CBB Working Paper No. WP/14/6

MODELLING AND FORECASTING THE UNEMPLOYMENT RATE IN BARBADOS

BY

NLANDU MAMINGI, DE'NELLE WILLIAMS AND RUDOLPH BROWNE

CENTRAL BANK OF BARBADOS
Research and Economic Analysis Department

Modelling and Forecasting the Unemployment Rate in Barbados

by

Nlandu Mamingi
University of the West Indies
Cave Hill Campus
P.O. Box 64, Bridgetown Barbados
Email:nlandu.mamingi@cavehill.uwi.edu
Tel: (246) 417 4278

De'nelle Williams
Intern
Research Department
Central Bank of Barbados

&

Rudolph Browne
Research Department
Central Bank of Barbados
P.O.Box 1016, Bridgetown, Barbados
Email: rudolph.browne@centralbank.org.bb
Tel: 1(246) 436 6870

ABSTRACT

One of the major problems challenging policy makers in developing countries is coping with high and persistent fluctuation in the level of unemployment. The objective of this paper is to identify the best approach to forecasting unemployment in Barbados using seasonal autoregressive integrated moving average (SARIMA), Basic Structural Time Series (BSTS) and General Structural Time Series (GSTS) models. Applying quarterly data for Barbados from 1983Q1 to 2013Q4 to the rate unemployment, this study evaluates the forecasting performance of the three competing models, using forecast accuracy criteria, such as the root mean squared error (RMSE), mean absolute percentage error (MAPE) and Theil's inequality coefficient. With respect to the techniques used the seasonal autoregressive integrated moving average (SARIMA) model produces superior results, as the forecasts horizon increases, but the General Structural Time Series model performs better in the shorter term. Thus for policy purposes, a seasonal autoregressive integrated moving average (SARIMA) model is relevant for decision-making.

Keywords: Unemployment Rate, Modeling, Forecasting, Time Series Models, Barbados.

INTRODUCTION

Unemployment has been a major issue for policy makers from as far as the late 1800s (Craigwell and Warner 2003). This is understandably so given the wide-ranging potential economic, social and by extension political consequences if rising unemployment is left unabated. At a macro level, higher levels of unemployment can be the result of lower national output. Additionally, rising unemployment can put a stain of fiscal policy, not only through lower revenue from falling output, but also increased expenditure through higher welfare costs. More importantly, at the individual level, unemployment is believed to contribute to increased wider social ills, such as crime, prostitution, alcoholism, mental health problems, drug abuse, and poverty (Craigwell and Warner 2003).

Given the importance of this issue, successive governments in Barbados have placed this concern as a high priority of public policy. As a result, the government has made significant strides in lowering the unemployment rate from as high as 18 percent in the 1980s to as low as 7.4 percent in 2007. Nevertheless, the issue of rising unemployment has again resurfaced since the outset of the global economic and financial crisis in 2008. Indeed, since 2008 the unemployment rate has been steadily creeping up as Barbados continues to grapple subdued economic growth due to falling demand from its trading partners. Moreover, the move by Government to retrench public sector employees has made the issue even more pronounced in policy debates. This along with further private sector lay-offs can have a significant impact on not only national output but places additional burden on the National Insurance Scheme and welfare provisioning.

Given the foregoing issues, it is important for policy makers to have reasonable expectations of future levels of unemployment levels if they were to implement timely policy interventions (Lewis and Brown 2001). Indeed, having adequate forecast can also assist the private sector in their investment plans for the future. The aim of this thesis is to provide an update to Craigwell and Warner (2010) since the economic landscape has changed throughout the years; and while Craigwell and Warner (2000) used only two methods for forecasting employment rate in Barbados, we intend to performed forecasting competition using three methods: seasonal autoregressive integrated moving average (SARIMA), basic structural time series (BSTS) and general structural time series (GSTS) models.

The literature explaining and forecasting the unemployment rate for both developed and developing countries are limited. Studies exploring the determinants of unemployment can be investigated from a micro and macro perspectives as have been undertaken by, among others, Okun (1962); Phillips (1958) and Nickell (1997). For the Caribbean only a few studies was done investigating the determinants of unemployment (Craigwell and Warner 1999; Downes et al. 2004; Ball and Hofsette 2009; Archibal et al. 2011; Borda and Mamingi 2014).

Moreover, literature on forecasting the unemployment rate is also limited. A sample of studies that have been using models such as univariate and multivariate linear and non-linear models to forecast the unemployment rate in countries other than the Caribbean includes Ray (1993); Crato and Ray (1996); Montogomery et al. (1998); Jaafar (2006). Of note, empirical studies relating to the Caribbean are also rare as handful of author tackled the issue of unemployment rate (Boamah 1988; Henry et al. 1990 and Craigwell et al. 2000).

The study used quarterly data that spans from 1983Q1 to 2013Q4. In this study, we employed several econometric methodologies to model and forecast the unemployment rate for Barbados. These methods are: seasonal autoregressive integrated moving average (SARIMA), basic structural time series (BSTS) and general structural time series (GSTS) models. By applying several forecast accuracy criteria such as the root mean squared error

(RMSE), mean absolute percentage error (MAPE) and Theil's inequality coefficient (U-STATISTICS), the result concludes that the seasonal autoregressive integrated moving average (SARIMA) model seems to be more steady over the entire forecast horizon but the general structural time series (GSTS) model performs better in the shorter term.

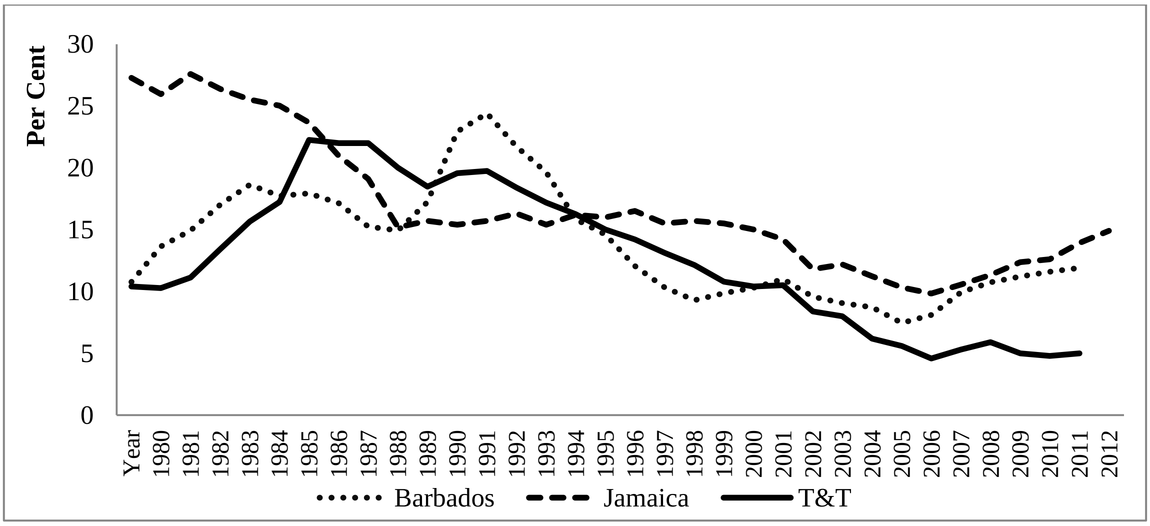
The remainder of this paper is structured as follows: Section 2 reviews the nature of unemployment in Barbados. Section 3 provides a brief overview of the related literature and section 4 outlines the data and econometric methodology employed. Section 5 presents the results of estimations coupled with an analysis of the forecasting performance of the estimated seasonal autoregressive integrated moving average (SARIMA) model and both structural time series models, and finally, Section 6 concludes.

2. BARBADOS LABOUR MARKET: STYLISED FACTS

One of the most stringent economic problems faced by most Caribbean countries is high level of unemployment. Overtime, there have been compelling changes in the labour market for most English-Speaking Caribbean countries. As these countries move from agricultural to service based economies the level of unemployment rate fluctuated over the years. Based on the availability of information, only three English-Speaking Caribbean countries were chosen to demonstrate graphically the fluctuation of the unemployment rate in the Caribbean.

As shown in Figure 1, following an increase at the beginning of the 1990's in Barbados, Jamaica and Trinidad and Tobago, unemployment has steadily declined since the mid-1990 and stands at approximately 10.5% in Trinidad and Tobago, 14.2 % in Jamaica and 10.8% in Barbados (2002), down from 19.8%, 15.7% and 24.3% in 1992, respectively. After 1992, Jamaica unemployment has hovered around 15% with surprising consistency, whereas, the unemployment rate in Trinidad and Tobago and Barbados has been decreasing gradually throughout the years. To date, Trinidad and Tobago has the lowest unemployment rate among the Caribbean countries, followed by Barbados and Jamaica, 5%, 11.9% and 14.9% respectively (See Figure1).

