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Detecting Change in a Volatile Curve United State Stock Market (US SM) with the Use of Automated Decomposition for Time Series Components

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Authors' contributions

This work was carried out in collaboration among all authors. Author AEO did analyzing, producing the results and writing the paper. Author AA works on the contents and setting standard of the paper. Author OTO type setting and organizing flow of the paper. All authors read and approved the final manuscript.

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ABSTRACT

The main reason for this investigation is to use manual process of identification of time series components with two types of automated decomposition for time series known as automated BFTSC (break for time series components) and, automated GFTSC (Group for time series components) in detecting change in a volatile curve united states stock market (US SM). In identification of components of time series present in the seasonal data of US stock market. The data US Stock Market was a monthly data from January 2001 until December 2018 and a total of 18 years. The stock market of US is also available as a secondary data at the DataBank of University Utara Malaysia Library. The weaknesses of BFAST were corrected by the extension of BFAST to BFTSC and GFTSC. Both were created to capture the cyclical and irregular components that were not captured by BFAST technique and it was included in the methodology of this study. BFTSC and GFTSC were considered to provide a combined image of all the four components of time series while GFTSC had additional advantage of providing equations to the components automated. Evaluation using simulation data and empirical data vindicated the accuracy of BFTSC and GFTSC based on linear trend less volatile data. They are effective and better than BFAST because it was able to identify 100% of the data with the basic four time series components monthly. Both techniques detects 99 % of the entire components in the time series data in a linear trend data.

Keywords: United State; break for time series components; seasonal data; stock market; cyclical components; irregular components.

1. INTRODUCTION

"The main reason for this study is to use manual process of identification of time series components, automated BFTSC (break for time series components) and automated GFTSC (Break for time series components) in identifications of the mechanisms of time series present in the experiential data of periodical seasonal data which is the stock market (SM) data of United State. BFTSC and GFTSC are presumed to be more proficient in identification of all the components of time series statistics. Both techniques are upgraded BFAST. BFAST known as Break for Additive Seasonal and Trend) is a method used for identification of trend and seasonal components in a remote sensing (RS), trend breaking" [1]. Jong, Verbesselt, Schaepman and Bruin [2]. This methodology was also included in Zewdie, Csaplovics and Inostroza (2017) as procedure that described and utilized by Verbesselt et al. [3] idea.

"The method BFAST was the excruciating of time series into seasonal, trend and leftovers element by the approach for breaks sensing software in R studio core 2012" **(**Cunha**,** 2013).

Zewdie et al. (2017) opines suggested that "the performance of BFAST indicates that it can envisage landscape forest movement in northwest of Ethiopia with the assistance of standardized change 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 (Cesta, Cortellessa, Pecora, & Rasconi, 2005 ; Buhalau, 2016 ; DeVries, [4]. The procedure is accessible (in R extension Core Team, 2012). Package 'bfast'which portray the foremost scope of BFAST [5].

"The improvement of BFAST is an innovative method that classifies all-time series components. This double new methods are known as BFTSC (Break for time series components) and GFTSC (Group for time series components). Many of the automated techniques of pattern detection are not flexible enough to be used by non-experts in statistic. GFTSC and BFTSC are very flexible and easy to use by non-statistics experts, this is the first extension of BFAST in history which can produce equations together with time plots automatically" [6] .

BFTSC and GFTSC method that splits each component of time series. Flicek & Birney [7]. The procedure cogitates the innovation and enhancement of the BFAST to BFTSC, breaks for additive, seasonal and trend to be modified to break's for time series components BFTSC. GFTSC has the improvement of generating equations of each time series components displayed together on the same time plot, this makes GFTSC to be a step further to BFTSC.

Both techniques are programmed into computer EZEE forecasting software as a package available, scholars who need it can freely use it Flicek & Birney [7].

BFTSC and GFTSC streamlined in the aspect of derivative steps like BFAST but diverged in the aspect of equation extraction automatically. “BFTSC and GFTSC are both method used in investigating the generality of time series data by mining the trend and seasonal components, cyclical components and irregular components during time series decomposition” [7]. Given the general time series additive model as in equation (1.1) of the form:

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

where Y_P is the observed value at time period p (See Ajare and Suzilah 2019 for details on T_p , while S_p, C_p and I_p) and also (Box, Jenkins, Reinsel, & Ljung, 2015 :Maggi, 2018; Cleveland & Tiao, [8] Caiado, [9], Bohn, [10], Cipra, & Romera, 1997).

