Evaluating Short Term Bridge Model Forecasts of Real GDP in Belize: A Quarterly Approach

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Abstract

Short term econometric forecasts of real GDP is an analytical tool that has been conspicuously absent in Belize. This study attempts to assess three types of econometric models and their accuracy in out of sample forecasts, namely (i) factor models, (ii) indicator models and (iii) a sectoral model of the supply side of the economy. Fourteen different models of quarterly GDP were estimated and the most precise were chosen using descriptive measures of accuracy, namely the Mean Absolute Deviation (MAD), Root Mean Squared Error (RMSE), the Mean Absolute Percentage Error (MAPE). The results show that the indicator models provide the most precise estimates and that combination techniques improved forecast accuracy over the period of evaluation. Furthermore, reliable estimates of growth are provided within one month of the end of the quarter, half the time it takes to disseminate the actual GDP information.

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1.Introduction

Despite significant advancements in data collection and statistical methodologies, Gross Domestic Product (GDP), the aggregate measure of production in economies, continues to be the most important gauge of a country's growth and development. Analytical research on development relies heavily on the current and projected values of GDP to inform the policy making process.

In Belize, GDP was initially prepared only on an annual basis, and it was not until 2002 that quarterly estimates of GDP began to be compiled with an eight week lag[1] in the distribution of the data. While this is approximately twice the time it takes to get reliable growth estimates in the United States and United Kingdom, the lag compares favourably[2] with emerging market economies such as Russia (13 weeks); South Africa (11 weeks); Brazil and India (9 weeks). Nevertheless, it is felt that the focus should be on improving the timeliness[3] of official GDP releases to improve their usefulness in policy making. Reliable forecasts of national income would also be very beneficial.

The Central Bank of Belize (Bank) is the only national body that provides biannual forecasts of annual GDP. Hitherto, the Bank has relied on the financial programming framework developed by the International Monetary Fund (IMF) rather than on econometric techniques in preparing these forecasts. This study attempts to fill the gap by assessing three types of econometric bridge models, namely (i) factor models, (ii) indicator models and (iii) a sectoral model of the supply side of the economy. In contrast to the more complex dynamic stochastic general equilibrium (DSGE) models, which have been used in many advanced economies[4], the selected models are considered more suitable for forecasting in Belize because of existing data constraints. The construction of the aforementioned bridge models would enable GDP estimates to be provided in a timelier manner to inform policy decisions.

In bridge modelling, quarterly estimates of GDP or its components are prepared using a set of higher frequency indicators. The forecasting power of the models is determined by the evaluation of activities that are known to have a significant impact on the national accounts. The introduction of these econometric forecasts requires the development of large data sets, which can lay the foundation for much larger, more complex and longer term econometric models of the Belizean economy.

The results of the study showed that the indicator bridge models provided the most accurate forecast of GDP growth, and the estimates could be made within four weeks after the end of the period. Simple averaging of the results generated by the various models further enhances the precision of the forecasts.

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[1] Eight week lag from the end of the quarter to the dissemination of the quarterly GDP values.

[2] It must be noted that all the economies mentioned are substantially larger than Belize and data collection is more tedious.

[3] Improvements have been made in the process as the time lag was reduced from approximately 12 weeks to 8 in 2013.

[4] Methods used by the Federal Reserve Banks and European Central Bank to provide current information on national income.

Section II provides a review of the literature on short term forecasting, while Section III looks at the data set, the criteria for selection of the variables, and the statistical tests that were applied. Section IV takes a more in-depth look at the bridge models, forecasting methods and model evaluation. Section V posits the most suitable models and indicators of Belize's GDP growth, their implications and the way forward for econometric forecasting of GDP.

2. Literature Review

Numerous econometric methods have been used to forecast GDP and tend to fall under three categories - naive, factor and indicator models[5]. Naive or pure time series models come in many functional forms, such as moving average, constant growth and random walk processes, and their methodology does not use indicators to forecast future values of GDP. These models have been known to "enhance accuracy owing to their robustness to instability (structural breaks, regime change, economic policy shifts and technological discoveries), which generates misspecification in the economic models"(Chevillion2005).This implies that the relationship defined by economic indicators tends to evolve over time. Conversely, the simplified movements traced by past values of GDP give a more reliable signal. Consequently, naive models have been used widely as a benchmark to evaluate the forecast performance of more complex models of economic activity (Barhoumi, Benk et al. 2008; Schumacher 2005; Zeng 2011). In this paper, two types of naive models were utilized as a point of reference - an autoregressive (AR) model and a random walk equation.

I. AR(3): An autoregressive model was estimated in the general form:

$$Y_t = \propto + \beta(L)Y_{t-k} + \varepsilon_t \quad \text{for } k = 1, \dots, 3 \tag{1}$$

Where Y_t represents real GDP, α is a constant, $\beta(L)$ is a set of coefficients for the lagged values of real GDP and $\varepsilon(t)$ is the error term with well defined properties

II. AR(1) : An autoregressive model was estimated using one lag of the dependent variable

$$Y_t = \propto + \beta(L)Y_{t-1} + \varepsilon_t \tag{2}$$

Where Y_t represents real GDP, α is a constant, $\beta(L)$ is a set of coefficients for the lagged values of real GDP and ε_t the error term at time t with well defined properties

Factor models can take advantage of a large number of economic indicators in the forecasting process. The covariances of the variables of interest are extracted and combined into one or a few common factors, which are then used as independent variables in GDP models. Two variants of the factor extraction method have evolved[6]. Stock and Watson (1999, 2002) proposed a univariate forecasting model, which predicted GDP based on static factors extracted using

[5] See Chalaux and Schwellnus (2014) for definitions of the categories.

[6] There are more than two methods of extracting factors from large datasets, however these fall under the two broad categories.

static principal component analysis. This method has gained traction within forecasting circles and empirically has exhibited superior forecast performance in many studies (Camacho & Sancho 2003; Artis et al. 2004; Bernanke and Boivin 2003). Doz, Giannone and Reichlin (2005) utilized the Kalman Filter in the extracting process[7], with the main difference from the initial Stock & Watson (1999, 2002) model being the dynamic nature of the derived factors. Allowing for explicitly dynamic relationships among variables should provide a clear advantage in the forecasting process. Nevertheless, empirical assessments of the dynamic factor models in comparison to the static ones showed mixed outcomes (Forni et al 2003; Kapetanios 2004; Schumacher 2005). The indicators of activity in Belize have different dynamics, including marked differences in the standard deviation, which make extraction using the Kalman filter a more difficult task (See Table A2, Appendix). Therefore, the technique proposed by Stock and Watson will be utilized in the study, given the statistical characteristics of the data set and the ease of the process.

