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Impact of Economic Uncertainty Related to Stock Market Uncertainty during the COVID-19 Pandemic Epidemic

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Abstract

This paper examines the impact of economic uncertainty on the stock market crisis during the COVID-19 epidemic. We construct a GARCH type of model to measure the daily skewness of S&P 500 for the tail risk of the U.S. stock market. We measure economic uncertainty using three indices including the EPU (Economic Policy Uncertainty Index), EMU (Equity Market-related Economic Uncertainty Index), and EMI (Equity Market Volatility: Infectious Disease Tracker). The empirical findings reveal a positive correlation between daily skewness and economic uncertainty and this correlation gets stronger after the outbreak of the COVID-19 pandemic. Our results embrace consistent economic policy schemes for overall stock market stability.

Keywords

COVID-19, Economic Policy Uncertainty, Stock Uncertainty, Skewness, EPU (Economic Policy Uncertainty Index), EMU (Equity Market-Related Economic Uncertainty Index), EMI (Equity Market Volatility: Infectious Disease Tracker)

1. Introduction

In terms of human losses and economic repercussions, the COVID-19 pandemic has devastated the world economy in a way that has never happened (Padhan & Prabheesh, 2021), and the spread of COVID-19 has resulted in a considerable slowdown in economic activities (Brodeur et al., 2021). We use stock market volatility as a predictor of economic uncertainty (Chen & Ranciere, 2019). In general, the pandemic lowered stock values significantly (Zhang et al., 2020; Ziemba, 2020; Mazur et al., 2021). However, it resulted in a significant rise in the risk of volatility (Moore, 2017) and uncertainty (Liu, 2020; Baker et al., 2020a, 2020b). As shown by

Altig et al. (2020), economic activity is affected by high levels of uncertainty, and these impacts are largely compatible with hypotheses on the effects of economic uncertainty. In contrast to previous research, this paper focuses on the connection between economic uncertainty and stock market volatility. We explore the impact of economic policy uncertainty on stock market uncertainty using empirical analysis. In our article, we employ conditional skewness of market returns to measure the stock market, and we use EPU (Economic Policy Uncertainty Index) (Baker et al., 2022a), EMU (Equity Market-related Economic Uncertainty Index) (Baker et al., 2022b), and EMI (Equity Market Volatility: Infectious Disease Tracker) (Baker et al., 2016) to quantify economic uncertainty, as described in Baker et al. (2020b). Given these effects, economic uncertainty should be considered in policy and empirical research. Stock market volatility, newspaper-based economic uncertainty, and subjective uncertainty in business expectations surveys are three measures that are used to describe economic uncertainty (Baker et al., 2020a). Based on the frequency of newspaper coverage, an indicator of policy uncertainty was established (Baker et al., 2020b).

From the stock market price chart of S&P 500 (**Figure 1**), we can observe that from March to April 2020, there was a sharp decrease in the S&P 500 daily closed price (−$109.58). During this time, the market was extremely volatile; as we notice from the graphs of EPU (**Figure 2**), EMU (**Figure 3**), and EMI (**Figure 4**), there was a sharp increase in the values of all three charts from January to June 2020. The highest increase in EPU was 620, the highest increase in EMU was 766.48, and the highest increase in EMI was 48.56. After that time, the S&P 500 price fluctuated slightly and increased steadily, and the values of EPU, EMU, and EMI are fluctuating slightly and decreased steadily. From the charts, we can find that stock uncertainty and economic uncertainty have a negative relationship. High economic policy uncertainty would lead to a stock market crash and low economic policy uncertainty help to reduce stock market uncertainty.