BFTSC and GFTSC identifies all the of time series components relatively trend, seasonal, cyclical and irregular components to be randomized equation while GFTSC identifies all the of time series components together with addition of the equations that produces each components.

“The remaining component in BFAST now changed to confined cyclical and irregular component using GFTSC and BFTSC. The breakpoint which represents 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 using BFTSC method. In BFAST only random component can be observed but BFTSC cyclical and irregular components are identified alongside with trend and seasonal components” (Zdravevski, Lameski, Mingov, Kulakov & Gjorgjevikj, 2015).

Data behaviour are not the same, some data are very noisy, corrosive, harsh and volatile while some data are gentle and less volatile. Data that follow log linear, polynomial, curve trend can be considered volatile while data that follow simple linear trend are less volatile.

United State Stock Market (US SM). The data US Stock Market was a monthly data from January 2001 until December 2018 and a total of 18 years. The data was obtained from the Yahoo Finance using Nasdaq adjusted close data which was the closing price after adjustment for all applicable splits and dividend distribution and also available in the University Utara Malaysia Library databank section (research section RR-2567).

1.1 Strength of BFTSC and GFTSC

BFTSC and GFTSC includes the ability to clearly identify all the time series components (trend, seasonal, cyclical, irregular) automatedly and presenting them neatly in time plots that belongs to each of the components (Ajare, & Ismail, [11], Ajare & Adefabi [11], Ajare, & Ismail, [12], Ajare, Adefabi & Adeyemo, 2023).

Both BFTSC and GFTSC can be used to estimate for missing values in trend, in seasonal, in cyclical and irregular components. The fit components are very reliable in forecasting, as BFTSC and GFTSC proof and pass reliability test of 99% accurately identifying time series components in a linear data. The fit components are also very consistent, and durable to be used by non-experts in forecasting, as BFTSC and GFTSC proof and passed consistency test of 99% accurately consistently identifying time series components in a linear data (see Ajare, & Ismail, [12], Ajare & ADEFABI 2023; Ajare, & Ismail, [12], Ajare, Adefabi & Adeyemo, 2023). BFTSC and GFTSC are both fast in generating subsequent trend, data processing, and extrapolation in an automated process. Both techniques can be employed for use in big data, panel data and can be advanced for use for multivariate data processing. Being super-hybrid of BFAST automated technique of time series decomposition, both technique can be used in remote sensing field [13,14]. Both techniques (BFTSC and GFTSC) are not affected by extreme values or missing values or points. Finally both techniques involves less human (expert) supervision unlike manual process that requires full attention of the expert. GFTSC had additional strength of providing and presenting equations that produces each components with their values automatically attached to the headings of each time plot (see Ajare, & Ismail, [12], Ajare & Adefabi 2023; Ajare, & Ismail, [12], Ajare, Adefabi & Adeyemo, 2023).

2. MATERIALS AND METHODS

BFAST procedure uses the simplification of time series data to extract trend and seasonal componence during time series breakdown(17). The general time series additive model:

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

Where Y_P is the observed value at time period p and T_p is the trend value at time period p, (See Ajare and Suzilah 2019 for details on T_p , while S_p, C_p and I_p) and also (Maggi, 2018 ; Zhao, Li, Mu, Wen, Rayburg, & Tian, 2015).

From equation (3.1) BFAST takes left over components to be randomized (R_p) and the equation was expressed as

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

The residual haphazard entails cyclical and irregular component, (Zdravevski, Lameski, Mingov, Kulakov & Gjorgjevikj, 2015). To spawn trend using BFAST, we need a piecewise rectilinear model method. Suppose T_p is a piecewise linear archetypal with a definite slope and intercept on q+1 subdivisions broken with q points and P period; $p_1^{\neq}$,………., $p_q^{\neq}$ then T_p can takes the form

$$T_p = \alpha_k + \beta_k \mathrm{P}$$

where $p_{k-1}^{\neq} < \mathrm{p} \leq p_k^{\neq}$

and If k = 1,..,q then $p_0^{\neq}$ = 0 and $p_{q+1}^{\neq}$= n.

