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The Changes in U.S. Labor Market under Covid-19 Pandemic: Based on Time Series Model

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Abstract: In February 2020, the COVID-19 pandemic originally broke out in Wuhan, China and spread out with an extraordinarily rapid rate, resulting the outbreak of pandemic in the global scale and resulting in various economic problems in many countries including change in U.S. labor market, specifically the unemployment rate. This paper applies a non-seasonal autoregressive integrated moving average (ARIMA) model to investigate how much the three categories of unemployment rate (overall, adult, youth) was affected by COVID-19 pandemic while the classification of unemployment is the innovation of this paper. The outcomes of ARIMA model reveals that the impact on all three types of unemployment rate reached the peak at April 2020 whereas the youth unemployment rate was affected the most severely by COVID-19 pandemic compared to overall and adult unemployment rate. From secondary research, border closure, the pause of transportation in the international scale and the restriction of marketing caused by COVID-19 pandemic may be the key of the change in labor market since the oversea transaction was greatly undermined so that the income of many firms declined significantly and they needed to carry out job cut to decrease the cost to make staff's living. To reduce this kind of impact, governments, investors and public are required to prepare well to reduce the unemployment when encountering a pandemic so that the basic social well-being can be guaranteed as much as possible in this type of emergency circumstances.

Keywords: COVID-19, unemployment rate, time series, ARIMA model

1. Introduction

Dating back to December 2019, the COVID-19 virus was discovered and broke out accidentally in Wuhan, China and rapidly transmitted in the global scale [1]. And after about 90 days on 11 March 2020, the World Health Organization (WHO) announced to globe that COVID-19 virus has leaded to a grievous pandemic according to the extremely powerful infectivity [2]. As a result, in the following three years, people's life and industries were significantly affected in numerous concepts such as education, medical service, transport and also including unemployment. The unemployment rate, defined as people losing their occupations but still expecting for a new job and used to manifest the proportion of people of unemployment, can be an indicator of the economic level of a particular area [3]. According to the data collected by International Labor Organization (ILO), it is shown that since the COVID-19 pandemic started, there were at least 220 million people who became unemployed and even after the infection peak in 2022, approximately 205 million people were in the state of unemployment [4]. Meanwhile, in the COVID-19 pandemic, with the economic recession highlighted in certain countries [5], researchers composed reports that the unemployment rate in the second quarter of 2020 would be greater than those throughout the Great Recession in the United States, the world's largest economy and the subject of this article [6].

It is affirmative that comprehending how the unemployment rate reflects or represents the social or economic problems and what the detriments were brought is exceedingly meaningful to clarify the significance of this paper. A study concluded that it is the unemployment which can be an immediate flashpoint of crime according to the positive correlation between these and a further conclusion was obtained: High unemployment rate means high crime rate, which was extremely risky to residents' security [7]. Another article proposed that there arises a mutual interaction and a vicious circle between poverty and job loss: Unemployment raises the probability of suffering from poverty and correspondingly, poverty exacerbates the status quo of being rough to seek a job [8]. What is worth referring to is that despite not sufficient evidence to reveal unemployment is related to physical problems, a substantial number of researchers carried out analysis on the psychological issues coming from unemployment. For instance, many enterprises utilize job cut to improve the enormous financial burden while a huge organization made up by laid-off people especially by elderly people was produced, regarded as people with inferior capabilities and becoming victims of discrimination [9]. Consequently, those victims are prone to psychiatric problems such as depression and substance abuse due to individual level of analysis implemented in a study and even the tendency of suicide based on another research using random-effects meta-analysis executed on five population-based studies [10,11]. Hence, unemployment is an indispensable reason of these severe issues from an individual to the whole society and analyzing the pandemic's effect and the cause of formation for unemployment rate are consequential.

