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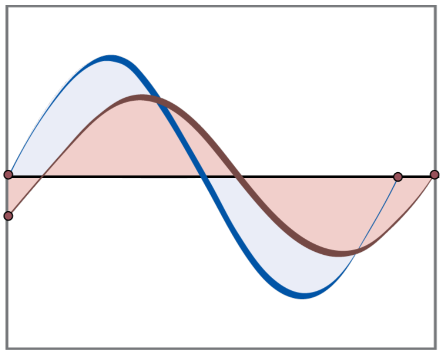

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Exploring the Use of Internet Searches to Predict Unemployment in Trinidad and Tobago

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Abstract

This paper explores the use of Internet user searches from the freely available statistical tool "Google Trends" to estimate and predict Trinidad and Tobago's unemployment rate. The main research question was: Does a model for estimating Trinidad and Tobago's quarterly unemployment rate using Google search volumes significantly improve the baseline forecasting model? The data spanned the period 2004 to 2018 on a quarterly frequency. Google search volumes of four keywords related to job search were used for the analysis. A univariate time series model was used to estimate the unemployment rate for Trinidad and Tobago. Given the possibility of a seasonal component in the unemployment rate time series, a Seasonal Autoregressive Integrated Moving Average (SARIMA) model was used. The benchmark SARIMA model showed that while the unemployment rate is non-stationary, the rate has a stationary seasonal nature. The predictive accuracy performance of the different model specifications was assessed and the benchmark SARIMA model yielded "good" forecasts. The results showed that the model specifications that included Google search terms did not improve the predictive accuracy of the benchmark SARIMA model. We hypothesise that in the context of Trinidad and Tobago, given that most workers have at most low to mid-level education and the relatively low internet (subscription) penetration rates, jobseekers may still rely heavily on networking and in-print newspaper job advertisements when looking for employment opportunities.

JEL Classification Numbers: C22; E32; F41

Keywords: Google Trends, unemployment rate, seasonal ARIMA, forecasting, Trinidad and Tobago

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1.0 Introduction

The Big Data Revolution is having an impact on the way businesses and policy makers execute their mandates. The ability to collect and analyse detailed information about individuals holds tremendous power for those seeking to supply or support citizens. In executing their role of monetary policy oversight, currency and price stability, central banks are acutely placed to benefit from a better, more granular understanding of the people they serve. Historically, central banks rely heavily on information that the National Statistical Offices have collected via surveys, reports, and other manual data collection methods, which often suffer from excessive time lags and the need for constant revisions when more up-to-date data becomes available.

The widespread use of the internet and its 'big data' capability now presents a repository of human activity. Individuals use the internet to research products, make purchases, search for jobs, and socialise. Since so many of our day-to-day decisions are being logged electronically, there is great potential to understand the individual, as an economic unit, in real time. The granularity and multidimensionality nature of big data offers several advantages to economists, including the ability to identify economic trends as they occur (nowcasting[2]), to test behavioural theories of previously untested agents, and create tools for manipulating and analysing this data. Hence, big data can enable regulators to assess the 'now-state' of the economy and make predictions about economic conditions in advance of traditional statistics.

There are many search engines from the infinite database of the world wide web, that perform the function of searching for, and identifying items based on keywords or characters specified by a user. However, Google has proven itself to be the market leader in this field. Data to October 2020 suggests that Google's global search engine market share totalled 88 per cent while the second most popular search engine, Bing, accounted for 6 per cent of the global market (Clement, 2020).

In 2008, in an attempt to capitalise on its market leader position, Google launched 'Google Insights for Search' to provide information on the search terms people use to query the internet via the Google browser (this later became the tool we now know as Google Trends). Google Trends provides an index of the volume of Google queries by geographic location and category. It should be noted that Google Trends does not report on the raw level of inquiries for a given search term; it instead reports a query index[3].

[1] The authors would like to thank members of the Research Department of the Central Bank of Trinidad and Tobago for their comments received at the department's Discussion Series held on June 23, 2021, and the Bank's Working Paper Series Committee.

[2] Nowcasting involves predicting the present, the near future, and sometimes the very recent past of an indicator, using auxiliary information and statistical or data science techniques.

[3] The query index starts with the query share: the total query volume for search term in a given geographic region divided by the total number of queries in that region at a point in time. The query share numbers are then normalised so that they start at 0 in January 1, 2004. Numbers at later dates indicate the percentage deviation from the query share on January 1, 2004.

The development of future work using 'big data' would require improvements in the quality and accessibility of the relevant data sets and more appropriate economic modelling frameworks. Richardson (2018) noted that big data sets provide new and useful sources of information for economic analysis, but also warrant further refinement, development, and monitoring in parallel with other macroeconomic indicators and forecasting techniques. As such, the 'big data' potential of internet searches offers an opportunity for analysts, economists, and statisticians to broaden their arsenal of analytical tools. The earliest applications in economics using 'big data' were published in 2009 by Choi and Varian, who looked at short-term predictions of retail sales, automotive sales, real estate market activity, and travel in the US.

According to the BIS (2016), *"Central banks do not have to be ahead of the curve, but they should not miss this opportunity to extract economic signals in almost real time, learn from the new methodologies, enhance their economic forecasts and obtain more precise and timely evaluations of the impact of their policies."*

According to UNSTATS, the COVID-19 pandemic has negatively impacted the work of National Statistical Offices (NSOs) due to massive disruptions to lives and livelihoods. More than ever, now is the time when governments, firms, civil society organisations, and the general public require timely and reliable information to navigate, cope, and respond to the impacts of the pandemic (UNSTATS, 2020). Like other NSOs, much of the Central Statistical Office of Trinidad and Tobago (CSO) work has been stymied by the COVID-19 pandemic, and some of the key national surveys have been postponed.

Closely monitoring current economic activity is an important aspect of policymaking. However, policymaking in Trinidad and Tobago is affected by the lack of timely official economic statistics, which are generally published with a lag. At the time of writing, official unemployment data was published with a significant lag of approximately six quarters due to an array of issues, including internal institutional challenges at the national statistical office as well as a large non-response rate from participants[4]. The COVID-19 pandemic has exacerbated this issue as the work of the CSO has been negatively impacted by lockdown measures and massive disruptions to lives and work processes. Internet search data can bridge this gap and can be useful for economic surveillance and policymaking (McLaren and Shanbhogue, 2011).

This paper seeks to bridge this information gap in Trinidad and Tobago by exploring the use of Google search data from Google Trends to construct leading and coincident indicators[5] of the unemployment rate. Google search data was utilised to develop a benchmark short-term model that includes the Google-indicators to estimate the past values (for which official rates are unavailable) and forecast the quarterly unemployment rate for Trinidad and Tobago. In particular, the following research questions are investigated: 1) Is the volume of Google keyword searches related to unemployment correlated with the unemployment rate in Trinidad and Tobago?; 2) Does the volume of Google keyword searches related to unemployment contain predictive power for the official unemployment rate in Trinidad and Tobago?; and 3) Does a model for estimating Trinidad and Tobago's quarterly unemployment rate using Google search volumes significantly improve baseline forecasting techniques?

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[4] John-Lall, Raphael. 2019 "Here's What the CSO needs – stakeholder participation". Trinidad and Tobago Business Guardian, January 19, 2019, p. BG6-BG7.

[5] Leading indicators point toward possible future financial or economic trends and/or events, while coincident indicators occur in real-time and help clarify the current state of the economy.

The rest of the paper is organised as follows. The proceeding section reviews the literature on using Google econometrics to forecast the unemployment rate in both advanced and developing economies. Section 3 provides some stylised facts on the labour market in Trinidad and Tobago. Section 4 outlines the data and methodology used for analysis, while section 5 discusses the results. Section 6 concludes the paper with some policy implications and recommendations.

2.0 Literature Review

Askitas and Zimmermann (2009) looked at the benefits of Google econometrics in forecasting unemployment, particularly in times of crises when the flow of information from traditional sources may be too slow to provide meaningful results. They focused on showing the correlation between the unemployment rate in Germany and the level of search activity for certain keywords. Google Trends data for four (4) word groupings were examined: 1) k1 – Unemployment office or agency (the assumption was that activity in this category would relate to people who contacted or were in the process of contacting the unemployment office. As such, it was assumed to have some level of correlation with the "flow into unemployment"); 2) k2 – Unemployment rate (this being the easiest and most natural keyword when dealing with unemployment); 3) k3 – Personnel consultant (this variable was expected to be correlated with high-skilled workers reacting to fears of layoffs and companies preparing for layoffs or personnel restructuring); and 4) k4 – Eight of the most popular job search engines in Germany (this was directly related to job searching activities and was also associated with the "flow out of unemployment").

An important consideration that arose was that job searching engines and job searching services may come and go over time. Therefore, when performing a time series analysis, a popular job search agency in one decade may be taken over by a more popular site in a different decade. Accordingly, it is important to use keywords that remain relevant during the entire period under observation. Askitas and Zimmermann (2009) also emphasised that the accuracy of a model must be based on parsimony, prediction success, usefulness, and have a sound economic basis. The economic variables included should have short- and long-run effects that are consistent with economic intuition relevant to the country in question. There should be a long-run stationary solution of the model. To ensure the statistical model is parsimonious, information criteria like the Bayesian information criterion (BIC) or the Akaike information criterion (AIC) can be used to ensure that as few explanatory variables are used as possible. Finally, Askitas and Zimmermann (2009) highlighted the fact that a model is only as good as its usefulness and placed high value on prediction success, which can only be judged in practice after the model has been used several times *ex-ante*. The core regression equation used was an error correction model (ECM). Their results justified a more economical approach since the model using two explanatory variables performed better than more complex specifications.

