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Forecasting employment rate in service sectors in Bangladesh: An application of autoregressive integrated moving average model

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Abstract
Background/ Objectives: The employment growth rate reflects the socioeconomic development of a country. The service sector makes an important part of the economy in most countries. Service sectors are the top rising sectors in Bangladesh. Specially provides employments, inputs, and public services for the economy. A forecast of employment rate in service sectors can help the implementation of policies, strategies, and budgets to encourage entrepreneurs of service sectors within the target range. One of the most common methods of forecasting this is the ARIMA or autoregressive integrated moving average model applied in this study.
Methods/ Statistical analysis: The objective of the study is to give details of the ARIMA model to forecast the employment growth rate in service sectors (2019–2028). Secondary data analysis and forecast model are done for the available year and employment data extracted from WDI, world bank database, and Bangladesh Labor Bureau website and it has been collected over 28 years. We applied Augmented Dickey-Fuller (ADF), Phillips–Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests to investigate the stationary character of the data. Stata and R studio software was applied to build a structure of the ARIMA method to model and forecast the employment growth rates.
Findings: In this study, the employment of Bangladesh from 1991 to 2018 is modeled using ARIMA (P, I, Q) methodology. The forecast of the sample period (1991–2018) showed accuracy by the selected the best two ARIMA (0, 2, 0) and ARIMA (1,1,0) model. The model was validated by the lowest values of AIC and BIC, fewer P-values, graphical arrangements of ACF and PACF plots. Both of the post sample forecasts with ARIMA (0,2,0) and (1,1,0) showed an increasing trend of (2019–2028) employment growth rate in service sectors. If the increasing trend persists, according to ARIMA (0.2.0) the forecast employment rate for 2028 is 43.33% in the service sectors. On the other hand, the employment growth rate in service sectors of Bangladesh would be approximately 47.28% in 2028, based on another ARIMA (1,1,0). Statistical outcomes illustrate that Bangladesh's employment growth rate in service sectors is an increasing trend that will continue growing in the future.
Improvements/Applications: These findings will help policymakers, researchers, and academicians to formulate employment-related strategies and policies more precisely.

Keywords: forecasting, ARIMA, employment growth rate, national labor policy

Introduction

The service sectors are important components of any nation's economy. It contributes direct and significant inputs to the national economy and provides crucial job creation for the rest of the economy, thus having a significant effect on the overall investment climate, which is an essential determinant of growth, employment, and development. Some service sectors such as the health, education, electricity, water and sanitation sectors, are also directly relevant to achieving socio-economic development goals. The Government of Bangladesh recognizes the importance of promoting growth in services sectors and provides several incentives in wide diversity of sectors such as health care, tourism, communications, transportation, education, health, information technology, banking, share market, finance, engineering, internet, management, among others. Service sector provides micro and macro-finance, marketing, transport, insurance for the development of the agricultural and industrial sectors. So the growth of service-related sectors activities boosts the other secondary sectors as well. On the other hand, the service sector can play a major role in reducing inequalities in the distribution of income in the economy. At present, there is widespread consensus among academicians, scholars, and policymakers that budgets in human capital confer benefits to citizens, firms, and societies. Better educated and skilled people have higher employment probabilities, and receive on average higher income, and are subject to a lesser risk of unemployment (OECD, 1998) [9]. Also, other external effects from education accumulate in the forms of economic growth, social cohesion, consciousness, empowerment, and lower crime. However, the benefits of a better-trained workforce should not lead governments to support human capital investments irrespective of quality concerns. Even though effective education, training, and lifelong learning policies seem to be a promising form of investment, resources need to be allocated efficiently.

Literature Review

The literature review of this paper was spotlighted on forecasting employment in various sectors. However, we found fewer efforts to forecast employment in services (% of total employment) in the Bangladesh context in addition to the other countries.

