

# COVID-19 Pandemic and Financial innovations

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## Abstract

This study is motivated around the COVID-19 pandemic as a source of rising financial market risks. Hence, we investigate whether pandemic-induced risks can be hedged by alternative investment in financial innovations captured in exchange traded funds (ETFs). We explore the hedging effectiveness of sectoral ETFs along with a battery of robustness measures. Following the predictability analyses, we find that financial innovations captured in ETFs can effectively hedge both pandemic-induced and financially engineered market risks especially after controlling for the role of oil price in the predictive model. Our model provides better in-sample and out-of-sample forecasting accuracy and economic gains than the benchmark model and this is more pronounced for the COVID-19 pandemic period.

**Keywords:** Pandemic, Hedge, Financial innovation, ETFs, Predictability

**JEL codes:** I19; G11; G15; F21; C53

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## 1. Introduction

In this study, we assess whether uncertainties associated with pandemics (including COVID-19 pandemic) could be hedged with financial innovations. The current (COVID-19) pandemic whose consequences have transcended beyond public health concerns to global economic upshots due to policy responses aimed at containing the spread such as social distancing and lock down measures, global travel restrictions, testing and quarantining policies, and income support packages, among others (Salisu and Vo, 2020; Ngwakwe, 2020; Utomo and Hanggraeni, 2021; Gao, Ren and Umar, 2022). A number of corroborating studies have also documented, in most cases, negative consequences of pandemics, including the recent one, on various economies (Bloom et al., 2005; McKibbin and Sidorenko, 2006; Correia et al., 2020; Nicola et al., 2020; Li et al., 2021)<sup>5</sup>, as well as its impact on market dynamics (Maghyereh, 2022). From economic intuition, the negative consequences of the pandemic could also be linked to disruptions in demand and supply chains, job losses, as well as increased production costs across many sectors (Abu Bakar and Rosbi, 2020; Gössling et al., 2020; Hilmola et al., 2020; Goel et al., 2021; Pujawan and Bah, 2022).

The major contribution of this study lies in the consideration of financial innovations with particular focus on exchange traded funds (ETFs) for hedging the new market risks i.e. pandemic-induced market risks. One of our strongest motivations for pursuing this contribution is the support from previous studies that reveal the negative impact of the COVID-19 pandemic on financial markets (Ashraf, 2020; Baker et al., 2020; Bouri et al., 2021; Corbet et al., 2020; Gherghina et al., 2020; Ngwakwe, 2020; Salisu, Raheem and Ndako, 2020; Schoenfeld, 2020; Sharif et al., 2020; Hong et al., 2021; Insaaidoo et al., 2021; Li et al., 2021; Mazur et al., 2021; Gao et al., 2022). The second motivation is about the choice of financial innovation as an alternative hedging instrument due to previous findings indicating that traditional instruments have been failing in their hedging role<sup>6</sup> (Sharma and Rodriguez, 2019; Brim and Wenham, 2019; Cheema, Faff, and Szulczuk, 2020). Unlike many other conventional investment options, ETFs offer passive and flexible investment strategies that allow investors to hold diversified basket of securities as a single stock rather than

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<sup>5</sup> The relationship between pandemics particularly the current pandemic and different financial markets such as stock market (Salisu and Vo, 2020; Salisu, Ebuh & Usman, 2020; Li et al., 2020; Salisu & Sikiru, 2020; Sharma, 2020; Sikiru and Salisu, 2022) and foreign exchange market (Narayan, 2020a&b; Narayan, Devpura & Wang, 2020), has been documented in the literature.

<sup>6</sup> The literature on hedging effectiveness with relatively safe assets is vast with varying conclusions (Junttila, Pesonen & Raatikainen, 2018; Salisu and Adediran, 2019; Cheema, Faff, & Szulczuk, 2020; Salisu, Raheem & Ndako, 2020).

separately (Kraft, 2012; Dannhauser, 2017; Marskz and Lechman, 2018; Sarkarya and Ekinici, 2020; Naeem et al., 2020; Ozdurak and Ulusoy, 2020; Liu et al., 2020; Sakarya and Ekinici, 2020). Further, among financial innovations, exchange-traded funds are one of the most recognized categories of financial innovations with evidence in support of their risk-free nature and portfolio diversification, hence, hedging alternatives, and low correlation with most traditional portfolios, further attesting to their hedging potentials (Cao, 1999; Asness et al., 2001; Gao, 2001; Liang, 2001; Massa, 2002; Alexander and Barbosa, 2008; Tari, 2010; Madhavan and Maheswaran, 2016).

With the emergence of new wave of crisis ushered in by the COVID-19 pandemic, there is need to look for alternative instruments that can effectively provide cover for other assets exposed to the market crisis (Jin, Han, Wu, and Zeng, 2020). In the hedging framework, we consider both the predictability (statistical) as well as the economic significance of hedging effectiveness of ETFs for pandemic-induced market risks. On the pandemic-induced risks, we utilize the new index constructed by Baker et al. (2020) which comprehensively accommodates relevant pandemics and epidemics since 1986 with their associated risks. We have included this note to Section 1 of the revised manuscript to further highlight our contributions. In terms of predictability, we explore both the in-sample and out-of-sample predictability including multiple forecast horizons for the out-of-sample predictability. This is the first study, to the best of our knowledge, which clearly demonstrates the connection between financial innovations and health risk from the perspective of both forecast gains and utility gains. We also explore a number of options including the attempt to improve the forecast performance of the predictive model with the inclusion of oil price as a control variable for global factor and the Chicago Board Options Exchange Volatility Index (CBOE-VIX) as an alternative (financial) risk. This additional consideration allows us to see if financial innovations respond differently to risks (health risk, financial risk and commodity risk).

Consequently, our results show that ETFs are able to withstand higher levels of uncertainty triggered by pandemics, thus indicating the hedging potentials of the financial innovation. Similarly, the introduction of oil price as an additional predictor of the asset returns further improves the forecast performance as the augmented model performs better than the benchmark model. This further confirms that investors can take advantage of the economic gains imbedded in securities ETFs to inform their investment decisions (Narayan and Sharma, 2014). While financial innovations can be used to hedge against both health and financial risks, their forecast outcomes differ under the two sources of risks.

