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# Modeling and Forecasting Total Labor Size in Bangladesh: An ARIMA Approach

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***Abstract- Labor force participation in the economy is increasing every year in Bangladesh; as a result, the labor force in the industry and service sectors also shows fast growth. The study was focused on identifying appropriate forecasting model for total labor force participation in the Bangladeshi economy. Secondary labor force data for the period of 1990 to 2019 were obtained from the world development indicators. The stationary of the series was tested by several popular tests such as ADF, PP, and KPSS test. The key purpose of this study is to forecast total labor participation in the economy of Bangladesh. We applied STATA and R-studio software to check the stationary and to build an appropriate ARIMA model. Based on previous data (1990-2019) we got ARIMA (0,1,0) is the best model for our research and it was validated by the lowest AIC and BIC, and minimum P-value. If the labor participation continues to increase, according to ARIMA (0,1,0) the forecasted labor participation in the economy for 2029 will be 82245415.***

***Indexed Terms- ARIMA, Labor forecasting, Bangladesh***

## I. INTRODUCTION

Labors are the architect of human civilization. The labor force participation rate is an important indicator of an economy because through this indicator we can assess the market activities, overcome the market failure, achieve macroeconomic stability, and gain higher a GDP growth rate. Bangladesh is a labor surplus economy. If we utilize these surplus labors in a proper way, we can reduce poverty and gain higher foreign remittance inflows that will in turn increase the country's foreign reserve. To ensure the employment opportunity for the surplus labors, the government as well as private entrepreneurs have undertaken proper policy and investment strategy that will create employment opportunities to absorb these surplus labors. According to standard labor market theory, labor forecasting is important because a shortage of labor supply increases labor wage. On the other hand, if labor demand in a sector increases it raises the wage of labor in another sector. For example, if the demand for skilled labor increase in one sector then the supply of unskilled labor exceeds its demands, so skilled labor wage increases, and unskilled labor wage declined. Haskel and Martin (1996) conducted a study on the UK from 1983 to 1989 and they identified that productivity growth reduces by 0.4 percent per year if a skill shortage of labor exists. Although surplus labor exists in Bangladesh we need skilled labor rather than unskilled to boom our economic growth. Therefore, the objective of this research work is to forecast the labor force of Bangladesh.

## II. LITERATURE REVIEWS

Bae-Geun Kim (2018) has conducted a study on Korea to assess the impact of the material price change on labor share by using the structural VAR model. He found that the labor share declined due to the rise of material prices. In the short run, this declination is higher compare to the long run.

Feng Lu and Yang Yewei (2012) have undertaken a study on China to determine the labor force in agriculture share the in total labor force from 1990 to 2030. Their study reveals that agricultural labor will decline to 11.42 million from 20.23 million from 2005–2010 to 2025–2030.

Yinhua Mai & Xiujian Peng (2012) applied the computable general equilibrium (CGE) model to determine the surplus labor of china's rural agriculture. As of 2015, they found that surplus labor of the agriculture sector declined from 184.6 million to 171.2 million because of more than 60 percent of rural works engaged in service and industry.

## III. THE OBJECTIVE OF THE WORK

To recognize the proper ARIMA techniques for forecasting the total labor force in Bangladesh.

## IV. METHODOLOGY

An annual labor force participation data from 1990 to 2019 were obtained from annual reports of world development indicators (WDIs).

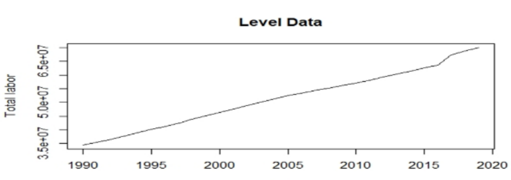
The ARIMA method requires more than 30 observations of time-series data. One of the key requirements is the data series should be stationary. There are three major parts of the ARIMA(P,D,Q) models:

P is here orders of the lag observations in the AR term. D is here to make stationary of our data how many times the numbers of differencing are required. Q is here the orders of the MA term.