Currently, the academic circle has conducted in-depth research on the impact of the COVID-19 on the economy, particularly its effects on the labor market. With the retrospect to preceding analysis, previous researchers used numerous mathematical methods to analyze the economic data and estimate them or produce forecast on them using statistical models. Here are examples of research placing an emphasis on economic issues and applying statistical models. The exertion of difference-in-difference model is exerted in order to determine how great the COVID-19 pandemic affected the minority unemployment and simultaneously, a decomposition was implemented to find which factors had relatively large contribution to this effect [12]; Regression analysis, correlation analysis and analysis of variance were used for investigating and predicting the Albanian economic situation quantitatively to derive the conclusion that the quantity of workers and the price of product are contributory factors to the income level [13]; The "Bartik shock" strategy were applied in the evaluation of whether an unemployment insurance is an important and essential adjustment to alleviate the sensitivity in the economy [14]; The Auto Regressive Distributed Lag (ARDL) estimator was put into the establishment of long-term correlation between trade openness and income equalities in China, assisting researchers to obtain the conclusion that a positive correlation exists between these two variables [15]; A paper that focused on a similar topic of this paper but concentrated on the unemployment rate in the United States throughout the pre-pandemic time prior to 2020, invoking a Autoregressive Integrated Moving Average (ARIMA) model and a Seasonal Autoregressive Integrated Moving Average (SARIMA) model, revealed that ARIMA (2,2,0) is the most appropriate model to produce forecasts of unemployment rate in the short run by checking and contrasting the mean square error (MSE) of all conceived statistical models [16]. The diverse models applying on different economy circumstances are proved to be feasible and successful among the bygone economic studies. In this case, a suitable model will be picked in this paper to help derive an answer (Specific clarification of the model will be given in methodology part).

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Eventually, it is indispensable to check the common answers towards the question of COVID-19 pandemic's impact on unemployment rate in the United States summarized in previous papers as supportive pillars to this thesis. One piece of research, as a representative of preceding pieces of research and functioning ARIMA model with X-12 decomposition, claimed that the COVID-19 epidemic caused an overall employment loss of 10.51% (95% confidence interval [10.28%, 10.73%]) and the most predominant influence by the pandemic was during the period April to December, 2020 [17].

However, in this paper, a highlight and also an innovation ignored by bygone researchers is that the unemployment is categorized into three types: overall, adult (aged 25-54) and youth (aged 15-24) unemployment rate, discussing the unemployment rate considering the ages in the United States. The discussion part will compare the consequences produced in results part with the conclusion mentioned by the previous researchers.

The following sections of this paper will be written as follows: Section 2 is research design, which clarifies data sources as well as used model; Section 3 will present the results from the analysis of statistical model; Section 4 will discuss the latent reasons of results based on previous researchers; Section 5 will summarize the main discovery, known as the conclusion, derived in this paper.

2. Research Design

2.1. Data Source

Among all the countries in the world, the United States was chosen to analyze the pandemic's impact on unemployment rate as mentioned in section 1. The dominant reason is that as the world's largest economy, the economic circumstance or more specifically, the labor market of the United States can be a representative of most of the countries or most of the developed countries, with preceding researcher's inference that a long-term economic downturn and unprecedented jeopardies will be initiated [18].

It is crucial to attain the data of unemployment rate in the United States from certain database. Among a variety of databases, the data from OECD were chosen for following analysis. Here are three reasons for utilizing data in OECD platform rather than in other platforms. Firstly, OECD provides monthly data whereas other databases barely offer quarterly or yearly data, which has less precision than monthly data. The second apparent benefit is that the data in the last 12 years are available for viewers including the data during the COVID-19 pandemic, supplying sufficient amount of data for statistical models to implement analysis. And what is the most vital is that the unemployment rate in OECD has been classified into three types via people's ages referred in Section 1. In that case, unemployment related to ages in the pandemic in the United States can be surveyed.

