RESERVE BANK OF FIJI

Economics Group

Working Paper

Quarterly Output Indicator Series for Fiji

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Suva

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Abstract

The unavailability of high frequency time series data is a common problem in Pacific Island Countries (PICs), and Fiji is no exception. To address this problem, this paper looks at disaggregating Fiji's annual GDP series into quarterly series using the Chow and Lin (1971) and Fernandez (1981) methods for the years 1994-2011. Tourism earnings and imports of goods and services were two of the nominal variables used to disaggregate the nominal annual GDP series. A quarterly GDP deflator series was also estimated to eventually obtain a quarterly real output indicator series. Results did not vary significantly between the Chow-Lin and Fernandez procedures, with the latter being chosen for disaggregation of Fiji's annual GDP.

1.0 Introduction

In Fiji, the main data body – the Fiji Bureau of Statistics (FBOS) publishes GDP data only on an annual basis, and this makes it difficult for end users of the data[3] to analyse short-term movements in output. Many countries face similar problems and to address this, temporal disaggregation methods are widely used. Temporal disaggregation methods involve the conversion of low frequency data (like an annual data series) into high frequency data (namely quarterly or monthly series)[4] and often aim to solve two common problems of distribution and interpolation.

Different countries may adopt different methods and other forms of temporal disaggregation techniques,[5] depending on the quality and availability of data, varying economic conditions, structural changes and the economic and political climate in their economies. For Fiji, the Chow and Lin (1971) and Fernandez (1981) methods were used to obtain a quarterly nominal GDP indicator series. The generated quarterly nominal GDP indicator series did not exhibit significant variations under the two different methodologies. Going forward, our study proposes to use the quarterly GDP series generated from the Fernandez approach, mainly because there was only weak evidence for co-integration between the two predictor variables[6] and GDP at the annual frequency. The possible

[3] Refers to researchers, policy makers, academics, students and the interested public.
[4] See Chen (2007).
[5] Some other methods for temporal disaggregation are the quadratic programming and multivariate methods to name a few.
[6] Refers to tourism earnings and imports of goods and services.

absence of co-integration raises the spectre that the residuals of the regression linking GDP to the predictor variables are non-stationary, i.e., they follow a random walk, therefore making them unsuitable for the Chow-Lin methodology.[7] Hence, it is safer to take the results of the Fernadez model as this model assumes a random walk process for the residuals and does not rely on co-integration.[8]

Given that the predictor variables were nominal indicators, a quarterly GDP deflator series was derived to get a quarterly real output indicator series. To be consistent with the methodology used for the derivation of quarterly nominal GDP indicator series, the GDP deflator quarterly series was also obtained using the Fernandez model. Deflating the quarterly nominal GDP series with the quarterly series for the GDP deflator yields the quarterly real output indicator series, which is the key output of this study, given that most analysis on the economy is concerned with real activity. Specifically, this study aims to provide support for further research work on estimating potential GDP and output gap for Fiji, which will be explored in future work.

The rest of the paper is divided into different sections as follows: Section 2 discusses literature on previous works on disaggregating low

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[7] For the Chow Lin methodology – co-integration is a pre-requisite.

[8] Having said that, the analysis below will show that unit root tests for our variables are inconclusive, which means we are not sure whether our variables are non-stationary to begin with. Hence, a case for using the Chow-Lin methodology certainly could be made. Fortunately, the results for the quarterly series using both approaches are quite similar.

frequency data into high frequency data using the Chow-Lin and Fernandez methods. Section 3 sets out the conceptual framework of the two models employed in this paper. Section 4 highlights the step by step approach taken to obtain a quarterly nominal GDP series and summarises how a quarterly GDP deflator was obtained, while section 5 looks at the results and finally, section 6 provides some concluding remarks.

2.0 Literature Survey

This section briefly reviews studies on some common types of temporal disaggregation methods and focuses in particular, on the Chow and Lin (1971) and Fernandez (1983) methods. Limited literature was found relating to this subject as it is assumed that most developed countries publish their national accounts at a higher frequency, while developing countries lack the expertise and resources to collect GDP data at a higher frequency. Hence, disaggregation techniques are assumed to be less commonly used by the latter. Additionally, it must be noted that most researchers [Abeysinghe and Lee (1998), Abeysinghe and Rajaguru (2004), (Muller (2005), Yadavalli (2008), Lahari et.al (2008) and Mikhael et.al (2012)] have employed the Chow-Lin method in their studies, and for future work have suggested the need for the use of the Fernandez or the Litterman (1983) methodologies. Only a few studies have used all three approaches.