The gradient (slope) of the modification before the breakpoints while β_{k-1} and the gradient of the breaks after the breakpoints are β_k (20, 21). The intercept and the gradient of the rectilinear model α_k and β_k with time p and it will be recycled to derive the magnitude and direction of modification.

To produce seasonal constituents 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.

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

where k = 1… q, $p_{k-1}^{\neq} < \mathrm{p} \leq p_k^{\neq}$ and also $\omega_{k,j}$, $\sigma_{K,j}$ (see Ajare & Suzilah [12], Ajare, Adefabi & Adeyemo, 2023; Zeileis, Kleiber, Krämer & Hornik, 2003).

To get random components, any statistics that does not fit to trend nor seasonal is categorized random R_p.

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

$$Y_P = T_p + S_p + R_p$$

“Both new methods (BFTSC and GFTSC) considered excruciating the random into cyclical and irregular constituents which is an innovation of BFAST”. “This was prepared through the ation of cyclical direction” (Ajare & Suzilah 2019; Ajare, Adefabi & Adeyemo, [15]. (Bornhorst, Dobrescu, Fedelino, Gottschalk & Nakata, [16]. Derivation of cyclical code, let CMA be the center moving average of t objects, then CMA can be computed as

$$\sum_t^n \frac{Yt}{nt} \quad (2.5)$$

t = 1,2…………n

Let $\overset{\wedge}{CMA}$ be the regression trend line of CMA for a given time series data

The CMA regression line is represented by

$$\overset{\wedge}{CMA} = \alpha_0 + \beta_1 \mathrm{P} \quad (2.6)$$

For a given α_0 and β_1 being the slope and intercept of the time series observations (Ajare & Suzilah [12], Ajare, Adefabi & Adeyemo, [17].

The cyclical components at time p is computed as

$$C_p = \frac{CMA}{\overset{\wedge}{CMA}} \quad (2.7)$$

The innovative equation becomes

$$Y_P = \alpha_k + \beta_k \mathrm{P} + \sum_{j=1}^{J} \omega_{k,j} \,\mathrm{Sin}\frac{2\pi jt}{F} + \sum_t^n \frac{Yt}{nt} + I_p \quad (2.8)$$

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

where Y_P is the observed value at time period p and See Ajare and Suzilah 2019 for details on T_p , while S_p, C_p and I_p (Ajare &Suzilah 2019; Ajare, Adefabi & Adeyemo, 2023).

3. RESULTS

3.1 Manual Time Series Components Identification Approach of United States Stock Market Data

The same four steps used in the manual identification approach previously was adopted for US stock market data (see Ajare &Suzilah [12], Ajare, Adefabi & Adeyemo, [17]. This helps in obtaining deep understanding regarding the behaviour of the data. The monthly data of US Stock Market is available with the author and can be given out to anyone who needed it based on request [18,19].

Fig 1 displays the time series plot of monthly US Stock Market from January 2001 until December 2018. There was steady increment from 2001 until 2007 but dropped in 2008 due to economic crisis and slowly increased from 2009 to 2018 (Shirvani, 2020). The dropped in 2008 that related to economic crisis was considered as cyclical component (C1). Fig 1 also shows a curve trend.

The manual time series plot in Fig. 1 is capable of identifying the time series components in US Stock market data but the limitation is that its required the supervision of an expert, also very slow and rigorous process, not easy to learn but more of personal judgement. Hence this study proceed to BFTSC and GFTSC which are automated in process.

3.2 Comparison of BFTSC and GFTSC with Manual Identification Approach using US Stock Market Data

Fig. 2 show the plots produced by BFTSC for US Stock Market monthly data respectively. BFTSC managed to identify one cyclical but failed to identify curve trend and display linear trend instead, which contradict with manual approach identification as in previous studies (Ajare & Suzilah [12], Ajare, Adefabi & Adeyemo, [17]. These indicated the limitation of BFTSC when the trend deviated from linear which reflected similar findings.

