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An Estimation of Seasonal GDP Gap in Iran: Application of Adaptive Least Squares Method

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Abstract

This paper estimates the long-term trend of seasonal real GDP in Iran, using a new econometric technique called Adaptive Least Squares (ALS). ALS is a special case of Kalman Filter that allows a time-varying parameter model to be estimated relatively easy. The estimated trend is used to proxy the output gap.

Since the coefficients of the GDP lags are significantly different from zero, the model with intercept and trend and with three lags of the dependent variable has been tested in this article. The comparison of the results of ALS, OLS, HP and Kalman Filter show that the ALS method provides a better estimate. Therefore, it is suggested that the output gap estimation method provided in this paper be used in dealing with the monetary policies.

Keywords: Adaptive Least Squares, Iran, Output Gap, seasonal data.

1- Introduction

Many studies have been done for finding optimum monetary policies. Despite different suggested methods in different articles, all models use output gap variable to find optimum monetary policies. But, not only in Iran, but also in other developing countries, not enough attempts have been

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exerted for the exact estimation of this variable. For the ease of usage, researchers usually use Hodrick-Prescott (HP) Filter.

In this article, a new econometric method named Adaptive Least Squares (ALS) which developed by McCulloch (2005) is used to estimate seasonal output gap in Iran. ALS technique is a modification of the Kalman Filter that allows for a time varying parameter model to be estimated relatively easy. The estimated trend is then used to estimate the output gap. The changes inside the trend are determined by the model, not by the researcher. GDP gap is calculated by distracting GDP from potential output. To calculate this variable, first, potential output should be estimated. Potential output from supply view is the maximum output that the economy can produce without inflation. Estimating potential output is essential in microeconomic models and in the analysis of the performance of exerted policies. It is also a useful tool for evaluating inflationary pressures in goods/services market in short-term. If GDP exceeds potential output level, it reveals inflation pressure. So, contraction policies should be used or else expansion policies should be exerted. This point reveals the effect of accuracy in computing output gap in economic policy-making. Potential output and its deviation extent is one of the pretty new, but challenging discussions in economic analyses. Its importance stems from the fact that nowadays, creating opportunities for economic growth is reducing for discovering and using new productive sources at global level. Thus, researchers look for the ways to utilize present resources in maximum level to reach potential output. In this respect, information about potential output and its deviation can be very useful at directing monetary and financial policies and controlling increasing inflation and unemployment. But, there is no consensus on the methods of measuring deviation from potential output (Kavand and Bagheri, 2008).

The structure of this paper is as follow: Second section reviews potential output and output gap literature. Third section introduces ALS method. Fourth section represents data and econometric methodology. Section 5 calculates gap amount in real seasonal GDP of Iran (from 1986-2010) in the frame of ALS model and compare it with the alternative methods. Section 6 shows the results of calculated output gap by OLS and HP methods and examines their strength and weakness points.

2- Potential output and output gap literature

Output gap results from the difference between potential output and realoutput. Time series of real output data are published by Central Bank of Iran but the potential output have to be computed. Nowadays, output gap is increasingly used in the literature of monetary policies. Despite the differences in suggested monetary rules, Central Bank should know the amount of output gap at every moment. For example, in an article titled “monetary policies knowledge”, Clarida, Gali and Gertler (1999) used New Keynesian Philips Curve to analyze optimum monetary policies. The key component in New Keynesian Philips Curve was inflation expectations and output gap. Their study was an adoption of Taylor’s work (1993) that used output gap for determining optimum monetary policies. Ball, Mankiw and Reis (1988) used Philips Curve with sticky information in which output gap was one of the variables. The dominant technique of calculating output gap is supposing that the linearity of GDP and output gap is calculated as a deviation from calculation deterministic trend. So, GDP stationary is very important, since its non-stationary means the lack of deterministic time trend. In that case, deviation from trend will be insignificant statistically.

Based on the previous results of stationary test, GDP in most countries has I (1) process. This led to creating wide economic literature for proving GDP stationary. Among pioneer studies in this case; Pierre Perron’s articles in 1989 and 1997 can be mentioned. He regarded a structural lag in America’s GDP in 1973. In his idea, this structural lag was created for the shock of increasing oil price. Changing trend slope in 1973, GDP got stationary in %5 level. However, the problem was that instead of selecting structural lag by the data, it was imposed by Perron himself. In the article of 1997, Perron didn’t consider the time of lag occurrence as fixed. This point was regarded as an advance, compared with his previous article. But, the number and type of the lags were determined by the researchers yet. Another drawback of Perron’s method was its inability in predicting future structural lags. In 1989, Hamilton developed a two-state switching regime model for GNP growth. In this model, Markov process was used. Hamilton’s idea was developed by Lam (2004), regarding the probability of two states’ transition during time to remove two existing states. This model had also the drawback of considering just two states for the economy.

