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Abstract

Output gap is generally used in assessing both the inflationary pressures and the cyclical position of a nation's economy. However, this variable is not observable and must be estimated. In this paper, we accomplish two tasks. First, we estimate the output gap for the United Arab Emirates (UAE) using four different statistical methods (i.e. the linear method, the Hodrick-Prescott filter, Band-pass filter and the unobserved components model). Second, we evaluate to what extent the fluctuations of output gap, however constructed or measured, are a good predictor of inflation in the UAE. This is carried out by comparing the out-of-sample forecasts generated by the output gap based models to those of the model with alternative indicator, and the benchmark models. Interestingly, although the different measures of output gap produce a broadly similar profile of the UAE business cycles, we could not find any statistical evidence that this variable is a useful predictor of inflation in the UAE.

Keywords: Output Gap; Inflation; Forecast; Forecast Accuracy; Forecast Encompassing

JEL-Codes: C32, E31, E32, E37.

Introduction

One of the fundamental objectives of monetary policy authorities in both developed and developing countries is to maintain price stability. The crucial role of this goal cannot be underestimated since it has significant macroeconomic benefits with economic wide ramifications. For instance, it is generally accepted that price stability contributes to the economic well-being of the nation by increasing the efficiency of it's monetary system and consequently reduce uncertainty about the future.[1] In pursuit of this goal, UAE monetary policy authorities are expected to continuously monitor the inflationary pressures that emerge as the economy grows overtime. Hitherto, the UAE has dealt with the inflation problem by pegging its currency to the U.S. dollar and by making further adjustments using government switching deposits and open market operations to achieve certain level. Despite these measures, inflation has been rising lately due to the depreciations of the U.S. dollar and the reinvestment of oil revenues to build infrastructure in the country. Therefore, understanding the relationship between real economic activity and inflation is of paramount importance for monetary policy authorities in the UAE. A key component of this relationship is naturally the concept of output gap. This concept plays a vital role in assessing inflationary pressures and the cyclical position of the economy.[2]

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[1] There are also microeconomic benefits that are associated with the pursuit of this goal. For details, see Taslim and Chowdhury (1995).

[2] The monetary policy authorities usually use different indicators for monitoring and predicting inflation. These indicators are generally grouped into two different categories in the literature. The first category includes the nominal variables, such as money growth, interest rates and the exchange rate that central banks use to predict inflation because these variables provide information on current or expected monetary policy actions. The second category includes only variables that provide information on conditions of the real economic activity. These variables include the output gap and the unemployment gap.

Output gap is normally defined as deviations of actual output from its potential level and represents a summary and quantification of resource usage. Positive output gap indicates an excess aggregate demand and this has a propensity to put upward pressure on prices that can potentially give rise to higher rates of inflation. On the other hand, negative output gaps indicate excess capacity and exert an importunate downward pressure on prices and as a result, inflation is expected to decline accordingly. Both these circumstances call for different macroeconomic policy responses from the policymakers. Particularly, when output gap is positive and inflation is on the rise, central bankers can adopt monetary policies that are designed to restrict aggregate demand in order to maintain price stability. Correspondingly, when output gap is negative, expansionary policies that are formulated to stimulate aggregate demand can be adopted to restore macroeconomic stability. Hence, output gap is an important indicator in that it helps us understand and forecast the evolution of prices in the future.

The standard approach in the literature used to capture the relationship between output gap and inflation is the ordinary Phillips curve. This theory is essential in providing helpful insights to monetary policy authorities who are targeting low inflation and it represents their yardstick in the determination of inflation. Nevertheless, the literature on the sources of inflation in Less Developed Countries (LDC, hereafter) indicates that, contrary to industrialized nations where inflation is determined by real factors, it is the nominal factors that play a significant role in the determination of inflation in the LDCs (IMF, 1996). This study shows that changes in money growth and nominal exchange rates have considerable explanatory power in the determination of inflation in these countries. Consequently, one of the main objectives of this paper is to ascertain whether the output gap, given the uncertainty and the controversy surrounding its measurement, is a useful indicator of inflationary pressures in the UAE.

There is little or no debate among economists regarding the relationship between output gap and inflation embodied in the short run Phillips curve. However, the controversy centers mostly on the potential output and the corresponding output gap, since these variables are inherently unobservable and must be estimated. There have been several approaches proposed in the literature: linear trend, quadratic trend, H-P filter, Band-pass filter, etc. Each of these methods of estimating capacity output carries the potential of over- or under- estimating output gap.[3] Consequently, this could entail forecast errors that may cause policy errors since policy authorities rely on these forecasts when formulating and designing policies. In order to minimize this, we use four different measures of output gap derived from different models and examine how well they explain inflationary pressures in the UAE, as measured by the log differences of the GDP deflator.

