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How Has the COVID-19 Pandemic Affected GDP Growth?-Empirical Study on USA and China-

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Abstract

This paper anticipates trends in the digital economy during a COVID-19 epidemic worldwide. The United States and China are considered the world's largest economies and have attempted to transition to fully digital economies over the last few years. Therefore, this paper used the auto-regressive integrated moving average (ARIMA) model and the gross domestic product (GDP) for the USA and China over the period 1960-2019. As we arrive at the peak of the COVID-19 pandemic, one of the most squeezing questions confronting us is: How has the COVID-19 crisis affected the USA and China's GDP growth? The results have shown first that the GDP growth for both years 2020 and 2021 are approximately 6% and 10% for the USA and China, respectively. Second, the COVID-19 pandemic cannot influence the countries that depend on technology and the digital economy. It can be seen that technology is playing a very significant role in our daily life and nations' economies.

Keywords: Digital economies; Forecasting; COVID-19; Time series analysis; GDP; ARIMA Model.

1. Introduction

The current economic crisis has highlighted a number of strengths in the nation's digital economy. Indeed, digital economy, demand is likely to rise with increasing risk in COVID-19 crisis, at a time when traditional economy is more difficult to raise, which may result in an economic downturnsc (Alipour *et al.*, 2020; Watanabe *et al.*, 2018). To address this problem, the developed countries have recently advocated that the nations should shift to the digital economy by using the advance technology and limit their traditional economy in order to be able to stand fast the recessions (Caseiro and Coelho, 2019; Mirchandani and Gaur, 2019). Technology is playing very significant roles in digital economies today. Therefore, integration, and complexity of information technology and communications is changing our society and economy. It can be seen that the customers now regularly use the internet networks to find products and services, particularly after the nation's fir strict regulation to limit people moving during COVID-19 crisis (Singh *et al.*, 2020; Solomon and Van Klyton, 2020; Yasenov, 2020). Likewise, organizations use networks significantly more generally to smooth out buying strategies, arrive at new clients, and oversee inner activities (Watanabe *et al.*, 2018). Computerized change is an adjustment in our reality brought about by the upheaval such as the recent crisis (Agarwal *et al.*, 2020).

The spread of COVID-19 is predicted to bring about an extensive slowdown of economic actions (Brodeur *et al.*, 2020). As indicated by an early estimate of the International Monetary Fund (2020a), the worldwide economy would decrease by around 3 percent in 2020. The constriction is relied upon to be of far more noteworthy size that that of the 2008-2009 Global Financial Crisis. In any case, in its most recent update (June 2020), the International Monetary Fund (2020b) reconsidered the estimate to 4.9 percent will decrease in 2020. The report refers to the accompanying explanations behind the refreshed figure: I) more prominent tirelessness in social, separating exercises; ii) lower action during lockdowns; iii) more extreme decrease in efficiency among firms which have opened up for business; and iv) more noteworthy uncertainty[1]. The monetary ramifications will be wide-running and unsure, with various impacts on the work markets, creation flexibly chains, monetary business sectors, and the World economy. The negative economic impacts may shift by the toughness of the social, separating measures (e.g., lockdowns and related arrangements), its length of execution, and the level of compliance[2].

[1] World Bank (2020) forecasts a 5.2 percent contraction in global GDP. Similarly, OECD (2020) forecasts a fall in global GDP by 6 percent to 7.6 percent, depending on the emergence of a second wave of COVID-19.
[2] According to CDC (2020), social distancing (or physical distancing) means keeping space between yourself and other people outside home. To practice social/physical distancing: i) stay at least 6 feet (about 2 arms' length) from other people: ii) do not gather in groups; and iii) avoid crowded places and mass gatherings.

The ascent of the New Digital Economy is undeniable adjusting the elements of economic development. For instance, in the course of recent years, business spending on computerized administrations, including cloud computing, information services, and other data administrations in major progressed economies, (for example, the United States, and China) quickly expanded. However, the COVID-19. emergency makes a significant problem, the economy default at a quick movement. Accordingly, to answer the question; what is the potential impact of the recent crisis on the digital economy's growth rate? To answer this question this research used the ARIMA model to forecast the digital economy trends. The result has been shown that the countries such as USA and china there economy will grow approximately 6% to 10% respectively through the end of year 2021.Worldwide efficiency development has been amazingly delayed during the emergency, and there is a sign that the New Digital Economy has helped economy development (Erdmann and Ponzoa, 2021; Petrenko *et al.*, 2017; Solomon and Van Klyton, 2020).

The rest of the paper is organized as follows. Section 2 features the ARIMA model. Section 3 presents the displaying, gauging, and archives the principle results, while Section 4 gives the concluding remarks of the paper.

2. Methodology

2.1. Data Collection

The Gross Domestic Product (GDP) is the fundamental index of public economics. It is a significant indicator to quantify the general economic circumstance of some nation. It mirrors the nation's financial quality, auxiliary design, and market scale. The World Bank offers GDP information for several nations, including the USA and China over the period 1960-2019. This research has been used the GDP data as a proxy to investigate the impact of COVID -19 on digital economy nations during the period.

2.2. ARIMA Model

Box and Jenkins proposed the ARIMA model, a time series estimation technique, in the 1970s. The model comprises of AR, I, and MA. Here AR speaks to the Autoregressive model, I embody to the Integration showing the request for a single number, and MA is to the Moving Average model. Broadly, a fixed grouping can set up a metrology model. The unit root test is utilized to pass judgment on the stationary of the series. Concerning a non-fixed series, it ought to be changed over to a fixed series with distinction activity. The quantity of comparing contrast is called as the order of single whole number. The ARIMA (*p*, *D*, *q*) model is basically a blend of differential activity and ARMA (*p*, *q*) model (Alzahrani *et al.*, 2020; GEORG *et al.*, 2016; Hernandez-Matamoros *et al.*, 2020). A non-fixed I (*D*) measure is one that can be made fixed by taking *D* contrasts. The cycle is frequently called distinction fixed or unit root measures. A series that can be demonstrated as a fixed ARMA (*p*, *q*) measure subsequent to being distinction *D* times is indicated by ARIMA (*p*, *D*, *q*) (Lihua Ma *et al.*, 2018; Singh *et al.*, 2020; Zhao and Shang, 2012). The type of the ARIMA (*p*, *D*, *q*) model is.

