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Abstract

This paper examines the hedging effectiveness of US stocks against uncertainties due to equity market (financial risk) and pandemics (health risk), including COVID-19 pandemic. Consequently, we consider two categories of US stocks – defensive and non-defensive stocks drawn from ten different sectors and distinctly analysed over two data samples – pre- and post-COVID periods. We construct a predictive panel data model that simultaneously accounts for both heterogeneity and common correlated effects and also complementarily determine the predictive power of accounting for uncertainties in the valuation of US stocks. We find that hedging effectiveness is driven by the types of stocks and measures of uncertainty. Defensive stocks provide a good hedge for pandemic-induced uncertainty, and the hedging effectiveness is higher during calm market conditions as compared to turbulent conditions, while both categories lack hedging capability in the face of equity-induced uncertainty. Finally, we find that the inclusion of uncertainty in the predictive model of US stock returns improves its forecasts and this conclusion is robust to alternative measures of uncertainty and multiple forecast horizons.

Keywords: US stocks, Defensive stocks, Non-defensive stocks, Uncertainty, Pandemics, COVID-19, Panel data, Forecast evaluation

1. Introduction

The novel coronavirus (COVID-19) that was first reported in Wuhan, China has transcends borders, sending economic and social ripples across the world. The virus was first discovered on 31 December, 2019 and by March 2020, the World Health Organisation (WHO) declared COVID-19 a global pandemic. According to data from Johns Hopkins University tracker, global confirmed cases of the disease are more than 13 million as at 16 July 2020, and the reported deaths are now above a million.[4] There are currently no commercially available treatments or vaccines for COVID-19. Consequently, many countries have resorted to behavioural changes and non-clinical interventions. Some of these include quarantines and physical distancing practices, increased hand hygiene, shutting businesses and schools, working from home, and closure of national borders to restrict the movement of people in and out of the country. Essentially, the world, as we know, has been put in a great lockdown. The resulting economic disruption is unprecedented in scale and speed (Baldwin & Weder di Mauro, 2020, Baker et al. 2020). The global economy is in turmoil, negative economic growth is being reported across major economies, and many people have lost their jobs.

The pandemic has particularly pilled pressure on the financial markets around the world. While the precise global economic impacts are not yet clear, financial markets have already responded with enormous movements. For example, in March 2020, the US stock market hit the circuit breaker mechanism four times in ten days. The breaker has only ever been triggered once in 1997 since its inception in 1987. Together with the US crash, stock markets in Europe and Asia have also plunged. The rapid spread of COVID-19 has exerted dramatic impacts on financial markets all over the world. It has created an unprecedented level of risk and volatility, causing investors to suffer significant loses in a very short period of time (Zang, Hu & Ji, 2020). Stock prices are in a 10-year record low, with anticipation of greater fall (OECD, 2020).

In uncertain times as these, investors across the world are searching to identify assets that could hedge against uncertainty and/or shocks. In plain term, an asset is said to possess hedging features if it could withstand the attendant effects of some shocks. Put differently, in periods of market uncertainties or turbulent market conditions, an asset (stocks) is considered to hedge effectively if it does not lose its value. There is a huge literature that has examined

[4] It is important to note that the confirmed cases of COVID-19 do not capture the true extent of cases in each country. The number of confirmed cases is heavily dependent on the extent of testing in each country, and inadequate testing capacity has been widely reported across the word. Thus, the reported confirmed cases are likely to be less than the actual cases of the disease.

the hedging effectiveness of stocks against various forms of uncertainty (Arouri et al., 2016; Abul Basher and Sadorsky, 2016; Badshah et al., 2019). This literature has identified two types of stocks: defensive and non-defensive. It is argued that defensive stocks would provide hedge (insurance) against uncertainty. This stance is attributable to the fact that they provide consistent and stable earnings, irrespective of the phase of the business cycle. They provide a form of financial "immunity" to investors during economic crisis due to their low market-related risks or beta value, which is usually less than one (Novy-Marx, 2016). Typical examples of defensive stocks include utility and essential retail stocks.[5] Defensive stock strategies have seen explosive growth over the years. These strategies typically overweight or place a high value on defensive stocks, and under-weight or place a low value on risky stocks, and these weights are generally defined by a stock's volatility or market beta (Novy-Marx, 2016). Low-risk investing strategy is based on the idea that safer stocks like defensive stocks deliver higher risk-adjusted returns than do riskier stocks (Asness, Frazzini & Pedersen, 2014). Blitz and Van Vliet (2007) found that low risk stocks like defensive stocks exhibit significantly higher risk-adjusted returns than the market portfolio, while high-risk stocks significantly underperform on a risk-adjusted basis.

