Automated Detection Trend Breaks in the Identification of Ireland's Gross Domestic Product (GDP) for Accurate Forecasting

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Abstract: - The main objective of this study is to use automated forecasting tools in identification of Ireland Gross Domestic Product (GDP). Accur ate GDP forecas ting is essential for eff ective economic planning and policy formation. It enables policymakers to anticipa te economic downturns and plan accordingly to m itigate their impacts. Economists benefit significantly from improved forecasting m odels as th ey provide deeper insights into the underlying economic dynamics. Ireland's economy has experienced several structural shifts over the past few decades. BFAST (Break for Additi ve, Season and Trend) to i dentify the components of time series present in the seasonal data of Gross Fixed Ca pital Formation know as Gross Do mestic Product of Ireland GDP. This data is the GDP y early data of Ireland gross domestic pr oduct (Ireland land GDP). The (Ireland GDP) data spanned for the period of thirteen years (2010 to 2022) then 2023 and 2024 is used for data training. The GDP of Ireland is a secondar y data obt ained from the DataStream of National Univ ersity Singapore Library. The BFAST (Break for Additive Seasonal and Trend) was utilized to identify the time series components. BFAST only identifies trend and seasonal co mponents while considering all ot her components as random. Empirical data were em ployed to BFAST an d subsequently determine the next forecasting technique after which f orecast is made ahead. The real data fi ndings suggested that BFAST can provide a better time series components identification better than manual pro cess and hence caution should be taken serious. Ireland GDP is sliding, im provement on GDP is urgently necess ary or else it get to ruin. Im provement in Iceland GDP is recommended.

Key-Words: - Ireland Gross Do mestic Product (GDP), Automa ted Forecasting, BFAST (Br eak for Additive Seasonal and Trend), Time Series Analysis, Economic Forecasting, Structural Change Detection

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1 Introduction

Time series analysis involves statistic al techniques that analyze sequences of data points, ty pically measured at successive points, to uncover trends, cycles, and other patterns (17). It form s the cornerstone of many economic and financial studies, providing a robust framework for understanding and predicting patterns in sequential data. At its core, tim e series analysis is concerned with the exa mination of data points collected or recorded at s uccessive time intervals (Box et al., 2015). Time series identification starts with historical time serie s. Analysts examine the historical data and check for patterns of tim e decomposition such as tr ends, seasonal patterns, cyclical patterns, and irregular patterns (33).

Gross Domestic Product (GDP) is a crucial indicator of economic health, measuri ng the total value of goods and services produced within a country over a specified period (20). In macroeconomics, GDP is often used to assess a country's economic performance, comparing growth rates across dif ferent periods and regions (27). For Ire land, a small open econ omy highly integrated with global markets, GDP data is especially significant in understanding its economic growth trajectories over the past several decades (19).

Ireland's economic transformation is often referred to as the "Celtic Tiger" period, spanning the mid-1990s to the mid-2000s, during which the country experienced unprecedented economic growth. This period was marked by high GDP growth rates, driven by factors such as foreign direct investment (FDI), access to the European Union's (EU) single market, and a favorable corporate tax regime (38). However, Ireland's growth has also been subject to significant volatility, most notably during the global financial crisis of 2008 and the subsequent European debt crisis (37). Understanding the dynamics behind these growth patterns requires sophisticated tools, such as time series analysis, to detect changes and trends. Traditional time series analysis methods, however, often fail to capture abrupt structural shifts in economic data, leading to an incomplete understanding of how Ireland's economy responds to internal and external shocks (39,40).

However, traditional time series models, such as ARIMA (Auto-Regressive Integrated Moving Average) and exponential smoothing, have limitations in detecting sudden shifts or "breaks" in data (35). To address these limitations, methods like Breaks For Additive Season and Trend (BFAST) have been developed. BFAST is a decomposition-based approach that detects breaks in the seasonal and trend components of a time series, providing a more nuanced view of structural changes (36). Unlike traditional methods, BFAST can simultaneously detect and decompose time series into trend, seasonal, and irregular components, making it particularly suitable for analyzing economic data, which often exhibits non-linear changes due to economic crises, policy shifts, or other external factors (33).

The time series identification using BFAST in studying the general behavior of Ireland Gross domestic products (GDP), identifying the fluctuations in its total monetary value indicators on the distribution of resources and market value, of finished goods and services produced within, is important (22,23,31). It tracks the health of Ireland economy and determines whether the economy is growing or experiencing a recession (25).

