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The Influence of Gender Disparities on the Unemployment Rate in the United States amid the Covid-19 Pandemic

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Abstract: The COVID-19 pandemic, which emerged in late 2019 and quickly spread globally in 2020, hit economic activity tough in most countries. In the United States, the socially enforced shutdown and economic stagnation caused by the pandemic led to a rapid rise in unemployment from the first quarter of 2020 onwards. Although the rise in unemployment rates in the US during the pandemic involves individuals of every gender, the COVID-19 pandemic's effects on the rise in unemployment rates were different for men and women, according to examination of statistics on unemployment for both genders from 2010 to 2023, with women experiencing a greater increase in their unemployment rate compared to men during the pandemic. Moreover, by constructing an ARIMA model based on the unemployment rates of different genders from 2010 to 2019, this paper predicts the unemployment rate of the United States from 2020 to 2023 under the assumption of no pandemic effects. It can be observed that the pace of decline in female unemployment rates during the pandemic was larger than that for male unemployment rates by comparing the gap between the prediction model and the actual data, and by January 2023, whether overall unemployment rates or unemployment rates across different genders were significantly higher than those predicted by the ARIMA model. The data compilation and analysis presented within this paper are useful in understanding the impact of public health events on employment status based on gender differences, and in providing a reference for post-COVID-19 mitigation policies.

Keywords: Covid-19, gender, unemployment, ARIMA model

1. Introduction

The COVID-19 pandemic has exerted a substantial influence on the US economy [1]. First, policies implemented by the state and federal governments to ensure social distancing have severely affected the normal functioning of businesses and investor expectations [2]. Within a week from February 24th to 28th, the value of the world stock market fell by around $6 trillion, with the US Standard & Poor's 500 index shedding more than $5 trillion of its worth. The top 10 S&P 500 index businesses were responsible for a loss of more than $1.4 trillion overall [3]. Second, deteriorating business conditions have led to a surge in unemployment. The unemployment rate in the United States, as reported by the US Bureau of Labor Statistics, experienced a significant increase from 4.4% in March 2020 to 14.7% in April 2020 [4]. In this unemployment crisis, which rivals the Great Recession of

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2008, the impact is asymmetric across genders. For the March-April 2020 period, the increase in the unemployment rate was significantly higher for women than for men [5].

In this paper, the author analyzes and argues for the gender disparity observed during the unemployment crisis during the Covid-19 pandemic. It employs unemployment rate data spanning from 2010 to 2019 in order to develop a prognostic framework for analyzing the influence of the pandemic on gender-specific unemployment rates. Overall, the increase in the unemployment rate for women was significantly higher than for men following the pandemic, which is different from the situation in which male employment was more severely affected by the regular recession than female employment. One possible explanation for this phenomenon is that industries predominantly affected by the "standard" recession, such as manufacturing, employ a larger number of men, while women are more concentrated in service and education sectors characterized by weaker cyclicality. In contrast, the current crisis has had a significant impact on service-related occupations where women have higher employment rates, such as the restaurant and hotel industry [6].

A substantial body of literature has focused on examining the effects of pandemics on different genders, yielding conclusions similar to those of this study, namely that the effect on female unemployment is greater than that on male unemployment [5]. For example, Titan Alon et al. argue that, unlike previous recessions, this crisis has a greater impact on female employment than male employment [6]. Stefania Albanesi et al. also note that, unlike traditional recessions, the COVID-19 pandemic has led to a decline in demand for jobs in high-touch and inflexible service industries, while there are less options for quality childcare and on-site education, which has affected the labor pool. Women, who are normally more resilient to recessions than males, saw a significant fall in employment and labor force participation rates as a result of this circumstance. [7].

However, in this paper, the author applied the ARIMA predictive model to analyze the growth rate, the decline rate, and the subsequent effect on the unemployment rate for different genders. First, by subtracting the fitted values of the male and female unemployment rates from their actual rates using the ARIMA model, it is observed that the difference indicates a larger effect for women compared to men. Secondly, tracking the actual rates and fitted values of male and female unemployment rates from April 2020 to January 2023 reveals that after the initial surge in unemployment rates, the rate of decline for female unemployment slightly outpaced that for males, and starting from October 2020, the difference between the actual and fitted values for female unemployment rates became lower than that for males. This phenomenon may be attributed to the rapid recovery of service-related industries, where female employment rates are relatively high, following the gradual relaxation of social distancing policies implemented due to the pandemic.