Following this seminal work, policy makers began noting the potential internet searches had to inform economic policy by assisting in the way they monitor economic activity. McLaren and Shanbhogue (2011) of the Bank of England (BoE) explored how internet search data could be used to enhance the BoE's understanding of the economy, by considering whether internet search data contain information over and above existing survey indicators for the UK housing and labour markets. McLaren and Shanbhogue (2011) highlighted a few valuable properties of internet search data. Namely, this type of data is extremely timely and covers a potentially vast sample of respondents. Moreover, since search data is collected as a by-product of normal activity, it avoids problems associated with non-response or inaccurate responses. Finally, internet search data facilitates the continuous collection of information on a wider range of issues and the analysis of issues that arise unexpectedly.

On the other hand, McLaren and Shanbhogue (2011) noted several difficulties (limitations) when using internet search data. First, since the widespread use of the internet is a relatively new phenomenon, the data would have a short back-run compared to other economic indicators. Second, there is a high correlation between internet use and other factors such as age and income, which presents a potential issue of having a sample that may not be very representative. Third, given the open-ended nature of a search engine, different users interested in the same topic could enter entirely different search queries, while users with entirely different intentions could enter very similar search queries. Fourth, there are economic activities that still involve little use of the internet. Lastly, there are also some limitations to how data is extracted from search engines. The data provided may not represent the actual level of interest in a search term because the popularity of each search is reported as an index rather than a volume of searches. Since the index is based on a random sample of total searches, back-run of data can change, which can be particularly problematic for less popular search terms (McLaren and Shanbhogue, 2011).

McLaren and Shanbhogue (2011) compared simple regression models for unemployment and house prices, to models augmented with internet search variables to assess the value of search data in the United Kingdom. Existing indicators were also considered to examine if internet search data would explain better than official data. The models were then used to nowcast official data and the performance of each model was compared. The Office for National Statistics produced the unemployment rate under observation and measured by a Labour Force Survey. The labour market related searches assessed included 'jobs', 'Jobseeker's Allowance', 'JSA', 'unemployment benefit', 'unemployed', and 'unemployment'., 'Jobseeker's Allowance' (JSA) had the highest correlation with official data of all possible search terms used. It was also chosen as the best indicator since it was likely to be used by those who think they may soon become unemployed and so search for more information on unemployment benefits (McLaren and Shanbhogue, 2011).

The baseline model was regressed on previous observations of unemployment. Alternating indicators of unemployment, such as the claimant count, and a consumer confidence question on changes in expected unemployment for the next year, were then added one by one and compared to the baseline model. The results suggested that the baseline model explained a large proportion of the changes in unemployment. When the 'JSA' internet search term was added to the model, the results suggested that the term did in fact contain relevant information for explaining changes in unemployment. The variable was significant at the 1 per cent level and produced an expected positive coefficient. The 'JSA' model also improved the fit according to in-sample goodness of fit measures, giving a higher adjusted R-squared and a lower AIC than the baseline model. However, the model using 'claimant count' as the additional explanatory variable outperformed the 'JSA' model producing the lowest AIC of all the models. When both search data and the claimant count are simultaneously included in the equation, each term is significant at the 5 per cent level. This suggests that the best way to use search data is to add it to data received from existing surveys to provide additional insight on a wider range of issues that traditional business surveys might not cover (McLaren and Shanbhogue, 2011).

One perspective missing from the literature was the experience of non-Western countries that often grapple with weak institutions[6]. Lasso and Snijders (2016) tackled this issue by attempting to provide real-time estimates of unemployment in Brazil. Much like previous works, the paper sought to answer the following research question: 'To what extent do Google keyword search volumes contain explanatory and predictive power for the monthly unemployment rate of Brazil?' Their analysis began similarly with a search guided by parsimony. The initial variables selected were chosen based on economic theory, intuition, and investigations into the Brazilian society's habits[7].

Lasso and Snijders (2016) chose to select the five most significant explanatory variables (excluding the constant) to avoid an excessive number of independent variables. To determine the optimal combination of keywords, permutation selection (that is, using the explained variance R-squared) was used as the indicator of model performance. Such that, a high R-squared with significant coefficients was viewed as evidence for the existence of a correlation between Google search volumes and the monthly Brazilian unemployment rate. Once an optimal combination of keywords was found, the model was evaluated using both in-sample and out-of-sample statistics (Lasso and Snijders, 2016).

Lasso and Snijders (2016) used a standard linear model combining search levels and first differences. A second model, which included an autoregressive term, provided no significance in any specification. The linear model was tested against two baseline scenarios. The first scenario utilised the change in the previous period as the current estimate for the change in unemployment, while the second baseline model utilised yearly seasonal patterns to estimate the current unemployment rate. By establishing these baselines, the Root Mean Square Error (RMSE) and hit rates were used to compare with the search-based models to examine whether they provided any (greater) predictive power.

The OLS results suggested that all the search variables under investigation were highly correlated with Brazil's unemployment rate, which simply meant that Brazil's search behaviour exhibited patterns similar to the unemployment rate. However, there was a slight timing difference in the publishing of the unemployment rate and the frequency of the variables. While the model specification treated with this issue, the results did show that it was possible to predict the direction of the monthly Brazilian unemployment rate halfway through the month with more than 80 per cent accuracy, solely based on Google search volumes (Lasso and Snijders, 2016).

Interestingly, Lasso and Snijders (2016) results do not differ much from previous research on developed nations. The proposed models had a lower RMSE of 0.29 compared to 0.35 in the baseline model based on seasonal patterns, thus, improving performance by approximately 18 per cent. Lasso and Snijders' (2016) work made a valuable contribution to the 'big data' research by concluding that predictive Google-based models are achievable in a developing country such as Brazil. Furthermore, because these models proved to be especially effective during the economic downturn in 2015, these techniques could be useful in discerning early warning signals for volatile unemployment rates and recessions in Brazil (Lasso and Snijders, 2016).

Notably, the Lasso-Snijders result is not always the case for non-Western or developing countries. Simionescu and Zimmerman (2017) underlined the fact that limited access to the internet and lower literacy rates in some developing

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[6] Lasso and Snijders (2016) describe weak institutions of developing countries as those that may not possess the desired level of accuracy needed for a fundamental and reliable analysis of their economies.

[7] The variables investigated included: Social security programme; Jobs; Severance Indemnity Fund; National Institute for Social Security; Employment Insurance; Google's unemployment and social benefits index (to gauge the general interest in unemployment); and Google's Job vacancies index (to gauge the general interest in job searches).

countries sometimes make it more difficult to extrapolate Western models. However, this is expected to change over time as the internet plays a more substantial role in the economic life of people living in non-Western and developing countries. Results such as these should in no way deter developing or non-Western countries from using search engine data, especially in ways that aim to complement or supplement existing data sources. Internet search data can narrow the information gap that often exists in many developing counties. Simionescu and Zimmermann (2017) explain:

> *"There is valuable, useful and useable information in the internet activity data. However, we need more experience with using the new technique and see to what extent this new data can replace traditional sources of information. It is not yet a priori clear that one can fully replace traditional data by internet data…There is a strong potential that needs to be further explored. In most of the countries, internet data improved the models and the forecasts of unemployment. However, the forecast accuracy depends on the internet penetration in each country, the age structure of the internet users and the stability of the constructed internet variables."* (Simionescu and Zimmermann, 2017).

3.0 Stylised Facts

3.1 The Labour Market in Trinidad and Tobago (2004-2018)

The official source of labour statistics in Trinidad and Tobago is the CSO. The CSO collects labour market data through the National Census, which takes place every ten years, and a multi-purpose household survey referred to as the Continuous Sample Survey of Population (CSSP). The CSSP is conducted quarterly and is administered within the last two months of every quarter. International Labour Organisation (ILO) standards are used to record and report all labour market statistics in the country. The CSSP was first administered in 1987 and was revised in 1974, 1987, and 1994. The COVID-19 pandemic has had a significant impact on the CSO's ability to effectively conduct these surveys. As such, producing official labour market data has experienced significant lags.

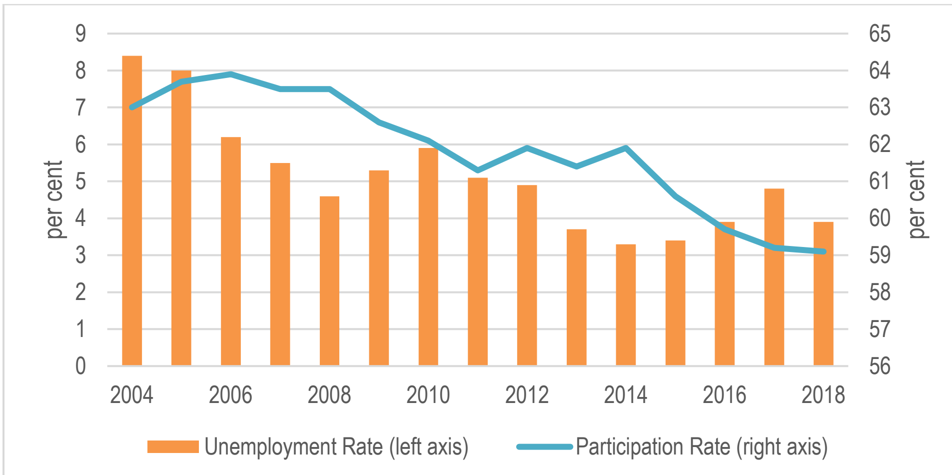
Trinidad and Tobago's labour market has been characterised by low and relatively stable unemployment for over a decade. Latest labour market statistics reveal that as of 2018, Trinidad and Tobago's labour force comprised of 634,700 persons. Of that figure, 609,100 persons were employed and 24,900 were unemployed, resulting in an unemployment rate of 3.9 per cent. While a low unemployment rate is often a positive sign for any economy, another statistic commonly used for assessing labour market conditions, the labour force participation rate, has also declined in Trinidad and Tobago. The labour force participation rate is a measure of the percentage of a country's working-age population that is actively engaged in the labour market.

