# Forecasting Australia Gross Domestic Product (GDP) under Structural Change (SC) using Break for Time Series Components (BFTSC)

**Abstract:** *The reason for this research is to enable us know the use BFTSC (break for time series components) identification of the structural change and the time series components existing in Australia GDP. The data (Australia GDP) statistics spanned for period of fifty five years (1960 to 2014). The GDP of Australia is a higher information gotten from the StreamData of Universiti Utara Malaysia Library. The precincts of BFAST in terms of structural change was advanced to become an improvement of BFAST to BFTSC. BFTSC was created from basic research conducted on BFAST, results shows an innovative technique that captures the recurring (cyclicals) and non-recurring cyclical (irregular) components that was not included in the original BFAST technique and it was included in the methodology of this study. BFTSC is created to give a mutual image of all the required time series components. The subsequently forecasting technique was determined and forecast is made.*

***Keywords**: Australia, Break for Time Series Components, Seasonal Data, Gross domestic product, Structural change, cyclical components, Irregular components.*

## 1. Introduction

Australia was established on 26th January 1788. The date was very significant in the Australian calendar (Australia national day), the region was officially actualized by Governor Philip on February 1788 at Sydney. Australia averaged GDP was about 502.19, 503.19 USD Billions from 1961 until 2022, attaining a real-time height of 1676.43 USD Billions in 2022 and a presented low as 18.622 USD Billions in 1960 and 1961. This research makes available Australia GDP - definite values, historic information, prediction, chart, measurements, economic calendar and trend (32). In the 90s, and the 2nd half of the 90s in precise, statuses of Australia's superlative phases in reference to historical productivity was encouraging, robust GDP progression and GDP development per/capital, short fall inflation and falling redundancy, a time which not only strengthened success and wealth from Australia's own (32). Despite resemblances to some countries GDP (Australia, Canada and US) in the past in term of law and philosophy, Australia followed reasonably diverse macro-economic histories. Australia's GDP per-capital was above that of Britain and the United State in 1870s, more than two times that of Canadian level. At 80s, nevertheless, deregulation of the Australian economy was activated under the Hawke Labour management, which started the procedure of economic improvement by concluding a remunerations solidarity with the trade union program. In altercation for remuneration restraint and an upsurge in the "community remuneration" the trade unification program approved to upkeep economic improvement and reject industrial engagement (i.e. strikes). The achievement of the "Agreement" tolerate the Labour government to implement economic reforms that is common in other countries; tariffs were gradually cut, the Australian currencies was hovered (1984), and the monetary system was liberalized. Hawke was also able to privatize some huge government enterprises. Sector extensive 'Industry organizations' for economic reform were familiarized in communications and engineering. The Australian Stock Market Limited (ASX) was designed in 1986 through the incorporation of six autonomous stock market exchanges that previously functioned in the capital of the state. Each of the exchanges had an account of share market trading courting back to the 19th century (32).

The worldwide early 90s decline/recession arose fast resulting from a stock collapse of unparalleled size that saw the Dow Jon Industrial mean decline of 22.6%. This fall, greater than the normal stock market falls around 1930s, this was touched successfully by the comprehensive frugality and the typical stock market started to rapidly recuperate (This is known as Australia miracle growth (32)). The subsequent decline-recession thus thwarted the progress of some closely linked countries such as the United States, also likewise Australia. Keating Paul, who was accountant, was legendarily raised to it as "the recession of Australia breakthrough". During the downturn, GDP and revenue generated falls rapidly by 1.8%, employment falls by 3.3%. However, as is typical behaviors during recessions, there was an advantageous decrease in inflation. These economic restructurings and modifications have helped in Australia now being noticed as one of the furthermost open economies in the world, nevertheless polarizing estimations concerning the long term achievement that allowed open trade and its unavoidable effect on national workers. Australia has appreciated for almost 2 decades of economic progress, joined with low inflation and comparatively low-slung unemployment - until 2019 when the nation entered into a transitory recession where unemployment went very high amid the worldwide COVID-19 pandemic.

Due to the epidemic of COVID-19, professional disputes with China, also with the ongoing war in Ukraine, as resulted into some significant and political shift, the deliberation toward General Security and transformed interest in Australia's developed industry. Though free trade continue to take place, the significance of a thriving local production has gained popularity as an imperative consensus (32). The financial reforms realized since the 80s have led to a large contraction of the Australian manufacturing sector, along with trade union membership; with the percentage of workforce unionization dropping from over 50% in the 1970s, to only 14% presently. 2020 recession. The Covid-19 epidemic got to Australia at 2021. On 20th March, Australian boundaries were shuts to all non-indigenes, impacting particularly tourism and the entrance of foreign students. Social separation rules were forced on 22 March, and "non-important" services were closed, which encompassed social congregations such as hotels, bars and churches but, unlike many other nations, this did not contain some business operations such as manufacture, engineering and many retail categories (32). A second trend of infections occurred around May, and strict law was imposed to effect lockdown, which was until September. The governments also enforced embargoes on cross state border activities. On September, as a consequence of the Covid-19 epidemic, Australia legitimately went into economic downfall- recession with GDP dropping below 6.5% but around June, the prevalent drop was recorded.