Following this introduction, the remainder of the paper is structured as follows: Section 2 describes the data and offers some preliminary analyses of the variables used; Section 3 discusses the empirical methodology; Section 4 presents the results and discussion and Section 5 concludes the paper.

## **2. Why financial innovations?**

Emergence of crisis usually prompts investors to be on the look for instrument to hedge their assets against risk associated with the crisis. In other words, there would be no need for hedging if there is stability in the market. Similarly, literature have a number of evidence where some assets have been used to hedge against risk (Junttila, Pesonen and Raatikainen, 2018; Salisu, Vo and Lawal, 2020; Garcia-Jorcano and Muela, 2020), and in some cases, where hedging efficacy of one asset have been tested against another (Salisu and Adediran, 2019; Cheema, Faff, and Szulczuk, 2020; Salisu, Raheem and Ndako, 2020 among others). However, some of these traditional assets have been ineffective in their hedging role (Sharma and Rodriguez, 2019; Brim and Wenham, 2019; Cheema, Faff, and Szulczuk, 2020), thus, the need to consider other alternatives that can effectively hedge against risk associated with pandemics, hence, our consideration for financial innovations. Similarly, there are plethora of evidence that financial innovations have imbedded in them, a number of new prospects including incentives as related to stock market (Chen, 1995; Partnoy and Thomas, 2007; Chou, 2007; Beck et al., 2016).

Given their diversification benefit, ETFs have gained unprecedented market momentum since the first ETF was introduced in the United States in 1993 (Madhavan and Maheswaran). In 2015, index options accounted for eight of the top 20 most-traded index derivatives globally, with ETF-index options taking up four of those seats. Also in 2016, there were 12 seats for index options, of which four were still taken by ETF-index (Gang et al., 2019). Similarly, the five-year average returns of the top 100 exchange-traded funds globally<sup>7</sup>, have been encouraging, emphasizing the investment opportunity imbedded in them. For example, a year after 50ETF was listed in the Shanghai Stock Exchange in 2015, 202,013 new trading accounts were opened in 2016, an increase of 147.7 percent compared to that of 2015. Similarly, its average market value rose to 5.857 Yuan - a percentage increase of 243 (Gang et al., 2019).

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<sup>7</sup> <https://etfdb.com/compare/highest-5-year-returns/>

It is therefore against this backdrop that we investigate the relationship between pandemics and financial innovations, albeit, with particular focus on exchange-traded funds (ETFs). Even though the role of these innovations as effective hedges against risk is not new in the literature as evidence support their low or zero correlation with most traditional portfolios (Asness et al., 2001; Liang, 2001).

Moreover, exchange-traded funds are one of the most recognized categories of financial innovations. They are rapidly expanding and extensively transforming the financial market. Generally, ETFs are defined as basket of securities similar to mutual funds but traded on security exchanges which are based on an index and aim to reflect the performance of its base index to the investor (Sarkarya and Ekinici, 2020). Despite similarities, ETFs differ inherently from mutual funds in various ways such as in the estimation of their cost for investors, valuation of units and distribution channel to mention but a few (Marszk and Lechman, 2018). ETFs also serve as passive investment for investors by allowing those willing to invest in a particular index, invest in an ETF rather than purchasing the equities of the index separately.

Through this, ETF has been able to serve as either hedges or safe-haven for investors during market crises and helped minimize risks of uncertainty.

### **3. Data description and preliminary analysis**

The data set used in the estimation comprises daily prices of top ranked sectoral Exchange Traded Funds (ETFs) of the United States, tagged by the ETF database<sup>8</sup> as well as a measure of uncertainty due to pandemics and epidemics [*UPE*] using the Baker et al. (2020) data christened as Equity Market Volatility for Infectious Diseases Tracker (Salisu and Adediran, 2020). We cover the period between 1/2/2009 and 9/21/2020 where the Pre-COVID sample is defined from 1/2/2009 to 9/21/2020 while the COVID sample covers the period 1/2/2020 to 9/21/2020. The sectors covered are eleven in all namely Consumer Discretionary, Consumer Staples, Energy, Financials, Healthcare, Industrials, Materials, Real Estate, Technology, Telecoms and Utilities. The selected ETF proxies are highlighted in Table 1. Daily data on the sectoral ETF series are

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<sup>8</sup> <https://etfdb.com/etfs/sector/> - Sector power rankings are rankings between U.S.-listed sector ETFs on certain investment-related metrics, including 3-month fund flows, 3-month return, AUM, average ETF expenses and average dividend yields.

sourced from *finance.yahoo.com* (<https://finance.yahoo.com/news/top-ranked-etfs-stocks-top-150003045.html>), while the *UPE* data are obtained from Federal Reserve St. Louis databank.

The *UPE* 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.<sup>9</sup> Additional variables such as the equity-induced uncertainty of the Chicago Board Options Exchange, often times described as the VIX index or the fear index is equally obtained from FRED St. Louis databank and the West Texas Intermediate crude oil spot prices are available at the US Energy Information Administration (EIA) Database (<https://eia.gov>). In addition to the broad analysis of the relationship between pandemics and financial innovations, we also partition our data into two samples namely periods before and during COVID-19 pandemic in order to distinctly capture the examined relationship for the latter sample. Thus, the analysis is not only conducted to examine the potential of financial innovations (using ETFs) as a good hedge against pandemics and epidemics but to further establish if this hedging potential is episodic or time varying.