Figure 1: English-Speaking Caribbean Countries Unemployment Rates 1980-2013



Source: International Monetary Fund, World Economic Outlook Database, April 2014.

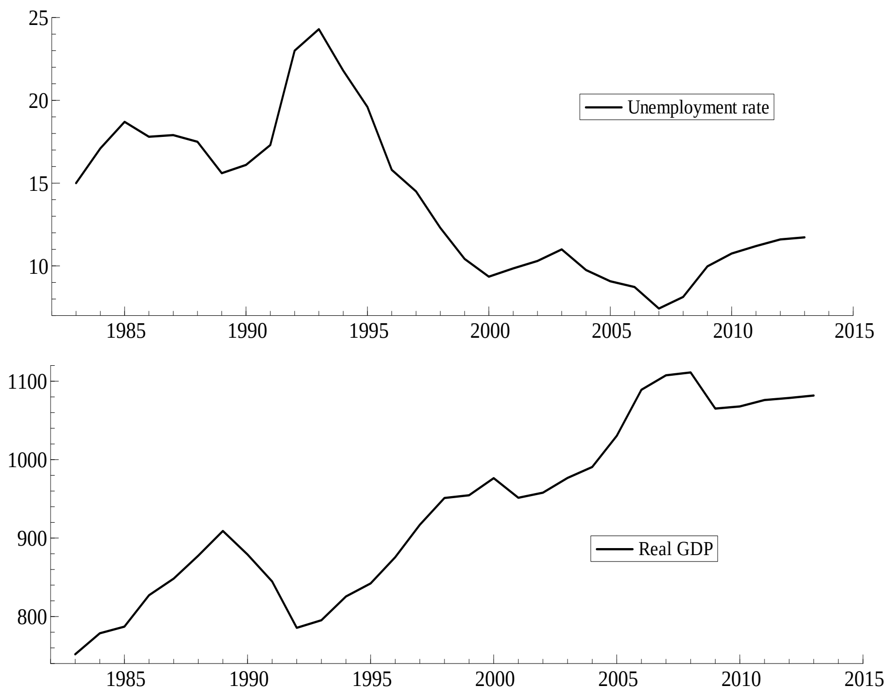
The primarily focus of this study is on the nature of Barbados' labour market. The data used in this section are yearly unemployment rate for the period 1983 to 2013. Table 1 exhibits the descriptive statistics for the unemployment series. It is noted that the average unemployment rate for the period 1983 – 2013 is 13.9 percent and the medium is 12.5 percent. The standard deviation of unemployment rate is 4.7 percent and the movement in the series can additionally be determined by the skewness coefficient, which is positive for Barbados (0.6), this shows that the rate of unemployment for Barbados has asymmetric fluctuations.

Table 1: Descriptive Statistics for Unemployment Rate of Barbados

Mean	Med	Max	Min	Std. Dev	Skew-ness	Kurt-osis	Jarque-Bera	Prob.
13.9	12.5	26.2	6.7	4.7	0.6	2.4	8.9	0.012

Figure 2 plots the Barbados unemployment rate over the sample period. It is clear from this graph the country has had significant success in reducing its unemployment rate from as high as 18% in the mid-1980s to 7.4 percent in 2007. This was driven in large part by the GDP of the economy (Figure 2). Although not perfect, a close examination of both series highlights the close negative relationship between GDP growth and unemployment.

Figure 2: Barbados Unemployment Rate and Real GDP 1983 - 2013



Over the period, the level of unemployment has fluctuated during years 1980-1989, moving from 11.4% in 1980 to 14.1 % in 1989. During this period there was a decline in agriculture and manufacturing which resulted to the increase in the unemployment rate. However, during the years 1990 to 1992, the Barbadian economy went through a period of severe recession, which resulted in lower public sector wage bills and public sector layoffs (Warner, 1998). These adjustments led to increasing the rate of unemployment from 15% in 1990 to 25.6% in 1993. Thereafter, the average annual rate of unemployment fell steadily to 9.3% by the end of 2000. After the September 11th terrorist attacks in the United Stated in 2001, the Barbados tourism sector suffered from the knock-on effects in source markets, resulting in an increased in unemployment during the 2000s.

After reaching an all-time low of 7.4% in 2007 due to generation of new jobs, the unemployment rate again crept up during the global recession in 2008. Decline output in Barbados' major trading partners meant that the foreign exchange earning sectors suffered from the effects of reduced external demand which later had a pass-through effect on the domestic economy. By the end of 2013, the unemployment rate increased from 10.1 percent at the end of 2009 to 13.2 percent. This increase was mainly driven by the layoffs in the construction sector which downsize the labour force by 11% in 2012.

Recently, the Barbadian economy have been experiencing a sluggish economic growth and prolonged period of weak cash flows, because of these shortcomings, it has made it increasingly difficult for public and private sector employers to maintain staff levels. The Barbados government laid off 3000 workers, which is 10 percent of the civil service labour force from their duties in an effort to reduce its expenditure on salaries and wages. This reduction was estimated to save $145 million dollars over the course of the next 5 years. Although this decision will help revive the economy, there is the possibility that it may increase the unemployment rate in the future.

3. LITERATURE REVIEW

There are several studies investigating the cause of unemployment for developed and developing countries. The studies have covered the topic from both micro and macro perspective. We review theories of the determinants of unemployment, discuss the empirical studies with a Caribbean focus, and succinct with a brief review of the forecasting literature.

3.1 Unemployment Theories and World Evidence

Studies investigating the determinants of unemployment rate from a micro perspective approach used the job search theory proposed by Lippman and McCall (1976) and Mortensen (1970). This theory stipulates the expected duration of unemployed persons depends on the prospect of receiving a job offer. It depends on personal characteristics such as level of education, skill level, experience and local demand conditions such as unemployment and vacancy rates. This model further assumes that the probability of the individual accepting the offer depends on their salary, which is determined by equating the cost of searching to the present value of future labour income at the margin. An example of this type of analysis is provided in the paper by Nickell (1997). The author studied the relation between unemployment and labour supply and labour market institutions. His research concludes that high unemployment is highly associated to unemployment benefits, unionization and poor education levels.

From a macro-perspective, Okun (1962) was the first economist to explore the interrelationship between unemployment and the business cycle. His study posits a negative correlation between unemployment and GNP recognized as Okun's law. Using the gap model the author studied the conjunction between GNP and unemployment in the United States during the period 1947:Q2 to 1960:Q4. Results indicate as the unemployment reduces at 1%, output would increase approximately by 3%. For this reason, continuous expansion of the economy is imperative to avoid the waste of unemployment. Since then a number of authors tested this relationship for a wide range of countries. For instance, Freeman (2001) experiments using new developments in trend/cycle decomposition to test Okun's Law for a panel of ten industrial countries. He found that the one percent reduction in the unemployment rate now averages at just less than two points of real GDP growth for the sample countries, which is similar to Okun's original estimate for the US. Pooled estimates for Europe are smaller than estimates for the rest of the sample. Further, this article highlights that omission of capital and labor inputs may have biased previous estimates.

On the contrary, with more recent data and advanced econometrics techniques, results shows that the 2:1 ratio between output and the rate of unemployment is more representative because of asymmetric problems (Samuel and Nordhaus 2001). Empirical work done by Lee (2000) found that be using a static framework on the unemployment variable on 16 OECD countries over the sample period 1955-1996, the coefficients for various countries such as (e.g. Finland, Japan, the USA) were higher than what Okun proposed.

Irfan et al., (2010) checked the soundness of Okun's law of a few Asian countries[1] using annual data from 1980-2006. They investigate the significance between the unemployment gap and output gap in the short and long run. For this reason the unit root and co-integration test was employed to verify the stationarity of variables and long-run relationship respectively and error correction mechanism for short-run dynamics. The results do not coincide with Okun's Law, mainly cause of the asymmetric problems. Various Asian developing countries usually have a low unemployment rate, because they tend to grow fast since there is political stability and good governance.

Other studies focused on other macroeconomic variables to explain the unemployment rate such as inflation rate. The correlation between inflation and unemployment in an economy is described as the Phillips Curve (Phillips 1958). The underlying ideas of this theory is, as employment increases GDP increases, causing wages to increase, causing consumers to have more purchasing power, resulting to consumers demanding more goods and services, thus causing prices of goods and services to increase. Fundamentally, Phillips showed that there was an inverse relationship between unemployment and inflation: inflation rose as unemployment decrease and vice versa.