According to (36), there are four components of time series, they are also referred to as variations. The first component is the trend. The second component is the seasonal component. The third component is the cyclical component. The fourth component is the irregular component. The most common one is trend because of its flexibility to be used for extrapolation and to study the direction of change (30).

According (1,2,34) the trend component (Tp) at the period (p) is described as the direction of movements that represent the general activities of a given process. The trend also represents long-run growth or decline over a given period. According to Ord and Fildes (24), the trend can also be defined as an escalation or growth in a given direction. The trend is also referred to as decay, degeneration in a stable remarkable manner. It is the tendency for a series of data to change position either positively or also decrease negatively in a comparatively steady manner over a given period (p) (7,8,10,11). A trend can occur in a mixture with other components like seasonal components and random variations (Wong-Fupuy & Haberman, 2004).

Seasonal component (Sp) at time p is also known as a seasonal variation which was also observed in time series data. It can appear in a mixture form with other components of the time series (Chatfield, 30). Yaffee and McGee (33) view seasonal variation as an identical pattern in time series that regularly flows over some time. A seasonal variation is a form of fluctuations that occur regularly which are recurring from season to season at the same and equal period and stage of intensity. According to (21,22,35), deseasonalizing is a necessity in some cases.

The cyclical component (Cp) at time p was observed as a periodic fluctuation around the trend components (14,15,16,17). The cyclic disturbance is common swings of a given sequence in an unpredictable period. It is the unbalanced and irregular changes observed in a sequence of data that are due to changes that occur in each series. (32), as well as Mitchell (36), stand to consider some relevant statistics which should give an index that mimics cyclical and also irregular components only. The cyclical period is generally more elongated than the seasonal period. Cyclical components are more obvious in yearly time series data but seasonal components are more obvious in monthly. If cyclical components are successfully determined, it is also necessary to estimate the irregular components to produce a reliable forecast (19,20,21,22).

The last component is the irregular components (I) which is considered as the sporadic movement of a sequence of time series data (11,12,14). It was also observed that irregular component (I) is any form of fluctuation that is not classified as one of the trends, seasonal and cyclical. The irregular component of the time series statistics is complex to define, so it is unpredictable. Assessment of irregular components is expected to occur only when the variance of the data is not large or else decomposition of the series may not be possible. For data with a large magnitude of deviation, the extrapolation for future data will not be accurate due to the large deviations (30). (24,25,27) observed that to determine the common irregular variation in a data level, the seasonal index must be calculated in a succession of irregular series. Theoretically, natural data always contains four components but the deseasonalized data would still contain irregular variation, cyclical variation, and trend components (35,36).

This study aims to apply BFAST to Ireland's GDP data, offering a comprehensive framework to pinpoint significant shifts and model the long-term trajectory of the country's economic growth. Ireland's economic trajectory, particularly since the late 20th century, has been remarkable. Dubbed the "Celtic Tiger," Ireland experienced rapid economic growth from the mid-1990s until the global financial crisis in 2008 (37,38,39,40). During this period, Ireland's GDP grew significantly due to a combination of foreign direct investment, an educated workforce, and favorable corporate tax policies. However, the 2008 financial crisis led to a severe recession, and Ireland's GDP contracted sharply (13,15).

The country's recovery, driven by export growth and a return of foreign investment, has led to a complex economic landscape with varying patterns of growth, stagnation, and recovery over the past few decades. Given these dynamic changes, analyzing Ireland's GDP using time series methodologies that can detect structural breaks is crucial. These breaks can reflect external shocks such as Brexit, global pandemics, or internal policy adjustments that have contributed to the volatility of Ireland's GDP (Breuss, 2015). Understanding these shifts is essential for making informed predictions about Ireland's future economic growth (39,40).

Time series analysis has long been employed to model and forecast GDP growth, helping policymakers and economists understand the long-term direction of the economy (14,15,16). The use of time series models such as ARIMA (Auto-Regressive Integrated Moving Average) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models has allowed for the prediction of economic indicators, including GDP, inflation, and unemployment (Engle, 1982). However, these models often assume stationarity, which implies that the statistical properties of the series do not change over time. In real-world economic data, however, shifts or "breaks" in trends frequently occur due to factors such as policy changes, economic crises, and technological innovations (9,10,11).