The summary statistics as presented in Panel A of Table 2 show positive return to ETF across the periods, although ETF returns becomes negative and more unstable (given higher standard deviation value) after the outbreak of COVID-19 pandemic. This may be connected to reduced investments due to uncertainty around the pandemic. The result of uncertainty due to pandemics (*UPE*) showed rapid surge in the level of uncertainty after the outbreak of COVID-19. This further goes to reveal the impact of the outbreak on investment by way of reduced investor's confidence. Panel B in Table 2 illustrates the behaviour of ETF under different level of uncertainties (i.e. when the *UPE* value is below and above its mean value). The results show that before the outbreak of COVID-19, ETF returns is positive and stable for both scenarios when *UPE* was below and above its mean value. Meanwhile, after the outbreak of COVID-19, ETF returns becomes negative and more unstable especially when the *UPE* value is above its mean. In general, the result showed that across both periods, ETF returns is positive and fairly stable.

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<sup>9</sup> See Baker et al. (2020) for computational details of the *UPE* index.

**Table 1: Non-energy ETFs**

Sector	ETF Proxy
Consumer discretionary	Consumer Discretionary Select Sector SPDR Fund (XLY)
Consumer staples	Consumer Staples Select Sector SPDR Fund (XLP)
Energy	Energy Select Sector SPDR Fund (XLE)
Financials	Financial Select Sector SPDR Fund (XLF)
Health	Health Care Select Sector SPDR Fund (XLV)
Industrials	Industrial Select Sector SPDR Fund (XLI)
Materials	Materials Select Sector SPDR Fund (XLB)
Real estate	Vanguard Real Estate Index Fund (VNQ)
Technology	Invesco (QQQ)
Telecom	Vanguard Communication Services ETF (VOX)
Utilities	Utilities Select Sector SPDR Fund (XLU)

Source: [www.etfdb.com/etfs/sector](http://www.etfdb.com/etfs/sector)

**Table 2: Summary statistics for panel samples**

<b>Panel A: Summary statistics of baseline scenario for ETF returns and UPE</b>				
		Pre-Covid Sample [1/2/2009-9/21/2020]	Covid Sample [1/2/2020-9/21/2020]	Full Sample [1/2/2009-9/21/2020]
Returns	Mean	0.039618	-0.0413	0.03503
	SD	1.233663	2.586627	1.354931
UPE	Mean	0.407977	20.62458	1.64221
	SD	1.072385	15.02338	6.187233
	Nobs	2753	179	2932
<b>Panel B: Scenario analysis of ETF returns in different periods</b>				
		Pre-Covid Sample [1/2/2009-9/21/2020]	Covid Sample [1/2/2020-9/21/2020]	Full Sample [1/2/2009-9/21/2020]
Below	Mean	0.04348	-0.02012	0.035946
	SD	1.1582	1.50495	0.026651
Above	Mean	0.03155	-0.06725	1.214415
	SD	1.378043	3.481339	2.266669
	Nobs	2753	179	2932

Note: UPE denotes uncertainty due to pandemics, Pre-COVID and COVID denote periods before and after the announcement of COVID-19 as a world pandemic. Below represents the values of ETF returns when uncertainty due to pandemics (UPE) is below its mean, above is the value of stock returns when UPE values is above its mean. SD represents standard deviation. Nobs is the number of observations.

### 3. Methodology

This study constructs a predictive model that relies on the capital asset pricing model where asset returns respond to systemic risks (in the present case is measured with uncertainty indices) as systemic risk leads to loss of confidence in the underlying market (Smaga, 2014). Two measures of uncertainty are considered in this study; one that is associated with pandemics (for the main analysis) and the other that is due to equity market. For robustness purposes, we choose as an alternative measure of market uncertainty - the Chicago Board Options Exchange's (CBOE)

Volatility Index which is one of the widely held measure of the stock market's expectation of volatility based on S&P 500 index options to further evaluate the hedging potentials of ETFs beyond risk associated with health. Similarly, for the econometric analysis, we utilize the heterogeneous panel approach which is suitable to account for the inherent heterogeneity in the sectors under consideration that involve the use of panel data with distinct sectoral ETFs (Chudik and Pesaran, 2015; Chudik et al., 2016; Reese and Westerlund, 2016; Westerlund et al., 2017; Westerlund and Narayan, 2016). We equally favour the dynamic common correlated effect (DCCE) as these sectoral securities may be driven by unobserved common factors such as policy and international/global shocks which in a way can affect the performance of these stocks.<sup>10</sup> Thus, following the heterogeneous panel data techniques of Chudik and Pesaran (2015), Chudik et al. (2016), we construct a predictive panel data model for ETFs returns<sup>11</sup>:

$$r_{it} = \alpha_i + \sum_{j=1}^5 \lambda_{ij} UPE_{i,t-j} + \phi_i Oil_{it} + \psi_{it} \quad [1]$$

$$\psi_{it} = \delta_i f_t + u_{it} \quad [2]$$

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

where  $r_{it}$  denotes the log-return series computed as  $100 * \log(s_{it}/s_{i,t-1})$  with  $s_{it}$  being the asset price data for sector  $i$  at period  $t$ ;  $UPE$  is the uncertainty index;  $\alpha_i$  and  $\lambda_i$  represent the heterogenous intercept and slope coefficients which are allowed to vary across units ; and  $\psi_{it}$  is the error term. It is important to note that  $\psi_{it}$  is a composite error term comprising an unobserved common factor loading ( $f_t$ ) accompanied with a heterogeneous factor loading ( $\delta_i$ ) and the remainder error term ( $u_{it}$ ). The coefficient  $\lambda_i$  measures the relative impact of the uncertainty on ETF returns and we allow for up to five lags given the daily data frequency (five-day of the week) as well as the need to capture more dynamics in the estimation process. Thus, the underlying null

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<sup>10</sup> Some of the computational advantages of allowing for the DCCE in return predictability and the estimation procedure are well documented in Chudik and Pesaran (2015), Westerlund et al. (2017) and Ditzgen (2018, 2019).

