Pandemic uncertainty and sectoral stock returns predictability in South Africa

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Abstract

Purpose – In this paper, the author examines the role of uncertainty due to pandemic on the predictability of sectoral stock returns in South Africa. This is motivated by the ongoing global pandemic, COVID-19, in predicting sector stock returns.

Design/methodology/approach – The study considers estimation of dynamic panel data with dynamic common correlated effects estimator and two pair-wise forecast measures, namely Campbell and Thompson (2008) and Clark and West (2007) tests in dealing with the nested predictive models.

Findings – The results show that pandemic uncertainty has a negative and statistically significant effect on the different sector returns, implying that sector stock returns decline as the pandemic outbreak becomes more pronounced. While the single predictor model consistently outperforms the historical average model both for in-sample and out-of-sample, controlling for other macroeconomic variables effect improves the forecast accuracy of infectious diseases uncertainty. These results are consistently robust to both the in-sample and out-of-sample forecast periods, outliers and heterogeneity. These results have implications for portfolio diversification strategies, which we set aside for future research.

Originality/value – The empirical literature is satiated with studies on how news can predict economic and financial variables, however, the role of uncertainty due to infectious diseases in the stock return predictability especially at the sectoral level is less understudied, this is the main contribution of the study.

Keywords Predictability, Stock returns, COVID-19, Infectious disease uncertainty

Paper type Research paper

1. Introduction

Over the years, the South African financial market has been faced with different systemic risks/shocks that are triggered by series of internal and external factors with inevitable detrimental effects on the performance of the stock market. These shocks range from financial events (see, PWC, 2021; e.g. Asian Crisis of 1998, the “dotcom” bubble collapse and 2001 currency crisis, the 2008 Global Financial Crisis (GFC), 2016 European Monetary Crisis); natural factors (such as earthquakes, air disasters, volcanoes) or human factors (see, Wang and Cui, 2013; such as wars, political instabilities, insurrections, terrorist attacks, epidemics/pandemic- and now the COVID-19 pandemic). Often times, these unpleasant events lead to unfavorable movements in the stock prices where certain sectors of the market are expected to be severely affected than others.

Theoretically, the classical finance schools hold that stock prices only echo the discounted present value of cash flows, and as such stocks fully reflect their past pricing behavior. This further implies that in the presence of market anomalies, prices of stocks are driven back to their normal values by the rational arbitrageurs (De Long *et al.*, 1990) who disregard

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suboptimal trading actions by not giving preference to factors unconnected to the fundamental value of the asset (Dalik and Seetharam, 2015). However, the turnout of economic events at the global and national levels in the recent years have disproven the postulation of the classical finance theories that posit that investors' sentiments induce no risks to stocks. With continued experience of economic and financial turmoil including the most recent GFC of 2008 which have led to stock markets' crashes and consequently losses on investments, there is increasing renewed interest in the determination of factors to explain the complex nature of modern financial markets.

In particular, the traditional asset pricing models have shown relative weakness in addressing the concerns of modern stock markets as their performances seem to be significantly driven by many other factors relating to real life occurrences. A growing number of studies have identified these events/occurrences that might affect the behavior of the stock market, for example, disasters (Kowalewski and Śpiewanowski, 2020), sports (Buhagiar *et al.*, 2018), environmental (Alsaifi *et al.*, 2020) and political events (Bash and Alsaifi, 2019; Shanaev and Ghimire, 2019) and pandemic diseases, for example, Severe Acute Respiratory Syndrome (SARS) outbreak (Chen *et al.*, 2009), and Ebola Virus Disease (EVD) outbreak (Ichev and Marinč, 2018). One of the most important factors recently reckoned with to induce stock market performances is health pandemic. For instance, Baker *et al.* (2020) point out the extent of the devastating influence of the current COVID-19 health crisis on stock markets globally. Other recent studies have reiterated this stand by disclosing how different stock markets, such as in the airline industry and in many countries most affected by the pandemic, were adversely impacted (see Goodell, 2020; Salisu and Vo, 2020; McKibbin and Fernando, 2020; HaiYue *et al.*, 2020).

Notably, the influence of the outbreak of major health pandemics on stock markets is often indirectly observed through uncertainties they induce (Sobieralski, 2020). They cause emergencies in global health which lead to pessimistic expectations of future economic outcomes. Meanwhile, the uncertainties are obviously known to lead to emotional actions of investors which are often reflected in their investment decisions (HaiYue *et al.*, 2020; Baker and Wurgler, 2006). Thus, as rightly argued by Rupande *et al.* (2019), the behavioral finance is a quick intervention to the limitation of the traditional finance which assumes that investors are rational when engaging in investment decisions. Against this old theoretical assertion, the concept of behavioral finance supposes that investors may not always be rational as their investment decisions can be influenced by behavioral prejudice resulting from uncertainties induced by health pandemics.

The recent COVID-19 outbreak has triggered the direction of the crisis in the world economy. Different activities in eliminating the outbreak have really slowed down the global financial economy which has often discourages investment and consumer confidence at large. The contraction of the South African economy from 5% to as little as −23.5% has been predicted by experts for 2020 with certain industries to be more severely affected than others (PWC, 2021). For investment to be sustained, necessary actions must be taken to prevent the economy not in going into recession. In this case, 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.