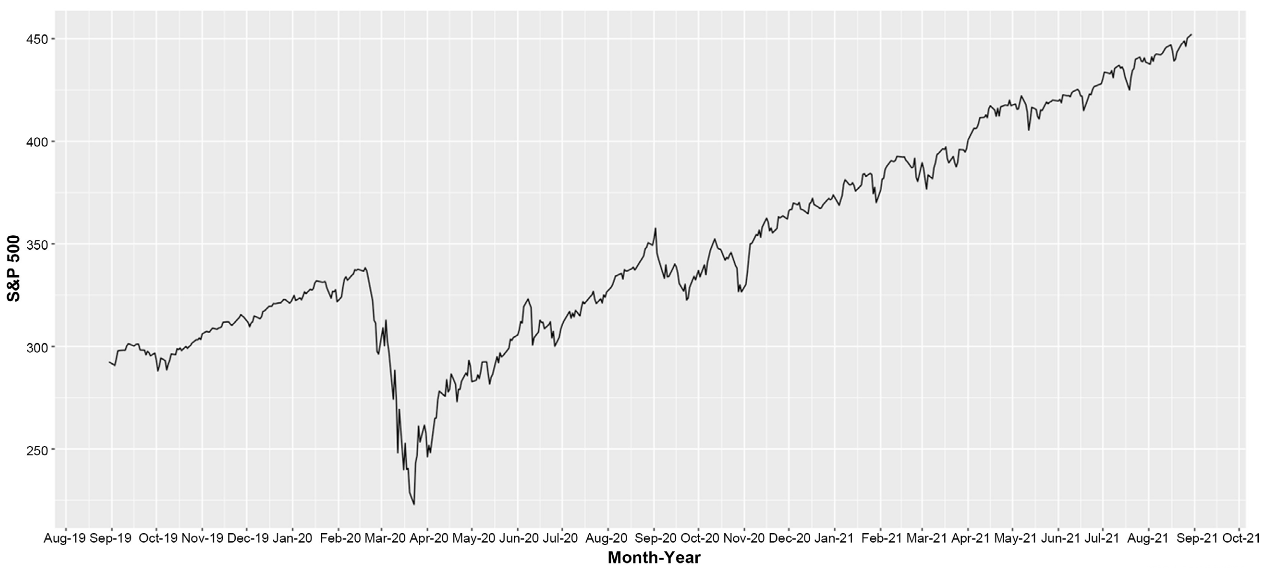

Figure 1. S&P 500 daily closed price.

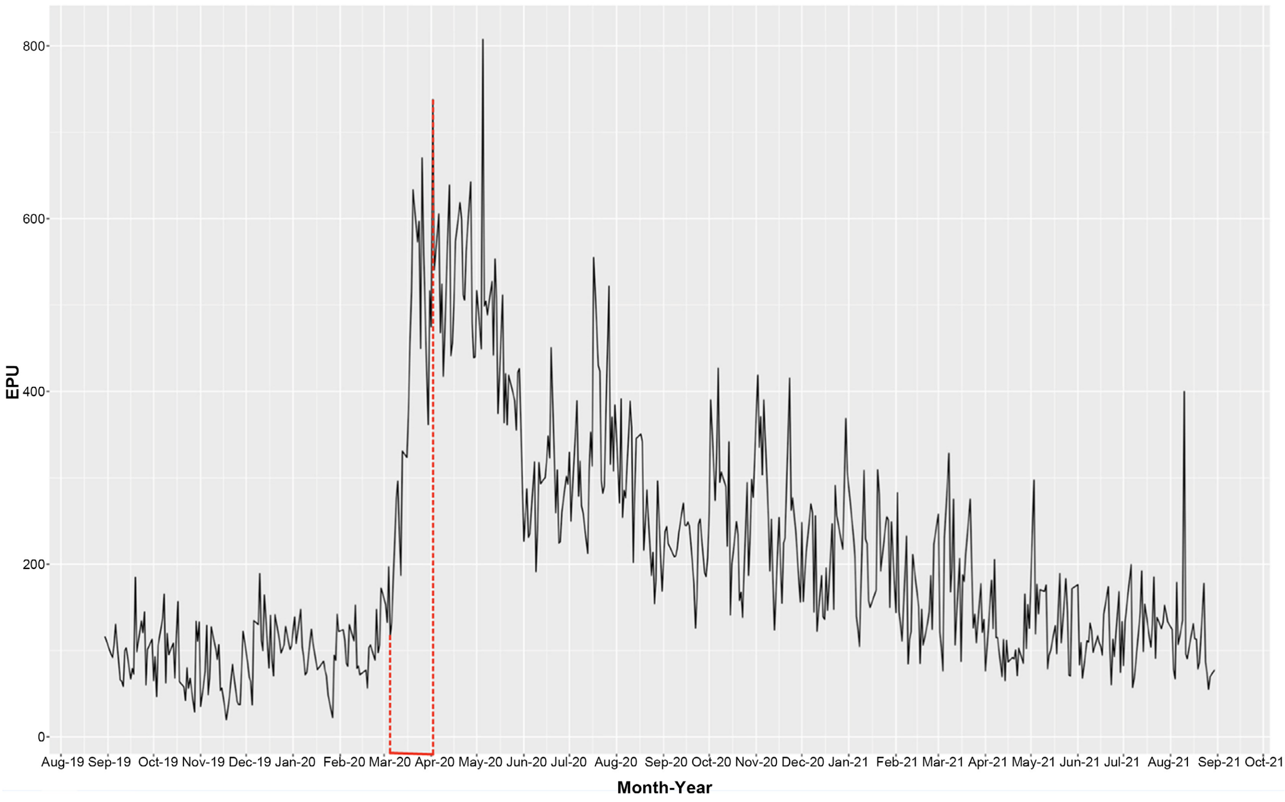

Figure 2. EPU daily changes.