Using Australia periodical recurrent data which was the GDP annual data on BFTSC (Break for time series) for identifications of time series components existing in the observed statistics. BFTSC is known to be further proficient in recognizing all the components of time series statistics better than BFAST. BFTSC is an amended BFAST. BFAST (Break for Additive Seasonal and Trend) is a method used for identification of trend movement and seasonal components of time series, trend breaking was first recommended by (10). (23, 31) suggested a method of simple swing identification to identify the time series component. This method was also used by (27) as the modern time series component recognition method which is a method that was first designated and applied by (31).

## 2. Literature Review

The method BFAST was for distinguished in terms of structural change with the help of seasonal and trend breaks using loes (STL), it smooths the exposure of trend in a given statistics. The fundamental standard of the BFAST method is the breaking of time series to seasonal, trend and also remnants element by the method for breaks identifying software in R studio core 2012 **(**30, 31).

(9) Was one of the earliest expert to clearly identify time series constituent using time plot. However, the constraint of this method was the complication, it was very byzantine to distinguish the time series constituents using unplanned manual time plot and the manual method may be tremendously challenging for non-experts. (20 & 21) established DBEST (Detection Breakpoint and Estimating Segment Trend) which was reformed from BFAST. DBEST take in (NDVI) normalizes difference vegetation index data. The constraint of DBEST method is that, the procedure was constructed to solve the problems of topographical vegetation trend identification and cannot classify cyclical and irregular constituents of time series measurements. It is not malleable time series component identification technique and this problem of identification of time series components is still a problem that needs to be fully addressed,

(23 & 22) Debate and gave support to the body of knowledge by examining the combined change identification called BFAST. The method called BFAST is used for conceding breaks for additive seasonal and trend in order to validate for seasonal condition and also permits the identification of breaks that take place in trend within the system (31). The method is manageable in BFAST pack for R (R developments Core Team, 2012).

(16, 31) discusses that the method of BFAST which can foresee and examine a topographical forest movement with the support of normalized change vegetation index's branded as (NDVI). Thus, by expansively exploring the period of disparities of the shriveled share of land for an improved understanding of the seasonal discrepancy pathway in the arid topographic area, this was done by sensing and defining factors of arid area breaks using (NDIV) data to monitor the variations (13,14,19). The method is available in BFAST pack for R. Package 'bfast' which describe the actual scope of BFAST. Many intellectuals hire the use of BFAST in classifying trend in topographical data (26).

The addition of BFAST is an innovative technique that categorizes all-time series components. This novel innovative technique is accepted as BFTSC (Break for time series components). Several automated methods of components detection are computer oriented. BFTSC is one of the first addition of BFAST in history which also emphasis more on computer approach strategy rather than manual theoretical approach strategy (1, 3 & 4).

BFTSC method considers every vigorous component of time series measurements. BFAST is branded to be feeble in identifying and breaking random variants, also very weak in applicability to other types of empirical data (21, 24). The method considers the extension and upgrading of the BFAST to BFTSC, breaks for additive, seasonal and trend to be modified to break's for time series components BFTSC.

BFTSC is automatic technique in computer R package and can be recycled and utilized by anyone who wishes to be a legatee or need the package that will be developed. For improved identification, the illustrative representation of the BFTSC is shown and represented (in 1).

BFTSC is flexible to additives models when obligatory considering the arrangement of the system and exponentiation models of the given system. The issue of time series constituent's recognition is a problem that need to be solved in the earliest stage of time series forecasting (21).

BFTSC trailed similar plagiaristic steps like BFAST but diverged in the toting of cyclical and irregular components. BFTSC is the technique used in investigating the simplification of time series data by mining the trend components and seasonal components, cyclical components and irregular components during time series breaks. Given the general time series additive model as in equation (1.1) of the form:

$$Y_P = T_p + S_p + C_p + I_p \qquad (1.1)$$

where $Y_P$ ( observed value), $T_p$ (trend value), while $S_p$ (seasonal values), $C_p$ (cyclical values) and $I_p$ (irregular values) components (8, 12, 15, 18).

BFTSC categorizes all the time series components relatively trend, seasonal, cyclical and irregular components to be randomized equation.

The remaining constituent in BFAST now rehabilitated to contained cyclical and irregular component in BFTSC. The breakpoint which epitomize the breaks in time series caused by common noise such as natural phenomenon and human activities can be experiential in both seasonal and trend components using BFTSC technique.

In BFAST, only random component can be witnessed but in BFTSC the cyclical and irregular components is identified alongside with trend and seasonal components (2, 21,22).

## 3. Material and Methods

BFAST is the method used in examining the simplification of time series data by mining the trend and seasonal components during decomposition of time series data. Given the general additive model of the form:

$Y_P = T_p + S_p + C_p + I_p$ (3. 1)

where $Y_P$ ( observed value), $T_p$ (trend value), while $S_p$ (seasonal values), $C_p$ (cyclical values) and $I_p$ (irregular values) components (28, 29).