$$\Delta^D y_t = C + \emptyset_1 \Delta^D y_{t-1} + \ldots + \emptyset_p \Delta^D y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} \qquad (1)$$

where $\Delta^D y_t$ is a *D*-the distinction arrangement, and ε_t is an uncorrelated cycle with mean zero. In slack administrator documentation, $L^i_{y_t} = y_{t-i}$. The ARIMA (*p*, *D*, *q*) model can be composed.

$$\emptyset^*(L) y_t = \emptyset(L)(1-L)^D y_t = c + \theta(L)\varepsilon_t \qquad (2)$$

where, $\emptyset^*(L)$ is a temperamental AR administrator polynomial with precisely *D* unit roots. Somebody can factor this polynomial as $\emptyset(L)(1-L)^D$, where $\emptyset(L)\big(1-\emptyset_1 L - \cdots - \emptyset_p Lq\big)$ is a steady degree *p* AR slack administrator polynomial. Essentially, $\emptyset(L)\big(1+\emptyset_1 L + \cdots + \emptyset_p Lq\big)$ is an invertible degree *q* MA slack administrator polynomial. At the point when two out of the three terms in ARIMA (*p*, *D*, *q*) are zeros, the model might be alluded to, in light of the non-zero boundary, dropping "AR", "I" or "MA" from the abbreviation portraying the model. For instance, ARIMA (1,0,0) is AR (1), ARIMA (0,1,0) is I (1), and ARIMA (0,0,1) is MA (1).

The ARIMA model is a generally utilized time arrangement model and a transient expectation model with high accuracy. The essential thought of the model is that some time arrangement are a bunch of irregular factors that rely upon time, however the progressions of the whole time arrangement have certain standards, which can be approximated by the comparing numerical model. Over the investigation of the mathematical model, it can comprehend the structure and qualities of time series, even more generally and accomplish the ideal forecast in the feeling of least fluctuation. The future estimation of a time series can be gauge with the ARIMA model. A significant utilization of EViews programming is demonstrating and expectation dependent on ARIMA model. If the time series is a non-fixed succession, it ought to be right off the bat changed over to a fixed series. The best model boundaries are chosen, and the ARIMA (*p*, *D*, *q*) model is set up.

3. Modeling and Forecasting

ARIMA modeling approach fundamentally has three stages: model recognizable proof, parameter assessment, and analytic registration of the model. The model recognizable proof stage decides the time series for stationarity and irregularity, which should be demonstrated before parameter assessment. The stationarity of time series can be decided from an autocorrelation (AC) plot, and if there should be an occurrence of non-fixed time arrangement, differencing transformation can be applied to acquire fixed information. Irregularity can be displayed by taking seasonal differencing and recovering autocorrelation (AC) and incomplete autocorrelation (PAC) plots. These plots are additionally useful in distinguishing the estimations of parameters p and q (GEORG *et al.*, 2016; Hernandez-Matamoros *et al.*, 2020; Lihua Ma *et al.*, 2018; Singh *et al.*, 2020). Boundary assessment of the properly chosen model is made by greatest probability, which is a commonly utilized technique for assessment. At long last, the general sufficiency of the model is checked (GEORG *et al.*, 2016; He and Tao, 2018; Lihua Ma *et al.*, 2018). This paper applies the ARIMA model by uses the dataset consists of GDP for the largest two countries (America and China) over 60 years' time span (1960–2019), as follows.

3.1. First: American GDP Data

3.1.1. Stationarity Test

Figure 1 shows the GDP data series over the period 1960-2019. Furthermore, Table 1 illustrates the aftereffect of the stationary test (ADF test) on the information is given.

Figure-1. The USAGDP data during 1960 to 2019

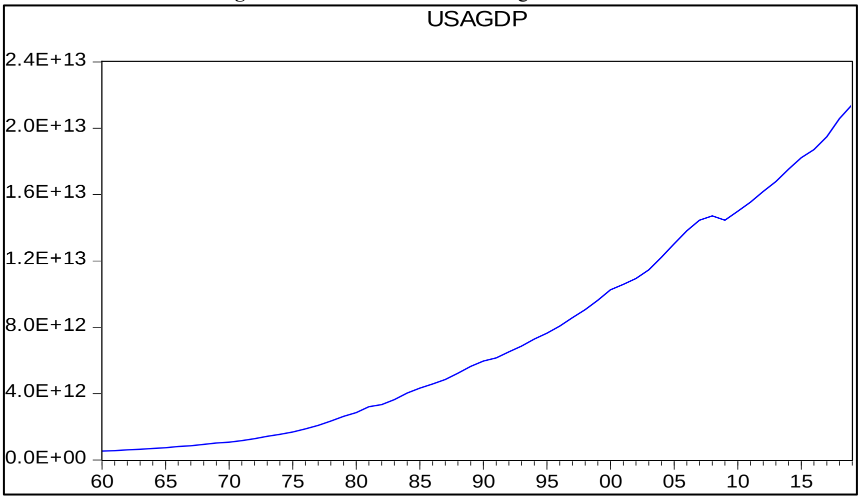


Table-1. Augmented Dickey-Fuller unit root test on USAGDP

Null Hypothesis: USAGDP has a unit root

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		3.615070	1.0000
Test critical values:	1% level	-3.548208	
	5% level	-2.912631	
	10% level	-2.594027	
*MacKinnon (1996) one-sided p-values.			

Table 1 has been shown that the ADF = 3.615070 is greater than the critical value of the significance level of 0.01, 0.05 and 0.1, and the P value is greater than 0.05, that is to say, the original USAGDP sequence is non-stationary. Figure 1 shows that the first sequence is exponential. Taking the natural logarithm of the USAGDP data to eliminate its non-stationary and obtaining the LUSAGDP sequence. In addition, taking LUSAGDP for ADF test, ADF = 2.910894 is still greater than the critical value of the significance level of 0.01, 0.05 and 0.1. Moreover, the P value = 0.9989 is greater than 0.05. The LUSAGDP sequence still accepts the null hypothesis with a large P value. The LUSAGDP sequence is still nonstationary. Further, the first-order difference is performed and a D LUSAGDP sequence is obtained. The results of the ADF test for the D LUSAGDP sequence is given in Table 2.