There is a huge literature on measuring uncertainty (Baker et al., 2016; Chilia et al., 2017; Su et al., 2019). The existing measures are related to what the researchers consider to be uncertainty or risk. The first set of studies have focused mainly on macroeconomic fundamentals. Thus, sharp changes in the trend of inflation, GDP, consumptions, and/or exchange rate are considered to be macroeconomic uncertainty (see Segal, et al., 2015; Bloom, 2014). Also, Baker et al. (2016) developed policy induced measures of uncertainty, coined Economic Policy Uncertainty (EPU). This index is constructed from three components: changes in tax codes, media reportage (news) on policy inconsistency of governments and dispersion in individual forecasters predictions about future levels of economic variables. Another set of studies have focused more on financial related measures of uncertainty. For instance, Ludvigson et al. (2017) developed the financial uncertainty (FU) for the Unites States. Unlike other measures, FU is limited to the financial markets and it expunges components not directly driven by uncertainty. Another popular financial measure of uncertainty constructed

[5] Utility stocks are company stocks that provide basic but essential services including electricity, water, and natural gas, while essential retail stocks may include stocks in Walmart Grocery, Tesco, Asda, Procter & Gamble, and Johnson & Johnson etc. The essential goods and services provided by these companies are always in demand, irrespective of the state of the economy. Apart from being everyday necessities, the goods and services offered by these companies take a relatively small amount from consumer's income, on the average. Thus, Consumers rarely cut back on them during economic recession.

by the Chicago Board Options Exchange (CBOE) is the investors' perception of future uncertainty and is derived from the co-movement of the front-page coverage of the Wall Street Journal and options-implied volatility (VIX). Studies have shown that higher levels of VIX index are associated with higher volatility of the US financial markets (Su et al., 2017; Fang et al., 2018). More recently, Baker et al. (2020) developed the Equity Market Volatility: Infectious Disease (EMV-ID) Tracker, based on three components: stock market volatility, newspaper-based economic uncertainty, and subjective uncertainty in business expectation surveys that provide real-time forward-looking uncertainty measures. The Baker et al. (2020) measure of uncertainty is more associated with pandemics including COVID-19 pandemic. The conclusion in the literature is that these various measures of uncertainty have differing effects on the financial markets. For instance, Su et al., (2019) concluded that EPU is positively associated with the stock market volatility of non-U.S. G7 countries, while VIX conforms to the a priori expectation and FU performs poorly in predicting stock markets volatility.

Given the severe adverse effects of the current pandemic on the global economy, we extend the literature on market-based uncertainty to accommodate the new dataset involving uncertainty due to pandemics. While there are alternative market-based indices as previously highlighted, we favour the CBOE VIX as it is now an established and globally recognized gauge of U.S. equity market volatility, the most widely cited uncertainty index particularly when dealing with US equity market (see Kuepper & Scott, 2020) and most related to the stock market data (S&P 500) used in this study. Thus, we consider both equity-based uncertainty using the CBOE VIX and the pandemic-induced uncertainty using the Baker et al. (2020) EMV-ID index which measures uncertainty due to pandemics and evaluate the hedging effectiveness or vulnerability of the US stocks in the face of these uncertainties. This study is at the confluence of two interesting strands of the literature: defensive vs non-defensive stocks and measures of uncertainty literature. Based on the following, we seek answers to the following questions (i) do aggregate stocks hedge against uncertainty? (ii) are defensive stocks more effective in providing hedging features in a predictive model? (iii) is the hedging effectiveness of stocks sensitive to the measures of uncertainty?, and (iv) how useful are these measures of uncertainty in enhancing the forecast accuracy of US stock returns? Note that in-sample predictability may not necessarily translate into improved out-of-sample forecasts.

Foreshadowing our results, we find that both defensive and non-defensive stocks are vulnerable to the equity induced uncertainty. However, the reverse is the case when pandemic-induced measure is considered. In other words, these stocks tend to be resilient to uncertainty due to pandemics. Furthermore, defensive stocks provide better hedging options for investors.

We also find that the degree of hedging effectiveness is higher during calm market conditions as compared to turbulent condition. These results have important implications for policymakers.
The rest of the paper is structured as follows. Data issues are presented in Section 2. Section 3 discusses the Methodology. Empirical results are presented in Section 4, while Section 5 conceives the concluding remarks and some policy implications.

2. Data and Preliminary Analyses

2.1 Data Issues

Our analyses are based on a daily data for the period 7 August, 2019 – 22 May, 2020. This time frame is divided into two parts: 7 August, 2019 – 31December, 2019 and 1 January 2020 – 22 May, 2020. The first part captures the pre-COVID period, while the latter part represents the post-COVID period. The reason for this demarcation is to examine the sensitivity of the hedging effectiveness of stocks to turbulent and calm market conditions. Sectoral data is collected for the S&P500 index. The index categorises data into 10 sectors: Discretionary, Energy, Financial, Industrial, Information and Technology, Materials, Staples, Telecommunication, Utilities and Health. As stated earlier, this study makes a comparison between defensive and non-defensive stocks[6].