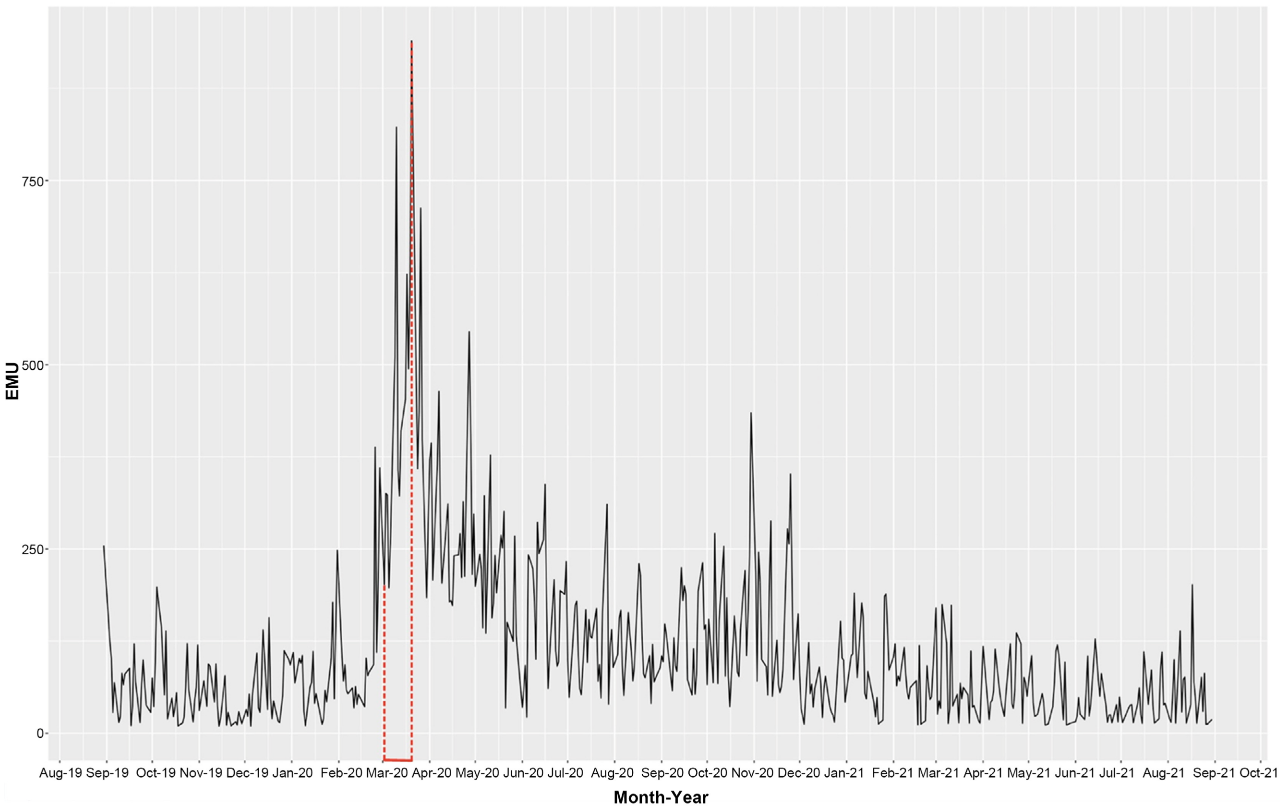

Figure 3. EMU daily changes.