The different temporal disaggregation methods can be broadly classified into univariate or multivariate methods. Univariate methods are commonly used due to their simplicity and can be categorised either into plausible methods, model-based or smoothing methods. Plausible methods involve either linear interpolation or simply dividing the annual series by four to get quarterly data. The work of Lisman and Sandee (1964) further accentuates this method. Model-based methods can be further sub classified into regression and Auto-Regressive Integrated Moving Average (ARIMA) methods. Widely practiced regression methods include those of Chow and Lin (1971) and its variants Bournay and Laroque (1979), Fernandez (1981), and Litterman (1983). These models are also known as Best Linear Unbiased Estimator (BLUE) models and can generally be used when a higher frequency set of related indicators are available. Other common regression mathematical models are those of Denton Adjustment (1971), and its variant Causey Trager Growth Preservation method (see Causey Trager 1981). The ARIMA models involve finding the ARIMA structure of the reference series. There are two types of ARIMA models, namely time series and smoothing models. Widely used time series ARIMA models are those of Hillmer and Trabelsi (1987), Guerrero (1990) and Nijman and Palm (1990). More recent time series models are those of Durbin and Quennville (1997) and Chen et al (1997). These models use a signal to benchmark the high frequency series. Additionally, state space representation for interpolation and distribution models have also been developed by Harvey and Pierse (1984), Gudmundson (1999) Proietti (1999) and Adland (2000).[9] Smoothing models tend to minimise the sum of squared first or second differences so that the smoothest curve can be found subject to a given constraint. Cubic splines[10] Boot, Feibes and Lisman (1967), Stram and Wei (1986), Jacob et.al (1989) and Hodgess and Wei (1996) are some of the other commonly used smoothing methods.

Out of the above methods, related studies in developed countries that have used the Chow-Lin and Fernandez methodologies to splice national accounts involve those of Muller (2005) and Hall and McDermott (2009). In his research, Muller (2005) points out that the disadvantage of Chow and Lin (1971) procedure is the need for repeated estimation of the high frequency residual for updating the related series until convergence is achieved. Hence, he looks at an alternative maximum likelihood short cut to the Chow-Lin procedure. Hall and McDermott (2009) obtain a quarterly GDP data series for New Zealand for years prior to 1977 – a period when quarterly GDP series were not published - using the Chow-Lin, Fernadez and Litterman models. The stylised facts for these three models highlight no compelling evidence to prefer one model over the other. Consistent results were obtained for long run trends in all three models, suggesting that any one of the generated quarterly GDP series could be used for measuring economic growth or testing growth theories.

[9] See Chen (2007).
[10] See Baxter, 1998.

In developing countries, the works of Abeysinghe and Lee (1998), Abeysinghe and Rajaguru (2004), Yadavalli (2008), Rizk (2010) and Mikhael et.al (2010) look at similar topics. In Abeysinghe and Lee (1998) , the authors disaggregate annual GDP to quarterly GDP by sectors for Malaysia using the Chow-Lin approach and obtain superior results under the assumptions that firstly, basic regression forms a co-integrating regression[11] and secondly that their approach takes care of the seasonality problem. Nevertheless, the authors do highlight the need to use the Fernandez (1981) and the extended Litterman (1983) methods to address a non co-integrating regression. Additionally, the authors highlight that the Chow-Lin method can distort trends and seasonal components when extrapolations/forecasts are carried too far away from the estimation period but conclude that without an extensive empirical evaluation, the advantages of the Chow-Lin method is difficult to be ascertained. In another research, Abeysinghe and Rajaguru (2004) find the possibility of non stationary residuals to be a drawback for the Chow-Lin approach in obtaining quarterly real GDP series from annual series for the ASEAN 4 countries. Hence, reference is made on how the Fernadez method can take care of this problem. Abeysinghe and Rajaguru (2004) further suggest that to use the Chow-Lin approach, first a co-integrating regression must be found, then the adjustment for serial correlation should be made if needed. On balance, the authors highlight that the success of the Chow-Lin method or its variants (Fernandez and Litterman methodologies) depend on the

[11] This is because the disturbance term is assumed to be representative of mainly stationary errors.

availability of good related data series at higher frequencies. Similarly, Rizk (2010) constructs a monthly GDP series from the quarterly series using the Chow-Lin method and obtains favourable results for her purpose. On the flip side, she suggests the need to use either the Fernandez or Litterman methodologies to address the unit root problems present with the Chow-Lin method.

In contrast to the above findings, which mostly indicate the need to employ either Fernandez or Litterman methods, the findings by Yadavalli (2008) revealed the Chow-Lin model to be superior amongst the Fernandez, Litterman and Santos Cardoso methods for South Africa. This is because the Chow-Lin model preserved the movement of the generated GDP monthly series with the observed quarterly series the most, compared to other models in usage. Another research by Mikhael et.al (2012) only employs the Chow-Lin model to obtain quarterly GDP from an annual series and gets satisfactory results. However, this may be the case because the Fernandez and Litterman models were not used for comparison purposes.

For Fiji, the sole study that looks at disaggregating annual GDP data into a quarterly series is that of Lahari et.al (2008). The authors derive a quarterly GDP series for selected PIC's, including Fiji using the Chow-Lin model for the 1980 to 2006 period and arrive at consistent and reliable quarterly series. However, the authors highlight the modifications of the

Chow-Lin method in the form of Fernandez and Litterman approaches, implying that these methods could also be used.

3.0 Conceptual Framework

In this section, key features and the differences of the two models that we have used - Chow and Lin (1971) and Fernandez (1981) - to disaggregate annual GDP data into a quarterly series is briefly presented.

3.1 Chow and Lin (1971) Framework

In the original Chow and Lin (1971) paper, Chow and Lin derive monthly GDP estimates from a quarterly series, given observable monthly indicators.