Indicator models use an array of variables, functional forms and estimation techniques to predict the future values of a country's GDP and have been criticized because the causal relationship identified in theory tends to change over time, impairing its predictive power (Favero and Marcellino 2005). However, they are still widely used in forecasting, and the weakness introduced by the changes in causal relationships can be addressed by various adjustment techniques, such as intercept correction (Clements and Hendry 1998). Forecasting agencies, to avoid the aforementioned problem, often utilize econometric time series models with less theoretical restrictions in short term forecasts.

Indicator bridge models can use high frequency indicators that are released earlier and consequently allow GDP to be forecasted within a short time frame (Baffigi, Golinelli and Parigi 2004). In general, these models are estimated by aggregating indicators to a quarterly value (including projected figures if necessary) and using them to forecast national income growth in individual or multiple equations. When multiple equations are used, the average of the resulting forecasts or alternative combination techniques[8] can be employed to calculate the overall growth rate of GDP for the given quarter. The combination of the different forecasts compensates for the tendency of some of the models to under or over forecast the dependent variable. A combination of the forecasts can provide more accurate estimates without encountering the problems that may arise from attempting to estimate a large scale multivariate equation. Golinelli and Parigi (2004) note that bridge models are not concerned with behavioural relations and that their underlying structures are not macro econometric models. They further postulate that the choice of explanatory indicators is not based on causal relationships but rather that the variables contain statistically significant information about the dependent variable at that specific point in time.

[7] This method was first utilized by the U.S. Fed and European Central Bank.

[8] Simple or weighted averaging methods have been utilized in different studies; Kitchen and Monaco in 2003 used a weighted average based on the R^2 of each forecasting equation.

The choice of variables may be difficult, and individual indicators sometimes give the wrong signal, hence this method allows for the use of a wide range of indicators, which minimizes the bias associated with a small pool of variables (Molzahan 2011). Indicator models in different forms also provide more flexibility, as the estimation method for each set of indicators can be tailored towards the functional form that provides the optimal in-sample fit for each variable. These models have provided a superior alternative to naive models, especially in economies where data availability may be a concern (Iacoviello 2001; Zheng and Rossiter 2006), making them ideal for Belize.

Of the three different bridge models used in this study (factor, indicator and sectoral models), multivariate indicator estimation was particularly difficult, since the productive sectors and activities in the Belizean economy were closely related. Modelling with the high probability of multicollinearity made it virtually impossible to include all relevant indicators in individual equations, thus models which produced the best in-sample forecasts[9], although incomplete, were chosen and assessed.

The three types of models are as follows:

I. FACTOR MODELS: VAR and OLS regressions used the following functional form

$$Y_t = \propto + \sum \delta_j(L)F_{j,t-k} + \sum \beta(L)Y_{t-1} + \varepsilon_t \text{ for } k = 1, \ldots, 3 \tag{3}$$

Where Y_t represents real GDP at time t, α is a constant, β(L) is the set of coefficients for the lagged and present values of GDP, δ(L) is the set of coefficients for the lagged and present values of the factor F, and ε_t is the error term at time t with well defined properties.

II. SECTORAL MODEL: Bivariate regressions were estimated of general form

$$C_t = \sum \delta_j(L)Z_{j,t-k} + \varepsilon_t \text{ for } k = 1, \ldots, 3 \tag{4}$$

Where C_t represents the sub-sectors of real GDP at time t, $\delta_j(L)$ is the set of coefficients for the lagged and present values of the indicator variables Z and ε_t the error term at time t with well defined properties.

III. INDICATOR MODELS (OLS): OLS in the log difference of the variables were estimated in the form

$$Y_t = \propto + \beta(L)Y_{t-k} + \delta_n(L)Z_{n,t-k} + \varepsilon_t \quad \text{for } k = 1, \ldots, 3 \tag{5}$$

Where Y_t represents real GDP, α is a constant, β(L) is a set of coefficients for the lagged values of the GDP variable, $\delta_n(L)$ is the set of coefficients for the lagged and present values of the ***n indicator variables*** in the vector Z and ε_t the error term at time t with well defined properties

[9] In sample forecasting power can be assessed by the goodness of fit (R^2) of the model.

3. Data

3.1 Data

Three criteria have been identified as desirable characteristics in modelling: timeliness, reliability of data and the statistical significance of the variables to the dependent variable in the model (Golinelli and Parigi 2007; Cobb et al 2011). The chosen variables should be reliably released before the official release of the GDP estimate, which for Belize is eight weeks following the end of the reporting period. Data availability remains a huge concern in the country as the release of information by a number of economic agents is often tardy or, in some cases, data are not reported at all. Model estimation was done approximately four weeks after the quarter when most indicators were available, and information that was unavailable at this point was estimated using an AR (1) process. The reliability criterion was met when data was not revised significantly after their initial release. Data revision has not been frequent with most of the identified indicators, save for aggregate GDP itself[10]. Because of this, all estimates were generated using the current available data and revisions were incorporated into the subsequent period's evaluation. The indicator variables were found to be timely and reliable enough to be included in the analysis. The data sets were also examined to evaluate their statistical properties.

Quarterly data for the study were gathered from the Statistical Institute of Belize (SIB) and the Bank for the time period, 1994Q1 to 2013Q4. Observations of some variables were only available from 2000Q1. The pool of data is summarized in Table A1 in the Appendix and is comprised of real GDP, its components and a series of economic indicators. Variables from the supply side of the economy, guided by SIB's indicator list, were chosen for the study, with economic assumptions used in specifying additional information. Belize’s economy depends for the most part on tourism, agriculture and manufacturing, so aggregate indices relating to these activities were used. All were constructed using the weights given by SIB and proved to be useful in their predictive power in the forecast models. Variables such as exports, imports and central government expenditure were chosen using the Keynesian Identity, while the loan and deposit variables were identified using the finance-growth theoretical relationship. Data were not adjusted for seasonality[11], as it was found that this modification did not significantly add to the predictive power of the models. All financial variables were deflated using the Consumer Price Index (CPI), and all indicators were incorporated into the models in their natural logs. A total of thirty-two indicators of economic activity were used in the study.

3.2 Statistical Analysis of Data

The relationship between indicator variables and real GDP was assessed and tested using correlation and granger causality tools. Upon examining the correlation matrix of the variables (See Table A3), it was clear that there was a high degree of correlation between the indicators

[10] Both current and past GDP data were constantly modified during the period of study.