<sup>11</sup> 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.



hypothesis of no predictability involves a joint (Wald) test -  $\sum_{j=1}^5 \lambda_{ij} = 0$ . Similarly, the hedging potential of this financial innovation against UPE is determined using Wald test, wherein the tolerance or otherwise of this asset is determined by the sign of the estimated parameter. That is, in the presence of *UPE*, if  $\sum_{j=1}^5 \lambda_{ij} \geq 0$ , ETF is considered tolerant; otherwise, it is more likely to be vulnerable. We also account for an additional predictor, oil price, using the West Texas Intermediate (WTI)<sup>12</sup> crude oil price ( $Oil_{it}$ ) as a proxy, given the evidence of its strong connection with the stock market (Smyth and Narayan, 2018; Salisu et al., 2019) as well with the covid-19 pandemic (Narayan, 2020c, Devpura and Narayan, 2020; Salisu and Adediran, 2020; Qin, Zhang and Su, 2020).

We further assess the ability of the uncertainty index included in Eq. [1] to improve the forecast accuracy of asset returns relative to the historical average which ignores any potential predictor of asset returns specified as follows:

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

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] & [3] in this case) is statistically significant. For a forecast horizon,  $h$ , the CW (2007) test is specified as:

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

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:  $P^{-1} \sum (r_{i,t+h} - \hat{r}_{ri,t+h})^2$  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 as  $P^{-1} \sum (\hat{r}_{ri,t+h} - \hat{r}_{ui,t+h})^2$ ;  $P$  is the amount of predictions that the averages are computed. Lastly, the statistical significance of regressing  $\hat{f}_{t+h}$  on a constant confirms the CT test. The null hypothesis of a zero coefficient is rejected if the t-statistic is greater than +1.282 (for a

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<sup>12</sup> Among alternative proxies, WTI is considered a better reflector of movements in global oil prices (Narayan & Gupta, 2015).

one-tailed test at level of significance,  $\alpha = 0.10$  ), +1.645 (for a one sided test at  $\alpha = 0.05$  ) and +2.00 (for a one-tailed test at  $\alpha = 0.01$  ) (Clark and West, 2007).

## **4. Empirical Results**

### **4.1 Results for uncertainty due pandemics and epidemics**

In this sub-section among the other two, we present the hedging effectiveness of ETF against uncertainty due to pandemics and epidemics (UPE). An asset is said to possess hedging potential if it is able to, in worst case, retain its value during periods of crisis or uncertainty. Conversely, an asset is vulnerable to market risks or uncertainty if it sheds its value during turbulent period. In other words, if the estimated parameter is positive (or negative), it implies such asset is tolerant (vulnerable) and therefore can (cannot) be regarded as an effective hedge (see Table 3). In terms of presentation of results, two regressions are considered: one without control variable and the other with control variable (i.e. the addition of oil returns). Each regression is further estimated for the full sample and both the pre-COVID and COVID periods in order to assess the response of these financial innovations to uncertainty during calm and turbulent market conditions.

We present the results of the hedging behaviour of ETFs in Table 3. First, we examine the effect of the sole predictor (i.e. the model without control), and results show that ETF returns is tolerant to uncertainty due to pandemics. In essence, higher level of uncertainty did not affect returns to ETF negatively. Hence, this result validates our hypothesis that ETF (financial innovations) can serve as an effective hedge especially during periods of economic turbulence. This conforms to what is obtainable in the extant literature (Partnoy and Thomas, 2007; Chou, 2007; Beck et al., 2016). Another important observation from this result is that although the pre-COVID period yield negative but not significant coefficient, the COVID period revealed otherwise with improved positive and significant estimated parameters for the models with UPE and the other measure of uncertainty. Further, the inclusion of WTI oil returns as a control variable in the ETF returns predictive models proved justified. The inclusion improved the hedging effectiveness of the models for both pre-COVID & COVID periods and the full-sample period, thereby corroborating the role of macroeconomic factors as previously argued in the asset-returns hedging framework. In essence, the results indicate that the inclusion of oil is crucial when forecasting ETF returns.

**Table 3: Predictability results for pandemics and ETF returns**

	<b>Full Sample</b> <b>[1/2/2009-9/21/2020]</b>		<b>Pre-COVID Sample</b> <b>[1/2/2009-9/21/2020]</b>		<b>COVID Sample</b> <b>[1/2/2020-9/21/2020]</b>	
	<b>UPE</b>	<b>VIX</b>	<b>UPE</b>	<b>VIX</b>	<b>UPE</b>	<b>VIX</b>
<b>Without</b>	0.0199 <sup>a</sup>	0.0393 <sup>a</sup>	-0.0093	0.0325 <sup>a</sup>	0.1106 <sup>a</sup>	0.0996 <sup>a</sup>
<b>Control</b>	(12.42)	(118.40)	(0.34)	(115.28)	(48.74)	(64.46)
<b>With</b>	0.0161 <sup>a</sup>	0.0260 <sup>a</sup>	0.0221 <sup>c</sup>	0.0334 <sup>a</sup>	0.1116 <sup>a</sup>	0.0932 <sup>a</sup>
<b>Control</b>	(7.58)	(120.06)	(2.94)	(130.99)	(56.12)	(71.71)
<b>Nobs</b>	2932		2753		179	

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. Full, Pre- COVID & COVID data samples] is the sum of the coefficients of the five lags whose significance are jointly evaluated using the Wald test for coefficient restriction. As such, the values in parentheses - () are the F statistics for the joint coefficients; a, b & c indicate statistical significance at 1%, 5% and 10% levels respectively. UPE is Uncertainty die to pandemic and epidemics, VIX represents volatility index. Nobs is number of observations per sample