Our results indicate that the different approaches have produced a broadly similar profile of the economy. Particularly, the different measures of output gap give comparatively consistent indication of the magnitude of slack in the UAE economy. However, we could not find any clear support that this variable however measured is capable of predicting inflation in the UAE. Regardless of the model used, the coefficient of the output gap remains statistically insignificant at the 5 percent level and its inclusion in the regression equation does not improve the forecast accuracy of the model.

[3] For a detailed discussion on the issues of the relationship between the output gap and inflation, See Orphanides and van Norden (2004).

The remainder of the paper is organized as follows. Section 2 discusses the methodology related to the estimation of the output gap, while section 3 presents the results associated to the different methods of the output gap measurements. Section 4 discusses the forecast methodology while section 5 presents the forecast performances of the different models. Finally, section 6 presents the conclusion of the paper.

2. Output Gap: Estimation Methodology

The concept of potential output and the corresponding output gap are inherently unobservable and must be estimated using information contained in other observable macroeconomic variables. To this end, there are a number of approaches that are available in the literature which can be grouped mainly into three categories: statistical methods, structural methods and mixed methods. The first method includes for instance, the linear trend, the quadratic trend, the H-P filter, etc, and is purely mechanical in its estimations of these variables and does not rely on economic theory. On the other hand, the second method is theory based in that it requires one to first estimate the potential levels of inputs in order to arrive at the potential level of output using the neoclassical production function. The third method is a combination of the first two methods. Nonetheless, in this paper, we use only the statistical approach in our computations of the UAE output gap. Particularly, we use the four most popular statistical methods in the literature, namely the linear trend method, the Hodrick and Prescott filter, the frequency domain filter and the unobserved components model to estimate the output gap of UAE.[4]

2.1. The Linear Trend Method

[4] The choice of these atheoretical statistical techniques is dictated by the availability of data. For instance, the use of the structural or the mixed approaches require data on employment and capital stock for the UAE that is not available.

This method is the first and oldest statistical technique used empirically to estimate both the potential output and the output gap in the literature. This method assumes that output is approximated as a simple deterministic function of time. In other words, this approach decomposes output into a trend component and a cyclical component.[5] The general criticisms of this technique, however, are well documented in the literature (Gibbs 1995; Diebold and Senhadji 1996; de Brouwer 1998; Billmeier 2004). Notwithstanding the violations of time series properties, one of the main drawbacks of this technique is that it assumes that potential output grows at a constant rate, which implies that only demand shocks influence this variable overtime, an interpretation that goes against the consensus that supply shocks also contribute to variations in output (Claus, 2000). Moreover, cognizant of the fact that the growth of output depends on the growth of the factors of production and improvements in technology, there is no reason for these factors of production to be constant over time, especially when economies are subject to considerable structural changes over the years. For instance, Graff (2004) notes that potential GDP is evolving along a path that shows considerable inertia.

2.2. The Hodrick-Prescott Filter

The palpable shortcomings of the linear trend method have necessitated the need for alternative detrending methods. These methods include the development of several statistical filters that are widely used in the literature to estimate both the potential output and the corresponding output gap. The most popular filter among these is that of the Hodrick-Prescott method (H-P filter, hereafter). Similar to the linear trend, this method is

[5] This method was very popular because it is easy to construct and interpret the results. The following equation is usually estimated.

$$Y^* = \alpha + \beta t \quad \text{where } Y^* = \text{the potential output}$$

not based on economic theory or on a structural relationship, but it instead gives a useful approximation of the growth rate of potential output. A desirable feature of the H-P filter is that it makes output gap stationary over a wide range of smoothing values (Hodrick and Prescott 1997) and allows the trend to change overtime. In addition, it is flexible and very simple to implement, which has contributed significantly to its wide application in the literature.

The H-P filter identifies a long-term trend component of output by minimizing a loss function of the form:

$$L = \Sigma_s^t (y_t - y_t^T)^2 + \lambda \Sigma (\Delta y_{t+1}^T - \Delta y_t^T)^2 \quad (1)$$

Which is a weighted average of the gap between actual and potential output and the rate of change of trend output. According to this method, the weighting factor, λ , is an exogenous detrending parameter and is set arbitrarily. Hodrick and Prescott suggest to set λ at 1600 for quarterly data and 100 for annual data. But the size of the weighting factor has been very contentious in the literature with some authors using different values for λ (See Billmeier 2004; Ross and Ubide 2001; and Slevin 2001). The central argument is that the magnitude of the weighting factor determines how potential output responds to movements in actual output since it controls the smoothness of the series, by setting the ratio of the variance of the cyclical component and the variance of the actual series.[6] Needless to say that the magnitude of the output gap varies with the size of the smoothing factor, but most importantly, it also affects the relative scale and timing of the peaks and troughs in output.