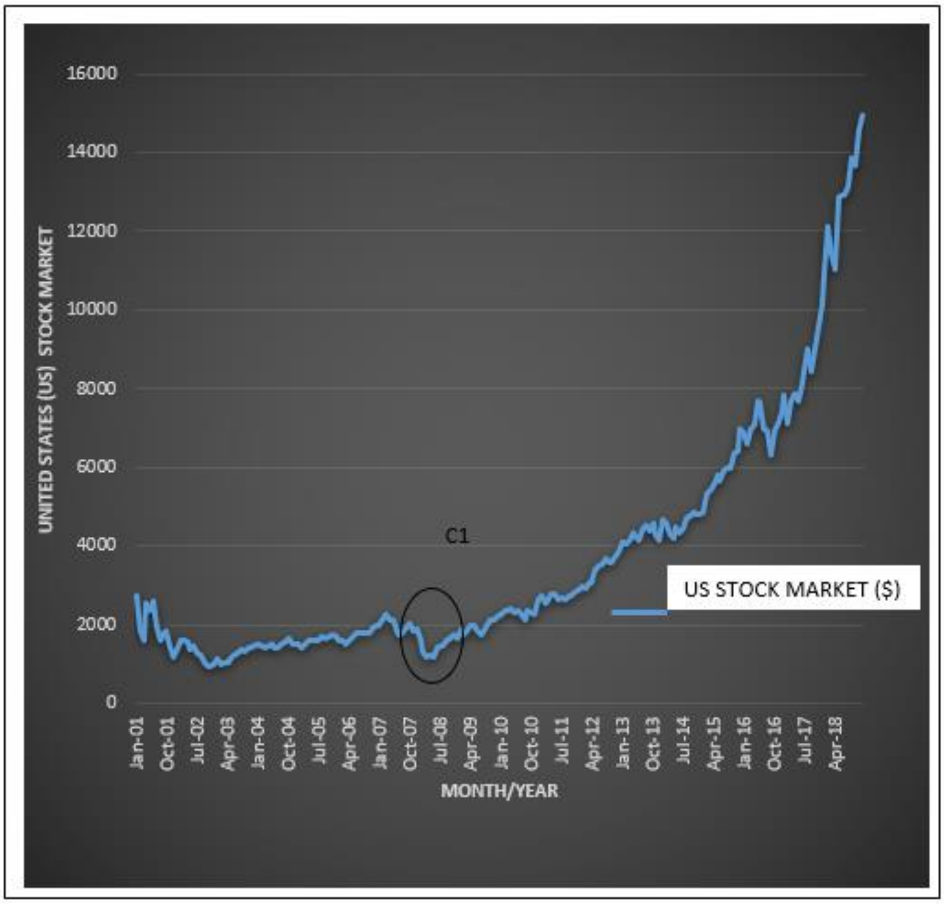

Fig. 1. Manual time series plot of US Stock Market

The Automate*d* BFTSC was perfectly able to identify the data which was in the observed plot, also it was able to automatically identify one cyclical but as for the trend BFTSC was weak in identification of curve trend, polynomial and highly volatile data. BFTSC converted the curve trend to a straight line trend. Hence BFTSC is weak in identification of exact trend in a very high volatile data.

Fig. 3 show the plots produced by GFTSC for US Stock Market monthly data respectively. GFTSC successfully identified one cyclical but failed to identify curve trend and displayed linear trend instead, which contradict with manual approach identification as in previous studies (Ajare & Suzilah [12], Ajare, Adefabi & Adeyemo, [17]. GFTSC had a special advantage as part of its features, GFTSC was able to displayed the equation of each time series components produced and attached as the heading of each plots automatically. As seen in Fig 3 (Equation of observed data displayed above observed data, equation of trend displayed above trend, equation of cyclical displayed above cyclical) this is a kind of features cannot be found anywhere except by automated GFTSC. These indicated the limitation of GFTSC when the trend deviated from linear which reflected similar findings to previous studies (See Ajare. Adefabi & Adeyemo, [17].