[11] See Plosser, 1979 who postulated that the use of data with seasonality can at times provide better insight into the sources and type of seasonal structure and does not distort the economic relationships at work in the economy. Evidence of the usefulness of unadjusted data can be found in Franses and Van Dijk (2005), Ghysels et al (2006), Camacho et al (2012).

and GDP over the period, except the fishing variable which had a correlation coefficient of 0.09. This may be partially attributed to the low statistical importance of the fishing sector to real GDP, as it has contributed approximately 3.9% to the aggregate since 1994. The loan, deposit and money supply variables were highly correlated to real GDP, reflective of the finance- growth nexus. Indicative of the high dependence on services in Belize, GDP is highly correlated with the tourism variable (0.78) and the transportation index (0.81). Government expenditure was also highly correlated with income, as cyclical changes in GDP have been associated with fiscal expansion and contraction throughout the country's economic history. It is also worth noting that the correlation matrix shows that many productive activities in the economy are closely correlated as displayed by the relationships between manufacturing and agriculture (0.79), current expenditure and deposits (0.79) and tourism and agriculture (0.78), among others. These results indicate that multivariate analysis within the economy would be difficult, since multicollinearity would be present in the models that try to encompass all the productive sectors of GDP. Once the co-movements were affirmed, it was necessary to establish the direction of causality using the granger causality tests.

The Granger causality test examines whether one data set will provide useful information if used for forecasting another. A variable Z is said to granger cause another variable Y if it is proven that the lagged values of variable Z provides useful information regarding the future values of Y. This is done by running two regressions on the variable Y, one of the form:

$$\hat{Y}_{t+1} = \propto + \beta(L)Y_t + \varepsilon_t \tag{6}$$

in which the future values of the dependent variable are predicted based on the lagged values of itself and a second equation of the form:

$$\hat{Y}_{t+1} = \propto + \beta(L)Y_t + \delta(L)Z_t + \varepsilon_t \tag{7}$$

in which the regressions are carried out using lagged values of both variables Y and Z. The null hypothesis is that variable Z does not granger cause Y and is accepted if and only if there are no significant values of Z retained in the second equation when the model is reduced using a general to specific approach.

Table 1: Granger Causality Results of Indicators on Real GDP at 2 Lags

Variable	Obs	Statistic	Probability	Result
*LAG**	*56*	*25.2266*	*0.0000*	*Agricultural Production Index Granger Causes GDP*
LAR	***56***	***1.5106***	***0.2305***	***Arrivals Index does not Granger Causes GDP***
*LCEM**	*54*	*4.9033*	*0.0115*	*Cement Imports Granger Causes GDP*
LCEX	*56*	*12.071*	*0.0000*	*Current Expenditure Granger Causes GDP*
LDEP	*56*	*10.7745*	*0.0001*	*Deposits Granger Causes GDP*
*LE**	*54*	*29.7389*	*0.0000*	*Electricity Production Granger Causes GDP*
*LEX **	*56*	*7.5507*	*0.0013*	*Exports Granger Causes GDP*
LFISH	***56***	***2.1460***	***0.1274***	***Fishing Index does not Granger Cause GDP***
*LGTAX**	*56*	*9.12695*	*0.0004*	*General Sales Tax Granger Causes GDP*
*LM**	*56*	*3.29330*	*0.0452*	*Imports Granger Cause GDP*
*LMANU**	*54*	*36.6877*	*0.0000*	*Manufacturing Production Index Granger Causes GDP*
*LOAN**	*56*	*44.3715*	*0.0000*	*Loans Granger Cause GDP*
LREV	*56*	*2.7346*	*0.0744*	*Current Revenues Granger Cause GDP*
*LTOUR**	*56*	*25.1275*	*0.0000*	*Stay over Tourists Granger Cause GDP*
*LTRAN**	*56*	*7.4665*	*0.0014*	*Transportation Index Granger Causes GDP*
*LWS**	*56*	*14.6919*	*0.0000*	*Wages and Salaries Granger Cause GDP*

* Indicates that there was evidence of bi-directional causality between real GDP and the variable

Because the objective of the analysis is to predict the current value of real GDP, a lag length of two was chosen in which to carry out the assessment, the results of which were placed in Table 1. The null was rejected in all the tests, except for the arrivals index and fishing index, indicating that at two lags these variables do not granger cause GDP. On the other hand, the positive test results were particularly strong as most of the variables were shown to granger cause GDP at the one percent level of significance. Having identified the correlation and in certain cases the direction of causality between the variables in the model, the indicators were then assessed for their suitability to be placed in econometric models.

The stationarity property of variables is very important, as it was shown by Granger-Newbold (1974) that estimation involving non-stationary or trending variables can produce spurious regressions as the standard t and F tests would result in a type I error of rejecting a valid null hypothesis. These spurious regressions could produce a high R^2 even though two series are unrelated and hypothesis testing within the models would be unreliable. Forecasting from this base will lead to erroneous estimates. Stationarity of the variables can be assessed by both informal and formal tests. This was informally done in this study through the 'eyeball' test of all the time series and formally through the Augmented Dickey Fuller (ADF) and the Phillips Perron (PP) tests. In the case where the two tests provided conflicting results as to the order of integration, the test from Kwiatkowski, et. al. (KPSS) was carried out and the results were used to make the final determination. The null hypothesis of both the ADF and PP tests is that the variable contains a unit root or is non-stationary and is rejected if the probability value is less than the 10% threshold. The null for the KPSS test is that the variable is stationary, and is rejected if the LM statistic is higher than the critical values.

The tests were carried out on the variables between the Q1 of 2000 and Q4 of 2013, the range of the estimation period for the forecast equations. Most of the time series exhibited an upward trend while others seemed to fluctuate around a mean, hence the order of integration would be determined by the statistical tests. The ADF test was first carried out on the actual values of the variables, followed by the PP test and if the null was not rejected in each case, a follow up test was then carried out on the first-difference of the variable. The results are given in Table A4 in the Appendix. There were ten variables that were stationary in levels, and nineteen that were first-difference stationary, including the GDP variable. This result left the door open to cointegration analysis, which will be explored in the upcoming sections.