[6] Higher values of λ leads to higher weight attached to the smoothness of the trend and vice versa. More precisely, as λ approaches infinity this resembles the linear trend method and as λ approaches zero the potential output will be equal to actual output.

Even with the two-sided filters, the H-P filter has been criticized due to its end-of-sample problems.[7] Other statistical methods seem to suffer from the same weakness. A number of authors have noted that the end-of-sample estimates of output gap at the end of the sample is likely subjected to substantial revision as new data become available, a period that is of most relevance to policymakers. A number of corrective measures have been proposed –at least partially- to resolve this issue. The most preferred solution, as suggested in the literature, is that of extending the dataset with forecast variables. However, these corrective measures are in turn dependent on the accuracy of these forecasts. Nonetheless, if these remedial procedures are not undertaken, such as using output projections to augment the observations, this could lead to policy failures for users who are by and large interested in the most recent observations in order to make projections for the immediate future.

2.3. Frequency Domain Filters

Most macroeconomic time series variables such as real GDP are generally non-stationary and often exhibit fluctuations that are radiating from different sources. These fluctuations echo on the specific features of the data generating processes that occur with certain frequencies. The frequency domain filter decomposes these fluctuations into sums of different periodic components or frequencies, which are usually assumed to be distinct and mutually independent. These periodic components or frequencies are described as the number of cycles per period. Hence, macroeconomic time series variables - such as real GDP - are partitioned into three periodic components which are high, medium and low-frequency components. The high-frequency components are described as the variations in

[7] The difference between the two-sided filters and the one-sided filter is that the two sided-filter uses both past and future information while the one-sided filters use only past information.

the time series data that are either seasonal or irregular. The low-frequency components are associated with the trend component of the time series data. Lastly, the medium-frequency components are described as the cyclical component or business cycles of the time series data. This filtering method is often referred to as Band-Pass filter and the most popular one in the literature is that of Baxter and King (1999).

Following Burns and Mitchell (1946), Baxter and King also observe that the business cycle consists of periodic components whose frequencies lie between 1.5 and 8 years per cycle. Cycles that are either too long or too short to be considered as part of the business cycle are eliminated in order to isolate the medium-frequency components of the data. Since, the filter cannot handle non-stationary time series variables in the frequency domain, the data must be transformed into a time domain. The advantage of this filter over the H-P filter is that it relies on the theory of spectral analysis of time series, which mainly computes infinite moving average process of the variable of interest such as the real GDP. The resulting filtered series is a centered moving average with symmetric weights.

The Baxter and King filter has some desirable features that have contributed appreciably to its extensive application in the literature. Firstly, it is imperative to note that this approach is more flexible than the H-P filter. It can easily handle data sampled monthly or annually and also estimates the output gap directly and potential output is computed as the actual output plus the estimated output gap. Secondly, since the resulting filtered series is stationary and symmetric, it does not introduce phase shift. Thirdly and finally, this filter has the capability to track closely the NBER dating of business cycles.

Similar to other band-pass filters, the Baxter and King filter is also subject to many limitations. Filtering in the time domain involves the loss of K observations at the beginning and at the end of the sample. This filter is also criticized on the basis that it produces spurious dynamics in the cyclical component.

2.4. The Unobservable Components Model

As suggested by Watson (1986), the unobservable components model decomposes output into a permanent and a transitory component which corresponds to potential output and output gap respectively. That is:

$$y_t \equiv y_t^p + z_t \tag{2}$$

This methodology assumes that potential output follows a random walk with a drift

$$y_t^p = \mu^p + y_{t-1}^p + \varepsilon_t^y \tag{3}$$

Where μ^p is a drift term that can be used as a measure of the rate of growth of potential output, and $\varepsilon_t^y \approx (0, \sigma_y^2)$. This equation implies that the rate of growth of potential output not only depends on temporary shocks captured by $\varepsilon_t^y \approx (0, \sigma_y^2)$ but also on the more persistent growth factor μ^p. Following Clark (1989), we assume that the drift parameter follows a random walk and can be written as:

$$\mu^p = \mu_{t-1}^p + \varepsilon_t^\mu \tag{4}$$

Where $\varepsilon_t^\mu \approx N(0, \sigma_\mu^2)$[8] and represents a permanent shock to the rate of growth of potential output. Finally, we assume that the output gap follows an AR(2) process:

$$z_t = \phi_1 z_{t-1} + \phi_2 z_{t-2} + \varepsilon_t^z \tag{5}$$

Where $\varepsilon_t^z \approx (0, \sigma_z^2)$ and the roots of $(1 - \varphi_1 L - \phi_2 L^2) = 0$ lie outside the unit circle.

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[8] Watson (1986) in his analysis of the U.S. data made the assumption that the rate of growth is constant over the sample period which implies that $\varepsilon_t^\mu = 0$. This assumption is very restrictive when applied to other economies as indicated by Gerlach and Smets (1997). Since our estimation exercises include periods where the economies of this country have undergone structural changes, we assume that the rate of growth varies over time.

