Estimations of Output Gap and its Role in the Inflation Targeting Model

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Chapter I

Introduction

Philippine monetary policy makers have been avid fans of output gap stability post the financial crisis. As highlighted in Siok Kun Sek's (2009) empirical work on the reaction of the monetary policy of an inflation-targeting-country to exchange rate changes, Philippines "pays higher concerns on output gap stability" even though an inflation-targeting regime has been implemented. This may be due to the intuitive relationship between output gap and inflation. Output gap is the difference between the economy's actual output and potential output and the actual output (Yap, 2003), where potential output is a function of expected productivity and labor force. If actual real GDP exceeds the potential then upward pressure will be put on production costs, especially labor costs, therefore leading to higher prices of commodities. The usefulness of output gap in inflation targeting has been the subject of many research studies on monetary policy. In the Philippines, Yap (2003), McNelis and Bagsic (2007) and Besinio (2007) try to assess the significance of output gap in inflation targeting. Since the output gap is not directly observable they use different ways of estimating output gap. Although they have different estimations, their results show that in general, output gap, combined to the leading indicators of inflation such as growth of broad money, nominal wages and oil prices, can be significant in the inflation model.

In this paper, the authors will examine the validity of the aforementioned findings at present. They will also assess the degree of the output gap's significance in the inflation model through observing its role in inflation targeting in both quarter and annual basis. The data to be used for the quarter models are from 1994 while the data for the annual data are from 1980[1]. Furthermore, in order to estimate the Philippine output gap, the authors employ univariate models such as (1) Quadratic time, (2) Hodrick-Prescott filter and multivariate structural models such as the (3) Structural Vector Autoregresive and (4) Cobb-Douglas function. The generated output gap estimates are then used as an additional explanatory variable to the existing inflation model currently used by the Bangko Sentral ng Pilipinas (BSP) and to the proposed inflation model of the authors.

[1] The difference in the time frame of the general models is due to data availability.

Chapter II

Review of Relevant Literature

Inflation Targeting in Other Countries

Inflation targeting is a macro-monetary policy, which aims to lower and stabilize inflation at a specific target or range, to improve credibility and transparency of the central bank, and to enhance accountability of the central bank. It induces different outcomes in different countries. This signifies that inflation targeting is not a one-size-fits-all monetary policy. Its effectiveness depends on the situation and circumstance of a certain country. In addition, central banks of other countries may have other monetary targets aside from inflation.

Based on the study of Ghazanfar and Sevcik entitled "Inflation Targeting Policies in Less-Developed Countries: Some Evidence and Potential," the effects of inflation targeting was observed to differ between developed and less-developed countries, since inflation targeting is seen to be more effective in less developed countries like Chile, Peru, South Korea, and Mexico than in developed countries like Canada, Sweden and United Kingdom. The reason for this was developed countries implemented inflation targeting during the time when their inflation rates are at lower levels and stable, and when their central banks are perceived to be reliable by the people. This eventually led to less influence and impact of the policy to their inflation rates. On the other hand, less-developed countries applied inflation targeting, when their inflation rates were at double-digits and when their governments were not entirely trusted by the people. This ultimately gave room for the employed policy to enhance the transparency, credibility and accountability of their governments through the achievement of stable inflation rates. In addition, cross-country studies proved that less-developed countries which have inflation targeting as policy have lower and stable inflation compared to those who do not employ inflation targeting, and using the time series approach, it was proven that throughout time, inflation rate remains stable if inflation targeting is implemented.[2]

Another study named "Interactions between Monetary Policy and Exchange Rate in Inflation Targeting Emerging Countries: The Case of Three East Asian Countries" by Siok Kun Sek focused on the East Asian countries, Thailand and Korea. Thailand and Korea shifted to inflation targeting as the focus of their monetary policy after the Asian Financial Crisis in 1997. However, the monetary policies of these two countries were said to target exchange rate more than inflation rate. To prove this claim, two econometric methods, which are structural vector autoregression or SVAR and Generalized Method of Moments or GMM, were applied. Results showed that exchange rate is not significantly affected by

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[2] Ghazanfar, S. M. and Candelaria L. Sevcik. 2008. "Inflation Targeting Policies in Less-Developed Countries: Some Evidence and Potential." *The Journal of Social, Political, and Economic Studies* 33 (1): 71-83. http://search.proquest.com/docview/216800903?accountid=28547.

monetary policy in Korea after adopting the inflation targeting regime. On the other hand, in Thailand, exchange rate was significantly influenced by monetary policy, based on the econometric results. This was due to the fact that before the Asian Financial Crisis, Thailand adopted a fixed exchange rate, and just shifted to a floating exchange rate regime after the said financial crisis. In addition, the monetary policies of Korea and Thailand influenced inflation after the financial crisis in 1997, which signifies that Korea and Thailand really adopted inflation targeting as what they have claimed.[3]

Thus, inflation targeting may be effective in some countries, and may not generate an impact in other countries similar to the case between developed and developing countries. In addition, some countries like Thailand may use other monetary policy tools aside from inflation targeting to stabilize prices and the economy. However, in general, inflation targeting is helpful in stabilizing and lowering prices.

Inflation Targeting in the Philippines

The Philippines is one of the countries that has adopted inflation targeting for the stabilization of prices. However, before it shifted to inflation targeting, the said country started off with targeting monetary aggregates.

From the 1980s up to the early 1990s, the Bangko Sentral ng Pilipinas (BSP) or the central bank of the Philippines focused on monetary aggregate targeting or controlling money supply to achieve price stability, since based on the Quantity Theory of Money, money supply has a direct relationship on inflation. However, after the financial liberalization in 1993, relationship between money supply and inflation weakened, and supply-side factors had more influence on inflation, based on the studies done by Diwa Guinigundo, present deputy governor of BSP. Because of this, the BSP modified its monetary framework, which is a mix of monetary aggregate targeting and inflation targeting, in 1994. Even though this was the claim of the BSP, monetary policy in the Philippines using the modified framework focused more on inflation targeting rather than monetary aggregate targeting, since the BSP provided flexibility for money supply target not to be achieved, according to Maria Socorro Gochoco-Bautista. Based on the Granger causality test results of Gochoco-Bautista with data from 1996 to 2001, exchange rate had the greatest impact on inflation, and vice versa. Term reverse repurchase rates also affected inflation. In addition, both exchange rate and inflation influenced growth of reserve money.[4]

In 2002, BSP officially shifted to inflation targeting. The inflation forecasting process at the BSP always starts with the central bank announcing its inflation target two years

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[3] Sek, Siok Kun. "Interactions between Monetary Policy and Exchange Rate in Inflation Targeting Emerging Countries: The Case of Three East Asian Countries." *International Journal of Economics and Finance* 1, no. 2 (2009): 27-44. http://search.proquest.com/docview/820912151?accountid=28547.