Table-2. Augmented Dickey-Fuller unit root test on DUSAGDP

Null Hypothesis: D(LUSAGDP) has a unit root

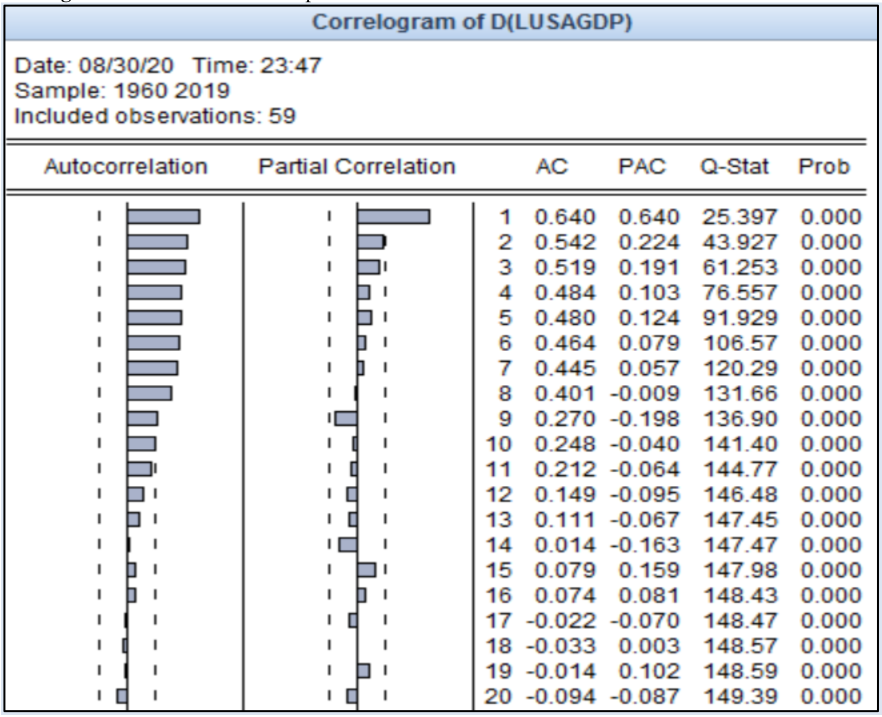
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.295409	0.0003
Test critical values:	1% level	-4.124265	
	5% level	-3.489228	
	10% level	-3.173114	
*MacKinnon (1996) one-sided p-values.			

The table above has been shown that the ADF = -5.295409 less than the critical values of the significance level of 0.01, 0.05 and 0.1. Furthermore, the P value = 0.0003 is less than 0.05. Which means the D(LUSAGDP) sequence after the logarithmic change and the first-order difference is a stationary series.

3.1.2. Model Identification

The EViews software has been used to plot the autocorrelation and partial autocorrelation function of the D(LUSAGDP) series as follows:

Figure-2. Autocorrelation and partial autocorrelation function tables of the main model series


Correlogram of D(LUSAGDP)

Date: 08/30/20 Time: 23:47
Sample: 1960 2019
Included observations: 59

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.640	0.640	25.397	0.000
		2	0.542	0.224	43.927	0.000
		3	0.519	0.191	61.253	0.000
		4	0.484	0.103	76.557	0.000
		5	0.480	0.124	91.929	0.000
		6	0.464	0.079	106.57	0.000
		7	0.445	0.057	120.29	0.000
		8	0.401	-0.009	131.66	0.000
		9	0.270	-0.198	136.90	0.000
		10	0.248	-0.040	141.40	0.000
		11	0.212	-0.064	144.77	0.000
		12	0.149	-0.095	146.48	0.000
		13	0.111	-0.067	147.45	0.000
		14	0.014	-0.163	147.47	0.000
		15	0.079	0.159	147.98	0.000
		16	0.074	0.081	148.43	0.000
		17	-0.022	-0.070	148.47	0.000
		18	-0.033	0.003	148.57	0.000
		19	-0.014	0.102	148.59	0.000
		20	-0.094	-0.087	149.39	0.000

Figure 2 illustrated that the autocorrelation coefficient of the *D* LUSAGDP succession is essentially non-zero when the lag request is one. Furthermore, it is fundamentally in the certainty band when the lag request is more noteworthy than 1, so *q* can be taken 1. The halfway autocorrelation coefficient is fundamentally nonzero when the lag order is equivalent to 1, it is additionally different unique in relation to 0 when the lag order is 2, so p = 1 or p = 2 can be thought of. Taking into account that the judgment is subjective, to set up a more exact model, the scope of estimations of *p* and *q* is fittingly loose, and different ARMA (*p*, *q*) models are established. Table 3 illustrates the test results of ARMA (*p*, *q*) for different parameters. The Adjusted R-squared, AIC worth, SC worth and S.E. of regression are exceedingly significant criteria for choosing models. The AIC and the SC standards are mainly used for positioning and select the ideal model. Normally, an increase in the coefficient of determination, will leads to decrease for the AIC and the SC values, besides the residual variance. The comparing ARMA (*p*, *q*) model is prevalent.