2.2. Augmented Dickey–Fuller (ADF) Unit Root Tests

Initially, testing whether or not the unemployment data is required using Unit Root Tests. If the data are stationary or in other words, do not have any predictable patterns chronically, then they will be applied in the forecasting model in Section 2.3; If not, a process is needed to be conducted, known as differencing, which is a method to make non-stationary data stationary. In Table 1, for raw data, the p-values for three types of unemployment data all exceed 5% level of significance, which means that they are all non-stationary. Therefore, a differencing process is executed to make them stationary and in the row of 'Difference', p values are all equal to 0, which are regarded statistically significant after differencing.

Table 1: ADF Test.

Variables		t-statistic	p-value
Raw			
	Overall	-2.522	0.3169
	Adult	-2.485	0.3354
	Youth	-2.954	0.1455
Difference			
	Overall	-8.939	0.0000
	Adult	-9.072	0.0000
	Youth	-9.611	0.0000

2.3. Autoregressive Integrated Moving Average (ARIMA) Model

To quantitatively investigate the impact from the COVID-19 pandemic on unemployment in the United States, an autoregressive integrated moving average (ARIMA) model and more specifically, a non-seasonal one is used shown in (1) [19].

$$y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \tag{1}$$

The series represents the differenced series, where parameters in the right contain both lagged values of y_t and lagged errors [19]. And this model is known as ARIMA (p, d, q) model, where p is the order of autoregressive part, d is the degree of first differencing included and q is the order of moving average part [19]. What has been mentioned in section 2.2 is that one-degree of first differencing was carried out to make the three groups of original data stationary and consequently, parameter d in three groups is 1.

The next phase, is to determine the other two unknown parameters, p and q. To accomplish this objective, partial autocorrelation function (PACF) plots and autocorrelation function (ACF) plots, which can help find approximate p and q respectively, are required to be displayed. After this step, the PACF plots (produce parameter p) and ACF plots (produce parameter q) are observed while the ACF values and PACF values of all the data will be compared with two categories of boundaries, which are defined using 95% confidence bands with formula $\pm 1/\sqrt{T}$ and Bartlett's formula for moving average of q respectively, so that any values above or below these boundaries can be attempted to be the p and q and vice versa for values within the 95% confidence bands.

In the next stage, all the possible p and q values will experience Portmanteau test which are used to check whether the residuals are white noises and thereby, the values of p and q that have the best performance in this test will be applied to establish the ARIMA model. Ultimately, the fitted values can be illustrated via computing shown in and hence the assessment with comments in terms of the impact on unemployment rate is accessible.

3. Results

3.1. The Order of ARIMA (p, d, q) Model

In section 2.3, it has been confirmed that the value of parameter d is 1 for all three categories of unemployment in the United States. The following content will illustrate the determination of other two parameters p and q using PACF and ACF plots.

3.1.1. Overall Unemployment Rate

In terms of the overall unemployment rate, apparently, there are 8 values of PACF which are outside the 95% confidence band (Values just reach the boundaries are ignored in all the plots.) referred in section 2.3 (Fig. 1). Via calculation from the programming software, parameter p=3 is the value whose consequence of residual test is the best one among all the values. (Specification of the residual test will be shown in section 3.2 and so do all the tests mentioned in section 3.1.

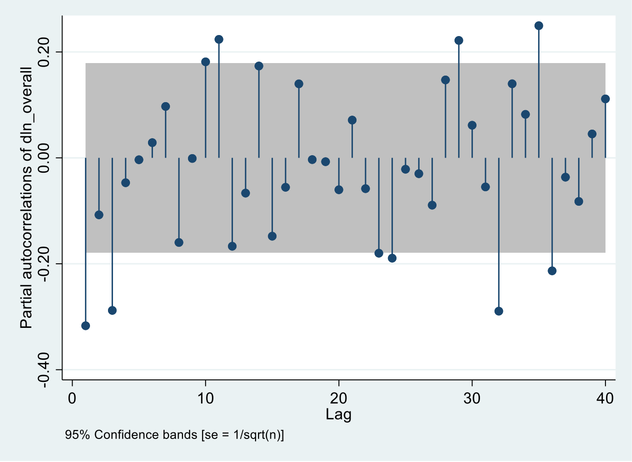

Figure 1: PACF plot for overall unemployment rate in the United States.
Photo credit: Original

Meanwhile, the ACF plot manifests that there are merely three values exceeding the critical values (Fig. 2). By contrasting the outcomes of residual tests, the most suitable parameter q=3 can be selected.