Accordingly, the literature is now witnessing increasing number of studies on the impact of infectious diseases-induced equity market volatility and emotions-based indicators, such as investors' sentiments on stock market performance from different empirical perspectives. Against this background and limited evidence in the literature, this study examines the impact of infectious diseases-induced equity market volatility on South African stock returns. While contributing to extant literature in other innovative ways, we address this issue from a sectoral perspective. To achieve this objective, we consider the following. First, we evaluate the predictability of infectious diseases as a potential predictor of stock returns during the pandemic period and beyond. We hypothesize that the impact of the infectious diseases-induced equity market volatility on stock returns may differ across sectors which are heterogeneous since their economic activities vary. Findings based on aggregate stock market performance could significantly suffer from aggregation bias as the distinct attributes of each economic sector is not revealed. Consequently, we evaluate both the in-sample and out-of-sample forecast performance of the pandemic uncertainty 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. To this end, the findings of this study offer useful insights to investors seeking to maximize returns in the presence of global health crisis.

The remainder of the paper is organized as follows. Section 2 presents a short review of the literature, Section 3 describes the econometric methodology, while Section 4 discusses the findings of the study. Section 5 concludes the paper.

2. Brief literature review

Among various studies that have analyzed the effect infectious diseases uncertainty on financial markets, there has been increasing concentration on stock markets. The empirical studies have also ranged between cross-country/time series analysis (see Iyke and Ho, 2021; Takyi and Bentum-Ennin, 2021; Fasanya *et al.*, 2021a, b; Oliyide *et al.*, 2021; Adenomon *et al.*, 2020; Ashraf, 2020; Ali *et al.*, 2020; Nwosa, 2021); and panel analysis (see Akinola *et al.*, 2021; Raifu *et al.*, 2021; Salisu *et al.*, 2020; Zaremba *et al.*, 2020; Zhang *et al.*, 2020), as well as aggregate and disaggregate stock market indices. For instance, Takyi and Bentum-Ennin (2021) used a state-space Bayesian structural model to quantify the possible impact of the COVID-19 outbreak on stock market performance across thirteen African and observed that stock market performances significantly drop throughout and after the incidence of the outbreak and there are restrictive effects of the pandemic on African's stock market productivity. In a similar study, Iyke and Ho (2021) examined the financial consequences of rising global investor attention or risk attitude related to the COVID-19 pandemic for 14 African stock markets using daily investor attention indices, which are based on global COVD-19-related Google search queries. The findings suggest that an increase in investor attention consistently reduces stock returns in three stock markets, namely Botswana, Nigeria, and Zambia, but may enhance stock returns in Ghana and Tanzania.

Akinola *et al.* (2021) analyzed the impact of the new wave of COVID-19 on twenty JSE listed companies in South Africa and provided evidence that there is a direct but slow link between the daily incidence of infectious COVID-19 and stock returns. However, Yan *et al.* (2020) posited that the possible negative results of COVID-19 on the stock market could only be for the short-term while in the long run, the invisible hands of the market would normalize this potential adverse effect. Though, there were actions introduced by the US Federal Reserve in helping to reducing the adverse effects created by the outbreak in the long run through funds transmission to the primary market (Falato *et al.*, 2021). In corroborating the views of Falato *et al.* (2021), Cox *et al.* (2020) applied a dynamic pricing model to characterize huge fluctuations in stock prices that are counter to risk aversion through announcements, outlined guidelines among others by the Apex Bank to boost the economy.

Using pooled OLS and panel VAR as estimation methods, Raifu *et al.* (2021) examined the reaction of stock returns of 201 firms listed on the Nigerian Stock Exchange to the COVID-19 pandemic and lockdown policy. The study observed that the stock market returns of the Nigerian firms reacted negatively more to the global COVID-19 confirmed cases and deaths than the domestic COVID-19 confirmed cases and deaths and lockdown policy. Adenomon *et al.* (2020) examined the effects of the COVID-19 pandemic on Nigerian's stock exchange performance by employing generalized autoregressive conditional heteroskedasticity (GARCH) models. They found that COVID-19 has negative effects on the stock market returns in Nigeria. In a related study, this was equally supported by the findings of Nwosa (2021) who argued that COVID-19 had shown significant negative impacts than the world recession of 2009 and 2016 on stock market output, exchange rate, and oil price, with implications for transactional corporations and FDI inflow to Nigeria.

Despite the growing literature on the effect of the COVID-19 pandemic on stock market performance, the discussions and empirical evidences from South Africa are few however studies across sectoral stocks are largely non-existent. This study fills the gap in the literature and thus contributes to the discussion and research on the economic impact of the COVID-19 pandemic on sectoral stock market performance in South Africa.

3. Methodology and data

3.1 Methodology

In this paper, we construct a predictive model that examines the relationship between infectious diseases uncertainty and stock returns of South African sector markets. To this end, we construct a predictive model for the stock returns of different firms across sectors in South Africa where pandemic uncertainty index (EMV_ID) is used as a predictor and its predictive power is comparatively evaluated with other plausible forecast models for stock returns. The considered sector stocks are good representations of the South African stock market and by extension results obtained offer reasonable generalizations for other stock markets (Rapach and Wohar, 2004). In addition, pooling the sector stocks helps to find a way round the problem of insufficient observations that may plague firm-by-firm analyses. The idea of pooling data to characterize a panel regression has some underlying advantages over cross-sectional and time series estimation and these are well documented in the literature (see for example, Hsiao, 2003; Baltagi, 2013). Different opinions exist in the empirical literature on the use of homogenous and heterogonous panels but given the short time span of the available data for pandemic index, we employ homogenous panel data procedures [1].