In our case, we estimate a quarterly series from an observed annual series using indicators available on a quarterly basis. Hence, with a little modification of the original Chow-Lin model, we can use it for our purpose. The Chow-Lin procedure is a regression model represented as below:

$$Y_q = X_q \quad + U_q \tag{1}$$

Where Y_q is a (n×1) vector of unobservable quarterly GDP series, X_q is a (n×p) matrix of p quarterly indicators, is a (p×1) vector of unknown coefficients and is estimated using Generalised Least Squares (GLS) method, while $U_{q,}$ is the error term and a (n×1) vector such that $E[u]=0$, $E[uu']=V_q$. From here onwards, the Chow-Lin method can be adopted to our case in three steps.

Step 1:Establishing an Aggregation Matrix

If T is a yearly observation of GDP, then quarterly observations n is equal to 4T. Then we need an aggregation matrix (T × n), which multiplied by any quarterly matrix (n×1) will yield a yearly matrix (T×1). Therefore, the aggregation matrix (T × n) can be identified as C below:

$$C=\begin{bmatrix} 1 & 1 & 1 & 1 & . & . & . & . & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & . & . & . & . \\ . & . & . & . & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & . & . & . & . & 1 & 1 & 1 & 1 \end{bmatrix}$$

Given the above, a quarterly relationship can now be presented in an annual frequency in the form below:

$$y_a = X_a\beta + u_a \qquad (2)$$

where $y_a = Cy_q$, $X_a = CX_q$ and $u_a = Cu_q$

Alternatively the above can be re-expressed as below:

$$y_a = Cy_q = CX_q\beta + Cu_q \qquad (3)$$

Step 2: Establishing the Chow and Lin (1971) Equation to disaggregate annual GDP estimates to quarterly estimates.

In this section an optimal or BLUE $(\hat{y})$ of *y* is derived in two steps.

a. Getting an optimal coefficient ($\hat{\beta}$)

First, an optimal coefficient needs to be determined and this can be achieved by applying a GLS estimation method to the quarterly regression. Hence, we get the following:

$$\hat{\beta}_{GLS} = [X_a'(CV_qC')^{-1}X_a]^{-1}X_a'(CV_qC')^{-1}y_a \tag{4}$$

b. Obtaining quarterly residuals (U_q) by disaggregating yearly residuals (U_a)

Secondly, to get the Chow-Lin equation that disaggregates annual GDP to quarterly GDP, we need to follow from equation (2), where we made $u_a = Cu_q$. Making u_q the subject of the formula and further expanding the function gives the following:

$$u_q = V_qC'(CV_qC')^{-1}u_a$$

$$u_q = V_qC'(CV_qC')^{-1}(y_a - X_a\hat{\beta}_{GLS}) \tag{5}$$

After establishing equations (4 and 5), now we can establish the Chow-Lin equation that disaggregates annual GDP to quarterly GDP as below:

$$\hat{y}_q = X_q \hat{\beta}_{GLS} + V_q C'(CV_q C')^{-1}(y_a - X_a \hat{\beta}_{GLS}) \qquad (6)$$

Step 3:Estimating Covariance under Chow-Lin Assumptions

A major difficulty associated with the Chow-Lin procedure is that V_q is unknown and such is the case with the Fernadez and Litterman approaches as well. Therefore, V_q needs to be estimated[12] and to do this, Chow-Lin assumes a simple autoregressive structure for the quarterly disturbance term as follows:

$$u_t = \rho\, u_{t-1} + \varepsilon_t \qquad |\rho| \prec 1 \qquad (7)$$

where ε_t is a white noise process; $E(\varepsilon_t) = 0$ and $E({\varepsilon_t}^2) = \sigma^2$. Based on this, the variance and covariance matrix V_q takes the below form:

[12] In practicality, V can never be estimated. For this reason, the Chow-Lin, Fernandez and Litterman methodologies assume different forms under which V could be better estimated.

$$V_q = \frac{\sigma^2}{1-p^2}\begin{bmatrix} 1 & \rho & \rho^2 & \cdots & p^{4n-1} \\ \rho & 1 & \rho & \cdots & \rho^{4n-2} \\ \rho^2 & \rho & 1 & \cdots & \rho^{4n-3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho^{4n-1} & \rho^{4n-2} & \rho^{4n-3} & \cdots & 1 \end{bmatrix}$$

To estimate the autoregressive parameter ρ by implication of V, Chow-Lin describes several procedures. As highlighted by Fernandez (1971), in case of generating a monthly series from quarterly aggregates, and if the monthly residuals follow an autoregressive parameter, then the first order auto-correlation of the quarterly residuals forms a polynomial expression in the autoregressive coefficient of the monthly residuals. Therefore, a process similar to the GLS can be constructed to obtain results implied by equations 5 and 7.

3.2 Fernandez (1981) Framework

The initial part of this framework is similar to the Chow and Lin (1971) framework, and this can be followed from equation (3) which derives $\hat{\beta}$ and $\hat{y}$ as given by equations (5) and (7), respectively. However, the Fernandez model differs from the Chow-Lin model and becomes a special case due to the classification of the disturbance term as follows:

$$u_t = u_{t-1} + e_t \tag{8}$$

where e_t is a random variable, serially independent, with 0 mean and constant variance. This model also assumes that u_0 equals to 0 so that $Var\ u_1 = \sigma^2$ for the initial period. Under these assumptions, the residuals of the model can be expressed as:

$$DY_q = DX_q \beta + Du_q \tag{9}$$

where D is the first difference operator and (n × n) matrix form is given as:

$$\begin{bmatrix} 1 & 0 & 0 & \cdots & 0 & 0 \\ -1 & 1 & 0 & \cdots & 0 & 0 \\ 0 & -1 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & -1 & 1 \end{bmatrix}$$

Now first differencing also needs to be performed on the annual series which can be expressed as:

$$DY_a = CDY_q \tag{10}$$

However C cannot be used at this stage because CDY_q is not observable and the sum of DY_q is not equal to any observable magnitude.