Ashipala and Eita (2010), investigates the main determinants of unemployment in Namibia used annual data over the period 1971-2001, the results indicate that there is a negative relationship between inflation and the unemployment rate; this gives evidence that the Phillips curve holds in Namibia. They also used other macroeconomic variables to model unemployment. As expected, there is a positive relationship between wage rate and unemployment. This means that an increase in the cost of labour causes unemployment to increase. Also, there is a negative relationship between investment and unemployment. An increase in investment causes unemployment to decrease; therefore, investment must be promoted in order to generate jobs for the majority of the unemployed people.

3.2 Caribbean Evidence

As we move further away from developed counties, there has been limited research investigating the causation of the unemployment phenomenon within the Caribbean region. Craigwell and Warner (1999) use an Autoregressive Distributed Lag approach to investigate the relatively high rates of unemployment experienced by Barbados over the years 1980 to 1996. The findings of the study suggest that the level of wages in the country affects the unemployment rate and therefore, a possible remedy is to reduce the social security taxes. Other factors affecting unemployment were the high levels of hiring and firing costs,

[1] The Asian countries are Pakistan, India, Bangladesh, Sri Lanka and China

indicating that labor market legislation should be re-examined as a policy to combat unemployment.

Using the Phillips-Loretan Nonlinear Least Squared method, Downes et al. (2004) conducted a study investigating how labour market regulations and its impact on employment creation in the English speaking Caribbean countries. The three main areas of labour market the study placed focus on are national insurance payments, severance payments and minimum wages. The investigation period of each country varied due to the availability of data (Barbados 1970 – 2001; Jamaica 1975 – 2001 and Trinidad and Tobago 1970 – 1999); also variables used differed across country depending on data availability. The results showed that the effect showed meager statistical significance in Barbados, Jamaica and Trinidad and Tobago. Once again a shortage of output growth has shown to be a determining factor of unemployment in the Caribbean. Cyclical trends were unable to determine due to data limitations.

To extend the literature, Ball and Hofsette (2009), constructed a new data set on unemployment rates in 19 Latin America and the Caribbean countries and examine the determinants of unemployment. The authors used IADB data and their own data set to clarify the difference in unemployment across countries. Measures of economic development were use to explain the unemployment rate. These measures include education, income per capital and the existing percentage of the population in rural areas. The results attest that short-run changes in unemployment influenced the natural rate (long-run unemployment). In testing cross section regressions by using a measure of long-run unemployment. The authors found that the natural rate is significantly predicted by cyclical factors – per capita growth. Importantly, the only result that stands out statistically significant, are those countries with larger rural population have lower rates of unemployment.

Rather than exploring the determinants of unemployment rate, Archibal et al. (2011) examined how the demand driven shocks affect the Caribbean regional labour market. Utilizing uneven panel model of more developed and less developed countries they uncovered that shocks to the global economy may have large effects on unemployment. During the estimated period 1970 -2008, the sample of twelve countries was chosen. The results estimated that the employment rate falls by 65000 every year. The adverse effect of employment is particularly tends to be related to the female work force. Additionally, the study includes a detailed assessment on how the current recession impacted on regional labour markets. The assessment pinpoints the main crisis impact as rising unemployment and underemployment along with threats to job security. Furthermore, it outlined that the fall out has severely impacted tourism dependent economies and it affects the vulnerable groups such as youths.

Craigwell and Maurin (2011) examined the unemployment hysteresis as well as the high and persistent unemployment in the Caribbean economies. Using nonlinear models, the quarterly series post 1970 were studied for the economies of Barbados and Trinidad and Tobago. The results confirmed that shocks to unemployment having a lasting effect in their Caribbean developments. Moreover, after re-estimating the model the non-linear Smooth Transition Autoregressive (STAR) models were more applicable than the linear autoregressive (AR) models.

Most recently, Borda and Mamingi (2014) measured the persistent effects of structural shocks to labour market fluctuations, particularly unemployment in the period 1974-2010 in relation to small open economies: Barbados with a fixed exchange rate regime and Trinidad and Tobago with a flexible exchange rate regime by using a rational expectations model. The finding indicates that external and supply shocks are the main source of unemployment or labour market fluctuations in Barbados and the world interest rate and domestic demand (monetary) shocks the primary attribute of unemployment in Trinidad and Tobago.

3.3 Forecasting Unemployment

The literature on forecasting unemployment rate for developed and developing countries is rather limited. Forecasting unemployment rates like any other macroeconomic variable has been undertaken traditionally by building in the first instance econometric models. These models range from a single variable model to multivariate models. This section will explore both univariate and multivariate linear and non-linear models used in forecasting the unemployment rate.

3.3.1 Global Evidence and Methods

The most widely used methodology for projecting future macroeconomic variables likewise unemployment rates has been the (Box and Jenkins 1970). Ray (1993) and Crato and Ray (1996) demonstrate that using AR (MA) models to predict long-memory time series does not result in a large loss of forecasting accuracy. Similarly Clements and Krolzig (1998) proposed that AR models have a competitive forecasting performance for nonlinear (Markov Switching and threshold autoregressive) time series, when extensions for two or more regimes are allowed (see also Rothman 1998).

Studies that implemented Threshold Autoregressive (TAR) models found that the models are more prominent when compared to others (Hansen (1997) and Koop and Porter (1999). Their study focused on the monthly rate of unemployment for men aged 20 and over. On the other hand, Montgomery et al. (1998) conducted a rolling forecast experiment during periods of rapidly increasing unemployment, which highlighted that TAR and Markov-switching models outperform the linear benchmark model; also, they found forecasting accuracy is improved by using date of monthly frequency for forecasting quarterly rates, however only in the short run.

By using a logistic smooth autoregressive (LSTAR) model, Skalin and Terasvirta (1999) were incapable of rejecting linearity for the U.S quarterly seasonally unadjusted data. However, employing the model to the seasonally unadjusted monthly series for men aged 20 and performing an out-of-sample forecast accuracy analysis showed that the LSTAR model outdo the linear AR counterpart at long run forecast horizons during downturns and at short run horizons during expansions (Van Dijk, Boswijk and Franses 2000). The main advantage of using the logistic smooth transition autoregressive model is that it allows a higher degree of flexibility in model parameters.

When comparing the *ex-post* forecasting accuracy for the rate of unemployment in the United Kingdom, Floros (2005) established that, though an MA (4) model performed satisfactory, while both MA (1) and AR (4) proved to be the best forecasting models, the MA (4)-ARCH (1) model provided superior forecasts of rate of unemployment in the UK. Zhou et al. (2006), recommended a new telecommunication system forecast model based on non-linear time series ARIMA/GARCH. Their findings suggested that the ARIMA/GARCH model outperformed the Fractional Autoregressive Integrated Moving Average (FARIMA) model initially used, in terms of prediction accuracy.

However, neither, the ARIMA models nor the ARCH/GARCH models have proven their suitability in some economies or when used to model some macroeconomic variables. Jaafar (2006) established that the Holt's method with two parameters was suitable to forecast five major labour force indicators i.e. labour force, employed, unemployed, unemployment rate and underemployed in Malaysia. Nasir et al. (2008) used different univariate modelling techniques: the naive with a trend model, average change model, double exponential smoothing and Holt's model, to forecast future unemployment rate in Malaysia. They used the minimum value of mean square error (MSE) to identify the most suitable model and evidently concluded that the Holt's model outperformed other techniques.

3.3.2 Caribbean Evidence and Methods

Empirical studies forecasting unemployment rates in the Caribbean are rare. Moreover, the few studies with a Caribbean focus mainly concentrate in employment rather than unemployment although this is not an issue since unemployment story can be derived from employment development. That said, Boamah (1988) was the first study that forecasted the employment sector of Barbados; using estimates from both traded and non-traded sectors. In traded sector, employment was a function of real output and real wages in that sector and employment in the previous period. A similar equation was estimated for non-traded sector and all the variables except wages in the tradable sector were significant. The author forecasted both ex-post simulations for the period 1970 to 1982 and ex-ante forecast for 1983 to 1990. Results illustrations that the mean square errors for both forecasted were small in the non-traded and traded sectors respectively. However, the estimates fell short of duplicating the employment function in both sectors, possibly due to the unreliability of the estimated disaggregated employment data.

Henry et al. (1990) paper forecast the unemployment for Trinidad and Tobago economy using a function of labour supply and labour demand and treated unemployment as one of the regressors in the wage equation. The model was used to produce forecasts for 1987 and 1988, and results produced large forecast errors of about 10% to 25%.

More recently, Craigwell and Warner (2000) forecasted the aggregated employment in Barbados for the period 1974Q1 to 1998Q4 using univariate forecasting techniques BSTS model and ARIMA. The result shows that the BSTS model is superior to ARIMA for ex-ante (out- of - sample) dynamic forecasting because of the stochastic nature of its parameters. The forecasts show a general rise in the level of employment over the following five years with seasonal fluctuations during the quarter. Employment was expected to increase on average by 1.35% per annum with the rate of growth slowing year to year. They further mentioned that although the model developed in the paper was adequate, it is by no mean complete or perfect. In fact, some may argue that a forecast is based not only on historic time series but also on perceived changes in the structure of the economy.