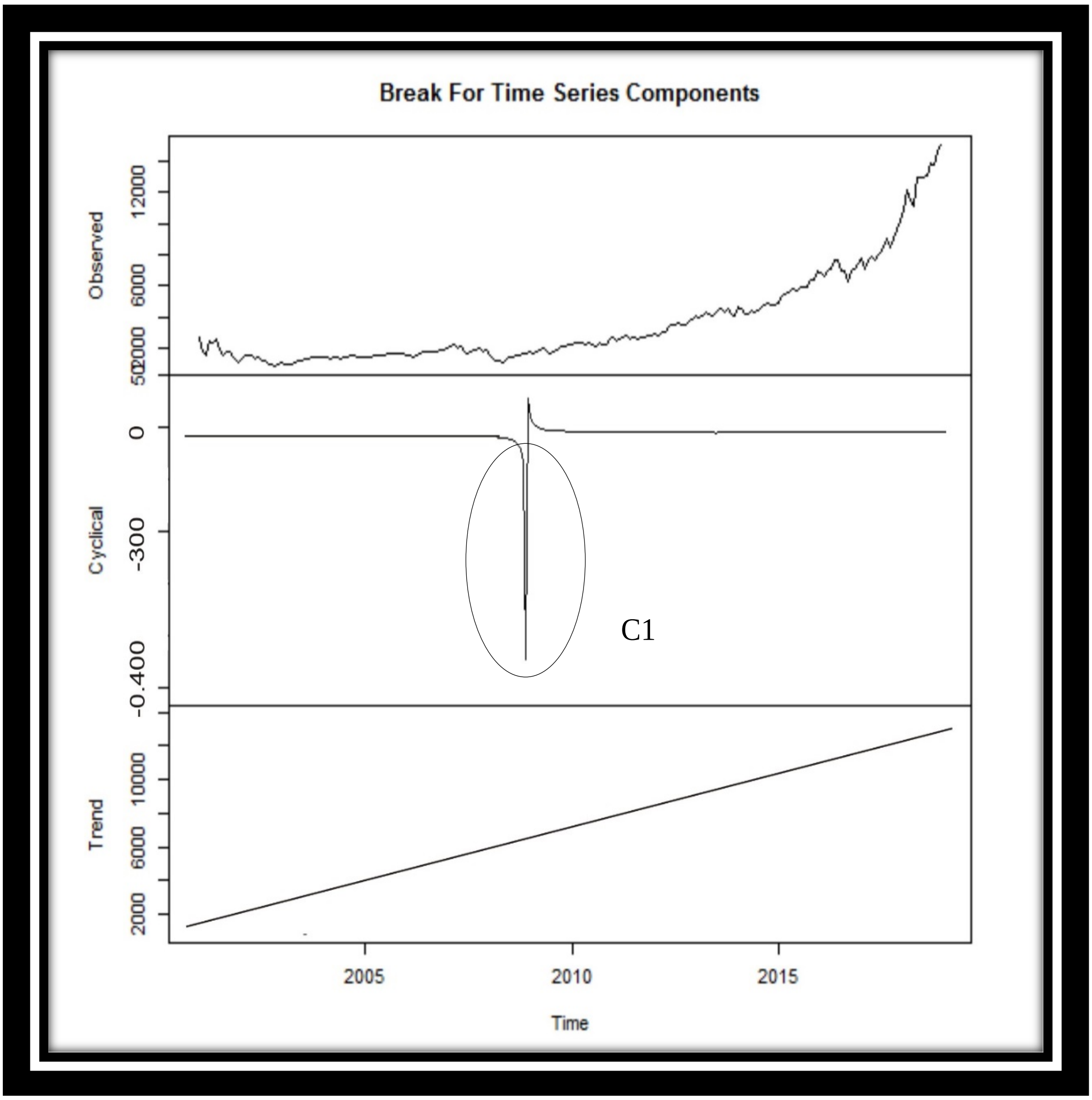

Fig. 2. Automated BFTSC plots of monthly US stock market

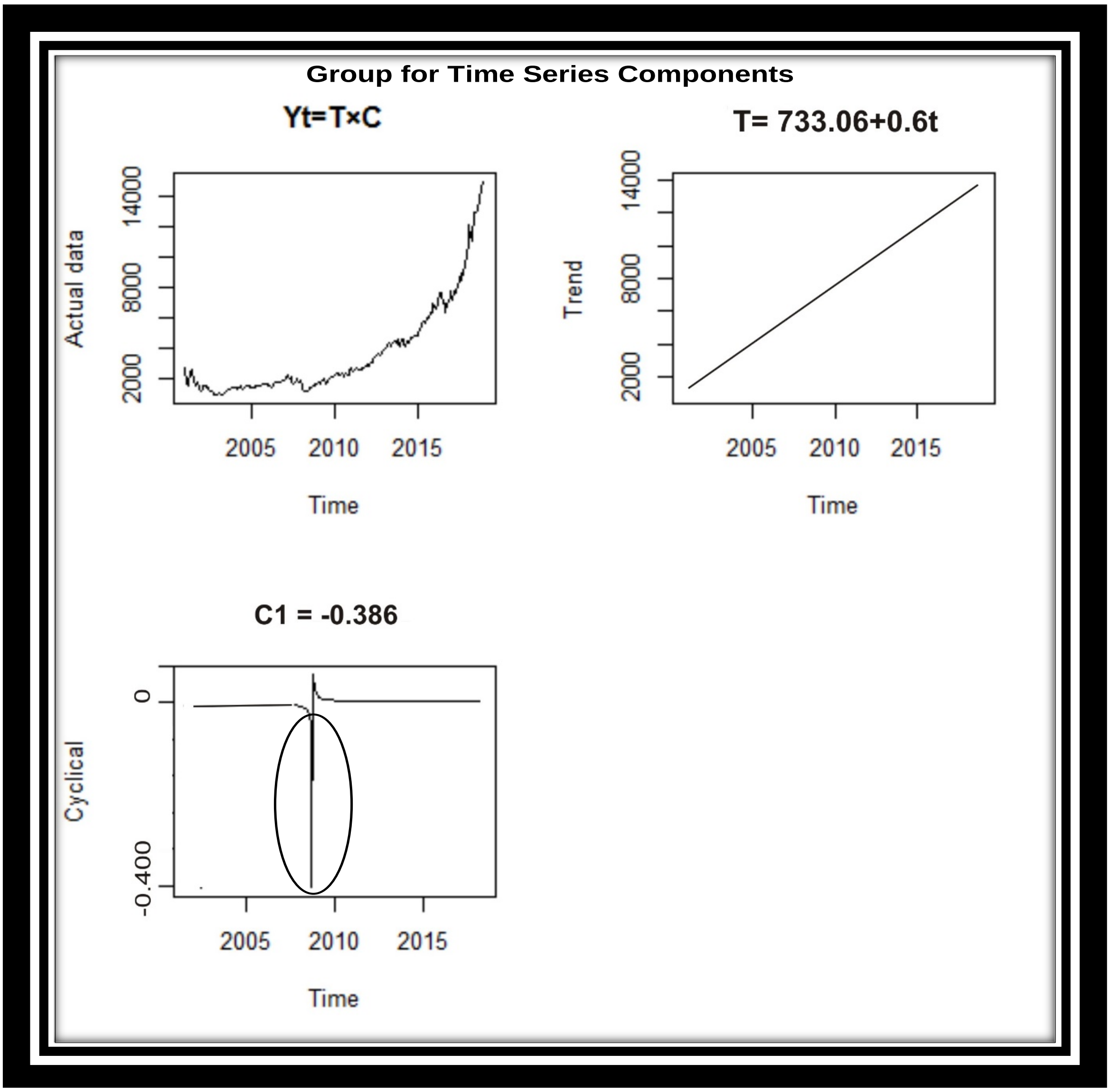

Fig. 3. Automated GFTSC plots of Monthly US stock market

Figs. 2 and 3 show the plots produced by BFTSC and GFTSC for US Stock Market monthly data respectively. Both BFTSC and GFTSC successfully identified one cyclical but failed to identify curve trend and display linear trend instead, which contradict with manual approach identification as in previous studies (Ajare & Suzilah 2019; Ajare, Adefabi & Adeyemo, 2023).

These indicated the limitation of BFTSC and GFTSC when the trend deviated from linear which reflected similar findings with manual process of time series identifications.

Both *Automated* Both BFTSC and GFTSC was perfectly able to identify the data which is the observed plot, also it was able to automatically identify one cyclical but as for the trend both BFTSC and GFTSC was weak in identification of curve trend, polynomial and highly volatile data. both BFTSC and GFTSC converted the curve trend to a straight line trend. Hence both BFTSC and GFTSC are weak in identification of exact trend in a very high volatile data.