**Table 4: In-Sample and Out-of-Sample Forecast Evaluations using the Clark & West test**

<b>In-Sample Forecast Evaluation</b>					
	<b>UPE</b>		<b>VIX</b>		<b>Nobs</b>
	<b>Model 1 vs Model 2</b>	<b>Model 1 vs Model 3</b>	<b>Model 1 vs Model 2</b>	<b>Model 1 vs Model 3</b>	
<b>Full Sample</b>	0.1069 <sup>a</sup> [18.37]	0.1201 <sup>a</sup> [20.70]	0.6443 <sup>a</sup> [41.23]	0.5697 <sup>a</sup> [40.36]	2199
<b>Pre-Covid Sample</b>	0.1133 <sup>a</sup> [16.36]	0.1405 <sup>a</sup> [19.16]	0.6305 <sup>a</sup> [41.24]	0.5331 <sup>a</sup> [39.22]	2065
<b>Covid Sample</b>	3.9912 <sup>a</sup> [12.48]	3.7563 <sup>a</sup> [12.44]	6.1068 <sup>a</sup> [11.73]	5.4639 <sup>a</sup> [11.70]	134
<b>Out-of-Sample Forecast Evaluation [h=10]</b>					
<b>Full Sample</b>	0.1064 <sup>a</sup> [18.35]	0.1194 <sup>a</sup> [20.68]	0.6414 <sup>a</sup> [41.23]	0.5671 <sup>a</sup> [40.35]	2209
<b>Pre-Covid Sample</b>	0.1128 <sup>a</sup> [16.36]	0.1399 <sup>a</sup> [19.17]	0.6278 <sup>a</sup> [41.25]	0.5308 <sup>a</sup> [39.23]	2075
<b>Covid Sample</b>	3.7408 <sup>a</sup> [12.54]	3.5228 <sup>a</sup> [12.51]	5.6994 <sup>a</sup> [11.74]	5.1040 <sup>a</sup> [11.73]	144
<b>Out-of-Sample Forecast Evaluation [h=20]</b>					
<b>Full Sample</b>	0.1060 <sup>a</sup> [18.37]	0.1192 <sup>a</sup> [20.71]	0.6386 <sup>a</sup> [41.22]	0.5647 <sup>a</sup> [40.36]	2219
<b>Pre-Covid Sample</b>	0.1122 <sup>a</sup> [16.36]	0.1391 <sup>a</sup> [19.15]	0.6258 <sup>a</sup> [41.30]	0.5293 <sup>a</sup> [39.29]	2085
<b>Covid Sample</b>	3.5686 <sup>a</sup> [12.75]	3.3616 <sup>a</sup> [12.72]	5.3747 <sup>a</sup> [11.83]	4.8169 <sup>a</sup> [11.82]	154
<b>Out-of-Sample Forecast Evaluation [h=30]</b>					
<b>Full Sample</b>	0.6370 <sup>a</sup> [41.29]	0.5633 <sup>a</sup> [40.43]	0.6370 <sup>a</sup> [41.29]	0.5633 <sup>a</sup> [40.43]	2229
<b>Pre-Covid Sample</b>	0.6233 <sup>a</sup> [41.33]	0.5273 <sup>a</sup> [39.32]	0.6233 <sup>a</sup> [41.33]	0.5273 <sup>a</sup> [39.32]	2095
<b>Covid Sample</b>	5.0636 <sup>a</sup> [11.85]	4.5350 <sup>a</sup> [11.83]	5.0636 <sup>a</sup> [11.85]	4.5350 <sup>a</sup> [11.83]	164

Note: Model 1 is the Historical Average model; Model 2 is the model without control; Model 3 is the model with control variable. The Clark & West test measures the significance of the difference between 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) (Clark and West, 2007). Values in square brackets – [ ] are t-statistics. a, b & c indicate statistical significance at 1%, 5% and 10% levels respectively. The out-of-sample forecast evaluations are conducted for h= 10, 20 and 30-days ahead respectively, due to small COVID period sample size.

We also evaluate the forecast power of the uncertainty indicators and therefore we partition the data sample into in-sample and out-of-sample periods using the 75:25 data split respectively. The results of the in-sample and out-of-sample forecast evaluations are presented in Table 4. The forecast evaluations are based on the Clark and West (2007) test and the decision rule is that a

positive and significant value of the parameter estimate in the test equation shows that the model of choice (say, Model 2 – the model with uncertainty indices as the predictor) outperforms the benchmark model (i.e. Model 1 – the historical average model). An overview of the Table 4 shows that our proposed model, with or without control variable provides better forecasting results in contrast to the benchmark model. Importantly, the results reveal higher magnitude of the coefficients during the COVID period compared with the pre- COVID & full-sample periods and across the two market uncertainty indices. Interestingly, the results of the out-of-sample forecast evaluations are similar to the in-sample forecast evaluations across the data samples. In essence, our predictive models (with and without control variable) are shown to generate reliable forecasts for ETF returns both in- and out-of-sample forecast evaluations.

## 4.2 The results of equity-based 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). In the case of financial innovations, we seek to verify this claim by considering other sources of uncertainty such as VIX-based uncertainty. The predictability results have been presented along in Table 3. Across the entire estimated models, results show that ETF return is able to hedge against VIX-based uncertainty as it proved to hedge pandemic induced uncertainty risks. The implication of the result is that ETF returns is an effective portfolio diversifier against equity-based uncertainty in either calm or turbulent market conditions.

The results of the in-sample forecast evaluation are presented in Table 4. We show that the forecast performances of models 2 and 3 (i.e. without control and with control, respectively) bests the benchmark model (historical averages). Similar to the pandemic-induced uncertainty, we also examine the out-of-sample forecast evaluations for  $h=10$ -day, 20-day and 30-day ahead forecast horizons. The results of these analyses are also embedded in Table 4. The summary of the results of these tables show that the benchmark model is least preferred to the uncertainty-based models. Also, the forecasting prowess of the predictive models are shown to be prominent at higher out-of-sample forecast horizons. We also highlight the differences between the forecast performances of pandemic-induced and VIX-based uncertainties and show that the ETF returns are predominantly tolerant to the pandemic-induced uncertainty, especially during COVID-19 period, but shown to be more tolerant of equity-based uncertainty outside the COVID-19 period.

### 4.3 Analysis of Economic Significance

In an attempt at in-depth assessment of the research objective, we further examine the perceived economic gains that our preferred model, with its constituent predictor variables, offers over the benchmark model. This is to, in addition to the statistical confirmation of outperformance of the former over the latter, provide economic validation on the inclusion of the UPE or VIX in the predictive model for ETF returns. This finds roots as one of the recent advancements in financial economics literature traced to Liu et al. (2019) study. It is expected that a model incorporating additional predictors should provide more information or economic gains than the benchmark model that does not include the said predictor variable(s). We consider in this study asset pricing predictive model with and without control variables in a panel form, in comparison to the historical average model.