Therefore, to obtain a quarterly series, the following would need to be solved:

$$\Delta Y = QDY = QDX\beta + QDu \tag{11}$$

Where Δ is a similar matrix as D but of a different size (m × m) and Q is a square matrix which specifies that for the first period the relationship will be as follows:

$$Y_1 - Y_0 = 4dy_i + 3dy_i + 2dy_i + dy_i \tag{12}$$

The above can only hold if the quarterly estimates are constant in year 0. To get $\hat{y}$, the trace of the covariance matrix ($D\hat{Y}_q - DY_a$) must be minimised under the linear unbiased estimator condition which is:

$$RQDX - DX = 0 \tag{13}$$

where R is a (n × m) matrix for the linear estimator $D\hat{Y}_q - DY_a$

Therefore, the first differential of equation 10 with respect to R gives us:

$$D\hat{Y}_q = DX\hat{\beta} + Q'(QQ')^{-1}[\Delta Y - QDX\hat{\beta}] \tag{14}$$

$$\hat{\beta} = [X'D'Q'(QQ')^{-1}QDX]^{-1}X'D'Q'(QQ')^{-1}\Delta Y \tag{15}$$

However using $QD = \Delta C'$ equations (11) and (12) can also be written as:

$$\hat{Y}_q = Z\hat{\beta} + (D'D)^{-1}C(C'(D'D)^{-1}C)^{-1}[Y - B'X\hat{\beta}] \qquad (16)$$

$$\hat{\beta} = [X'C(C'(D'D)^{-1}C)^{-1}C'X]^{-1}X'C(C'(D'D)^{-1}C)^{-1}Y$$

(17)

Hence, the above results are similar to those obtained under the Quadratic Loss Function (QLF)[13] with $[A = D'D]$. Thus, the QLF approach is a BLUE method that we have adopted in this paper to get our quarterly GDP estimates.

Empirically, the difference between the Chow-Lin and the Fernandez models is that the former does not allow for a random walk process in the residuals as the latter[14] and the Litterman (1983) methodologies do. If the GDP series and indicators used for disaggregation are non-stationary, for Chow-Lin to be appropriate, these variables should be co-integrated to ensure that the residuals do not have a random walk,

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[13] See original Fernandez (1981) paper for derivation of the QLF.

[14] Fernandez (1981) allows for a random walk process by assuming the autoregressive parameter to be equal to 1 $\rho = 1$ whereas, the Litterman (1983) model is a generalised version of the Fernandez model, as it assumes $\rho = 1$ and a moving average structure for the residuals.

i.e., they are stationary. Hence, part of our procedure below includes testing for co-integration. Given that GDP data is available only at the annual frequency, the co-integration tests have to take place at the annual frequency as well; while it is a fairly a safe assumption that finding co-integration at the annual frequency will transfer to the quarterly frequency, it is less clear that absence of co-integration at the annual frequency implies that there is no co-integration at the quarterly frequency. However, in the later part, we find weak co-integration results, therefore, as a cautious approach we favour the Fernandez methodology over the Chow-Lin methodology.

4.0 Steps Involved in Estimating a Quarterly GDP and a GDP Deflator Indicator Series

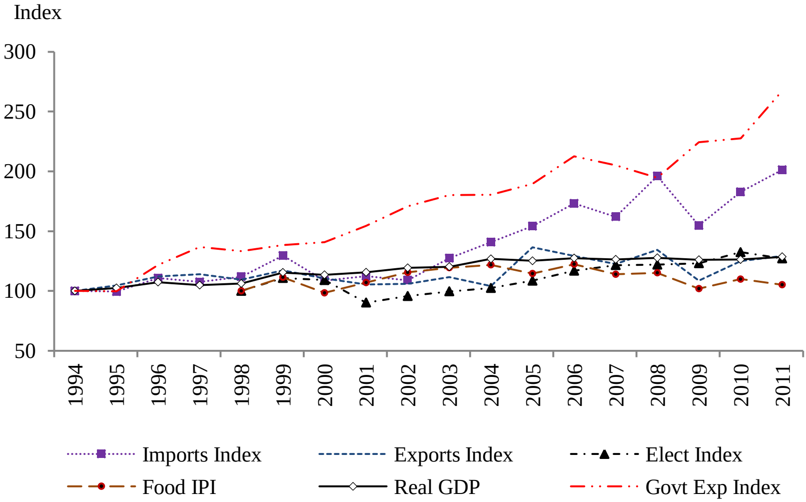
4.1 Time Series Data

The data used for our analysis is time series data for the years 1994 to 2011. As a first step, potential quarterly indicators that could closely proxy Fiji's GDP were identified, followed by a whittling down of the list of potential candidates using a pre-filtering exercise.