4. Forecast Methodology, Evaluation & Results

4.1 Forecasting Method & Model Evaluation

In contrast to the larger economies[12], which take advantage of the frequent and large volume of data releases, estimates for Belize are done optimally four weeks after the end of the quarter being assessed. At that point, the data is collected and the indicators are formulated, tested transformed for inclusion in the models. Forecasting the current quarter's GDP ($\hat{Y}_t$) is done based on the information which is available up to the end of that quarter ($Z_{n,t}$). The variables are incorporated into the equations; the model is estimated and subsequently checked for specification errors. All equations were reduced using the general to specific approach, with the exception of the VAR specifications whose lag lengths were chosen based on the Akaike information criteria. The models are then used to forecast the current quarter's GDP, after which the results are recorded and evaluated against the actual values at the time of official release, approximately one month after the estimates are derived. In this period, all information regarding the indicators is released, and the missing data that were initially estimated are updated with actual values and the model is re-estimated, recording any significant changes.

The models were assessed over a period of twelve quarters from Q1-2011 to Q4-2013. At the end of each subsequent quarter, a pseudo real-time exercise following the aforementioned method was carried out to produce the forecast. The forecast errors, calculated by the formula $\varepsilon_t = Y_t - \hat{Y}_t$, were evaluated to assess the accuracy of the forecast equations. All models were compared using descriptive measures of accuracy, namely the Mean Absolute Deviation (MAD), Root Mean Squared Error (RMSE) and the Mean Absolute Percentage Error (MAPE). Forecasting superiority was established if the model outperformed its peers in at least two of the three measures, with the lowest possible deviation from the actual out-turn being desirable for each of the calculated statistics. The sectoral results and two of the most accurate models from

[12] Some models utilized by the Fed are updated once a week while European Central Bank Models are updated twice a month.

the factor and indicator categories were chosen using the aforementioned criteria. The results of these models, along with that of two combination techniques were then compared to the benchmark using the statistics[13].

4.2 Estimation & Results

Except for the factor augmented VARs, which are specified using the Akaike information criterion, all other model specifications were determined using the general-to-specific approach in which the equations are specified with three lags of each variable, after which the insignificant ones are removed. After the different models were estimated, two different combination techniques were used to gauge whether such calculations could provide more accurate forecasts during the exercise. In one instance, an estimate using an average of all the forecasting models was evaluated, while in the second instance, an average of the estimates of the three most accurate models was calculated. The results are compared with that of the individual models in section five.

4.2.1 Factor Models

Six factor models of GDP were estimated, two from an OLS estimation and four factor augmented VARs. The factor augmented VAR (FAV) models are those in which the extracted factors enter the model as an exogenous variable, while the OLS estimation is a bivariate model with GDP as the dependent variable and a single factor being the independent variable. The results were as follows:

Table 2: Factor Estimation Results

	OLS_1	OLS_2	FAV_1	FAV_2	FAV_3	FAV_4
MAD ($mn)	9.1	7.7	8.3	13.9	11.1	10.2
RMSE ($mn)	11.5	9.9	10.2	16.4	12.8	12.3
MAPE	1.43%	1.18%	1.27%	2.14%	1.73%	1.58%

Table two highlights the evaluation of errors for the factor model estimation of each independent variable over the three year assessment period. Of the models assessed, the second factor augmented VAR provided the least accurate forecasts with average errors over the period of

[13] Mean Absolute Deviation is calculated using the formula $\frac{\sum_{t=1}^{N}|\varepsilon(t)|}{N}$

Root Mean Squared Error is calculated using the formula $\frac{\sum_{t=1}^{N}\varepsilon(t)^2}{N}$

Mean Absolute Percentage Error is calculated using the formula $\frac{\sum_{t=1}^{N}|\varepsilon(t)/y(t)|}{N}$*100%

$13.9mn, which is slightly over 2.0% of GDP[14] between the first quarter of 2011 and the last quarter of 2013. The remaining models provided an average percentage error below 1.7%, with three of the six having an average error below $10.0mn per quarter. The most accurate model, labelled OLS_2, had a mean average error of $7.7mn per quarter, or 1.2% of GDP over that period. The factor in that model was generated by extracting the principal components from eleven[15] leading indicators of GDP, of which the most important were the agriculture, manufacturing and transportation indices along with tourism and loans. The VAR labelled FAV_1 used the same factors as OLS_2, and was estimated as an error correction model due to the cointegration between the other variables.

While OLS_2 consistently underestimated GDP, FAV_1 consistently over estimated the aggregate, but none gave significant information on the effect of individual indicators over time, with the factors being the focus of the assessment. However, both models yielded small errors over the period of assessment, and may be used in real-time forecasting, applying adjustment techniques, or used in combination with other models. The functional form of the representative factor models are:

OLS_2

$$D(LGDP) = -0.520*D(LGDP(-1)) - 0.468*D(LGDP(-2)) + 0.043*D(FAV) + 0.047*D(FAV(-1)) \quad (8)$$

FAV_1

LONG TERM EQUATION

$$LGDP = 0.017*LEX - 0.003*LM + 0.093*LFISH + 0.226*LREV + 0.040*LCEM + 4.462 \quad (9)$$

SHORT TERM EQUATION

$$D(LGDP) = -1.516*ECM + 0.535*D(LGDP(-1)) + 0.139*D(LGDP(-2)) - 0.006*D(LEX(-1)) + 0.062*D(LEX(-2)) - 0.159*D(LM(-1)) - 0.004*D(LM(-2)) - 0.088*D(LFISH(-1)) - 0.007*D(LFISH(-2)) - 0.021*D(LREV(-1)) - 0.114*D(LREV(-2)) - 0.062*D(LCEM(-1)) - 0.038*D(LCEM(-2)) + 0.051*D(FAV) - 0.01 \quad (10)$$

4.2.2 Indicator Models

Seven indicator models were assessed for their forecasting accuracy over the period. In the estimation process, the variable combinations were chosen based on the correlation coefficients

[14] The percentages were calculated by dividing the error by the average of the quarterly values of GDP over the assessment period.

[15] LAG, LE, LOAN, LTOUR, LTRAN, LMANU, LDEP, M2, LCEX, LWS, LGTAX

between these indicators, with lower coefficients being desired to avoid multicollinearity. Variables with correlation coefficients in excess of 0.75 were not used in the same model, as this level of co-movement could negatively affect the standard hypothesis tests. Five of the seven indicator bridge models of quarterly GDP provided accurate estimates with an average deviation at or below $9.0mn per quarter, or 1.4% of real income over the assessment period.