Figure 1 illustrates the overall downward trend in the unemployment rate and the country's labour force participation rate. The unemployment rate has trended downward, moving from 8.4 per cent at the beginning of the study period (2004) to 3.9 per cent in 2018, while the participation rate has decreased by 6.2 per cent and stood at 59.1 per cent in 2018. This is the lowest the participation rate has been for over two and a half decades, since 1992. This decline in labour force participation can be partly attributed to demographic changes – such as an ageing population[8]. Further,

[8] The United Nations defines a country as 'ageing' when 10 per cent or more of its population is over the age of 60 years. For 2018, data from the CSO revealed that 13.4 per cent of the population was over the age of 60 years (Source: Review of the Economy, 2020).

the share of persons classified as "out of the labour force"[9] increased by 21.8 per cent over the review period, with members of the non-institutional population who are 60 years and over increasing by 40.6 per cent. **Figure 2** shows the trend of some other key labour market statistics. The labour force has shown a slow and steady pace of increase from 2004, peaking at 658,600 persons in 2014; thereafter, the labour force has been declining steadily to its current position of 634,700 persons in 2018. Persons with jobs follow a similar pattern while the number of unemployed persons has shown consistent declines over the 15-year period, dipping to a low of 21,800 persons in 2014 before inching up by 3,100 persons to its current position of 24,900 persons in 2018.

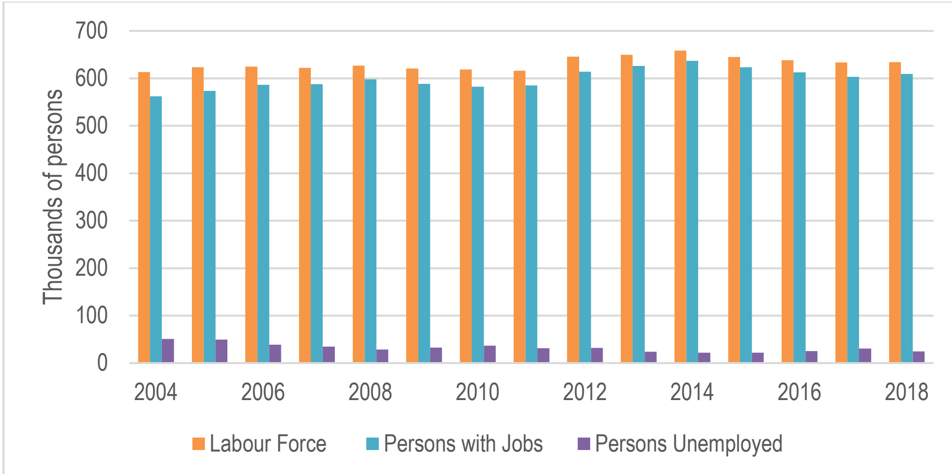
Figure 1: Trinidad and Tobago's Unemployment Rate and Participation Rate 2004 – 2018



Source: Central Statistical Office of Trinidad and Tobago

[9] "Out of the labour force" refers to those persons of working age (15-64 years) who are not economically active for diverse reasons (such as, education, retirement, infirmity, discouraged, etc.).

Figure 2: Trinidad and Tobago's Labour Force 2004 – 2018



Source: Central Statistical Office of Trinidad and Tobago

The Government is the single largest employer in Trinidad and Tobago and the low unemployment rate has often been attributed to the existence of government-funded Social Sector Investment Programmes (SSIP). The aim of these SSIPs has been to provide short-term employment opportunities to citizens with limited skills while also reducing crime and alleviating poverty. However, these programmes have inadvertently contributed to labour market distortions such as underemployment. Underemployment occurs as a consequence of these programmes, given that they provide employment for less than 8 hours a day. Moreover, elevated remuneration levels also contribute to underemployment, as the average hourly wage associated with these SSIPs are usually higher than the national minimum wage. Two of the largest programmes are the Unemployment Relief Programme (URP) and Community-Based Environmental Protection and Enhancement Programme (CEPEP). URP was introduced in 1992 and is charged with the responsibility of upgrading physical and social infrastructure, while CEPEP was implemented in 2002 to provide environmental protection, enhancement, and beautification of environmental work areas.

Based on 2018 data, the most labour-intensive industry in Trinidad and Tobago is the Community, Social and Personal Services sector[10], which employed approximately 34.0 per cent of all persons with jobs. This was followed by the Wholesale and Retail Trade, and Restaurants and Hotels sectors, which employed 20.0 per cent of all persons with jobs. Other labour-intensives sectors included Construction (13.2 per cent); Financing, Insurance, Real Estate and Business Services (10.5 per cent); Other Manufacturing (excluding sugar and oil) (7.7 per cent); and Transport, Storage and Communication (6.4 per cent) **(Figure 3a)**.

When disaggregated by occupation, the data showed that in 2018, the greatest proportion of persons with jobs engaged in Elementary Occupations[11] (17.6 per cent), followed by Service Workers (including the Defence Force), Shop Sales

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[10] Includes workers from government-sponsored employment programmes like the Community-Based Environmental Protection and Enhancement Programme (CEPEP) and the Unemployment Relief Programme (URP).

[11] According to the International Labour Organization's International Standard Classification of Occupations, elementary occupations consist of simple and routine tasks that mainly require the use of hand-held tools and often some physical effort. Tasks performed by workers in elementary occupations usually include selling goods in streets and public places; cleaning, washing, pressing; taking care of apartment houses, hotels, offices and other buildings; delivering messages or goods; carrying luggage collecting garbage to name a few.

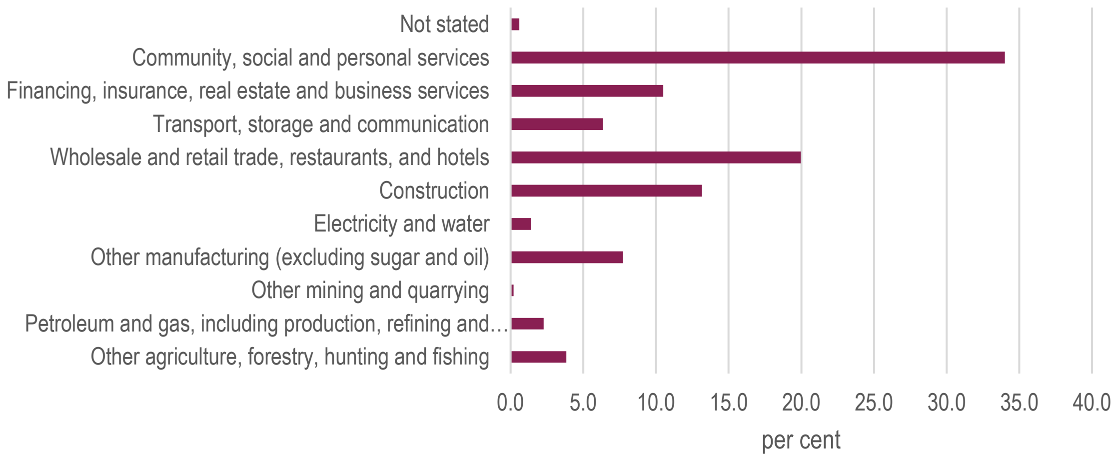
Workers (15.6 per cent), and Craft and Related Workers (15.5 per cent). Technician and Associate Professionals accounted for 13.8 per cent of persons with jobs while Legislators, Senior Officials and Managers accounted for 10.9 per cent of persons with jobs. The smallest occupational group in Trinidad and Tobago is the Agricultural, Forestry and Fishery category, which made up 3.0 per cent of all employed persons **(Figure 3b)**.

An analysis of the educational attainment of the labour force revealed that in 2018, on average 21.1 per cent of persons with jobs were university-educated or held a university degree, diploma or certificate. Approximately 36.1 per cent of the persons employed in Trinidad and Tobago in 2018 had no more than a secondary school education. An additional 42.1 per cent had a secondary school education plus some level of additional training **(Figure 3c)**.

More information can be derived from Bureau of Statistics, work unit of the Policy Integration Department (ilo.org).