4.2 Pre-filtering

At the beginning of the pre-filtering exercise, quarterly available data for potential indicators for the period beginning at least in 1994 were collected from the real, monetary, external and fiscal sectors and stored in a database. At this point, electricity production, food industrial production index, real government expenditure and real exports and imports of goods and services were identified as potential real predictor variables (Figure 1) whereas, tourism earnings, imports of goods and services, broad money, private sector credit and value added tax (VAT) were highlighted as potential nominal predictor variables (Figure 2). Each of these potential real and nominal indicators were then converted into an annual frequency and plotted in a graph against the annual GDP indexes[15] for visual inspection.

Figure 1: Real Predictor Variables

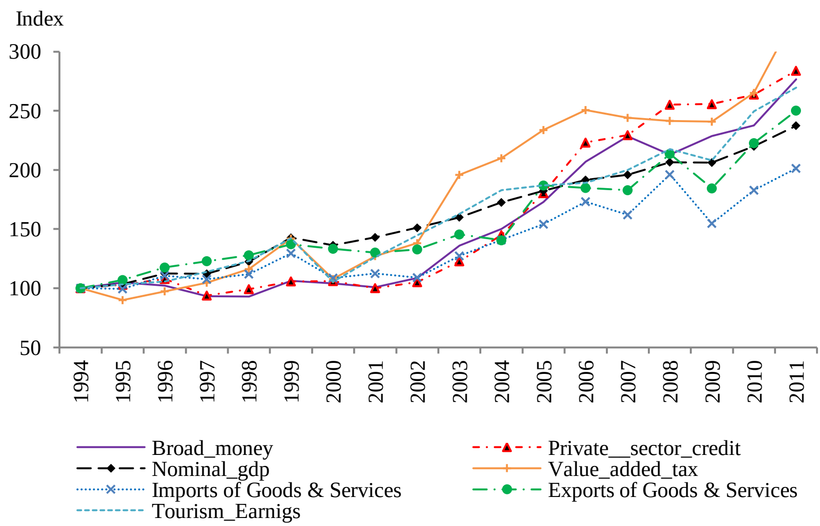


Source: RBF and Fiji Bureau of Statistics (FBOS)

[15] Refers to nominal and real GDP series.

In Fiji's case, many real indicators did not show sufficient co-movement with the real GDP series to be further considered. However, visual inspection suggested exports of goods & services, imports of goods & services and electricity production could potentially be used as indicators as these moved somewhat in line with the real GDP index. However, given the need for a longer quarterly GDP series, the use of electricity production fell out as an indicator as it lacked historical data. The next option was to rely on exports and imports of goods & services and given that these were nominal variables that were deflated to be used as real indicators, it made more sense to use them as nominal indicators to generate a quarterly nominal output indicator that could be later deflated with a GDP deflator to obtain a real quarterly output indicator.

Figure 2: Nominal Predictor Variables



Source: RBF and FBOS

In comparison, the nominal indicators turned out to be better, as satisfactory co-movement appeared to be present between the tourism earnings and nominal GDP[16] indices, as well as between exports and imports of goods & services and the nominal GDP index.

Exports of goods & services variable exhibited quite a good co-movement when compared to the other two indicators but we chose to focus on tourism earnings as an indicator given that it is a large component of exports of goods & services and more likely to have strong links to domestic activity than other components of exports such as exports of agricultural commodities.

In contrast, broad money and private sector credit indexes did not show any co-movement with the nominal GDP index between 1994 and the early years of post 2000, while the VAT index was adequate but less convincing than the other three indicators mentioned above. Overall, neither the real nor the nominal indicators seemed to perfectly track the real or the nominal GDP indexes. Nevertheless, tourism earnings and imports of goods and services stood out to be the most promising indicators. Hence, these indicators became the final choice as our two predictor variables. To ascertain whether the Chow-Lin or Fernandez methodologies

[16] Nominal GDP refers to GDP at current factor cost.

are more appropriate for Fiji, we continue with unit root and co-integration tests.

4.3. Unit Root Tests

Each of the predictor variables and the GDP series were tested for unit root properties[17] using the standard Augmented Dickey Fuller (ADF) (Said and Dickey 1984) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (Kwiatkowski et al (1992)) test.

Under the ADF test, based on the existence of unit roots in the variables as the null hypothesis (H_0), against the existence of no unit roots as the alternative hypothesis (H_A), each of the variables (including the GDP series) was tested using a constant with a trend. As expected, results from the ADF test showed each of the variables to contain unit roots, i.e., the null hypothesis was not rejected at the 1 and 5 percent levels.

Under the KPSS test, the null hypothesis asserted each variable to be stationary against the alternative hypothesis of unit roots in each of the variables. To confirm this, the three variables were again tested with a constant and trend, using the KPSS test. Results of this test could not reject the null hypothesis of stationarity both at the 1 and 5 percent level. The tests results are provided in Table 2.

[17] To test for unit root, first each of the variables was converted into logs.

Table 3: Unit Root Test Results		
Variables	ADF Test With a Constant and a Trend (Level)	KPSS Test With a Constant and a Trend (Level)
tour_ear	-3.3660	0.0845
imports	-3.1245	0.1025
gdp_cfc	-3.2138	0.1151

Note: The critical values for the ADF test were -4.6162 and -3.7105 at the one and five percent levels, whereas the critical values for KPSS at the one percent and five percent levels were 0.2160 and 0.1460, respectively.

