Forecasting AustraliaGross Domestic Product (GDP) under Structural Change (SC) using Break for Time Series Components (BFTSC).

Abstract:

The main objective of this study *is to use BFTSC (break for time series components) to identify the structural change and components of time series present in the seasonal data of Australia GDP. The (Australia GDP) data spanned for the period of fifty five years (1960 to 2014). The GDP of Australia is a secondary data obtained from the DataStream of Universiti Utara Malaysia Library. The weaknesses of BFAST in terms of structural change were corrected by the extension of BFAST to BFTSC. BFTSC was created to capture the cyclical and irregular components that was not captured by BFAST technique and it was included in the methodology of this study. BFTSC is designed to give a combined image of all the four time series components captured in a single time plot. Evaluation using simulation&empirical dataverified the accuracy of BFTSC. BFTSC is effective and better than BFAST because it was able to identify 100% of the data with the basic four time series components. BFTSC detects 99.97% of the entire components in the time series monthly data that was tested. The subsequently forecasting technique was determined and a forecast is made.*

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

Introduction

Australia is a country that was created on 26th January 1788. This date became Australia national day, Australia Day, the colony was proclaimed by Governor Phillip on 7th February 1788 at Sydney.Gross Domestic Product (GDP) in Australia averaged 502.19 USD Billion from 1960 until 2022, reaching an all time high of 1675.42 USD Billion in 2022 and a record low of 18.61 USD Billion in 1960. This page provides - Australia GDP - actual values, historical data, forecast, chart, statistics, economic calendar and news (32). In the 1990s, and the second half of the 1990s in particular, ranks as one of Australia's best periods in terms of historically high productivity, strong GDP growth and GDP growth per capital, low inflation and falling unemployment, a period which not only reinforced prosperity and wealth from Australia's own (32). Despite similarities (Australia, Canada and US) in history, law and culture, Australia followed quite different macroeconomic histories. Australia's GDP per capital was well above those of Britain and the United States in 1870, and more than twice the Canadian level. By the 1980s, however. Economic liberalization and deregulation of the Australian economy began in the early 1980s under the Hawke Labor government, which commenced the process of economic reform by concluding a wages accord with the trade union movement. In exchange for wage restraint and an increase in the "social wage" the trade union movement agreed to support economic reform and oppose industrial conflict (i.e. strikes). The success of the "Accord" allowed a Labor government to implement economic reforms that in other nations had been implemented by conservative political parties; tariffs were progressively cut, the Australian dollar was floated (1983), and the financial system deregulated. Hawke was also able to privatize several large government enterprises. Sector wide 'Industry Plans' for economic reform were introduced in telecommunications and manufacturing. The Australian Stock Exchange Limited (ASX) was formed in 1987 through the amalgamation of six independent stock exchanges that formerly operated in the state capitals. Each of those exchanges had a history of share trading dating back to the 19th century (32).

The global early 1990s recession came swiftly after the Black Monday of October 1987, resulting from a stock collapse of unprecedented size which saw the Dow Jones Industrial Average fall by 22.6%. This collapse, larger than the stock market crash of 1929, was handled effectively by the global economy, and the stock market began to quickly recover (This is known as Australia miracle growth (32)). The following recession thus impacted the many countries closely linked to the United States, including Australia. Paul Keating, who was treasurer at the time, famously referred to it as "the recession that Australia had to have. During the recession, GDP fell by 1.7%, employment by 3.4% and the unemployment rate rose to 10.8%. However, as is typical during recessions, there was a beneficial reduction in inflation. These economic reforms have resulted in Australia now being considered one of the most open economies in the world, notwithstanding polarising opinions regarding the long term success of free and open trade, and its inevitable effect on domestic workers. Australia has enjoyed over two decades of economic growth, coupled with low inflation and relatively low unemployment - until 2020 when the country entered into a brief recession where unemployment skyrocketed amid the global COVID-19 pandemic. Due to the outbreak of COVID-19, trade disputes with China, and the war in Ukraine, there has been a significant political shift in focus toward National Security and renewed interest in Australia's manufacturing industry. Although free trade continues to take place, the importance of a thriving local industry has regained traction as an important consensus (32). The economic reforms implemented since the 1980s 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 pandemic reached Australia in January 2020. On 20th March, Australian borders were closed to all non-residents, impacting especially tourism and the entry of overseas students. Social distancing rules were imposed on 21 March, and “non-essential” services were closed, which included social gathering venues such as pubs and clubs but, unlike many other countries, did not include most business operations such as construction, manufacturing and many retail categories(32). A second wave of infections in Victoria emerged during May to June, and Victoria imposed a strict lockdown, which continued into September. State governments also imposed bans on cross state border movements. On 2 September 2020, as a result of the Covid-19 pandemic, Australia officially went into recession (defined as two quarters of negative growth) with GDP falling 7% in the June 2020 quarter, the largest drop on record. GDP fell 0.3% in the March quarter(32)