Table 3: Indicator Estimation Results

	AGLOAN	MANAR	LEVELS	MSUPPLY	TOUR	MANU	NEWTRAN
MAD ($mn)	8.9	9.0	6.5	11.1	7.7	8.2	10.2
RMSE ($mn)	10.3	10.3	8.1	15.3	8.9	9.8	13.3
MAPE	1.38%	1.39%	1.01%	1.70%	1.20%	1.27%	1.59%

The model with the best performance, labelled "LEVELS", gave a mean average deviation of $6.5mn over the assessment period, the equivalent to an average percentage error of 1.0%. This makes the model useful in estimating GDP growth. The model persistently overestimated GDP, indicating that the estimates could benefit from adjustment techniques. The import and tourism indicators were most pertinent in the estimation. The effects of the former is indicative of the importance of the intermediate and capital goods to domestic production with spending on fuel and machinery being two of the largest categories in the overall composition of the country's import expenditure.

Since its inception, the tourism industry has had a significant impact on the economy through foreign exchange generation, employment and other channels, which is confirmed here, as the tourism variable had the largest impact on GDP. Surprisingly, the agricultural production index did not have a stronger relationship with GDP in any of the models assessed[16], even though agriculture is deemed to be a major pillar of production. This may be due to the fact that agricultural produce have comparably low prices and the more valuable contributions of the sector lies in the value added production of sugar and citrus concentrates, which are two of the country's chief export commodities. The functional form is as follows:

LEVELS

$$LGDP = 0.087*LAG + 0.019*LAG(-2) + 0.044*LAG(-3) + 0.20*LAR(-1) + 0.043*LCEM(-1) + 0.10*LCEX(-1) + 0.057*LCEX(-2) + 0.087*LE + 0.092*LE(-2) + 0.162*LM + 0.111*LM(-1) + 0.075*LEX - 0.167*LEX(-1) + 0.607 \quad (11)$$

[16] This includes other models that were estimated and not reported in the study.

The forecasting power of the "TOUR" model was also good with an average deviation of 1.2% from actual GDP figures. The only significant variables in this particular model were stay-over tourists and loan. The finance-growth nexus is demonstrated here and, buttressed further by results which showed that loans granger-cause economic growth, implies that monetary policies can play an important role in influencing growth. The change in total stay-over tourist arrivals in the previous period was shown to have a positive impact on GDP in the current period, once again indicating the importance of the external market to Belize's growth. The functional form of the model is as follows:

TOUR

$$D(LGDP) = -0.389*D(LGDP(-1)) - 0.286*D(LGDP(-2)) + 0.248*D(LTOUR) + 0.196*D(LTOUR(-1)) + 0.066*D(LTOUR(-3)) + 0.544*D(LOAN) - 0.566*D(LOAN(-1)) + 0.503*D(LOAN(-3)) \quad (12)$$

4.2.3 Sectoral Model

The sectoral model was estimated using eleven linear dynamic equations[17], representing the ten productive sectors of the economy, and an estimation of the tax contribution to the aggregate. These equations were estimated using the contribution of each sector to GDP as the dependent variable and a representative indicator(s) (as identified by the SIB) of these activities as independent variables. In addition to the indicators provided by the SIB, financial variables were also used, the results of which were compared to their bivariate counterparts to determine their precision. All equations were assessed using the proper model diagnostics before the forecasting exercises were conducted and for those sectors that had multiple estimates, the most accurate, based on the MAD, was chosen to represent that specific industry. The resulting forecasts were then summed to give the GDP value for the given quarter and measured against the actual values. The lag length chosen for each sector was four, and each equation was reduced using the general to specific approach. The bivariate models using SIB's indicators outperformed the multivariate counterparts in most cases, except for the "Fishing", "Hotels & Restaurants" and "Taxes less subsidies" sub-sectors. The sectors, as well as their indicator variables, are presented in Table 4 below.

[17] The sole exception being the manufacturing sector which was estimated using solely the manufacturing production index.

<u>Table 4: Sectoral Model of Belize's GDP and Indicators</u>

Sector	Indicator
Agriculture	*Agricultural Production Index*
Fishing	*Growth Rate of Fishing Production; Loans to the Fishing Sector*
Manufacturing	*Manufacturing Index*
Electricity & Water	*Domestic Electricity Generation*
Construction	*Cement Imports*
Hotels and Restaurants	*Arrivals Index; Loans to the Tourism Sector*
Wholesale & Retail Trade	*Stay-Over Tourists*
Transportation & Communications	*Transportation Index*
Other Private Services	*Deposits*
Government Services	*Wages and Salaries*
Taxes less Subsidies	*Imports; General Sales Tax*

The sectoral model on average underestimated GDP over the assessment period, posting a mean deviation of $8.9mn in that time span or a percentage deviation of 1.4%. The most difficult sector to forecast was the fishing industry with the seasonal fluctuations causing a rather high average error of 27.3% or $6.5mn. This was the largest numerical deviation among the forecasted sectors, despite the sector being among the smallest on average for the period. Estimates of "Other Private Services" proved to be the most accurate, posting mean average deviation and percentage errors of $1.8mn and 1.7% respectively. The remaining equations were fairly accurate posting errors between 1.9% and 7.5% over the assessment period, with all sectors accurately predicting the direction but not the magnitude of the change in each sector in that time.

5. Model Selection, Implications & The Way Forward

5.1 Model Selection

The selection of the best quarterly models for estimation of Belize's GDP was based on an evaluation across categories and against the benchmark model. Prior estimation of benchmark models for quarterly income led to the selection of an AR (3) model (An AR equation with three first difference lags of the dependent variable) which outperformed all the naive models in all three measures of forecast accuracy. The AR (3) model had an average deviation of $16.9mn, which equated to a 2.3% error, values that were in the range of some indicator models, signalling its usefulness as a measure for the more specialized equations. All the chosen models provided more accurate estimates of GDP than the benchmark. The indicator bridge models outperformed all the other categories with those at the lower spectrum of accuracy in this category being marginally more accurate than their counterparts.

The indicator bridge model, "LEVELS", was the best overall and was twice as accurate as the benchmark over the estimation period. This model, which stresses the importance of the external market and the public sector, also had the lowest overall MAD and MAPE, making it optimal for use in producing real time forecasts of the economy. The "TOUR" model also performed well in the assessment and had an average deviation that was 48.3% better than the benchmark over the period. The factor model, OLS_2, performed as well as the aforementioned indicator model, and overall, the category provided estimates that were marginally less accurate than the indicator models, while the sectoral model lagged behind both categories. Surprisingly, the factor models had the largest RMSE of the groups assessed. Further examination of the use of factors, or different extraction methods, may help this class of models, as its major benefit is enabling users to incorporate a large number of variables in the forecast without specification issues.