Overall, given that mixed results were obtained from the two different unit root tests, we could not conclude with certainty on the stationarity or non-stationarity of the variables.

4.4. Co-integration Tests

To test for any long run relationship between the chosen predictor variables and the GDP series, the Engel Granger (1987) and Phillips Ouliaris (1990) co-integration tests were used.;[18] Given the uncertainty about the stationarity properties of our time series, this set of tests has to assume that the series are non-stationary; while the same assumption is relaxed in a second set of tests below. Results of the different co-integration tests are summarised in Table 3.

[18] Ideally, we would have liked to use bi-variate Johansen co-integration tests for our exercise but the estimated VAR models turned out to be unsatisfactory due to the limited number of observations available on hand at the annual frequency level.

Table 3: Co-integration Test Results Summary		
Variables	Engle Granger	Philips Ouliaris
Null Hypothesis	r=0	r=0
tou_ear and gdp_cfc (in Level)	(2.7602)	(2.7514)
	[0.2262]	[0.2290]
	(10.2120)	(10.0524)
	[0.2304]	[0.2405]
imports and gdp_cfc (in Level)	(3.0319)	(2.8339)
	[0.1622]	[0.2041]
	26.0284	(11.5911)
	[1.0000]	[0.1554]

Notes: For Engle Granger and Philips Ouliaris, the tau-statistics results are followed by the z-statistics results, respectively. Underneath the calculated tau and z statistics are the p-values in parenthesis.

Using the Engle Granger and the Phillips Ouliaris tests, the null hypothesis of no co-integration in the series could not be rejected for both predictor variables at the conventional 5 percent and 10 percent significance levels. Rather, evidence for co-integration using these two tests was found only at the 15-25 percent significance levels for both variables, which means there is at best weak evidence for co-integration.

Given the uncertainty about the stationarity properties of our variables, alternatively, bounds testing approach to the analysis of level relationships by Pesaran et al (2001) was also considered. The Bounds testing does not require a priori assumption on the stationarity properties. It is based on jointly testing the significance of each of the predictor variables and GDP using the Wald Test (1943) in an autoregressive distributed lag (ARDL) model. Results are summarised in Table 4 below.

Table 4: Wald Test Results		
Variables	F-statistic	Results
imports and gdp_cfc (in Level)	0.5990	no long-run relationship
tou_ear and gdp_cfc (in Level)	4.0451	possible long-run relationship

Note: The critical values for the Bounds test at the 5 percent and 10 percent significance levels for I(0) and I(1) are 4.04 , 4.78 and 4.94, 5.73, respectively, assuming unrestricted intercept and no trend.

Based on the Wald test results, we find no evidence for a long run relationship between imports of goods & services and the GDP series, even if we were to assume that both variables are stationary. For the tourism earnings variables, there is mild evidence for a long-run relationship at the 10% significance level, but only if we assume that both variables are stationary.

On balance we find that both stationary and co-integration tests to be inconclusive. Given the uncertainty regarding the stationarity properties of the individual variables, the existence of co-integration is often best solved by the bounds test by Pesaran et al. However, in our case, results were disappointing as only mild evidence for such a relationship between GDP and tourism earnings and no evidence for a long-run relationship with imports were found. Despite this drawback, the same variables were decided to be maintained to estimate a quarterly GDP series given that these were most viable indicators that we had. Regarding the suitability of the Chow-Lin or Fernandez methodologies, the fact that our results on stationarity and co-integration results are inconclusive – this implies that both methodologies are potentially viable. However, as discussed above, we consider the Fernandez methodology to be the safer option in this scenario as it is robust to non-stationary residuals, which we cannot rule out.

5.0 Results

This section looks at generating a quarterly real GDP series using the quarterly nominal GDP and GDP deflator under the two different methodologies mentioned in Section 3.

5.1 Nominal Quarterly GDP Series Using Chow-Lin and Fernandez Model

Generally speaking, our two final predictor variables in the form of tourism earnings and imports of goods and services generated plausible results in estimating a nominal quarterly GDP indicator series using either the Chow-Lin or Fernandez models, as the quarterly nominal GDP indicator series generated by the two models closely tracked the observed GDP series (Figures 3 and 4) without being overly noisy.[19]

[19] At an annual frequency, the fit between the nominal quarterly GDP indicator and the GDP series is ensured by construction, given that the quarterly values of nominal quarterly GDP indicator have to add up to the value for annual GDP.