BFAST is a more flexible method that can detect multiple breaks in both the seasonal and trend components of a time series. It provides a robust framework for understanding the complexities of GDP, especially when these series are subject to external shocks or internal policy changes. By incorporating BFAST into GDP forecasting for Ireland, this study will identify structural breaks that traditional time series models might miss, offering a more accurate representation of Ireland's economic landscape (36).

Ireland's economic history over the past few decades is marked by several significant events that have introduced volatility into its GDP data. For instance, the global financial crisis of 2008 caused a significant dip in GDP, which was followed by a recovery driven largely by multinational corporations and export-led growth (37,38,39). More recently, the implications of Brexit, the COVID-19 pandemic, and global inflationary pressures have introduced new challenges to Ireland's economy (40). Traditional time series models, which often assume smooth transitions over time, may fail to capture the abrupt structural breaks caused by these events (39,40).

The detection of these breaks is crucial for accurate GDP forecasting. Structural breaks can result in biased parameter estimates if they are not correctly accounted for, leading to poor predictions and misguided economic policy recommendations (36). BFAST, with its ability to decompose time series into trend, seasonal, and remainder components while detecting structural breaks, offers a solution to this problem. By applying BFAST to Ireland's GDP data, this study aims to provide a clearer understanding of the impact of external shocks on economic growth and improve the accuracy of GDP forecasts. Economic forecasting has evolved significantly over the years. While traditional models like ARIMA and exponential smoothing have been valuable, the increasing complexity of global economies necessitates the use of more sophisticated techniques (35). The BFAST method, which stands for Breaks For Additive Seasonal and Trend, was initially developed for environmental and remote sensing data but has proven its utility in economic and financial time series as well (36). This method allows for the decomposition of time series into seasonal, trend, and noise components while simultaneously identifying structural breaks in these components (3,4,5).

2 Problem Formulation

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 of equation 1.1 (27, 28, 36).

From equation (1.2) BFAST takes all other components relatively trend and seasonal component to be randomized (Rp) and the equation was expressed as

$$Y_p = T_p + S_p + R_p \qquad (1.2)$$

The residual random consist of cyclical and irregular component (17, 18, 19, 20, 22).

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; $p_1^*, \ldots, p_q^*$; then T_p can takes the form as follows: $T_p = \alpha_k + \beta_k p$ where $p_{k-1}^* < p < p_k^*$ and If $k = 1, \ldots, q$, then; $p_0^* = 0$ and $p_{q+1}^* = n$; the slope of the change before the breakpoints while β_{k-1} and the slope of the breaks after the change breakpoints are β_k. The intercept and the slop of the linear model α_k and β_k with time period p and it will be used to derive the magnitude and direction of change (1, 2, 3, 4, 5).

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; $j = 1, \ldots, J$ and time t.

$$S_p = \sum_{j=1}^{J} w_{k,j} \sin\left(\frac{2\pi jt}{F} + \sigma_{k,j}\right) \qquad (1.3)$$

where $k = 1, \ldots, q$, $p_{k-1}^* < p < p_k^*$ and also $w_{k,j}$, $\sigma_{k,j}$ are the segment amplitude and F is the frequency (1,2,3).

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

$$Y_p = (\alpha_k + \beta_k p) + \left\{\sum_{j=1}^{J} w_{k,j} \sin\left(\frac{2\pi jt}{F} + \sigma_{k,j}\right)\right\} + R_p \qquad (1.4)$$

$$Y_p = T_p + S_p + R_p$$

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

To calculate cyclical components, center moving average is involved (14, 15, 16).

Derivation of cyclical code, let CMA be the center moving average of t objects, then:

$$CMA = \sum_{t=1}^{n} \frac{Y_t}{n_t} \qquad (1.5)$$

$$C_p = \frac{CMA}{\hat{CMA}} \qquad (1.6)$$

After extracting the trend, seasonal and cyclical components, the left out components is called irregular components, the new equation becomes:

$$Y_p = (\alpha_k + \beta_k p) + \left\{\sum_{j=1}^{J} w_{k,j} \sin\left(\frac{2\pi jt}{F} + \sigma_{k,j}\right)\right\} + C_p = \frac{CMA}{\hat{CMA}} + I_p \qquad (1.7)$$

$$Y_p = T_p + S_p + C_p + I_p$$

For identification of Yp , Sp , Cp , and Ip (See the paper: 1,2, 5,6, 33).

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 Ireland 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 (1,2,3,4,).