In a bid to optimize available portfolio, as consistent with mean-variance utility investors, certain shares are allocated to investors' investment options in a determined proportion to a risk free asset. Consequently, the optimal weight -  $w_t$ , is given by

$$w_t = \frac{1}{\gamma} \frac{\theta \hat{r}_{t+1} + (\theta - 1) \hat{r}_{t+1}^f}{\theta^2 \hat{\sigma}_{t+1}^2} \quad (5)$$

where  $\gamma$  represents the coefficient of risk aversion;  $\theta$  denotes the leverage ratio (Zhang et al. 2018);  $\hat{r}_{t+1}$  and  $\hat{r}_{t+1}^f$  are respectively ETF returns forecast and a risk-free asset at time  $t + 1$ ; and  $\hat{\sigma}_{t+1}^2$  represents the estimate of the return volatility, which is estimated using a 60-days moving window of daily returns. Given the obtained optimal weight, a certainty equivalent return (CER hereafter) is defined as

$$CER = \bar{R}_p - 0.5(1/\gamma)\sigma_p^2 \quad (6)$$

where  $\bar{R}_p$  and  $\sigma_p^2$  are the out-of-sample mean and variance of the portfolio return, respectively;

$R_p = w\theta(r - r^f) + (1 - w)r^f$  defines the portfolio returns; its variance is given by

$Var(R_p) = w^2\theta^2\sigma^2$ , where  $\sigma^2$  denotes the excess return volatility. The economic gains is

empirically obtained by maximizing the utility objective function in (7)

$$\begin{aligned} U(R_p) &= E(R_p) - 0.5(1/\gamma)Var(R_p) \\ &= w\theta(r - r^f) + (1 - w)r^f - 0.5(1/\gamma)w^2\theta^2\sigma^2 \end{aligned} \quad (7)$$

Following the maximisation of the utility function, the portfolio returns, the volatility, the certainty equivalent returns as well as the Sharpe ratio, defined by  $SP = (R_p - r^f) / \sqrt{Var(R_p)}$ , are computed and reported accordingly. We specify two different leverage ratios -  $\theta = 5$  and  $\theta = 8$ , under the assumption that investors often maintain a 10% margin account; and two levels of risk aversion -  $\gamma = 1$  and  $\gamma = 2$ . In the comparison of our predictive models with the benchmark historical average, the former provides economic gains over the latter if it yields maximum returns and minimum volatility (Liu et al., 2019). The results are presented in Table 5, for our predictive model with and without control.

The different variants of our predictive models (distinctly incorporating UPE and VIX) are found to yield higher returns than the benchmark historical average model, with higher return being associated with higher volatilities. This feat is consistent across the specified leverage ratio, risk aversion levels, and model construct (model with and without control). It is also observed that the returns and associated volatilities are smaller in the case of the model without control than model with control; larger in model incorporating VIX than in the model incorporating UPE; and increases as the leverage ratio is increased. From the Sharpe ratio results, our predictive model yields more economic gains at the observed high volatility than the benchmark historical average that yields lower returns and volatility. The observed economic significance results are not sensitive to the leverage ratios and risk aversion levels. Conclusively, incorporating UPE or VIX are statistically and economically significant in the prediction of ETF returns.

**Table 5: Out-of-sample economic gains [Covid+Pre-covid]**

$\gamma$	Model	$\theta = 5$				$\theta = 8$			
		returns	volatility	CER	Sharpe ratio	returns	Volatility	CER	Sharpe Ratio
1	<b>Benchmark</b>	4.00	5.59	3.12	1.02	4.49	6.72	3.61	1.12
	<b>UPE</b>	31.13	74.59	30.25	3.42	32.67	78.49	31.78	3.51
	<b>VIX</b>	39.24	94.68	38.35	3.87	40.84	98.64	39.95	3.95
	<b>UPE*</b>	30.66	72.97	29.78	3.40	32.18	76.82	31.30	3.49
	<b>VIX*</b>	36.82	88.40	35.93	3.75	38.38	92.27	37.49	3.83
2	<b>Benchmark</b>	2.80	1.40	2.36	1.02	3.04	1.68	2.60	1.12
	<b>UPE</b>	16.36	18.65	15.92	3.42	17.13	19.62	16.69	3.51
	<b>VIX</b>	20.42	23.67	19.97	3.87	21.22	24.66	20.77	3.95
	<b>UPE*</b>	16.13	18.24	15.69	3.40	16.89	19.20	16.45	3.49
	<b>VIX*</b>	19.21	22.10	18.76	3.75	19.99	23.07	19.54	3.83

Note: The \* is used to indicate the model with control. CER denotes certainty equivalent return.

#### 4.4 Additional analyses

We present additional results using an expanded datasets in order to see if covering more waves of the pandemic will authenticate or refute the outcome from the first wave. Apparently, the first draft of this study was prepared during the first wave where the data scope only covers 1/2/2020 to 9/21/2020. However, given the opportunity to revise the paper after experiencing several waves of the pandemic, we further extend the data scope to spanning till August 01, 2022 in order to cover recent realities. Buttressing our previous results, the findings from our extended datasets show the financial innovation captured by ETF is still able to tolerate both health/pandemic-induced (UPE) and market (VIX) risks. Thus, ETF – a measure of financial innovations can really serve as an effective hedging tool during turbulent periods. Similarly, this result equally holds having accounted for dynamics in the oil market as captured in model with control (Model 1 vs Model 3).

Furthermore, evaluating the forecast performance of our models (in Table 7) using C-W test equally attests to our results for first wave, as proposed models (with and without control) outperform the benchmark model. Similar to the first round of results, the results from our extended datasets for the Covid period, across all the forecast horizons as well as both measures of uncertainty (UPE and VIX) reveal higher magnitude of the coefficients compared with the full sample period. The results here is not unexpected as an innovation that was able to retain its value during the height of the pandemic (Covid-19) period should be able to do the same when normalcy is being restored, following development of vaccines and open up of economies from lockdown.