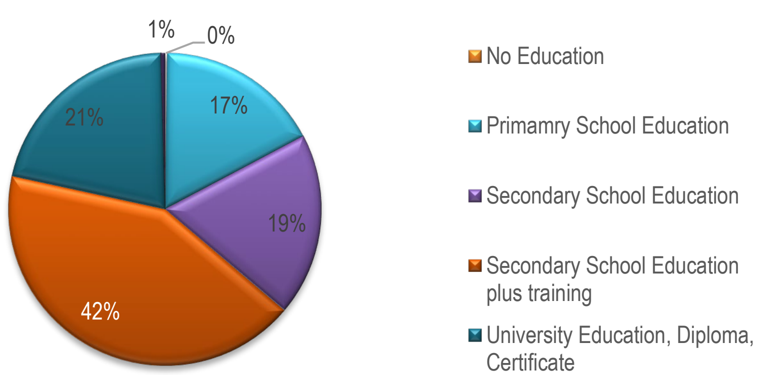
Figure 3: Trinidad and Tobago's Labour Market by Industry, Occupation, and Educational Attainment (2018)

a) Persons with Jobs by Industry



b) Persons with Jobs by Occupation

c) Persons with Jobs by Educational Attainment



Source: Central Statistical Office of Trinidad and Tobago

4.0 Data and Methodology

4.1 Data

This study used quarterly unemployment rate data for Trinidad and Tobago from the first quarter of 2004 to the fourth quarter of 2018 (the latest available data at the time of writing), with a total of 60 observations collected from the CSO. The first 52 observations were used in the model estimation and the remaining 8 observations were used to evaluate the model forecasting performance.

For the Google search terms, Google Trends provides a weekly index of the volume of Google queries by geographical location and category. However, as of November 2018, the frequency of data output is set to monthly when retrieving the search intensity for a period exceeding five years. The data is based on query share, which is the number of searches for that particular category in the chosen geographical region, at a point in time, as a share of the total number of queries. The index represents the search interest relative to the highest point for the selected region and time. A value of 100 is the peak popularity of the term, whilst a value of 50 means that the term is half as popular. Since Google Trends data starts from January 01, 2004, this analysis covered the period 2004:Q1 to the latest available quarterly data for the unemployment rate (2018:Q4). The search data was aggregated on a monthly level and then averaged to obtain a quarterly index figure.

The search terms chosen to reflect the unemployment rate included: 'Caribbean Jobs'; 'Jobs TT'; 'Service Commission of Trinidad and Tobago'; and 'Regency Recruitment'[12]. Established in 2005, the website *CaribbeanJobs.com* has become a popular platform for both recruiters and job seekers. The website has over 80 per cent market share, works with over 1,400 businesses throughout the Caribbean each month, and is visited by over 180,000 individual job seekers per month. The Government is the single largest employer in Trinidad and Tobago – in 2018, public sector workers (Public Service, Statutory Boards, and State Enterprises) accounted for 25 per cent of the labour force[13]. The Public Service Commission has the power to appoint, promote, and transfer persons in the Civil Service, Prison Service, and Fire Service. As such, Google searches for the Public Service Commission was included in the analysis. Regency Recruitment and Resources Limited is Trinidad and Tobago's leading recruitment agency and has been operating since 1996. This employment recruitment agency specialises in contract and permanent placement of administrative, accounting and support professionals, and has worked with more than 18,000 job seekers.

4.2 Methodology

A univariate time series analysis was used to model, estimate, and forecast the unemployment rate for Trinidad and Tobago. Before fitting any particular model to time series data, the stationarity of the series must be checked. The popular Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests were used to test the quarterly unemployment rate stationarity. The Zivot-Andrews endogenous structural break test was also used, where the null hypothesis of a unit root without a structural break is tested against the alternative of a stationary structural break.

[12] Other recruitment agencies were considered, but their pairwise correlation coefficients with the unemployment rate were not statistically significant. Only 'Regency Recruitment' had a statically significant correlation with the unemployment rate.

[13] Data sourced from national labour force survey data (Continuous Sample Survey of Population, CSSP) for 2018.

Lag length selection has strong implications for time series modelling. Taking too few lags leads to misspecification of the model whereas taking too many lags could lead to higher forecast errors. An important precursory when performing the ADF test is the specification of the lag order. If the lag order is too small, serial correlation of the residuals will make the test biased, whereas, taking too many lags will reduce the power of the test. Hence, choosing the optimal lag length is important. As such, the appropriate lag length was chosen based on the lowest value of information criterion such as the AIC, FPE, LR, and SBIC.

Given the possibility of a seasonal component in the unemployment rate time series, a Seasonal Autoregressive Integrated Moving Average (SARIMA) model was considered, which is a generalised form of an ARIMA model but takes into account both seasonal and non-seasonal characteristics of the data. Similar to the ARIMA model, the forecasting values are assumed to be a linear combination of past values and past errors. The SARIMA model, sometimes referred to as the Multiplicative SARIMA, is denoted as *ARIMA(p,d,q) (P,D,Q)S*. The lag form of the model is as follows:

$$\phi(L)\varphi(L^S)(1-L)^d(1-L^S)^D y_t = \theta(L)\vartheta(L^S)\varepsilon_t \qquad \text{Eq. (1)}$$

where y_t is the time series being modelled (in our case, the quarterly unemployment rate), d is the order of non-seasonal differencing, D is the order of seasonal differencing, S is the seasonal order (in this case, $S=4$ for quarterly data), and L is the lag operator.

The first step in developing a SARIMA model is to examine whether the series is stationary. To do this, the study used the Hylleberg Engle-Granger (HEGY) test to ascertain the presence of seasonal unit roots in the unemployment data. The HEGY test checks for seasonal and non-seasonal unit roots in a time series. The HEGY test can detect seasonal unit roots at different seasonal frequencies, as well as at zero frequency.

The seasonal and non-seasonal autoregressive and moving average component lags p, P and q, Q were determined by plotting the ACF and PACF (autocorrelation and partial autocorrelation functions). Both the ACF and PACF have spikes and cut off at lag k and lag k^s at the non-seasonal and seasonal levels, respectively. The order of the model is given by the number of significant spikes.

Based on the plots of the ACF and PACF, there can be different *SARIMA(p,d,q)(P,D,Q)* models with different significant lags of p, P and q, Q. Hence, the study used both the Akaike Information Criterion (AIC) and Schwartz and Bayes Information Criterion (BIC) to determine the best model. The best *SARIMA(p,d,q)(P,D,Q)* model has the smallest AIC and BIC.

Model diagnostics took the form of residual analysis. The residuals of the chosen fitted model should be white noise, that is, the residuals should be normally distributed with mean zero and constant variance and have no autocorrelation. When residuals are not white noise the estimated variances of parameters become biased and inconsistent; also, forecasts will be inefficient due to high variance in the forecast errors. The univariate Portmanteau test was used to check the autocorrelation structure of the residuals. For this test, the null hypothesis is residuals are not serially correlated and the alternative is at least one successive residual is serially correlated. The common test for normality of residuals, the Jarque-Bera (JB) test was used. The Jarque-Bera test assumes a variable is normally distributed with zero skewness and kurtosis equal to three. The null hypothesis of the JB test is that residuals are normally distributed.

This study aims to estimate the past values (for which official rates are unavailable) and predict the unemployment rate using an out-of-sample forecasting method with an appropriate model. Sometimes, the forecast ability of models, which are best in the in-sample fitting, may not provide more accurate results in out-of-sample forecasts. To avoid this problem, both the in-sample and out-of-sample forecasting performance methods were used. In general, empirical evidence from the out-of-sample forecasting performance is considered as more trustworthy than evidence from in-sample performance, which can be more sensitive to outliers and data mining. Consequently, a model with good performance in the out-of-sample forecasting models should be picked as the best model.

To measure the forecast performance of the models (the benchmark SARIMA model against those inclusive of the Google search terms), the in-sample data ran from 2004: Q1 to 2016: Q4 while the out-of-sample evaluation data ran from 2017: Q1 to 2018: Q4. There are two types of out-of-sample forecasting methods: direct out-of-sample and recursive out-of-sample. In practice, the recursive out-of-sample forecasting method provides more accurate and unbiased forecasts. Hence, for this current research, we used the recursive out-of-sample forecasting method. The recursive multistep forecasting method is a step-by-step predictive method that re-estimates at each step after the current predicted value is added to the data to predict the next value. This process continues until all the demanded values have been predicted.

To examine whether the Google search-based models provide better predictive power over the baseline SARIMA (p,d,q)(P,D,Q) model, error statistics (criteria) and hit rates were used. The three error statistics used to measure model performance were the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE), and the Mean Absolute Percent Error (MAPE). The better the forecasting performance of the model, the smaller the error statistics. In applied work, researchers have used Lewis' (1982) interpretation of MAPE results to judge the level of accuracy of forecasts — less than 10 per cent is a highly accurate forecast, 11 per cent to 20 per cent is a good forecast, 21 per cent to 50 per cent is a reasonable forecast, and 51 per cent or more is an inaccurate forecast.

The hit rate is defined as the fraction of correctly predicted directions of change in the variable of interest; that is, a positively predicted change corresponds to a positive change in the measured variable and a negatively predicted change in the variable of interest to a negative measurement.

Finally, the Diebold-Mariano (DM) test was used to compare the forecasting performance of the Google search-based models against the benchmark model. The DM test checks for the existence of significant differences between the forecasting accuracy of any two models. The null hypothesis of the DM test is that there is no difference between the forecast accuracy of the two models.

5.0 Results and Discussion

In this section we discuss the benchmark model specification used for estimating and forecasting the unemployment rate [SARIMA (0,1,1) $(1,0,0)_4$] and the results with and without Google search terms. Six model specifications were analysed – the benchmark model (which excluded Google search terms); the benchmark model plus each of the four Google search terms added separately; and the benchmark model plus the Google search terms altogether.