Consequently, the predictive models constructed in this paper for the return predictability are structured in panel form as elaborated in Salisu *et al.* (2020) paper. We begin our analyses with the historical average (constant return) model which ignores any potential predictor of stock and is specified as [2]:

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

where r_{it} denotes stock returns computed as log returns; α is a constant parameter; and e_{it} is the error term. Following the investor recognition hypothesis (see Merton, 1987) of assuming incomplete market information, we augment the historical average model of equation (1) with the pandemic uncertainty index as a single predictor. The investor recognition hypothesis, suggests that investors are not aware of all securities in a market and therefore they prefer to choose familiar stocks in constructing portfolios (see for extensive literature, Zhu and Jiang, 2018; Salisu and Vo, 2020). The single predictor model is given as:

$$r_{it} = \alpha + \sum_{k=1}^{5} \delta_k EMV\_ID_{i,t-k} + e_{it} \tag{2}$$

where EMV_ID_{it} denotes the pandemic uncertainty index expressed in natural logs, a measure of investors' emotion and attention. Note that we allow for up to five lags given the underlying frequency for our analysis which is daily and therefore the proximity of the data points can be exploited to account for more dynamics in the predictive model. Thus, in addition to the behavior of the individual parameters, testing for the overall sign and significance of these parameters jointly is crucial to arrive at a distinct conclusion on the predictability of EMV_ID on sector stock returns. The testable null hypothesis of no predictability can therefore be expressed as $H_0 : \sum_{k=1}^{5} \widehat{\delta} = 0$ against the alternative hypothesis of $H_0 : \sum_{k=1}^{5} \widehat{\delta} \neq 0$.

For completeness, we also account for some other important factors that can influence stock returns (see also Devpura *et al.*, 2018; Salisu *et al.*, 2019). Premised on the Arbitrage Pricing Theory, we extend the single predictor model by incorporating systemic or macroeconomic risks in the predictability of stock returns. This is specified as:

$$r_{it} = \alpha + \sum_{k=1}^{5} \delta_k EMV\_ID_{i,t-k} + Z_{it}' \varnothing + e_{it} \tag{3}$$

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 [3]. Again, to circumvent having so many parameters in the predictive model and in the spirit of Westerlund *et al.* (2016), we adopt the same procedure followed in the computation of the day-of-the-week-adjusted stock returns. In other words, we regress the return series on the selected macro variables, that is, $r_{it} = \vartheta + Z_{it}'\phi + u_{it}$ and thereafter, the macro-adjusted returns series is regressed on the pandemic uncertainty index predictor. Ideally, the choice of the return series will be determined by the relative forecast performance of r_{it} from the single-predictor case.

Finally, the forecast evaluation of the predictor is rendered for both in-sample and out-of-sample periods. Since there is no formal procedure of splitting the data for this purpose, we consider 75 and 25% split for the in-sample and out-of-sample periods, respectively. This choice is informed by the need to have sufficient observations that will allow for meaningful regression analyses from which the forecasts will be obtained. For robustness purpose, we also consider multiple out-of-sample forecast horizons – 10-day, 20-day, 60-day and 120-day ahead forecasts. We adopt two pair-wise forecast measures, namely Campbell-Thompson (CT, 2008) and Clark and West (CW, 2007) tests for the forecast evaluation. These measures are particularly useful when dealing with nested predictive models. The (CT, 2008) test is specified as:

$$CT = 1 - \left(M\widehat{S}E_u \big/ M\widehat{S}E_r \right) \tag{4}$$

where $M\widehat{S}E_u$ is the mean squared error obtained from the unrestricted model, in this case the pandemic-based model (equation (2)) and $M\widehat{S}E_r$ is the mean squared error obtained from the restricted model (for example, the historical average or constant return model, equation (1)). In this case, equation (2) outperforms equation (1) if $CT > 0$ and vice versa. The CW (2007) test on the other hand is used to establish the statistical significance of the forecast evaluation procedure in the CT (2008). For a forecast horizon h, the CW (2007) test is specified as:

$$\widehat{f}_{t+h} = M\widehat{S}E_r - \left(M\widehat{S}E_u - adj \right) \tag{5}$$

where $\widehat{f}_{t+h}$ is the forecast horizon; $M\widehat{S}E_r$ and $M\widehat{S}E_u$, respectively, are the squared errors of restricted and unrestricted predictive models and they are respectively computed as:

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

3.2 Data and data description

This paper covers eight (8) different sectors (industrials, Financials, Health care, Telecoms, Materials, Consumer services, Consumer goods and Technology) across 121 firms arranged in panel form within the different sectors to provide suitable hedge and serve as possible assets for investment portfolio diversification in the face of market risks arising from infectious diseases uncertainty. Therefore, we adopt daily data from February 08, 2016 to May 07, 2021 based on data availability and the need to have the same start and end dates for the series. The analyses are conducted using full sample, pre-COVID and the sample covering the COVID-19 pandemic. Data on sectoral stocks are obtained from the Thomson Reuters DataStream, and the Infectious Disease Equity Market Volatility (EMV-ID), which is a proxy for uncertainties due to pandemics and epidemics, was developed by Baker *et al.* (2020) and are available for download from http://www.policyuncertainty.com. It is expedient to note that the returns of the series (r_t) are computed as the first difference of the natural logarithm of the level series (P_t); this is expressed in the equation: $r_t = (\Delta\log(p_t)) \times 100$. Where ($r_t$) represents the calculated returns of sector stocks and (P_t) represents their respective price levels.