UsingAustralia quarterly seasonal data which is the GDP yearly data on BFTSC (Break for time series components) to identify the components of time series present in the empirical data. BFTSC is considered to be more efficient in identifying all the components of time series statistics better than BFAST. BFTSC is an improved BFAST. BFAST (Break for Additive Seasonal and Trend) is a technique used for identification of trend and seasonal components of time series observations, trend breaking was first suggested by (10). (23, 31) recommended an approach of basic swing identification to spot time series component. This approach was also used by (27) as the latest time series component recognition approach which is a technique that was first described and utilized by (31).

The technique BFAST was for recognizing breaking points with the help of seasonal and trend decomposition using loess (STL), it facilitates the detection of trend change in a given information. The elementary standard of the BFAST technique is the splitting of time series into seasonal, trend and also remnants element by the approach for breaks detecting software in R studio core 2012 **(**30, 31).
(16, 31) opines thatthe technique of BFAST canpredict andanalyze a topographical forest movement with the help of normalized difference vegetation index's branded as (NDVI). Thus, by extensively examining the period of variations of the desiccated portion of land for an enhanced perceptive of the seasonal variation path in the arid topographic area, this was done by detecting and determining factors of arid area changes using (NDIV) data to monitor the variations(13,14,19). The technique is accessible in BFAST pack for R (R developments Core Team, 2012). Package 'bfast'which portray the main scope of BFAST. Many scholars employ the use of BFAST in identifying trend in topographical data (26).

The extension of BFAST is an improved technique that identifies all-time series components. This new technique is known as BFTSC (Break for time series components). Many of the automated techniques of pattern detection are computer oriented. BFTSC is one of the first extension of BFAST in history which also focus more on computer approach strategy rather than theoretical approach strategy(1,3 & 4).

BFTSC technique considers every vital component of time series statistics. BFAST is known to be weak in identifying and breaking random variations, also very weak in applicability to other types of empirical data(21,24). The technique considers the extension and improvement of the BFAST to BFTSC, breaks for additive, seasonal and trend to be modified to break's for time series components BFTSC.

BFTSC is programmed into computer R package and can be used by anyone who wishes to be a beneficiary or need the package that will be developed. For better identification, the diagrammatic representation of the BFTSC is shown and represented in Figure 1.

BFTSC is tolerant to additives models when necessary considering the structure of the system and multiplication models of the given system. The problem of time series components detection is a problem that should be solved in the earliest stage of time series forecasting (21).

BFTSCfollowed similar derivative steps like BFAST but deviated in the addition of cyclical and irregular components. BFTSC is the technique used in analyzing the generality of time series data by extracting the trend components and seasonal components, cyclical components and irregular components during time series decomposition. Given the general time series additive model as in equation (1.1) of the form:

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

where Y_P is the observed value at time period p and T_p is the trend value at time period p, while S_p is the seasonal component value, C_p is the cyclical component and I_p is the irregular component all with time period p (8, 12, 15, 18).

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

The residual component in BFAST now converted to contained cyclical and irregular component in BFTSC. The breakpoint which represent the change in time series caused by common noise such as natural phenomenon and human activities can be observed in both seasonal components and trend components using BFTSC technique. In BFAST only random component can be observed but in BFTSC the cyclical and irregular components is identified alongside with trend and seasonal components (2, 21,22).

Material and Methods

BFAST is the technique used in analyzing the generality of time series data by extracting the trend and seasonal pattern during time series decomposition. Given the general time series additive model of the form:

$Y_P = T_p + S_p + C_p + I_p$(2.1)

Where Y_P is the observed value at time period p and T_p is the trend value at time period p, while S_p is the seasonal component value, C_p is the cyclical component and I_p is the irregular component all with time period p (28, 29).

From equation (2.1) BFAST takes all other components apart fromtrend and seasonal component to be randomized (R_p) and the equation was expressed as (1, 3, 5 & 31).