Table-3. Test results of ARMA (*p*,*q*)

(*p*, *q*)	**Adjusted R-squared**	**AIC**	**SC**	**S.E. of regression**
(0,1)	0.285531	-4.698529	-4.628104	0.022712
(0,2)	0.183044	-4.564484	-4.494059	0.024286
(1,0) *	**0.410457**	**-4.889496**	**-4.818446**	**0.020638**
(1,1)	0.290099	-4.687371	-4.615685	0.022826
(1,2)	0.460803	-4.962300	-4.855725	0.019737
(2,0)	0.399882	-4.855253	-4.748678	0.020822
(2,1)	0.429272	-4.888846	-4.781317	0.020467
(2,2)	0.361801	-4.777108	-4.669579	0.021643

It ought to be stressed that in spite of the fact that the proper ARMA model is generally chosen utilizing the AIC esteem and the SC esteem. Nevertheless, the lower values of the AIC and the SC are not adequate conditions for the ideal ARMA model. Following (Lihua Ma *et al.*, 2018; Zhao and Shang, 2012). This work used to first establish a model with the lowest AIC and SC values, Then do a parameter significance test and a residual randomness test on the assessment result. If the model passes the test, the model can be viewed as the ideal model; on the off chance that it fails the test, the second littlest AIC worth and SC esteem are chosen and the pertinent factual test is performed. And so on, until the suitable model is chosen. Table 3 illustrated the model that passes the parameter significance test and the residual randomness test, it was determined by "*", the ARMA (1, 0) model chosen.

3.1.3. Model Establishment and Inspection

The estimated results with the ARIMA model are as follows:

Table-4. Estimation results of the ARIMA model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.062868	0.007679	8.187317	0.0000
AR(1)	0.647078	0.101447	6.378480	0.0000
R-squared	0.420800	Mean dependent var		0.062735
Adjusted R-squared	0.410457	S.D. dependent var		0.026879
S.E. of regression	0.020638	Akaike info criterion		-4.889496
Sum squared resid	0.023852	Schwarz criterion		-4.818446
Log likelihood	143.7954	Hannan-Quinn criter.		-4.861820
F-statistic	40.68501	Durbin-Watson stat		2.197625
Prob(F-statistic)	0.000000			
Inverted AR Roots	.65			

Table 4 above have been shown the LUSAGDP sequence is ARIMA (1, 1, 0). In addition, the equation (3) illustrates the specified shape of the model. Besides, the t-Statistic values of all the model variables are significant and the P values are less than 0.01. The information in brackets beneath the equation is the t-test statistic of the corresponding gauge esteem.

$$\Delta LUSAGDP = 0.062868 + 0.647078 * AR(1) \qquad (3)$$

It can be seen in the Equation (4) the variance of the corresponding error estimated as follows:

$$\hat{\sigma}_a = 0.020638 \qquad (4)$$

Figure-3. Actual series, fitted series, and residual series of the DLUSAGDP sequence

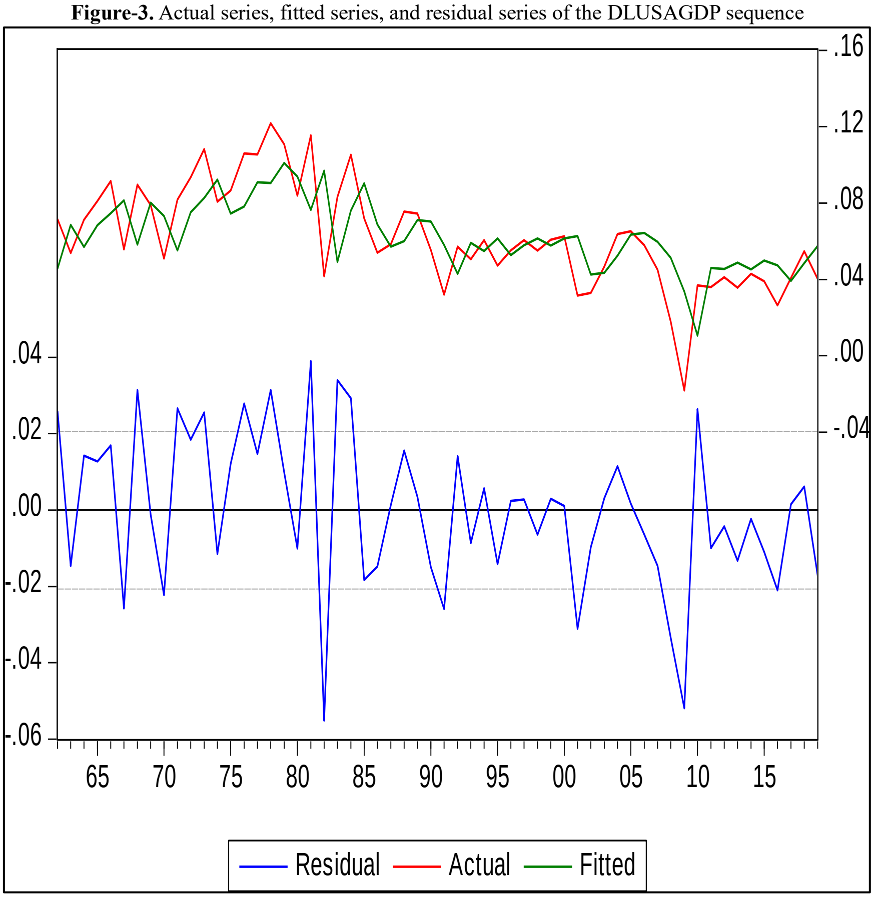
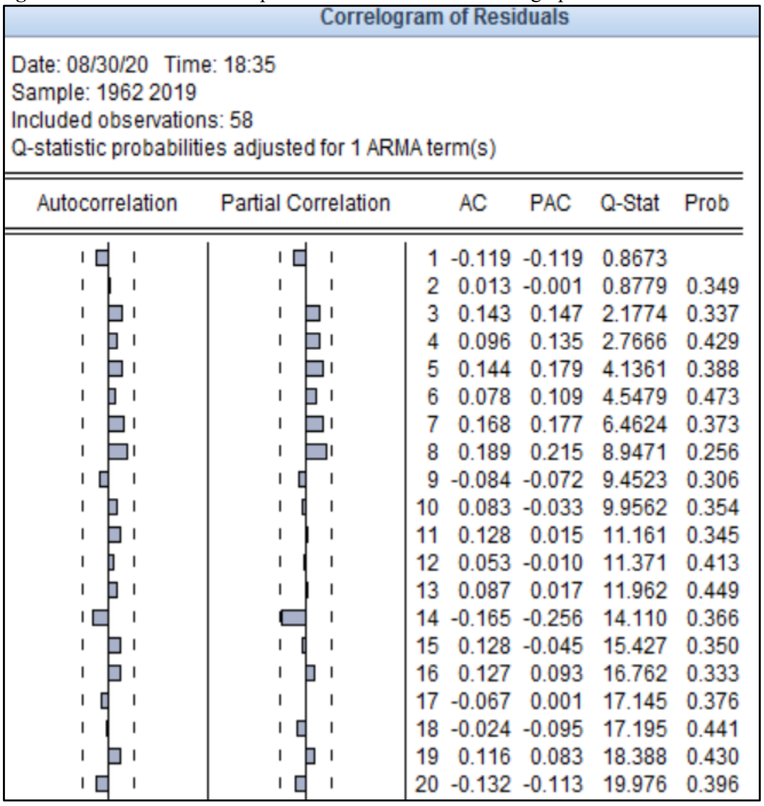