In order to estimate the model, we must write it in a state space form.[9] The state space formulation consists of two equations, the measurement equation (or the observation equation) which describe the observed variables as a function of the unobserved variables and the transition equation (or the state equation) which describes the evolutionary processes of the unobserved state variables. Let $\zeta_t = \begin{bmatrix} y_t^p & z_t & z_{t-1} & \mu_t \end{bmatrix}$ denote the vector of state variables and $\beta = \begin{bmatrix} 1 & 1 & 0 & 0 \end{bmatrix}$ be a matrix of coefficients.

The measurement equation in a vector notation can be written as:

$$y_t = \beta\zeta_t \tag{6}$$

To complete the model, the transition equation which describes the evolutionary Processes of the state variables can be written as:

$$\zeta_t = \Gamma\zeta_{t-1} + e_t \tag{7}$$

Where:

$$\Gamma = \begin{bmatrix} 1 & 0 & 0 & 1 \\ 0 & \phi_1 & \phi_2 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

and $e_t = \begin{bmatrix} e_t^y & e_t^z & 0 & e_t^\mu \end{bmatrix}$. Estimates of the parameters of the model and of the state variables can be obtained by maximizing the following likelihood function using the Kalman Filter. The likelihood function is defined as:

[9] The state space modeling generally deals with dynamic time series that involve unobserved state variables such as the trend output, output gap, time-varying parameters, etc and the basic tool used to estimate these variables is the Kalman Filter which is a recursive algorithm. For details, see Hamilton (1994).

$$\log \Pi = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\sum_{1}^{T}\log\left|F_t\right| - \frac{1}{2}\sum_{1}^{T} v_t^T F_t^{-1} v_t \qquad (8)$$

where "T" is the sample size, "v" is the prediction error matrix and "F" is the mean square error matrix of the prediction errors.

In sum, our perusal of the different techniques available in literature to estimate output gap indicates that there is no one methodology that is superior to others. Therefore, by using a number of different estimates, we are able to produce robust results as to the importance of output gap in forecasting inflation in the UAE. The next section discusses the results of the different estimation methods.

3 Output Gap Estimation Results

A number of important features are easily perceptible from the estimation of the output gap of the UAE which are worth commenting on. First, the different statistical methods used have produced a broadly similar pattern of output gaps for the UAE. Secondly, though these methods are based on different theoretical assumptions and are meant to portray different dynamics of the economy, our results illustrate how comparable and consistent they are in capturing the business cycles of the UAE economy. More specifically, the output gap estimates from the different statistical methods move closely in the sense that expansions and contractions occur at the same periods (see Table 1) though there are some differences in terms of volatility and magnitude. The turning points emerging from linear method, the H-P filter gap and that of frequency domain or the band-pass filter are very similar while that of the UC gap is more volatile.

Figures 1-4 displays the estimated output gap for the UAE from the four statistical methods explained above. The output gaps obtained are approximately indistinguishable demonstrating that the UAE output gap has turned sharply negative or had major recessions on two occasions for most of the estimates: that of the mid to late 70s and mid 80s. This is especially true for the linear, the H-P filter and the band-pass filter while that of the UC gap has turned negative on three occasions (i.e. mid 70s, early and mid 80s). Particularly, the output gap estimates obtained from the linear trend model and the H-P filter are exceedingly comparable as confirmed by their bilateral correlation coefficient of 0.97 (see Table1). Table 1 shows the correlation coefficients between the different statistical methods used in this study. As expected, these correlation coefficients are generally high, with the exception of the UC gap and range from 0.429 to 0.969. Therefore, there is a high degree of synchronization among the different measures obtained, and together they are capable of capturing the dynamics of the UAE economy.