From equation (2.1) BFAST breaks the components of time series data apart to form trend and seasonal component but the left over components are term random component ($R_p$) and the equation was expressed as (1, 3, 5 & 31).

$Y_P = T_p + S_p + R_p$ (3. 2)

The remaining components not capture as trend nor seasonal is called random, this consist of cyclical and irregular component, the breaks which epitomizes the abrupt change in time series initiated by disturbance/noise such as natural occurrence and normal behaviours can be dotted in both seasonal-trend components using BFAST method (21).

To produce trend modules using BFAST, we requisite a piecewise rectilinear model approach. Supposing $T_p$ is a piecewise model which is linear with an authentic slope and intercept on q+1 fragments broken with q breaks at some points and P period; $p_1^{\neq}$,………., $p_q^{\neq}$ then $T_p$ can takes the form

$T_p = \alpha_k + \beta_k$P (3, 4 &5)

To produce seasonal components by means of BFAST, we required a simple harmonic model.

Accordingly, $S_p$ can be characterized by a simple harmonic model per j terms; j = 12….J and period t.

$$S_p = \sum_{j=1}^{J} \omega_{k,j}\,\mathrm{Sin}\frac{2\pi jt}{F} + \sigma_{K,j}) \qquad (2.3)$$

Where k = 1… q, $p_{k-1}^{\neq} < \mathrm{p} \leq p_k^{\neq}$ and also $\omega_{k,j}$, $\sigma_{K,j}$ are the subdivision amplitude and $F$ is the frequency (1, 3, 5 & 31).

To produce random modules, any statistics that does not belong to trend nor seasonal is categorized as random $R_p$.

$$Y_P = \alpha_k + \beta_k\mathrm{P} + \sum_{j=1}^{J} \omega_{k,j}\,\mathrm{Sin}\frac{2\pi jt}{F} + \sigma_{K,j}) + R_p \qquad (2.4)$$

$Y_P = T_p + S_p + R_p$

The novel technique called BFTSC reflected splitting the random into cyclical-irregular components which is an addition to BFAST. This was done completed through the capture of cyclical components and its direction.

Cyclical modules can be gotten through the regression cyclic movement. The regression function at the breaks maybe sporadic but the model can be transcribed in such a way that the function remains at all point including breakpoints. To estimate cyclical components, center moving average is involved (1, 3,4,5).

Derivation of cyclical code

(See Ajare et al., 2023(1,3,4, &5))

The new equation becomes

$$Y_P = \alpha_k + \beta_k \mathrm{P} + \sum_{j=1}^{J} \omega_{k,j} \, \mathrm{Sin} \frac{2\pi jt}{F} + \sum_{t}^{n} \frac{Yt}{nt} + I_p \qquad (2.5)$$

$$Y_P = T_p + S_p + C_p + I_p$$

where $Y_P$ ( observed value), $T_p$ (trend value), while $S_p$ (seasonal values), $C_p$ (cyclical values) and $I_p$ (irregular values) components .

$I_p$ is the remainder variations which is not captured by trend, seasonal variations and cyclical components, every variations apart from trend, seasonal and cyclical are classified as remainder ( $I_p$) (1, 3, 5 & 31).

## 4. Results

**Evaluation of BFTSC with forty eight months (small monthly sample size) data.**

The forty eight months (small monthly sample size) trend data was generated from the model

$$Y_t = 95.68699 + 0.560847 x_t \qquad (4.2)$$

equation 4.2. See Ajare et al., 2023 (1,2 &5))

BFTSC was very effective in the detection of trend components $(T_t)$. BFTSC was also able to detect 100% trend components $(T_t)$ that was in the data series. BFTSC was able to detect 100% seasonal components $(S_t)$ that was in the data series. BFTSC was also able to detect 100% of the irregular components $(I_t)$ that was present in the one hundred data set.

BFTSC was able to detect 99% of the cyclical components in the one hundred data of cyclical when combined with trend which was prepared for evaluation of BFTSC. It was able to detect only 99.5 % of all the entire cyclical combination components present in the data set. The overall performance of BFTSC of monthly small sample size of 48 is 99.9 % (1, 11 & 17)

**Evaluation of BFTSC with ninety six months (medium monthly sample size) data.**

The ninety six months (medium monthly sample size) trend data was generated from the model in equation 4.2. One hundred data was generated for trend $(T_t)$ components at time t, each of the one hundred data contains ninety six monthly data. BFTSC is evaluated based on each set of one hundred set of data. Ninety six monthly trend data is generated in one hundred different replications. The ninety six months trend data in one hundred places is involving only trend component. BFTSC was used to uncover and to detect the trend components hidden in the one hundred set of ninety six months data generated from equation 4.2 (3,4)**.** BFTSC was very effective in the detection of trend components $(T_t)$. BFTSC was also able to detect 100% trend components $(T_t)$ that was in the data series. BFTSC was able to detect 100% seasonal components $(S_t)$ that was in the data series. BFTSC was also able to detect 100% of the irregular components $(I_t)$ that was present in the one hundred data set. BFTSC was able to detect 100 % of the cyclical components in the one hundred data that was prepared for evaluation of BFTSC, it was able to detect only 100 % of all the entire components present in the one hundred data set of ninety six months each. The overall performance of BFTSC of monthly medium sample size of 96 is 100 % (See (1, & 5)).