Therefore, the authors of the paper reviewed the studies related to employment forecasting in various sectors across the world. An econometric model of Hawaii, USA, for making short-run forecasts on local people's income and employment constructed by Chau (1970) [1]. He applied popular multiple regression models for forecasting. He concluded that the forecasting ability of the model is quite accurate in employment forecasting. Paquet, Sargent, and James (2006) [6] examined the past and future behavior of the employment rate of both genders in Canada using a semi-log model. Model validation and verification confirmed that the projections of fitted models are reliable for short-term forecasting, but in the long run this is in doubt. Vitartas and Ford (2008) [10] forecasted employment demand in the local government area in Australia using logistic regression. In their findings the forecasting ability of the model was low. Chang and Sung (2010) [2] forecasted employment in various industries for a resource-based economy in a state of Georgia. They developed the Bayesian vector autoregressive models for their research purpose. Their findings showed that the fitted models execute well in long-run. Raoufinia (2016) [7] used VAR models to forecast employment growth in Sweden. Up to a certain point, the findings of the study were satisfactory in short-term forecasting. One of the key lessons to be learned from (Neugart and Schömann 2002) [5] is that forecasts very likely will not eliminate cycles in the demand and supply of skills. However, instead of the frequent fire-fighting role performed by policymakers, forecasts enable a more strategic approach to identifying and subsequently solving problems. In this way, forecasts may help to reduce adjustment costs arising from imbalances in the labor and product markets. The contributions of Barnow (2002) and Sexton (2002) [9] showed that these forecasts have valid, applicable, and useful information on labor market trends.

Model Specification

A stationary time series are so important to avoid spurious regression (Yule, 1926; Granger and Newbold, 1974). Numerous tests have been applied for testing stationarity; the unit root test will be adopted. A test of stationarity or non-stationarity that has become widely popular over the past several years is the unit root test. In the following regression model, we can run to distinguish a unit root.

$$\Delta Y_t = b_0+\sum_{j-1}^{k} bj\Delta Yt - j + \beta_t+\gamma Y_{t-1}\, u_t$$

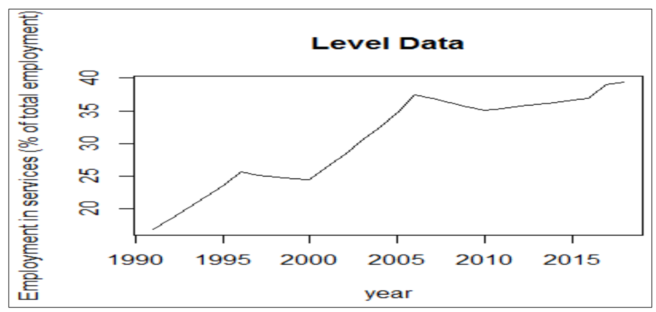
If a time trend is unnecessary this model may be run without t. If the unit root is absent, differencing Y should result in a white-noise series (no correlation with Y_{t-1}). The Augmented Dickey-Fuller (ADF) test of the null hypothesis of no unit root tests; Ho: $\beta=\gamma=0$ if the is a trend (we apply F-test) and Ho: $\gamma=0$ if there trend is absent (we utilize t-test). When the null hypothesis is accepted, it is assumed that there are a unit root and difference the data before running a regression. When the null hypothesis is discarded, we can conclude that the data are stationary and we do not need differencing (Salvatore & Reagle, 2002) [8].

The ARIMA model is a popular model that incorporates the moving average and the autoregressive option (Dobre & Alexandru, 2008) [3].

The Box-Jenkins (BJ) methodology is the pioneer in this context, theoretically, it is known as the ARIMA methodology (Gujarati, 2003) [4]. The emphasis of these methods is not on constructing single-equation or simultaneous-equation models but on analyzing the probability, or stochastic, properties of economic time series on their own under the philosophy 'let the data speak for themselves'. Unlike the regression models, in which Y_t is explained by several regressors X_1, X_2. . . X_k, the BJ-type time series models allow Y_t to be explained by previous data, or lagged, values of Y itself and stochastic error terms. For this reason, sometimes ARIMA Models are called theoretic models because they are not derived from any economic theory. Overall, the Box-Jenkins or ARMA (p,q) model is a combination of the AR and MA model as follows;

$$\mathbf{y_t= a_0+a_1y_{t-1}a_2y_{t-2}+\ldots \ldots+ a_py_{t-p} - b_2u_{t-2}- \ldots \ldots - b_qu_{t-q}+u_t}$$