3 Statistical Analysis and Simulation

The simulation required lists equations and conditions for monthly and yearly data simulation. First, three different types of trend (linear, quadratic and cubic) were generated randomly based on different values of the coefficient a, b, c, d by using the time variable (t) to replicate 100 set of data for trend component condition. Next, the trend equations were adjusted accordingly by adding other components conditions which were seasonal, cyclical and irregular for monthly data; and cyclical and irregular for yearly data (1 &2).

The evaluation using simulation study were both performed very well in large sample size but deteriorated when using small sample size in identifying linear trend, seasonal, cyclical and irregular components. But performed poorly when curve trend (quadratic and cubic) was embedded in the simulated data. Four s ets of empirical data and manual identification approach were al so used to validate the performances in identif ying the time series components automatically. The algorithms performed as good as manual identification approach where they were able to identify the time series components embedded in the Ibadan Rainfall and UK GDP data. However, perform ed poorly in LSE and US Stock Market data due to the curve trend exhibited by both data sets.

Table .1: Monthl y and Yearly Data Sim ulation (Equations and Conditions)

Time Series Components	Types of Trend	Equations
Trend (T_t)	Linear	$T_t = a + bt$ $100 \leq a \leq 200$, $201 \leq b \leq 300$
	Quadratic	$T_t = a + bt + ct^2$ $100 \leq a \leq 200$, $201 \leq b \leq 300$, $301 \leq c \leq 400$
	Cubic	$T_t = a + bt + ct^2 + dt^3$ $100 \leq a \leq 200$, $201 \leq b \leq 300$, $301 \leq c \leq 400$. $401 \leq d \leq 500$
Seasonal (S_t)	Adjusted at 12 places using average value of the trend generated data	
Cyclical (C_t)	Adjusted at 3 places using maximum value of the trend generated data	
Irregular (I_t)	Adjusted at 2 places using double maximum value of the trend generated data	
Overall Equation	$Y_t = T_t + S_t + C_t + I_t$ (monthly) $Y_t = T_t + C_t + I_t$ (yearly)	

4 Problem Solution

This analysis focuses on exploring quarterly and yearly Ireland GDP data from 2010 to 2022, along with forecasted values extending t o 2027. The summary statistics present ed in Table 4.2.1 reveal the range and distributi on of GDP values across four quarters (Q1, Q2, Q3, and Q4) with m inimum values range from 15.91 to 30. 13 with mean GDP around 98.50, and the median is approxim ately 87.53. Similarly, the time series de composition shown in Figure 4.3 breaks down t he data into its core components: the observed data, trend, seasonality, and noise. The original time series data reveals significant fluctuations, with noticeable peaks towards the end of the period. The trend component captures the long-term movement of the data which shows gradual increases and decreases over time (Clements & Hendry, 1999).

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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 deco mposition of time series component into seasonal, trends and miscellany elements with the tech nique for recognizing structural similarity and difference. (33) Recommended that the technique of BFAST is for identifying topographical pattern and also for improvement to be ap plied in o ther related disciplines (31, 33).

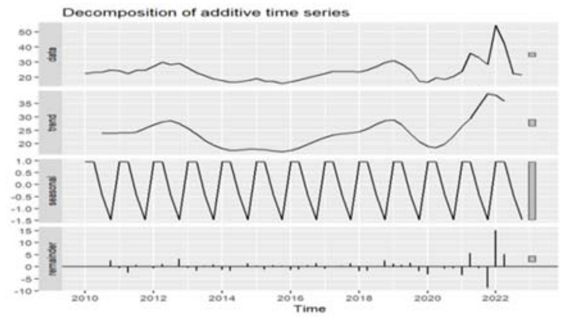

Fig. 1: Ireland BFAST Visualization

In Figure 1 above, the data panel of the plot represents the original time series data, showing the overall fluctuations over ti me with values ranging from 2010 to 2022 and noticeable peaks toward the end the period while the second panel shows the trend component which captures the long- term direction of the tim e series, though the trend is not linear, it reflects the underly ing gradual increases and decreases over tim e as the trend rem ains relatively stable, with a slight rise until around 2016 and dips somewhat and rises sharply again around 2020-2021 before tapering off slightl y at the end. The third panel also illustrates t he seasonal component, which reveals repetitive patterns that occur at regular intervals (e.g., quarte rly effects). The seasonality here shows a consistent pattern of fluctuations within each y ear, indicating that certain periods regularly experience similar ups and downs. Thee last component which represents th e noise or ran dom variation in t he data i s relatively small and stable through m ost of the series but shows some larger spikes towards the end, particularly around 2 020-2022. These spikes indicate that there were so me unusual variations in the data during this period that were not captured by the trend or seasonal components.