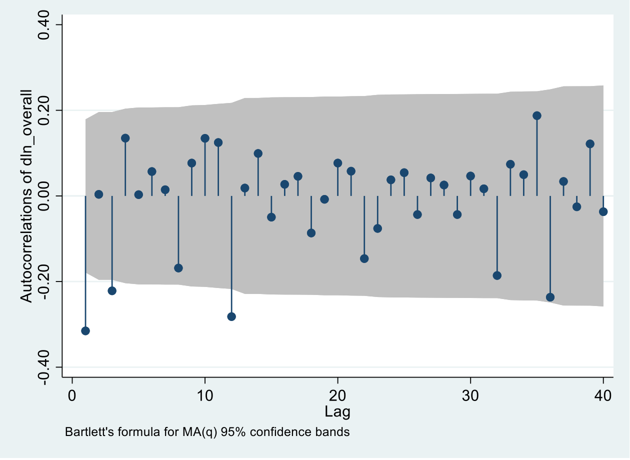

Figure 2: ACF plot of overall unemployment rate in the United States.
Photo credit: Original

Therefore, according to all the results above, the most adequate model for overall unemployment rate is ARIMA (3,1,3).

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3.1.2. Adult Unemployment Rate

Using the same approach for adult unemployment rate, it is clear to be spotted that there are 8 values of PACF surpassing the boundaries (Fig. 3). The residual test indicates that the p value of 2 has the best performance and hence p is equal to 2.

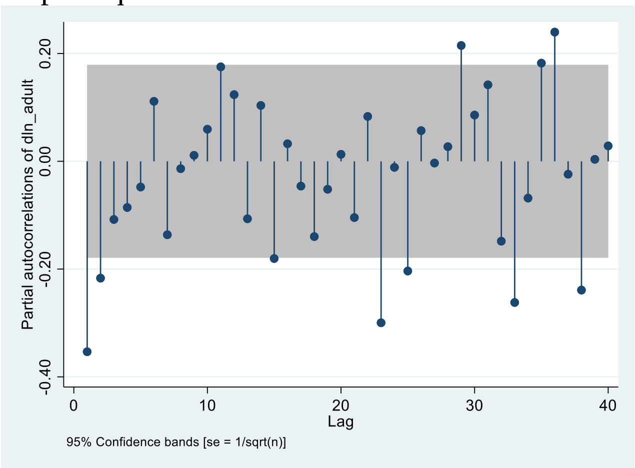

Figure 3: PACF plot for adult unemployment rate in the United States.
Photo credit: Original

Particularly, only one ACF value in this group of data is out of the 95% confidence band hence with a good result in residual test q in this circumstance is 1 (Fig. 4).

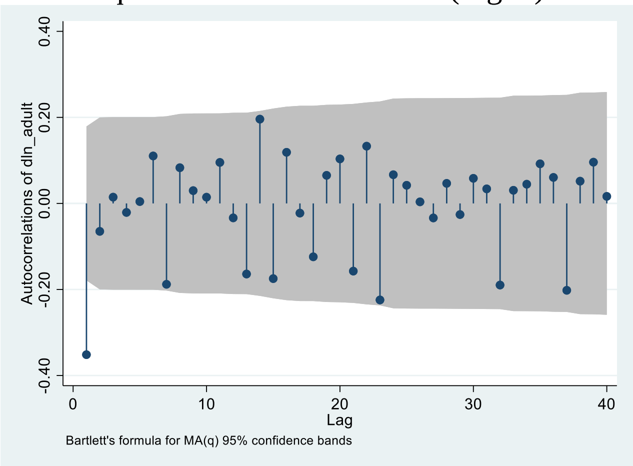

Figure 4: ACF plot for adult unemployment rate in the United States.
Photo credit: Original

To summarize, the model established for adult unemployment rate is ARIMA (2, 1, 1).