Figure 1: The Linear Output gap

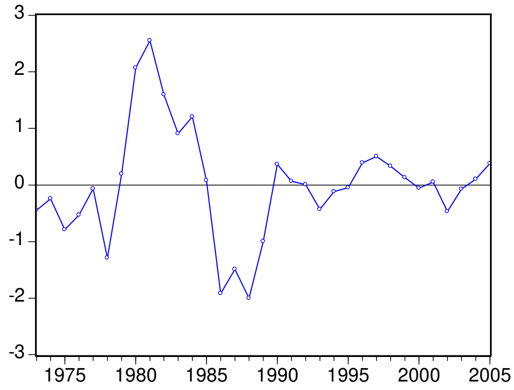

Figure 2: The H-P Output gap

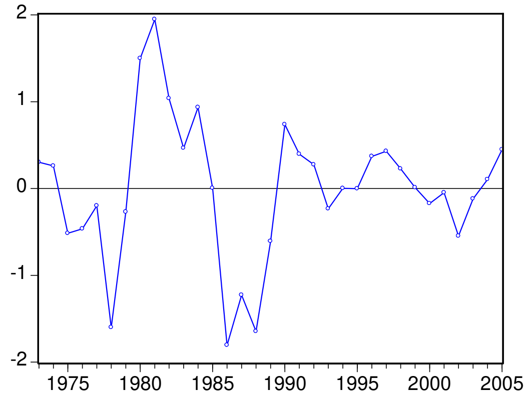

Figure 3: The BP Output gap

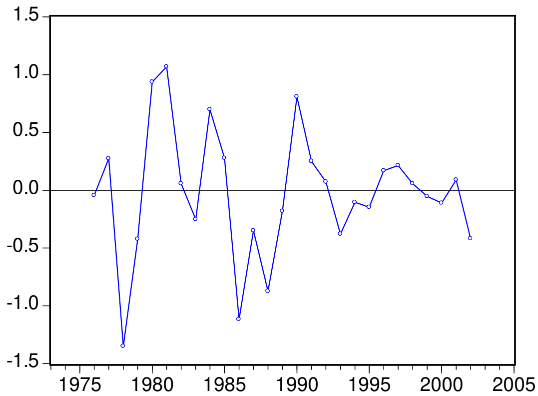

Figure 4: The UC Output gap

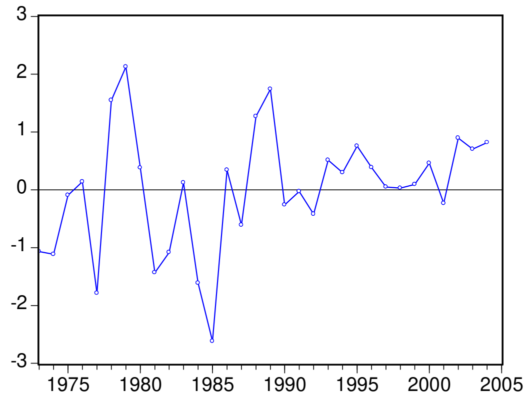

Table 1. UAE Correlation Matrix

Models	Linear	H-P filter	B-K filter	UCM
Linear	1.00	0.969	0.814	0.429
H-P filter		1.00	0.897	0.456
B-K filter			1.00	0.582
UCM				1.00

4. Forecast Methodology

The last section presented and compared succinctly the different estimates of output gaps produced by the different models. But, as noted at the outset, output gap is generally used as an indicator of inflationary pressures in the economy. Accordingly, we are interested in quantifying the extent to which the different output gap measures can provide reliable forecasts of inflation in the UAE. Particularly, we are determined to assess the information content of the different output gap measures as a leading indicator for future inflation developments in the UAE. This involves the estimation of different equations of inflation that includes the output gap as an explanatory variable. We test at each stage whether the addition of a particular measure of output gap improves the accuracy of the resulting inflation forecast. To this end, the methodology we follow is that of Orphanides and van Norden (2004) and Claus (2000) in estimating the following equations.

Model 1: $\pi_{t+h}^{h} = \alpha + \sum_{i=1}^{n} \beta_i \,.\, \pi_{t-i}^{1} + \sum_{i=1}^{m} \gamma_{\mathrm{i}} \,.\, \mathrm{Gap}_{\mathrm{t-1}} + \varepsilon_{t+h}$

Where π is inflation, n is the number of lags of inflation while Gap_{t-1} is output gap and m is the number of lags of output gap and $\varepsilon_{t+\mathrm{h}} =$ an iid regression residual.

To evaluate the forecasting accuracy of the different measures of output gap, we first use model 1 which is a standard linear Phillips Curve specification that relates current inflation to past inflation and to current and past output gaps. According to this specification, inflation develops gradually over time in response to aggregate demand factors as approximated by the different measures of the output gap variable while the residuals capture aggregate supply shocks. Since economic theory does not provide much guidance with regard to the time lag between movements in inflation and output gap, we use a general to specific approach to determine the optimum lag length.

Model 2: $\Delta\pi_t = \alpha_2 + \sum_{\mathrm{k=0}}^{\mathrm{p}} \beta_{2k}\Delta\mathrm{Gap}_{\mathrm{t\text{-}k}} + \varepsilon_{2\mathrm{t}}$

Model 2 relates the changes in inflation to the changes in output gap and as indicated by Claus (2000), this specification constrains the coefficients of the level of output gap to alternate in sign and to sum zero. It is also the case that the change in inflation depends on how fast aggregate demand is growing relative to potential output.

In order to compare the predictive capability of the different models, it is a standard practice in the literature to use benchmarks. In this paper, we use two such benchmark models. First, we use a univariate forecasting model of inflation and will refer this as the autoregressive (AR) benchmark. This specification essentially uses the recent behavior of inflation to predict the future course of inflation in the UAE.