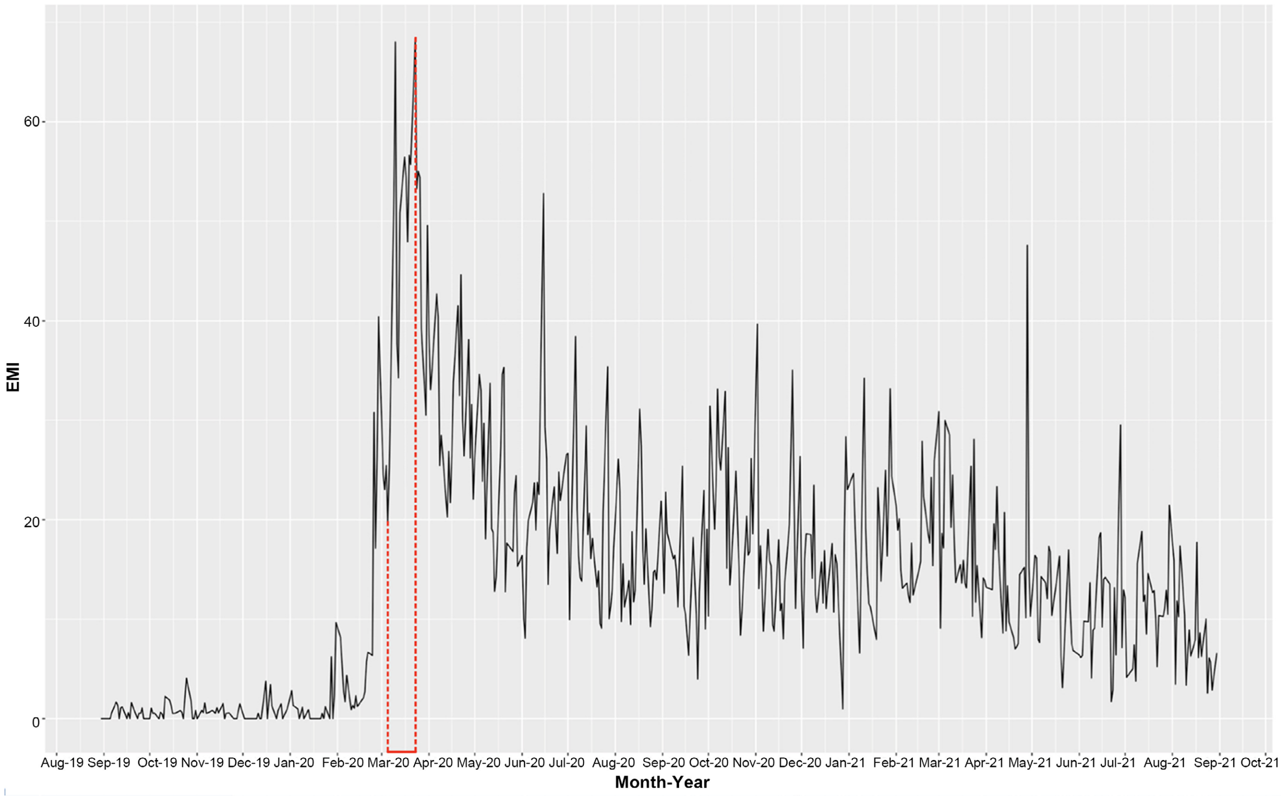

Figure 4. EMI daily changes.

2. Data Description

We constructed a GARCH (1, 1) model based on the daily stock prices of the S&P 500, taking into account the volatility of the original stock data. We calculate the skewness of the log-returns of the market (S&P 500 returns) as a proxy variable of economic impact. To get the skewness, we construct the skewness by selecting a data range of 2 years starting with 1997/1/1. We need to cover a sufficient number of crisis periods in order to prevent the estimation findings from being impacted if the data is not lengthy enough. From 1997/1/1 to 1999/1/1, calculates the skewness_1, and then 1997/1/2 to 1999/1/2 calculates the skewness_2 and so on. After doing that, we get the data named Y_{record} (**Table 1**).

The first factor in the model is the log change of Equity Market Volatility: Infectious Disease Tracker (EMI) (**Table 1**). We pay attention to it because the COVID-19 pandemic is one of the most severe sources of economic impact in modern times. EMI uses three indicators, stock market volatility, newspaper-based economic uncertainty, and subjective uncertainty, to measure the economic uncertainty.

The second factor we use is the log change of the Economic policy uncertainty index (EPU) (**Table 1**). The change of Y_{record} is also correlated with the policy changes. EPU collects data from 10 large newspapers to get information about the economic and policy uncertainty in the United States.

The third factor we considered that could influence the Y_{record} is the Equity

Table 1. Variable description and data selection.

Name of variable	Description	Interpretation
Y_{record}	Dependent variable	The skewness of the rolling stock log return (S&P 500)
EMI_{record}	Independent variable	Log change of EMI (Equity Market Volatility: Infectious Disease Tracker)
EPU_{record}	Independent variable	Log change of EPU (Economic policy uncertainty index)
EMU_{record}	Independent variable	Log change of EMU (Equity Market-related Economic Uncertainty Index)
$COVID_{dummy}$	Independent variable	Dummy variable of COVID-19

Market-related Economic Uncertainty Index (EMU) (Table 1). Last, we consider the crash risk due to COVID-19, which shows as a dummy variable (Table 1) to reduce the bias and to express the COVID-induced uncertainty effect.

3. Methodology

When we try to construct a model to describe the correlation between variables, the most basic or safest assumption of the correlation would be a linear correlation. Therefore, we have the regression model named "Ordinary Least Squares", or simply OLSs.

After collecting the data, we noticed that there are several outliers, and they might reduce the efficiency of our model. Therefore, we use the logarithmic functional to calculate the skewness of the log returns of the market (S&P 500 returns) and all the independent variables to get log changes of EPU, log changes of EMI, log changes of EMU. In this case, taking logs not only mitigates the problems with outliers, but also helps to secure normality and homoskedasticity.

We calculate the skewness of the rolling log-returns of the market (S&P 500 returns). After that, we build up a regression model using skewness on a series of variables: the first lag of skewness of the rolling log-returns of the market (S&P 500 returns), the second lag of skewness of the rolling log-returns of the market (S&P 500 returns), the first lag of log changes of EPU, the second lag of log changes of EPU, the first lag of log changes of EMI, the second lag of log changes of EMI, the first lag of log changes of EMU, the second lag of log changes of EMU. In this case, we remove the COVID dummy as the change due to COVID is probably taken into account in the coefficients for the lag terms.

We also estimate the GARCH model. To improve the ARCH model's fitting effect, it is necessary to increase the lag order, which causes certain difficulties in the selection and order determination of the model, followed by problems of multicollinearity and reduced degrees of freedom. Based on the improvement of the ARCH model, we use the low-order GARCH (1, 1) model to reduce the estimation of the parameters to be estimated. GARCH (1, 1) can describe a large number of financial time series data and has a good performance in predicting the unconditional volatility of the market. In the meanwhile, we have some events models including estimated coefficients, unconditional mean in the mean equation, unconditional variance, persistence, constants on parameters < 1, and GARCH Model Forecast. They are all alternative models to study market uncertainty.