We have reviewed several studies on the determinants of unemployment. Most aggregate studies suggested macroeconomic variables as the major influence of the unemployment rate. For a comprehensive analysis, this study will incorporate one macroeconomic variable that may have an influence on the unemployment rate in Barbados. Additionally, a large portion of the literature on forecasting unemployment rate focus more on pure time series methods, since the results are quite adequate and precise. This study will adopt three (3) time series forecasting techniques and will compare the performances of each method using accuracy tests. The study will be contributing to the previous literature since the empirical studies on forecasting the unemployment rate for Barbados are out dated.

4. DATA AND MODELS

The dataset is of quarterly frequency and spans from 1983Q1 to 2013Q4. This era was selected due to availability of data. The unemployment data was extracted from the Barbados Statistical Service (2014), and the gross domestic product (GDP) was sourced directly from the Central Bank of Barbados. This study employs the multivariate structural time series model for forecasting the unemployment rate in Barbados. The multivariate structural time series model takes the basic form and incorporates various explanatory variables to boost the predictive power of the model. In this study, we included the business cycle components into the model since this variable tends to have an effect on the movement of the unemployment rate. The model is presented below:

Ln $\boldsymbol{UN_t = f(lnGDP_t, T, S, C, I)}$

Where, $lnUN_t$ = logarithm of the unemployment rate during the time period t, lnGDP = logarithm of the real GDP, *T* is a time trend, *S* represents seasonality, *C* is the cyclical component and *I* is the irregular component

4.1 Forecasting Techniques

The study utilises three different approaches to forecast the unemployment rate in Barbados. The multivariate structural time series methodology is used to estimate the model and the univariate structural time series and the autoregressive integrated moving average (ARIMA) approach are used as benchmarks for this forecast.

4.1.1 Univariate Structural Time Series Approach

The structural time series models proposed by Harvey (1989) are based on a decomposition of the time series into four components, which are normally familiar visually in a time, plot of the series. These components include a stochastic trend, a periodic cycle, a seasonal component, and an irregular component assumed with zero mean, and serially uncorrelated. Unlike the earlier time-series models, structural models are more advanced because they allow for stochastic change. Therefore, structural time series models offer clear interpretations through the decomposition into components (Kendall and Ord 1990) and this is a major attraction of time series forecasting generally. The basic model (BSM) can be formally represented as follows:

$$Y_t = trend + cycle + seasonal + irregular \qquad (1)$$

<u>Trend:</u> The trend element in the first equation is modeled as:

$$\text{(level) } \mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \qquad \eta_t \simeq NID\,(0, \sigma_\eta^2) \qquad (2)$$

$$\text{(slope) } \beta_t = \beta_{t-1} + \xi_t \qquad \xi_t \simeq NID\,(0, \sigma_\xi^2) \qquad (3)$$

Where η_t and ξ_t are the level and slope disturbances, which are uncorrelated and have variance σ_η^2 and σ_ξ^2. μ_t and β_t represent the level and slope of the trend, respectively. NID$(0, \sigma^2)$ signifies normally and independently distributed with mean zero and variance σ^2. The effect of the η_t is to allow the level of the trend shift up and down, while, ξ_t allows the slope to change. When σ_ξ^2 is zero($\beta_t = \beta_{t-1} = \beta$) with non-zero σ_η^2, the model will have a fixed slope, which is a random walk with a constant drift β.

Seasonal: The seasonal element in the first equation is modeled as:

$$\gamma_t + \cdots + \gamma_{t-s-1} + \omega_t \ : \ \omega_t \ \simeq \ NID\ (0, \sigma_\omega^2) \tag{4}$$

Without the disturbance term, ω_t, one has the deterministic case and the seasonal components sum to zero over the previous year. This is the dummy variable form of stochastic seasonality. The trigonometric form of stochastic seasonality may be expressed as:

$$\gamma_t \ \sum_{j=1}^{s/2} \gamma_{j,t} \tag{5}$$

Where each $\gamma_{j,t-1}$ is generated by

$$\gamma_{j,t} \ = \ \gamma_{\ j,t-1} \ \cos\lambda_j + \ \gamma^{\neq}{}_{j,t-1} \sin\lambda_j \ + \ \omega_{jt} \tag{6}$$

$$\gamma_{j,t-1} \ = \ -\gamma_{j,t-1} \sin\lambda_j + \ \gamma^{\neq}_{j,t-1} \cos\lambda_j + \ \omega^{\neq}_{jt} \qquad \forall\, j = 1, \ldots, [s/2\ ] \tag{7}$$

Where ω_{jt} and $\omega^{\neq}_{jt}$ are zero mean white noise processes, which are uncorrelated with each other with a common variance σ_j^2 are j = 1,…, [s / 2]. Again one can use the hyperparameter estimates of σ_ω^2 to determine whether seasonality of deterministic or stochastic form should be modeled.

Cycle: The cycle element in the first equation ψ_t, is modeled as:

$$\begin{pmatrix} \psi_t \\ \psi_t^{\neq} \end{pmatrix} = \ \rho \begin{pmatrix} \cos\lambda_c & \sin\lambda_c \\ -\sin\lambda_c & \cos\lambda_c \end{pmatrix} \begin{pmatrix} \psi_{t-1} \\ \psi_{t-1}^{\neq} \end{pmatrix} + \begin{pmatrix} K_t \\ K_t^{\neq} \end{pmatrix}, t = 1, \ldots\ T \tag{8}$$

where λ_c is the frequency, in radians, in the range $0 \leq \ \lambda_c \ \leq \ \pi$, and ρ is the damping factor such that $0 \ < \ \rho \ \leq 1. K_t$ and $K_t^{\neq}$ are two white noise disturbances which are mutually uncorrelated with zero mean and common variance $\sigma_{k\,.}^2$ upon estimation, the hyperparameter which is shown is the variance of the cycle itself, σ_ψ^2, rather than σ_k^2 (Harvey 1995).

4.1.2 Multivariate Structural Time Series Approach

This time series model can be developed into a multivariate structural time series model (STSM) now more commonly referred to as General Structural Modelling (GSM) by including explanatory variables. The multivariate Structural Time Series Model is as follows:

$$Y_t = \ \mu_t + \ \gamma_t + \ \psi_t + \ \lambda_1 x_1 + \ \lambda_2 x_2 + \cdots + \lambda_k x_k + \varepsilon_t \qquad \text{t = 1, 2….T} \tag{9}$$

where

Y_t = observed series

μ_t = trend component,

γ_t = seasonal component,

ψ_t = cyclical component,

$x_1, x_2, \ldots x_k$ are explanatory variables, in this study we only used one explanatory variable which is Gross Domestic Product (GDP).

$\lambda_1, \lambda_2, \ldots \lambda_k$ are unknown parameters,

ε_t =irregular component.

When the linear combination of explanatory variables is removed from the equation, the multivariate General Structural Modelling (GSM) collapses to Basic Structural Modelling (BSM):

$$Y_t = \mu_t + \gamma_t + \psi_t \quad t = 1,2, \ldots T \tag{10}$$

4.1.3 Seasonal Autoregressive Integrated Moving Average Approach

The Autoregressive Integrated Moving Average (ARIMA) model was developed by George Box and Gwilym Jenkins (Box and Jenkins 1970). The Box-Jenkins model is the result of combining two models: autoregressive (AR) and moving average (MA). The model assumes that the time series is stationary, Box and Jenkins recommend differencing non-stationary series one or more times to achieve stationarity. This process produces an ARIMA model with the 'I' standing for 'Integrated', and is represented by ARIMA (*p*,*d*,*q*):

The ARIMA model has the form:

$$y_t = \theta_0 + \phi_1 \gamma_{t-1} + \phi_2 \gamma_{t-2} + \cdots + \phi_p \gamma_{t-p} + \varepsilon_t -$$

$$\theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \tag{11}$$

Where y_t and ε_t are actual values and random error at time t, respectively. $\emptyset_i$ $(i = 1, 2, \ldots p)$ and θ_j $(j = 1, 2, \ldots q)$ are normal parameters. The integer's p and q are referred to as the autoregressive and moving average orders of the model, respectively and identically distributed with a mean of zero and a constant variance of σ^2. If in equation (1), q=0, the equation above becomes an AR model of order. Also, if p=0, the model reduces to an MA model of order q.