The indicator bridge models were highly accurate despite the possibility of multicollinearity affecting the equations, as the principle of parsimony came into effect in this estimation. The sectoral model's primary benefit is that it constantly predicted the direction of change of the various sectors, which is information that is not captured in the estimates of aggregate income. One significant discovery in the exercise was the notable improvement in forecasting that resulted from the combination of techniques. The simple average of all the quarterly estimates, except for the sectoral model, produced results that were significantly improved, with a MAD of $4.2mn or 0.65% of real GDP over the three years. A trimmed mean, using the averages of the three most accurate forecasts, also significantly improved the end of period estimates to an error of approximately $4.7mn per quarter. The equations utilized in the aforementioned trimmed mean calculation were those labelled 'LEVELS', 'TOUR' and 'MANU'. Both combination techniques provided estimates that were approximately three times better than the benchmark and yielded a 27.7% improvement on the most accurate indicator model in the study. In an attempt to improve precision, the combined techniques provide a viable option for forecasting GDP in Belize.

Table 5: Root Mean Squared Forecast Error-Estimated Models

	LEVELS	TOUR	OLS_2	FAV_1	SECTORAL	AVG	AVG_TR	AR3
MAD ($mn)	6.5	7.7	7.7	8.3	8.9	4.2	4.7	14.9
RMSE ($mn)	8.1	8.9	9.9	10.2	9.6	4.8	5.9	16.9
MAPE	1.01%	1.20%	1.18%	1.27%	1.38%	0.65%	0.73%	2.34%

Individual indicators of economic activity also stood out in the numerous equations assessed. The dominant ones were tourism, imports and loans. All were significant in models in which they were incorporated and had coefficients, which were markedly higher than the alternative independent variables. The tourism industry indicators are important to the services sector on a whole, with stay-over arrivals affecting "Hotels & Restaurants", "Wholesale & Retail Trade" and "Transportation & Communication". Combined over the last three years, these sectors have contributed approximately $190.0mn per quarter to GDP and approximately 53.7% to the services industry of Belize. The sustainable expansion in tourism activities would obviously bring many benefits to the country, if policies successfully target the areas where this growth could have the most significant effects. Because of the smallness of the economy and its import dependence, the external market continues to exert much influence on the economy's growth performance. Imports of industrial supplies, fuel and capital goods have traditionally comprised a significant share of Belize's international purchases. However, the issue of sustainability remains pertinent as sizeable increases in imports can cause a build up in external current account pressures through a widening of the trade deficit. This has implications for the domestic design of fiscal and monetary policy.

5.2 Conclusion & Discussion

This study has helped to identify econometric models that can be used to forecast the GDP of Belize. Its most important contribution is the facilitation of reliable and accurate forecasts of GDP within one month after the end of the quarter, a one-month improvement on SIB's release time. The two most accurate models, from the indicator bridge model category, gave estimates of quarterly GDP that were on average marginally higher than one percent in terms of their deviation from the actual values between the first quarter of 2011 and the fourth quarter of 2013. The sectoral model performed rather well in the assessment, despite not being very accurate across the board in its forecasts of the different sectors.

The accuracy of the forecasts was improved by averaging the results from different approaches. However, the study was complicated by data constraints due to lack of timeliness, availability and, in some cases, reliability. Many of the firms are the sole producer in their industry and obtaining high frequency data from them was a problem. The SIB in some cases was unable to release data on these firms due to its confidentiality policy. The country could benefit from improvement in the data collection mechanism and guidelines on releasing company information, which would make the forecasting process less challenging. While this exercise was successful, there are other applications, improvements and methods that can be used going forward.

Internationally, combination techniques have been used to improve the forecasting process and there will be further attempts to refine the combination techniques used in this study. It was shown that the individual indicators in Belize introduced bias into the models; however the process of building a macro-model (such as the DSGE model) from microeconomic foundations can improve future forecasts.

The production of fairly accurate, more timely estimates of GDP is a first step in providing more current information to stakeholders that may be useful in their decision making.

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Appendix

Table A1: Naming Conventions for Economic Indicators

Name	Variable	Composition/Measurement
LGDP	Natural log of Real GDP	Bz Dollars
LAG	Natural log of the Agricultural Production Index	Sugarcane, Banana & Citrus (Orange and Grapefruit)deliveries
LAR	Natural log of the Arrivals Index	Land, Air, Sea and Cruise Arrivals
LCEM	Natural log of Cement Imports	Hundred weight (Cwt)
LCEX	Natural log of Public Current Expenditure	Bz Dollars
LDEP	Natural log of Domestic Bank Deposits	Bz Dollars
LE	Natural log of Electricity Production	Megawatt hours
LEX	Natural log of Commodity Exports	Bz Dollars
LFISH	Natural log of Fishing Production Index	Farmed Shrimp, Conch, Whole Fish and Lobster
LGTAX	Natural log of General Sales Tax	Bz Dollars
LM	Natural log of Gross Imports	Bz Dollars
LMANU	Natural log the Manufacturing Production Index	Sugar, Citrus Juices, Flour, Soft drink, Beer and Oil
LOAN	Natural log of Loans to the Private Sector	Bz Dollars
LREV	Natural log of Public Current Revenue	Bz Dollars
LTOUR	Natural log of Tourist Arrivals	Air, Land and Sea Arrivals
LTRAN	Natural log of Transportation Index	Sugar Production Index, Gross Imports and Tourist Arrivals Index
LWS	Natural log of Public Wages and Salaries	Bz Dollars
LM2	Natural log of M2 - Broad Money	Bz Dollars

Table A2: Statistical Properties of Economic Indicators

	LGDP	LAG	LAR	LCEM	LCEX	LDEP	LE	LEX	LFISH	LGTAX
Mean	6.31	4.55	4.93	6.19	4.72	7.07	10.77	4.64	4.88	3.45
Median	6.34	4.53	4.93	6.14	4.76	7.10	10.71	4.64	4.86	3.57
Maximum	6.54	5.15	5.31	6.83	5.14	7.47	11.67	5.15	5.39	3.96
Minimum	5.94	3.18	4.43	5.59	4.28	6.63	9.93	3.95	4.29	2.95
Std. Dev.	0.15	0.39	0.19	0.26	0.23	0.28	0.44	0.25	0.28	0.31
Skewness	-0.61	-0.69	-0.21	0.48	-0.40	-0.02	0.31	-0.30	-0.08	-0.12
Kurtosis	2.51	3.74	3.10	3.12	2.15	1.41	2.36	3.18	2.14	1.57
Jarque-Bera	4.04	5.72	0.44	2.19	3.17	5.88	1.84	0.92	1.79	4.89
Probability	0.13	0.06	0.80	0.33	0.21	0.05	0.40	0.63	0.41	0.09
Sum	353.24	254.61	275.92	346.42	264.30	395.93	603.07	259.59	273.32	193.26
Sum Sq. Dev.	1.29	8.37	2.04	3.82	2.81	4.17	10.53	3.40	4.22	5.23
Observations	56	56	56	56	56	56	56	56	56	56