Following negotiations with the IMF, a package of $4.6 billion was agreed on 19 November, with the IMF loaning $2.1 billion and another $2.3 billion in loans and currency swaps from Norway, Sweden, Finland and Denmark. In addition, Poland has offered to lend $200 million and the Faroe Islands have offered 300 million Danish kroner ($50 million, about 3 per cent of Faroese GDP). The next day, Germany, the Netherlands and the United Kingdom announced a joint loan of $6.3 billion (€5 billion), related to the deposit insurance dispute. The assistance bolstered the Central Bank of Iceland's foreign currency reserves, which was an important first step in the economic recovery. By the end of 2015, Ireland had repaid all the loans that it received in relation to the IMF program. The IMF did not impose the kind of strict conditions on the assistance as it had done in similar past situations in Asia and Latin America. According to economists Ásgeir Jónsson and Hersir Sigurjónsson, "Iceland was treated differently from developing countries and former IMF clients. There was no call for Ireland to adopt sharp austerity measures at the inception of the joint economic plan. Instead, the government would be allowed to maintain large public deficits in the first year – 2009 – allowing fiscal multipliers to counteract the output contraction that was underway. Iceland also was not asked to downsize its Scandinavian-type welfare system." Iceland is the only country in the world to have a population under two million yet still have a floating exchange rate and an independent monetary policy.

In Figure 2, the free fitted value and the real data of the Iceland Gross Domestic Product (GDP). This reveal that for the next five years period, the Iceland Gross Domestic Product (GDP show evidence of decline and the fitted value did not fit well and match intact to the original Iceland Gross Domestic Product (GDP) data so the model can be applied for prediction of more years GDP of Iceland.

Fig. 2: Original Manual Ireland Gross Domestic Product (GDP) plot

Fig. 2: above shows that the dataset covers the years from 2010 to 2022. The Total GDP values range from a minimum of 82.28 to a maximum of 131.54 while the mean and the median of the Total GDP is approximately 98.50 and 87.53 respectively. The first quartile of 84.35 indicates that 25% of the values are below this threshold, and the third quartile is 101.63, accounts for 75% of the values that fall below this point

In Figure 3, starting from 2022 in figure 4.4 above, the forecasted values are depicted with a central prediction line and shaded areas which represent the confidence intervals. This forecast suggests that the values will generally remain stable with slight ups and downs from 2022 to 2027.

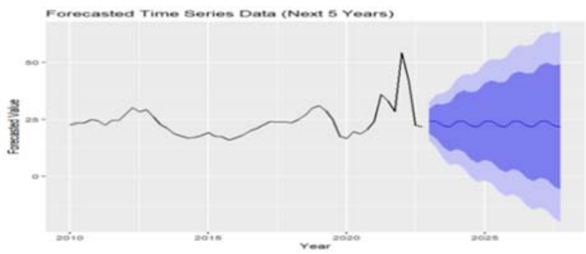

Fig. 3: Graphical representation of time series forecasting of Ireland GDP

Automated ARIMA models were fitted and the best model was selected based on the ARIMA with the smallest AIC (Akaike's Information Criterion). Based on the AIC models, the ARIMA(1,2,3) is the best model to be used in fitting the Iceland GDP . ARIMA (1,2,3) is selected and used for fitting the model.

5 Conclusion

The study concluded that both manual and automated methods could identify time series components in Ireland 's GDP, but the BFAST technique outperformed manual methods in precision, accuracy, and depth of analysis. While manual plotting provides basic visual cues about the time series, it cannot adequately detect complex shifts, making it an inefficient tool for real-time economic forecasting. The analysis showed that Ireland's GDP exhibited various structural changes over the years, with breakpoints corresponding to significant events such as the financial crisis, Brexit, and the global pandemic.

The BFAST technique was effective in capturing these shifts by decomposing the time series into trend, seasonal, and remainder components. This allowed for a better understanding of how Ireland's economy has responded to both internal developments and global economic shocks. The identification of breakpoints through BFAST provided clear indications of periods of rapid growth, stagnation, and recovery, making it easier for economists to predict future trends and create more robust economic models.