4. Results and discussion

We begin the empirical application of uncertainty due to infectious diseases (EMV-ID) by evaluating its predictability of stock returns across different sectors in South Africa. We estimate a single factor predictive model with the EMV-ID as the predictor, and compared the forecast performance with the historical average model across three different sample periods, namely, full sample, pre-COVID and COVID periods. The estimation was further extended to account for relevant control variables across the same specified sample periods. Table 1 presents the estimated joint coefficients of EMV-ID lags with the original and control models. The predictability results vary from one sector to another and across different periods except for the technology and telecom sectors that seem insignificant at all levels considered. From the result, it is apparent that the financial sector is more significantly affected than any other sector. The estimated joint coefficients of EMV-ID lags show that the predictors are correctly signed and statistically significant for the financial stocks across all periods barring only pre-COVID era that were not correctly signed for both original and control models. This indicates that the overall effect of uncertainty due to infectious diseases on financial stocks is increasing in the lags for both whole sample and COVID period but behaves in an opposite direction for the period before the COVID crisis. Another implication of the positive effect of uncertainty on financial stocks in the pre-COVID period is explained by the hedging property of the stock before the COVID crisis started. We probed further to examine the individual lag effects rather than joint effects on the sectoral stock returns (see Table 2). This is necessary to further justify the predictability of uncertainty due infectious diseases on these sector stocks before concluding on the relevance of sectors which seem not significant in Table 1.

Interestingly, at different lags and sample periods, we observed that at least two lags of EMV-ID significantly predict the behavior of sector stocks in South Africa. Of note, both technology and telecom sectors that were insignificant for joint effects presented a more

Table 1. Results for the hedging behavior of sectoral stocks

	Without control			With control		
	Full sample	Pre-COVID	COVID	Full sample	Pre-COVID	COVID
Consumer goods	−0.0016 (0.34)	0.1800[b] (3.89)	0.0023 (0.09)	0.0053 (1.13)	0.1835[b] (3.97)	0.0105 (2.63)
Consumer Services	−0.0202[a] (19.25)	0.1771[a] (23.02)	−0.0116[b] (3.83)	−0.0154[b] (4.98)	0.1790[a] (23.51)	−0.0047 (0.44)
Financials	−0.0180[a] (51.12)	0.0992[a] (59.25)	−0.0131[a] (15.89)	−0.0255[a] (58.07)	0.1001[a] (59.18)	−0.0133[a] (14.97)
HealthCare	0.0003 (0.00)	0.3823[a] (12.11)	0.0061 (0.52)	0.0002 (0.00)	0.3834[a] (12.31)	0.0072 (0.67)
Industrials	−0.0139[a] (32.29)	−0.0055 (0.02)	−0.0039 (0.53)	−0.0188[a] (9.12)	−0.0027 (0.01)	−0.0080 (0.99)
Materials	−0.0002 (0.01)	0.1898[a] (18.83)	0.0064 (2.44)	−0.0135[b] (6.29)	0.1861[a] (18.77)	0.0041 (0.68)
Technology	−0.0030 (0.24)	−0.0137 (0.03)	0.0014 (0.02)	−0.0078 (0.31)	−0.0106 (0.02)	−0.0024 (0.03)
Telecoms	−0.0055 (0.91)	0.1480 (1.40)	−0.0061 (0.79)	−0.0022 (0.05)	0.1557 (1.50)	−0.0015 (0.02)

Note(s): "Without Control" implies the original model with the predictor of interest only while "With Control" is an extension of the original model to include relevant control variables. Irrespective of the model, the coefficient reported under each data sample [i.e. pre-COVID and COVID] is the sum of the coefficients of the five lags whose significance are jointly evaluated using the Wald test for coefficient restriction. Thus, 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