Figure 3 shows the utilized model to fit the D(LUSAGDP) data, and the outcome appears that the strong line and the upper give shows the actual data and lower spotted lines compared to the fitted qualities and lingering of the model. Figure 4 illustrates the result of testing the ARIMA (1, 1, 0) model. The graph of the autocorrelation and partial autocorrelation function represent that the residual is a white noise. In addition, the Q-Stat. test values are significant, which means the model is appropriate.

Figure-4. Autocorrelation and partial autocorrelation function graphs of the residual series


Correlogram of Residuals

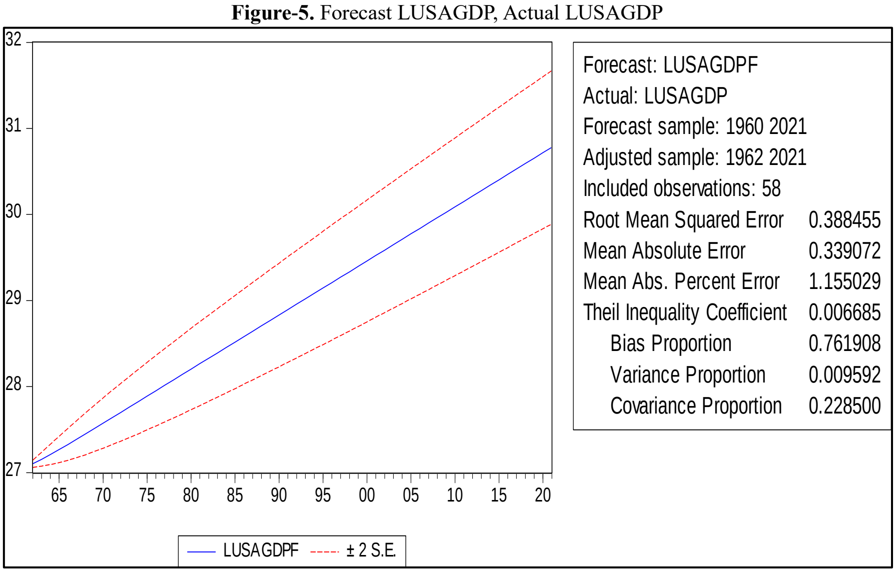
Date: 08/30/20 Time: 18:35
Sample: 1962 2019
Included observations: 58
Q-statistic probabilities adjusted for 1 ARMA term(s)

	AC	PAC	Q-Stat	Prob
1	-0.119	-0.119	0.8673	
2	0.013	-0.001	0.8779	0.349
3	0.143	0.147	2.1774	0.337
4	0.096	0.135	2.7666	0.429
5	0.144	0.179	4.1361	0.388
6	0.078	0.109	4.5479	0.473
7	0.168	0.177	6.4624	0.373
8	0.189	0.215	8.9471	0.256
9	-0.084	-0.072	9.4523	0.306
10	0.083	-0.033	9.9562	0.354
11	0.128	0.015	11.161	0.345
12	0.053	-0.010	11.371	0.413
13	0.087	0.017	11.962	0.449
14	-0.165	-0.256	14.110	0.366
15	0.128	-0.045	15.427	0.350
16	0.127	0.093	16.762	0.333
17	-0.067	0.001	17.145	0.376
18	-0.024	-0.095	17.195	0.441
19	0.116	0.083	18.388	0.430
20	-0.132	-0.113	19.976	0.396

3.1.4. Data Forecasting

Following the same methodology at first, the model is used to test the appropriate effect with the USAGDP worth in 2019. The forecast worth in 2019 is (2.14277E+13) USA Dollar. The real worth is (2.05612E+13) USA Dollar and the relative error is 4%. It can be seen that the forecast value is close to the actual result, indicating that the model has a good fitting effect.

Figure-5. Forecast LUSAGDP, Actual LUSAGDP



It can be seen in Figure 5 that the forecasting of the U.S.A GDP through the EViews software plot, which is showing the actual GDP with solid line and the upper and lower dashed line shows the forecasting deviation. The Dynamic forecast by EViews software has been used to predict the USAGDP values over the years 2020 and 2021. Table 5 illustrates the results as follows:

Table-5. United States of America GDP forecast from 2019 to 2021

Year	Forecast USAGDP	variation	Growth rate
2019	20561193480000	-	-
2020	21895328740000	1334135260000	0.0648860807276446
2021	23316030810000	1420702070000	0.0648860808106780

The table above shows that the USAGDP forecasting values of the years 2020 and 2021 is (2.18953E+13), and (2.3316E+13) USA Dollar, respectively. Moreover, the relative growth rate 6.49%, approximately the same for the years 2020 as well 2021. Which indicates that the COVID -19 epidemic crisis cannot influence the advance countries depend on digital economies such as America.

3.2. Second: China GDP Data

3.2.1. Stationarity Test

ARIMA Model proposed that the variables used in the model have to be stationary. The variables involved in our model have the time series characteristics. It is observed that the mean of the interested variables is not stationary over time. To make them constant the natural logarithm was taken. It can be seen the behavior of GDP before and after taking the natural logarithm of the data in Figure 6.