4. Result

The dependent variable is the skewness of the rolling stock return. We use the data to run a regression by the Change of skewness as the dependent variable. We logged and calculated the difference of the dependent variable, and add the absolute min value of skewness, EMI, EMU, and EPU, to each data to make sure there is no negative or zero value in the form. Then, we plus 1 for all the original data to calculate the regression to get Table 2 and Equation (1).

$$\begin{aligned} Y_{record} = {} & 1.226 - 0.0081 * EMI_{record} + 0.0015 * EMU_{record} - 0.0017 * EPU_{record} \\ & - 0.1145 * COVID_{DUMMY} \end{aligned} \tag{1}$$

The results are not very satisfactory as most of the p-values are still large. In this case, we tried to eliminate the possibility of multicollinearity. Based on the inde-pendent variable EMI, EPU, and EMU, we run three regressions using only one of them plus the COVID dummy to obtain Table 3 and Equation (2), Table 4 and Equation (3), and Table 5 and Equation (4). In this case, we got three regressions with only two variables, one of the three indicators above and COVID dummy.

$$Y_{record} = 3.4095 - 0.00217 * EMI_{record} - 0.3806 * COVID_{DUMMY} \tag{2}$$

$$Y_{record} = 3.4000 - 0.00001 * EPU_{record} - 0.3806 * COVID_{DUMMY} \tag{3}$$

$$Y_{record} = 3.4028 - 0.00048 * EMU_{record} - 0.3806 * COVID_{DUMMY} \tag{4}$$

The result looks still not very good, as it shows that EMI, EPU, and EMU are not statistically significant. In this case, we tried to run another regression with lagged information. Keep using the left-hand variable as Y_{record}, but on the right-hand

Table 2. Residuals and coefficients.

Residuals:				
Min	1Q	Median	3Q	Max
−1.21452	−0.06027	0.02653	0.08907	0.34613
Coefficients:				
	Estimate	Std. error	T-value	Pr (>|t|)
(Intercept)	1.225715	0.030234	40.541	$<2 \times 10^{-16}$***
EMI_{record}	−0.008124	0.014960	−0.543	0.587
EMU_{record}	0.001572	0.008650	0.182	0.856
EPU_{record}	−0.001736	0.012333	−0.141	0.888
$COVID_{dummy}$	−0.114522	0.009688	−11.821	$<2 \times 10^{-16}$***

Table 3. Residuals and coefficients.

Residuals:				
Min	1Q	Median	3Q	Max
−2.4003	−0.2260	0.0575	0.2795	1.2676
Coefficients:				
	Estimate	Std. error	T-value	Pr (>|t|)
(Intercept)	3.409536	0.047279	72.115	$<2 \times 10^{-16***}$
EMI_{record}	−0.002173	0.011052	−0.197	0.844
$COVID_{dummy}$	−0.380587	0.029224	−13.023	$<2 \times 10^{-16***}$

Table 4. Residuals and coefficients.

Residuals:				
Min	1Q	Median	3Q	Max
−2.40032	−0.22650	0.05738	0.27957	1.25864
Coefficients:				
	Estimate	Std. error	T-value	Pr (>|t|)
(Intercept)	3.400	3.897 × 10−2	87.246	$<2 \times 10^{-16***}$
EPU_{record}	−1.042 × 10−5	9.293 × 10−3	−0.001	0.999
$COVID_{dummy}$	−3.806 × 10−1	2.922 × 10−2	−13.024	$<2 \times 10^{-16***}$

Table 5. Residuals and coefficients.

Residuals:				
Min	1Q	Median	3Q	Max
−2.40046	−0.22609	0.05739	0.27944	1.26882
Coefficients:				
	Estimate	Std. error	T-value	Pr (>|t|)
(Intercept)	3.4028146	0.0287793	118.238	$<2 \times 10^{-16***}$
EMU_{record}	−0.0004828	0.0054379	−0.089	0.929
$COVID_{dummy}$	−0.3806081	0.0292237	−13.024	$<2 \times 10^{-16***}$

side with the first lag and second lag of Y_{record}, the other variables in the three regressions as they are, plus the first lag and second lag of the EMI, EPU, and EMU. After this running, the results are more promising. Table 6 and Equation (5), Table 7 and Equation (6), and Table 8 and Equation (7) may all be obtained in this situation. With the lag terms in the prediction, the coefficients are much improved in all three regressions. Then, we tried to remove the COVID dummy in this case as the change due to COVID is probably considered in the coefficients for the lag terms already.

Table 6. Residuals and coefficients.