**Evaluation of BFTSC with one hundred and forty four months (large monthly sample size) data.**

The one hundred and forty four months (large monthly sample size) trend data was generated from the model in equation 4.2. One hundred data was generated for trend $(T_t)$ components at time t, each of the one hundred data contains one hundred and forty four monthly data. BFTSC is evaluated based on each set of one hundred set of data and the percentage of accuracy is recorded in table 4.6. One hundred and forty four monthly trend data is generated in one hundred different replications. The one hundred and forty four months trend data in one hundred places is involving only trend component. BFTSC was used to uncover and to detect the trend components hidden in the one hundred set of one hundred and forty four monthly data generated from equation 4.2 (4 &5).

BFTSC was also able to detect 100% trend components $(T_t)$ that was in the data series. BFTSC was able to detect 100% seasonal components $(S_t)$ that was in the data series. BFTSC was also able to detect 100% of the irregular components $(I_t)$ that was present in the one hundred data set. BFTSC was able to detect 100 % of the cyclical components in the one hundred data that was prepared for evaluation of BFTSC, it was able to detect only 100 % of all the entire components present in the one hundred data set of one hundred and forty four months each . The overall performance of BFTSC of monthly large sample size of 144 is 100% (111, 2, 4, 5).

The overall performance of BFTSC all the sample size of (small, medium and large) is 99.97%. BFAST is considered best for time series data without cyclical and irregular components. (See (1 & 5 ))

## 5. Structural Change (SC) using BFTSC for time series components identification of Australia GDP

The primary phase in forecasting is to understanding the data and to scrutinize all the components of time series existing in that data in order to choose the most suitable forecasting practice. The yearly periodical GDP data constituents' identification was conducted with the assistance of the new innovative technique called BFTSC. This innovative technique helps to have a clear image of the entire variants presents in the time series statistics.