$Y_P = T_p + S_p + R_p$ (2.2)

The residual random consist of cyclical and irregular component, the breakpoint which represents the sudden change in time series caused by uproar noise such as natural phenomenon and human activities can be spotted in both seasonal components and trend components using BFAST technique (21).

To generate trend components using BFAST, we need a piecewise linear model approach.Suppose T_p is a piecewise linear model with an actual slope and intercept on q+1 segments broken with q breakpoints and P period; $p_1^{\neq}$,……….,$p_q^{\neq}$ then T_p can takes the form

$T_p = \alpha_k + \beta_k$P

To generate seasonal components using BFAST, we need a simple harmonic model.

Thus, S_p can be represented by a simple harmonic model with j terms; j = 12….J and time t.

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

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

To generate random components, any data that does not belong to trend nor seasonal is classified randomR_p..

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

$$Y_P = T_p + S_p + R_p$$

The new technique called BFTSC considered splitting the random into cyclical components and irregular components which is an extension of BFAST. This was done through the inclusion of cyclical components direction.

Cyclical components can be calculated through the regression cyclical movement. The regression function at the breakpoint maybe discontinuous but the model can be written in such a way that the function continues at all point including breakpoints. To calculate cyclical components, center moving average is involved (Bornhorst, Dobrescu, Fedelino, Gottschalk & Nakata, 2011).

Derivation of cyclical code

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

The new equation becomes

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

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

where Y_P is the observed value at time period p and T_p is the trend value at time period p, while S_p is the seasonal component value, C_p is the cyclical component and I_p is the irregular component at period p.

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).

Results

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

The forty eight months (smallmonthly sample size)trend data wasgenerated from the model

Y_t=95.68699+0.560847x_t (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 wasgenerated 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 and the percentage of accuracy is recorded in table 1. 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.

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 wasgenerated 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 2. 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.

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%.

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))

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

The first stage in forecasting is to view the data and to examine all the components of time series present in that data in order to select the most appropriate forecasting technique. The yearly quarterly GDP data components identification was carried out with the help of the new technique called BFTSC. This new technique helps to have a clear image of the entire variations presents in the time series data.