Two measures of uncertainty are considered in this study. The first is the equity-induced uncertainty of the Chicago Board Options Exchange, oftentimes called the VIX index or the fear index. It measures the level of risk averseness of investors. The higher the index, the higher is the level of averseness of investors, which implies high level of market volatility. The second measure is the pandemic induced uncertainty developed by Baker et al. (2020) and utilizes four sets of terms namely (i) E: economic, economy, financial; (ii) M: "stock market", equity, equities, "Standard and Poors"; (iii) V: volatility, volatile, uncertain, uncertainty, risk, risky; (iv) ID: epidemic, pandemic, virus, flu, disease, coronaviruses (i.e. COVID-19, MERS & SARS), Ebola, H5N1, H1N1.[7] Data on stock returns are collected from the Bloomberg terminal, while data on uncertainty are sourced from FRED St. Louise databank.

[6] Staples, Utilities and Health stocks are classified as defensive stocks, while others are categorized as non-defensive stocks.
[7] Computational details of the EMV-ID index can be obtained from Baker et al. (2020).

2.2 Preliminary Analysis

We start the results discussion by presenting key descriptive statistics in Table 1. As expected, the volatility index (VIX) is higher in the post-COVID-19 era than in the previous period. This reflects high market uncertainty and return fluctuations. The descriptive statistics indicate that the average return on defensive stock is lower in the post COVID-19 announcement in relation to the preceding period. This suggests that defensive stocks may not hedge against the COVID-19 induced financial shock. However, these results are only raw comparative differences in average returns, which do not control for other relevant variables that could cause variations in stock returns over time. The average return on non-defensive stocks is largely the same for both pre and post COVID-19 announcement, while the aggregated stock return is slightly higher in the pre-COVID-19 periods.

Table 1: Descriptive Statistics

	All Stocks		Defensive Stocks		Non-Defensive Stocks		VIX	
	Pre-Covid	**Post-Covid**	**Pre-Covid**	**Post-Covid**	**Pre-Covid**	**Post-Covid**	**Pre-Covid**	**Post-Covid**
Mean	0.024	0.0149	0.221	-0.341	-0.228	-0.247	15.048	33.685
Std Dev.	8.436	10.150	7.925	6.901	7.745	9.389	2.581	18.064

Source: Authors' computation. Note: Std. Dev is Standard deviation.

Table 2 illustrates the descriptive analysis of sectorial stock returns and evaluates its relationship with uncertainty, as measured by VIX index. The table summarizes the mean and standard deviation of stock returns across sectors as well as the behaviour of stock returns when uncertainty increases or declines beyond the threshold mean value. The statistics in Column 1 shows the behaviour of stock returns, on average, when the volatility index is above its overall mean. Subsequently, column II reports the response of stock returns when the mean value of VIX is below its and Column III makes similar case for overall mean of VIX. Starting with Column I, Table 2 reveals that the increase in volatility is accompanied by decline in stock returns. This stance holds for all the individual sectors. Examining how the sectors respond on the average (i.e. defensive vs non-defensive), we find that the panel non-defensive sectors record more losses as compared to the panel of defensive stocks. This implies that defensive stocks are able to hedge against uncertainty. Different scenarios emanate in the case of column II. An overview of the column shows that all sectors, with the exception of energy, have positive returns. Hence, in a tranquil market condition, all sectors tend to report positive return, a situation that conforms to theoretical underpinning. In a case of panel of defensive vs non-defensive stocks, statistics reveal that the former gains the most when there is relative stability in the financial markets. The general implication of the statistics is that investments follows the pattern of volatility. Hence, more investments are made when the market is perceived to be calm and vice-versa. Figure 1 shows the trend movements of the individual sectors and VIX. The main import of the figure is that post-COVID announcement (i.e. the shaded area) is earmarked with high volatility in stock returns. This situation holds for all the 10 sectors, however with varying degree.[8]