**Table 6: Predictability results for pandemics and ETF returns**

	Full Sample [8/9/2017- 8/1/2022]		COVID Sample [1/2/2020-8/1/2022]	
	UPE	VIX	UPE	VIX
<b>Without Control</b>	0.0180 <sup>b</sup> (5.26)	0.0356 <sup>a</sup> (69.79)	0.018 <sup>b</sup> (5.26)	0.0356 <sup>a</sup> (69.79)
<b>With Control</b>	0.0166 <sup>b</sup> (4.86)	0.0313 <sup>a</sup> (74.31)	0.0166 <sup>b</sup> (4.86)	0.0313 <sup>a</sup> (74.31)

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. Full, Pre- COVID & COVID data samples] is the sum of the coefficients of the five lags whose significance are jointly evaluated using the Wald test for coefficient restriction. As such, the values in parentheses - () are the F statistics for the joint coefficients; a, b & c indicate statistical significance at 1%, 5% and 10% levels respectively. UPE is Uncertainty die to pandemic and epidemics, VIX represents volatility index. Nobs is number of observations per sample.

**Table 7: In-Sample and Out-of-Sample Forecast Evaluations using the Clark & West test**

<b>In-Sample Forecast Evaluation</b>				
	<b>UPE</b>		<b>VIX</b>	
	<b>Model 1 vs Model 2</b>	<b>Model 1 vs Model 3</b>	<b>Model 1 vs Model 2</b>	<b>Model 1 vs Model 3</b>
<b>Full Sample</b>	0.4402 <sup>a</sup> [14.04]	0.4257 <sup>a</sup> [13.84]	0.9754 <sup>a</sup> [22.46]	0.8693 <sup>a</sup> [22.36]
<b>Covid Sample</b>	0.2540 <sup>a</sup> [13.77]	0.2582 <sup>a</sup> [13.91]	0.6540 <sup>a</sup> [15.99]	0.6304 <sup>a</sup> [15.72]
<b>Out-of-Sample Forecast Evaluation [h=10]</b>				
<b>Full Sample</b>	0.3963 <sup>a</sup> [2.45]	0.3885 <sup>a</sup> [2.54]	0.9521 <sup>a</sup> [7.62]	0.8454 <sup>a</sup> [7.02]
<b>Covid Sample</b>	0.7786 <sup>a</sup> [2.90]	0.7713 <sup>a</sup> [2.92]	1.0554 <sup>a</sup> [5.18]	1.0354 <sup>a</sup> [5.07]
<b>Out-of-Sample Forecast Evaluation [h=20]</b>				
<b>Full Sample</b>	0.3387 <sup>b</sup> [1.78]	0.3329 <sup>b</sup> [1.84]	0.9171 <sup>a</sup> [6.38]	0.8120 <sup>a</sup> [5.84]
<b>Covid Sample</b>	0.7198 <sup>a</sup> [2.04]	0.7149 <sup>a</sup> [2.05]	1.0074 <sup>a</sup> [3.82]	0.9883 <sup>a</sup> [3.73]
<b>Out-of-Sample Forecast Evaluation [h=30]</b>				
<b>Full Sample</b>	0.4621 <sup>a</sup> [2.24]	0.4479 <sup>a</sup> [2.29]	1.0217 <sup>a</sup> [6.61]	0.9137 <sup>a</sup> [6.10]
<b>Covid Sample</b>	0.7857 <sup>b</sup> [1.92]	0.7808 <sup>b</sup> [1.94]	1.0514 <sup>a</sup> [3.44]	1.0331 <sup>a</sup> [3.37]

Note: Model 1 is the Historical Average model; Model 2 is the model without control; Model 3 is the model with control variable. The Clark & West test measures the significance of the difference between 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) (Clark and West, 2007). Values in square brackets – [ ] are t-statistics. a, b & c indicate statistical significance at 1%, 5% and 10% levels respectively. The out-of-sample forecast evaluations are conducted for h= 10, 20 and 30-days ahead respectively, due to small COVID period sample size.

## 5. Conclusion

This study sets out to see how we can hedge against the risk associated with pandemics – including COVID-19 pandemic, using financial innovations. The study places its contribution among previous studies that assess risk hedging potentials of various assets (Junttila, Pesonen and Raatikainen, 2018; Salisu, Vo and Lawal, 2020; Garcia-Jorcano and Muela, 2020), and others that compared the hedging efficacies of assets (Salisu and Adediran, 2019; Cheema, Faff, and Szulczuk, 2020; Salisu, Raheem and Ndako, 2020). The contribution becomes apparent since many traditional assets are increasingly being shown to be ineffective in their hedging roles in the face of recent realities (Sharma and Rodriguez, 2019; Brim and Wenham, 2019; Cheema, Faff, and Szulczuk, 2020), thus, the need to consider financial innovations as possible alternative. The need to seek alternative hedging instruments in Exchange-traded funds (ETF) is further justified for a new type of market risk posed by the COVID-19 pandemic.

Results obtained from the study show that the information contained in ETF can be explored to provide effective hedge for the various types of uncertainties studied, although it appears to be more effective against pandemic-induced uncertainty during the COVID-19 period than VIX-based uncertainty outside COVID-19 period. The results of the forecast evaluation show



that our predictive models containing the pandemic-related and financial-induced market risks have better predictive performances in relation to the historical average benchmark model under both conditions of uncertainty considered. These results hold sway for both in-sample and out-of-sample forecast analysis. Our choice of predictive models is further validated beyond statistical forecast evaluation to deliver economic gains ahead of the baseline predictive model in out-of-sample forecast evaluation. The policy implication of the findings is that investors interested in minimizing their risks, heightened in turbulent times should note the uncertainties associated with equity markets and pandemics before making decisions on composition of portfolios. More importantly, the use of financial innovations is crucial when confronted with global health-related risks like the COVID-19 pandemic as well as financial risks like stock market risk as these financial assets can serve as useful hedging instruments against risks and uncertainties. Thus, policy makers and relevant authorities are encouraged to pursue agenda/reforms as well legislations that will promote the use of financial innovations as hedging instruments by relevant economic agents.