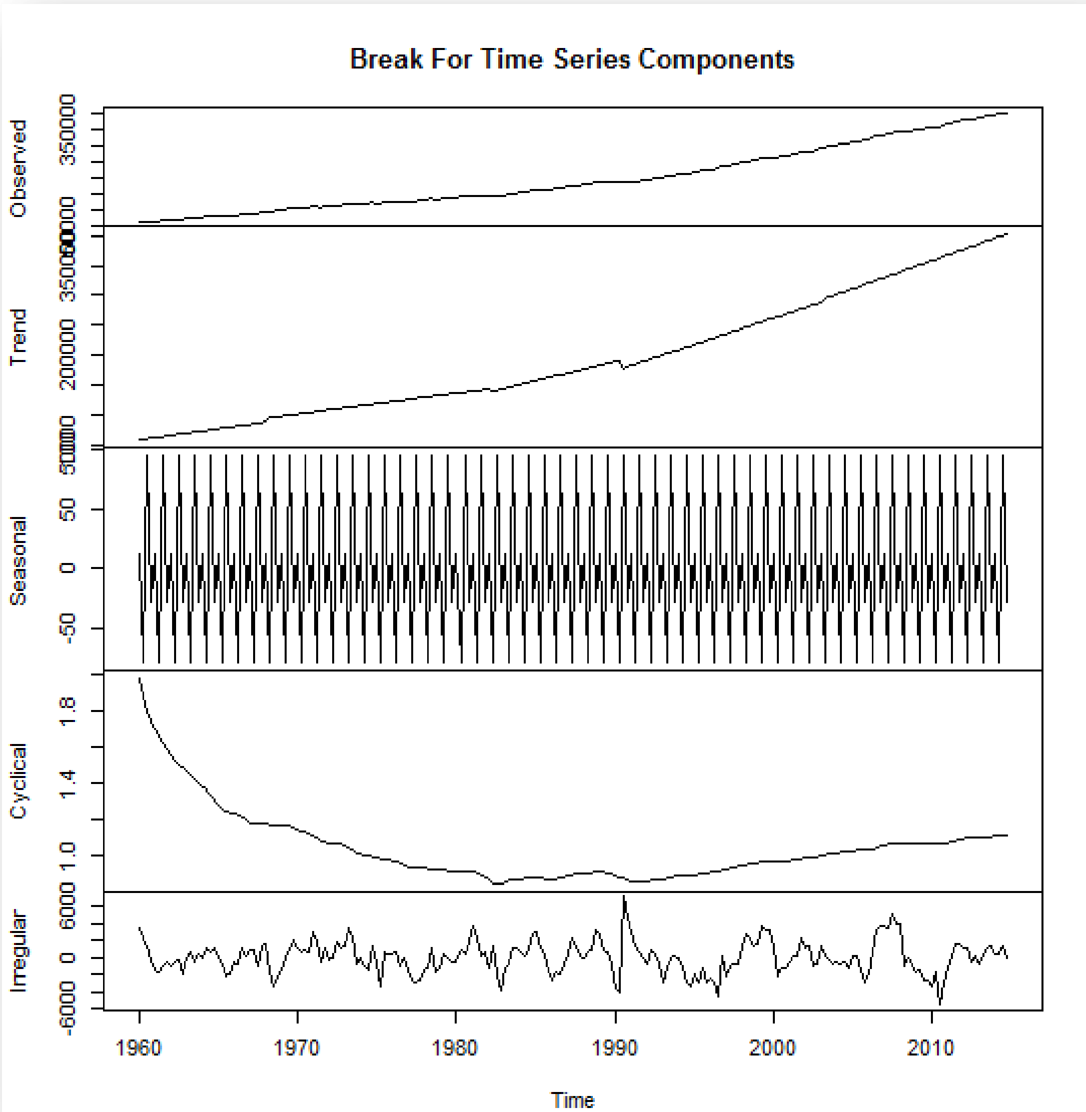


Figure 1. BFTSC for Quarterly Australia GDP data

Figure 1 exposes all the time series modules concealed in the periodical Australia GDP data for 55 years, the appearance in the figure above specified the existence of trend, seasonal, cyclical and irregular components, Henceforward, the furthermost suitable methods for examining such data is ARIMA.

Some ARIMA models are established and the best model is selected grounded on the ARIMA with the smallest AIC (Akaike's Information Criterion). Centered on the AIC models, the ARIMA(2,2,3) is the finest model to be utilized in fitting the Australian periodical GDP . ARIMA(2,2,3) is designated and utilized for fitting the model (6,7).

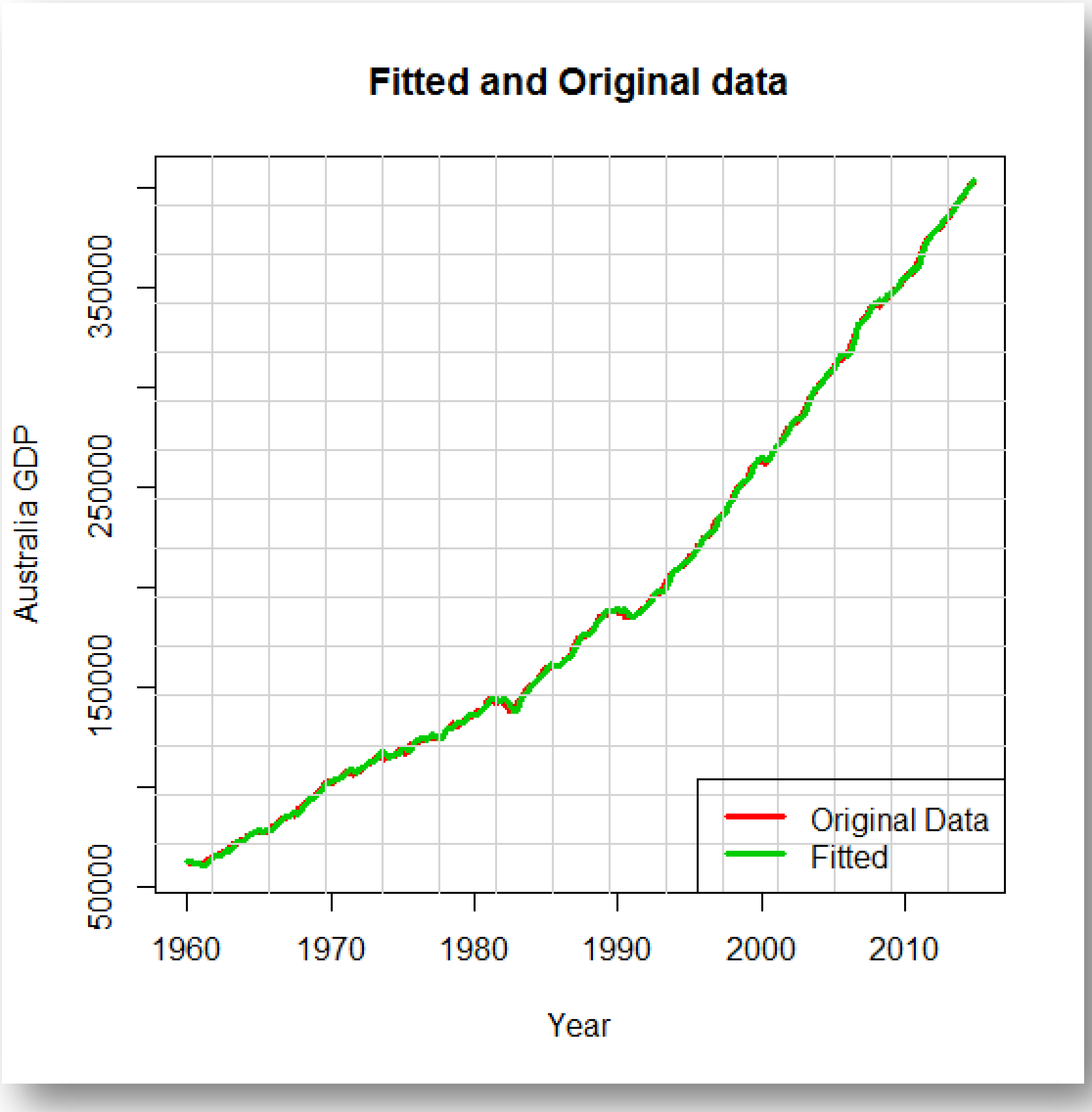


Figure 2. Manual original Australia GDP and the fitted value of US GDP

Figure 2. The close-fitting assessment and the actual data of the annual quarter GDP statistics of Australia gross domestic product (Australia GDP). This expose that for the subsequent three years' time, the Australia, the GDP demonstrated no evidence of decline, based on the behaviour of the GDP data and the close-fitting value fit well and contest intact to the original