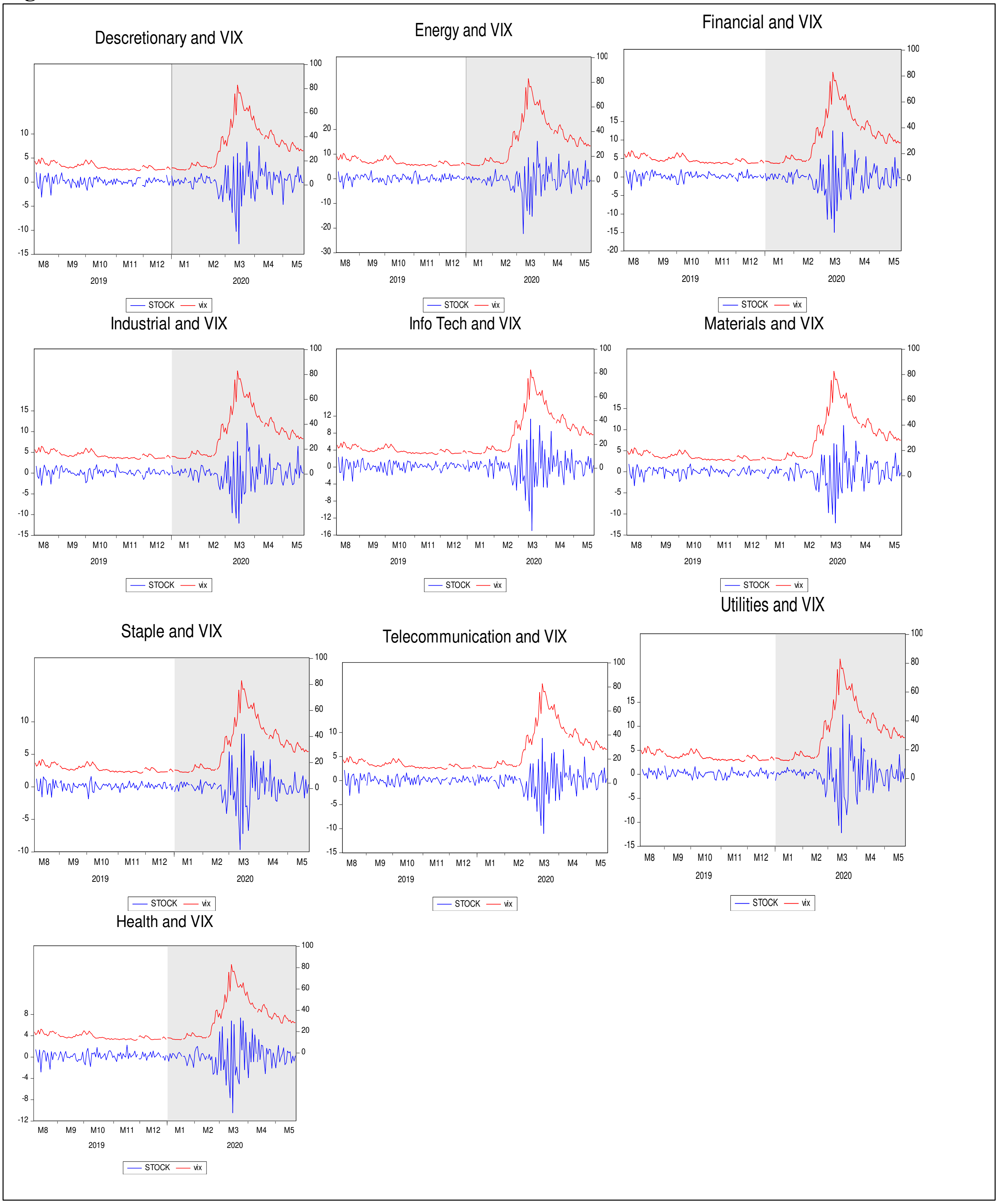
Table 2: Summary Statistics of Scenario Simulations

		Case I	**Case II**	**Case III**
Discretionary	Mean	-0.129	0.136	0.004
	Std Dev	0.540	0.120	0.322
Energy	Mean	-0.086	-0.005	-0.031
	Std Dev	1.116	0.217	0.658
Financial	Mean	-0.084	0.017	-0.015
	Std Dev	0.084	0.152	0.495
Industrial	Mean	-0.063	0.013	-0.011
	Std Dev	0.684	0.141	0.406
Info Tech	Mean	-0.008	0.027	0.015
	Std Dev	0.602	0.145	0.362
Material	Mean	-0.032	0.008	-0.005
	Std Dev	0.731	0.158	0.435
Staple	Mean	-0.273	0.010	-0.001
	Std Dev	0.501	0.091	0.294
Telecommunication	Mean	-0.016	0.022	0.010
	Std Dev	0.683	0.162	0.410
Utilities	Mean	-0.055	0.199	-0.004
	Std Dev	0.794	0.110	0.461
Health	Mean	-0.007	0.015	0.008
	Std Dev	0.486	0.114	0.291
All Stock	Mean	-0.039	0.014	-0.003
	Std Dev	0.716	0.145	0.426
Defensive	Mean	-0.030	0.015	0.0005
	Std Dev	0.608	0.106	0.357
Non-Defensive	Mean	-0.043	0.014	-0.004
	Std Dev	0.758	0.158	0.452

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

[8] The summary statistics for pandemics are suppressed for want of space but can be available upon request.