The integrated autoregressive moving average models (ARIMA) proposed by (Box and Jenkins 1970) have been the most widely used methods for time series analysis and forecasting applications. The Box– Jenkins methodology includes four iterative steps of model identification, estimation, diagnostic checking and forecasting. The identification process starts by testing for stationarity, which is a necessary condition for building ARIMA models. Analyzing the correlogram or carrying out a simple unit root test can do this. To determine the order of the model, (Box and Jenkins 1970) proposed to use the autocorrelation function and the partial autocorrelation function of the sample data as the basic tools to identify the order. After determining the order, the estimation process is straightforward; this can be done with a nonlinear optimization procedure. The last step of the model building is the diagnostic checking of the model adequacy. This is a test to ensure all the model assumptions are satisfied. It can be tested by several model selection criteria such as Akiake Information Criteria, Schwarz Bayensian Criteria and Adjusted R^2. A new model will be identified once the model is not adequate, which will again followed the steps of estimation and model verification. Diagnostic information may help suggest alternative model(s). Until a satisfactory model is selected the third step will be repeated several times. Only then can the model be used for predictive purposes.

A time series is said to be seasonal if there exists a tendency for the series to exhibit a periodic behaviour after certain time interval. The usual autoregressive integrated moving average (ARIMA) models cannot really cope with seasonal behaviour, it only model time series with trends. Seasonal autoregressive integrated moving average (SARIMA) models are formed by including an additional seasonal terms in the ARIMA models and are defined by seven parameters.

The seasonal autoregressive integrated moving average (SARIMA) proposed by Box and Jenkins (1976) denotes the ARIMA (p,d,q)*(P,D,Q)$_s$ as:

$$(1-\phi_1 B-\phi_2 B^2-\cdots\phi_p B^p)(1-\beta_1 B^s-..-\beta_p B^{ps})(1-B)d(1-B^s)D\,\gamma_t$$
$$=c+(1-\psi_1 B-\psi_2 B-\cdots-\psi_q B^q)(1-\theta_1 B-\theta_2 B^{2s}-\cdots-\theta_Q B^{Qs})\varepsilon_t \qquad (12)$$

Where, *AR(p)* is an autoregressive process of order p, *MA(q)* is a moving average process of order q, *I(d)* is differencing of order d, *AR$_s$ (P)* is Seasonal AR part of order P, *MA$_s$ (Q)* = Seasonal MA part of order Q, *I$_s$ (D)* = seasonal differencing of order D, and S = is the seasonal period.

5. MODELS AND FORECASTING: RESULTS AND THEIR INTERPRETATIONS

5.1 Structural Time Series Models

The Structural Time Series Models were estimated using the statistical software STAMP 6.3. The model was estimated using the sample range of 1983(1)-2009(4), this range was chosen to be consistent with the Central Bank of Barbados forecast horizon. According to the estimation criteria the model supposed to converge reaching steady state. The best fit for both models showed very strong convergence with both models reaching steady state. See Table 2.

Table 2: Structural Times Series Models

	Basic Model		**General Model**	
Equation	**Parameters**	**P-Values**	**Coefficient**	**P-Values**
Level	2.53	[0.00]***	4.78	[0.00]***
Slope	0.02	[0.15]	0.02	[0.20]
Cycle 1 amplitude	0.00	n.a	n.a	n.a
Seasonal Factors				
1	0.00	[0.86]	0.00	[0.63]
2	0.02	[0.32]	0.03	[0.11]
3	0.02	[0.39]	0.00	[0.59]
4	-0.04	[0.05]	-0.05	[0.00]***
Seasonal Chi2 test	4.70	[0.19]	8.49	[0.04]**
Regression Parameters				
LGDP	n.a	n.a	-0.44	[0.05]**
Summary Statistics				
R^2	0.95		0.95	
Normality	0.64		1.69	
D W	1.94		1.99	
Q (12, 3)	6.54		9.07	
H(38)	1.31		2.12	
N	124		123	

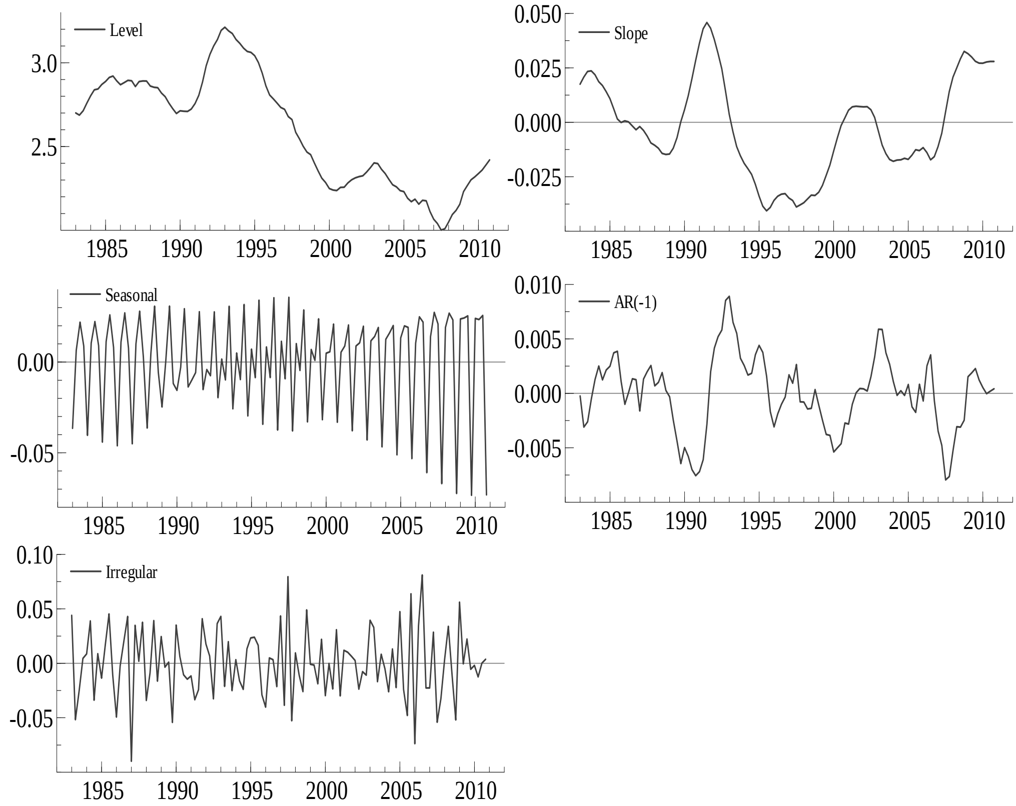
Note 1: ***, ** and * indicates significance at 1, 5 and 10 percent levels, respectively. All diagnostics tests were performed. R^2 - coefficient of determination; DW - Durbin Watson statistic, Q - Box-Ljung Q statistic, H - unconditional heteroskedasticity test and normality test.

5.1.1 Basic Structural Time Series Model

As shown in Table 2, the basic model consists of only the underlying time series components. The model was first estimated using the most basic form, where the slope, cyclical, seasonal and irregular components were assumed to be stochastic. For each component the value of each hyperparameters were assigned non-zero q-ratios, confirming the initial stochastic specification of each component. The model was then re-estimated with the stochastic components and several approximations for the cyclical component. The model with the lowest AIC and SIC contained an AR (1) term for the cyclical approximation with a stochastic trend seasonal and irregular components (Table 2). The p-values for the t-statistics indicated that only the level was significant while the slope and seasonal factors are insignificant. However, since q-ratios established the existence of the stochastic trend and seasonality they were retained in the model. The model passed all standard diagnostics tests such as the coefficient of determination, normality, Durbin Watson, heteroskedasticity and Box Ljung Q Statistic indicating the model is well specified.

Figure 2 provides a graphical representation of each component in the basic model. The first graph on the top left represents the level of the series. Over the sample period the level of unemployment has been declining. Of note, however, are the three turning points where unemployment began to rise: these are the 1991 balance of payments crisis, the external shock following the 911 terrorist attacks in the United States in 2001 and the most latest global recession in 2008. This is also reflected in the slope of the series (top right). The slope of the series lies below zero for most of the sample period and is consistent with the overall trend in the level of the series. It also highlights the drastic upturn in the rate of growth over the same three periods identified above. The seasonal component seems to suggest that seasonality of unemployment has been increasing since the early 2000s. This result in consistent with the fact that the GDP growth has become increasing seasonal during the same period (See figure 3). The AR(1) bears no economic interpretation meaning that it depends on the past but is included since it provides a better fit of the model.