Australia GDP data so the model can be useful for prediction of more quarterly years GDP of Australia.

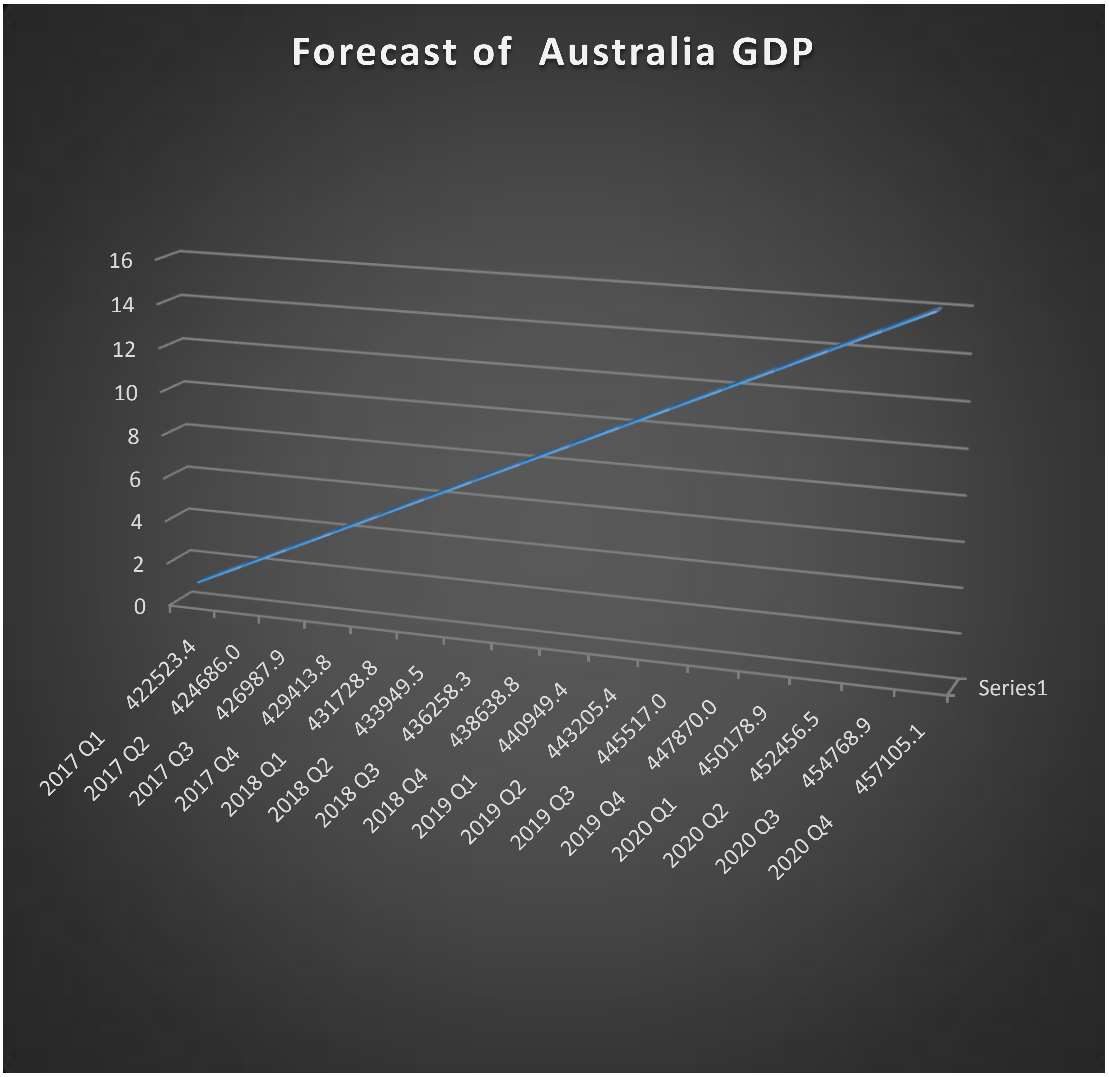


**Figure 3 Forecast Data for Australia GDP.**

Based on the forecast seen in Figure 3 , there is no scientific evidence of Australia GDP bankdrut/crash in the period 2019 to 2025. This details can be used for projection of Australia GDP for the next five years. Australia GDP appears to be in a steadily increasing state.