Figure 1: Trends in sectoral stock returns and VIX



3. Methodology

We construct a predictive model that relies on the underlying intuition behind the standard theory of asset pricing such as the capital asset pricing model where individual stock returns respond to systemic risk which is measured with uncertainty indices in this study. We consider two measures of uncertainty: (i) one that is associated with equity market and (ii) the other that is due to pandemics. The former relies on the Chicago Board Options Exchange's (CBOE) Volatility Index, a popular measure of the stock market's expectation of volatility based on S&P 500 index options while the latter utilizes the new dataset by Baker et al. (2020) which measures uncertainty due to infectious diseases. In line with the asset pricing theory of stock valuation, we also account for relevant control variables such as oil price and interest rate (see also Narayan & Gupta, 2015; Bannigidadmath and Narayan, 2015; Narayan et al., 2016; Devpura et al., 2018; Salisu et al., 2019a,b,&c; Salisu & Vo, 2020). Since our study involves the use of panel data with distinct sectoral stocks, we favour the heterogeneous panel approach (see also, Chudik and Pesaran, 2015; Chudik et al., 2016; Reese and Westerlund, 2016; Westerlund et al., 2016; Westerlund and Narayan, 2016; Salisu and Isah, 2017; Ditzen, 2018; and Salisu and Ndako, 2018). One of the attractions to this approach lies in its ability to deal with heterogeneity typical of cross-sections with large T as well as the inherent heterogeneity in the considered sectoral stocks.

In addition, we allow for common correlated effect (CCE) as these stocks may be driven by unobserved common factors such as policy and international (exogenous) shocks which in a way can affect the performance of these stocks. Some of the computational advantages of allowing for the CCE in return predictability and the estimation procedure are well documented in Chudik and Pesaran (2015), Westerlund et al. (2016) and Ditzen (2018, 2019). Thus, following the heterogenous panel data techniques of Chudik and Pesaran, (2015), Chudik et al. (2016) and Westerlund et al. (2016), we construct a predictive panel data model for stock returns[9]:

$$r_{it} = \alpha_i + \sum_{j=1}^{5} \lambda_{ij} uc_{i,t-j} + Z_{it}'\phi_i + \eta_{it} \qquad [1]$$

$$\eta_{it} = \delta_i f_t + u_{it} \qquad [2]$$

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

[9] In addition to the suitability of the model for long T, it also helps resolve any inherent nonstationarity which is a suspect when dealing with long T. It also accommodates mixed order of integration and facilitates the estimation of long run and short run dynamics including the speed of adjustment.

where r_{it} denotes the log-return series computed as $100*\log\left(s_{it}/s_{i,t-1}\right)$ with s_{it} being the stock price data for sector i at period t; uc is the uncertainty index; α_i and λ_i represent the heterogenous intercept and slope coefficients which are allowed to vary across units ; and η_{it} is the error term. Note that η_{it} is a composite error term comprising an unobserved common factor loading $\left(f_t\right)$ accompanied with a heterogeneous factor loading $\left(\delta_i\right)$ and the remainder error term $\left(u_{it}\right)$. The coefficient λ_i measures the relative impact of the uncertainty on stock returns and we allow for up to five lags given the data frequency (daily five-day of the week) as well as the need to capture more dynamics in the estimation process (Salisu et al., 2020). Thus, the underlying null hypothesis of no predictability involves a joint (Wald) test - $\sum_{j=1}^{5}\lambda_{ij}=0$.[10] In addition to the issue of predictability, equation [1] is also used to evaluate the hedging potential of US defensive and non-defensive stocks against financial and health risks. This methodology is in line with a typical framework for inflation hedging in which the standard computations for hedging analysis such as optimal portfolio weight and optimal hedge ratio are not required. Thus, an asset that serves as a good hedge against inflation is expected to retain or increase in value as inflation increases (see for a review, Arnold & Auer, 2015). Thus, the uncertainty index due to pandemics and epidemics (UPE) is considered as a form of macro-economic risk and therefore a similar predictability model is constructed to evaluate the hedging potential of US stocks. However, the interpretation of hedging potential here slightly differs from the conventional inflation hedging since the UPE cannot play the role of inflation in terms of the relationship between real and nominal variables. Thus, in this paper, there are three possible outcomes in relation to UPE. Assume the coefficient on UPE is "b", the three possible outcomes are: (i) b>0 (ii) b<0; and (iii) b=0.The vector of control variables involving oil price returns and interest rate is denoted as Z_{it} and the corresponding vector of parameters is symbolized as ϕ_i (Salisu & Sikiru, 2020). Similar methodology is adopted by Salisu & Sikiru (2020) to analyse the hedging potential of Islamic stocks to pandemics.

Finally, we further assess the ability of the uncertainty index to improve the forecast accuracy of equation [1] for stock returns relative to the historical average which ignores any potential predictor of stock returns and is specified as:

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$$r_{it} = \alpha + \eta_{it}\,; \quad t = 1,2,3,...,T;\; i = 1,2,3,...,N \qquad [3]$$

We employ a pair-wise forecast measure, the Clark and West (CW, 2007) test, which helps to determine whether the difference in the forecast errors of two competing nested models (equations [1] & [2] in this case) is statistically significant. For a forecast horizon h, the CW (2007) test is specified as:

$$\hat{f}_{t+h} = M\hat{S}E_r - \mathbf{(}M\hat{S}E_u - adj\mathbf{)} \qquad [4]$$

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

4. Empirical Results

4.1 The results of the equity-based uncertainty

The main aim of this sub-section is to present the results of the hedging effectiveness of stock returns to VIX. An asset is revered to have hedge features if it is able to, in the worst case, retain its value during periods of shock or uncertainty. On the flipside, an asset is vulnerable to shock or uncertainty if it sheds its value during turbulent period. For simplicity, when an estimated parameter is positive, it implies that such an asset has hedging feature. Conversely, a stock is said to be vulnerable to shock if it reports negative estimated coefficients. In terms of presentation of results, two regressions are considered: one without control variables and the other with control variables and both are carried out for two categories of stocks - defensive and non-defensive stocks while aggregate stock is also included for completeness. Each regression is further estimated for both the pre- and post-COVID periods in order to assess the response of these stocks to uncertainty during calm and turbulent market conditions.