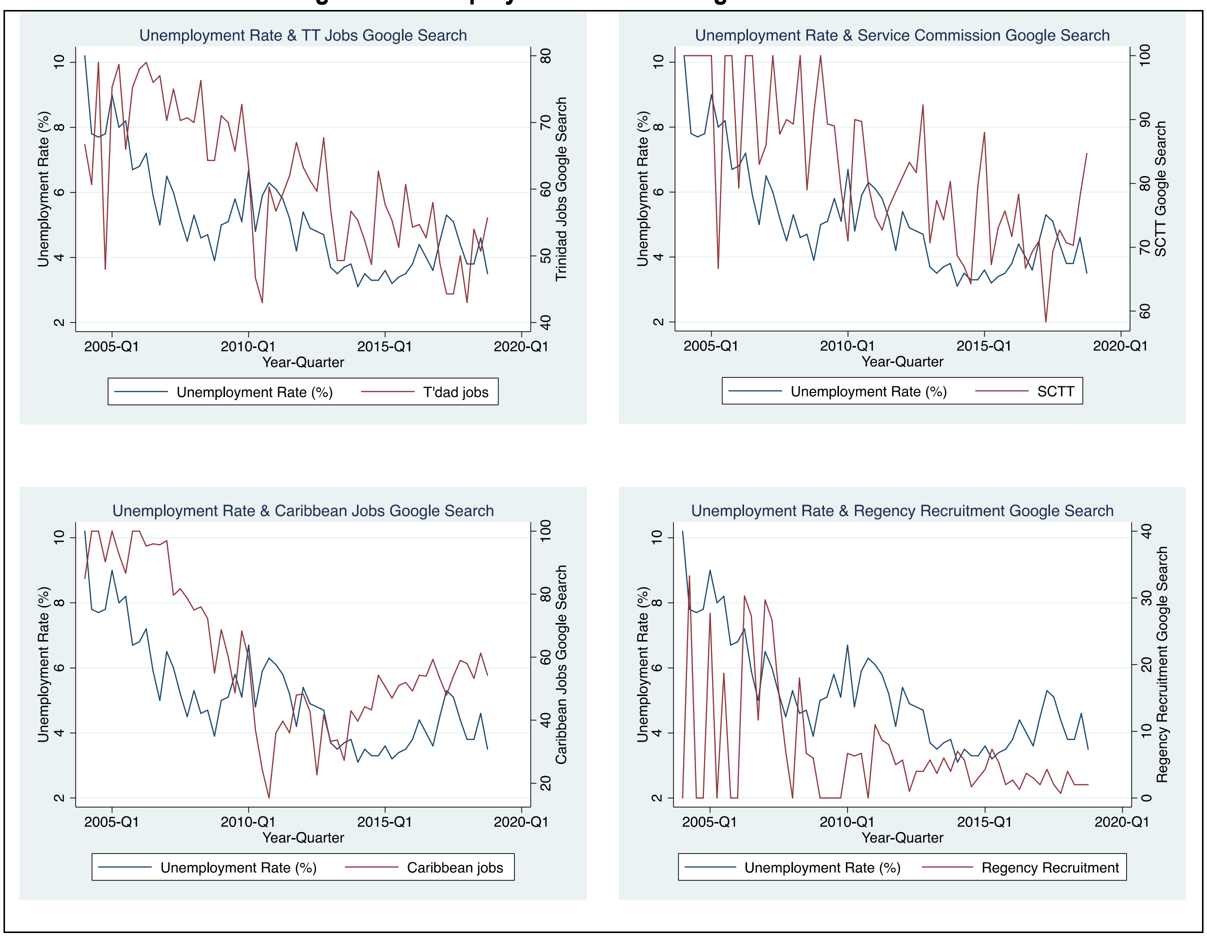
5.1 Descriptive Analysis

Table 1 shows the descriptive statistics of the unemployment time series and the Google search terms. The number of observations totalled 60 with a mean unemployment rate of 5.2 per cent, and a minimum and maximum rate of 3.1 per cent and 10.2 per cent, respectively. All of the chosen Google search terms are positively and statistically correlated with the unemployment rate **(Figure 4)**, with 'Caribbean jobs' having the highest pairwise correlation coefficient of 0.61 and Regency Recruitment having the lowest correlation of 0.34 **(Appendix Table A2)**.

Table 1: Descriptive Statistics of the Unemployment Rate Series and Google Search Terms (2004: Q1 to 2018: Q4)

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Unemployment Rate	60	5.2	1.6	3.1	10.2
Trinidad jobs	60	61.3	10.4	43.0	79.0
Service Commission of Trinidad and Tobago	60	82.1	11.7	58.3	100.0
Caribbean Jobs	60	60.5	22.9	15.3	100.0
Regency Recruitment	60	6.9	8.6	0.0	33.3

Figure 4: Unemployment Rate & Google Search Terms



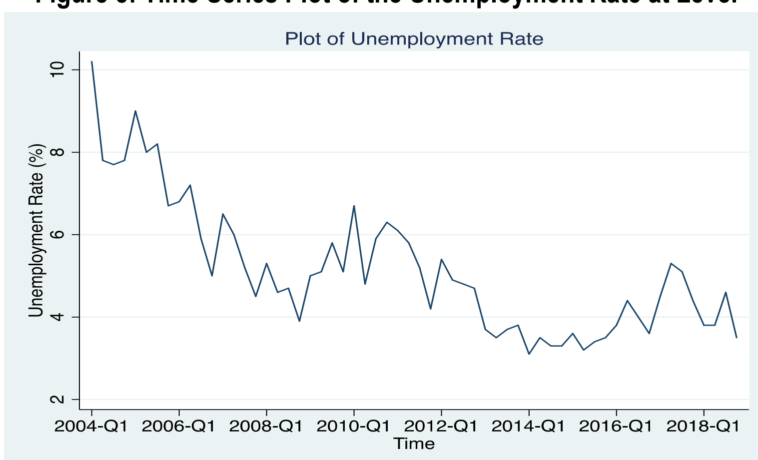
5.2 Stationary Test Analysis

A graphical representation of the unemployment rate series shows that the series may not be stationary at levels, that is, does not remain at a constant level over time **(Figure 5)**, and shows a downward trend. To formally test the stationarity of the series, the ADF and PP unit roots tests were used, and a lag length of four chosen based on the information criterion (FPE, AIC, and HQIC) and the likelihood ratio test. The results of the ADF and PP tests based on the chosen lag length is presented in **Table 2**.

Table 2: Unit Root Test Results (at level)

Series	Level with Intercept				Level with Intercept and Trend			
	Test Statistic		Prob.		Test Statistic		Prob.	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
Unemployment Rate	-2.518	-3.408	0.1113	0.0107	-2.342	-4.270	0.4107	0.0035
Critical value 5%	-2.926				-3.495			

Figure 5: Time Series Plot of the Unemployment Rate at Level



The results of the ADF and PP tests give conflicting results – at the 5 per cent critical value level, the results of the ADF tests are not more negative than the critical value, which implies the existence of a unit root; the opposite is true for the PP tests. Given this, the DF-GLS test was used to counteract the problems of the ADF tests of lack of power in small samples. The results of the DF-GLS test shows that the null hypothesis of a unit root is not rejected for all (10) lags at the 5 per cent level.

Additionally, the unemployment rate series was also tested for structural breaks in the data. The presence of structural break(s) can bias the results of the standard unit root tests as these tests do not allow for structural breaks. Consequently, in the presence of structural breaks, the ADF and PP tests are biased toward accepting non-stationarity of the data due to misspecification bias and size distortions. Given this, to examine whether the standard unit root tests failed to reject the non-stationarity hypothesis due to the existence of a structural break in the unemployment rate series, the Zivot-Andrews unit root test, which allows for structural breaks in the data, was performed. The results of the Zivot-Andrews unit root test is presented in **Table 3**. The results show that there is not enough evidence to reject the null hypothesis that the unemployment rate has a unit root with structural break in trend and in both intercept and trend. Therefore, the unemployment rate series should be differenced.

Table 3: Zivot-Andrews Unit Root Test with Structural Break

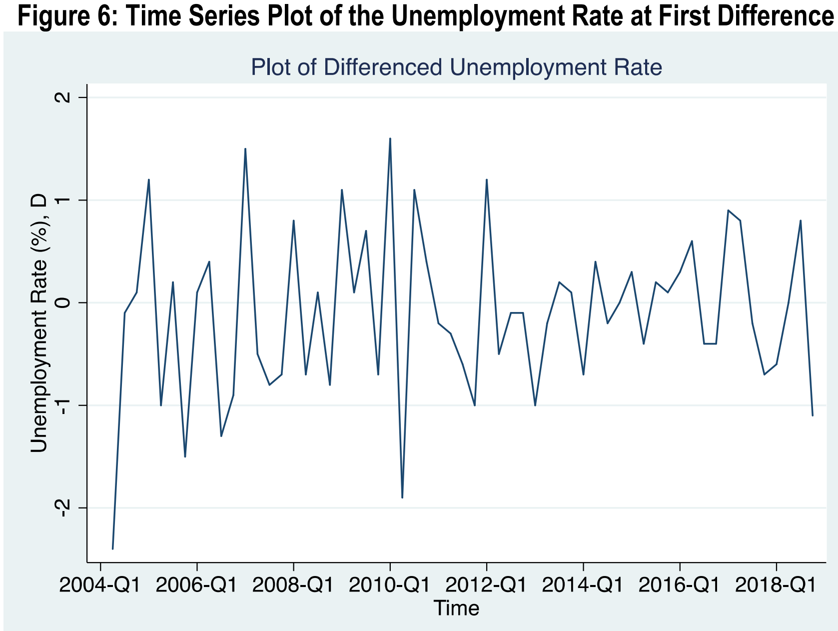
Series	Allowing for Break in Trend				Allowing for Break in Both Intercept and Trend			
	Minimum t-statistic	Critical Values			Minimum t-statistic	Critical Values		
		1%	5%	10%		1%	5%	10%
Unemployment Rate	-3.281	-4.93	-4.42	-4.11	-3.441	-5.57	-5.08	-4.82
	Potential breakpoint at 2007-Q1				**Potential breakpoint at 2009-Q1**			

Figure 6 shows the unemployment rate after first-differencing. The results from the ADF and PP tests based on the first-differenced unemployment rate series shows that the null hypothesis for both tests can be rejected **(Table 4)**. Hence, the unemployment rate is stationary at first-difference.