6. **Discussion and Conclusion**

(31). Bundle ‘bfast’which describes the main space of BFAST. Various scholars utilize the use of BFAST in recognizing trend in landscape data (26). (24) Discusses BFAST as complicated to understand for non-exerts in statistics, this resulted to a gap that lead this study to seek out for pellucidity concerning apropos BFAST. (31) Recommend a technique for broad trend detection for image classification-representative. This method integrates the breaks of time series components into the some predictable elements of the series, seasonal-trends and remnants, it was actualized with the help of the procedure for recognizing change which is embodied in the system of BFAST (6, 7 & 9).

Therefore, from these argument, it is essential for BFAST to be innovated and upgraded to a method that can identify the entire four time series components. The BFAST method was for distinguishing components in time series. This method helps to diagnose components of time series to produce trend and seasonal only. The crucial guide of the BFAST method is the decomposition of time series component and recognizing structural similarity and difference. (31) Also suggested that “the technique of BFAST is for recognizing landscape pattern be improved such that can be applied in other related disciplines”.

(25) Suggested that “BFAST not being proficient enough in identifying natural landscape vegetation component perfectly, though satellite sensor device image have made geographical vegetation information accessible for some many years but yet the recognition of landscape trend and variation are not yet clearly defined”. (16) Advocated “the insufficiency of trend identification techniques, this may be due to the inadequate and limited number of obtainable trend and change detection methods, algorithm suitable in recognizing and describing sudden changes without forfeiting accuracy and efficiency”.

“Based on preceding revisions, BFAST is used for geographical landscape green forest image data at some definite time. Presenting BFAST to time series data and how to contrivance BFAST on such data which comprise of only limited variable for each time is another form of challenge. BFAST is a method that take in statistics time series information then processed to extract each component point of the data” (22).

“BFAST method give a very substantial outcome and was indorse as a modern instrument for statistics information breaks and recognitions but could not detached random noise and is a tailored additive decomposition method, from all suggestion experimental so far, it expose that BFAST need to be extended for the purpose of coping with other multiplicities of uses” (Tolsheden, 2018; Mok et al., 2017; Maus, Câmara, Appel & Pebesma, 2017). BFTSC was suggested for effectual use in time series components identification but need to be improved for forecasting. (1, 3, 3 & 31).

Based on the suggestion and the outcome above, BFTSC was a improved substitute for time series components breaks. BFTSC is suggested as noble to BFAST. This is because BFTSC recognizes the entire four components of time series measurements, this bridge the gap that makes BFAST to be inefficient. Based on the forecast value for 2019 and 2025 , it divulge no scientific signal of bankrupt, drop and crash in Australia GDP so improvement can be establish to improve on the yearly quarterly Australia GDP.

The involvement and contribution of this study to the scientific community is that the BFTSC provides noble results that advance the existing BFAST. BFTSC estimate output is more reasonable for effective policy making. Hence BFTSC can be utilized as an alternative to BFAST.

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**Authors Contributions**

Dr. Ajare Emmanuel Oloruntoba: Produced the innovative automated BFTSC, analyzing, producing the results and writing the paper. Dr. Adefabi Adekunle was part of the analysis, guiding the flows and structure of the paper and Adeyemo Abiodun supplied technical advices to the actualization of the paper.

**References**

1) Ajare, E.O., & Ismail, S. (2019)
Break for Time Series Components (BFTSC) and Group for Time Series Components (GFTSC) in Identification of Time Series Components in Univariate Forecasting. Advanced Research in Dynamical and Control Systems, Volume 11, 05-Special Issue 2019, Pages: 995-1004. http://www.jardcs.org/special-issue.php.

2) Ajare, E.O., & Ismail, S. (2019)
Simulation of Data to Contain the Four Time Series Components in Univariate Forecasting. Advanced Research in Dynamical and Control Systems, Volume 11, 05-Special Issue, 2019 Pages: 1005-1010. http://www.jardcs.org/special-issue.php. Google scholar.

3) Ajare E. O. and Ismail .S. (2019)
Comparative study of Manual time series components identification with automated Break for Time Series Components (BFTSC) and Group for Time Series Components (GFTSC) in Identification in Univariate Forecasting. Published by TEST, Engineering and Management Journal.November-December 2019 ISSN: 0193-4120 Page No. 2826 – 2844. Publication Issue: November-December 2019.

4) Ajare. E.O and Adefabi .A (2023).

Group for Time Series Components (GFTSC) Identification of Gross Domestic Product (GDP) of United Kingdom (UK ). International Journal of Innovative Science and Research Technology. Academia.edu, Google search.Volume 8, Issue 7, July 2023, IJISRT1410, ISSN NO;2456-2165. DOI : https://doi.org/10.5281/zenodo.8304849.

5) Ajare. E, Adefabi and Adeyemo. A (2023).
Examining the Efficacy of Break for Time Series Components (BFTSC) and Group for Time Series Components (GFTSC) with Volatile Simulated and Empirical Data. Asian Journal of Probability and Statistics. Academia.edu, Google search. Volume 8, Issue 7, July 2023, AJPAS 103577, 2023, ISSN NO; 2456-2165

6) Abbes, A. B., & Farah, I. R. (2017). Prediction Changes for Nonstationary Multi-Temporal Satellite Images using HMM. In Handbook of Research on Geographic Information Systems Applications and Advancements (pp. 387-406). IGI Global.