Table 3: Results for the hedging behavior of defensive and non-defensive stocks

	All stocks		Defensive stocks		Non-defensive stocks	
	Pre-Covid	**Post-Covid**	**Pre-Covid**	**Post-Covid**	**Pre-Covid**	**Post-Covid**
Without	-0.219	-0.424[a]	-0.168	-0.489[a]	-0.261[c]	-0.453[a]
Control	(2.64)	(58.43)	(0.22)	(27.12)	(3.12)	(85.28)
With	**0.051**	**-1.196[a]**	-0.135	-1.916[a]	**0.119**	**-1.47[a]**
Control	**(0.11)**	**(27.66)**	(0.31)	(13.46)	**(0.33)**	**(30.75)**

Note: "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 & Post-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 & c indicate statistical significance at 1%, 5% and 10% levels respectively.

Results of the hedging behaviour are presented in Table 3. Statistics emanating from the table pose four issues to note. First, examining the sole effect of the predictor (model without control), results show that uncertainty due to equity market constitutes a significant drag towards stock returns. In essence, higher levels of uncertainty negatively impact on stock returns. Hence, the results validate our hypothesis that stock markets are vulnerable to exogenous shocks. A section of the literature has confirmed this stance (Drechsler, 2013; Su et al., 2017; Qadan et al., 2019). Second, the potency of the negative effect is more obvious, judging by the estimated coefficient, for the post-Covid period, in relation to pre-Covid period. This result is not unexpected, as stock returns have exhibited an erratic behaviour since the announcement of the emergence of the pandemic (see Figure 1 for a graphical illustration). Third, the inclusion of some control variables further worsens the poor hedging prowess of stocks against uncertainty. A plausible explanation could be linked to the high volatile nature of oil prices[11] (Sharif et al. 2020). Fourth, these results are robust to the three classifications of assets (i.e. all stock, defensive stock and non-defensive stocks). This thus suggests that there tend not to be difference between defensive- and non-defensive stocks. In sum, equity market-induced uncertainty (based on the CBOE VIX) has proved to be a significant predictor of stock returns and the vulnerability of stocks, to this type of uncertainty, particularly during covid-19 pandemic and the outcome is similar across the three asset types.

4.2. Forecast evaluations of the equity-based uncertainty

We also assess the forecast power of the uncertainty indicator and therefore we partition the data sample into in-sample and out-of-sample periods using the 75:25 data split respectively. Results of the in-sample forecast analysis are presented in Table 4 while the out-of-sample

[11] For the first time in human history, oil price plummeted to negative sometime in April.

forecasts are presented in Tables 5 and 6 respectively for 10 days and 20 days ahead forecast horizons. Forecast evaluation is based on the Clark and West (2007) test and the decision rule is that a positive and significant value of the constant parameter in the test equation shows that our model's performance outperform the benchmark model (i.e historical average). An overview of the table shows that our proposed model whether with or without control variables provides better forecasting results in contrast to the benchmark model. Worthy of note is that the significance of the CW test is higher in the post-Covid period as compared to the pre-Covid period. In other words, the inclusion of the uncertainty measure when forecasting stock returns is crucial during the covid-19 pandemic. The results of the out-of-sample forecasts as presented in Tables 5 and 6 are similar to those of the in-sample. In essence, our models have the prowess to make reliable forecast for both in- and out-of-sample periods.

Table 4: In-Sample Forecast Evaluation

	Clark & West test			
	Pre-Covid		**Post-Covid**	
	Model 1 vs Model 2	**Model 1 vs Model 3**	**Model 1 vs Model 2**	**Model 1 vs Model 3**
All Stocks	0.263[a] [6.76]	0.265[a] [7.98]	16.058[a] [10.74]	16.260[a] [10.79]
Defensive stocks	0.100[a] [3.25]	0.137[a] [4.05]	21.003[a] [6.05]	21.402[a] [6.06]
Non-defensive stocks	0.290[a] [6.58]	0.320[a] [7.16]	18.263[a] [9.28]	18.492[a] [9.30]

Note: Model 1 is the Historical Average model; Model 2 is the model without control; Model 3 is the model with control. The Clark & 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 & c indicate statistical significance at 1%, 5% and 10% levels respectively.