Residuals:				
Min	1Q	Median	3Q	Max
−1.80195	−0.00700	0.00043	0.00768	1.77687
Coefficients:				
	Estimate	Std. error	T-value	Pr (>|t|)
(Intercept)	−0.0213083	0.0250468	−0.851	0.395
EMI_{record}	0.0013417	0.0020008	0.671	0.502
Y_{lag1}	0.8251120	0.0127129	64.903	$<2 \times 10^{-16***}$
Y_{lag2}	0.1651505	0.0127126	12.991	$<2 \times 10^{-16***}$
EMI_{lag1}	0.0023776	0.0022495	1.057	0.291
EMI_{lag2}	0.0025989	0.0020046	1.296	0.195
EMU_{lag1}	0.0012881	0.0009075	1.419	0.156
EMU_{lag2}	0.0005280	0.0009218	0.573	0.567
EPU_{lag1}	0.0025350	0.0015845	1.600	0.110
EPU_{lag2}	0.0018204	0.0015587	1.168	0.243

Table 7. Residuals and coefficients.

Residuals:				
Min	1Q	Median	3Q	Max
−1.80219	−0.00698	0.00034	0.00766	1.77779
Coefficients:				
	Estimate	Std. error	T-value	Pr (>|t|)
(Intercept)	−0.0218305	0.0221940	−0.984	0.3253
EPU_{record}	0.0016702	0.0016490	1.013	0.3112
Y_{lag1}	0.8246848	0.0127158	64.855	$<2 \times 10^{-16***}$
Y_{lag2}	0.1655712	0.0127156	13.021	$<2 \times 10^{-16***}$
EMI_{lag1}	0.0015907	0.0018951	0.839	0.4013
EMI_{lag2}	0.0021354	0.0018951	1.127	0.2599
EMU_{lag1}	0.0011359	0.0009247	1.228	0.2193
EMU_{lag2}	0.0004598	0.0009244	0.497	0.6189
EPU_{lag1}	0.0034340	0.0018187	1.888	0.0591
EPU_{lag2}	0.0023115	0.0016285	1.419	0.1558

Table 8. Residuals and coefficients.

Residuals:				
Min	1Q	Median	3Q	Max
−1.79919	−0.00717	0.00029	0.00785	1.77885

Continued

Coefficients:				
	Estimate	Std. error	T-value	Pr (>|t|)
(Intercept)	−0.0309821	0.0208969	−1.483	0.1382
EMU_{record}	0.0023005	0.0009372	2.455	0.0141*
Y_{lag1}	0.8253796	0.0127071	64.954	$<2 \times 10^{-16}$***
Y_{lag2}	0.1648958	0.0127068	12.977	$<2 \times 10^{-16}$***
EMI_{lag1}	0.0013750	0.0018957	0.725	0.4683
EMI_{lag2}	0.0021268	0.0018942	1.123	0.2616
EMU_{lag1}	0.0024833	0.0010215	2.431	0.0151*
EMU_{lag2}	0.0011841	0.0009590	1.235	0.2170
EPU_{lag1}	0.0024583	0.0015840	1.552	0.1207
EPU_{lag2}	0.0019109	0.0015582	1.226	0.2201

$$\begin{aligned} Y_{record} = & -0.021 + 0.0013 * EMI_{record} + 0.8251 * Y_{lag1} + 0.1651 * Y_{lag2} \\ & + 0.00237 * EMI_{lag1} + 0.0026 * EMI_{lag2} + 0.0013 * EMU_{lag1} \\ & + 0.0005 * EMU_{lag2} + 0.0025 * EPU_{lag1} + 0.0018 * EPU_{lag2} \end{aligned} \tag{5}$$

$$\begin{aligned} Y_{record} = & -0.021 + 0.0016 * EPU_{record} + 0.8247 * Y_{lag1} + 0.1656 * Y_{lag2} \\ & + 0.00159 * EMI_{lag1} + 0.0021 * EMI_{lag2} + 0.0011 * EMU_{lag1} \\ & + 0.0005 * EMU_{lag2} + 0.0034 * EPU_{lag1} + 0.0023 * EPU_{lag2} \end{aligned} \tag{6}$$

$$\begin{aligned} Y_{record} = & -0.031 + 0.0023 * EMU_{record} + 0.8253 * Y_{lag1} + 0.1649 * Y_{lag2} \\ & + 0.00138 * EMI_{lag1} + 0.0021 * EMI_{lag2} + 0.0025 * EMU_{lag1} \\ & + 0.0012 * EMU_{lag2} + 0.0025 * EPU_{lag1} + 0.0019 * EPU_{lag2} \end{aligned} \tag{7}$$

We can get the following graph according to the GARCH (1, 1) model. Because the actual volatility is unobservable, the prediction of S&P 500 future data is based on historical data volatility. Since all the p-values for the Ljung-Box Test (**Table 9**) of residuals are >0.05, which means that there is no evidence of serial correlation in the squared residuals. In this case, we can say that they behave as white noise process. Looking at the ARCH LM Tests (**Table 10**), all the p-values > 0.05 and we fail to reject the null hypothesis hence there is no evidence of serial correlation in squared residuals. This confirms that the residuals behave as a white noise process. From the Goodness-of-fit test (**Table 11**), we observe that for group 30 and group 40, the p-value < 0.05 and hence we can reject the null hypothesis that this model is adequate for this process.