In terms of x, the general forecasting equation is:

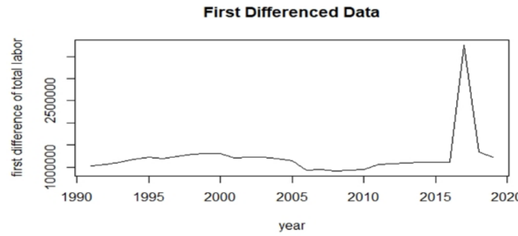
$\hat{x}_t = \mu + \phi_1 x_{t-1} + \dots \dots + \phi_p x_{t-p} - \theta_1 e_{t-1} - \dots - \theta_q e_{t-q}$

Figure 1. The total labor force in Bangladesh over the three decades



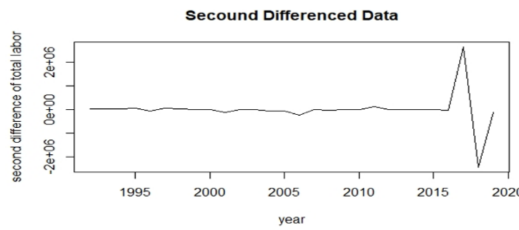

Source: Authors' estimation

Figure 2. First Differenced data of labor force in Bangladesh




Source: Authors' estimation

Figure 3. Second differenced data of labor force in Bangladesh




Source: Authors' estimation

The above figure 1-3 shows that, various presentations of labor force data. figure 1 shows the level of data. On the other hand, figures 2 and 3 represent the first and second differences of data.

- Finding the best model applying ADF Test:

```
> fit1 <- auto.arima (labordata, trace=TRUE, test="adf", ic="aic")
```

Table1. Several ARIMA models and AIC values based on ADF test

| | |
|---|---|
| ARIMA (2,1,2) with drift | : 854.4571 |
| ARIMA (0,1,0) with drift | : 846.632 |
| ARIMA (1,1,0) with drift | : 848.4686 |
| ARIMA (0,1,1) with drift | : 848.4752 |
| ARIMA (0,1,0) | : 901.6727 |
| ARIMA (1,1,1) with drift | : 850.4573 |

- The appropriate model: ARIMA(0,1,0) with drift

```
> summary(fit1)
Series: labordata
ARIMA(0,1,0) with drift

Coefficients:
        drift
```

1223606.17
s.e. 91632.32

sigma^2 estimated as 2.522e+11: log likelihood=-421.32
AIC=846.63 AICc=847.09 BIC=849.37

Training set error measures:
ME RMSE MAE MPE MAPE MASE ACF1
Training set 1110.038 485205.6 195382.6 -0.03509833 0.3425383 0.1596777 0.07504958
> jarque.bera.test(fit1$residuals)

Jarque Bera Test

data: fit1$residuals
X-squared = 700.5, df = 2, p-value < 2.2e-16

> Box.test(fit1$residuals,lag=10, type="Ljung-Box")

Box-Ljung test

data: fit1$residuals
X-squared = 2.3065, df = 10, p-value = 0.9934

- Finding the best model applying PP Test:

> fit2 <- auto.arima(labordata, trace=TRUE, test="pp", ic="aic")

Table2. Several ARIMA models and AIC values based on PP test

| | |
|---|---|
| ARIMA (2,1,2) with drift | : 854.4571 |
| ARIMA (0,1,0) with drift | : 846.632 |
| ARIMA (1,1,0) with drift | : 848.4686 |
| ARIMA (0,1,1) with drift | : 848.4752 |
| ARIMA (0,1,0) | : 901.6727 |
| ARIMA (1,1,1) with drift | : 850.4573 |

- The appropriate model: ARIMA(0,1,0) with drift

> summary(fit2)
Series: labordata
ARIMA(0,1,0) with drift

Coefficients:
drift

1223606.17
s.e. 91632.32

sigma^2 estimated as 2.522e+11: log likelihood=-421.32
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Training set 1110.038 485205.6 195382.6 -0.03509833 0.3425383 0.1596777 0.07504958
> jarque.bera.test(fit2$residuals)

Jarque Bera Test

data: fit2$residuals
X-squared = 700.5, df = 2, p-value < 2.2e-16

> Box.test(fit2$residuals,lag=10, type="Ljung-Box")

Box-Ljung test

data: fit2$residuals
X-squared = 2.3065, df = 10, p-value = 0.9934

- Finding the best model applying KPSS test:

> fit3 <- auto.arima(labordata, trace=TRUE, test="kpss", ic="aic")

Table 3. Several ARIMA models and AIC values based on KPSS test

| | |
|---|---|
| ARIMA (2,1,2) with drift | : 854.4571 |
| ARIMA (0,1,0) with drift | : 846.632 |
| ARIMA (1,1,0) with drift | : 848.4686 |
| ARIMA (0,1,1) with drift | : 848.4752 |
| ARIMA (0,1,0) | : 901.6727 |
| ARIMA (1,1,1) with drift | : 850.4573 |