Another method of trend determination in a time series which was commonly used was Hodrick-Prescott (HP) Filter. This popular method had two defects. First, it needed giving a diffuse to Lambda parameter. An econometrist should select the period length which he wishes to remove from the trend. Cogley and Nason (1995) found that the cycles, found in filtered data by HP, may be created for the effects of filter itself not for their real existence among the data. The second drawback was its inability in prediction. To prevent from mentioned defects, some researchers have used time-varying parameter (TVP) models in which any structural lag can enter provided that its value changes during time. Moreover, such models have prediction capabilities. Their drawback is that many parameters should be estimated for them. This issue for GDP data can be changed into unsolvable problem since GDP time series are not long enough to provide the possibility of estimating many parameters. To solve this problem, Cooley and Prescott (1973) permit only the intercept to vary over time. Stock and Watson (1998) also exerted a similar process like Cooley and Prescott. Calculation difficulties of potential output are studied in the related literature too. For example, Rudebusch (2002) believes in the uncertainty of computations in previous studies. For modeling this uncertainty in estimating output gap, he supposed that output gap estimation accompanies with some errors. Orphanides (2002) suggested using nominal income in monetary rules' policies because of the uncertainty of potential output estimation.

In Iran, two studies have concerned estimating output gap. Nasr Esfahani, Akbari, and Bidram (2005) computed seasonal GDP gap and its effective factors using HP technique. Likewise Kavand and Bagheri (2008) also used Kalman Filter and HP technique to calculate GDP gap.

Many working papers that have published in IMF website[1] calculated output gap in different countries using various econometrics techniques. For example Oomes and Dynnikova (2006) estimates output gap in Russia using a utilization-adjusted production function approach. Konuki (2008) estimates potential output and the output gap for Slovakia applying two broad sets of approaches: conventional methods, represented by a statistical method and a production function approach; and a multivariate (MV) Kalman filter method. El-Ganainy and Weber (2010) employs several econometric

1- Imf.org

methods to estimate the Armenian output gap. They used the result of output gap to estimate a New Keynesian Phillips Curve for Armenia.

The output gap estimation procedure is divided into two categories: non-Bayesian estimation and Bayesian estimation. Maliszewski (2010) construct a new output gap measure for Vietnam by applying Bayesian methods to a two-equation AS-AD model, while treating the output gap as an unobservable series to be estimated together with other parameters. Magud and Medina (2011) in their working paper estimate the potential output in Chile using several different methodologies. Four univariate methods including piecewise linear trend (LT), HP filter, a Baxter and King band-pass filter and Christiano-Fitzgerald (2003) filter have been used. Among the multivariate procedures, Magud and Medina (2011) use three different versions of Kalman filter. Furthermore they apply three econometric approaches including a production function method, a structural vector auto-regression and the IMF's Global Projection Model. Bersch and Sinclair (2011) compare the output gap estimates for Mongolia based on a number of different methods. Univariate methods includes linear trend, HP filter, Christiano-Fitzgerald Frequency Filter and The Blanchard-Quah (BQ) Decomposition is the only multivariate technique that have been used.

3- Adaptive Least Squares (ALS)

Adaptive Least Squares (ALS) is an adoption of Kalman Filter, introduced by McCulloch (2005) for estimating variable relations in time. This estimation technique has some advantages in comparison with mentioned methods in previous section. ALS method enables the researcher to regard all model parameters as variable in time without confronting him with the problematic reduction of freedom degree; because, the only parameter estimationρ determines model behavior.Therefore, ALS has all the advantages of variable models in time without a basic drawback of them. Another advantage of it is that in such technique all parameters are variable in time while in previous models only fixed components are time -varying. This ALS feature means that time series can have infinite states. This feature leads to solving the problem of Markov-Switching Models in which time series are limited to two states.

Superiority of ALS to HP filter is in two cases. First, despite HP, in ALS there is no need to impose arbitrary diffusion smoother parameter. Another issue is ALS predictability. In ALS, data analysis is done by two methods: ALS filter method and ALS smoother. ALS filter only uses previous data. So, estimation adoption speed lengthens with real data but in return it is more exact. ALS smoother uses both past and future data. The speed of proxy adoption with real data is higher and estimated trend line has less volatility. Both methods are useful. But, this study uses only ALS Filter to prevent extra length. For detailed explanation of ALS, one can refer to McCulloch (2005). A public frame for time-based models is linear regression model with time-varying parameter (TVP) in the following form:

$$y_t = x_t \beta_t + \varepsilon_t \qquad \varepsilon_t \sim NID(0, \sigma_\varepsilon^2)$$

$$\beta_t = \beta_{t-1} + \eta_t \qquad \eta \sim NID(0_{k\times 1}, Q_t) \tag{1}$$