3.1.3. Youth Unemployment Rate

Likewise, the corresponded PACF for youth unemployment rate plot ought to be observed and there are 6 value laying outside the boundaries (Fig. 5). From residual test, it turns out that p=1 is the most suitable parameter for this group of data.

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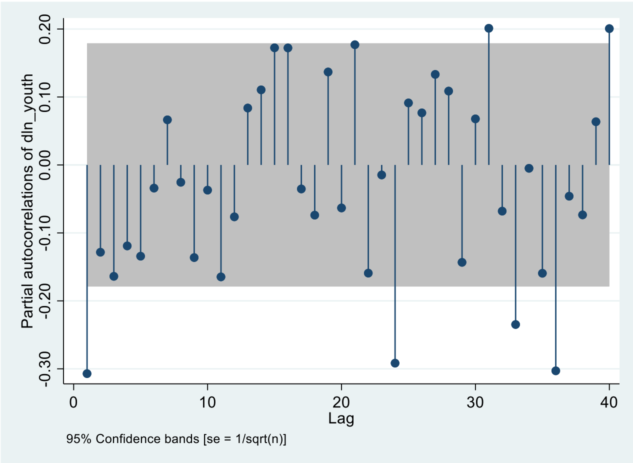

Figure 5: PACF plot for youth unemployment rate in the United States.
Photo credit: Original

Similarly, ACF plot is viewed and there are 3 values within the critical region (Fig. 6). By checking the residual, setting parameter q=1 is filtered and has the best performance thus q is equal to 1 in the ARIMA model.

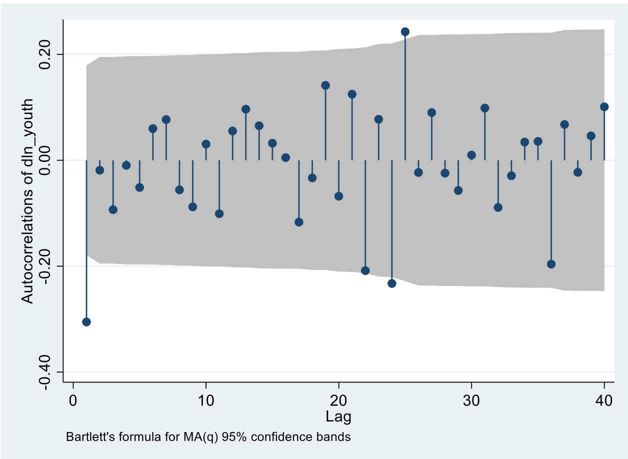

Figure 6: ACF plot for youth unemployment rate in the United States.
Photo credit: Original

Overall, the used model for youth unemployment rate is ARIMA (1, 1, 1).

3.2. Analysis for Results

3.2.1. Residuals Check

It has been suggested that the residuals check is used to pick out the best parameter in the ARIMA model. Then in this part, the specific clarification will be given according to quantitative results.

From Table 2, with the significance level of 1.0000 and 0.9960 corresponded to adults and youth unemployment rate respectively, the two ARIMA models chosen from computing are proved to be accurate and feasible as white noises whereas, despite the best performance among all the values in section 3.1.1, the significance of overall unemployment rate is merely 0.0274, which means less accuracy and feasibility compared to other two outcomes.

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Table 2: Residual test results.

Model	Portmanteau (Q) statistic	Prob > chi2
Overall	58.8760	0.0274
Adult	9.9108	1.0000
Youth	20.2567	0.9960

3.2.1. Analysis of Outcomes of ARIMA Models

After the parameter selection, the following content will focus on the outcomes of ARIMA model derived from programming software.