Figure-6. The CGDP data during 1960 to 2019

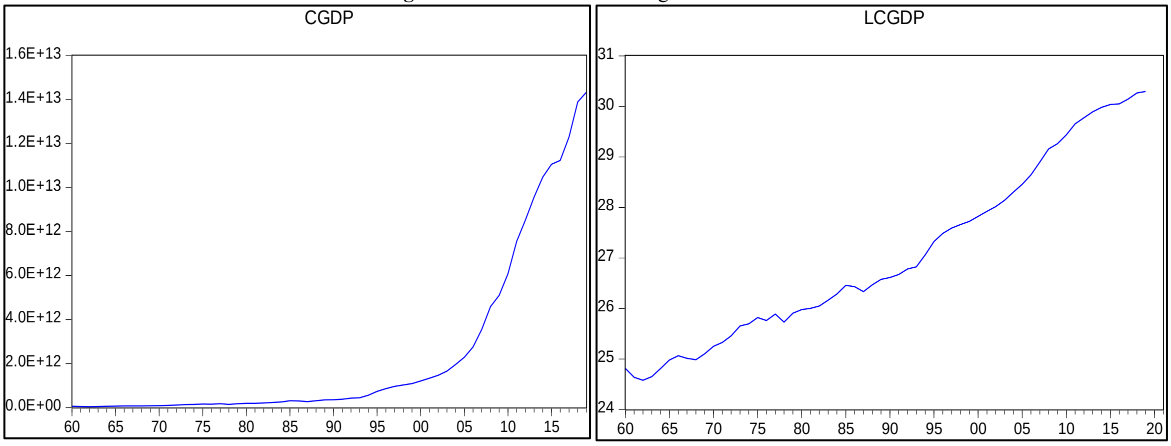


Table-6. Augmented Dickey-Fuller unit root test on CGDP

Null Hypothesis: CGDP has a unit root

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		6.466357	1.0000
Test critical values:	1% level	-3.568308	
	5% level	-2.921175	
	10% level	-2.598551	
*MacKinnon (1996) one-sided p-values.			

Results of the Augmented Dickey-Fuller test statistic are reported in Table 6. the ADF = 6.466357 is greater than the critical value of the significance level of 0.01, 0.05 and 0.1, and the P value is greater than 0.05, that is to say, the original CGDP sequence is non-stationary.

Table-7. Augmented Dickey-Fuller unit root test on DCGDP

Null Hypothesis: D(LCGDP) has a unit root

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.173999	0.0000
Test critical values:	1% level	-3.548208	
	5% level	-2.912631	
	10% level	-2.594027	
*MacKinnon (1996) one-sided p-values.			

After taking the natural logarithm of the CGDP data to remove its non-stationary and gaining the LCGDP sequence. The ADF = 2.110614 is still larger than the critical value of the significance level of 0.01, 0.05, and the P value = 0.9999 is > 0.05. Which means the GDP concatenation cannot reject the null hypothesis. Thus, the first-order variance is accomplished and a DCGDP sequence is found. The ADF test results for the DCGDP sequence is provided in Table 7. Above. The ADF = -6.173999 less than the critical values and, the P value = 0.0000 < 0.05. Which implies the DCGDP sequence after the logarithmic change and the first-order variance is a stationary series.

3.2.2. Model Identification

The autocorrelation and partial autocorrelation function of the LCGDP has plot by The EViews programming as shown in Figure 7. The autocorrelation coefficient of the LCGDP in Figure 7 shows succession is fundamentally non-zero when the lag demand is one. Additionally, it is essentially in the certainty band when the lag request is more noteworthy than one, so q can be considered one. The midway autocorrelation coefficient is nonzero when the lag order is equal to one, it is also different in relation to zero when the lag order is two, therefore $p = 1$ or $p = 2$ can be supposed of. To consider that the verdict is subjective, to establish a more exact model, the scope of valuations of *p* and *q* is appropriately loose, and dissimilar ARMA (*p*, *q*) models are proven.

Figure-7. Autocorrelation and partial autocorrelation function tables of the main model series

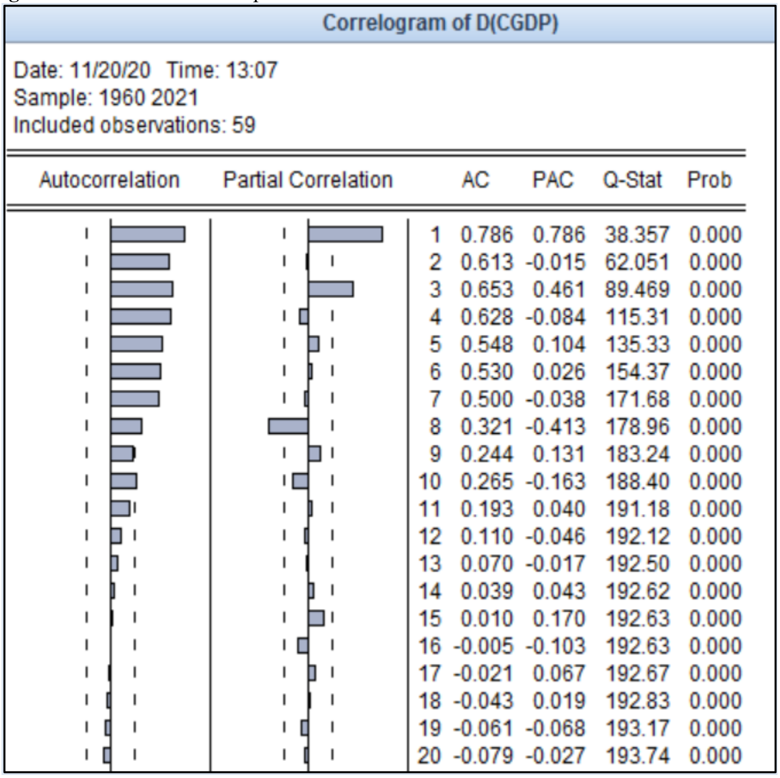


Table-8. Test results of ARMA (p, q)