Where X_t is a 1×k row vector of ideally exogenous explanatory variables. β_t Is a k×1 column vectorof time-varying coefficient in time t and η_t is a k×1 column vector of transition errors which are independent of observation errors. y_t is t×1 vector of dependent variables observed up to and including time t. ordinarily the first element of each X_t is unity, so that the first element of β_t is the intercept. So, Q_t is k×k covariance matrix of transition errors η_t. Equation 1 can be solved by extended Kalman Filter.

$$\beta_t | y_t \sim N(b_t, P_t) \tag{2}$$

Where, P_t is a covariance matrix. Time varying equation system 1 and its answer are too general for the purpose of this study. Because, even if Q_t is time- varying, k(k+1)/2 time- varying random parameters and observation variance σ_ε^2 exist that should be estimated. ρ Is scalar uncertainty index of transition errors compared with observation errors and calculated from equation 3 shows effective sample size:

$$T_t = (1 + \rho T_{t-1})^{-1} T_{t-1} + 1 \tag{3}$$

It must be remembered that in LLM[1], noise variance (i.e. observation error) is related to that of estimation errors at time t-1 by

$$\sigma_{\varepsilon}^{2} \equiv T_{t-1}\sigma_{t-1}^{2} \tag{4}$$

In LLM, Q_t is a 1×1 matrix σ_{η}^{2} and P_{t-1} is simply σ_{t-1}^{2}, so that the variance of the signal, i.e. the scalar transition error η_t is given by:

$$Q_t = (\sigma_{\eta}^{2}) \equiv \rho(\sigma_{\varepsilon}^{2}) = \rho T_{t-1}(\sigma_{t-1}^{2}) = \rho T_{t-1}P_{t-1} \tag{4}$$

In TVP model, we suppose that $T_{t-1}P_{t-1}$ measuresthe measurement error per effective observation as of time t-1, just as does in the LLM, and thus that the transition covariance matrix Q_t of η_t that exists in equation 1, is as follows:

$$Q_t = \rho T_{t-1}P_{\ t-1} \tag{5}$$

When random coefficients model (1) only includes an intercept term and no regressors, equation 5 becomes 4.

Under specification 5, extended Kalman Filter is simplified in the following form:

$$b_t = W_t^{-1}z_t \tag{6}$$

$$P_t = \sigma_{\varepsilon}^{2}W_t^{-1} \tag{7}$$

Where,

$$z_t = (1+\rho T_{t-1})^{-1}z_{t-1} + x_t'\,y_t \tag{8}$$

$$W_t = (1+\rho T_{t-1})^{-1}W_{t-1} + x_t'x_t \tag{9}$$

And T_t is updated as in equation 3.

If there is a diffuse prior about the coefficients at time 0, the initial covariance matrix P_0 is infinite in all its eigenvalues or equivalently, the precision or information matrix P_0^{-1} is all zeroes, hence:

1- Local Level Model (LLM) is a prerequisite of ALS. To avoid lengthening, it is not mentioned in the article. In the case of need, one can correspond to the author or refer to McCulloch (2005).

$$W_0 = 0_{k \times k} \tag{10}$$

For any choice of b_0 (6) then implies

$$z_0 = 0_{k \times 1} \tag{11}$$

With such a diffuse prior, W_t is of rank t for t<k and hence b_t and P_t may only be computed for $t \geq k$. Note that in the fixed coefficient case $\rho = 0, z_t$ then becomes $X_t' y_t, w_t$ becomes $X_t' Y_t$, and (6) becomesthe familiar OLS formula $(X_t' X_t)^{-1} X_t' Y_t$

Having thus initialized and updated the filter, the prediction error decomposition will be:

$$y_t \,|\, y_{t-1} \sim N(x_t b_{t-1}, \sigma_\varepsilon^2 s_t^2) \tag{12}$$

Where

$$s_t^2 (1 + \rho T_{t-1}) x_t W_{t-1}^{-1} x_t' + 1$$

The log likelihood is then

$$L(\rho, \sigma_\varepsilon^2 \,|\, y_t) = \sum_{t=k+1}^{n} \log p(y_{t-1})$$

$$= -\frac{n-k}{2} \log(2\pi) - \frac{n-k}{2} \log \sigma_\varepsilon^2 - \sum_{t=k+1}^{n} \log s_t - \frac{1}{2\sigma_\varepsilon^2} \sum_{t=k+1}^{n} u_t^2 \tag{13}$$

Where the scale-adjusted residuals

$u_t = e_t / s_t$

Equal the actual predictive errors,

$$e_t = y_t - x_t b_{t-1}$$

Adjusted by their time–varying scales S_t. under the maintained assumptions, these adjusted residuals are homoskedastic with variance σ_ε^2, even though the predictive errors themselves are highly heteroskedastic. As in the LLM, the observation variance σ_ε^2 may be concentrated out of the log likelihood function in such a way that for any value of ρ, the likelihood is maximized with σ_{ε}^{2} estimated in closed form by (14):

$$s_{\varepsilon}^{2}=\frac{1}{n-k}\sum_{t=k+1}^{n}u_{t}^{2} \tag{14}$$

A numerical maximization search is then required only over the single parameter ρ.