Table 4: Unit Root Test Results (after first difference)

Series	Level with Intercept				Level with Intercept and Trend			
	Test Statistic		Prob.		Test Statistic		Prob.	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
Unemployment Rate	-7.421	-11.511	0.0000	0.0000	-7.430	-11.462	0.0000	0.0000
Critical value 5%	-2.924				-3.493			

Figure 6: Time Series Plot of the Unemployment Rate at First Difference



After first-differencing the unemployment rate series, **Figure 6** reveals the possibility of seasonality. Given this, a seasonal autoregressive integrated moving average (SARIMA) model was used, instead of a non-seasonal ARIMA.

The first step involves checking whether the seasonality component is stationary. The existence of a structural break may not only affect the level and trend of a series, but it may also affect the observed pattern of seasonality. The HEGY test (without structural breaks), whose null hypothesis is the series has a non-stationary seasonal cycle, was performed on the level series of the unemployment rate.

Table 5: HEGY Test of Stationarity for Level Unemployment Rate[1]

	Test Statistic	Critical Value 5%	Critical Value 10%
$t[\pi_1]$	-1.795	-3.682	-3.347
$t[\pi_2]$	-3.480	-3.058	-2.715
$t[\pi_2]$	-4.603	-3.632	-3.258
$t[\pi_4]$	-2.079	-1.915	-1.485
F[3-4]	14.345	6.558	5.393
F[2-4]	18.304	6.075	5.130
F[1-4]	14.973	6.521	5.705

[1] Includes 1 lag and the following deterministic variables: seasonal dummies, constant, and trend.

The test statistic for $t[\pi_1]$ reveals insuffcient evidence to reject the null hypothesis of a non-seasonal unit root at frequency 0. Since, the test statistics for $t[\pi_2]$ is -3.480, which is less than both the 5 per cent and 10 per cent critical values, the seasonal unit root at bi-annual frequency is rejected. The statistics for F[3-4] is 14.345, which is higher than the critical values 6.6 and 5.4 at 5 per cent and 10 per cent levels of significance, respectively, the unit root pair +/- *i* is rejected. Consequently, the series has no seasonal unit roots at the semi-annual and annual frequencies. In general, the joint tests reject all seasonal unit roots in the series but there is convincing evidence of a unit root at frequency 0 ($t[\pi_1]$), which shows the presence of a non-seasonal unit root in the series **(Table 5)**. Therefore, seasonal differencing is not needed. Consequently, there is no need of performing an extended test (HEGY under structural break) for seasonal unit roots. It was therefore concluded that the time series process of the unemployment rate is integrated of order one. Thus, the rate of unemployment will be modelled at the first difference of the series.

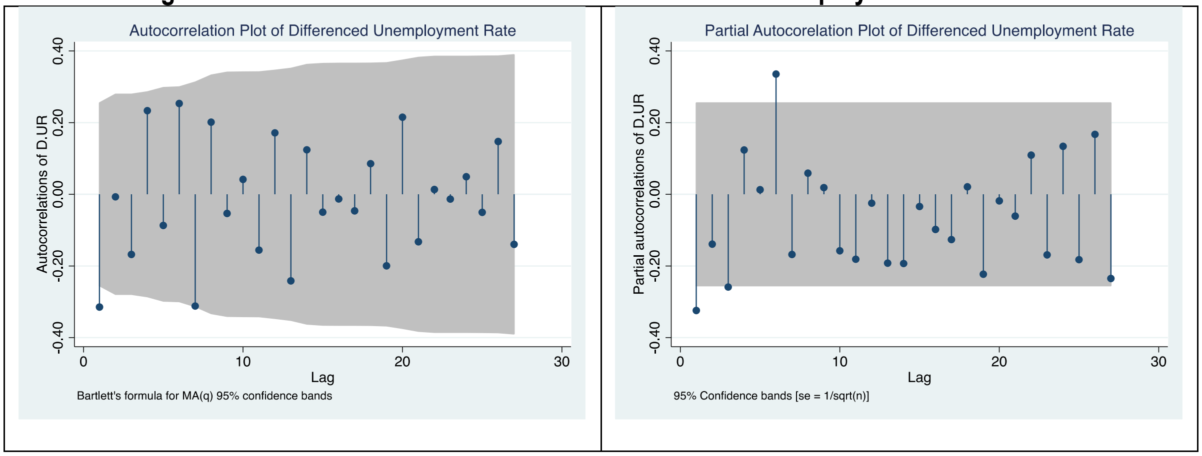
5.3 Modelling the SARIMA

In this section the structure of the SARIMA model is discussed. To determine the appropriate autoregressive orders *p* and *P* and moving average orders *q* and *Q,* both the ACF and PACF functions were plotted on the differenced unemployment rate series as there is a non-seasonal unit root in the series. The ACF plot in **Figure 7** reveals that only the first lag is significant, which implies a non-seasonal MA(1) and seasonal MA(0) components[14], respectively. The PACF shows lags 1 and 6 are significant, which point to possible non-seasonal AR(1) and seasonal AR(1). However, choosing a SARIMA model by looking at the plots of the ACF and PACF functions is not sufficient. Therefore, both AIC and BIC were used to select a reasonable SARIMA model. The results show that the SARIMA $(0,1,1)(1,0,0)_4$ model has the smallest AIC and BIC values[15]. Therefore, SARIMA $(0,1,1)(1,0,0)_4$ was chosen as the benchmark model for the unemployment rate series in Trinidad and Tobago.

[14] Seasonal components of the SARIMA model are determined by examining the significant spikes around multiples of 4 since quarterly data is being used.

[15] See **Appendix Table A1** for the AIC and BIC values for various SARIMA models.

Figure 7: The ACF and PACF Plots of the Differenced Unemployment Rate Series



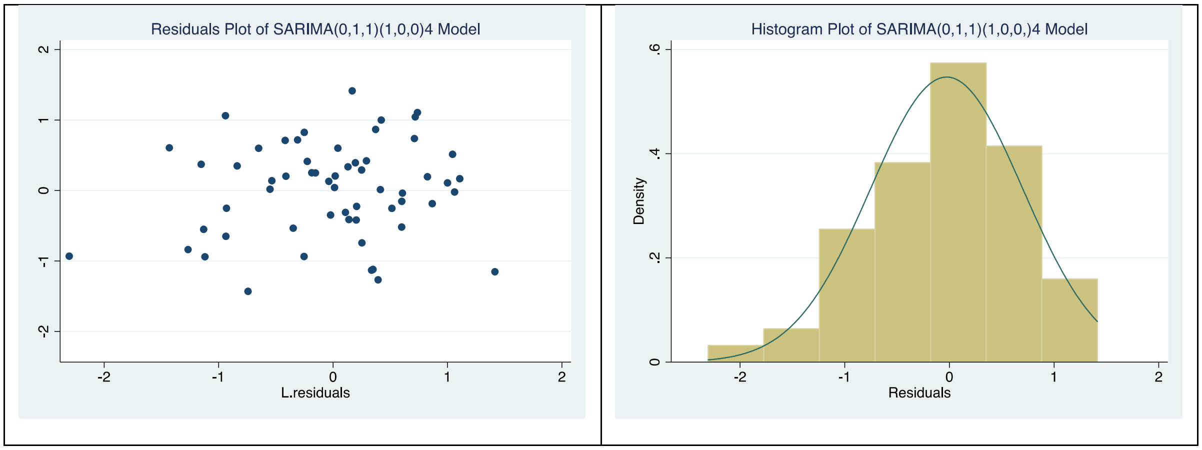
The adequacy of the fit of the benchmark model was evaluated using residual analysis. The Portmanteau test of autocorrelation with two lags suggests there is insufficient evidence to reject the null hypothesis of residual independence (white noise). The probability values for Skewness, Kurtosis, and the Jarque-Bera normality test of the residuals are sufficiently large (greater than 0.05), leading to the non-rejection of the null hypothesis that the residuals are normally distributed **(Table 6)**.

Table 6: Residual Analysis in SARIMA (0,1,1) (1,0,0)$_4$ Model

Type of Test	Test Statistic	Prob > χ^2
Portmanteau (Q) statistic	0.8964	0.6388
Joint Jarque-Bera normality test	3.366	0.1858
Pr(Skewness)		0.0651
Pr(Kurtosis)		0.3637

Moreover, both the scatterplot and histogram of the residuals show that the residuals in the chosen benchmark SARIMA model are randomly distributed and are approximately normally distributed **(Figure 8)**. Therefore, the residuals in the SARIMA (0,1,1) (1,0,0)$_4$ model are white noise indicating that the chosen benchmark model is adequate.