[4] Gochoco

ahead. This implies that discussions at BSP regarding monetary policy are focused on monthly forecasts two years forward of the inflation rate and on other developments and factors that might affect inflation expectations. In addition, central bankers also make use of models in inflation targeting. At BSP, some of the models used in inflation forecasting are the Multi-Equation Model (MEM) and the Single-Equation Model (SEM). The MEM is comprised of eight behavioral equations and four identities, wherein all of these equations capture output gap in a limited way, while the SEM is composed of inflation rate as the dependent variable; and M4/nominal GDP, the national government's cash position, 91-day Treasury bill rate, domestic oil price, nominal wage, non-oil import prices and a dummy variable representing the rice crisis in 1995 as independent variables.[5]

However, a study done by Siok Kun Sek entitled "Interactions between Monetary Policy and Exchange Rate in Inflation Targeting Emerging Countries: The Case of Three East Asian Countries" proves that the Philippines after it shifted to inflation targeting in 2002 still does not target inflation. This result is based on econometric results using SVAR and GMM. In addition, the results also show that the monetary policy of the Philippines influences significantly output gap rather than inflation. Thus, the Philippines is said to be not focusing on inflation targeting as what it has claimed.[6]

The Philippines has shifted from monetary aggregate targeting to inflation targeting, similar to what other countries are doing to stabilize prices. However, some studies show that the Philippines does not implement what it claims. This implies that the Philippines does not have inflation targeting as its dominant monetary policy framework.

Output Gap and Its Influence in Inflation Forecasting

A lot of factors influence inflation. In the case of the Philippines, inflation is said to be influenced by M4/nominal GDP, the national government's cash position, 91-day Treasury bill rate, domestic oil price, nominal wage, non-oil import prices, and many more variables. However, the mentioned factors impact demand, which is just one component that influences inflation. Another factor that invisibly affects inflation is output gap. Thus, researchers and central bankers argue if output gap has a significant impact on inflation or does not have any influence on inflation at all.

The output gap is considered as the difference between the economy's actual output and potential output, wherein potential output is the ideal level of production given existing labor, capital and technology. Potential output provides enough for existing

[5] Paul D. McNells and Cristeta B. Bagsic, "Output Gap Estimation for Inflation Forecasting: The Case of the Philippines,"*BSP Working Paper Series* no. 1 (August 2007): 1-27.

[6] Sek, Siok Kun. "Interactions between Monetary Policy and Exchange Rate in Inflation Targeting Emerging Countries: The Case of Three East Asian Countries." *International Journal of Economics and Finance* 1, no. 2 (2009): 27-44. http://search.proquest.com/docview/820912151?accountid=28547.

demand, which signifies that it does not impose pressure on inflation.[7] Because of this, a positive output gap, wherein there is deviation between actual and potential output, can be said to be a signal of inflationary pressure that is not visible in actual inflation. In curbing inflation, the central bank usually can control interest rates, which affects demand, but not potential output. Thus, the central bank should determine if output gap should be taken into consideration in inflation forecasting.[8]

Potential output is not easily observed, which implies that there are difficulties in estimating output gap. Because of this, different methodologies are adapted to estimate potential output and output gap. There are three approaches in measuring output gap. These three approaches are statistical or atheoretical, structural and mixed. Statistical or atheoretical approach uses actual data on output to estimate potential output, while structural approach utilizes economic theories like constructing a production function to derive potential output. On the other hand, mixed approach combines atheoretical and structural approach. Some of the atheoretical approaches are time trend method, Hodrick-Prescott (H-P) filter and unobservable components method (UC), while the Cobb-Douglas production function is an example of a structural approach.[9]

In the study of Josef T. Yap of Philippine Institute for Development Studies (PIDS), linear trend, H-P filter and unobserved components model were used to measure output gap. On the other hand, in measuring inflation or the logarithm of the Consumer Price Index (CPI), Yap utilized the error correction model with the following independent variables: (1) logarithm of the Dubai price of crude oil, (2) logarithm of exchange rate, (3) logarithm of broad money supply, (4) square of time trend, and (5) output gap. Results showed that all of the output gaps derived from the time trend method, H-P filter and UC method have a significant impact on inflation. In addition, the output gap from the time trend method had improved more the fit or the adjusted R-square of the inflation model compared to the other estimated output gaps.[10]

In 2007, the BSP also conducted a study on estimating output gap and its impact or importance on inflation forecasting. They used Hodrick-Prescott (HP) filter, constant elasticity of substitution (CES) production function and structural vector autoregression (SVAR) to measure the output gap. Results illustrated that the estimated output gap using SVAR is more volatile compared to that of HP filter and CES production function. On the other hand, they employed alternative models, in-sample performance and out-of-sample performance in determining if output gap has an impact on inflation. All three estimated output gaps were said to have a significant relationship with inflation. Therefore, the

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[7] Josef T. Yap, "The Output Gap and Its Role in Inflation-Targeting in the Philippines," *Philippine Institute of Development Studies (PIDS)* (Publication date): page nr.

[8] Paul D. McNells and Cristeta B. Bagsic, "Output Gap Estimation for Inflation Forecasting: The Case of the Philippines,"*BSP Working Paper Series* no. 1 (August 2007): 1-27.

[9] Josef T. Yap, "The Output Gap and Its Role in Inflation-Targeting in the Philippines," *Philippine Institute of Development Studies (PIDS)* (Publication date): page nr.

[10] Ibid.

central bank should take into consideration the importance of output gap in inflation forecasting.[11]

Aside from demand factors, output gap also has an impact on inflation, based on the results of different studies. Thus, the central bank should take output gap into consideration in inflation modelling and targeting.

[11] Paul D. McNells and Cristeta B. Bagsic, "Output Gap Estimation for Inflation Forecasting: The Case of the Philippines,"*BSP Working Paper Series* no. 1 (August 2007): 1-27.

Chapter III

Methodology

Estimation of output gap

Output gap can be calculated using the formula:

$$\text{Output gap}^{12} = \frac{\text{Actual output (Y) - Potential output (Y*)}}{\text{Potential Output (Y*)}}$$

It is mainly composed of actual and potential output (GDP[13]), wherein the potential output is based on the expected productivity and labor force. Nonetheless, potential output is difficult to estimate. Hence, the estimation of output gap can follow several approaches such as the application of a univariate procedure and the use of production functions which require structural multivariate models are adopted.

- Quadratic Time

  Among the simplest approaches of estimating the output gap is through the time trend models. A simple equation assumes that potential output is a function of deterministic time, which can be linear, geometric, cubic or quadratic. Since various studies already did the first three time models of output gap estimation, this paper shall only focus on the fourth time model, i.e. quadratic time. In the quadratic time model, potential output is a taken as a function of quadratic time Y(T) or in a simple equation:

  $$Y^* = B_0 + B_1(time)$$

  where: Y^* = potential output
  B_0 = intercept
  B_1 =estimated coefficients
  Time = quadratic time 1,16,81,...n

  Output gap is then calculated as the residual from the trend line or the difference between the actual and the potential output.