If the model is well-specifies and ρ equal to its true value, the adjusted residuals u_t must be $iidN(0,\sigma_{\varepsilon}^{2})$. Since hyperparameter ρ is consistently estimated by ML, routine large-sample specification tests such as Q statistics, Jarque-Bera test, and etc. may be applied to these, as noted by Durbin and Koopman (2001).

It can easily be shown, setting $R_t = W_t / T_t$, that the ALS filter (13)-(16) is equivalent to the variable gain Recursive Least Squares (RLS) formula

$$b_t = b_{t-1} + \gamma_t R_t^{-1} x_t (y_t - x_t b_{t-1}) \tag{15}$$
$$R_t = R_{t-1} + \gamma_t (x_t' x_t - R_{t-1}) \tag{16}$$
$$P_t = \gamma_t \sigma_{\varepsilon}^{2} R_t^{-1} \tag{17}$$

In fixed coefficients case that is equivalent to OLS, the gain γ_t in (15)-(17) is 1/t. The previous AL literature (e.g. Sargent 1993, eq.10 or Evans and Honkapohja 2001, eq. 2-9) commonly replaces this gain by a constant γ as in Cogan's original adoptive expectations formulation (1).

4- Data and Econometric Methodology

4-1- Data

This article uses seasonal GDP in Iran in fixed prices of 1997, published by Central Bank of Iran (fig.1). Seasonally data shows economy's fluctuations more accurately. Seasonally or quarterly data refers to data that are collected on a monthly or quarterly basis. Iran's quarterly GDP has oscillatory properties and characteristics of the cosine over the years. It's arises from the way that data have been adjusted. This means that the seasonal data are the results of the different methods of changing the annual data to seasonal ones. These methods include Kalman Filter, Lisman and

Sander technique or a combination of these two approaches. Another useful method to turn annual data to quarterly has been suggested by Tabibian (Tabibian, 1997). Comparing two successive seasons isn't true, and just the same seasons in different years can be compared with each other. (Nasr Esfahani et al., 2004)Quarterly GDP data there are only since 1986.The continuous increases in quarterly GDP between 1986 and 2008 is due to the relative stability of the economy after the war and positive oil price shocks.

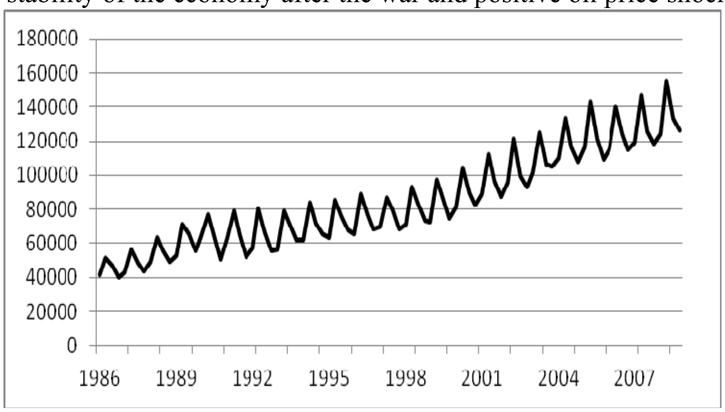

Fig 1: Seasonal GDP of Iran in Fixed Prices of 1997(in Billion Rials)

Source: central bank of Iran

4-2- Methodology

First, the stationarity of GDP was examined which is a function of an intercept in time t(α_t), linear trend with variable slope in time $(\beta_t t)$ and unlimited lags of dependent variable AR (P) with variable coefficients in time t $(\gamma_{i,t})$.

Determining the number of optimum lags of dependent variable, the estimation is done with ALS Filter. Although in most articles, GDP of Iran revealed I(1) process, but testing unit root of this study revealed different results. For testing unit root, stationarity test of Becker, Enders and Lee was used which was based on KPSS test. Necessary program was written in Gauss to perform the unit root test. The KPSS test statistics was 0.0252 for 92seasonal observations with critical value of 0.1386 at1% level through the use of GAUSS software. Null hypothesis of this test implies stationarity. So, Null hypothesis of GDP stationarity can't be rejected. If output variables stationarity would be rejected, the difference between real and estimated values couldn't be used for estimating output gap.