Figures 3 and 4: Quarterly Nominal Indicator Series (Using Imports of Goods and Services and Tourism Earnings)

Figure 3

Chow-Lin Results

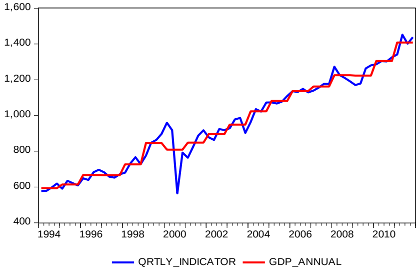
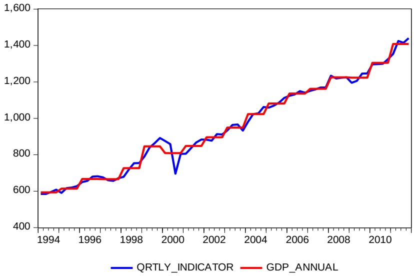


Figure 4

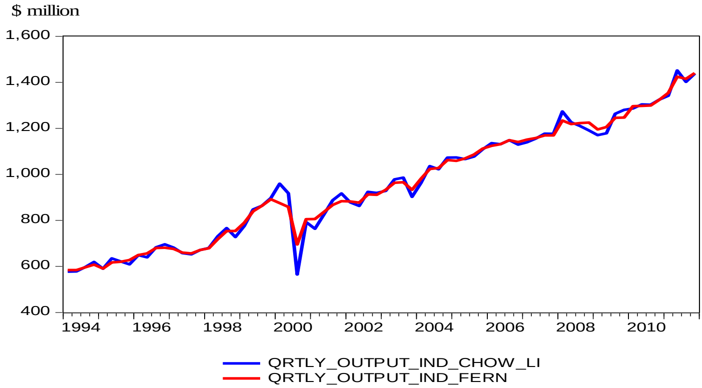
Fernandez Results



Source: RBF

Moreover, the results generated by the two programs were fairly similar, as shown in Figure 5. Even though the results generated by the Chow-Lin procedure show a larger quarterly volatility than those by the Fernandez procedure, overall the differences are not very large.

Figure 5: Quarterly Nominal Indicator Series Using Chow-Lin and Fernandez Models



Source: RBF

Furthermore, it should be noted that compared to the Chow-Lin results, the Fernandez model results worked better for Samoa – the only country in the Pacific that publishes a quarterly GDP series and therefore, allows for an outright comparison of the relative success of the two procedures. Based on all of these considerations, we take the Fernandez model to be our preferred model for both nominal GDP and the GDP deflator.

5. 2 Estimating a Quarterly GDP Deflator Series

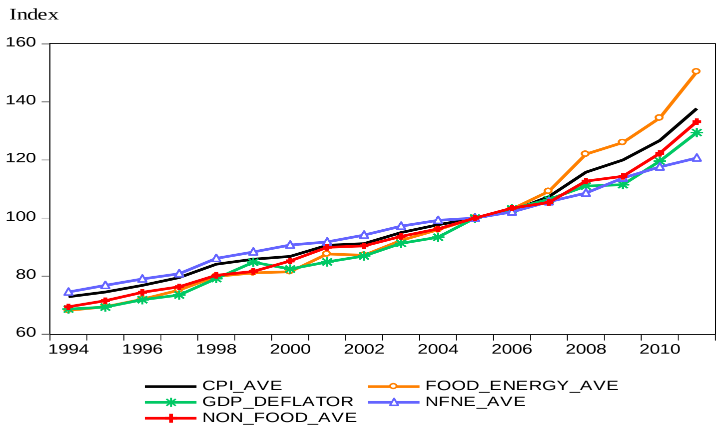
A GDP deflator series was estimated in a similar manner as the nominal quarterly GDP indicator series. As a first step, the annual GDP deflator[20] series was computed using the formula below:

$$\textit{Gdp deflator} = \textit{(nominal gdp/real gdp)*100} \qquad (18)$$

Next, a list of indicators was identified that could proxy the GDP deflator. A number of consumer price indices (CPI's) such as total CPI, non-food, food and energy, and non food and non energy indices were re-normalised and plotted against the annual GDP deflator series. Many of these showed a close co-movement with the annual GDP deflator series (Figure 6).

[20] The GDP deflator is not published by the FBOS.

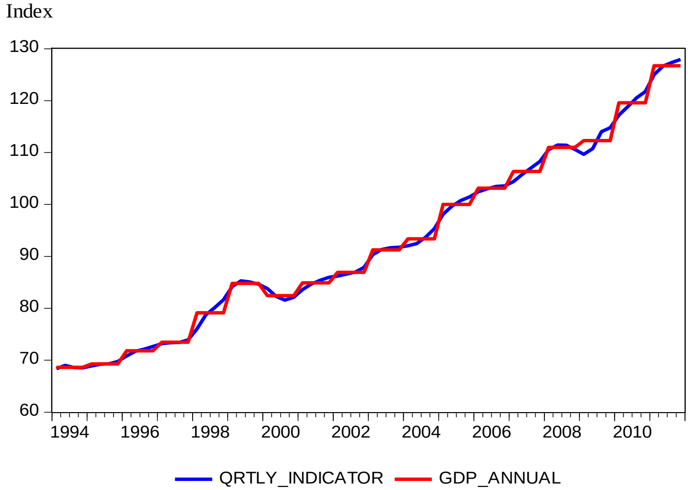
Figure 6: Potential GDP Deflator Indicators



Source: RBF

However, the non-food non-energy CPI stood out and almost perfectly fitted the GDP deflator index. In addition, this tied up well with the theoretical argument that non food non energy index tends to filter out the food and oil price shocks to which Fiji is most susceptible. This is a desirable property for estimating an indicator series for the GDP deflator, as it distinguishes the GDP deflator from the overall CPI, which in Fiji is very sensitive to import price shocks, and supports the argument for the usage of an indicator that is less sensitive to these shocks. Using the Fernandez model and non-food non-energy CPI as the quarterly indicator series, we obtain a GDP deflator series as seen in Figure 7.