From the Garch (1, 1) Data Analysis Features (**Figure 5**), we can know that any shocks that are experienced by the conditional variance will be highly persistent. The prediction graph (**Figure 6**) is roughly the same as the previous comparison of the actual return volatility graph; using the static prediction method, both fluctuate sharply at the same time and slowly over a while, indicating that the model is a better fit for the data. Since stocks are financial data suitable

Table 9. Weighted Ljung-Box Test on standardized residuals.

	Statistic	*p*-value
Lag[1]	0.0004234	0.9836
Lag[2 * (p + q) + (p + q) − 1][2]	0.4015735	0.7417
Lag[4 * (p + q) + (p + q) − 1][5]	1.4663785	0.7482

Note: d.o.f = 0; H0: No serial correlation.

Table 10. Weighted ARCH LM Tests.

	Statistic	Shape	Scale	*p*-value
ARCH Lag[3]	0.05078	0.500	2.000	0.8053
ARCH Lag[5]	0.26866	1.440	1.667	0.9485
ARCH Lag[7]	0.34335	2.315	1.543	0.9903

Table 11. Adjusted Pearson Goodness-of-Fit Test.

	Group	Statistic	*p*-value (g^{-1})
1	20	30.12	0.05030
2	30	47.70	0.01579
3	40	57.82	0.02659
4	50	55.24	0.25069

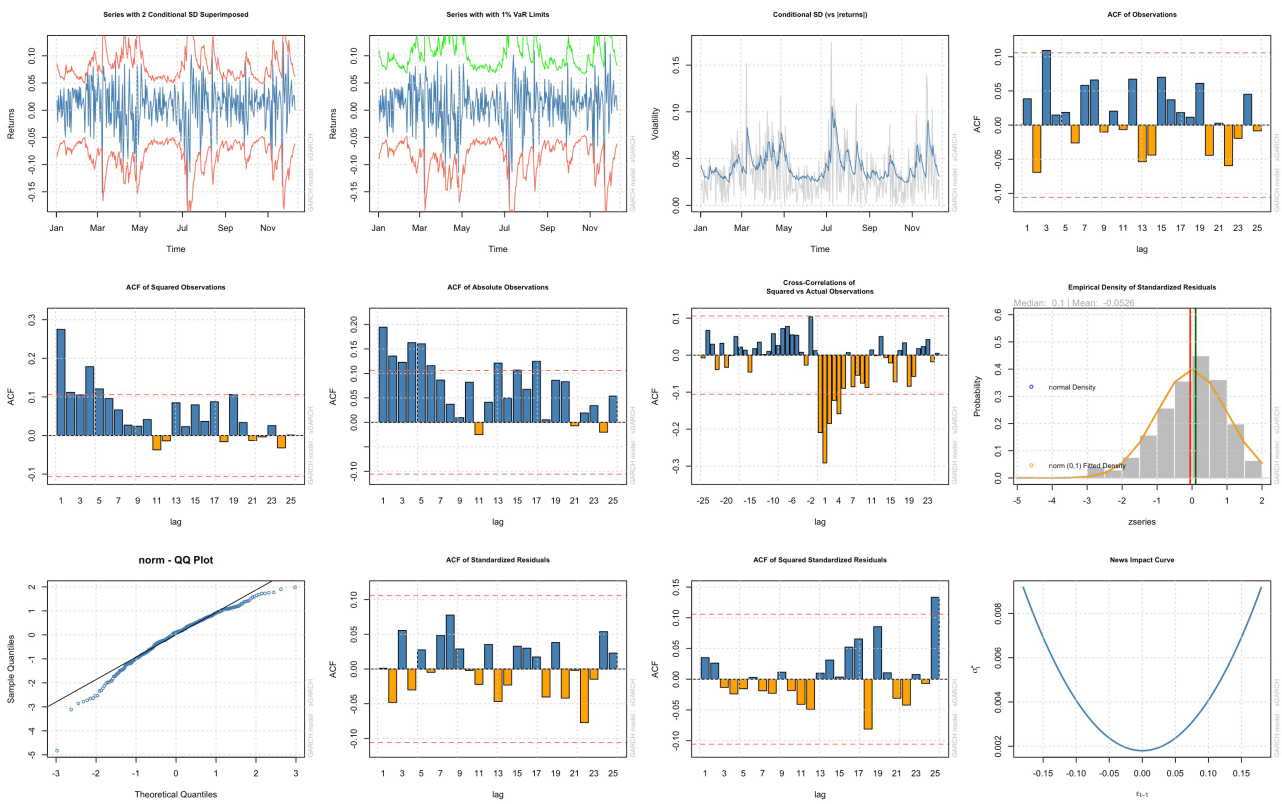

Figure 5. Garch (1, 1) data analysis features.