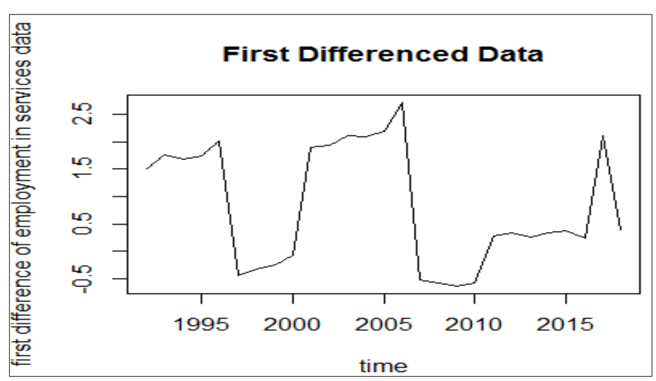
Differencing non-stationary series one or more times to achieve stationarity this process is recommended by Box and Jenkins. So introduces a popular ARIMA model, with the 'I' standing for 'Integrated'. But its first difference $\Delta Y_t=Y_t-Y_{t-1}=u_t$ is stationary, so y is 'Integrated of order 1' or y~I (1). Three necessary primary stages are required to construct a Box-Jenkins or ARIMA time series model; they are model identification; model estimation and model validation.



Source: Author's calculation

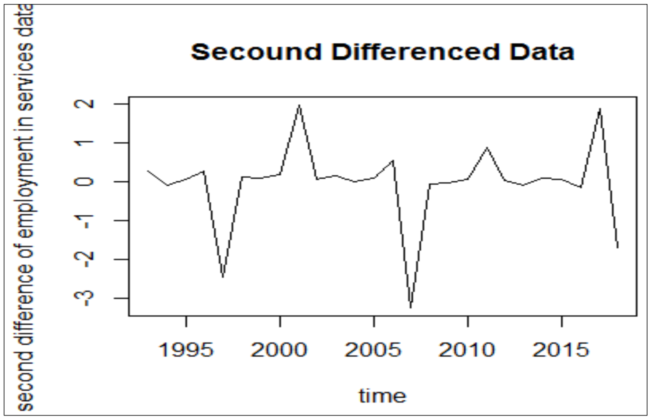
Fig 1: The employment in the service sector in Bangladesh

Figure 1 shows the total employment size in Bangladesh over 28 years from 1991 to 2018. The figure was given as the value of the millions of employments.



Source: Author's calculation

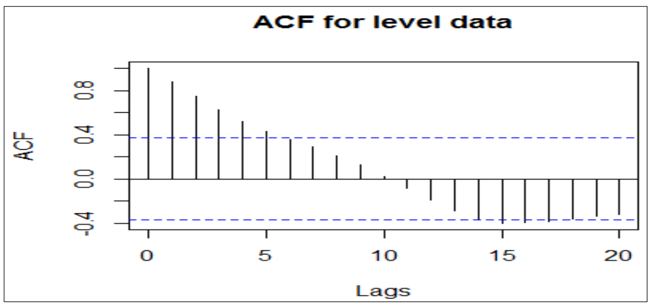
Fig 2: First Differences Employment Growth Rates in Bangladesh



Source: Author's calculation

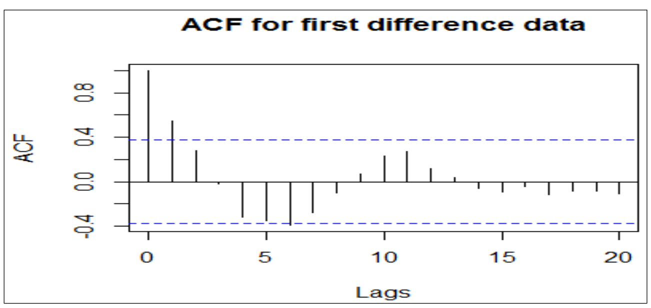
Fig 3: First Differences Employment Growth Rates in Bangladesh

The above figure 1-3 shows that, various presentations of Employment in services (% of total employment) data. figure 1 shows the level data. On the other hand, figures 2 and 3 represent the first and second differences of data over the time.