(p, q)	Adjusted R-squared	AIC	SC	S.E. of regression
(0,1)	0.058600	-1.951745	-1.881320	0.089684
(0,2)	-0.000203	-1.891154	-1.820729	0.092442
(1,0) *	**0.067918**	**-2.105000**	**-2.033950**	**0.083045**
(1,1)	-0.003635	-2.073358	-2.001672	0.084344
(1,2)	0.066319	-2.086821	-1.980247	0.083116
(2,0)	0.055638	-2.075446	-1.968872	0.083590
(2,1)	0.019139	-2.079572	-1.972043	0.083382
(2,2)	-0.019962	-2.040482	-1.932953	0.085028

Table 8 reports the test results of ARMA (p, q) for several parameters. It can be seen that the Adjusted R-squared, Akaike info criterion (AIC) worth, Schwarz criterion (SC) worth and S.E. of regression are exceedingly significant standards for selecting models. The AIC and the SC criteria are essentially used for determined, and choice the best model. It has to be stressed that in spite of the truth that the suitable ARMA model is usually selected applying the AIC esteem and the SC esteem. However, the minimize values of the AIC and the SC are not enough circumstances for the optimal ARMA model. Following (Lihua Ma *et al.*, 2018), This work first creates a model with the minimized AIC and SC values, after that, make a parameter significance test and a residual randomness test on the assessment result. If the model pulls off the test, the model can be considered as the best model. Table 8 reports the model that had success the parameter significance test and the residual randomness test, it specified via "*".

3.2.3. Model establishment and inspection

The estimated results with the ARIMA model are as follows. Table 9. Reports that the LCGDP sequence is ARIMA (1, 1, 0). Moreover, the Equation (5) illustrates the specified shape of the model. Besides, the t-Statistic values of all the model variables are significant and the P values are less than 0.05.

Table-9. Estimation results of the ARIMA model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.098869	0.014935	6.619996	0.0000
AR(1)	0.268840	0.118426	2.270114	0.0271
R-squared	0.084270	Mean dependent var		0.097549
Adjusted R-squared	0.067918	S.D. dependent var		0.086017
S.E. of regression	0.083045	Akaike info criterion		-2.105000
Sum squared resid	0.386200	Schwarz criterion		-2.033950
Log likelihood	63.04499	Hannan-Quinn criter.		-2.077324
F-statistic	5.153418	Durbin-Watson stat		2.109763
Prob(F-statistic)	0.027069			
Inverted AR Roots	.27			

The information in brackets beneath the equation is the t-test statistic of the corresponding gauge esteem

$$\Delta\ LUSAGDP = 0.098869 + 0.268840 * AR(1) \qquad (5)$$

Equation (6) illustrates that the estimated of the variance of the corresponding error expression is

$$\hat{\sigma}_a = 0.083045 \qquad (6)$$

Figure 8 reports the model is used to appropriate the DLCGDP data. The real data are given by the rigid line, and the upper and lower dotted lines harmonize to the suited, values residual of the model.

Figure-8. Actual series, fitted series and residual series of the DLCGDP sequence

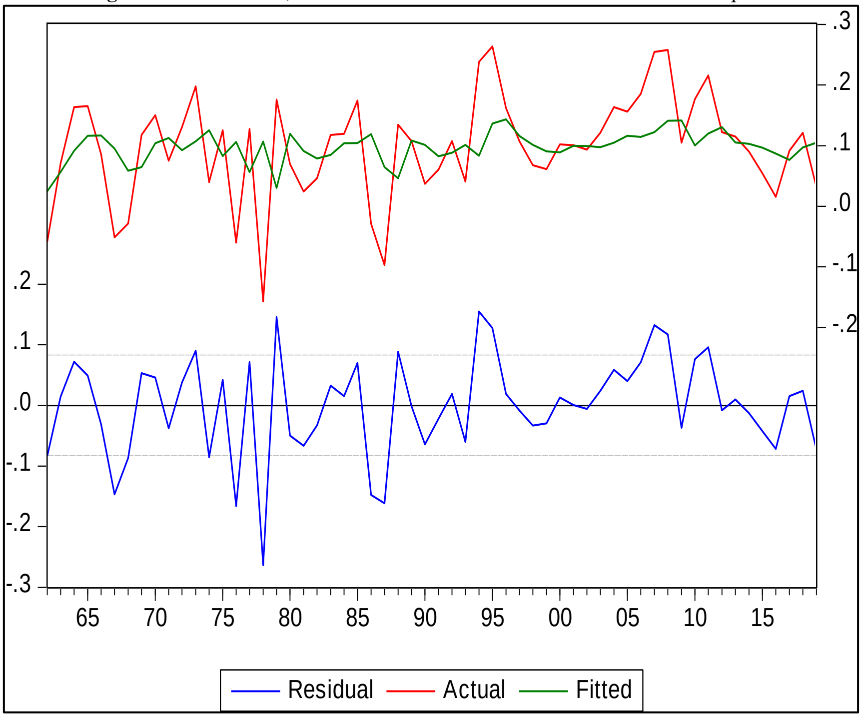
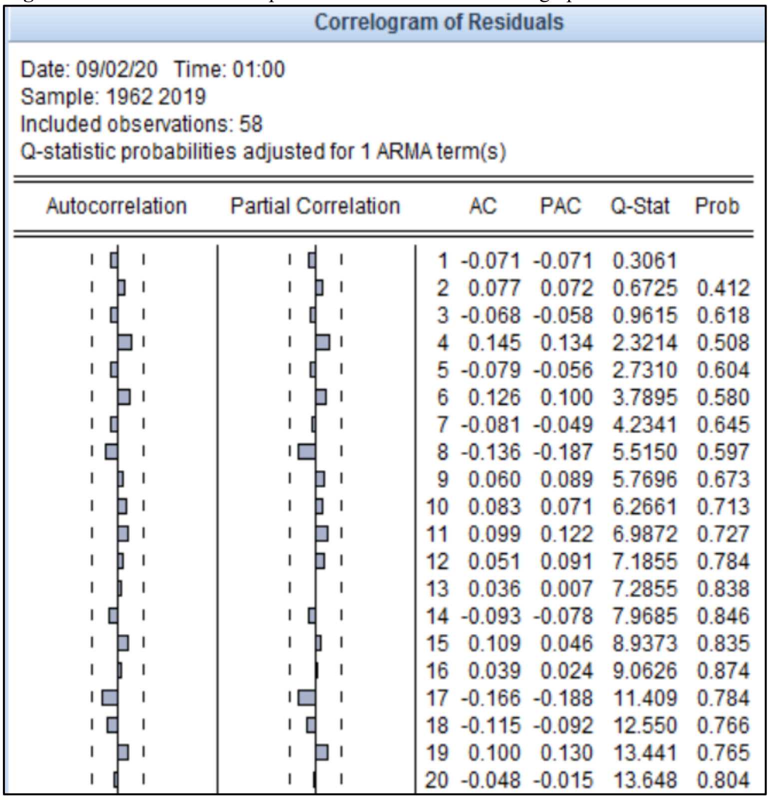


Figure 9 illustrates the autocorrelation and partial autocorrelation function graphs of the residual series, and the residual is a white fuss, representing that the model is adequate.

