A. (2004). The effect of uncertainty on UK investment authorisation: Homogeneous vs. heterogeneous estimators. *Empirical Economics, 29*, 115–128 (dynamic panel data models with weakly exogenous regressors. Journal of Econometrics 188(2): 393-420).

Ekinci, C., & Bulut, A. E. (2020). Google search and stock returns: A study on BIST 100 stocks. *Global Finance Journal*. https://doi.org/10.1016/j.gfj.2020.100518.

Even-Tov, O. (2017). When does the bond price reaction to earnings announcements predict future stock returns? *Journal of Accounting and Economics*. https://doi.org/10.1016/j.jacceco.2017.05.002.

Gavin, W. T., & Theodorou, A. T. (2005). A common model approach to macroeconomics: Using panel data to reduce sampling error. *Journal of Forecasting, 24*, 203–219.

Jacobs, H., & Hillert, A. (2016). Alphabetic bias, investor recognition, and trading behavior. *Review of Finance, 20*(2), 693–723.

Joseph, K., Wintoki, M. B., & Zhang, Z. (2011). Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search. *International Journal of Forecasting, 27*(4), 1116–1127.

Kim, N., Lučivjanská, K., Molnár, P., & Villa, R. (2019). Google searches and stock market activity: Evidence from Norway. *Finance Research Letters, 28*, 208–220.

Liebmann, M., Orlov, A. G., & Neumann, D. (2016). The tone of financial news and the perceptions of stock and CDS traders. *International Review of Financial Analysis*. https://doi.org/10.1016/j.irfa.2016.05.001.

Maddala, G. S., Trost, R. P., Li, H., & Joutz, F. (1997). Estimation of short-run and long-run elasticities of energy demand from panel data using shrinkage estimators. *Journal of Business & Economic Statistics, 15*, 90–100.

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. *The Journal of Finance, 42*(3), 483–510.

Nam, K. H., & Seong, N. Y. (2018). Financial news-based stock movement prediction using causality analysis of influence in the Korean stock market. *Decsup*. https://doi.org/10.1016/j.dss.2018.11.004.

Narayan, P. K. (2019). Can stale oil price news predict stock returns? *Energy Economics*. https://doi.org/10.1016/j.eneco.2019.07.022.

Narayan, P. K., & Bannigidadmath, D. (2015). Are Indian stock returns predictable? *J. Bank. Rev. 50*, 1267–1287.

Narayan, P. K., & Bannigidadmath, D. (2017). Does financial news predict stock returns? New evidence from Islamic and non-Islamic stocks. *Pacific-Basin Finance Journal, 42*, 24–45.

Narayan, P. K., & Gupta, R. (2015). Has oil price predicted stock returns for over a century? *Energy Economics, 48*, 18–23.

Narayan, P. K., Phan, D. H.. B., Sharma, S. S., & Westerlund, J. (2016). Are Islamic stock returns predictable? A global perspective. *Pac. Basin Finance J. 40*(A), 210–223.

Newbold, P., & Harvey, D. I. (2002). Forecast combination and encompassing. In M. P. Clements, & D. F. Hendry (Eds.). *A companion to economic forecasting* (pp. 268–283). Oxford: Blackwell.

Nguyen, P. C., Schinckus, C., & Nguyen, T. V. H. (2019). Google search and stock returns in emerging markets. *Borsa Istanbul Review, 19*, 288–296.

Nofsinger, J. R., & Sias, R. W. (1999). Herding and feedback trading by institutional and individual investors. *The Journal of Finance, 54*(6), 2263–2295. https://doi.org/10.1111/0022-1082.00188.

OECD (2020). *Coronavirus: The world economy at risk*. OECD Interim Economic Assessment.

Pesaran, M. H., & Smith, R. P. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics, 68*, 79–113.

Phan, D. H. B., Sharma, S. S., & Narayan, P. K. (2015). Stock return forecasting: Some new evidence. *International Review of Financial Analysis, 40*, 38–51, 276.

Preis, T., Moat, H. S., & Stanley, H. E. (2013). Quantifying trading behavior in financial