The approach to estimate the impact from COVID-19 pandemic is to make contrast between the data in the reality (blue) and fitted values (orange) produced by forecast. And as the forecast producing by ARIMA model is based on the data in the past without the pandemic, the difference between two values can demonstrate the influence by the pandemic. However, as the time proceeds after the outbreak of pandemic (February 2020), the forecast would use the data in the pandemic and the ingredients for forecast would contain more and more proportion of the impact of pandemic. Hence, the estimation efficiency decreases with the time scale and this method is the most efficient at the beginning of the pandemic, with a quantitative and specific range using p value in ARIMA (p, d, q). Consequently, a slight difference between two lines in the first two months after the outbreak of pandemic in terms of overall unemployment rate with ARIMA (3, 1, 3) but then a sharp growth occurs, extending greatly the gap between two lines to 10.7517% in April 2020 (Fig. 7).

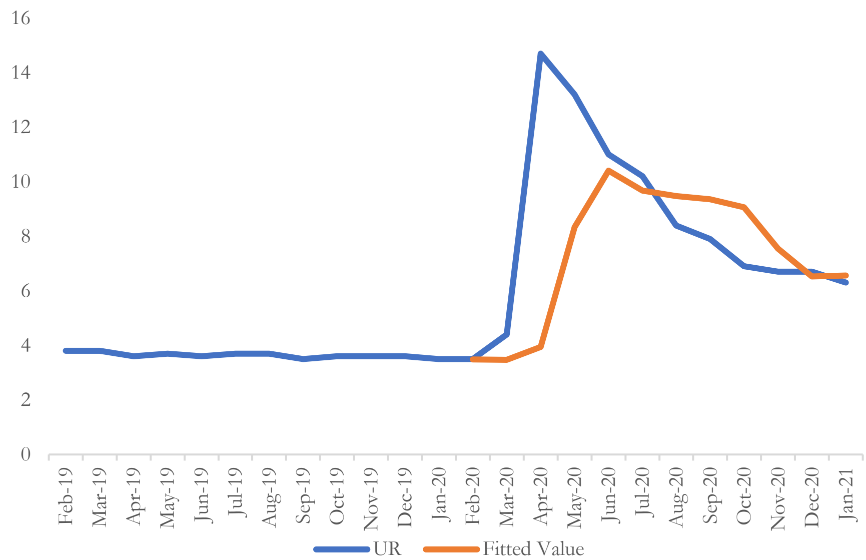

Figure 7: Outcomes of ARIMA model for overall unemployment rate.
Photo credit: Original

A similar pattern can be monitored for adult unemployment rate with ARIMA (2, 1, 1) (Fig. 8). Although the parameter p=2 restricts the estimation-efficiency region to less than two months, adult unemployment rate in April 2020 is the most influenced by the pandemic with a gap of 9.1563% between fitted and real values.