	LOAN	LM	LMANU	LOAN	LM2	LREV	LTOUR	LTRAN	LWS
Mean	7.00	5.63	4.64	7.00	7.18	4.79	10.90	4.82	3.86
Median	7.07	5.62	4.68	7.07	7.17	4.82	10.89	4.83	3.87
Maximum	7.25	5.91	5.17	7.25	7.54	5.14	11.36	5.19	4.11
Minimum	6.50	5.35	4.03	6.50	6.77	4.36	10.44	4.37	3.61
Std. Dev.	0.24	0.14	0.32	0.24	0.23	0.20	0.21	0.18	0.13
Skewness	-0.78	0.34	-0.25	-0.78	0.02	-0.27	0.07	-0.45	-0.24
Kurtosis	2.30	2.36	1.86	2.30	1.54	2.03	2.49	2.90	2.17
Jarque-Bera	6.77	2.02	3.64	6.82	5.00	2.84	0.64	1.95	2.14
Probability	0.03	0.36	0.16	0.03	0.08	0.24	0.72	0.38	0.34
Sum	392.05	315.38	259.71	392.01	402.02	268.34	610.57	269.84	216.08
Sum Sq. Dev.	3.11	1.06	5.61	3.09	2.96	2.24	2.34	1.81	0.96
Observations	56	56	56	56	56	56	56	56	56

Table A3: Correlation Matrix of Economic Indicators

	LGDP	LAG	LAR	LCEM	LCEX	LDEP	LE	LEW	LEX	LFISH	LGTAX	LM	LMANU	LOAN	LREV	LTAX	LTOUR	LTRAN	LWS	LM2
LGDP	**1.00**																			
LAG	**0.52**	1.00																		
LAR	**0.51**	0.38	1.00																	
LCEM	**0.42**	0.24	(0.20)	1.00																
LCEX	**0.81**	0.21	0.57	0.24	1.00															
LDEP	**0.88**	0.21	0.27	0.56	0.79	1.00														
LE	**0.48**	(0.30)	(0.05)	0.31	0.54	0.71	1.00													
LEW	**0.54**	(0.25)	(0.01)	0.32	0.58	0.75	0.99	1.00												
LEX	**0.62**	0.46	0.21	0.43	0.48	0.58	0.37	0.41	1.00											
LFISH	**0.09**	(0.20)	0.38	(0.36)	0.28	(0.00)	0.23	0.21	(0.08)	1.00										
LGTAX	**0.87**	0.22	0.32	0.50	0.80	0.95	0.66	0.72	0.58	0.06	1.00									
LM	**0.57**	0.01	(0.14)	0.45	0.42	0.68	0.66	0.68	0.40	0.02	0.70	1.00								
LMANU	**0.48**	0.79	0.34	0.19	0.23	0.24	(0.26)	(0.21)	0.42	(0.47)	0.20	(0.08)	1.00							
LOAN	**0.89**	0.17	0.49	0.33	0.87	0.92	0.67	0.73	0.50	0.25	0.92	0.57	0.18	1.00						
LREV	**0.90**	0.32	0.38	0.42	0.77	0.91	0.56	0.62	0.61	(0.01)	0.91	0.65	0.35	0.87	1.00					
LTAX	**0.82**	0.13	0.34	0.38	0.71	0.81	0.62	0.66	0.46	0.25	0.86	0.79	0.06	0.84	0.82	1.00				
LTOUR	**0.78**	0.78	0.69	0.30	0.59	0.52	(0.05)	0.01	0.55	0.01	0.55	0.19	0.67	0.52	0.63	0.50	1.00			
LTRAN	**0.81**	0.78	0.66	0.27	0.56	0.54	0.00	0.06	0.55	(0.08)	0.55	0.28	0.75	0.55	0.67	0.55	0.94	1.00		
LWS	**0.77**	0.11	0.29	0.32	0.75	0.80	0.71	0.73	0.39	0.34	0.77	0.61	0.08	0.85	0.72	0.78	0.39	0.42	1.00	
LM2	**0.88**	0.20	0.27	0.57	0.78	1.00	0.70	0.74	0.54	0.00	0.94	0.68	0.22	0.92	0.90	0.81	0.51	0.53	0.81	1.00

Table A4: Stationarity Test Results

VARIABLE	LEVEL ADF	LEVEL PP	LEVEL KPSS[1]		FIRST-DIFFERENCE ADF	FIRST-DIFFERENCE PP	RESULT
LAG	-5.9111	-8.5884					I(0)
	0.0000	0.0000					
LAR	-62.8977	-30.8021					I(0)
	0.0001	0.0001					
LCEM	-2.7806	-2.5621	0.5803				I(0)
	0.0676	0.1070	S				
LCEX	-1.8786	-3.0297	0.8588		-20.1903	-27.3346	I(1)
	0.3398	0.0382	NS		0.0001	0.0001	
LDEP	-0.9602	-0.9783			-7.0737	-6.7772	I(1)
	0.7613	0.7551			0.0000	0.0000	
LE	-1.0804	-3.8871	0.9679		-14.9885	-13.2695	I(1)
	0.7171	0.0039	NS		0.0000	0.0000	
LEX	-18.5444	-13.3987					I(0)
	0.0000	0.0000					
LFISH	-45.2901	-26.5080					I(0)
	0.0001	0.0001					
LGDP[2]	-2.8614	-6.5632	0.2464		-13.0378	-14.0538	I(1)
	0.1827	0.0000	NS		0.0000	0.0000	
LGTAX	-0.9027	-0.6432			-7.0018	-7.7191	I(1)
	0.7803	0.8520			0.0000	0.0000	
LM	-2.4988	-3.6015	0.7725		-12.5579	-16.6349	I(1)
	0.1212	0.0087	NS		0.0000	0.0000	
LM2[2]	-1.1796	-1.1915			-6.6405	-6.6042	I(1)
	0.6773	0.6722			0.0000	0.0000	
LMANU	-1.4363	-6.0906	0.2220				I(0)
	0.5572	0.0000	S				
LOAN[2]	-0.4992	-0.4027			-6.4565	-7.1982	I(1)
	0.9808	0.9852			0.0000	0.0000	
LREV	-1.6288	-2.1680			-9.4756	-18.1640	I(1)
	0.4614	0.2200			0.0000	0.0000	
LTOUR	-1.6467	-5.3641	0.8165		-2.7420	-23.0912	I(1)
	0.4518	0.0000	NS		0.0741	0.0001	
LTRAN	-8.9592	-8.2321					I(0)
	0.0000	0.0000					
LWS	-1.6214	-1.9413			-8.0726	-24.6584	I(1)
	0.4652	0.3115			0.0000	0.0001	
LAGDP	-1.9616	-6.5543	0.3053				I(0)