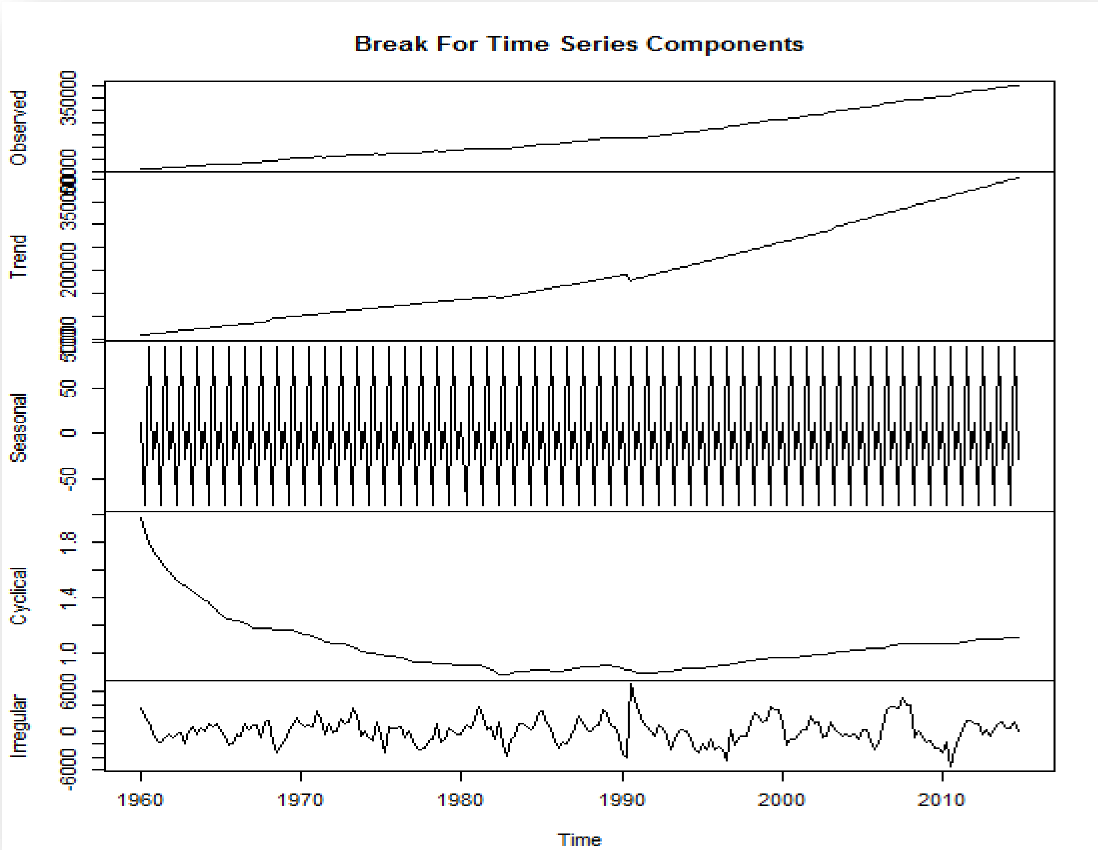

Figure 1. BFTSC for Quarterly Australia GDP data

Figure 1 reveals all the time series components hidden in the quarterly France GDP data for 55 years, the image in the figure above indicate the presence of trend, seasonal, cyclical and irregular components, Hence the most appropriate techniques for analyzing such data is ARIMA.

Ten ARIMA models are tested and the best model is selected based on the ARIMA with the smallest AIC (Akaike's Information Criterion). Based on the AIC models, the ARIMA(2,2,3) is the best model to be used in fitting the France quarterly GDP . ARIMA(2,2,3) is selected and used for fitting the model (6,7).