Table 2.
Sectoral stock returns predictability results

		Without control			With control		
		Full sample	Pre-COVID	COVID	Full sample	Pre-COVID	COVID
Consumer goods	EMVID (−1)	−0.0116 [−1.00]	−0.0623^{b} [−2.05]	−0.0033 [−0.26]	−0.0125 [−1.06]	−0.0628^{b} [−2.03]	−0.0130 [−0.91]
	EMVID (−2)	−0.0316^{b} [−2.06]	0.0330 [1.30]	−0.0351^{a} [−2.03]	−0.0288^{c} [−1.74]	0.0346 [1.37]	−0.0214 [−1.13]
	EMVID (−3)	−0.0031 [−0.23]	0.0575 [1.11]	−0.0026 [−0.17]	−0.0002 [−0.02]	0.0634 [1.21]	0.0030 [0.21]
	EMVID (−4)	−0.0170^{b} [−2.19]	0.0636^{b} [2.08]	−0.0207^{a} [−2.64]	−0.0169^{b} [−2.18]	0.0612^{b} [1.98]	−0.0234^{a} [−3.02]
	EMVID (−5)	0.0619^{a} [4.97]	0.0880^{c} [1.69]	0.0641^{a} [5.88]	0.0640^{a} [5.37]	0.0870^{c} [1.68]	0.0654^{a} [5.72]
	INT	–	–	–	0.1321^{c} [1.90]	0.2113^{a} [3.74]	0.2371^{a} [2.37]
	REXR	–	–	–	−0.1218 [−1.31]	−0.0540 [−0.55]	−0.6568^{a} [−3.13]
Consumer Services	EMVID (−1)	−0.0008 [−0.09]	0.0560^{a} [3.50]	0.0020 [0.21]	−0.0060 [−0.67]	0.0481^{a} [3.06]	−0.0133 [−1.32]
	EMVID (−2)	−0.0546^{a} [−4.89]	0.0133 [0.63]	−0.0544^{a} [−4.36]	−0.0450^{a} [−4.12]	0.0201 [0.95]	−0.0291^{a} [−2.54]
	EMVID (−3)	0.0126 [1.27]	0.0462^{a} [2.61]	0.0142 [1.25]	0.0199^{b} [2.07]	0.0827^{a} [4.32]	0.0231^{b} [2.05]
	EMVID (−4)	−0.0109 [−1.36]	−0.0053 [−0.40]	−0.0076 [−0.92]	−0.0160^{b} [−1.98]	−0.0272^{b} [−1.99]	−0.0155^{c} [−1.83]
	EMVID (−5)	0.0334^{a} [3.21]	0.0669^{a} [3.69]	0.0340^{a} [3.19]	0.0317^{a} [3.08]	0.0552^{a} [3.16]	0.0301^{a} [2.92]
	INT	–	–	–	0.0271 [0.39]	0.1242^{a} [2.52]	0.0774 [0.83]
	REXR	–	–	–	−0.4764^{a} [−9.09]	−0.3854^{a} [−7.14]	−1.1885^{a} [−9.89]
Financials	EMVID (−1)	−0.0121^{c} [−1.85]	−0.0146 [−1.39]	−0.0069 [−0.95]	−0.0167^{a} [−2.58]	−0.0194^{c} [−1.85]	−0.0209^{a} [−2.80]
	EMVID (−2)	−0.0463^{a} [−7.31]	0.0363^{a} [3.23]	−0.0516^{a} [−7.59]	−0.0399^{a} [−6.38]	0.0403^{a} [3.64]	−0.0250^{a} [−3.82]
	EMVID (−3)	0.0069 [0.82]	−0.0179 [−1.55]	0.0132 [1.49]	0.0104 [1.24]	0.0037 [0.35]	0.0212^{a} [2.35]
	EMVID (−4)	−0.0140^{c} [−1.83]	0.0373^{a} [3.52]	−0.0175^{b} [−2.07]	−0.0205 [−2.66]	0.0242^{a} [2.38]	−0.0284^{a} [−3.34]
	EMVID (−5)	0.0474^{a} [6.43]	0.0582^{a} [4.29]	0.0497^{a} [6.18]	0.0413^{a} [5.52]	0.0511^{a} [3.86]	0.0399^{a} [4.98]
	INT	–	–	–	−0.2202^{a} [−6.90]	0.0552 [1.54]	−0.2436− 5.34
	REXR	–	–	–	−0.3481^{a} [−8.43]	−0.2294^{a} [−5.62]	−1.2330^{a} [−16.32]
HealthCare	EMVID (−1)	0.0222^{c} [1.85]	0.0729 [1.62]	0.02770^{b} [2.19]	0.0197^{c} [1.68]	0.0697 [1.57]	0.0200 [1.57]
	EMVID (−2)	−0.0263^{a} [−9.72]	0.1263 [1.58]	−0.0312^{a} [−3.55]	−0.0223^{a} [−5.10]	0.1291^{c} [1.65]	−0.0175^{b} [−2.28]
	EMVID (−3)	−0.0389 [−1.55]	0.0685 [1.48]	−0.0390^{c} [−1.70]	−0.0361 [−1.41]	0.0832^{c} [1.88]	−0.0346 [−1.49]
	EMVID (−4)	0.0041 [0.24]	0.0673 [1.33]	0.0041 [0.27]	0.0014 [0.08]	0.0586 [1.19]	−0.0011 [−0.07]
	EMVID (−5)	0.0393^{a} [5.21]	0.0471 [1.08]	0.0446^{a} [7.74]	0.0375^{a} [7.37]	0.0425 [0.95]	0.0404^{a} [10.49]
	INT	–	–	–	−0.0359 [−0.28]	0.0707 [0.63]	−0.0741 [−0.69]
	REXR	–	–	–	−0.2081^{a} [−2.55]	−0.1543 [−1.59]	−0.6405^{a} [−6.13]

(continued)