The values was fitted but not displayed here, but from the fitted value and the real data of the US Stock Market monthly data (US SM), its reveal that for the next five years period the United State Stock Market show no evidence of decline and the fitted value fit well and match intact to the original US Stock Market monthly data so the model can be applied for prediction of more US

Stock Market monthly data. Based on the forecast model, no scientific evidence of US Stock Market crash in the period 2019 to 2028. US Stock Market appears to be in a steadily increasing state.

4. DISCUSSION

Details about development of time series components identification is as follow, Manual methodology period. Box and Jenkins [20] was amongst "the earliest researchers that clearly recognize time series module using time plot. it was very complex to distinguish the components using casual manual plot" [21-23].

Manual method and computerization (automation) period. Ewing and Malik [17] advanced "DBEST (Detection Breakpoint and Estimating Segment Trend) which was adapted from BFAST. DBEST take in (NDVI) normalizes transformation vegetation index (VI) data. The restriction of DBEST procedure is that it is delinquent and cannot categorize cyclical and irregular statistics [24,25].

Jong, Verbesselt, Schaepman and Bruin (2012) Contributed to the team of knowledge by examining the joint change identification called BFAST (Morrison et al., 2018). The method is reachable in BFAST pack for R (R developments Core Team, 2012).

Verbesselt, Zeileis, Hyndman, & Verbesselt (2012). Package 'bfast'which uess the basic basis for BFAST. Many experts uses of BFAST in identifying trend in topographical data (Porter & Zhang, 2018).

Jain, Duin, and Mao [26] label "BFAST as byzantine in method, this lead this revision to seek out for pellucidity regarding BFAST". Verbesselt et al [3]. Commend "a new performance for comprehensive trend recognition for image cataloguing and representative, the method is called Break for Additive Seasonal and Trend known as BFAST". "This method incorporates the putrefaction of time series components into the predictable elements of the series such as data, seasonal, trends and remnants; it was done" (Abbes & Farah, 2017; Adewoye & Chapman [13,27,28].

Therefore, from this discussion, BFAST need to be better-quality so that it can identify the four time series components. GFTSC and BFTSC are both recommended for efficient time series components identification for an improved forecasting.

5. CONCLUSION

Verbesselt, Hyndman, Newnham, and Culvenor (2010). The method was for distinguishing Breaks for Additive Seasonal and Trend (BFAST). Verbesselt et al [3]. Suggested that the method of BFAST is for categorizing topographical pattern and also for upgrading to be applied in other related disciplines [29-31].

Jamali, Jönsson, Eklundh, Ardö, and Seaquist [14] label BFAST as not being capable of classifying topographical vegetation basic component accurately Chen [32] recommended that, this may be due to the limited method availability of trend and change detection methods accessible, procedure appropriate in identifying and exemplifying unforeseen changes without sacrificing accuracy and efficiency [33,34].

Based on preceding revisions and scientific evidence, BFAST is used for topographical green forest print data at certain time (Rikus, 2018; Gorelick, 2017; Zhu, 2017).

BFAST approach give a very substantial result and was indorse as a an instrument for statistics data decomposition but could not separate random noise into cyclical and irregular components (Tolsheden, [35], Mok et al., [18], Maus, Câmara, Appel & Pebesma, [19].

Based on the every result in the simulated and the empirical analysis, BFTSC and GFTSC are best and most appropriate for linear time series components identification For this reason. BFTSC and GFTSC are 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.

Ajare and Ismail, [21] created automated Break for Time Series Components (BFTSC) and Group for Time Series Components (GFTSC) in Identification of Time Series Components in Univariate Forecasting. BFTSC is for automated identification of time series components while GFTSC is for both automated identification of time series components and automated displaying of equations that produces each component.

Based on the models values, it reveal no scientific evidence of drop and crash in US Stock Market, so improvement can be established based on US Stock Market. BFTSC forecast output is more reasonable for effective policy making. Hence BFTSC and GFTSC is recommended for public use and academic use freely.

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Note BFTSC and GFTSC is waiting for license to allow it to be incorporated into R pack. As soon as it is in R then anyone can freely use it. Contact the author for BFTSC, GFTSC and US stock market data if you need it (ajareoloruntoba@gmail.com/ajare_emmanuel@ahsgs.uum.edu.my) Copies are also available at Universiti Utara Library (Section 546727 research bank 23).

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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