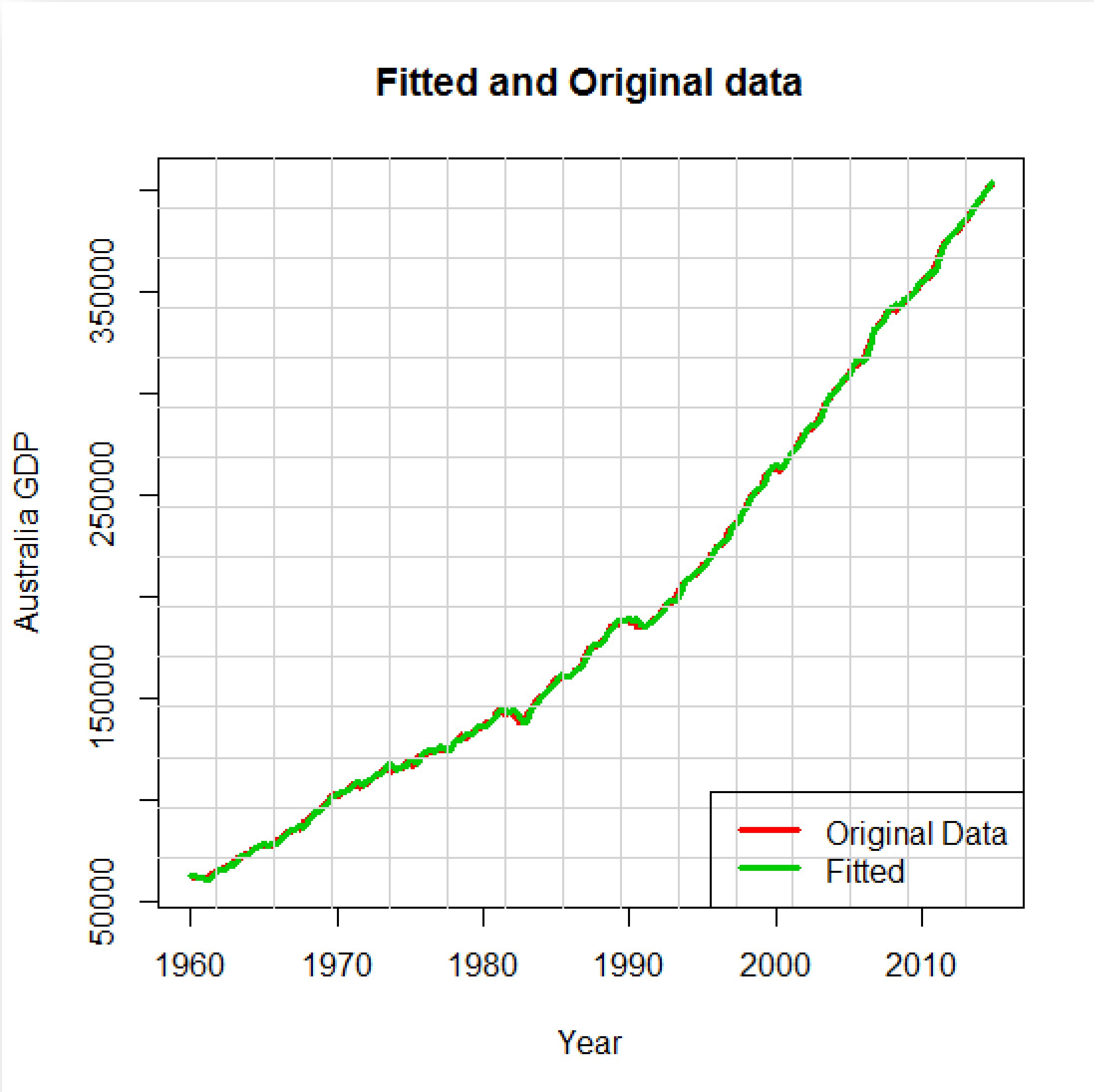

Figure 2. Manualoriginal Australia GDP and the fitted value of US GDP

Figure 2. The fitted value and the real data of the yearly quarter GDP data of Australia gross domestic product (Australia GDP). This reveal that for the next two years period the Australia, the GDP show no evidence of decline and the fitted value fit well and match intact to the original Australia GDP data so the model can be applied for prediction of more quarterly years GDP of Australia.

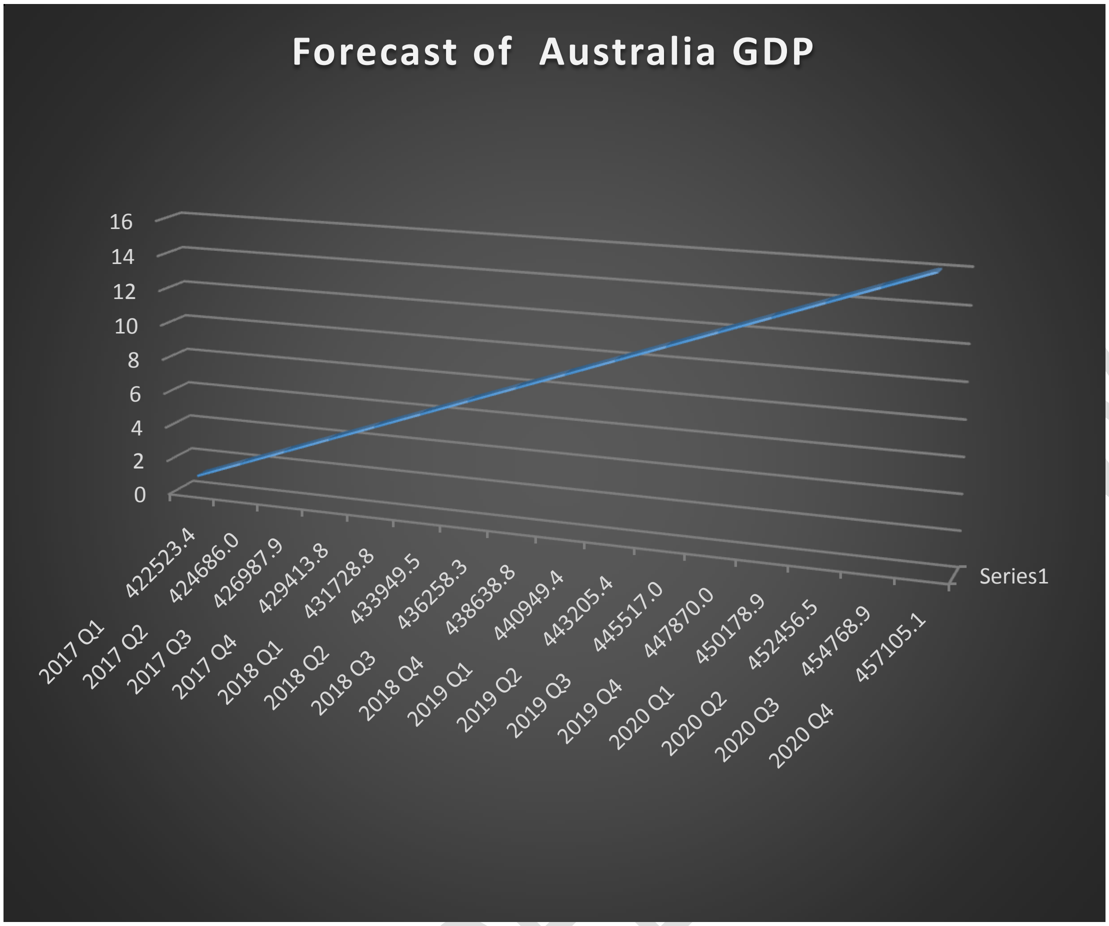

Figure 3 ForecastData for Australia GDP.