Table 5: Out-of-Sample Forecast Evaluation [h=10]

	Clark & West test			
	Pre-Covid		**Post-Covid**	
	Model 1 vs Model 2	**Model 1 vs Model 3**	**Model 1 vs Model 2**	**Model 1 vs Model 3**
All Stocks	0.298[a] [6.85]	0.285[a] [7.60]	14.452[a] [10.96]	14.654[a] [10.45]
Defensive stocks	0.077[b] [1.81]	0.111[a] [2.58]	18.920[a] [6.17]	18.813[a] [5.58]
Non-defensive stocks	0.332[a] [6.71]	0.358[a] [7.20]	16.446[a] [9.46]	16.567[a] [8.90]

Note: Model 1 is the Historical Average model; Model 2 is the model without control; Model 3 is the model with control. The Clark & 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 & c indicate statistical significance at 1%, 5% and 10% levels respectively.

Table 6: Out-of-Sample Forecast Evaluation [h=20]

	Clark & West test			
	Pre-Covid		**Post-Covid**	
	Model 1 vs Model 2	**Model 1 vs Model 3**	**Model 1 vs Model 2**	**Model 1 vs Model 3**
All Stocks	0.272^{a} [6.51]	0.261^{a} [7.15]	13.236^{a} [11.21]	12.890^{a} [10.09]
Defensive stocks	0.0532 [1.11]	0.085^{b} [1.80]	17.501^{a} [6.38]	16.309^{a} [5.26]
Non-defensive stocks	0.303^{a} [6.38]	0.335^{a} [7.01]	15.109^{a} [9.72]	14.506^{a} [8.53]

Note: Model 1 is the Historical Average model; Model 2 is the model without control; Model 3 is the model with control. The Clark & 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 & c indicate statistical significance at 1%, 5% and 10% levels respectively.

4.3 The results of the pandemic-induced uncertainty

A section of the literature has argued that the hedging effectiveness of stocks is sensitive to measures of uncertainty (Chilia et al., 2017; Su et al., 2019). While it is acknowledged that the equity induced uncertainty has been prominently used in the literature, there are other sources of uncertainty that are quite important (Baker et al., 2016 and 2020). Thus, an alternative measure, pandemic-induced uncertainty, is used in this section. This measure is particularly important at this time where the global uncertainty is attributed to COVID-19 pandemic. The predictability results are presented in Table 7. Across the entire estimated models, results show that stock return is able to hedge against pandemic-induced uncertainty. The implication of the result is that stock returns provide cover against pandemic uncertainty in either calm or turbulent market conditions. The important issue to note is that defensive stocks provide a higher degree of cover, during turbulent conditions, as compared to non-defensive or the entire stock market. As such, investors and hedging traders could easily diversify their portfolio to defensive stocks during period marked with uncertainty. This conclusion is in line with the finance and risk practice which have established over time that defensive stocks reflect companies whose earnings growth and performance have a low correlation to the economy and therefore their revenue, profit and cash flow are likely to remain stable regardless of the economic conditions (see for example, Gordon & Knowles, 2019).

The results of the in-sample forecast evaluation are presented in Table 8. We show that the performance of models 2 and 3 (i.e. without control and with control, respectively) outdoes that of the benchmark model of historical averages. Just like the equity-induced uncertainty, we also examine the out-of-sample forecast evaluation when h =10-day and 20-day ahead forecast horizons. The results of these analyses are presented in Tables 9 and 10, in that order. The summary of the results of these tables is that the benchmark model is least preferred to the uncertainty-based models. Also, the prowess of the forecasting model is higher at 10-day forecast as compared to that of 20-day forecast.

We next summarily highlight the differences between the forecasting performance of equity induced and pandemic-induced uncertainties (i.e. difference between Table 3 and Table 7). First, stock returns are predominantly vulnerable to the equity-induced uncertainty, whereas the reverse is the case for pandemic-induced uncertainty. Defensive stocks provide hedge perfectly for pandemic induced shocks (see Table 7) whereas, there are some instances when non-defensive stocks have better performance (most especially during post-Covid period (see Table 3). The only similarity between these tables is that there is a higher rate of return during the calm period in contrast to the turbulent market conditions.

Table 7: Results for the hedging behavior of defensive and non-defensive stocks

	All stocks		Defensive stocks		Non-defensive stocks	
	Pre-Covid	**Post-Covid**	**Pre-Covid**	**Post-Covid**	**Pre-Covid**	**Post-Covid**
Without	0.093	0.030[a]	0.122	0.039[a]	0.107	0.031[a]
Control	(1.76)	(54.43)	(0.86)	(13.16)	(1.81)	(38.15)
With	0.029	0.047[a]	0.105	0.051[a]	0.010	0.044[a]
Control	(0.20)	(120.27)	(2.25)	(17.15)	(0.01)	(61.42)

Note: "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 & Post-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 & c indicate statistical significance at 1%, 5% and 10% levels respectively.