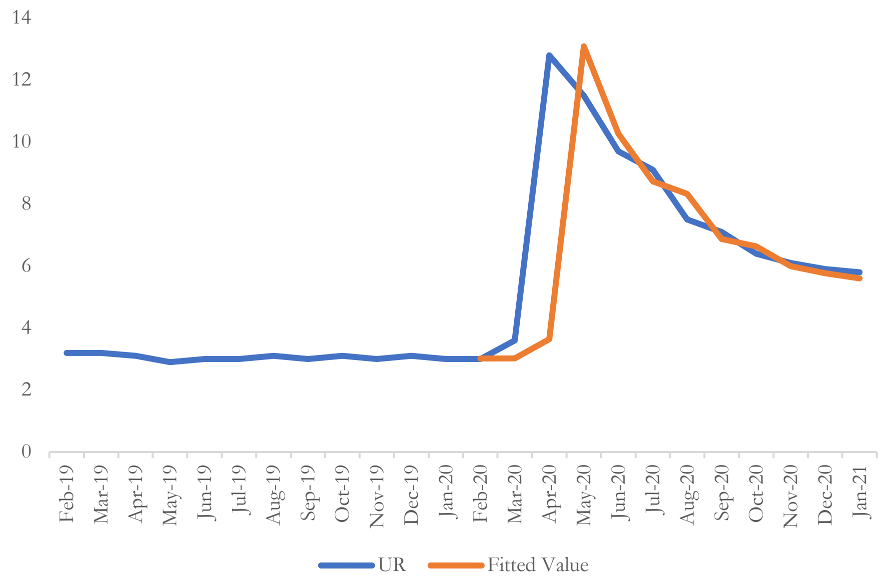

Figure 8: Outcomes of ARIMA model for adult unemployment rate.
Photo credit: Original

Likewise, an analogous shape is displayed for the youth unemployment rate (ARIMA (1, 1, 1)) while the gap between two lines peaked at 16.9242% in the same period- April 2020.

To summarize, a brief answer has emerged in these results: the impact of COVID-19 pandemic was the maximum in April 2020 and the youth unemployment rate was affected to the most predominant extent among all three types of unemployment rate discussed above.

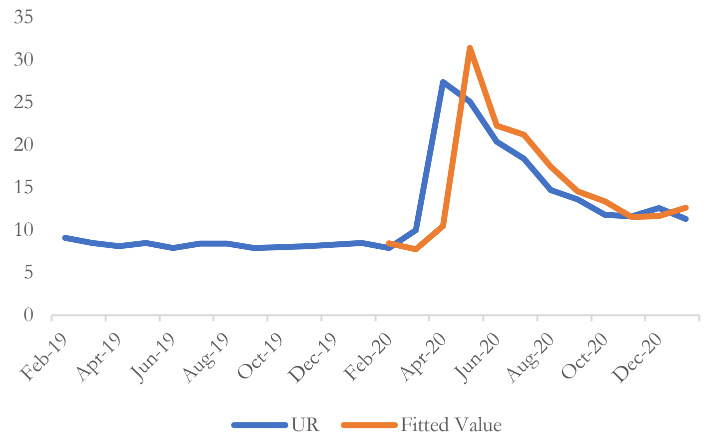

Figure 9: Outcomes of ARIMA model for youth unemployment rate.
Photo credit: Original

4. Discussion

With contrast to the previous studies, the results in section 3 can be verified. It is interesting that similar results were derived via both non-seasonal ARIMA model in this paper and X-12 ARIMA model in the previous paper. And the previous paper also indicates that the COVID-19 pandemic was the most influential on unemployment rate (overall) in April 2020, with quantitative loss 10.51%, which is very close to 10.7517% in this paper [17]. Hence, the results in this paper can be supported.

When it comes to the latent reason of the tremendous influence of COVID-19 on labor market in the United States, border closure, the pause of transportation in the international scale and the restriction of marketing caused by COVID-19 pandemic may be the key since the oversea transaction was greatly undermined so that many companies' income declined significantly and they needed to carry out job cut to decrease the cost to make staff's living [20].

5. Conclusion

The purpose of this whole paper is to explore to what extent COVID-19 pandemic had an impact on the variation of labor market in terms of three categories of unemployment rate (overall, adult, youth) in the United States. A non-seasonal autoregressive integrated moving average model (ARIMA) is exerted to explore at what period COVID-19 pandemic was the most influential on unemployment rate in the United States and compare this impact among three types of unemployment rate.

In conclusion, the impact on all three types of unemployment rate reached the peak at April 2020 whereas the youth unemployment rate was affected the most severely by COVID-19 pandemic compared to overall and adult unemployment rate. And looking ahead, it is vital for governments, investors and public to prepare well to reduce the unemployment when encountering a pandemic so that the basic social well-being can be guaranteed as much as possible in this type of emergency circumstances.