The number of optimum lags of dependent variable is determined by Eviews software. AIC statistics shows 3 lags of dependent variable but the final model doesn't necessarily contain optimum determined lag by AIC statistics; because, the hypothesis of time-varying coefficients being zero for some or all of the lags can't be rejected. Based on the given data, any (or even zero) number of lags (maximum to the determined lag by AIC) may be selected.

In the following section, it is seen that for seasonal data of GDP in Iran, final estimated model has all three dependent variable lags. Based on the output gap definition as the difference between potential and practical output, it seems that the lack of dependent variable lags provides a better proxy of output gap, since in this methodology GDP is regarded including a trend and cyclical component. The sum of intercept and trend line $(\alpha_t + \beta_t t)$ (show trend component and output gap reflects cycle component. If GDP lags are used for explaining for its own definition, a part of GDP changes that can alter trend and cyclical components is explained by the lags. This reduces explanatory power of trend and cyclical components as well as the accuracy of output gap estimates. A seen in Fig.2, and Fig. 3, a very exact proxy of dependent variable can be given without using dependent variable lags.

5- Model estimation

5-1- ALS Estimation

Specified model has an intercept, a trend and three dependent variable lags:

$$y_t = \alpha_t + \beta_t t + \gamma_{1,t} y_{t-1} + \gamma_{2,t} y_{t-2} + \gamma_{3,t} y_{t-3} + u_t \tag{18}$$

Based on the logic of ALS method, parameters coefficients and intercept are time-varying. So, for testing null hypothesis based on the coefficients of model lags being zero, a confidence interval as much as a standard deviation was used, since all coefficients in ALS method are time-varying. If the coefficient value in the range of a standard deviation is zero for all examined times, null hypothesis implying lag coefficient being zero can't be rejected. For all lags in model 18, null hypothesis can be rejected. This means that the model will have three lags. The results of ALS filter estimate from model 18 are as follows:

$$\rho = 2.129583, s.e.\ of\ \rho = 1.181687$$

$$effective\ samplesize = 1.348278,\ s.e.\ of\ it = 1.153584$$

$$LR = 125.771958, \qquad criticalvalue = 2.3$$

LR value shows that with 95% confidence, null hypothesis implying $\rho = 0$ or the lack of variables changes during time can be rejected. ALS

Filter estimate of real and estimated GDP of model 18 are shown in figures 2 and 3.

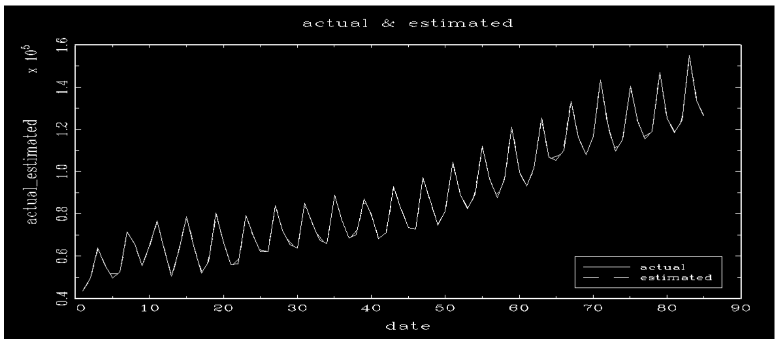

Fig 2: Estimated and Real Values of Seasonal GDP by ALS Filter (eq. 18 and Gauss Output)

Filter estimate of model 18 for seasonal data along with real GDP value have been shown in Fig. 3. The full line shows real GDP and dotted line shows ALS filter estimate of trend relation for GDP with an intercept. In the following table, estimated and real values of seasonal GDP and their difference which equals output gap are shown. ALS estimation of time-varying intercept α_t and time-varying coefficient of trend β_t are shown in figure 4. The full line in figure 4 shows α_t and dotted line shows ALS filter estimate of β_t .

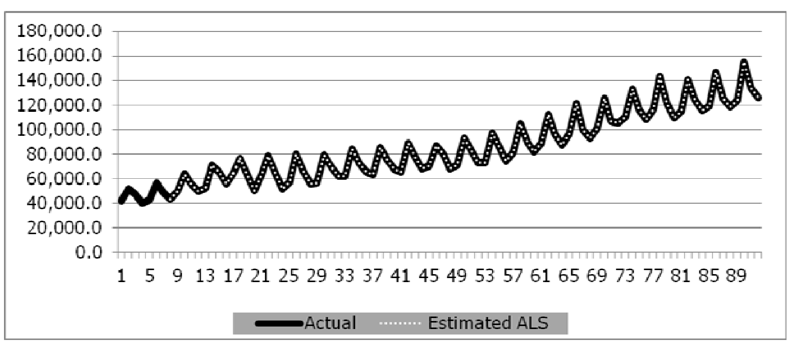

Fig 3: Estimated and Real Values of Seasonal GDP by ALS Filter (eq. 18 and Microsoft Excel 2010 Output)