		Without control			With control		
		Full sample	Pre-COVID	COVID	Full sample	Pre-COVID	COVID
Industrials	EMVID (−1)	0.0221 [1.13]	−0.0046 [−0.20]	0.0289 [1.40]	0.0176 [0.91]	−0.0099 [−0.42]	0.0192 [0.87]
	EMVID (−2)	−0.0696^{b} [−2.14]	−0.00006 [−0.00]	−0.0734^{b} [−2.10]	−0.0630^{c} [−1.91]	0.0050 [0.21]	−0.0525 [−1.47]
	EMVID (−3)	0.0025 [0.23]	0.0180 [0.74]	0.0045 [0.36]	0.0065 [0.57]	0.0441 [1.63]	0.0100 [0.81]
	EMVID (−4)	−0.0090 [−0.62]	−0.0270 [−1.14]	−0.0074 [−0.45]	−0.0149 [−0.97]	−0.0422^{c} [−1.78]	−0.0174 [−0.99]
	EMVID (−5)	0.0400^{c} [1.85]	0.0081 [0.41]	0.0434^{c} [1.83]	0.0349^{c} [1.77]	0.0001 [0.01]	0.0326 [1.58]
	INT	–	–	–	−0.1655 [−1.29]	0.1735^{a} [4.02]	−0.3646^{c} [−1.69]
	REXR	–	–	–	−0.3549^{a} [−5.93]	−0.2727^{a} [−4.75]	−0.9514^{a} [−6.58]
Materials	EMVID (−1)	−0.0302^{a} [−2.75]	0.0049 [0.17]	−0.0270^{b} [−2.29]	−0.0329^{a} [−2.91]	0.0035 [0.12]	−0.0385^{a} [−2.93]
	EMVID (−2)	−0.0555^{a} [−4.21]	0.0122 [0.44]	−0.0570^{a} [−3.82]	−0.0534^{a} [−4.21]	0.0120 [0.43]	−0.0338^{a} [−2.80]
	EMVID (−3)	0.0051 [0.53]	0.0963^{b} [2.12]	0.0041 [0.35]	0.0048 [0.50]	0.0986^{b} [2.26]	0.0108 [0.86]
	EMVID (−4)	−0.0127 [−0.78]	0.0631^{a} [2.87]	−0.0165 [−0.98]	−0.0179 [−1.17]	0.0605^{a} [2.87]	−0.0268^{c} [−1.76]
	EMVID (−5)	0.0931^{a} [7.67]	0.0131 [0.69]	0.1028^{a} [8.01]	0.0859^{a} [7.04]	0.0113 [0.56]	0.0925^{a} [6.79]
	INT	–	–	–	−0.3160^{a} [−3.84]	−0.2131^{b} [−2.31]	−0.3048^{a} [−3.15]
	REXR	–	–	–	−0.1482^{a} [−2.35]	−0.0324 [−0.60]	−1.0666^{a} [−4.70]
Technology	EMVID (−1)	−0.0040 [−0.32]	0.0524 [1.35]	−0.0079 [−0.56]	−0.0068 [−0.53]	0.0500 [1.28]	−0.0142 [−1.07]
	EMVID (−2)	−0.0334^{a} [−4.12]	−0.1565^{a} [−2.19]	−0.0239^{c} [−1.74]	−0.0297^{a} [−3.24]	−0.1535^{b} [−2.17]	−0.0097 [−0.77]
	EMVID (−3)	0.0515 [1.25]	−0.0037 [−0.15]	0.0558 [1.22]	0.0535 [1.34]	0.0100 [0.35]	0.0594 [1.32]
	EMVID (−4)	−0.0310 [−1.32]	0.0781 [1.59]	−0.0385 [−1.39]	−0.0349 [−1.40]	0.0706 [1.45]	−0.0456 [−1.53]
	EMVID (−5)	0.0139 [1.51]	0.0159 [0.14]	0.0158^{a} [8.18]	0.0101 [1.11]	0.0121 [0.10]	0.0077 [1.48]
	INT	–	–	–	−0.1367 [−0.82]	0.1883 [1.58]	−0.2928 [−1.31]
	REXR	–	–	–	−0.2058^{a} [−6.92]	−0.1407^{a} [−3.33]	−0.6441^{a} [−17.06]
Telecoms	EMVID (−1)	−0.0447 [−1.28]	0.0520 [1.02]	−0.0473 [−1.29]	−0.0496 [−1.38]	0.0459 [0.87]	−0.0611 [−1.50]
	EMVID (−2)	−0.0318 [−0.93]	0.0420 [0.83]	−0.0368 [−0.89]	−0.0230 [−0.64]	0.0493 [0.99]	−0.0134 [−0.31]
	EMVID (−3)	−0.0223 [−0.72]	−0.1066 [−3.90]	−0.0121 [−0.33]	−0.0157 [−0.54]	−0.0725^{b} [−2.15]	−0.0042 [−0.12]
	EMVID (−4)	0.0227 [1.09]	0.1085 [1.79]	0.0154 [0.76]	0.0177 [0.95]	0.0901 [1.39]	0.0075 [0.42]
	EMVID (−5)	0.0706^{a} [2.68]	0.0520 [2.31]	0.0747^{a} [2.74]	0.0685^{a} [2.38]	0.0427^{c} [1.90]	0.0696^{b} [2.26]
	INT	–	–	–	0.0016 [0.01]	0.4606^{a} [2.65]	−0.0060 [−0.02]
	REXR	–	–	–	−0.4389^{a} [−4.38]	−0.3473^{a} [−4.00]	−1.0981^{a} [−3.94]

Note(s): "Without Control" implies the original model with the predictor of interest only while "With Control" is an extension of the original model to include relevant control variables. Irrespective of the model, the coefficient reported under each data sample [i.e. Pre-COVID and COVID] is the sum of the coefficients of the five lags whose significance are jointly evaluated using the Wald test for coefficient restriction. Values in square brackets – [] are for t-statistics. a, b and c indicate statistical significance at 1%, 5 and 10% levels, respectively

Table 2.

statistically significant scenarios for at least two different lag periods (see Table 2). Above all, the predictability results at different EMV-ID lags confirm the relevance of uncertainty due to infectious diseases in forecasting the behavior of sectoral stocks in South Africa. In addition, the positive effects of EMV-ID on sector stocks at different lags suggest hedging behavior across different sample periods. In all, at different lag periods, there is evidence of a weak hedge against EMV-ID across sectors.

Having established evidence that indicates predictability of sector stock returns due to infectious disease driven market uncertainty, we now evaluate the forecast performance of our predictive model in comparison with the benchmark model – the historical average. As earlier stated, we adopt the RMSE and more formally, the C–W (Clark and West, 2007) [4] test statistic is used to establish the statistical significance of the forecast evaluation procedure which measures the significance of the difference in the forecast errors of two competing models presented for both in–sample and out-of-sample estimation results. The in-sample predictability evaluation, as described in the methodology section, is performed using 50% of the entire data sample for the in-sample forecasts and the remaining half for the out-of-sample forecasts. For robustness, we consider multiple out-of-sample forecast horizons using 60-day and 120-day ahead forecasts for both full and pre-COVID sample periods. Due to data scope, 10-day and 20-day ahead forecast were considered for the COVID period. For the predictability models evaluated, first we compare the performance of the single predictor with the EMV-ID – without control model (Model 2) with that of the historical average (Model 1). Second, we compare the predictability performance between the model that include relevant control variables – control model (i.e. Model 3) and the historical average model (i.e. Model 1). As previously discussed, the criteria for interpreting the forecast measures remain the same. Table 3 presents the in-sample predictability results at different sample periods. Based on the forecast measure, we observed that the EMV-ID predictability model for stock returns outperforms the historical average for all the sample sets. In addition, the predictability model of relevant control variables also outperforms the historical average model.