2. Method

2.1. Data Source

The data in this article is sourced from the OECD website, specifically the Organization for Economic Co-operation and Development. The unemployment rates for men, women, and all individuals in the United States were compiled by the author between January 2010 and January 2023. This paper predicts the unemployment rate from January 2010 to March 2020, before COVID-19's effects on employment rates, using a Stata16-built ARIMA forecasting model. The author conducted an examination and analysis of the gender-specific impact of the COVID-19 pandemic on male and female unemployment rates in the United States by comparing actual unemployment rates with fitted values derived from predictive models.

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2.2. ARIMA Model

In this paper, an ARIMA model is employed as its research methodology. For these objectives of this paper, the time series analysis technique known as the ARIMA (Autoregressive Integrated Moving Average) model is frequently employed. Its general form can be stated as follows:

$$GR_t = \beta_0 + \beta_1 GR_{t-1} + \beta_2 GR_{t-2} + \cdots + \beta_p GR_{t-p} + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q} \quad (1)$$

ARIMA models are widely used for forecasting and modeling time series data. By examining and fitting time series' previous data, it may forecast future patterns and changes. In contrast to the ARMA model, AR and MA have an additional difference step. Where p is the lag order of partial correlogram censoring, and is the number of terms of autoregressive (AR); The quantity d is the number of differentials needed for a stationary sequence to become a non-stationary one. q is the lagged value of the forecast error, that is, the lagged order of the auto correlogram censoring, and is the number of terms of the moving average (MA), with the aim of making the series smoother. The basic idea of the ARIMA model is to build a model that can describe the characteristics of the data through the transformation of autoregressive, moving average, and differential time series data, and use this model to predict future data changes. The ARIMA model can more accurately match the data and is better able to manage the many characteristics of time series data, including seasonality, trend, periodicity, etc. As a result, the ARIMA model has been widely used in economics, finance, meteorology, industrial production, and other fields [8].

2.3. Stationarity Test

After the model is constructed, a stationarity test is first performed on the data to determine the number of discrepancies with respect to the original data. The null hypothesis (H_0) is that the model sequence is not stationary, and the data are imported into Stata16 for testing. As can be seen from Table 1, for the log time series of the overall unemployment rate in the United States, the P-value after once differing is 0.0000, which can reject the null hypothesis (that is, the model series is stationary). For both the US male unemployment rate and the US female unemployment rate's logarithmic time series, the P-value after one difference is 0.0000, which can reject the null hypothesis (that is, the model series is stationary).

Table 1: Weak stationarity test.

	t	p
	Overall	
Raw	-3.116	0.1025
1st order difference	-9.036	0.0000
	Male	
Raw	-2.969	0.1409
1st order difference	-8.920	0.0000
2nd order difference	-14.414	0.0000
	Female	
Raw	-3.348	0.0587
1st order difference	-9.366	0.0000
2nd order difference	-14.570	0.0000

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2.4. Establishing the Moving Average Order Q and the Autoregressive Order P

The authors used Stata16 to create PACF (partial autoregressive function) and ACF (autoregressive function) graphs for the logarithmic time series of differential unemployment rates in order to establish the autoregressive order p and moving average order q of the ARIMA model. Based on these graphs, it was observed that the first order difference series of male and female unemployment rates did not provide significant information to determine the autoregressive order *p* and moving average order *q*. Consequently, it can be concluded that both male and female unemployment rate time series require second order differencing. The corresponding figure is presented below:

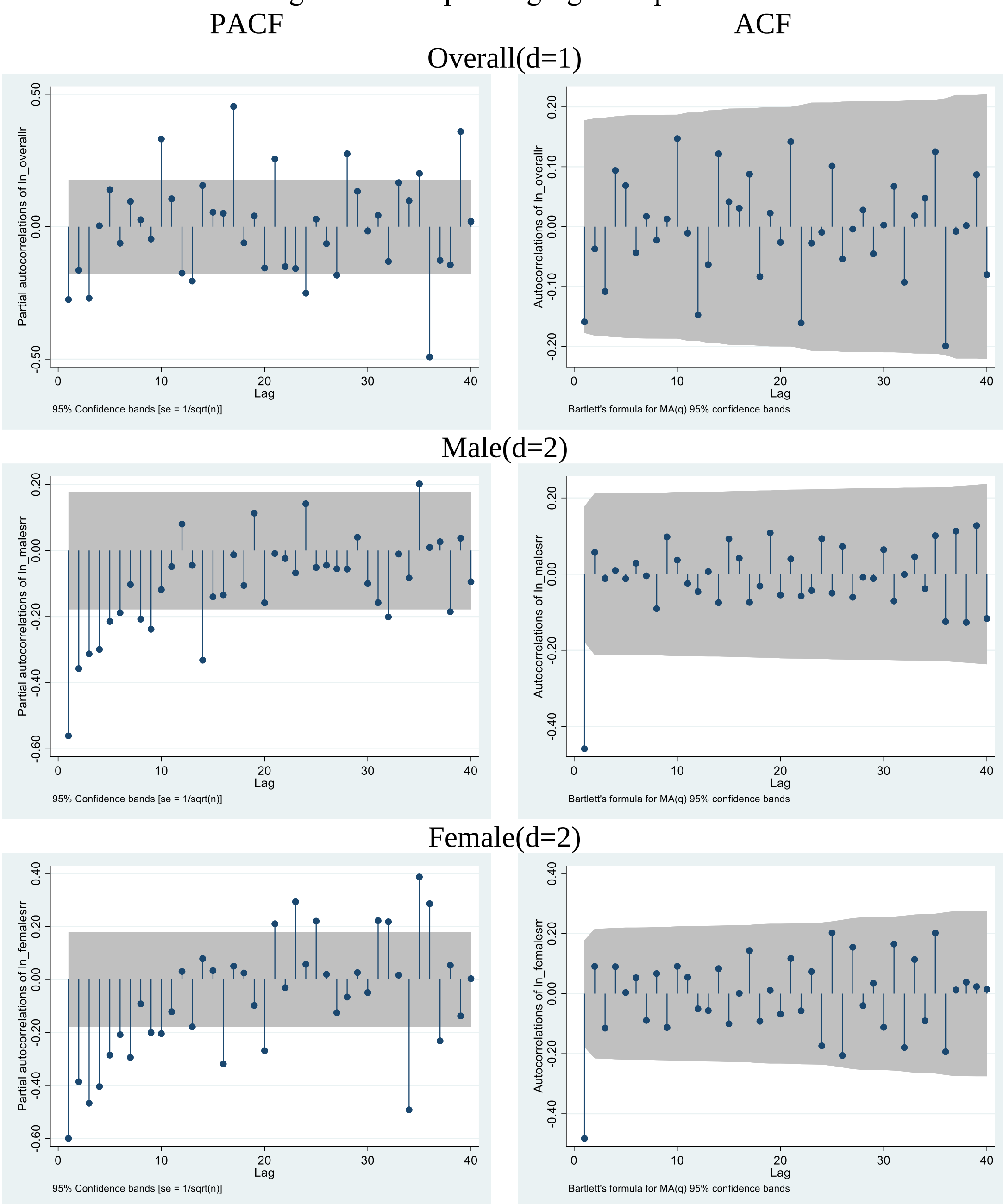

Figure 1: ARMA (p, q) identification.

Photo credit: Orignal

The optimal models determined for the overall unemployment rate, male unemployment rate, and female unemployment rate are ARIMA (10,1,0), ARIMA (9,2,1), and ARIMA (10,2,1) respectively.

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2.5. Residual Test

The author employed Stata16 to perform residual tests for the aforementioned three ARIMA models, with the null hypothesis (H_0) being Prob> chi_2. The corresponding results are presented in Table 2:

Table 2: Residual test.

Model	Portmanteau (Q) statistic	Prob > chi2
Overall-ARIMA (10,1,0)	79.8621	0.0002
Male-ARIMA (9,2,1)	40.7475	0.4374
Female-ARIMA (10,2,1)	150.6602	0.0000

The model residual test for the male unemployment rate fails, as evidenced by the data presented in Table 2. Despite this setback, the model remains applicable for predicting unemployment trends in a post-pandemic scenario; however, its accuracy may be compromised.