AR: $\pi_{t+h}^{h} = \alpha + \sum_{i=1}^{n} \beta_i . \pi_{t-i}^{1} + \varepsilon_{t+h}$

The second benchmark is also a variation of the first model in which we replace the output gap variable with the real GDP growth rate variable. The inclusion of this variable adds economic foundation as it allows for the use of a larger information set than the AR benchmark.[10] Furthermore, the use of this benchmark provides a somewhat stronger test of forecast performances to assess the models by adding economic structure and other restrictions embedded in the construction of the output gaps. Following along the lines of Orphanides and van Norden (2004), we refer to this benchmark as the TF benchmark forecast and is specified as follows:

[10] This specification is also used by St-Amant and van Norden (1998) and van Norden (1995).

TF: $\pi_{t+h}^{h} = \alpha + \sum_{i=1}^{n} \beta_i . \pi_{t-i}^{1} + \sum_{i=1}^{m} \gamma_{\mathrm{i}} . \mathrm{RGDP_t} + \varepsilon_{t+h}$

5. Forecasting inflation: Empirical results

In this section, we present the estimation results of models 1 and 2 and analyze their out-of-sample forecast performances. The forecasting accuracy of the different measures of output gap is evaluated in terms of their predicting ability of inflation in the UAE and also against the benchmark models. Particularly, we are interested in examining which of the output gap measures produces the best prediction of inflation in the UAE. Most importantly, to effectively evaluate the out-of-sample forecasting ability of the different output gap measures, we divide the data into two sub-samples. The first sub-sample period that starts from 1970 to 1996 is used to estimate the model's parameters, and the second sub-sample that runs from 1997 to 2006 is used for assessing the model's forecast performance. We perform h-step ahead forecast and examine the forecast accuracy of the models using: 1) the mean squared forecast error (MSFE), the mean absolute error (MAE), and the Theil's inequality coefficient, 2) the equal forecast accuracy of Diebold and Mariano (1995) as well as the Modified Diebold and Mariano statistic developed by Harvey, Leybourne and Newbold (1997) and 3) forecast encompassing.

5.1. Out-of-Sample Forecasts

We estimate models 1 and 2 on a sub-sample of the data and evaluate the out of sample forecasts of the different measures of the output gaps obtained from the different statistical methods. Table 1 provides the results of model 1. In order to assess and rank these results, we use the MSFE, MAE and Theil's inequality for comparative analysis. These three statistics are the most commonly used metrics of forecast accuracy in the literature and in general the lower their values are the better is the forecast. Particularly, when these statistics are close to zero, it implies that there is perfect forecast and vice versa

As can be gleaned from Table 1, all the different measures of the output gaps have produced a broadly similar results and it is not surprising that none of these models have outperformed the benchmark models. It appears that the band-pass filter model has performed slightly better than the other models in terms of having higher R^2 and lower values in the MAE and the RMSFE. But, all the output gap measures used in the estimations were statistically insignificant at the 5% level indicating that this variable has no explanatory power in the inflationary dynamics of the UAE. The low R^2s in all the output gap models is indicative that much of the variations remain to be explained. This finding is consistent with the literature in that real factors such as output gaps have no explanatory power in determining inflation in emerging markets (Loungani and Swagel, 2001; El-Sakka and Ghali, 2005; Ramakrishnan and Vamvakidis, 2002).

Although the MAE and the RMSFE are useful in evaluating the forecast performances of the different models, they are not devoid of limitations. Their most glaring shortcoming is that these tests provide purely descriptive statistics by allowing us to rank the forecast accuracy of different models but do not provide much guidance in evaluating whether one model is significantly better than the other. In this regard, we perform the equal forecast accuracy test. Our null hypothesis is that there is no difference in terms of forecast accuracy between the various measures of output gap and the benchmark models. To perform this test, we use the popular Diebold and Mariano (1995) statistic, which is based on a loss function that depends on the forecast errors of the competing models and determines whether one model is significantly better than the other.[11] The results are presented in Table 2 for both in MSE and in MAE with their respective p-values. More precisely, Table 2 displays the results of the formal tests for the differences in equal forecast accuracy between the benchmark models and the four measures of the output gaps in model 1. We observe that the results from the different tests are remarkably similar whether the forecast accuracy is measured in MSE or in MAE and or with those of the benchmark models. Hence, the Table noticeably shows that we fail to reject the null hypothesis of equal forecast accuracy between the models under any conventional statistical levels.[12] This insinuates that in terms of predictive accuracy, the different measures of the output gaps in model 1 and the benchmark models are not statistically different as they provide the same information of the inflation developments in the UAE. The D-M test clearly shows that the different measures of output gap included in the regression equation do not improve considerably the model's forecast precision. This is in concert with our earlier findings.