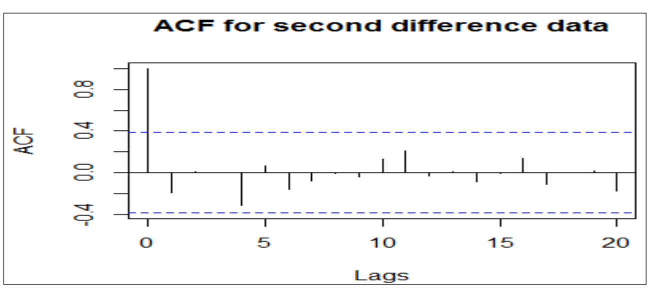
Source: Author's calculation

Fig 4: First Differences Employment Growth Rates in Bangladesh



Source: Author's calculation

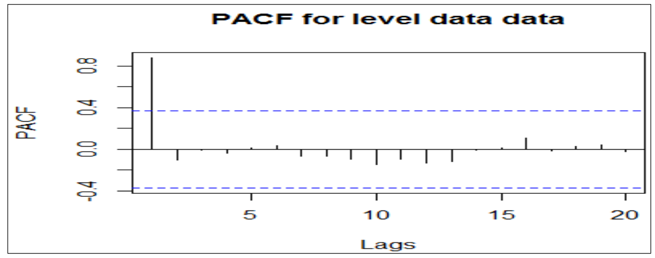
Fig 5: First Differences Employment Growth Rates in Bangladesh



Source: Author's calculation

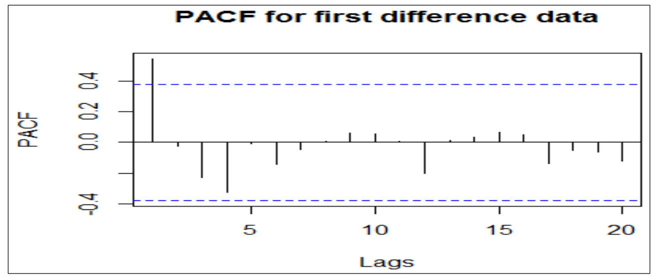
Fig 6: First Differences Employment Growth Rates in Bangladesh

The above figure 4-6 show the autocorrelation function representation of employment in services (% of total employment) data.



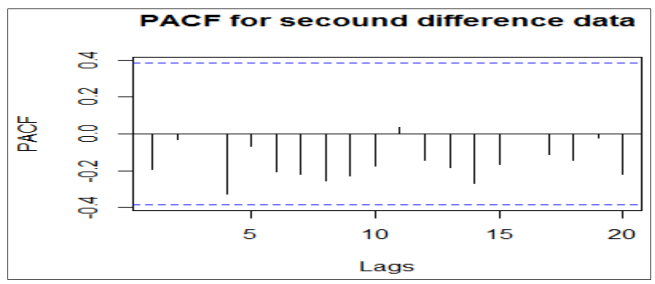
Source: Author's calculation

Fig 7: First Differences Employment Growth Rates in Bangladesh



Source: Author's calculation

Fig 8: First Differences Employment Growth Rates in Bangladesh



Source: Author's calculation

Fig 9: First Differences Employment Growth Rates in Bangladesh

The above figure 4-6 show the PACF representation of employment in services (% of total employment) data.