Figure 3: Components of the Basic Structural Time Series Model

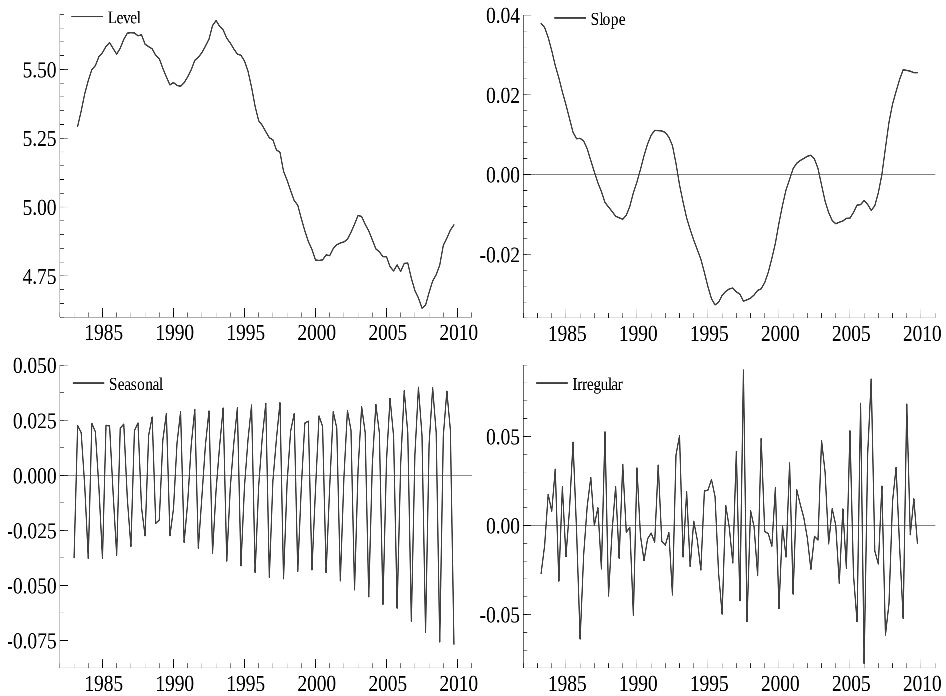


5.1.2 General Structural Time Series Model

Similar to the basic model, the general model was initially estimated assuming stochastic components. The only deviation from the basic model in the inclusion of real GDP lagged on period as an explanatory variable. Real GDP is included as a repressor to capture the impact of the business cycle on the underlying cyclical swings in the unemployment series.

Table 4, provides that output for the general model. An examination of the q-ratios indicates that all components are stochastic in nature, with both the level and seasonal components significant at the 1 percent and 5 percent, respectively. Quarter four seems to be the only quarter significant at all levels while the other seasonal are all insignificant. Real GDP is significant at the 5 % percent level and the model fit seems improve with the inclusion the GDP variable. Also, the real GDP variable seems to be approximating the cyclical swings in the series since there are no adequate specifications when we include the cyclical component. Again, as with the basic model, the general model passed all diagnostics tests. As with the basic model, the times components (Figure 5) seem to tell a similar story as it relates to the overall trend and turning point of the unemployment series.

Figure 4: Time Series Components of the General Structural Time Series Model



5.2 Results: Seasonal Autoregressive Integrated Moving Average Model

The SARIMA model was estimated using the statistical software PC Give. Based on the data plot in figure 1 the series appears to be non-stationary with downward trend. This was also confirmed by the slow gradual decay of the autocorrelation function of the series and significant Q statistics at all 36 lags. The Augmented Dickey-Fuller and Phillips Perron test indicate that the series was integrated of order one. Rather than assume a strict order of integration, however, the model was estimated using as an SARFIMA model with the order of integration determined within the estimation process. Table 3 presents the model output.

Table 3: Summary of Seasonal Autoregressive Integrated Moving Average

Equation	Parameters	P-Values	Summary Statistics	
d (order of integration)	(0.42)	0.00	Normality test: $Chi^2(2)$	0.74 [0.69]
Constant	2.52	0.00	ARCH 1-1 test F(1,97)	0.01 [0.94]
AR(1)	0.24	0.09	Portmanteau(12): $Chi^2(7)$	7.08 [0.42]
AR(2)	0.29	0.00	Asymptotic test: $Chi^2(2)$	0.11 [0.95]
AR(3)	0.10	0.31	Observations	108
AR(4)	0.21	0.05		
Season1	0.03	0.17		
Season2	0.04	0.04		
Season 3	0.06	0.00		

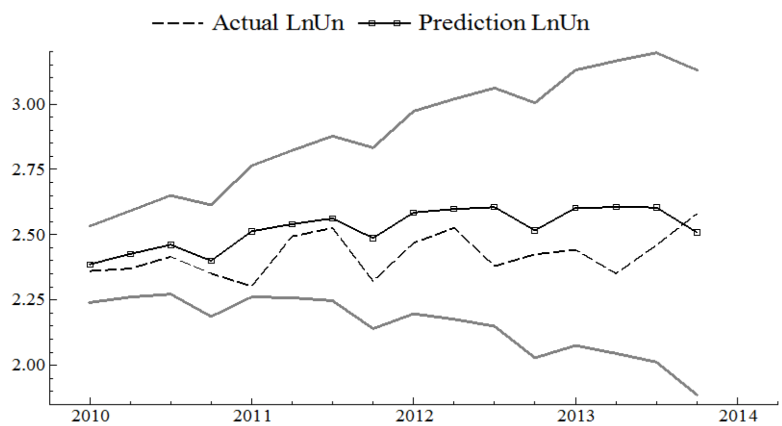
Note: ***, ** and * indicates significance at 1, 5 and 10 percent levels, respectively.

After a series of fitting a series of AR and MA terms, the SARIMA (4,0.4,0) with season dummies was found to be the most parsimonious model. Initially, the model was estimated without any seasonal dummies but given the presence of serial correlation and non-normality the model was fitted with season dummies. Although some of the AR terms and the seasonal dummy are insignificant, they were retained to improve the stability of the model. Nevertheless, the model appears to be well specified as diagnostic test rejects the presence of non-normal, serial correlated and heteroskedastic residuals.

5.3 Forecast Evaluation

The strength of any forecasting model lies in its predictive powers (Jackman and Greenidge 2010). In this section, the out of sample forecasting accuracy of the models are evaluated. The actual and the predicted values of the unemployment rate are plotted for the period 2010Q1 to 2013Q4 for each model (See Figure 6). Over the forecast period, both the GSTS model and the SARIMA outperform the BSTS model as this model consistently overshoots each quarter. Overall the SARIMA model seems to have a better forecast over the entire period; however, the GSTS model performance appears to be better in the shorter term, particularly in the first two years. The general model seems to breakdown over the latter two years.

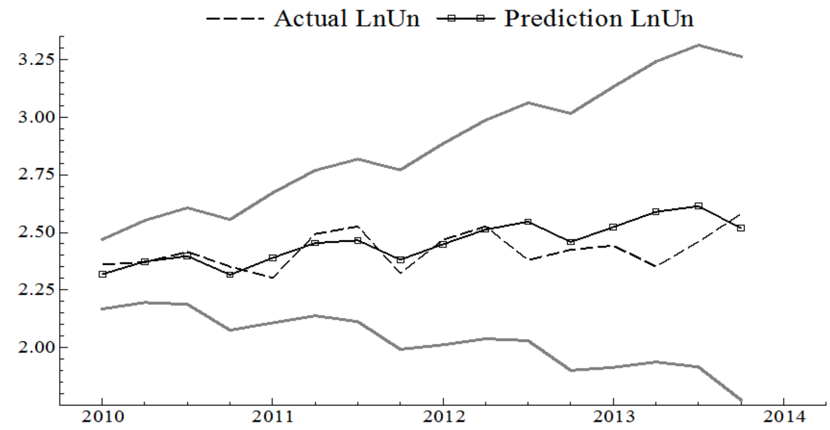
Figure 5: Basic Structural Time Series Multi-Step Forecast vs. Actual



\

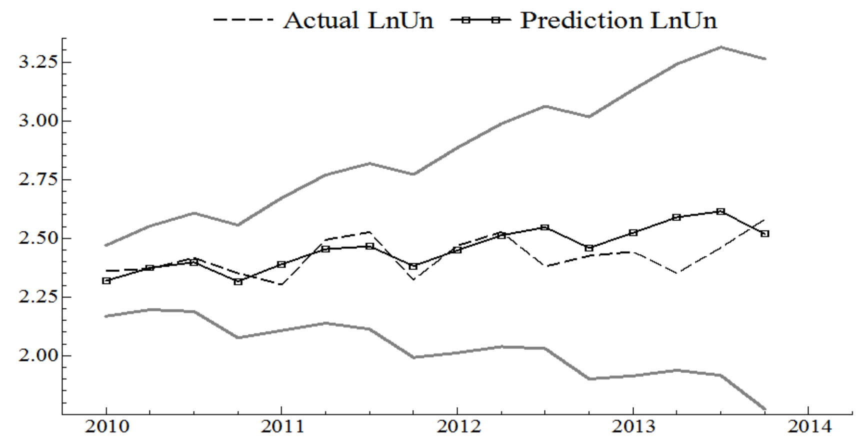
Note : The forecast is estimated within the standard error limits

Figure General Structural Time Series Multi-Step Forecast vs. Actual



Note : The forecast is estimated within the standard error limits

Figure 7: Seasonal Autoregressive Integrated Moving Average Multi-Step Forecast vs. Actual



Note : The forecast is estimated within the standard error limits

Table 4 gives further estimation of the cumulative out-of-sample forecast performances of the three models. The forecasts are evaluated using the MAPE, RSME and Theil's Inequality Coefficient. The results suggest that the GSTS model outperforms the BSTS model at all intervals along the forecast horizon. With regards to the SARIMA model, the GSTS model seems to perform just as good as the SARIMA over the first four quarters and even better by the end of the first 8 quarters. However, as indicated in Table 4 the performance of the GSTS model declines over the last 8 quarters. This seems to indicate that the GSTS model is better forecasting model over the shorter-term. Also, the model with the lowest accuracy value is highlighted in the Table 4.