Figure 8: Scatter Plot and Histogram of Residuals in SARIMA (0,1,1) (1,0,0)$_4$ Model



In the estimated SARIMA model of the unemployment rate for Trinidad and Tobago, both the non-seasonal MA component and the seasonal AR component are statistically significant with p-values equal to 0.000 and 0.0160, respectively.

$$y_t = -0.470\varepsilon_{t-1} + 0.336y_{s-1}$$

s.e. *(0.1086)* *(0.1390)*

5.4 Comparison of Forecasting Performance

The forecasting performance of the benchmark SARIMA (0,1,1) (1,0,0)$_4$ model and models including Google search terms were compared based on the error statistics (RMSE, MAE, and MAPE) and hit rates. Recall that the smaller the value of the error statistic, the better the model is at predicting the actual values. Based on Lewis' (1982) MAPE scale for forecast accuracy, both the in-sample and out-of-sample forecasts were "good" with MAPE values ranging between 11.3 per cent and 13.0 per cent. Additionally, the Diebold-Marino test was performed to examine whether the predictive accuracy of the models including the Google search terms were significantly different from the benchmark model. **Table 7** summarises the performance of the in-sample and out-of-sample forecasts.

Based on the predictive accuracy measures considered, the best performers were the benchmark model with no Google search terms and the model whose specification included all the Google search terms for the in-sample models. However, the p-value of the Diebold-Mariano test revealed that there is insufficient evidence to reject the null hypothesis of equal predictive accuracy between the benchmark in-sample model and the model including all the Google search terms.

For the out-of-sample models, the best performer was the model whose specification included all the Google search terms. However, the p-value of the Diebold-Mariano test revealed that there is insufficient evidence to reject the null hypothesis of equal predictive accuracy between the benchmark out-of-sample model and the model including all the Google search terms. Summarily, including Google search terms in a seasonal autoregressive integrative moving average model of unemployment for Trinidad and Tobago does not significantly improve forecasting performance.

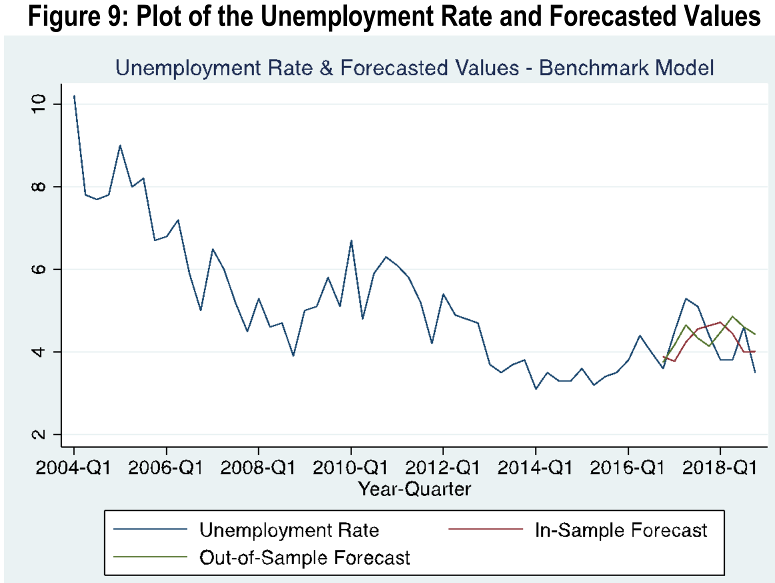
Based on the error statistics, the in-sample models performed better whereas in terms of the hit rate, the out-of-sample models performed better, except for the models containing the 'Trinidad and Tobago jobs' Google search term and the specification with all the Google search terms. For instance, the benchmark in-sample model with no Google search terms, has an RMSE of 0.72 compared with 0.80 for the out-of-sample benchmark model. Meanwhile, the benchmark out-of-sample model with no Google search terms, correctly predicts the direction of change in the unemployment rate 75 per cent of the time compared with only 62 per cent for the in-sample benchmark model. **Figure 9** plots the unemployment rate and the in-sample and out-of-sample (*ex-post*) forecasted values of the unemployment rate for the benchmark model.

Table 7: In-Sample and Out-of-Sample Forecasting Performance of Models

Prediction Accuracy Measure	Model					
	In-sample					
	No GIs	GI (C'bean jobs)	GI (SCTT)	GI (TT jobs)	GI (Regency)	All GIs
RMSE	0.72	0.71	0.72	0.72	0.72	0.71
MAE	0.57	0.58	0.57	0.57	0.57	0.57
MAPE	11.3	11.6	11.3	11.3	11.3	11.6
Hit Rate	0.62	0.63	0.63	0.63	0.62	0.64
Prediction Accuracy Measure	Out-of-Sample					
	No GIs	GI (C'bean jobs)	GI (SCTT)	GI (TT jobs)	GI (Regency)	All GIs
RMSE	0.80	0.80	0.79	0.79	0.80	0.78
MAE	0.63	0.63	0.62	0.62	0.63	0.61
MAPE	13.0	13.0	12.8	12.9	13.0	12.6
Hit Rate	0.75	0.75	0.75	0.63	0.75	0.63

Notes: GI = Google Indicators; C'bean jobs = Google search term "Caribbean jobs"; SCTT = Google search term "Service Commission of Trinidad and Tobago"; TT jobs = Google search term "Trinidad and Tobago jobs"; Regency = Google search term "Regency Recruitment".

Figure 9: Plot of the Unemployment Rate and Forecasted Values



To test whether public sector employment impacted the results above, we also modelled the private sector unemployment rate. The results[16] are qualitatively the same – that is, including Google search terms in a seasonal autoregressive integrative moving average model of non-government unemployment for Trinidad and Tobago does not significantly improve forecasting performance of the benchmark model.

6.0 Conclusion, Policy Implications and Recommendations

This study examined whether search intensity data obtained from Google Trends contributes to estimating (and forecasting) the Trinidad and Tobago unemployment rate, compared to a conventional seasonal ARIMA model (SARIMA). The benchmark SARIMA model was well-fitted and adequate. The pre-estimation analysis showed that the unemployment rate is non-stationary, and the rate also has a stationary seasonal nature. The predictive accuracy performance of the models, for both in-sample and out-of-sample forecasts, was assessed based on performance measures such as error statistics (RMSE, MAE, and MAPE), hit rates, and the Diebold-Marino test.

Based on Lewis' (1982) interpretation of MAPE results, the benchmark SARIMA model yielded "good" forecasts. The error statistics for both in-sample and out-of-sample models revealed that the benchmark model and the model specifications included the Google search term 'Caribbean jobs' and all of the search terms were the best performers. However, for both in-sample and out-of-sample forecasts, the Diebold-Mariano tests revealed that the predictive accuracy of the benchmark model and the models including 'Caribbean jobs' and all the Google search terms are statistically equal. In other words, the model specifications that included Google search terms did not improve the predictive accuracy of the benchmark SARIMA model. Notwithstanding this, all the out-of-sample models had higher hit rates compared with the in-sample models. Among the Google search terms considered, the highest pairwise correlation with the unemployment rate was the search term 'Caribbean jobs' at 0.61. Although this search term is 'moderately' correlated with the unemployment rate, it lacked any statistical significance when included in the benchmark SARIMA model.

We hypothesise that in the context of Trinidad and Tobago, given that a majority of workers have at most low to mid-level education, the ageing population, a relatively high degree of low-skilled informal employment[17], and relatively low Internet penetration rates, people still rely a great deal on networking and in-print newspaper job advertisements when looking for employment opportunities. In advanced countries like the US, college-educated job seekers were more likely to rely on online resources compared with job seekers with only high school education[18]. The same *may* be true for Trinidad and Tobago. Recall that 36 per cent of all workers have no more than secondary school education, and another 42 per cent had at most secondary school education plus some level of training. Moreover, in 2018, the country's mobile and fixed Internet subscription penetration rates were 49.9 and 25.1 per 100 of the population,

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[16] See **Appendix II** for these results.

[17] According to the International Labour Organisation (ILO), informal employment comprises those jobs, in law or in practice, not subject to national labour legislation, income taxation, social protection or entitlement to certain employment benefits (advance notice of dismissal, severance pay, paid annual or sick leave, etc.).
See: https://www.ilo.org/public/english/bureau/stat/download/papers/meas.pdf, p.7.

[18] Aaron Smith, "The Internet and Job Seeking," Pew Research Center: Internet, Science & Tech (Pew Research Center, November 19, 2015), https://www.pewresearch.org/internet/2015/11/19/1-the-internet-and-job-seeking/.

respectively. Simply put, at the end of 2018, approximately 50 out of every 100 persons were using mobile Internet services, while 25 out of 100 persons had a fixed Internet subscription (Telecommunications Authority of Trinidad and Tobago, 2018). The corollary data for 2004 was 0 and 4.2 per 100 of the population, respectively, for mobile and fixed Internet subscriptions (Telecommunications Authority of Trinidad and Tobago, 2017). In comparison, according to ITU World Telecommunication data[19], in 2018, in developing countries 60.1 and 10.3 per 100 inhabitants had mobile broadband and fixed broadband subscriptions, respectively. Meanwhile, the monthly daily average of job opportunities advertised in the print media[20] increased from 294 advertisements in 2010 (the first full year of data) to 356 daily average advertisements in 2018.

The results of this study suggest that Google search data does not significantly improve the performance of models used to estimate (and forecast) Trinidad and Tobago's unemployment rate. Our results support the findings of Simionescu and Zimmermann (2017), who stated that, "*forecast accuracy depends on the internet penetration in each country, the age structure of the internet users and the stability of the constructed internet variables*". Although the Google search terms used in this study did not statistically improve the country's benchmark forecast model of unemployment, the Google data could be used to develop coincident indicators to assess current overall labour market conditions.