- HP Filter

[12] Besinio 2007

[13] Output in the models using quarterly data series is first de-seasonalized using the Tramo Seats

HP filter is based on the filter proposed by Hodrick and Prescott in 1997 with their recommended smoothing parameter of 1600 for quarterly data and lambda of 100 for annual data. HP filter is similar to linear trend models in the sense that it splices a time series for output over time. It is unique nonetheless since it allows changes in growth rate through eliminated the constant growth rate assumption (Abat, 2006). Therefore, the filter finds the value of the potential output which can minimize the difference of the actual gap. At the same time, it imposes constraints on the model by letting the growth rate vary (Bjornland, and as cited by Besinio, 2007). It can be expressed in the minimized equation:

$$Min\{Y_t*\}_{t=1}^{T}\left\{\sum_{t=1}^{T}(Y_t-Y_t*)^2+\lambda\sum_{t=2}^{T-1}\left[\left(Y*_{t+1}-Y_t*\right)-\left(Y*_t-Y_{t-1}*\right)\right]^2\right\}$$

- Structural Vector Autoregression (SVAR)

SVAR models are commonly used in business cycle analysis in order to estimate the output gap. This approach has the significant advantage to combine together a robust statistical framework with the ability of integrating alternative economic constraints. Traditionally, within SVAR models the output gap or business cycle is defined as those output movements associated with shocks constrained to have no long run effects on output, i.e. "transitory" shocks. While many identification procedures are possible, the use of the Blanchard and Quah (1989) identification procedure (long run restrictions based on economic theory) are considered, and we do so as well in this paper.

SVAR-models with long run restrictions are implicitly or explicitly based on an economic model. In Blanchard and Quah's (1989) original paper, output was assumed to be driven by two types of shocks, supply and demand, where demand shocks were restricted not to affect output in the long run. A key feature of SVAR-models is that, given the identifying assumptions, the structural shocks (such as supply and demand shocks) explaining the historic development of output can be recovered. The output gap is calculated based on the absence of one or more shocks. In this paper, the authors follow the methodology used by BSP (2007), i.e. to compare the output generated by permanent shocks to GDP with the level of output generated by cyclical or demand-side variables within the VAR framework. SVAR is based on a vector autoregressive model of the form:

$$[I-A(L)]Y_t = u_t$$

where A(L) is a lag operator, Y a matrix of endogenous variables, and u a matrix of residuals. Equation <> is known as the Reduced Form (RF) Model. The idea behind this approach is to convert the multivariate AR given by equation <> into a restricted Wold moving average (MA) process:

$$
\begin{aligned}
Y_t &= [I - A(L)]^{-1} u_t \\
&= S(L)\varepsilon_t
\end{aligned}
$$

We impose linear restrictions relating the innovations of the MA process εt to the residuals of the reduced form estimated VAR model at time t, ut, for a k–variable model:

$$
\begin{aligned}
\varepsilon_t &= S(0)u_t \\
E(\varepsilon_t, \varepsilon_t') &= S(0)E(u_t u_t')S'(0) = \Sigma.
\end{aligned}
$$

The basic point of SVAR estimation is simple and straightforward. Knowledge of S(0), the matrix of contemporaneous effects of the structural disturbances εt on Yt allows us to recover the structural shocks from the reduced-form residuals ut. In estimating the SVAR, we first estimate a Bayesian VAR model. The logarithm of output enters in first-differences and is the first variable in the model. Thus, changes in potential output Δgdpp and the output gap Δgdpg can be written as:

$$
\begin{aligned}
\Delta gdp^p &= S_{11}(0)\varepsilon_{1,t} + S_{11}^*(L)\varepsilon_{1,t} \\
\Delta gdp^g &= S_{12}(L)\varepsilon_{2,t} + \ldots + S_{1k}(L)\varepsilon_{k,t}
\end{aligned}
$$

SVAR-models need, however, a pre-testing procedure before evaluating the output gaps. More specifically, we need to study the so-called impulse-response functions (IRFs). These tell us how the variables in the model respond to the identified structural shocks. If a response is at odds with theory, the model and/or the identifying assumptions are not valid, then it is not worth to evaluate it against the dependent variable. It is important to stress, however, that the process of accepting or disregarding models based on the IRFs is based on judgment and is hence somewhat arbitrarily; the identifying assumptions cannot be tested statistically. The Impulse Response function of each SVAR model can be found in Appendix.

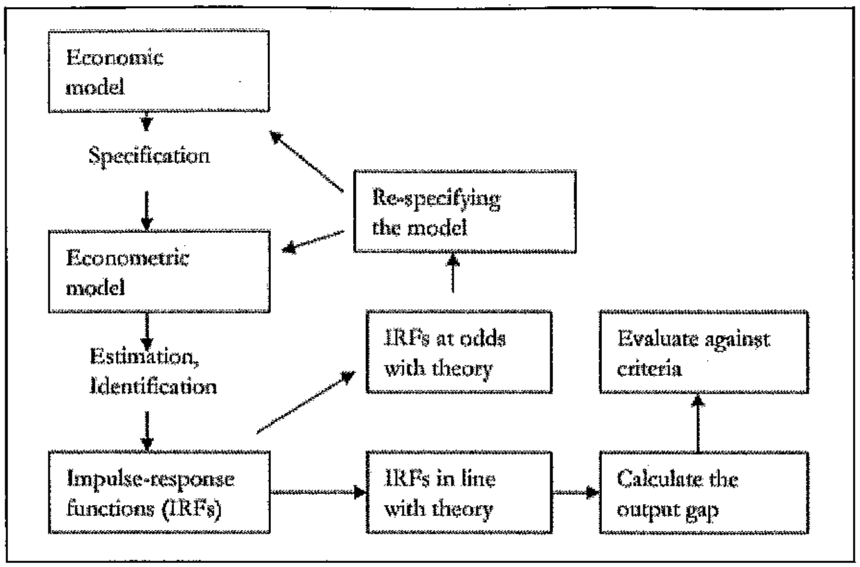

Figure 1. SVAR Approach

- Cobb-Douglas

Potential output can also be estimated through the Cobb-Douglas Function, another structural approach of output gap estimation. Cobb-Douglas assumes that output is a function of capital and labor Y = F(K, L). It has the formula:

$Y = AK^{a}L^{1-a}$
where A = *Total Factor of Productivity*
K = *capital*
L = *labor*

In order to estimate the potential output, the HP filter of the total productivity is used. The way to operationalize this approach is to first calculate *tfp* using actual output, published capital stock, and a measure of full-time equivalent labor. Deriving it from the general Cobb-Douglas formula:

$$\log Y = \log A + a \log K + (1-a) \log L$$
$$\log Y = \log A + a \log K + \log L - a \log L$$
$$\log Y = \log A + \log L + a (\log K - \log L)$$
$$\log Y - \log L = \log A + a (\log K - \log L)$$

Through regressing log Y – log L on the difference of the logarithms of capital and labor, the value of the alpha can be calculated. Going back to the general Cobb-Douglas equation, the total factor productivity can then be computed. After obtaining a historical series for *tfp*, a trend is fitted to this variable, usually using the H-P filter. Potential output can then be calculated by substituting trend tfp, full-employment effective labor, and the capital stock into the general equation. Full-time employment labor is assumed to the level of employment associated with the natural rate of employment. The production function approach has been criticized based on the ad hoc nature of the functional form used and the arbitrariness of the filter used to estimate trend *tfp* (Yap, 2003).[14]

The annual model used the data are from 1980 to 2011, while the quarter models used data from 1994. Originally, the authors were planning to combine the capital stock and the gross fixed capital formation (gfcf) to calculate the capital (K). Upon the first attempt however, the value of the alpha is greater than one, which is against economic theory.[15] Therefore, the authors cut the time frame of the sample: from using data from 1980 to 2011, they used data from 1997 to 2011 instead. This is due to the fact that the Philippines output gap was significantly negative before 1997. This may consequently bias the data which were used in the first trial. The second attempt was only done using quarterly data since an annual data series starting 1997 to 2011 would be insufficient to generate a reliable regression analysis. Nonetheless, the alpha of the second attempt was still greater than one. Because of this, instead of adding the capital stock and the gfcf together, the authors solely used the latter. Finally, the alpha of the production function became less than zero.