Based on the forecast seen in Figure 3, no scientific evidence ofAustraliaGDP crash in the period 2019 to 2020. This details can be used for projection of Australia GDP for the next five years. AustraliaGDP appears to be in a steadily increasing state.

Discussion/Conclusion

(9) was one of the first researchers that struggle to clearly identify time series component using time plot. However, the limitation of this technique was the complexity, it was very complicated to differentiate the time series components using casual manual time plot and the manual technique may be extremely difficult for non-experts.(20 & 21) developed DBEST (Detection Breakpoint and Estimating Segment Trend) which was modified from BFAST. DBEST take in (NDVI) normalizes difference vegetation index data. The limitation of DBEST technique is that, the algorithm was built to solve the problem of topographical vegetation trend identification and cannot identify cyclical and irregular components of time series statistics. It is not flexible time

series component identification technique and this is still a problem that needs to be fully addressed,

(23 & 22) argue and contributed to the body of knowledge by investigating the collective change identification called BFAST. The technique called BFAST is used for acknowledging breaks for additive seasonal and trend in order to justify for seasonal disorder and also enables the identification of breaks that take place in trend within the system (31). The technique is accessible in BFAST pack for R (R developments Core Team, 2012).

(31). Package 'bfast'which portrays the main scope of BFAST. Many scholars employ the use of BFAST in identifying trend in topographical data (26). (24) describe BFAST as complicated in technique, this lead this study to seek out for transparency regarding BFAST(31) recommend a new technique for broad trend detection for image classification and representative, the technique is called Break for Additive Seasonal and Trend known as BFAST. This technique integrates the decomposition of time series components into the conventional elements of the series such as data, seasonal, trends and remnants, it was done with the help of the technique for identifying change which is embodied in the system of BFAST (6,7 & 9).

Therefore, from these discussion, BFAST need to be improved to a technique that can identify the four time series components. BFTSC is recommended for efficient time series components identification for an improved forecasting.(31). The technique was for recognizing Breaks for Additive Seasonal and Trend (BFAST). This technique helps to recognize trend breaks enclosed by the series. The essential guide of the BFAST technique is the decomposition of time series component into seasonal, trends and miscellany elements with the technique for recognizing structural similarity and difference. (31) recommended that the technique of BFAST is for identifying topographical pattern and also for improvement to be applied in other related disciplines.

(25) describe BFAST as not being capable of identifying topographical vegetation basic component perfectly, though satellite sensor image have made topographical vegetation data available for so many years but yet the detection of topographic trend and variation is not yet clearly defined. (16) suggested that, this may be due to the limited number of available trend and change detection techniques accessible, algorithm suitable in identifying and characterizing abrupt changes without sacrificing accuracy and efficiency.

Based on previous studies, BFAST is used for topographical green forest picture data at certain specific time. Introducing BFAST to time series data and how to implement BFAST on time series data which contain only one variable for each time is another form of challenge. BFAST is a technique that take in data and processed to extract each component point of the data, it would be reasonable to use BFAST for time series components identifications (Rikus, 2018; Gorelick, 2017; Zhu, 2017).
BFAST approach give a very considerable outcome and was recommend as a modern instrument for statistics information decomposition and detections but could not separate random noise and is a customized additive decomposition method, from all indication observed so far, it reveal that

BFAST need to be extended for the purpose of coping with other varieties of uses (Tolsheden, 2018; Mok et al., 2017; Maus, Câmara, Appel &Pebesma, 2017).

Based on the every result in the simulated and the empirical analysis, BFTSC is the most appropriate for time series components identification. BFTSC is recommended as a good alternative to BFAST. This is because BFTSC identifies the four components of time series statistics which is one of the basic limitations of BFAST. Based on the forecast value for 2019 and 2020 , it reveal no scientific evidence of drop and crash in Australia GDP so improvement can be establish to improve on the yearly quarterly Australia GDP.
The contribution of this study to the scientific community is that the BFTSC gives good results that improve the weaknesses of the existing BFAST. BFTSC forecast output is more reasonable for effective policy making.

Ethics

This is the original manuscript; there will be no expectation of any ethical problemsafter the publication. The three authors
have read and approved the manuscript.

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.