3. Results

The authors have utilized the ARIMA (10,1,0) model to project the overall unemployment rate from April 2020 to January 2021. Additionally, they employed the ARIMA (9,2,1) model for male unemployment and the ARIMA (10,2,1) model for female unemployment. Table 3 exhibits the appropriate results:

Table 3: Actual and fitted value.

	Overall			Male			Female		
	Actual	Fitted	Diff	Actual	Fitted	Diff	Actual	Fitted	Diff
Jun-19	3.60			3.60			3.60		
Jul-19	3.70			3.70			3.70		
Aug-19	3.70			3.70			3.60		
Sep-19	3.50			3.60			3.40		
Oct-19	3.60			3.70			3.50		
Nov-19	3.60			3.60			3.60		
Dec-19	3.60			3.50			3.60		
Jan-20	3.50			3.50			3.50		
Feb-20	3.50			3.50			3.40		
Mar-20	4.40			4.40			4.40		
Apr-20	14.70	4.00	10.70	13.50	4.12	9.38	16.20	3.88	12.32
May-20	13.20	3.98	9.22	12.10	4.01	8.09	14.50	3.77	10.73
Jun-20	11.00	3.77	7.23	10.50	3.90	6.60	11.60	3.72	7.88
Jul-20	10.20	3.91	6.29	9.70	3.91	5.79	10.70	3.87	6.83
Aug-20	8.40	3.98	4.42	8.20	3.94	4.26	8.60	3.95	4.65
Sep-20	7.90	3.88	4.02	7.70	3.90	3.80	8.10	3.90	4.20
Oct-20	6.90	3.98	2.92	7.00	3.88	3.12	6.70	3.93	2.77
Nov-20	6.70	3.86	2.84	6.90	3.82	3.08	6.40	4.06	2.34
Dec-20	6.70	3.95	2.75	6.70	3.87	2.83	6.70	3.98	2.72
Jan-21	6.30	4.09	2.21	6.40	3.86	2.54	6.30	4.11	2.19

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Table 3 includes the fitted values determined by the model, the differences between the actual and fitted values, and the actual values for the overall, male, and female unemployment rates in the United States from January 2019 to January 2020. Figure 2 is obtained by utilizing the data presented in Table 3:

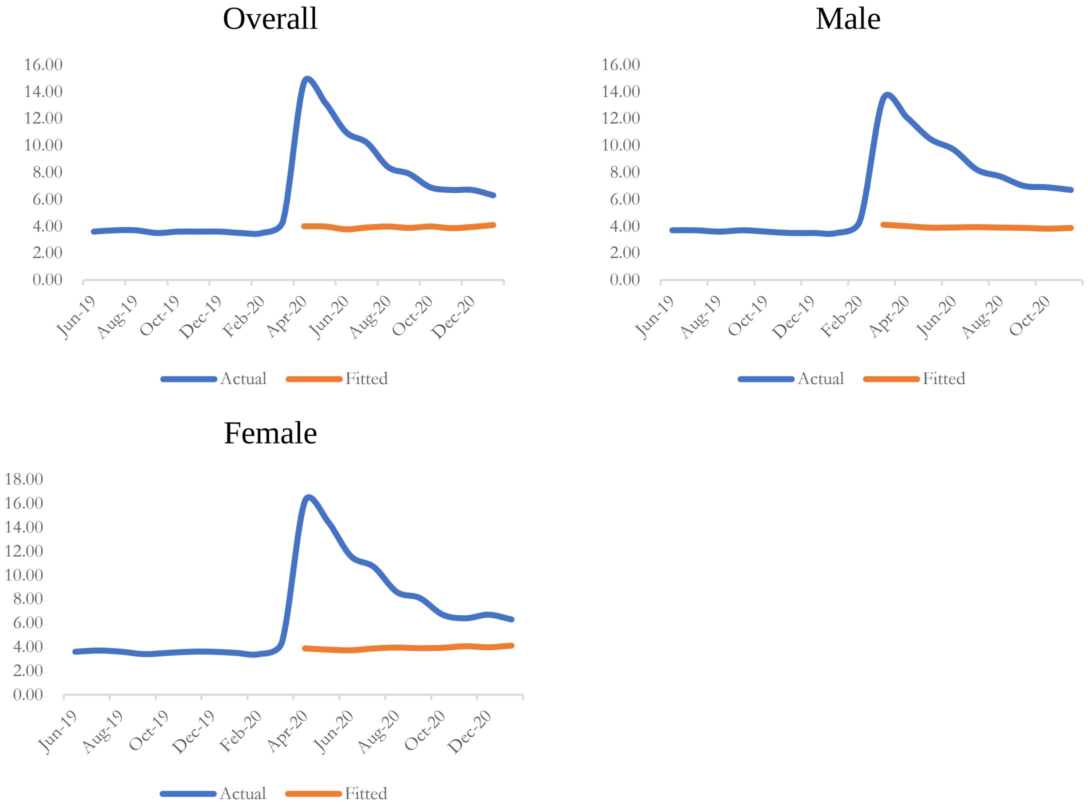

Figure 2: Actual value and fitted value.

Photo credit: Orignal

The authors derive two primary conclusions from their analysis of the discrepancy between the fitted and actual values of the model. Firstly, it is evident that women have been disproportionately impacted by the COVID-19 pandemic in terms of employment, as supported by numerous prior studies [9]. Secondly, following the initial wave of job losses in April 2020, the rate of female unemployment declined significantly faster than that of male unemployment. Moreover, from October 2020 onwards, the discrepancy between the fitted and actual values for female unemployment is significantly reduced when compared to male employment. This remarkable phenomenon has been overlooked in previous studies.

4. Discussion

Regarding the first conclusion of this paper, the average impact of the epidemic on the unemployment rate of women is significantly larger compared to that of men. Early in the pandemic, numerous studies supported this claim and proposed potential explanations for it. For instance, service occupations with a higher proportion of female workers were more heavily affected by government policies aimed at enforcing social distancing [6]. Additionally, the decision to close schools and day care facilities during the pandemic in various countries, including the United States, resulted in increased stress related to child and infant care responsibilities [10].

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The second conclusion of this paper highlights that the rate of decline in female unemployment is significantly higher than that of male unemployment. This phenomenon can be attributed to two factors. Firstly, after numerous service occupations predominantly employing women were shut down due to early-stage epidemic control measures, remote work through social software platforms became prevalent [6]. This development has considerably alleviated the operational pressure faced by the service sector under the pandemic control policy. In contrast to sectors such as construction and chemicals, which have a higher proportion of male employment, service sector jobs with a significant number of female employees offer workplace flexibility that contributes to a faster reduction in female unemployment. Secondly, online distance education has emerged as an effective solution to ease the burden of childcare on women [11]. The prevalence of this educational model enables women to effectively fulfill their job responsibilities online, while increasing labor force participation and mitigating the unemployment crisis within their respective industries [12].

5. Conclusion

The primary objective of this research is to compare how the Covid-19 epidemic affected men and women's unemployment rates in the US. To ensure accuracy, the authors analyzed gender-specific monthly unemployment rate data from 2010 up to the pre-pandemic. Utilizing an ARIMA predictive model, they simulated trends in male and female unemployment rates in the United States, without accounting for epidemics, and compared them to actual unemployment rate values. Based on data simulation and empirical analysis, two main conclusions are drawn.

In summary, this paper demonstrates that the Covid-19 pandemic has undoubtedly resulted in gender-based disparities in unemployment, with women experiencing a greater average impact on their employment status during the pandemic compared to men. However, following the implementation of remote working arrangements facilitated by social software to comply with government-mandated social distancing policies, female employment improved significantly faster than male employment. This phenomenon of gender discrimination in the job market based on public health events has not had serious consequences.

Based on the two conclusions of this paper, some laws for the rise of unemployment after a global public health event can be obtained and some policy recommendations can be given. First, recessions triggered by public health events disproportionately affect women. The government should pay extra attention to women who have lost their jobs due to social distancing policies in the wake of the epidemic. Second, social software-based remote work can effectively reduce the increase in female unemployment caused by the pandemic, and rapid government promotion of remote work can effectively mitigate the wave of female unemployment during the early stages of the pandemic. Third, men are worse off than women in the post-pandemic recovery, and governments should take steps to ensure the functioning of the labor market in industries where men are heavily employed.

The data analysis in this paper is deficient as the ARIMA (9,2,1) model fails to pass the residual test, potentially resulting in inaccurate predictions of male unemployment rates after April 2020. Furthermore, future research can expand upon the data analysis methodology employed in this study by incorporating intersecting factors such as race and gender to analyze fluctuations in unemployment rates.

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