Following the C–W test presented across the two out-of-sample forecast horizons, Tables 4 and 5 show that the estimated constant is observed to be positive and statistically significant. Based on the out-of-sample result presented in Tables 4 and 5, we observed that at both forecast horizons, the EMV-ID as well as the control predictive models for stock returns outperforms the historical average for all the sample sets. Combined with the evidence of in-sample predictability, the consistent out-of-sample outperformance of our predictive model shows that incorporating EMV-ID in the predictive model for stock returns can successfully improve the predictive accuracy of stock market models compared to the historical average model benchmark. Furthermore, the consistency of out-performance across the long and short horizons indicates that the results are insensitive to the forecast horizon considered. This is indeed an important consideration given the variety in the forecasting horizons employed by investors, practitioners and policy makers.

5. Conclusion and implication for policy

In this paper, we examine the role of uncertainty due to pandemic on the predictability of sectoral stock returns in South Africa. This is motivated from the on-going global pandemic, COVID-19, in predicting sector stock returns. Our analyses cover a total of 121 firms arranged in panel of 8 different sectors which include, industrials, Financials, Health care, Telecoms, Materials, Consumer services, Consumer goods and Technology. The empirical literature is satiated with studies on how uncertainty due to pandemic can predict economic and financial

Table 3. In-sample forecast evaluation

	Clark and West test					
	Full sample		Pre-COVID		COVID	
	Model 1 vs Model 2	Model 1 vs Model 3	Model 1 vs Model 2	Model 1 vs Model 3	Model 1 vs Model 2	Model 1 vs Model 3
Consumer goods	0.0995^{a} [4.85]	0.3107^{a} [12.64]	0.0889^{a} [4.23]	0.3042^{a} [12.91]	3.1869^{a} [4.24]	7.3316^{a} [5.03]
Consumer Services	0.0459^{a} [9.17]	0.5176^{a} [22.84]	0.0498^{a} [9.03]	0.5243^{a} [21.18]	3.2974^{a} [7.40]	12.0005^{a} [12.07]
Financials	0.0464^{a} [7.97]	0.3688^{a} [30.76]	0.0507^{a} [7.06]	0.3760^{a} [27.97]	5.1165^{a} [7.11]	14.3433^{a} [14.18]
HealthCare	0.0725^{a} [3.25]	0.1939^{a} [6.88]	0.0811^{a} [3.12]	0.1991^{a} [6.34]	1.7127^{a} [2.57]	4.4916^{a} [5.70]
Industrials	0.0373^{a} [6.15]	0.3629^{a} [15.91]	0.0475^{a} [6.85]	0.3906^{a} [15.33]	9.3510^{a} [2.04]	17.5557^{a} [2.66]
Materials	0.0623^{a} [6.12]	0.2160^{a} [11.38]	0.0825^{a} [6.69]	0.2544^{a} [11.46]	9.7313^{a} [6.16]	22.3981^{a} [8.91]
Technology	0.1270^{a} [3.47]	0.1872^{a} [4.09]	0.1605^{a} [3.60]	0.2102^{a} [3.87]	2.3576^{b} [1.83]	6.3920^{a} [2.73
Telecoms	0.0428^{a} [3.54]	0.4901^{a} [10.91]	0.0428^{a} [3.39]	0.4551^{a} [9.56]	5.4031^{a} [4.27]	11.2369^{a} [5.33]

Note(s): 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 in 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 and West, 2007). Values in square brackets – [] are for *t*-statistics. a, b and c indicate statistical significance at 1%, 5 and 10% levels, respectively

Table 4.
Out-of-sample forecast evaluation [h = 60]

	Clark and West test					
	Full sample		Pre-COVID		COVID#	
	Model 1 vs Model 2	Model 1 vs Model 3	Model 1 vs Model 2	Model 1 vs Model 3	Model 1 vs Model 2	Model 1 vs Model 3
Consumer goods	0.0909^{a} [4.35]	0.2864^{a} [6.33]	0.0882^{a} [4.16]	0.3077^{a} [4.87]	2.7923^{a} [4.12]	6.5168^{a} [5.02]
Consumer Services	0.0399^{a} [7.74]	0.5079^{a} [20.82]	0.0466^{a} [8.77]	0.5154^{a} [18.75]	2.8455^{a} [7.00]	9.8940^{a} [10.22]
Financials	0.0422^{a} [7.71]	0.3632^{a} [24.78]	0.0455^{a} [6.81]	0.3719^{a} [19.72]	4.4551^{a} [6.91]	12.3432^{a} [12.94]
HealthCare	0.0615^{a} [2.88]	0.1444^{a} [2.41]	0.0654^{a} [2.63]	0.2252^{a} [3.98]	1.5653^{a} [2.64]	4.3463^{a} [5.88]
Industrials	0.0350^{a} [6.07]	0.3306^{a} [11.99]	0.0431^{a} [6.54]	0.3892^{a} [11.92]	8.0366^{b} [1.99]	15.0977^{a} [2.57]
Materials	0.0532^{a} [5.49]	0.2439^{a} [7.07]	0.0814^{a} [6.98]	0.2257^{a} [5.10]	8.4634^{a} [5.99]	18.0202^{a} [7.74]
Technology	0.1110^{a} [3.24]	0.1810^{a} [3.73]	0.1532^{a} [3.65]	0.2027^{a} [2.91]	2.0120^{b} [1.76]	5.6367^{a} [2.68]
Telecoms	0.0518^{a} [4.05]	0.5294^{a} [6.20]	0.0414^{a} [3.34]	0.4734^{a} [5.15]	4.3810^{a} [3.81]	9.8603^{a} [4.91]