Table 8: In-Sample Forecast Evaluation

	Clark & West test			
	Pre-Covid		**Post-Covid**	
	Model 1 vs Model 2	**Model 1 vs Model 3**	**Model 1 vs Model 2**	**Model 1 vs Model 3**
All Stocks	0.074[a] [4.06]	0.088[a] [4.83]	3.398[a] [6.37]	3.718[a] [6.51]
Defensive stocks	0.042[a] [2.36]	0.074[a] [3.11]	3.813[a] [3.06]	4.205[a] [2.98]
Non-defensive stocks	0.077[a] [3.80]	0.093[a] [3.97]	3.504[a] [5.14]	3.757[a] [5.05]

Note: Model 1 is the Historical Average model; Model 2 is the model without control; Model 3 is the model with control. The Clark & 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 & c indicate statistical significance at 1%, 5% and 10% levels respectively.

Table 9: Out-of-Sample Forecast Evaluation [h=10]

	Clark & West test			
	Pre-Covid		**Post-Covid**	
	Model 1 vs Model 2	**Model 1 vs Model 3**	**Model 1 vs Model 2**	**Model 1 vs Model 3**
All Stocks	0.056^{a} [3.19]	0.087^{a} [3.42]	2.275^{a} [3.66]	2.138^{a} [3.31]
Defensive stocks	0.042^{a} [2.31]	0.0511^{c} [1.61]	3.573^{a} [2.58]	3.251^{a} [2.25]
Non-defensive stocks	0.059^{a} [2.95]	0.102^{a} [3.11]	2.646^{a} [3.31]	2.446^{a} [2.96]

Note: Model 1 is the Historical Average model; Model 2 is the model without control; Model 3 is the model with control. The Clark & 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 & c indicate statistical significance at 1%, 5% and 10% levels respectively.

Table 10: Out-of-Sample Forecast Evaluation [h=20]

	Clark & West test			
	Pre-Covid		**Post-Covid**	
	Model 1 vs Model 2	**Model 1 vs Model 3**	**Model 1 vs Model 2**	**Model 1 vs Model 3**
All Stocks	0.053^{a} [3.31]	0.0534^{b} [1.95]	2.014^{a} [3.46]	1.981^{a} [3.27]
Defensive stocks	0.039^{a} [2.35]	0.044 [1.23]	3.279^{a} [2.48]	3.166^{a} [2.31]
Non-defensive stocks	0.055^{a} [3.04]	0.057^{c} [1.64]	2.318^{a} [3.07]	2.257^{a} [2.91]

Note: Model 1 is the Historical Average model; Model 2 is the model without control; Model 3 is the model with control. The Clark & 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 & c indicate statistical significance at 1%, 5% and 10% levels respectively.

5. Conclusion and Policy Implications

The primary objective of this study is to examine the hedging effectiveness of stocks against uncertainty. This study is at the heart of two strands of the literature. The first strand made two classifications of stocks: defensive and non-defensive. In the case of the former, it is argued that such stocks are immune to shocks introduced into the financial markets, while the latter does not exclude the possibility of vulnerability of stocks to shocks (Novy-Marx, 2016; Asness, Frazzini & Pedersen, 2014). The second strand concludes that the vulnerability or otherwise of stock to shock is dependent upon the measure or type of shocks (Chilia et al., 2017; Su et al., 2019). Based on the foregoing, the objective of the study is to examine the vulnerability or hedging effectiveness of types of stocks on uncertainty. Uncertainty is viewed from the prism of equity- and pandemic- induced. In terms of scope, our analyses focus on the S&P500 index. Given the limited dimension of available data point, since the discovery of Covid-19, we rely on the use of panel data frequency for the period 7th August 2019 – 22nd May 2020.

Results obtained show that the hedging effectiveness is dependent upon the type of stocks and measures of uncertainty. Elucidating on the above, stock returns are vulnerable to the equity-induced uncertainty. This thus confirms the general position of literature. The defensive stocks are unable to escape the problem. However, stocks are able to effective hedge against the pandemic-induced uncertainty. The dichotomization of stocks, into defensive and non-defensive, shows that the effectiveness is more enhanced in the case of former. It is also proven that the degree of hedging effectiveness is higher during calm market conditions as compared to turbulent condition. The results of the forecast evaluation show that our models has better predictive performance in relation to the historical average benchmark model. These results hold sway for both in-sample and out-of-sample analysis.

There are two discerning policy implications of the estimated results. First, there is the need for investors, who are interested in maximizing their returns, to study the effects of uncertainty associated to equity and pandemic before making composition of portfolio decisions. Second, defensive stocks provides a stable source of hedging effectiveness for financial market stakeholders. In essence, these stakeholders could design their portfolios in include some defensive stocks. There are two avenues for future research. First, a section of the literature has argued for the importance of accounting for asymmetry and structural breaks in stock related models. Second, these analyses could be replicated for other financial markets, asides the United States and stock markets. As such, it would be interesting to see how the results would turn out for the equity markets and its implication for fund managers.

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