Inflation Targeting

In order to examine the significance of the output gap estimates in the inflation model, the authors will compare the initial inflation model (i.e. no output gap as explanatory variable based on the models of Yap, McNeil and Bagci) with the revised inflation model that incorporates the output gap estimates. The initial inflation mode[16] that will be used is a function:

LogCPI = f(logM2 logOilPrice, LogExchangeRate, 91-day Tbill rate, dummy 1995 for rice crisis)
where

logM2 = logarithm of Broad Money
logOil Price = logarithm of Oil Prices
logExchangeRate = logarithm of exchange rate
91-day T-bill rate = 91-day T-bill rate
dummy variable for rice crisis

which can be operationalized as:
logCPI = a + b1 logm2 + b2 logcroil + b3 logreer + b4 tbillrate + b5 dummy95

Inflation model with the output gap on the other hand is:
LogCPI = f(logM2, lognominal wages, logOilPrice, LogExchangeRate, 91-day Tbill rate, dummy 1995 for rice crisis, output gap)

or:

logCPI = a + b1 logm2 + b2 logcroil + b3 logreer + b4 tbillrate + b5 dummy95 + b6 outputgap

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[14]For the weakness of the Solow growth model in estimating potential output, see Yap, 2003.
[15]$0 < \alpha < 1$
[16] This inflation model is developed by the authors with reference to Yap's (2003) and BSP's (2007) inflation model

The inclusion of the variables nonetheless depends on the capacity of the model to explain variations in output. One weakness of such inflation model is the nature of the test, OLS, unlike Yap's Error Correction Model.

Chapter IV- A

Results and Discussion

(Models-Quarter)

This chapter is subdivided into two parts. Part A presents the output gap estimations and its role in inflation targeting using quarterly economic data from 1994 to 2011. While the second part of the chapter uses annual economic data from 1980 to 2011 in order to estimate the output gap and gather insights on its significance as an explanatory variable in the inflation model.

A. Estimation of output gap

In order to remove the seasonality of the real GDP data, the variable is first seasonally adjusted using the Tramo-Seats as shown in Figure 2. The seasonally-adjusted RGDP is then used as the actual output (y). It shall be the reference of the two univariate models – quadratic and HP filter – in estimating the output gap.

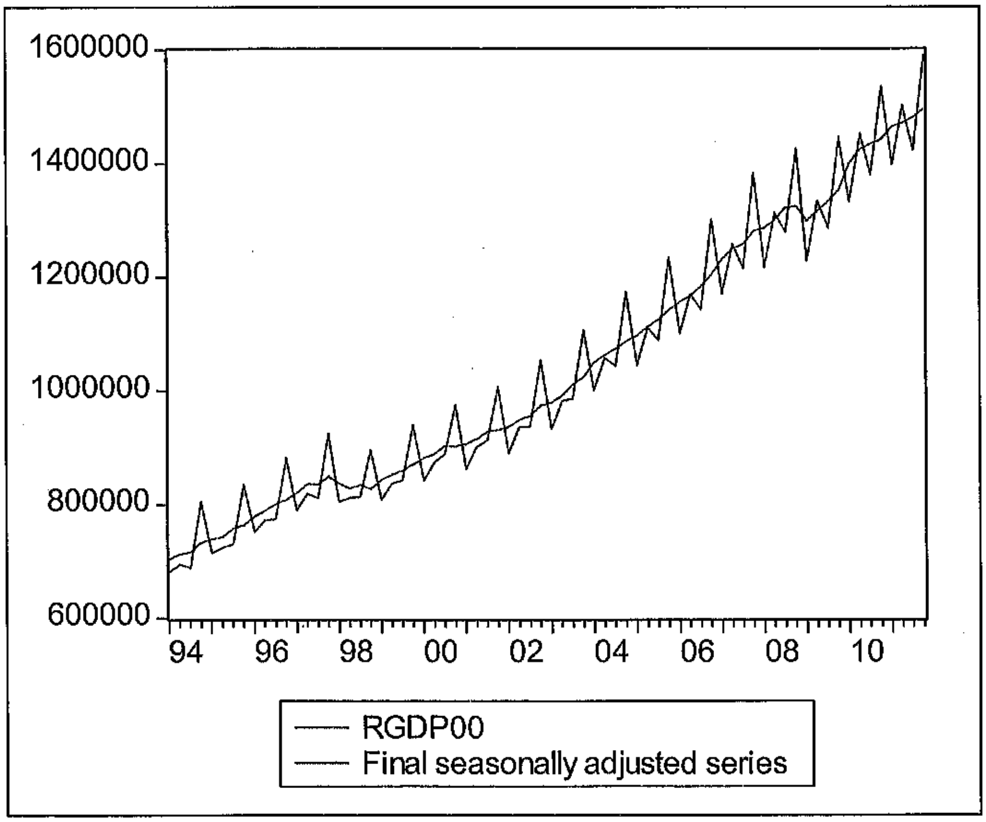
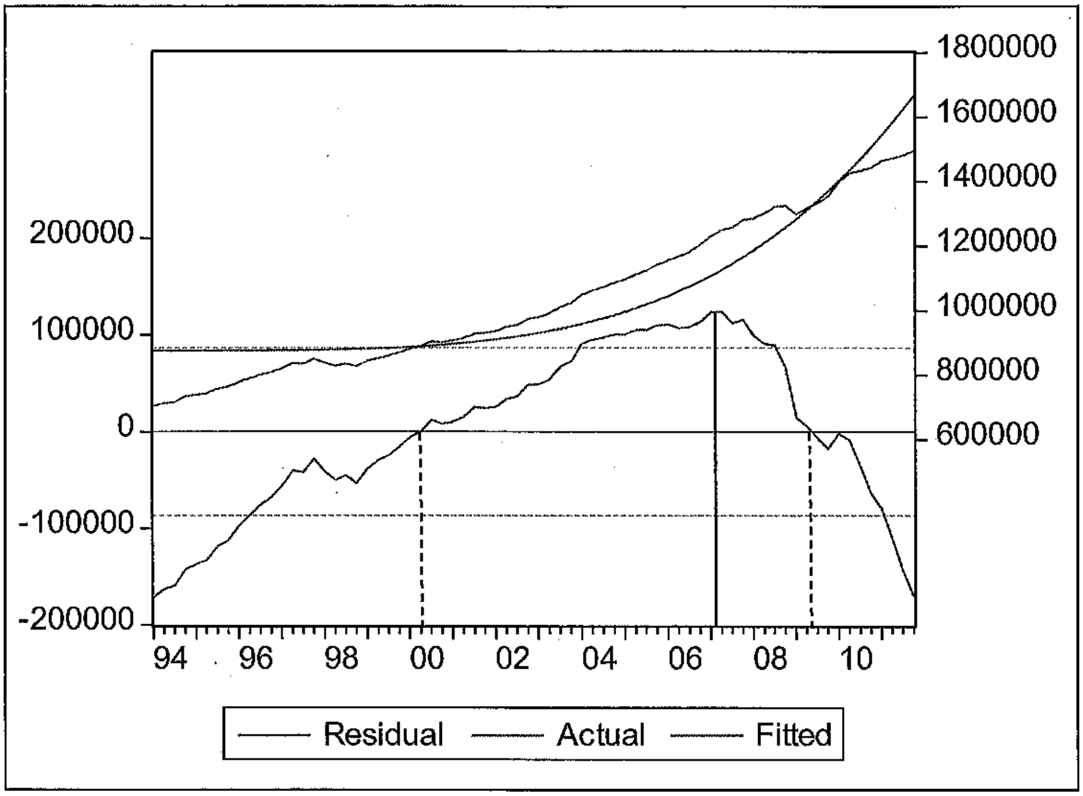