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### **Appendix**

Appendix A illustrates the summary statistics of ETF returns by sector. The result revealed that all sectors considered across both periods, recorded positive returns and are fairly stable with the exception of the energy sector (XLE) which recorded negative return. Similarly, in the pre-Covid period, all sectors also recorded positive returns and are relatively stable. Meanwhile in the COVID period, only the technology (QQQ), telecom (VOX), materials (XLB), consumer discretionary (XLY), and Health sector (XLV) recorded positive returns, all other sectors have negative returns and high volatility. Probing further, we present the result of scenario analysis in appendix B. it showed that all ETF returns are positive across the two periods for both scenarios with the exception of real estate sector (VNQ), energy sector (XLE) and financials sector (XLF) which

recorded negative returns when the UPE value was above its mean. In the pre-COVID period, all sectors recorded positive returns except the energy sector and financials sector which recorded negative returns when the UPE rose above its mean value. Similarly, in the COVID period, all sectors recorded positive returns in returns for both scenarios except for few who recorded negative when the UPE was above the mean.

**Appendix A: Summary statistics for ETF returns by sectors**

		<b>Pre-COVID</b>	<b>COVID</b>	<b>Full</b>
<b>QQQ</b>	mean	0.067016	0.113648	0.074285
	Sd	1.121963	2.296921	1.242102
<b>VOX</b>	mean	0.023311	0.028242	0.027052
	Sd	1.090694	2.120784	1.185354
<b>VNQ</b>	mean	0.034954	-0.09167	0.026291
	Sd	1.513414	2.563184	1.615048
<b>XLB</b>	mean	0.029983	0.020168	0.035113
	Sd	1.300988	2.891679	1.461734
<b>XLE</b>	mean	0.004276	-0.35271	-0.0137
	Sd	1.432968	3.964501	1.720698
<b>XLF</b>	mean	0.035352	-0.14108	0.029308
	Sd	1.625946	2.994357	1.77344
<b>XLI</b>	mean	0.039446	-0.03525	0.040489
	Sd	1.181167	2.552652	1.319966
<b>XLP</b>	mean	0.031539	-0.00196	0.032947
	Sd	0.779729	1.743903	0.873245
<b>XLU</b>	mean	0.021977	-0.06556	0.023015
	Sd	0.900752	2.360419	1.050523
<b>XLV</b>	mean	0.043297	0.008459	0.046479
	Sd	0.996577	1.818297	1.067336
<b>XLY</b>	mean	0.061229	0.063409	0.064046
	Sd	1.1578	2.447998	1.284036
<b>UPE</b>	mean	0.257037	20.62458	1.64221
	Sd	0.374797	15.0617	6.188192

Note: UPE denotes uncertainty due to pandemics, Pre-COVID and COVID denote periods before and after the announcement of COVID-19 as a world pandemic. Full is the combination of both periods.

## Appendix B: Scenario analysis of ETF returns in different periods by sectors

			Pre-COVID	COVID	Full
<b>QQQ</b>	below	mean	0.077916	0.091083	0.068543
		Sd	1.075653	1.710423	1.122137
	above	mean	0.057411	0.14129	0.12678
		Sd	1.268628	2.868282	2.036174
<b>VOX</b>	below	mean	0.015385	0.050403	0.024844
		Sd	1.072033	1.431257	1.089854
	above	mean	0.050211	0.001095	0.04724
		Sd	1.152254	2.749651	1.84445
<b>VNQ</b>	below	mean	0.028972	0.03336	0.036623
		Sd	1.418042	1.519363	1.50919
	above	mean	0.042956	-0.24483	-0.06816
		Sd	1.753145	3.44127	2.374934
<b>XLB</b>	below	mean	0.048289	-2.44E-02	0.028194
		Sd	1.255168	1.489194	1.299516
	above	mean	0.009027	0.074715	9.84E-02
		Sd	1.440654	4.000776	2.499433
<b>XLE</b>	below	mean	0.022902	-0.45147	0.0021
		Sd	1.396804	2.230952	1.430552
	above	mean	-0.02438	-0.23173	-0.15814
		Sd	1.58579	5.392267	3.366351
<b>XLF</b>	below	mean	0.072377	-0.06495	0.034646
		Sd	1.488149	1.754028	1.621622
	above	mean	-0.02742	-0.23435	-0.0195
		Sd	1.982216	4.036726	2.807125
<b>XLI</b>	below	mean	0.048119	0.004662	0.040039
		Sd	1.144534	1.493784	1.178875
	above	mean	0.038727	-0.08414	0.044607
		Sd	1.303948	3.44311	2.231904
<b>XLP</b>	below	mean	0.033836	0.014799	0.031771
		Sd	0.739225	0.81187	0.778584
	above	mean	0.037549	-0.02249	0.043701
		Sd	0.87355	2.450252	1.482889
<b>XLU</b>	below	mean	0.009439	0.112578	0.024451
		Sd	0.881753	1.150768	0.89905
	above	mean	0.06845	-0.28379	0.009885
		Sd	0.94653	3.281701	1.95327
<b>XLV</b>	below	mean	0.061094	-0.05114	0.042979
		Sd	0.921611	1.034053	0.996271
	above	mean	0.022796	0.081473	0.078468
		Sd	1.147176	2.466754	1.576969
<b>XLY</b>	below	mean	0.061229	0.063711	0.061217

	Sd	1.1578	1.43907	1.157103
above	mean	0.07173	0.063039	0.089911
	Sd	1.301391	3.299074	2.120186

Note: Below represents the values of ETF returns when uncertainty due to pandemics (UPE) is below its mean, above is the value of stock returns when UPE values is above its mean. Sd represents standard deviation.

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