	0.3026	0.0000	S				
LFGDP	-4.4597	-4.3899					I(0)
	0.0007	0.0008					
LMGDP	-1.7964	-4.8763	0.7324				I(0)
	0.3786	0.0002	S				
LEW	-0.7889	-3.8165	0.9843		-8.7723	-13.1310	I(1)
	0.8144	0.0048	NS		0.0000	0.0000	
LCGDP	-2.1407	-2.1754			-7.5218	-7.5218	I(1)
	0.2300	0.2173			0.0000	0.0000	
LWR	-2.4616	-4.7385	0.9298		-6.9164	-19.0702	I(1)
	0.1302	0.0003	NS		0.0000	0.0000	
LHR	-1.7081	-6.0982	0.7867		-4.3290	-20.5555	I(1)
	0.4217	0.0000	NS		0.0010	0.0001	
LTGDP[2]	-1.3784	-4.6747	0.2718		-4.6516	-12.1281	I(1)
	0.8567	0.0021	NS		0.0023	0.0000	
LOPS[2]	-0.1837	-0.6936			-5.6566	-3.1987	I(1)
	0.9919	0.9685			0.0001	0.0952	
LGGDP	-1.1094	-4.3530	0.9528		-4.6093	-26.7461	I(1)
	0.7061	0.0009	NS		0.0004	0.0001	
LTAX	-1.8783	-1.9260			-12.1088	-11.9766	I(1)
	0.3400	0.3183			0.0000	0.0000	

[1] The KPSS test was carried out if the results for the ADF and PP tests were inconclusive.

[2] Test equations specified with a trend and intercept.

Graph of Economic Indicators of Belize

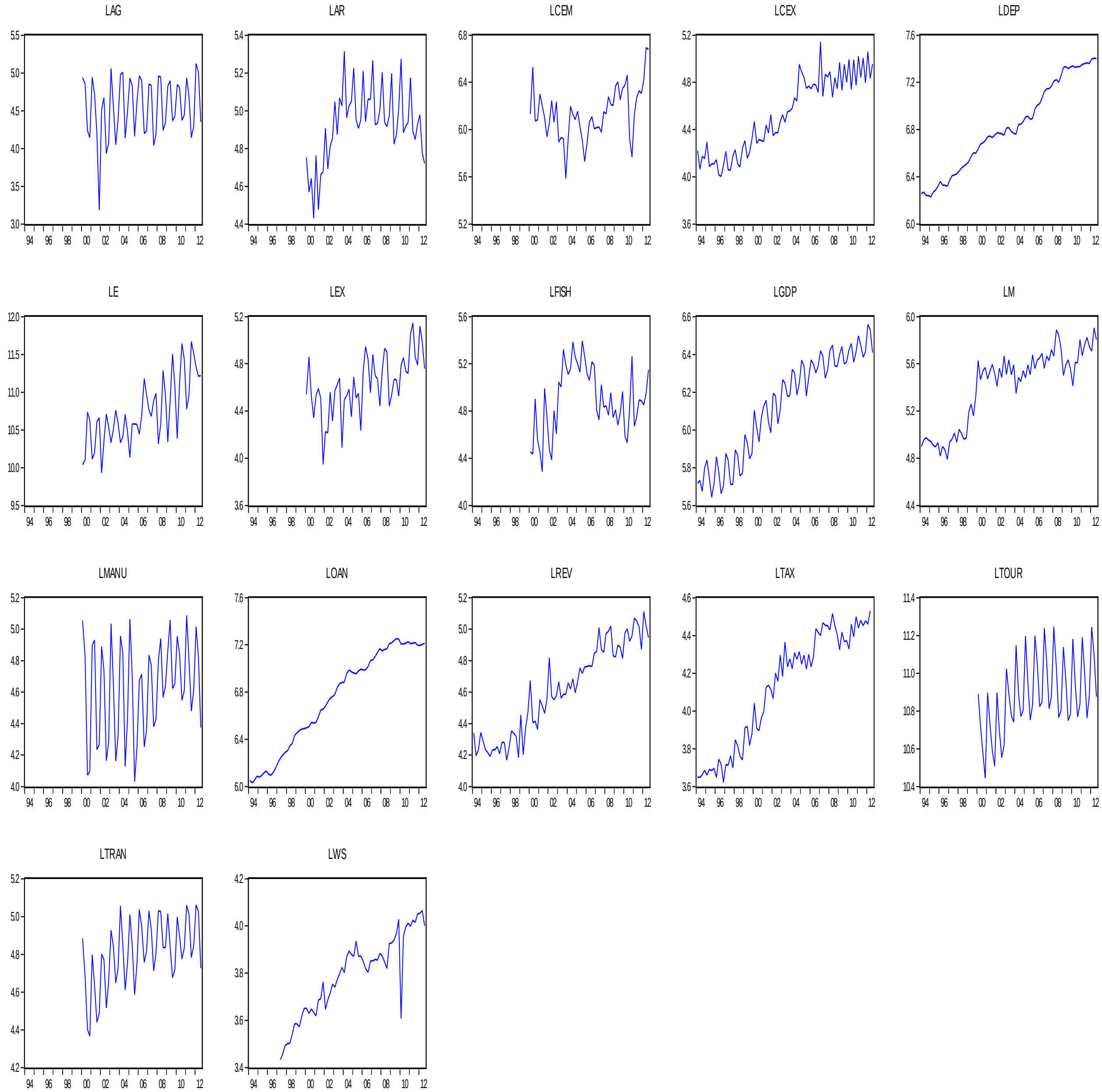

Chart of The Supply Side of Belize's Real GDP