Figure 2. Real GDP, 2000=100 vs Seasonally adjusted Real GDP

1. Quadratic Model

The output gap (residual) estimated by the Quadratic model is depicted in the figure below (see Appendix for raw data). The model suggests that the Philippine economy has been overheating for 9 years (2000 Q2 – 2009 Q2). The 2nd quarter of 2007 records the peak of the overheated economy.

Figure 3. Quadratic Model for Potential Output, Quarter



2. HP Filter

The smoothed trend generated by the HP Filter reflects the potential output while the cycle denoted by the green graph gives the estimated output gap of the model (Figure 4). The potential output nearly fits the actual observed output.

The output gap proposed in the HP filter model is more volatile as compared to the output gap estimates of the Quadratic model. The model implies that the first economic overheating happened in the 4th quarter of 1995, which may be due to the attempts of recovery from the rice crisis. It then ended in 1998 quarter 2 since the Asian financial crisis unraveled. Another overheating happened in the whole year of 2000. Unlike the quadratic estimates nonetheless, record of positive output gap is postponed until the 4th quarter of 2003 and 4th quarter of 2006. Finally, the output gap drops significantly at the end of 2008 due to the Global Financial crisis. After which, the Philippine economy is seen to be overheating once again during the opening quarter of 2010 up to the 3rd quarter of 2011.

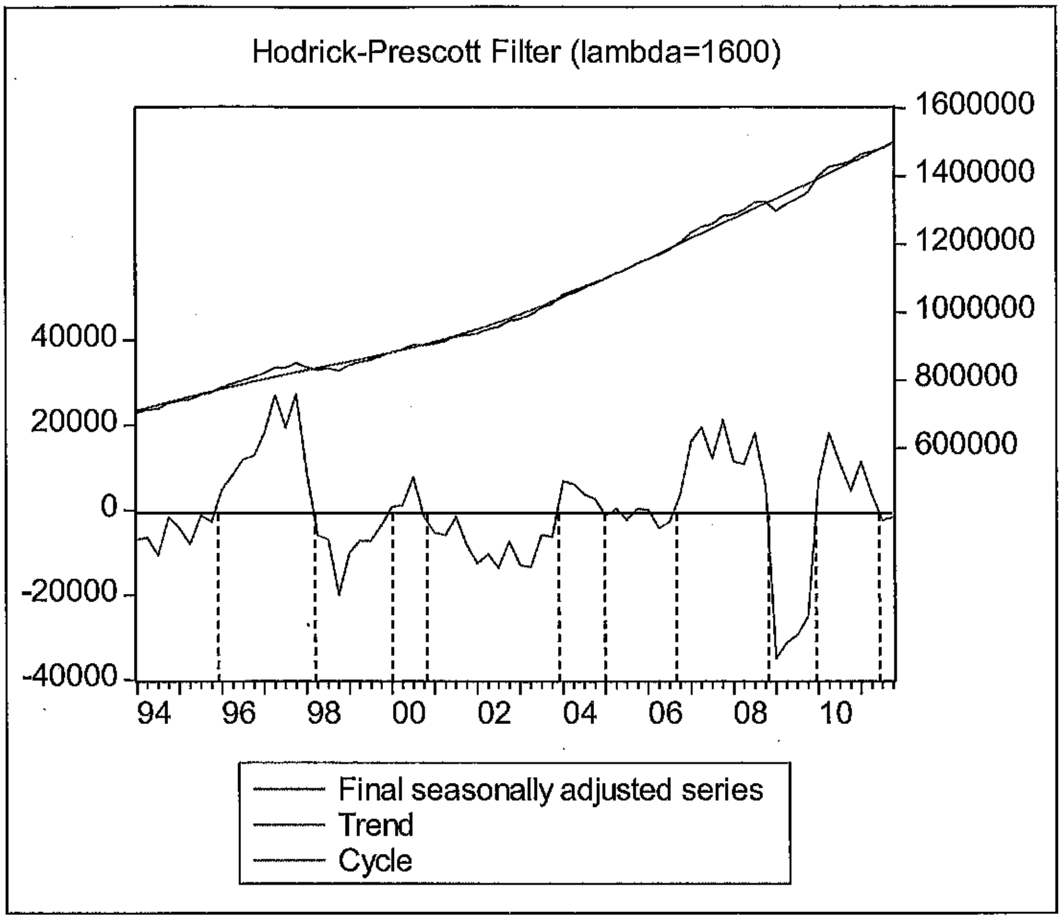


Figure 4. HP Filter of Seasonally Adjusted Real GDP, 2000=100

3. SVAR Approach

After pre-testing the seasonally-adjusted variables with the impulse response function, a 5-variable model is produced (the same as the BSP's SVAR model).[17] This will be the main model for the SVAR approach. Table 1 shows the correlation of the residuals of the five variables.

[17] See Appendix A for the impulse response function tests

Table 1. Correlation of Residuals

	Δgdp	Labor force	Real exrate	t-bill rate	Fiscal def-gdp
Δgdp	1				
Labor force	0.3942834	1			
Real exrate	0.6284570	0.5518984	1		
t-bill rate	-0.0131884	-0.0140902	-0.0589485	1	
Fiscal def-gdp	-0.0323458	0.0389196	-0.0616244	0.0305820	1

Unlike the univariate models which used the difference between the actual and potential output to calculate the output gap, SVAR approach estimates the gap as the difference between the expected GDP of the (1) model subjected to cyclical shock and of (2) the model exposed to permanent shocks. Figure 5 shows the output gap generated by the model.