- The appropriate model: ARIMA(0,1,0) with drift

> summary(fit3)
Series: labordata
ARIMA(0,1,0) with drift

Coefficients:
drift

1223606.17
s.e. 91632.32

sigma^2 estimated as 2.522e+11: log likelihood=-421.32
AIC=846.63 AICc=847.09 BIC=849.37

Training set error measures:
ME RMSE MAE MPE MAPE MASE ACF1
Training set 1110.038 485205.6 195382.6 -0.03509833 0.3425383 0.1596777 0.07504958
> jarque.bera.test(fit3$residuals)

Jarque Bera Test

data: fit3$residuals
X-squared = 700.5, df = 2, p-value < 2.2e-16

> Box.test(fit3$residuals,lag=10, type="Ljung-Box")

Box-Ljung test

data: fit3$residuals
X-squared = 2.3065, df = 10, p-value = 0.9934
Based on table 1-3, we got ARIMA (0,1,0) is the best model, because the AIC values are the minimum in all tables. Now we are going to point forecasting for the next decade.
> forecasted.data1

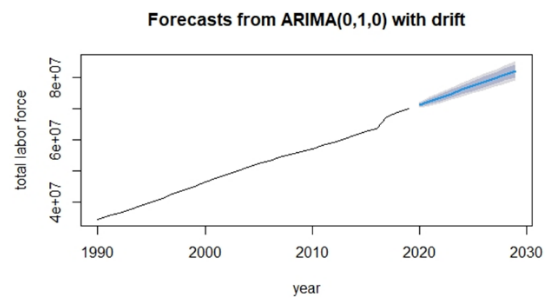
Table 4. Point forecasting for the next 10 years using ARIMA (0,1,0)

| Year | Point Forecast | Lo 80 | Hi 80 | Lo 95 | Hi 95 |
|---|---|---|---|---|---|
| 2020 | 71232959 | 70589318 | 71876600 | 70248596 | 72217323 |
| 2021 | 72456565 | 71546320 | 73366811 | 71064465 | 73848666 |
| 2022 | 73680172 | 72565353 | 74794990 | 71975204 | 75385139 |
| 2023 | 74903778 | 73616496 | 76191059 | 72935051 | 76872505 |
| 2024 | 76127384 | 74688160 | 77566608 | 73926280 | 78328488 |
| 2025 | 77350990 | 75774399 | 78927581 | 74939802 | 79762178 |
| 2026 | 78574596 | 76871683 | 80277509 | 75970215 | 81178977 |
| 2027 | 79798202 | 77977712 | 81618693 | 77014002 | 82582403 |
| 2028 | 81021809 | 79090886 | 82952731 | 78068718 | 83974899 |
| 2029 | 82245415 | 80210044 | 84280785 | 79132584 | 85358245 |

Source: Author's estimation

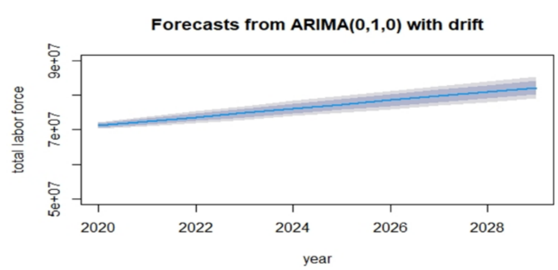
Table 4 shows the point forecasting from ARIMA(0,1,0) based on ADF, PP, and KPSS tests.

Figure 4. Total labor force forecasting for 10 years




Source: Author's estimation

Figure 5. Forecasting for 10 years with upper and lower bounds




Source: Author's estimation

In figures 4 and 5, forecasted growth lines are illustrated for the next ten years with an ARIMA (0,1,0) model. The forecasted line illustrated in figure 4 and figure 5, also the upper and lower bound are included. Both figures show that the total labor size in the future follows an upward trend.

## CONCLUSION

In the current study, around three decades of total labor data were used to forecast for the next 10 years. When we will get data for another year, the model can be checked for validity and probably more accurate forecasts can be performed. Overall, in this study, the ARIMA (0,1,0) model is the appropriate and suitable models to forecast labor participation in economics for the next decades. Among the several ARIMA models, the AIC and BIC's values for this model are the minimum. The forecasted data, based on ARIMA (0,1,0) showed that the labor force would increase from 12% in 2020 to 2029; unless and until more strict job, recruitment, foreign, or labor control policies and strategies are implemented in Bangladesh. Bangladesh is currently facing an unemployment problem. It is recommended that government should take various policies so that employment in various sectors will enhance. The increasing labor force shows that Bangladesh needs to increase industrial development. All findings are particularly essential for the government of Bangladesh as well as other organizations, particularly when it comes to planning for the upcoming decades.

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