Resource: Study results

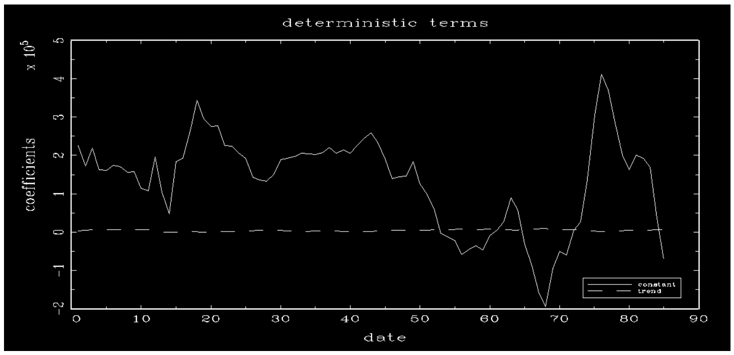

Fig 4: Estimated Values of α_t and β_t

Resource: Study Results

Table 1: Estimated and Real Values of Seasonal GDP and Output Gap (in Billion Rials) and Output Gap/ Real Value Percentage

Year	Real GDP	Estimated Value	Output Gap	(GAP/Real GDP)*100
1986	49498.61	49495.3	3.309	0.007
	63782.29	63774.58	7.715	0.012
	55657.79	55652.26	5.529	0.010
	49600.03	49594.91	5.118	0.010
1987	52537.39	52540.31	-2.92	-0.006
	71255.84	71256.22	-0.384	-0.001
	65680.43	65678.03	2.401	0.004
	55562.88	55563.12	-0.241	0.000
1988	64628.8	64619.78	9.017	0.014
	76672.7	76679.3	-6.602	-0.009
	63095.45	63138.15	-42.701	-0.068
	50425.47	50432.53	-7.062	-0.014
1989	63252.07	63262.41	-10.338	-0.016
	78787.11	78780.06	7.055	0.009
	64658.19	64658.84	-0.645	-0.001
	51904.05	51886.71	17.338	0.033
1990	57417.77	57418.79	-1.024	-0.002
	80229.16	80230.9	-1.741	-0.002
	66266.75	66265.54	1.212	0.002
	55962.7	55962.92	-0.22	0.000
1991	56296.71	56291.99	4.72	0.008
	79243.59	79244.61	-1.017	-0.001
	69845.96	69843.29	2.67	0.004
	62148	62144.82	3.185	0.005
1992	62160.41	62152.68	7.733	0.012
	84013.58	84000.9	12.679	0.015
	72252.98	72252.48	0.504	0.001
	65379.51	65383.09	-3.575	-0.005
1993	63703.05	63709.46	-6.41	-0.010
	85112.95	85117.34	-4.391	-0.005
	75282.74	75283.44	-0.695	-0.001
	67669.9	67671.25	-1.349	-0.002
1994	65813.79	65813.53	0.261	0.000

	88894.28	88890.87	3.411	0.004
	76997.94	76998.52	-0.577	-0.001
	68433.81	68435.56	-1.753	-0.003
1995	70124.5	70122.85	1.652	0.002
	86920.16	86926.3	-6.143	-0.007
	79721.32	79719.96	1.363	0.002
	68175.46	68179.72	-4.257	-0.006
1996	71066.32	71069.62	-3.295	-0.005
	92868.2	92857.1	11.105	0.012
	82832.87	82831.39	1.483	0.002
	73301.31	73295.53	5.777	0.008
1997	72969	72966.23	2.771	0.004
	97294.6	97295.54	-0.938	-0.001
	85633.9	85634.09	-0.19	0.000
	74667.7	74671.79	-4.086	-0.005
1998	81367.96	81362.48	5.476	0.007
	104612.5	104605.9	6.611	0.006
	89414.21	89410.79	3.42	0.004
	82275.45	82267.48	7.965	0.010
1999	89147.16	89146.09	1.066	0.001
	112161.5	112160.6	0.877	0.001
	96684.63	96680.71	3.921	0.004
	87635.98	87637.46	-1.484	-0.002
2000	96228.97	96230.16	-1.183	-0.001
	121171.3	121170.1	1.207	0.001
	99775.92	99779.83	-3.903	-0.004
	93253.26	93254.35	-1.087	-0.001
2001	101599.1	101601	-1.954	-0.002
	125284	125289	-4.998	-0.004
	106748.2	106745.3	2.845	0.003
	105268.9	105259.9	9.069	0.009
2002	110137.7	110131.9	5.728	0.005
	133260.3	133253.6	6.725	0.005
	116427.2	116422.8	4.417	0.004
	108104.5	108114.7	-10.16	-0.009
2003	116555.2	116559.2	-4.037	-0.003
	143461	143460.3	0.682	0.000
	121395.9	121401.1	-5.259	-0.004
	109686.8	109688.3	-1.518	-0.001
2004	115324	115331.7	-7.683	-0.007
	140573	140583.4	-10.406	-0.007
	123972	123980	-7.981	-0.006
	115397	115393.1	3.898	0.003
2005	119051	119044.9	6.149	0.005
	146864	146847.2	16.782	0.011
	125472	125469.8	2.153	0.002
	118507	118509.6	-2.578	-0.002
2006	124147	124146.4	0.568	0.000
	155075	155072.9	2.139	0.001
	133778	133770.8	7.243	0.005
	126219	126212.1	6.905	0.005