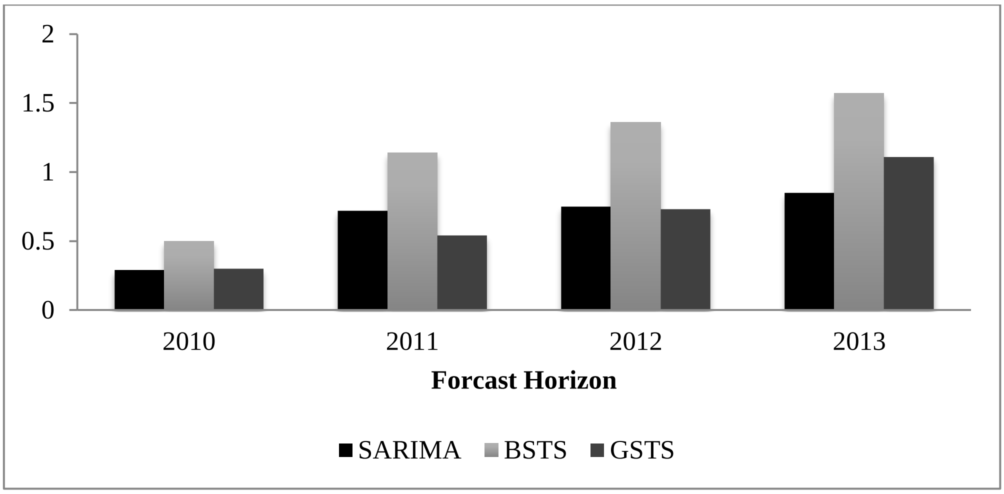
Table 4: Cumulative Forecasting performance of BSTS, GSTS and ARIMA Model

	RMSE			MAPE			U-STATISTIC		
	SARIMA	**BSTS**	**GSTS**	**SARIMA**	**BSTS**	**GSTS**	**SARIMA**	**BSTS**	**GSTS**
2010	0.29	0.50	0.30	2.4	5.0	3.5	0.01	0.32	0.01
2011	0.72	1.14	0.54	5.0	17.9	6.1	0.12	0.18	0.05
2012	0.75	1.36	0.73	2.2	9.6	3.4	0.08	0.40	0.11
2013	0.85	1.57	1.11	14.1	6.9	6.1	0.14	0.50	0.36

Note: The model with the lowest accuracy value is highlighted in the table.

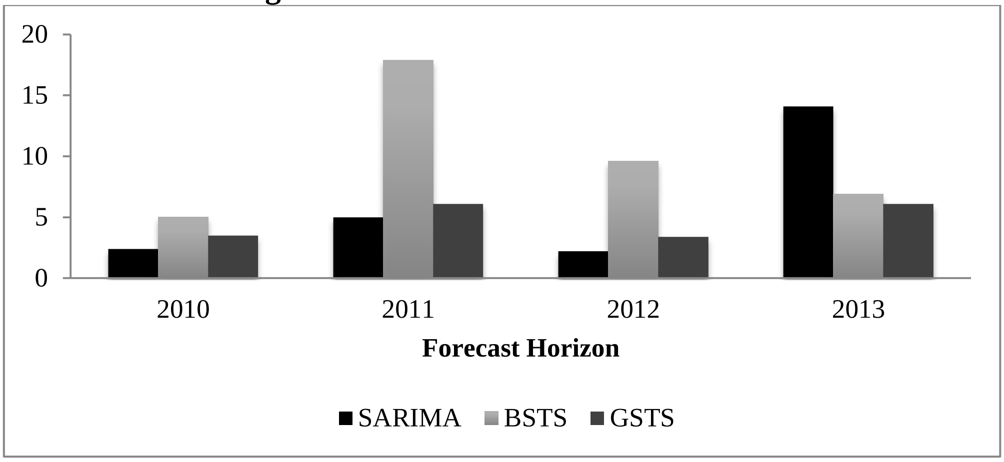
In Figure 6, the forecasting accuracy of the various forecasting models is assessed using the root mean square error (RMSE) as a measure. The forecasting method SARIMA clearly outperforms the other models, especially over shorter forecasting horizons (4 to 16 months). The GSTS model only shows some accuracy in short-term forecasts, but fails to perform in the longer run. It is also noteworthy that the BSTM performed the worst in almost all cases.

Figure 8 - Forecast Evaluation – RSME



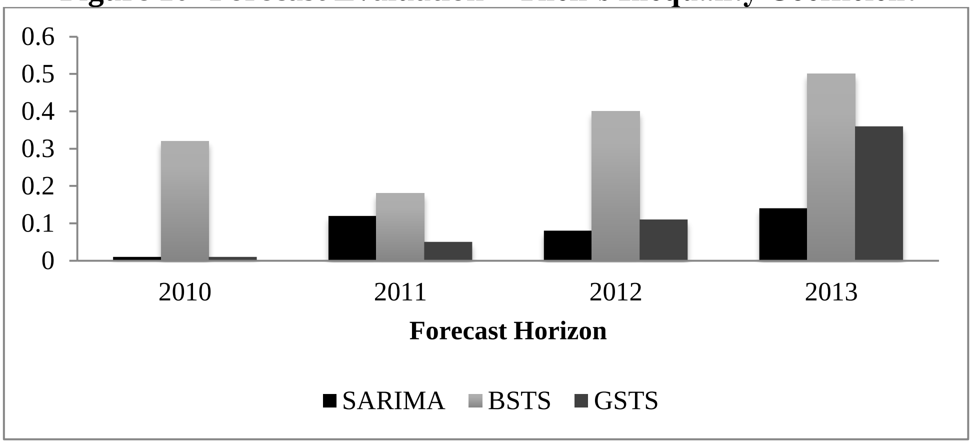
A similar pattern can be observed when MAPE is assessed to measure forecasting accuracy (See Figure 7). The SARIMA models outperform the other models in all three time horizons, followed by the GSTS model forecasts. For the first time, the SARIMA forecast didn’t take the pole position in forecasting accuracy – for the last quarter of forecast. However, across all the other time horizons, the SARIMA forecasts outperform the other models.

Figure 9- Forecast Evaluation – MAPE



In Figure 8, the Theil Inequality Coefficient is used to assess the forecasting accurateness of the various models. The graph depicts that the SARIMA models outperform the other models with the exception of the 2^{nd} quarter in all four time horizons. The GSTS model forecast struggle to outperform the SARIMA models, but breakdown after the 2^{nd} quarter. The BSM performs the worst of all the forecast over the entire period term

Figure 10- Forecast Evaluation – Theil's Inequality Coefficient



Based on the forecast evaluation results, we did further testing for predictive accuracy using the Diebold-Mariano Test (See Table 5). To establish which of the contending methods has the highest predictive accuracy in forecasting the (Diebold and Mariano 1995) test can be implemented. The result indicates that only the BSTS model was bias and the GSTS and SARIMA are not bias. Then we further test the accuracy among the three models.

Table 5: Diebold Mariano Test for Error Bias

	SARIMA	Basic STS	General STS
P-Value	0.22	0.00*	0.17

Note: ***, ** and * indicates significance at 1, 5 and 10 percent levels, respectively.

Table 6: Diebold – Mariano Test for Relative Accuracy (P- Values)

Models	SARIMA	Basic STS	General STS
SARIMA	0.50	0.98	0.81
Basic STM	0.02***	0.50	0.00***
General STM	0.19	0.99	0.50

Note: ***, ** and * indicates significance at 1, 5 and 10 percent levels, respectively.
The p-value (0.50) is the based value in the matrix.