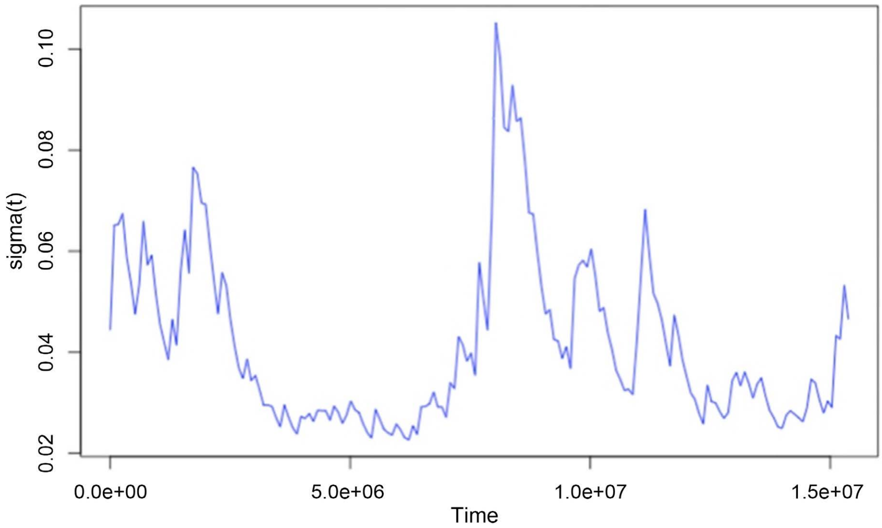

Figure 6. Predictions of volatility.

for short-term forecasting, these models can only predict short-term return fluctuations, so the model needs to be continuously improved in the long term.

5. Conclusion

To calculate the daily skewness of the S&P 500 index to the tail risk of the American stock market, we build a GARCH model. We use three indices to measure economic uncertainty, which are EPU (Economic Policy Uncertainty Index), EMU (Equity Market Related Economic Uncertainty Index), and EMI (Equity Market Volatility: Contagion Tracker). According to the empirical findings, daily skewness and economic uncertainty are positively correlated, and this relationship gets stronger during the COVID-19 pandemic epidemic. The outcomes serve as a reminder of the importance of sound economic policy in preventing market crises and boosting investor confidence. In future research, we can focus on the study of economic uncertainty in the future stock market in order to achieve the goal of predicting future economic conditions through uncertainty.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

Altig, D. et al. (2020). Economic Uncertainty before and during the COVID-19 Pandemic. *Journal of Public Economics, 191,* Article ID: 104274. https://doi.org/10.1016/j.jpubeco.2020.104274

Baker, S. R. et al. (2020a). *COVID-Induced Economic Uncertainty*. No. w26983, National Bureau of Economic Research. https://doi.org/10.3386/w26983

Baker, S. R. et al. (2020b). The Unprecedented Stock Market Reaction to COVID-19. *The Review of Asset Pricing Studies, 10,* 742-758. https://doi.org/10.1093/rapstu/raaa008

Baker, S. R. et al. (2022a, June 2). *Economic Policy Uncertainty Index for United States*.

FRED. https://fred.stlouisfed.org/series/USEPUINDXD

Baker, S. R. et al. (2022b, June 3). *Equity Market-Related Economic Uncertainty Index*. FRED. https://fred.stlouisfed.org/series/WLEMUINDXD

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics, 131,* 1593-1636. https://doi.org/10.1093/qje/qjw024

Brodeur, A. et al. (2021). A Literature Review of the Economics of COVID-19. *Journal of Economic Surveys, 35,* 1007-1044. https://doi.org/10.1111/joes.12423

Chen, S., & Ranciere, R. (2019). Financial Information and Macroeconomic Forecasts. *International Journal of Forecasting, 35,* 1160-1174. https://doi.org/10.1016/j.ijforecast.2019.03.005

Liu, Z. F. et al. (2020). *COVID-19, Economic Policy Uncertainty and Stock Market Crash Risk*.

Mazur, M., Dang, M., & Vega, M. (2021). COVID-19 and the March 2020 Stock Market Crash. Evidence from S&P1500. *Finance Research Letters, 38,* Article ID: 101690. https://doi.org/10.1016/j.frl.2020.101690

Moore, A. (2017). Measuring Economic Uncertainty and Its Effects. *Economic Record, 93,* 550-575. https://doi.org/10.1111/1475-4932.12356

Padhan, R., & Prabheesh, K. P. (2021). The Economics of COVID-19 Pandemic: A Survey. *Economic Analysis and Policy, 70,* 220-237. https://doi.org/10.1016/j.eap.2021.02.012

Zhang, D. Y., Hu, M., & Ji, Q. (2020). Financial Markets under the Global Pandemic of COVID-19. *Finance Research Letters, 36,* Article ID: 101528. https://doi.org/10.1016/j.frl.2020.101528

Ziemba, W. T. (2020). *The COVID-19 Crash in the US Stock Market*. https://doi.org/10.2139/ssrn.3632410