Figure-9. Autocorrelation and partial autocorrelation function graphs of the residual series


Correlogram of Residuals

Date: 09/02/20 Time: 01:00
Sample: 1962 2019
Included observations: 58
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.071	-0.071	0.3061	
		2	0.077	0.072	0.6725	0.412
		3	-0.068	-0.058	0.9615	0.618
		4	0.145	0.134	2.3214	0.508
		5	-0.079	-0.056	2.7310	0.604
		6	0.126	0.100	3.7895	0.580
		7	-0.081	-0.049	4.2341	0.645
		8	-0.136	-0.187	5.5150	0.597
		9	0.060	0.089	5.7696	0.673
		10	0.083	0.071	6.2661	0.713
		11	0.099	0.122	6.9872	0.727
		12	0.051	0.091	7.1855	0.784
		13	0.036	0.007	7.2855	0.838
		14	-0.093	-0.078	7.9685	0.846
		15	0.109	0.046	8.9373	0.835
		16	0.039	0.024	9.0626	0.874
		17	-0.166	-0.188	11.409	0.784
		18	-0.115	-0.092	12.550	0.766
		19	0.100	0.130	13.441	0.765
		20	-0.048	-0.015	13.648	0.804

3.2.4. Data Forecasting

Following the same methodology at first, the model is used to test the convenient effect with the CGDP worth in 2019. The estimated worth in 2019 is (1.43429E+13) USA Dollar. The actual worth is (1.39932E+13) USA Dollar and the proportional error is 2.4%. It can be observed that the prediction worth is near to the actual result, representative that the model has a good adequal effect.

Figure-10. Forecast LCGDP, Actual LCGDP

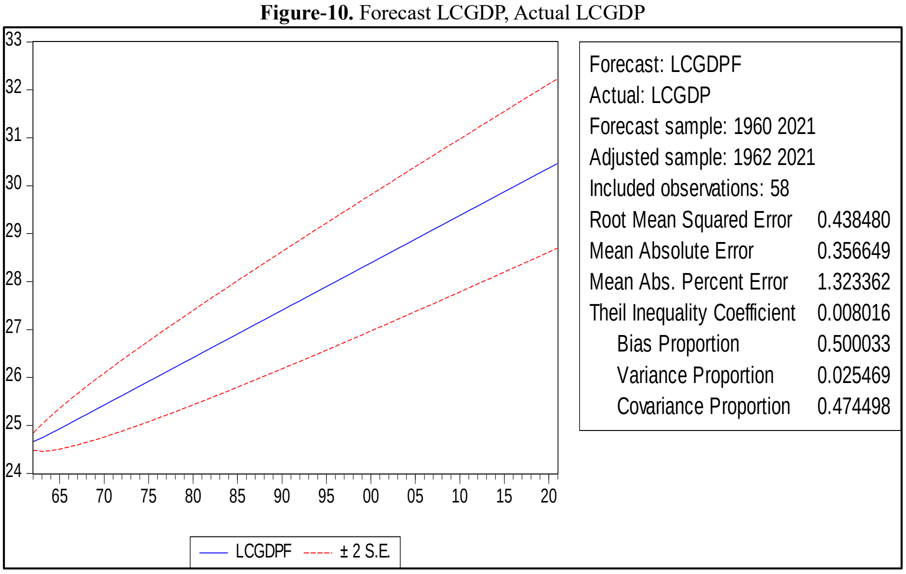


Figure 10 illustrates the prediction of the CGDP. The plot obtained by the EViews program shows the real GDP with solid line and the upper and lower dashed line shows the predicting deviation.

Table-10. China GDP forecast from 2019 to 2021

Year	Forecast USAGDP	variation	Growth rate
2019	13993213010000	-	-
2020	15447410400000	1454197390000	0.103921621786275
2021	17052730340000	1605319940000	0.103921621710782

Table 10 above reports that the CGDP determining estimations of the years 2020 and 2021 is (1.54474E+13), and (1.70527E+13) USA Dollar, respectively. In addition, the relative growth rate 10.39%, about the correspondent for the years 2020 also 2021.

4. Conclusion

ARIMA model gauge is a generally progressed time series forecast technique. It can reasonably depict the dynamic change rules. It very well may be utilized to perform factual investigation and gauge for time series under specific conditions. Exceptionally, the model is appropriate for short-term forecasts. It should be noticed that concerning a particular time series that is dependent upon numerous variables, model forecasts that depend exclusively on current values and historical data now and then have a specific level of deviation from the genuine circumstance. This paper proposed model for predicting GDP of digital economy nations. Where, The ARIMA forecasting model and the GDP for the USA and China are used over the period 1960-2019, to react to the request; what is the potential impact of the recent crisis on the digital economy's growth rate. Two main outcomes have been shown. First, in both 2020 and 2021, the GDP development around 6% for the USA and over 10% for China. Second, the COVID-19 pandemic cannot impact the nations rely upon innovation and digital economy. It tends to be seen that the innovation is assuming a huge function in our everyday life and countries' economies. For the future direction, the researchers recommend additional studies on the impact of COVID-19 pandemic on the digital economies in the world. This subject is addressed by investigating the amended new the GDP time series by the World Bank and measure the change of digital economy trend after the recent crisis.

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