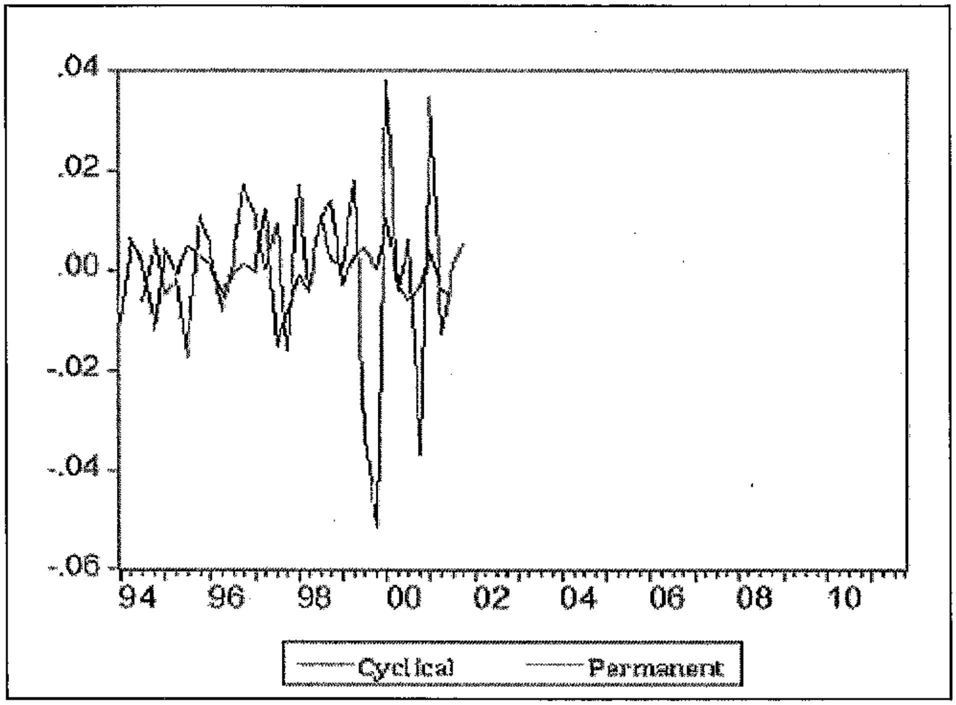


Figure 5. Output gap estimates of the SVAR Approach (Quarter)

4. Cobb-Douglas

Figure 6 shows the Cobb-Douglas model's estimations of the output gap. The potential output is derived using different estimates of the total factor of productivity (tfp). TFP estimates are computed using H-P filter, linear, geometric, cubic and quadratic time trend. Among the five trends, the quadratic estimations are more likely the most significant explanatory variable in inflation targeting. This is based on the simple regressions done between the output gaps and inflation (See Attached CD).

Therefore the output gap estimated with the quadratic trend will be used in the latter section of this chapter.

Shown in Figure 5, output gap derived from linear tfp estimates suggests that the Philippine economy is overheating from the first quarter of 1994 to the first quarter of 1997, and from the fourth quarter of 2010 to the fourth quarter of 2011. On the other hand, other estimates of output gap show otherwise.

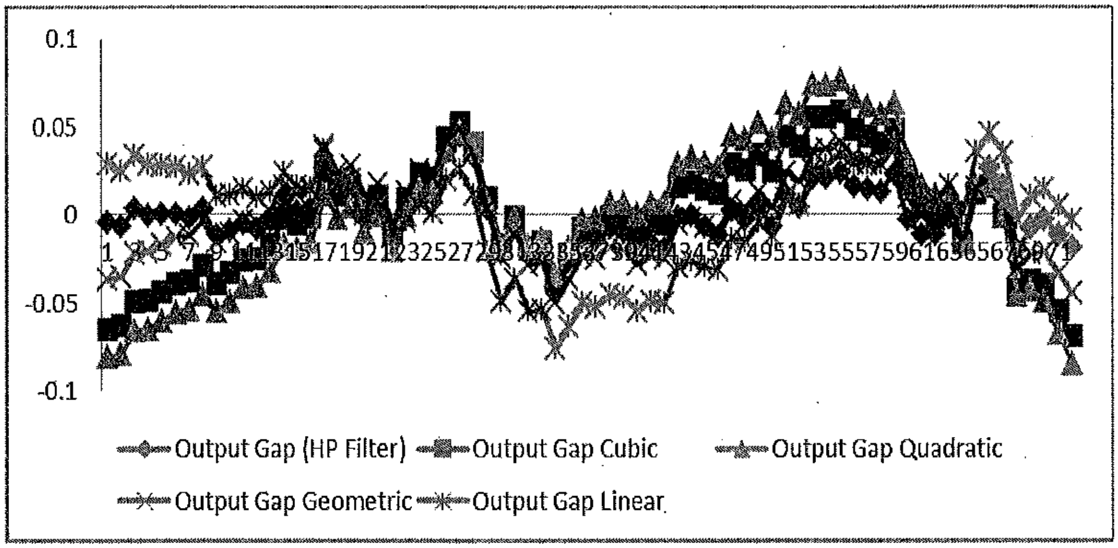


Figure 6. Output Gap Estimates of the Cobb-Douglas Model (Quarter)

Summary

Figure 7 summarizes the output gap estimates of the different approaches which the authors employed. Each approach of estimating the output gap shows different results. The Cobb-Douglas and the Quadratic approaches nonetheless have a more similar indication of the economy (i.e. whether it is overheating or not) through time excluding 1998 Q1- 2003 Q1 and 2010 Q1- 2010 Q3.