Figure 7: Quarterly GDP Deflator Series

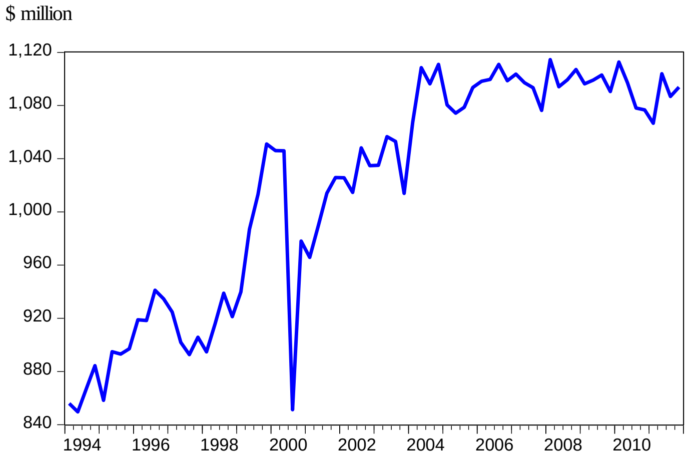


Source: RBF

5.3 Quarterly Real GDP Series

After obtaining the quarterly GDP deflator series, we can now obtain a real quarterly GDP indicator series using Equation 13. The real quarterly GDP indicator series obtained can be found in Appendix A. Figure 8 shows the results of the quarterly generated GDP series using the Fernandez methodology.

Figure 8: Quarterly Real GDP Indicator Series



Source: RBF

From the graph, and the generated quarterly GDP indicator series, we can pinpoint quarters in which economic activity was strong or weak. Generally speaking, having a quarterly GDP indicator series is useful as it helps identify movements in short term output which can help a central bank in terms of policy formulation. In our case, the quarterly GDP indicator series would be used to estimate potential GDP and output gap for Fiji for policy analysis.

6.0 Conclusion

Various methods can be used to temporally disaggregate a low frequency time series into a high frequency series. This paper applies two temporal disaggregation methods of Chow and Lin (1971) and Fernandez (1981) - also known as the BLUE methods to estimate a quarterly real GDP indicator series for Fiji.

This paper finds the Fernandez (1981) method to be preferable for two main reasons. Firstly, given that it cannot be ruled out that the residuals in our regression could follow a random walk process and secondly because this methodology yields a more plausible quarterly output path for Fiji that is less noisy. In any event, results from the Chow-Lin and Fernandez methods did not differ much for Fiji's case.

Going forward, the results of this paper - i.e. the estimates of the quarterly output series for Fiji - will form the basis for research on estimating potential GDP and output gap for Fiji.

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Appendix A: Disaggregated Quarterly Output Indicator and Output Deflator Series

Year/Quarter	GDP at Current Factor Cost (Base year = 2005)	GDP Deflator Index	Real GDP (Base year = 2005)
1994Q1	584	68	855
1994Q2	585	69	847
1994Q3	596	69	869
1994Q4	608	69	887
1995Q1	591	69	857
1995Q2	617	69	892
1995Q3	620	69	895
1995Q4	628	70	900
1996Q1	650	71	917
1996Q2	656	72	915
1996Q3	680	72	943
1996Q4	682	73	938
1997Q1	676	73	923
1997Q2	660	73	899
1997Q3	656	73	894
1997Q4	671	74	908
1998Q1	679	76	893
1998Q2	719	79	914
1998Q3	754	80	941
1998Q4	754	82	924
1999Q1	790	84	938
1999Q2	839	85	984
1999Q3	864	85	1015
1999Q4	892	85	1054

2000Q1	875	84	1044
2000Q2	859	82	1043
2000Q3	696	82	853
2000Q4	805	82	980
2001Q1	806	84	964
2001Q2	836	85	988
2001Q3	867	85	1016
2001Q4	884	86	1028
2002Q1	883	86	1024
2002Q2	877	87	1013
2002Q3	913	87	1050
2002Q4	911	88	1037
2003Q1	933	90	1033
2003Q2	964	91	1055
2003Q3	966	92	1054
2003Q4	933	92	1016
2004Q1	981	92	1065
2004Q2	1024	92	1107
2004Q3	1028	94	1097
2004Q4	1062	95	1114
2005Q1	1059	98	1079
2005Q2	1070	100	1073
2005Q3	1087	101	1078
2005Q4	1112	101	1096
2006Q1	1124	102	1097
2006Q2	1131	103	1098
2006Q3	1149	103	1110
2006Q4	1141	104	1101
2007Q1	1151	104	1103
2007Q2	1158	106	1095
2007Q3	1169	107	1092
2007Q4	1170	108	1080

2008Q1	1234	111	1116
2008Q2	1219	111	1094
2008Q3	1223	111	1098
2008Q4	1225	111	1108
2009Q1	1195	110	1090
2009Q2	1206	111	1089
2009Q3	1246	114	1093
2009Q4	1247	115	1086
2010Q1	1297	117	1106
2010Q2	1298	119	1092
2010Q3	1299	121	1078
2010Q4	1325	122	1088
2011Q1	1354	125	1083
2011Q2	1425	127	1125
2011Q3	1415	127	1111
2011Q4	1440	128	1126