The study demonstrated the importance of advanced time series analysis tools like BFAST in economic forecasting and decision-making. The traditional models often assume stationarity or smooth transitions, which fail to account for abrupt breaks caused by events like policy changes, economic crises, or technological innovations. BFAST's ability to detect these breaks makes it a crucial tool for developing more accurate economic predictions, particularly for small, open economies like Ireland that are heavily influenced by global markets.

BFAST represents a significant advancement in time series analysis for economic data. Its application in identifying structural breaks in Ireland's GDP allows for a deeper and more nuanced understanding of the country 's economic trends, which is essential for making informed decisions in policy formulation, economic planning, and investment strategies.

Details about development of time series components identification is as follow. Pure manual approach period; (8 & 9) was one of the first researchers that struggle to clearly identify time series component using time plot. This first information in the form of data was plotted on a time plot using manual technique and the behavior of time series data was observed. 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.

Manual approach and automation period (22) 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 & 24) 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 (24, 25). The technique is accessible in BFAST pack for R (R developments Core Team, 2012).

(33) Package 'bfast' which portrays the main scope of BFAST. Many scholars employ the use of BFAST in identifying trend in topographical data (24, 25,26).

(24) Describe BFAST as complicated in technique, this lead this study to seek out for transparency regarding BFAST. (24) 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).

Other techniques such as Break for Time Series Components and Group For Time Series Components were likewise created to capture components of time series clearly and forecast automatically (2, 3 & 4).

6 Weakness and Future Research

The issue of how large is large and maximum sample size to be accepted by BFAST and the maximum sample size for the Manual method of time series identification is yet to be addressed [28]. BFAST are not being fully utilized addressed because it's a new automated time series identification technique and depends on the nature of individual research and interest. More automated and innovated time series components identifications is a welcome development. Model that can predict epidemic like flood, fire outbreak, earthquake etc should be encouraged. A special technique that can forecast irregular time series component automatically is a good and welcome innovation in forecasting field.

7 Recommendation

1. Incorporation into Decision-Making Frameworks: Given the accuracy of BFAST in identifying key economic shifts, governments and financial bodies should incorporate its findings into

decision-making processes. For example, by detecting the structural breaks caused by Brexit, policymakers can better assess the long-term impacts on trade, investment, and employment, allowing for the implementation of more targeted economic policies.

2. Training and Capacity Building: It is recommended that statistical agencies, research institutions, and universities conduct training programs on BFAST and other advanced time series analysis techniques. Economists, data analysts, and statisticians should be equipped with the skills necessary to use these tools effectively, improving the quality of economic analysis and forecasting.

3. Further Research on BFAST and Its Applications: Future research should explore ways to improve the BFAST model, particularly its handling of complex data sets and non-additive decomposition models. Researchers should investigate how BFAST can be optimized for various sectors beyond GDP analysis, such as climate data, financial markets, and healthcare systems. The other basic recommendation of this paper is that Ireland government need to improve on its economy, improve on local production, local processing and also increase in export or else the economy may suffer set back tremendously. Though from the forecast, the economy gradually pick up at 2028 but never the less the government should not rest and relax on the forecast but put more effort on implementing programs that would help yield better economy.

Note: The data used for this paper can be gotten freely from the authors Dr Ajare Emmanuel (ajareoloruntoba@gmail.com) also the BFAST technique can be acquired from same author freely. But the forecast values can be acquired from the author likewise but not free, $1000/year forecast. If Iceland government can purchase the forecast data for 10 years it would be very beneficial and advantageous for domestic GPD growth (ajare_emmanuel@ahsgs.uum.edu.my).

This paper serve as forecasting guide and it makes it easier for any one that wants to venture into forecasting GDP or els otherwise both the technique used and the forecast values can be acquired per-year with a little money to support the author's academic development.

Note BFTSC and GFTSC is license to allow it to be incorporated into software pack but already in EZEE forecasting software. BFAST is already in R pack. As soon as it is in R then anyone can freely use it. Contact the author for BFAST, BFTSC, GFTSC and Ireland gross domestic product 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).

8 Future Research

This paper had successfully extract cyclical from random time series components to make it a complete series such as trend, seasonal, cyclical and irregular time series components automatedly but this is mainly for univariate time series statistics, relating it or using the guide to multivariate automated forecasting in statistics can make the study a whole and many discovery much more.

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