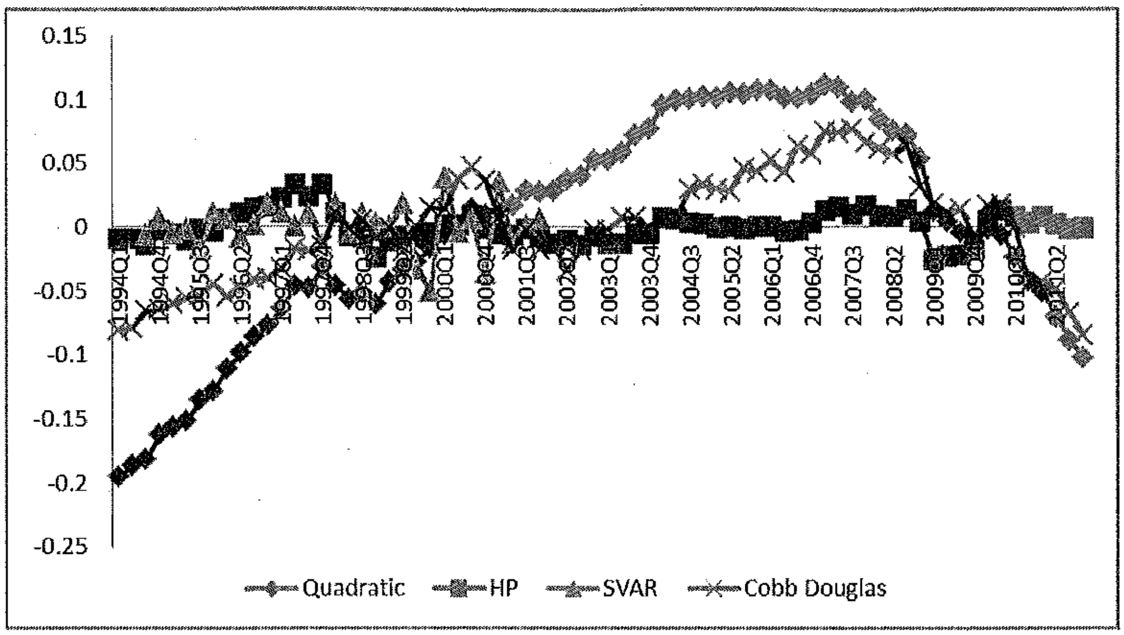


Figure 7. Output Gap Estimates of Different Approaches

5. Output Gap Estimates in the Inflation Model

The output gap estimates of the different approaches are incorporated in the BSP inflation model. The BSP inflation model includes variables such as broad money, exchange rate, 91 T-bill rate and dummies for the 1995 and 2008 rice crisis. However, regression analysis of the gathered data shows that only two of these variables appear to be significant in inflation targeting. They are the logarithm of broad money and rate of effective exchange rate. When the output gap is added as another explanatory variable in the inflation model, the output gap produced by the quadratic model and by the Cobb-Douglas is shown to be significant in explaining the inflation of the country (provided a 5% margin of error); while, output gap estimations of the HP filter and the SVAR approaches are not significant. The sign of the two output gap variables are furthermore consistent to the theory, i.e. a positive relation between inflation and the output gap. Nonetheless, in the inflation model with the Cobb-Douglas's output gap, the real effective exchange rate is not significant. The following tables present the compressed[18] inflation models with the different output gaps.

A. Quadratic

Dependent Variable: LOGCPI
Method: Least Squares
Date: 10/09/12 Time: 10:30
Sample: 1994Q1 2011Q4
Included observations: 72

[18] Drops insignificant variables

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.769894	0.397681	1.935959	0.0570
LOGM2	0.146010	0.067967	2.148232	0.0353
QOUTGAP	1.202065	0.140258	8.570376	0.0000
REER	0.003845	0.001698	2.264706	0.0267

R-squared	0.551109	Mean dependent var	2.051221
Adjusted R-squared	0.531305	S.D. dependent var	0.123170
S.E. of regression	0.084324	Akaike info criterion	-2.054351
Sum squared resid	0.483515	Schwarz criterion	-1.927870
Log likelihood	77.95664	F-statistic	27.82819
Durbin-Watson stat	0.130578	Prob(F-statistic)	0.000000

B. HP Filter

Dependent Variable: LOGCPI
Method: Least Squares
Date: 10/09/12 Time: 10:32
Sample: 1994Q1 2011Q4
Included observations: 72

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.729713	0.593358	1.229802	0.2230
LOGM2	0.225007	0.098875	2.275680	0.0260
REER	-0.003007	0.002171	-1.385305	0.1705
HPOUTGAP	-0.794960	1.316947	-0.603639	0.5481

R-squared	0.071210	Mean dependent var	2.051221
Adjusted R-squared	0.030234	S.D. dependent var	0.123170
S.E. of regression	0.121294	Akaike info criterion	-1.327247
Sum squared resid	1.000431	Schwarz criterion	-1.200766
Log likelihood	51.78090	F-statistic	1.737838
Durbin-Watson stat	0.018837	Prob(F-statistic)	0.167470

C. SVAR

Dependent Variable: LOGCPI
Method: Least Squares
Date: 10/09/12 Time: 10:35
Sample (adjusted): 1994Q3 2001Q4
Included observations: 30 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.

C	3.312618	0.252144	13.13783	0.0000
LOGM2	-0.210692	0.050745	-4.151991	0.0003
REER	0.000817	0.001677	0.487368	0.6301
SOUTGAP	-0.010108	0.395625	-0.025548	0.9798

R-squared	0.618621	Mean dependent var	1.942626
Adjusted R-squared	0.574616	S.D. dependent var	0.060869
S.E. of regression	0.039700	Akaike info criterion	-3.491369
Sum squared resid	0.040978	Schwarz criterion	-3.304543
Log likelihood	56.37054	F-statistic	14.05787
Durbin-Watson stat	0.312410	Prob(F-statistic)	0.000012

D. Cobb-Douglas

Dependent Variable: LOGCPI
Method: Least Squares
Date: 10/09/12 Time: 10:36
Sample: 1994Q1 2011Q4
Included observations: 72

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.475258	0.475737	0.998994	0.3213
LOGM2	0.238585	0.080210	2.974494	0.0041
REER	-0.000806	0.001810	-0.445427	0.6574
COBBOUTGAP	1.732727	0.303995	5.699863	0.0000

R-squared	0.368125	Mean dependent var	2.051221
Adjusted R-squared	0.340248	S.D. dependent var	0.123170
S.E. of regression	0.100045	Akaike info criterion	-1.712438
Sum squared resid	0.680614	Schwarz criterion	-1.585957
Log likelihood	65.64777	F-statistic	13.20539
Durbin-Watson stat	0.074872	Prob(F-statistic)	0.000001

Chapter IV- B
Results and Discussion
(Models-Annual)

1. Quadratic

The output gap (residual) estimated by the Quadratic time approach is shown in Figure 8 (see Appendix for raw data). Since the annual model covers a greater period of time than the quarterly model, it shows that the Philippines may be actually overheating since 1990. It ended in 2008, apparently due to the global financial crisis.

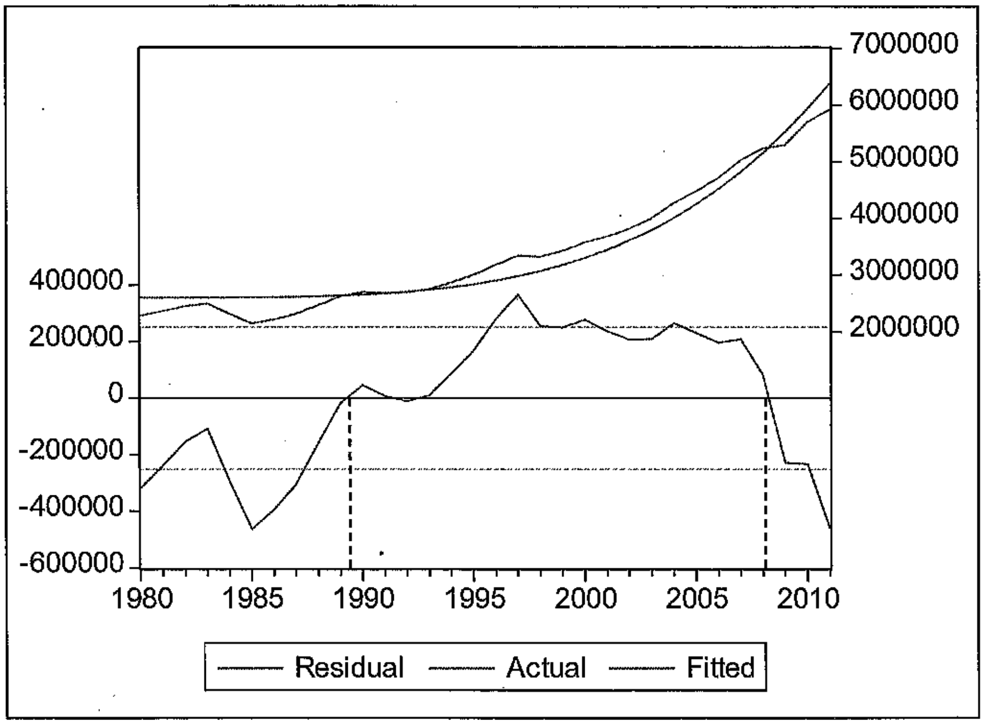


Figure 8. Quadratic Model for Potential Output (Annual)