Resource: Study Results

All estimations were done by GAUSS software version9 (GAUSS 9.0,0). The suggested model has been estimated using ALS filter estimate, introduced by McCulloch (2005).

Focusing on the right column shows that the output gap as a percentage of real GDP is very low in all the period. This shows the ALS method’s power to estimate the potential output. Maximum output gap as a percentage of real output never reaches 0.06% in the highest state. On the other hand, this result shows the relative stability of economy after 1986. This result was expected; since, from 1977-1986, Iran’s economy was exposed to successive shocks of oil price increase, Islamic Revolution, imposed Iraq War, and their repercussions. It is expected that these issues prevent the economy from its long-term trend, increasing output gap In Iran. But after Iraq war, general condition of economy tend to stability and output gap rate has never exceeded 0.06% of real output gap. This result agrees the general conditions of Iran’s economy because since 20 years ago up to now, Iran’s economy has found relative stability with an increasing trend. So, output gap has also decreased.

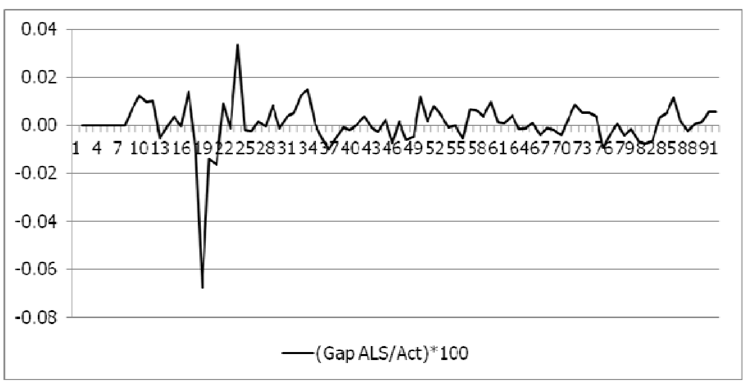

Fig 5: Output Gap (ALS Filter) as a Percentage of Real Output

Resource: Study Results

5-2- Comparing ALS Filter and the Alternative Methods

As mentioned, ALS method is one of the newest computation methods of unobservable variables such as output gap. There is no consensus on the best estimation method but this study showed that ALS method yields better results than HP Filter, Kalman Filter and ordinary least square method. To prove this claim, the results of mentioned methods are compared. Fig.6 show that the ALS yields better results comparing with OLS method but the sign of output gap in two methods completely differs. Figure 7 show that the ALS and Kalman filter estimation of output gap are too close together. The sign of output gap matches in two methods.

Considering Figure 8 show that the sign of output gap in two methods – OLS a.nd HP- are identical.