Finding best model applying ADF Test:
ARIMA (2,2,2): Inf
ARIMA (0,2,0): 77.88928
ARIMA (1,2,0): 78.83811
ARIMA (0,2,1): 78.82894
ARIMA (1,2,1): Inf

Best model: ARIMA (0,2,0)
Series: Employment in services (% of total employment) data
sigma^2 estimated as 1.084: log likelihood=-37.94
AIC=77.89 AICc=78.06 BIC=79.15
Training set error measures:
ME RMSE MAE MPE MAPE MASE ACF1
Training set -0.04006289 1.00343 0.5214601 -0.08829744 1.652348 0.4797242 -0.1917889

Finding best model applying PP Test:
ARIMA (2,2,2): Inf
ARIMA (0,2,0): 77.88928
ARIMA (1,2,0): 78.83811
ARIMA (0,2,1): 78.82894
ARIMA (1,2,1): Inf

Best model: ARIMA (0,2,0)
sigma^2 estimated as 1.084: log likelihood=-37.94
AIC=77.89 AICc=78.06 BIC=79.15

Training set error measures:
ME RMSE MAE MPE MAPE MASE ACF1 Training set -0.04006289 1.00343 0.5214601 -0.08829744 1.652348 0.4797242 -0.1917889
Jarque Bera Test data: fit2$residuals
X-squared = 19.921, df = 2, p-value = 4.724e-05
Box-Ljung test
data: fit2$residuals
X-squared = 7.0585, df = 10, p-value = 0.7199

Finding best model applying KPSS test:
ARIMA (2,1,2) with drift: 79.4252
ARIMA (0,1,0) with drift: 84.91659
ARIMA (1,1,0) with drift: 77.53664
ARIMA (0,1,1) with drift: 79.32055
ARIMA (0,1,0): 95.44942
ARIMA (2,1,0) with drift: 79.50619
ARIMA (1,1,1) with drift: 79.51969
ARIMA (2,1,1) with drift: 81.53652
ARIMA (1,1,0): 78.97231

Best model: ARIMA (1,1,0) with drift
Series: Employment in services (% of total employment)
Coefficients: ar1 drift
0.5360 0.8415
s.e. 0.1572 0.3601
sigma^2 estimated as 0.8834: log likelihood=-35.77
AIC=77.54 AICc=78.58 BIC=81.42
Training set error measures:
ME RMSE MAE MPE MAPE MASE ACF1
Training set -0.01582008 0.8881307 0.6986438 0.07681965 2.313213 0.6427268 0.03267396
Jarque Bera Test
data: fit3$residuals
X-squared = 1.8469, df = 2, p-value = 0.3971
Box-Ljung test
data: fit3$residuals
X-squared = 8.1917, df = 10, p-value = 0.6101

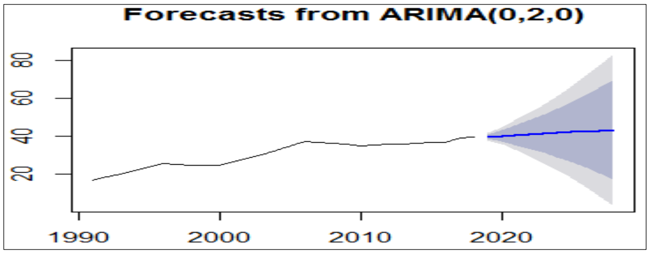
We got the best two ARIMA models from ADF, PP, and KPSS test. The ADF and PP test shows that ARIMA (0,2,0) is the best model, on the other hand, the KPSS test shows that ARIMA (1,1,0) is the best model. We consider both models in this paper.

Table 1: Point forecasting for the next 10 years using ARIMA (0,2,0)

Year	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2019	39.77	38.44	41.11	37.73	41.82
2020	40.19	37.18	43.15	35.60	44.73
2021	40.56	35.57	45.56	32.93	48.20
2022	40.96	33.65	48.27	29.78	52.14
2023	41.35	31.46	51.25	26.22	56.49
2024	41.75	29.01	54.48	22.28	61.22
2025	42.14	26.35	57.93	18.00	66.29
2026	42.54	23.48	61.60	13.39	71.69
2027	42.93	20.41	65.46	8.48	77.39
2028	43.33	17.14	69.51	3.28	83.38

***Source*: Author's calculation**

Table 1 shows the point forecasting from ARIMA (0,2,0) based on ADF and PP tests.