7) Adewoye, R., & Chapman, h. (2018) testing spectral variation hypothesis on the afromontane forest ecosystem of ngelnyaki, north eastern nigeria with landsat 8 (oli) and macro-ecological data.

8) Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). Time series analysis: forecasting and control. John Wiley & Sons.

9) Box, G. E., & Jenkins, G. M. (1976). Time series analysis: forecasting and control, revised ed. Holden-Day. Oakland, California.

10) Bai, J., & Perron, P. (2003). Computation and analysis of multiple structural change models. Journal of applied econometrics, 18(1), 1-22.

11) Bornhorst, F., Dobrescu, G., Fedelino, A., Gottschalk, J., & Nakata, T. (2011). When and how to adjust beyond the business cycle? A guide to structural fiscal balances. IMF Technical Notes and Manuals, 11(02).

12) Bohn, H. (1995). The sustainability of budget deficits in a stochastic economy. Journal of Money, Credit and Banking, 27(1), 257-271.

13) Buhalau, T. (2016). Detecting clear-cut deforestation using Landsat data: A time series analysis of remote sensing data in Covasna County, Romania between 2005 and 2015. Student thesis series INES.

14) Cesta, A., Cortellessa, G., Pecora, F., & Rasconi, R. (2005, May). Monitoring Domestic Activities with Scheduling Techniques. In Proceedings of the 2nd.

15) Cleveland, W. P., & Tiao, G. C. (1976). Decomposition of seasonal time series: A model for the Census X-11 program. Journal of the American statistical Association, 71(355), 581- 587.

16) Chen, C. (2006). CiteSpace II: Detecting and visualizing emerging trends and transient patterns in scientific literature. Journal of the American Society for information Science and Technology, 57(3), 359-377.

17) Caiado, J. (2009). Performance of combined double seasonal univariate time series models for forecasting water demand. Journal of Hydrologic Engineering, 15(3), 215-222.

18) Cipra, T., & Romera, R. (1997). Kalman filter with outliers and missing observations. Test, 6(2), 379-395.

.

19) DeVries, B., Pratihast, A. K., Verbesselt, J., Kooistra, L., de Bruin, S., & Herold, M. (2013, June). Near real-time tropical forest disturbance monitoring using Landsat time series and local expert monitoring data. In Analysis of Multi-temporal Remote Sensing Images, MultiTemp 2013: 7th International Workshop on the (pp. 1-4). IEEE

20) Ewing, B. T., & Malik, F. (2013). Volatility transmission between gold and oil futures under structural breaks. International Review of Economics & Finance, 25, 113-121.journal homepage: www.elsevier.com/locate/iref

21) Flicek, P., & Birney, E. (2009). Sense from sequence reads: methods for alignment and assembly. Nature methods, 6(11s), S6.

22) Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment, 202, 18-27

23) Jong, R., Verbesselt, J., Schaepman, M. E., & Bruin, S. (2012). Trend changes in global greening and browning: contribution of short-term trends to longer-term change. Global Change Biology, 18(2), 642-655. DOI:10.1111/j.1365- 2486.2011.02578.x

24) Jain, A. K., Duin, R. P. W., & Mao, J. (2000). Statistical pattern recognition: A review. IEEE Transactions on pattern analysis and machine intelligence, 22(1), 4-37. DOI: 10.1109/34.824819

25) Jamali, S., Jönsson, P., Eklundh, L., Ardö, J., & Seaquist, J. (2015). Detecting changes in vegetation trends using time series segmentation. Remote Sensing of Environment, 156, 182-195.
doi.org/10.1016/j.rse.2014.09.010

26) Porter, J., & Zhang, L. (2018). BisPin and BFAST-Gap: Mapping bisulfite-treated reads. bioRxiv, 284596.

27) Tolsheden, J. (2018). Detecting and testing for Seasonal breaks in Quarterly National accounts: Based on X-12-ARIMA and BFAST Methods.

28) Maggi, L. M. B. (2018). Times Series Analysis. In Multiscale Forecasting Models (pp. 1- 29). Springer,

29) Mok, T. S., Wu, Y. L., Ahn, M. J., Garassino, M. C., Kim, H. R., Ramalingam, S. S., ... & Lee, C. K. (2017). Osimertinib or platinum–pemetrexed in EGFR T790M–positive lung cancer. New England Journal of Medicine, 376(7), 629-640.

30) Maus, V., Câmara, G., Appel, M., & Pebesma, E. (2017). dtwSat: Time-Weighted Dynamic Time Warping for Satellite Image Time Series Analysis in R. Journal of Statistical Software.
31) Verbesselt, J., Hyndman, R., Newnham, G., & Culvenor, D. (2010). Detecting trend .
32) Foster.J (2016) The Australia growth miracle: An evolutionary macroeconomic explanation. Cambridge journal of Economics, 40(3), 871-894.