Turning to model 2, the results are presented in Tables 3 and 4. It is noteworthy to mention that the results in these Tables are very similar to those of Tables 1 and 2. Predominantly, the two models have produced similar statistics in MAE and RMSFE but

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[11] The loss function is defined as $d_t = g\left(e_{1t}\big|_{t-h}\right) - g\left(e_{2t}\big|_{t-h}\right)$ where e_{1t} and e_{2t} are the forecast errors of models 1 and 2 and is measured by using both the MSE and MAE. The null hypothesis for equal forecast error is given by $E(d_t) = 0$ which implies that $\frac{\bar{d}}{\sqrt{\hat{v}(\bar{d})}}$ where $\bar{d} = \frac{1}{n - h + 1}\sum_{t=T+h}^{t=T+n} d_t$ and $\hat{v}(\bar{d})$ is a consistent estimate of the asymptotic variance of $\bar{d}$. $\hat{v}(\bar{d})$ is defined as:

$$\hat{v}(\bar{d}) = \frac{1}{n - h + 1}\left[\hat{\gamma}_0 + 2\sum_{k=1}^{h-1}\hat{\gamma}\,k\right] \text{ where the } \hat{\gamma}_k = \frac{1}{n - h + 1}\sum_{t=T+h+k}^{T=n}\left(d_t - \bar{d}\right)\left(d_{t-k} - \bar{d}\right)$$

. For a detailed discussion on the Diebold and Mariano statistic see Cuñado and Gil-Alaña (2007); Orphanides and van Norden(2004); Slacalek (2004) and Song (2003).

[12] The results of the modified Diebold and Mariano are not reported here, (i.e. since they gave the same results as that of the Diebold and Mariano statistic) but are available upon request.

different statistics in the Theil's inequality and lower R^2. The Theil's U statistic generally assesses the predictive accuracy of a preferred model relative to a naïve no-change model and if it is less than one, then the predictions of the preferred model are more accurate than the naïve no-change model. This statistic indicates that model 2 has performed worse than the other models since its values are close to one.

The test results of equal forecast accuracy between model 2 and the benchmark models are presented in Table 4. First, by inspection, one can observe that the results in Table 4 are very similar to that of Table 2 and do not reveal any distinguishable pattern. Hence, the results in Table 4 support our previous finding that again we are not able to reject the null hypothesis of the equal forecast accuracy.

We now turn to forecast encompassing tests of the different models discussed in section 4. These tests are important in assessing whether the different models contain additional information that is not included in the other models. In essence, the forecast encompassing exercise tests the null hypothesis whether model 1 (i.e. the preferred model) encompasses model 2. If we fail to reject the null hypothesis, then model 2 has no useful or extra information beyond that is provided in the preferred model.[13] Hence, there is no linear combination of the two models that could produce a smaller mean squared error than that of the preferred model. The results of these exercises are presented in Table 5.[14] It is interesting to note that in all the different measures of output gap models we fail to reject the null hypothesis and this implies that the forecasts from model 2 does

[13] When model 1 encompasses model 2, this could also imply that model 2 contains information that is not contained in model 1, so it imperative to test also if model 2 encompasses model 1.

[14] These tests are performed by running the following regressions:

$e_{1t} = \alpha + \lambda(\mathrm{e}_{1t} - \mathrm{e}_{2t}) + \varepsilon_t$ where: e_{1t} is the forecast error of model 1, while e_{2t} is the forecast error of model 2. Hence, the null hypothesis is ; $H_0 : \lambda = 0$ against the alternative that $\lambda > 0$. For details on how to perform these tests, see Harvey et al (1998).

not embody any extra information that would be useful for improving the forecast precision of model 1. However, the band-pass filter and the H-P filter output gaps of model 2 are barely significant at the 5% of encompassing model 1's band-pass and H-P gaps. But, a visual inspection of the calculated p-values in the table indicates that none of the models is able to reject the null hypothesis. This means that the results from the forecast encompassing exercises confirm the previous results and lead to the inevitable conclusion about the lack of usefulness of the output gap measures in predicting inflation dynamics in the UAE. The policy implications of this finding is that assessments of demand pressure based on output gap alone to monitor inflation in the UAE should be used with caution and be supplemented with alternative indicators since this variable is not a good predictor of inflation.