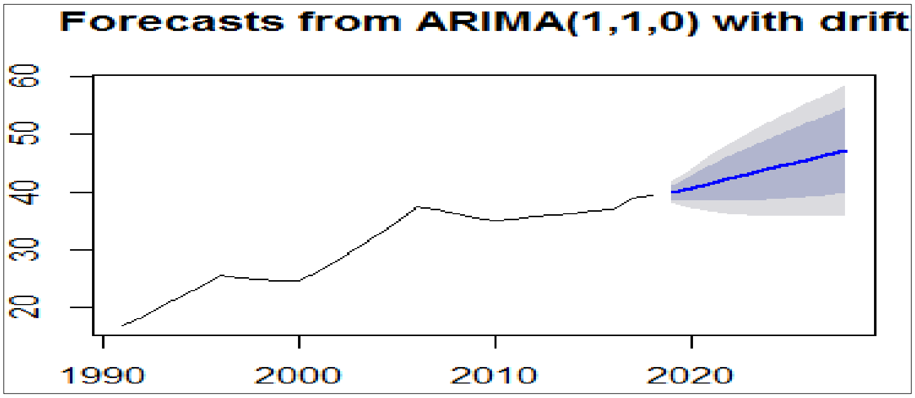
***Source*: Author's calculation**

Fig 10: Employment growth rate forecasting for 10 years

Table 2: Point forecasting for the next 10 years using ARIMA (1,1,0)

Year	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2019	39.98	38.78	41.18	38.14	41.82
2020	40.69	37.48	42.90	37.32	44.06
2021	41.47	38.352	44.58	36.70	46.23
2022	42.27	38.350	46.19	36.27	48.27
2023	43.09	38.453	47.73	35.99	50.19
2024	43.92	38.64	49.21	35.83	52.01
2025	44.76	38.88	50.63	35.77	53.74
2026	45.60	39.18	52.01	35.78	55.41
2027	46.44	39.52	53.35	35.85	57.02
2028	47.28	39.89	54.66	35.98	58.57

Table 2 shows the point forecasting from ARIMA (1,1,0) based on ADF and PP tests.



***Source*:** Author's calculation

Fig 11: Employment growth rate forecasting for 10 years

In figures 10 and 11, forecasted growth lines are illustrated for the next ten years with an ARIMA (0,2,0) and ARIMA (1,1,0) model. The forecasted line illustrated in figure 11 and In figure 12, the upper and lower bound are included.

Conclusion

In the current study, around three decades of employment in service sector time series data were used to forecast for the next 10 years. The forecasted data, based on ARIMA (0,2,0) showed that the employment rate in service sectors would increase from 39.77% in 2019 to 43.33% in 2028. On the other hand, based on another ARIMA (1,1,0) model, the forecasted data showed that the employment rate in service sectors would increase from 39.98% in 2019 to 47.28% in 2028; unless and until more strict employment control policies and strategies are implemented in Bangladesh. When we will get data for another year (2019), the model can be checked for validity and probably more accurate forecasts can be performed. Overall, in this study, the ARIMA (0,2,0) and ARIMA (1, 1, 1) models are the appropriate and suitable models to forecast the employment growth rate in service sectors for the next decades. Among the several ARIMA models, the AIC and BIC's values for these two models are the minimum. Also, P-value determines the significance of our model. This clearly shows that service sectors should be focused and concentrated on the future of Bangladesh. Bangladesh is currently experiencing high levels of unemployment so it is recommended that government should make them skilled so that they will adjust with service sectors requirements. The declining employment growth rates show that Bangladesh will be able to control employment. These findings are close to the findings reported by all other national and international bureau. These findings are particularly essential for the government of Bangladesh as well as other organizations, particularly when it comes to planning for the upcoming decades. Though we forecasted employment growth rates in service sectors for one decade, it is suggested that researchers should be aware of when forecasting for more than 5 years.

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