Base on this matrix presented here, we found that the BSTS model is less significant in terms of accuracy than the SARIMA model and the same holds for the GSTS models. As in the case of the GSTS model the results show that this model and the SARIMA model are not significantly different from each other in terms of accuracy.

6. CONCLUSION AND POLICY IMPLICATION

Projecting future unemployment rates like any other macroeconomic variable should be an important application to economists as well as policy makers. This paper investigated the different time series models used for forecasting unemployment rates in Barbados during the period 1983Q1: 2013Q4, namely SARIMA, BSTS model and GSTS model. Specifically, the forecasting techniques were compared based on the following criteria: RSME, MAPE and Theil U Statistic. Though all the models could be used for projection based on the significance of the parameters and the fitness of the models, the model selection criteria displayed that the SARIMA model surpassed the alternative models.

More specifically, the BSTS model consistently overshoots in each quarter. However, when we add the GDP variable the performance of the Structural Time Series model improves significantly. The Diebold Mariano test result proves that only the BSTS model produced biased forecast errors. And the GSTS model and the SARIMA models were both unbiased. Furthermore, we found that the GSTS model and SARIMA model produce forecast errors that are significantly more accurate than the basic model. On the other hand, the test indicates than the forecast accuracy of the GSTS model and SARIMA model are relatively the same.

Lastly, based on the results presented the SARIMA model seems to be steadier over the entire forecast horizon but the GSTS model performs better in the shorter term. The results suggest that unemployment rate in Barbados could be modelled and predicted using SARIMA (4,0,4,0) model.

REFERENCES

Archibal, X, D Lewis-Bynoe, and W Moore. "Caribbean Labour Markets and the "Great Recession"." *Mimeo, caribbean Development Bank*, 2011.

Ashipala, J, and J Eita. "Determinants of Unemployment in Namibia." *International Journal of Business and Management 5 (9),* 2010.

Ball, L, and M Hofsette. "Unemployment in Latin America and the Caribbean." *Mimeo, John Hopkins University*, 2009.

Boamah, D. "Short-term forecasting of Wages, Employment and Output in Barbados." *Modeling in OECD Countries*, 1988: 539-559.

Borda, Patrice, and Nlandu Mamingi. "On the persistence of unemployment in small open economics." *The Working Papers Series of Department of Economics of Cave Hill Campus*, 2014: 1-31.

Box, and Jenkins. *Time Series Analysis: Forecasting and Control Revised Edition.* London: Holden-Day, 1970.

Box, G, and G M Jenkins. "Time Series, Analysis Forecasting and Control." 1976.

Clements, M, and H Krolzig. "A comparison of the forecast performance of Markov-switching and threshold autoregressive models of US GNP." *Econometrics Journal 1*, 1998: C47-C75.

Craigwell, R, and A Warner. ""Unemployment in Barbados 1980-1996" , in A. Maurin and P. Watson (Eds)." *Empirical Studies in Caribbean Economy, Technical Papers, Caribbean centre for Monetary Studies, Trinidad and Tobago* Vol 5 and 6 (2000): 43-91.

Craigwell, Rolland, and Ann-Marie Warner. "Labour Market Dynamics in Barbados:Policies and Implication of Globalisation." 2003.

Craigwell, Rolland, and Annmarie Warner. "Unemployment in Barbados 1980-1996." In *Empirical Studies in Caribbean Economy*, by Maurin Alain and Patrick Watson, 42-88. Trinidad and Tobago: Caribbean Centre for Monetary Studies, 1999.

Craigwell, Rolland, and Maurin Allain. "Unemployment Hysteresis in the English- Speaking Caribbean:Evidence of Non-Linear Models." *International Research Journal of Finace and Economics Issue 65*, 2011: 98-111.

Crato, N, and B Ray. "Model Selection and Forecasting for long-range dependent processes ." *Journal of Forecasting 15*, 1996: 107-125.

Diebold, F X, and R S Mariano. "Comparing Predictive Accuracy ." *Journal of Business and Economic Statistics 13*, 1995: 253-263.

Downes, A, N Mamingi, and R Antoine . ""Labour Market Regulation and Employment in the Caribbean" in J. Heckman and C. Pages. (Eds)." *Law and Employment lessons from Latin America and the Caribbean*, 2004: 517-551.

Floros, C. "Forecasting the United Kingdom Unemployment Rate: Model Comparisons." *The International Journal of Applied Econometrics and Quantitative Studies (2-4)*, 2005: 57-72.

Freeman, G D. "Panel Tests of Okun's Law for Ten Industrial Countries." *Economic Inquiry*, 2001: 511-513.

Hansen, B E. "Inference in TAR models." *Studies in Nonlinear Dynamics and Econometrics 2*, 1997: 1-14.

Harvey, A. "Forecasting Structural Time Series Models and the Kalman Filter ." *Cambridge University Press: Cambridge*, 1989.

Harvey, A, and S Peters. "Estimation Procedures for Structural Time Series Models." *Journal of Forecasting 9*, 1990: 89-108.

Henry, A, A Hilaire, and S Nicholls. "Medium Term Forecasting with an Econometric Model of Trinidad and Tobago Economy." *Social and Economic Studies 39:4*, 1990: 107-148.

Irfan, Lal, S Muhammad, M Jalil, and A Hussain. "Test of Okun's Law in some Asian Countries: Cointegration Approach." *European Journal of Scientific Research,40 (1)*, 2010: 73-80.

Jaafar, J. "Peramalan Indikator Utama Tenago Buruh." *Research and Development Division, Department of Statistics Malaysia*, 2006.

Jackman, Mahalia, and Kevin Greenidge. "Modelling and Forecasting Tourist flows to Barbados using Structural Time Series Models." *Tourism and Hospitality Research 10*, 2010: 1-13.

Kendall, M, and J Ord. "Time Seried 3rd Edition." *Edward Arnold London*, 1990.

Koop, G, and S M Porter. "Dynamic asymmetrics in US unemployment." *Journal of Business and Economic Statistic 17*, 1999: 298-313.

Lee, j. ""The Robustness of Okun's law:Evidence from OECD Countries"." *Journal of Macroeconomics, 22(2)*, 2000: 331-356.

Lewis, R, and C Brown. "A Forecast of North Carolina Unemployment rates for 2001-2002 Using Past Inflation [online]." 2001.

Lippman, S, and J McCall. ""The Economics of Job Search: A Survey"." *Economic Inquiry*, 1976a: 155-89.

Lippman, Steven A, and John J McCall. ""Job Search in a Dynamic Economy,"." *Journal of Economic Theory*, 1976b: 365-90.

Makridakis , S, S Wheelright , and R Hymdman. "Forecasting Methods and Application." *Wiley:New York*, 1998.

Maurin, A, R Craigwell, and S Matheuraparsad. ""Unemployment Hystersis in the English-Speaking Caribbean: Evidence from Non Linear Models"." *International Research Journal of Finance and Economics*, 2011.

Montgomery, A L, V Zarnowitz, R S Tsay, and G C Tiao. "Forecatsing the U.S unemployment rate." *Journal of American Statictics Association 93*, 1998: 478-493.

Mortensen, Dale T. ""A theory of Wage and Employment Dynamics", in Microeconomic Foundations of Employment and Inflation Theory." 1970: 124-66.

Nasir, M, K Hwa, and H Mohammad. "An Initial Study on the Forecast Model for Unemployment Rate ." *Workshop Review of the Labour Force/Migration Survey*, 2008.

Nickell, S. "Unemployment and Labour Market Rigidities:Europe versus North America." *Journal of Economic Perspectives* , 1997: 55-74.

Okun, Authur. "Potential GNP: Its measurement and significance." *In American Statistical Association, Proceedings of the Busniness and Economic Statictics Section*, 1962: 98-104.

Phillips, A W. ""The Relation between Unemployment and the Rate of Change of Money Wage Rates in United Kingdom 1861-1957"." *Economica 25 (100)*, 1958: 283-99.

Ray, B. "Modelling long-memory process for optimal long-range prediction." *Journal of Time Series Analysis 14*, 1993: 511-525.

Rothman, P. "Forecasting asymmetric unemployment rates." *Review of Economics and Statistics 80*, 1998: 164-168.

Samuel, Paul A, and William D Nordhaus. *Economics.* Boston, Mass: Mc Graw-Hill, 2001.

Skalin, J, and T Terasvirta. "Modelling asymmetries and moving equilibria in unemployment rates." *Discussion Paper 262*, 1999.

Theil, H. "Applied Economic Forecasting." *Chicago, Rand McNally*, 1966.

Van Dijk, D, H P Boswijk, and P H Franses. "Asymmetric and common absorption of shocks in non linear autoregressive models." *Econometric Institute Research Report*, 2000.

Zhou, B, D He, and Z Sun. "Modelling and Simulation Tools for Emerging Telecommunication Networks." 2006: 101-12.