markets using Google trends. *Scientific Reports, 3*, 1684.
Psaradellis, I., & Sermpinis, G. (2016). Modelling and trading the U.S. implied volatility indices. Evidence from the VIX, VXN and VXD indices. *International Journal of Forecasting, 32*(4), 1268–1283. https://doi.org/10.1016/j.ijforecast.2016.05.004.
Rapach, D. E., & Wohar, M. E. (2004). Testing the monetary model of exchange rate determination: A closer look at panels. *Journal of International Money and Finance, 23*, 867–895.
Reese, S., & Westerlund, J. (2016). PANICCA - PANIC on cross-section averages. *Journal of Applied Econometrics, 31*(6), 961–981.
Robertson, D., & Symons, J. (1992). Some strange properties of panel data estimators. *Journal of Applied Econometrics, 7*, 175–189.
Rossi, B. (2013). Exchange rate predictability. *Journal of Economic Literature, 51*(4), 1063–1119.
Salisu, A., Ogbonna, A. E., & Adewuyi, A. (2020b). Google trends and the predictability of precious metals. *Resources Policy, 65*(September 2019), Article 101542. https://doi.org/10.1016/j.resourpol.2019.101542.
Salisu, A. A., Adekunle, W., Alimi, W. A., & Emmanuel, Z. (2019). Predicting exchange rate with commodity prices: New evidence from Westerlund and Narayan (2015) estimator with structural breaks and asymmetries. *Resources Policy, 62*, 33–56.
Salisu, A. A., & Isah, K. O. (2017). Revisiting the oil price and stock market nexus: A nonlinear panel ARDL approach. *Economic Modelling. 66(C). Economic Modelling* (pp. 258–271). Elsevier.
Salisu, A. A., Isah, K. O., & Akanni, L. O. (2019). Improving the predictability of stock returns with Bitcoin prices. *North American Journal of Economics and Finance, 48*, 857–867.
Salisu, A. A., Isah, K. O., & Raheem, I. D. (2019). Testing the predictability of commodity prices in stock returns of G7 countries: Evidence from a new approach. *Resources Policy, 64*. https://doi.org/10.1016/j.resourpol.2019.101520.
Salisu, A. A., & Ndako, U. B. (2018). Modelling stock price–exchange rate nexus in OECD countries: A new perspective. *Economic Modelling. 74(C). Economic Modelling* (pp. 105–123). Elsevier.
Salisu, A. A., Ogbonna, A. E., & Adewuyi, A. (2020a). Google trends and the predictability of precious metals. *Resources Policy, 65*. https://doi.org/10.1016/j.resourpol.2019.101542.
Salisu, A. A., Raheem, I. D., & Ndako, U. D. (2019). A sectoral analysis of asymmetric nexus between oil price and stock returns. *International Review of Economics and Finance, 61*, 241–259.
Salisu, A. A., Swaray, R., & Oloko, T. F. (2019). Improving the predictability of the oil–US stock nexus: The role of macroeconomic variables. *Economic Modelling, 76*, 153–171.
Shin, Y., Yu, B., & Greenwood-Nimmo, M. (2014). Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. *Festschrift in honor of Peter Schmidt* (pp. 281–314). Springer.
Shynkevich, Y., McGinnity, T. M., Coleman, S. A., & Belatreche, A. (2016). Forecasting movements of health-care stock prices based on different categories of news articles using multiple kernel learning. *Decision Support Systems*. https://doi.org/10.1016/j.dss.2016.03.001.
Stock, J., & Watson, M. (2006). Forecasting with many predictors. In G. Elliott, C. W. J. Granger, & A. Timmermann (Eds.). *Handbook of economic forecasting. North-Holland, Amsterdam* (pp. 515–554). .
Stock, J. H., & Watson, M. W. (2004). Combination forecasts of output growth in a seven-country data set. *Journal of Forecasting, 23*, 405–430.
Svensson, J. (1999). Is the bad news principle for real? *Economics Letters, 66*, 327–331.
Takeda, F., & Wakao, T. (2014). Google search intensity and its relationship with returns and trading volume of Japanese stocks. *Pacific-Basin Finance Journal, 27*, 1–18.
Tang, W., & Zhu, L. (2017). How security prices respond to a surge in investor attention: Evidence from Google search of ADRs. *Global Finance Journal, 33*, 38–50.
Taylor, N. (2019). Forecasting returns in the VIX futures market. *International Journal of Forecasting, 35*(4), 1193–1210. https://doi.org/10.1016/j.ijforecast.2019.01.009.
Timmermann, A. (2006). Forecast combinations. In G. Elliott, C. W. J. Granger, & A. Timmermann (Eds.). *Handbook of economic forecasting. North-Holland, Amsterdam* (pp. 135–196). .
Verardi, V., & Croux, C. (2009). Robust regression in Stata. *The Stata Journal, 9*(3), 439–453.
Verardi, V., & Wagner, J. (2011). Robust estimation of linear fixed effects panel data models with an application to the exporter productivity premium. *Jahrbücher für Nationalökonomie und Statistik, 231*(4), 546–557.
Wang, H. (2019). VIX and volatility forecasting: A new insight. *Physica A: Statistical Mechanics and its Applications, 533*. https://doi.org/10.1016/j.physa.2019.121951.
Westerlund, J., & Basher, S. A. (2007). Can panel data really improve the predictability of the monetary exchange rate model. *Journal of Forecasting, 26*, 365–383. 1508 https://doi.org/10.1093/rfs/hhm014.
Westerlund, J., Karabiyik, H., & Narayan, P. (2016). Testing for predictability in panels with general predictors. *Journal of Applied Econometrics*. https://doi.org/10.1002/jae.2535.
Xu, Q., Bo, Z., Jiang, C., & Liu, Y. (2019). Does Google search index really help predicting stockmarket volatility? Evidence from a modified mixed data sampling model on volatility. *Knowledge-Based Systems, 166*, 170–185.
Yun, J. (2020). A re-examination of the predictability of stock returns and cash flows via the decomposition of VIX. *Economics Letters, 186*. https://doi.org/10.1016/j.econlet.2019.108755.
Zhang, J., Lai, Y., & Lin, J. (2017). The day-of-the-week effects of stock markets in different countries. *Finance Research Letters, 20*, 47–62.
Zhu, H., & Jiang, L. (2018). Investor recognition and stock returns: Evidence from China. *China Finance Review International, 8*(2), 199–215.
Zhu, S., Liu, Q., Wang, Y., Wei, Y., & Wei, G. (2019). Which fear index matters for predicting US stock market volatilities: Text-counts or option based measurement? *Physica A: Statistical Mechanics and its Applications, 536*, Article 122567. https://doi.org/10.1016/j.physa.2019.122567.