In the 2021 Budget, it was announced that the Ministry of Public Administration and Digital Transformation would be charged with the mandate of ensuring high-speed broadband internet access, accompanied by the requisite ICT infrastructure, is made available for all citizens. The focus will be on schools and institutions: pre-school, primary, secondary, and tertiary, as well as other important institutions and agencies (Ministry of Finance, 2020). Additionally, effective January 1, 2021, all taxes were removed on mobile and digital equipment, mobile phones, software, computer accessories and peripherals. These initiatives are expected to have a positive impact on the number of persons with access to internet and internet capable devices. Furthermore, in the future, access to online resources will be an essential tool in finding and applying for jobs. The Internet can expand access to jobs and training, hence increasing employment opportunities and avenues to learn new career skills.

As a country's internet penetration improves, so too will the opportunity to utilise 'big data' to better understand, predict, and plan for economic cycles. It will therefore be prudent to conduct studies periodically, which monitor the growth in internet penetration and assess the usefulness of these data sources to accurately describe the economic landscape. Nymand-Anderson (2016) explains, "*it is important for central banks to take advantage of these new opportunities by exploring their value in contributing to our understanding of the complex and interrelated components of financial markets and the real economy*". Nymand-Anderson (2016) also suggested that central banks answer eight questions as a road map in defining a potential framework:

1. What relevant 'big data' sources could provide value and insights for central banking purposes?
2. Should banks be involved in the algorithms and machine learning techniques that extract economic intelligence or simply contribute by applying big data to conventional models?

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[19] See https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx.

[20] This indicator is constructed by the Central Bank of Trinidad and Tobago using the number of employment vacancies advertised in the three largest local newspapers (Daily Express, Newsday, and Guardian).

3. What are the challenges to produce indicators based on new data sources? Is new technology needed or should strategic partnerships be forged with the source owners and associations?
4. What kind of governance structure is needed to ensure sustainability of supply?
5. What kind the skill and resource requirements? Should new personnel be recruited, or existing staff be trained?
6. Are other public authorities considering these challenges and what are possible synergies?
7. Should central banks take part in the debate on the “ethics” of ‘big data’ or engage in validating ‘big data’ sources through training and transparency?
8. How can quality and trust in these statistics and institutions be communicated and preserved?

For future research, modelling the seasonal nature of the unemployment rate in a nonlinear framework and modelling the unemployment rate using a structural VAR model may prove useful. Using a multivariate approach, some additional variables to be considered when forecasting (and possibly nowcasting) Trinidad and Tobago’s unemployment rate could include industrial production, inflation rate, and Gross Domestic Product (GDP) growth rate. Notably, the country has only just begun to produce official quarterly GDP data[21]. This will pose some unique challenges for modelling the quarterly unemployment rate using such a short time-series for quarterly GDP.

[21] The earliest available official quarterly GDP statistics for Trinidad and Tobago are from the first quarter of 2012.

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Appendix I

Table A1: Comparision of (National) Unemployment Rate SARIMA Models

SARIMA Model	AIC	BIC
SARIMA (1,1,1) (1,0,0,4)	136.47	146.86
SARIMA (1,1,1) (0,0,1,4)	139.37	147.68
SARIMA (1,1,1) (1,0,1,4)	138.31	150.77
SARIMA (0,1,1) (1,0,0,4)	134.66*	142.97*
SARIMA (0,1,1) (0,0,1,4)	135.26	143.56
SARIMA (0,1,1) (1,0,1,4)	136.51	146.90
SARIMA (1,1,0) (1,0,0,4)	138.52	146.83
SARIMA (1,1,0) (0,0,1,4)	139.10	147.41
SARIMA (1,1,0) (1,0,1,4)	139.24	149.63

* Refers to the smallest AIC and BIC.

Table A2: Pairwise Correlations between (National) Unemployment Rate and Google Search Terms[1]

	Unemployment Rate	Caribbean Jobs	Jobs TT	SCTT	Regency Recruitment
Unemployment Rate	1.0000				
Caribbean Jobs	0.6114*	1.0000			
Jobs TT	0.4746*	0.6689*	1.0000		
SCTT	0.5649*	0.5538*	0.5728*	1.0000	
Regency Recruitment	0.3362*	0.4374*	0.3441*	0.4258*	1.0000

[1] Based on Evans (1996), a guide for the strength of correlation is as follows: .00-.19 – 'very weak'; .20-.39 – 'weak'; .40-.59 – 'moderate'; .60-.79 – 'strong'; and .80-1.0 – 'very strong'.
*Denotes correlation coefficients significant at the 5% level or better.

Appendix II

Forecasting the Private Sector Unemployment Rate

We first reviewed the correlation coefficients of several Google search terms to determine the ones most relevant for the modelling exercise. We chose only those terms whose correlation coefficients were statistically significant (except for 'Trinidad and Tobago Jobs', which had the weakest correlation among the Google search terms of 0.30). All of the chosen Google search terms ('Caribbean jobs', 'Service Commission of Trinidad and Tobago', and 'Recruitment Agency') are 'moderately' correlated with the non-government unemployment rate. 'Caribbean jobs' had the highest pairwise correlation coefficient of 0.41 and Services Commission of Trinidad and Tobago and Recruitment Agency had a similar correlation of 0.37 **(Table A3)**. Notably, all correlation coefficients are lower in the case of the non-government unemployment rate compared with the national unemployment rate.

Table A3: Pairwise Correlations between Non-Government Unemployment Rate and Google Search Terms

	Non-Government Unemployment Rate	Caribbean Jobs	Jobs TT	Service Commiss -ion of TT	Regency Recruitment	Recruitment Agency
Non-Government Unemployment Rate	1.0000					
Caribbean Jobs	0.4113*	1.0000				
Jobs TT	0.2992*	0.6689*	1.0000			
SCTT	0.3723*	0.5538*	0.5728*	1.0000		
Regency Recruitment	0.2496	0.4374*	0.3441*	0.4258*	1.0000	
Recruitment Agency	0.3694*	0.5315*	0.4313*	0.4851*	0.4920*	1.0000

*Denotes correlation coefficients significant at the 5% level.

The forecasting performance of the benchmark SARIMA (0,1,1) $(1,0,0)_4$ model and models including Google search terms were compared based on the error statistics (RMSE, MAE, and MAPE) and hit rates. Based on Lewis' (1982) MAPE scale for forecast accuracy, both the in-sample and out-of-sample forecasts were "good" with MAPE values amounting to around 13.0 per cent. Additionally, the Diebold-Marino test was performed to examine whether the predictive accuracy of the models including the Google search terms were significantly different from the benchmark model with no Google search terms. **Table A4** summarises the performance of the in-sample and out-of-sample forecasts of the private sector unemployment rate.

Based on the predictive accuracy measures considered, for the in-sample models, the best performers were the benchmark model with no Google search terms and the model whose specification included all the Google search terms; this result is similar to the results for the national unemployment rate. However, the p-value of the Diebold-Mariano test revealed that there is insufficient evidence to reject the null hypothesis of equal predictive accuracy between the benchmark in-sample model and the model including all the Google search terms.

For the out-of-sample models, the best performer was the benchmark model with no Google search terms; this result is dissimilar to the results of the national unemployment rate where the best performing model was the specification which included all the Google search terms. However, the p-value of the Diebold-Mariano test revealed that there is insufficient evidence to reject the null hypothesis of equal predictive accuracy between the benchmark out-of-sample model and the model including all the Google search terms. Summarily, much like the national unemployment rate forecasts, including Google search terms in a seasonal autoregressive integrative moving average model of non-government unemployment for Trinidad and Tobago does not significantly improve forecasting performance.

Based on the error statistics, unlike the models for the national unemployment rate, the out-of-sample models for the non-government unemployment rate performed better. The out-of-sample models performed better in terms of the hit rate, except for the models containing the 'Caribbean jobs' Google search term and the specification with all the Google search terms. For instance, the benchmark in-sample model with no Google search terms, has an RMSE of 1.05 compared with 0.84 for the out-of-sample benchmark model. Meanwhile, the benchmark out-of-sample model with no Google search terms, correctly predicts the direction of change in the unemployment rate 88 per cent of the time compared with only 60 per cent for the in-sample benchmark model.

Table A4: In-Sample and Out-of-Sample Forecasting Performance of Models Non-Government Unemployment Rate

Prediction Accuracy Measure	Model				
	In-sample				
	No GIs	GI (C'bean jobs)	GI (SCTT)	GI (Agency)	All GIs
RMSE	1.05	1.04	1.05	1.04	1.02
MAE	0.81	0.82	0.81	0.81	0.81
MAPE	13.4	13.5	13.4	13.3	13.4
Hit Rate	0.60	0.60	0.60	0.54	0.58
Prediction Accuracy Measure	Out-of-Sample				
	No GIs	GI (C'bean jobs)	GI (SCTT)	GI (Agency)	All GIs
RMSE	0.94	0.95	0.95	0.95	0.95
MAE	0.78	0.79	0.79	0.79	0.80
MAPE	13.1	13.3	13.3	13.3	13.3
Hit Rate	0.88	0.50	0.88	0.88	0.63

Notes: GI = Google Indicators; C'bean jobs = Google search term "Caribbean jobs"; SCTT = Google search term "Service Commission of Trinidad and Tobago"; Agency = Google search term "Recruitment Agency".