Furthermore, this paper excavates some recommendations to governments and investors. The phenomenon that the youth unemployment rate was influenced the most compared to adult unemployment rate by COVID-19 pandemic indicates that governments can fund those juvenile jobless (15-24 years old) via giving them appropriate financial welfare. Another suggestion coming from results is that investors ought to endure the risk of being unemployed after a pandemic breaks out especially for the period three months to one year after the pandemic, or they must do sufficient preparation to prevent them from unemployment or even going bankrupt. Also, for ordinary citizens, it is important to evaluate and choose a vocation which has a stability as high as possible so that it is less likely to for them to lose their jobs and meanwhile, they must prepare well with the coming of pandemic particularly in the two or three months after the start of pandemic by enhancing their performance on workplace and accumulating sufficient money for living.

References

[1] *L. Cui, D. Lee, (2020). CoAID: Covid-19 healthcare misinformation dataset. arXiv preprint arXiv:2006.00885: 1-9.*

[2] *Ö. Açikgöz., A. Günay, (2020). The early impact of the Covid-19 pandemic on the global and Turkish economy. Turkish journal of medical sciences, 50(9), 520-526.*

[3] *K. M. Murphy, R. Topel, (1997) Unemployment and Nonemployment. The American Economic Review, 87(2): 295-300.*

[4] *Z. Wang, X. Chen, (2022) Research on the Interference Process of China's Unemployment Rate Based on the Optimal Transformation Transfer Function. Mathematics in Practice and Theory, 52(7): 67-74.*

[5] *D. Guo, (2020) Research on the Economic Impact Effect of Disaster Risk and the Choice of Monetary Policy Mechanism——Economic simulation of COVID-19 based on DSGE model. International Financial Research, 8: 24-25.*

[6] *A. Gangopadhyaya, B. Garrett, (2020) Unemployment Health Insurance and the COVID 19 Recession. Health Insurance, and the COVID-19 Recession: 1-8.*

[7] *K. Edmark (2005) Unemployment and crime: Is there a connection? Scandinavian Journal of Economics, 107(2): 353-373.*

[8] *D. Gallie, S. Paugam, S. Jacobs, (2003) Unemployment, poverty and social isolation: Is there a vicious circle of social exclusion? European societies, 5(1): 1-32.*

[9] *R. Karren, K. Sherman (2012) Layoffs and unemployment discrimination: A new stigma. Journal of Managerial Psychology, 27(8): 848-863.*

[10] *D. Dooley, J. Fielding, L. Levi, (1996) Health and unemployment. Annual review of public health, 17(1): 449-465.*

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[11] A. Milner, A. Page, A. D. LaMontagne, (2014) Cause and effect in studies on unemployment, mental health and suicide: a meta-analytic and conceptual review. Psychological medicine, 44(5): 909-917.
[12] K. A. Couch, R. W. Fairlie, H. Xu, (2020) Early evidence of the impacts of COVID-19 on minority unemployment. Journal of Public Economics, 192: 104287.
[13] B. Shyti, D. Valera, (2018) The Regression Model for the Statistical Analysis of Albanian Economy. Int. J. Math. Trends Technol, 62(2): 90-96.
[14] M. Di Maggio, A. Kermani, (2016) The importance of unemployment insurance as an automatic stabilizer. National Bureau of Economic Research: 11-14.
[15] A. Jalil, (2012) Modeling income inequality and openness in the framework of Kuznets curve: New evidence from China. Economic Modelling, 29(2): 309-315.
[16] P. Shao, (2020) Research on the prediction of American unemployment rate based on ARIMA time series model. International Public Relation, 108(12): 395-396.
[17] W. Gui, J. Zhao, (2021) The impact of the COVID-19 on the unemployment rate of China US surveys. Research World, 338(11): 15-26.
[18] A. Sharif, C. Aloui, L. Yarovaya, (2020) COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. International review of financial analysis, 70, 101496.
[19] R. J. Hyndman, G. Athanasopoulos, (2018) Forecasting: Principles and Practice (2nd edition). OTexts.
[20] B. Kozicki, M. Gornikiewicz, (2020) Unemployment rate in Poland and USA during COVID-19 pandemic: a case study.