6. Concluding Remarks

The primary purpose of this paper has been to estimate the output gap of UAE and to test its usefulness in predicting inflation. In the process of estimating the output gap, we reviewed and used four different statistical methods to estimate the output gap since it is inherently unobservable. All the different methods have produced a broadly similar profile of the economy and are in agreement regarding the state of the UAE business cycle. More specifically, our results indicate that the estimates of output gaps obtained from the different methodologies share some important similarities as indicated by the high bilateral correlations between them. This insinuates that these different measures contain much the same information about inflation and other macroeconomic variables that monetary policy makers are interested in. To this end, we performed several econometric forecasting tests that are standard in the literature to evaluate whether the output gap variable however estimated is a useful predictor of inflation in the UAE. Our results suggest that the output gap variable is not a good predictor of inflationary dynamics in the UAE. This is consistent with other findings in the literature that output gap is not a useful indicator of inflation in the emerging market economies. The main policy implication is that monetary policy authorities should exercise considerable caution when using output gap to formulate policies. This paper therefore, suggests that assessment of demand pressures in the economy based on the uncertain output gap to monitor inflation could benefit from being supplemented with other indicators. Moreover, since there is considerable uncertainty on the measurement of the output gap, it may be essential to explore alternative approaches that utilize economic theory such as the production function approach or the mixed approach. Last but not least, our results are robust in that we use different statistical methods to estimate the output gap and different forecasting techniques to determine whether this variable is a useful indicator of inflation in the UAE.

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Appendix

Table 1: Forecast evaluation diagnostics:

Model 1	R^2	MAE	RMSFE	Theil's Inequality
LM-Gap	0.23	0.078	0.085	0.54
H-P-Gap	0.24	0.079	0.085	0.53
B-P-Gap	0.32	0.066	0.072	0.65
UC-Gap	0.32	0.082	0.088	0.58
BM1	0.37	0.078	0.087	0.57
BM2	0.43	0.079	0.090	0.57

The LM-Gap is the linear method output gap measure; H-P Gap is the Hodrick-Prescott method output gap; B-P Gap is the band-pass filter output gap and UC-Gap is the unobserved components model output gap, while BM1 and BM2 is the benchmark model 1 and 2 respectively.

Table 2: Diebold and Mariano Test

Test	Linear Model	H-P model	Band-Pass Model	UC Model
DM11 (MSE)	-0.29	-0.21	0.20	0.02
P Value	(0.78)	(0.83)	(0.84)	(0.98)
DM11 (MAE)	-0.00	0.05	0.26	0.40
P Value	(0.99)	(0.95)	(0.80)	(0.69)
DM12 (MSE)	-0.42	-0.36	0.10	-0.21
P Value	(0.67)	(0.72)	(0.92)	(0.83)
DM12 (MAE)	-0.06	-0.02	0.24	0.19
P Value	(0.95)	(0.98)	(0.81)	(0.85)

Notes: DM1 is the Diebold and Mariano statistic based on Model 1 and benchmark models 1 and 2 calculated in both mean squared errors (MSE) and mean absolute errors (MAE). The "P-Value" row denotes p values from the Diebold and Mariano test of forecast accuracy. The regressions are calculated using two lags of variables on the right hand-side and the Diebold and Mariano statistics are based on HAC standard errors with Newey-West window and 2 lags.

Table 3: Forecast evaluation diagnostics:

Model 2	R^2	MAE	RMSFE	Theil's Inequality
LM-Gap	0.12	0.082	0.095	0.91
H-P-Gap	0.14	0.078	0.093	0.94
B-P-Gap	0.28	0.077	0.092	0.88
UC-Gap	0.12	0.085	0.101	0.97
BM1	0.37	0.078	0.087	0.57
BM2	0.43	0.079	0.090	0.57

Table 4: Diebold and Mariano Test

Test	Linear Model	H-P model	Band-Pass Model	UC Model
DM21 (MSE)	0.31	1.57	0.05	1.05
P Value	(0.76)	(0.16)	(0.95)	(0.32)
DM21 (MAE)	0.17	1.22	-0.21	0.82
P Value	(0.86)	(0.26)	(0.83)	(0.43)
DM22 (MSE)	0.16	1.31	-0.05	0.11
P Value	(0.87)	(0.22)	(0.95)	(0.91)
DM22 (MAE)	0.11	0.96	-0.21	-0.13
P Value	(0.91)	(0.36)	(0.83)	(0.89)

Table 5: Forecast Encompassing Test

Test	Coefficient	P. Value
M1LM-Gap on M2LM-Gap	-0.29 (-0.38)	0.71
M1H-P-Gap on M2H-PGap	-1.31 (-1.39)	0.21
M1B-P-Gap on M2B-P-Gap	-0.60 (-0.95)	0.37
M1UC-Gap on M2UC-Gap	0.13 (0.22)	0.83
M2LM-Gap on M1LM-Gap	1.29 (1.67)	0.13
M2H-P-Gap on M1H-PGap	-2.31 (-2.46)	0.05
M2B-P-Gap on M1B-P-Gap	1.60 (2.55)	0.04
M2UC-Gap on M1UC-Gap	0.87 (1.53)	0.16

Notes: M1 in front of the variable stands for model 1 and M2 stands for model 2. values in parenthesis are the t-values of the corresponding coefficients. All the variables are as described before.