Note(s): 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 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 and West, 2007). Values in square brackets – [] are for *t*-statistics. a, b and c indicate statistical significance at 1%, 5 and 10% levels, respectively. #Due to the data scope for COVID, we use 10 and 20 days for out-of-sample forecast evaluation

Table 5.
Out-of-sample forecast evaluation [$h = 120$]

	Clark and West test					
	Full sample		Pre-COVID		COVID#	
	Model 1 vs Model 2	Model 1 vs Model 3	Model 1 vs Model 2	Model 1 vs Model 3	Model 1 vs Model 2	Model 1 vs Model 3
Consumer goods	0.0892[a] [4.23]	0.2764[a] [5.04]	0.1007[a] [4.50]	0.3975[a] [5.16]	2.4765[a] [4.04]	5.7999[a] [4.95]
Consumer Services	0.0341[a] [6.67]	0.5057[a] [19.87]	0.0444[a] [8.32]	0.5015[a] [16.79]	2.5197[a] [6.69]	9.3796[a] [9.78]
Financials	0.0376[a] [7.13]	0.3604[a] [21.56]	0.0427[a] [6.73]	0.3505[a] [16.97]	3.8129[a] [6.49]	10.6388[a] [11.82]
HealthCare	0.0546[a] [2.66]	0.1028[c] [1.63]	0.0593[a] [2.46]	0.1537[a] [2.08]	1.4538[a] [2.73]	3.8291[a] [5.48]
Industrials	0.0305[a] [5.27]	0.3098[a] [9.45]	0.0393[a] [5.99]	0.3625[a] [9.73]	7.3485[a] [2.03]	12.7912[a] [2.40]
Materials	0.0551[a] [5.89]	0.0966[a] [2.17]	0.0707[a] [6.27]	0.0860[c] [1.57]	7.8840[a] [6.17]	15.2597[a] [7.12]
Technology	0.1042[a] [3.22]	0.1720[a] [3.32]	0.1405[a] [3.57]	0.2089[a] [2.73]	1.8555[b] [1.80]	4.2805[a] [2.12]
Telecoms	0.0537[a] [3.64]	0.4602[a] [3.32]	0.0397[a] [3.14]	0.3429[b] [1.97]	3.9582[a] [3.73]	9.2347[a] [4.84]

Note(s): 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 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 and West, 2007). Values in square brackets – [] are for t-statistics. a, b and c indicate statistical significance at 1%, 5 and 10% levels respectively. #Due to the data scope for COVID, we use 10 and 20 days for out-of-sample forecast evaluation variables (see Periola-Fatunsin *et al.*, 2021; Bouri *et al.*, 2021; Alqaralleh and Alessandra, 2021; Camillo and Gradojevic, 2021; Fasanya *et al.*, 2021a, b; Al-Awadhi *et al.*, 2020; Abuzayed *et al.*, 2021; Baker *et al.*, 2020; Salisu and Vo, 2020). In this study, we employ panel data forecasting approach to examine the performance of infectious disease uncertainty for sectoral stock return predictability. For robustness, we account for an important feature of the stock returns series, the day-of-the-week effects as well as the macroeconomic-common factors in the disease-based predictive model for sector stock returns. From our findings, it is apparent that pandemic uncertainty has a negative and statistically significant effect on the different sector returns, implying that sector stock returns decline as the pandemic outbreak becomes more pronounced. While the single predictor model consistently outperforms the historical average model both for in-sample and out-of-sample, controlling for other macroeconomic variables effect improves the forecast accuracy of infectious diseases uncertainty.

These results provide practical implications for academicians, practitioners as rational investors, portfolio managers, policymakers. These implications are related in portfolio risk management, the diversification benefits and to propose new ınvestment tools among financial markets. Investors may need to consider the likely effects of global pandemics in the valuation of risk-adjusted returns for stocks in particular and perhaps in their diversification of financial assets in general. This conclusion complements the emerging literature on the vulnerability of the stock market to the COVID-19 pandemic. As part of future research, it would be interesting to extend the diversification properties of other financial markets such as cryptocurrencies, commodity, foreign exchange, bond and money markets, and real estate. Particularly examining the effects of uncertainties due to pandemics and epidemics will further enrich the extant literature. A major set-back of this study is not accounting for the role of government and market regulators. Hence, as part of research for future studies, the role of government and relevant market regulators may be included in the modeling of the effect of the financial sector impact of the pandemic.

Notes

1. See Baltagi (2013) and papers cited therein for computational advantages of using homogenous panel data approach when forecasting with short T.
2. This is well documented in the empirical literature on stock return predictability where historical average is used as the baseline model (see Devpura *et al.*, 2018).
3. 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.
4. The C-T (2008) test results compliment the C–W test. These results are available on request.

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