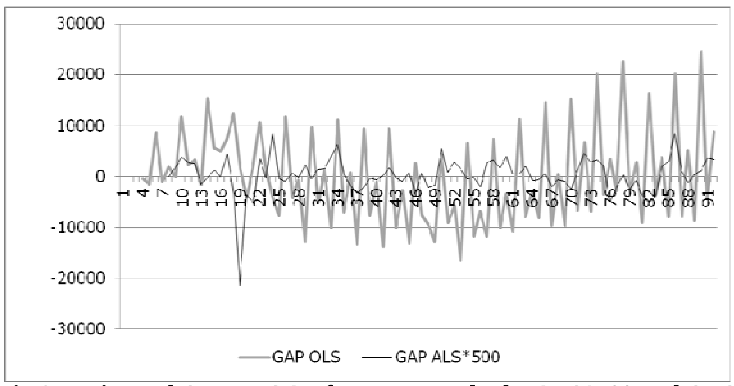

Fig 6: Estimated Output GAP from two methods: ALS*500 and OLS

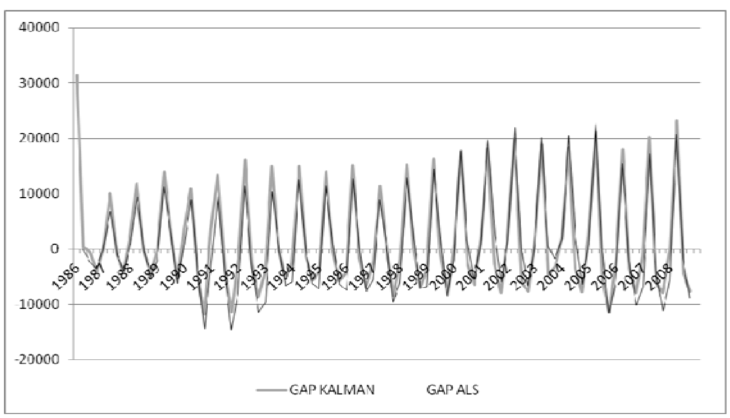

Fig 7: Estimated Output GAP from ALS and Kalman Filter

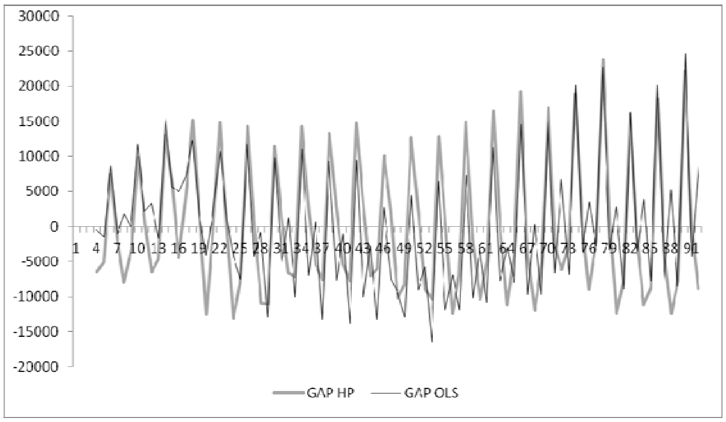

Fig 8: Estimated Output GAP from OLS and HP Filter

Resource: Findings of this study

These results may interpret in two conflicting ways. First, because of accuracy of ALS technique and Kalman filter, we would result that the sign of output gap of these two techniques is true and trustable; therefore OLS and HP results should be abandoned. The other result is that because the signs of output gap of two methods –OLS and HP filter- are similar and different from the two others, the ALS and Kalman filter results should not be trusted.

Because the HP filter can't estimate GDP trend from an equation like (18), an specification for potential GDP without lags has been written:

$$y_t = \alpha_t + \beta_t t + u_t \qquad (19)$$

With such an equation, all three methods can be compared through RSS. If the specification of GDP got the form of equation (19), then, output gap equals error term of regression equation estimation. Estimation accuracy means the smaller error term which is used in the form of RSS for calculating R^2. In estimating equation (19), the smaller the output gap, the more exact the estimation will be. This issue can be a measure for comparing estimation methods of output gap but this has also a drawback. For example, because of smaller RSS of first method compared with second method, estimation error of first method may be more than the second one. But if error component didn't show a specific variable, the same RSS would be enough for comparison. Now, if along with RSS estimation error value is compared during the period, this defect can be removed; since output gap of four methods can be compared based on the years using the chart. RSS values for four methods of ALS, Kalman filter, HP and OLS include 7,363,344,774(about 7.3billion), 7,526,329,217 (about 7.5 billion), 8,464,832,813 (about 8.4 billion) and 10,878,848,341 (about 10.8 billion) respectively. So, RSS value of ASL method is smaller than others. Therefore, it can be claimed that ALS estimation is more exact than three others.

6- Conclusion

Output gap is an important factor in economic policy makings, especially after Taylor (1993) work about monetary rules. Therefore accurate estimation of this variable can improve the results of monetary policies. Hence the output gap is an unobservable variable, before using it in any economic model, one have to estimate it. In this paper, the ALS technique has been introduced, and then we show that its results are more accurate than three other methods, Kalman filter, HP filter and OLS deterending.

It is observed that in all years, output gap of ALS method is smaller than three other methods, revealing more accuracy of this method. Fig. 2 to 8 complement above points and show the estimations of four methods of output trend line or potential output. Although used model in ALS lacks the lag of dependent variable, it can offer an exact output estimate in a way that ALS estimate and real output intersect during the period. Based on the findings, it can be concluded that in equal conditions, represented estimates by ALS Filter is more exact than other estimates. So, this can replace the existing methods for estimating unobservable variables like output gap or inflation gap.

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