2. HP Filter

HP Filter smoothed trend estimates the potential output as shown in figure 9. Similar to the Quadratic time approach, it suggests that the Philippine economy began to overheat in 1990 to 1984 and in the following time frames: 1988- mid 1991, 1995 - 1998, 2006-2008 and 2010-2011.

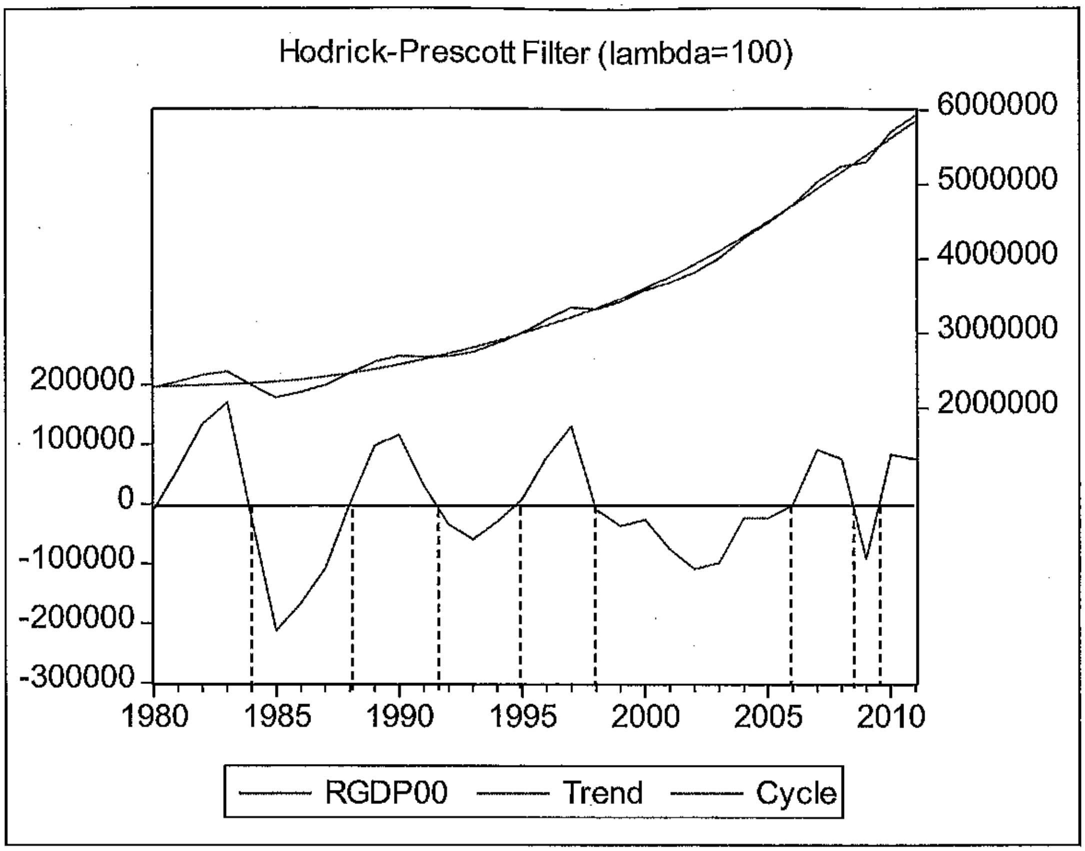


Figure 9. HP Filter of Real GDP, 2000=100

3. SVAR

Similar to the quarter SVAR model, the correlation of the residuals of the5-variable model is shown in Table 2. The output gap using the SVAR approach is estimated through the calculation of the difference between the potential output with cyclical shocks and the potential output which is subjected to permanent shocks (see Appendix).

Table 2. Correlation of Residuals

	Δgdp	Real exrate	Labor force	Tbill rate	Fiscal def-gdp
Δgdp	1				
Real exrate	0.3625163136	1			
Labor force	0.0459272064	0.0485724306	1		
Tbill rate	0.4203219731	-0.465438999	0.123634229	1	
Fiscal def-gdp	0.3621072071	0.5628455409	-0.164891232	-0.120191612	1

4. Cobb-Douglas

Figure 10 shows the output gap. The potential output gap is observed through different time series: linear, geometric, cubic to quadratic time. All the estimated output gaps of the Cobb-Douglas model are close to each other. In 1980, however, the estimated output gap using the HP filter trend does not suggest an overheating as opposed to other estimates. This discrepancy is only a matter of time trend difference.

Similar to the quarter models, the quadratic estimations are more likely to have the most significance in explaining inflation. This is based on the simple regressions done between the output gaps and inflation (See Attached CD).

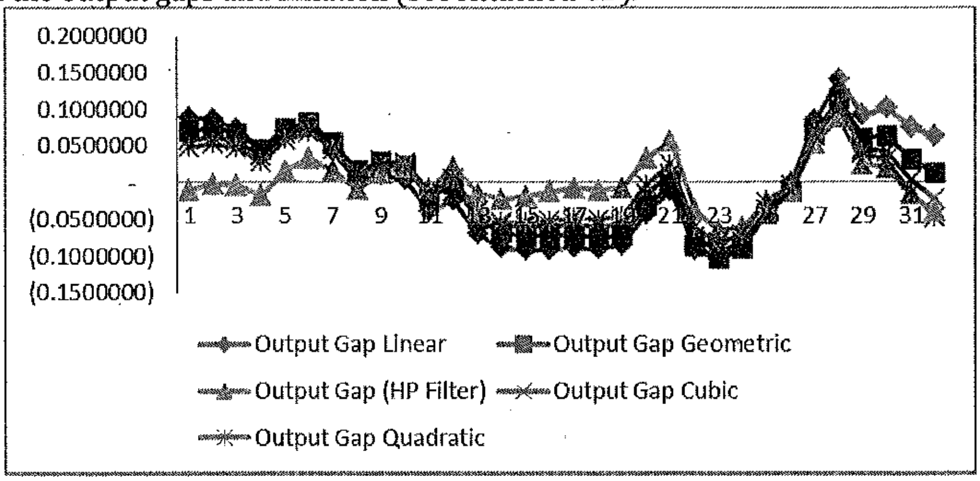


Figure 10. Output Gap Estimates of Cobb Douglas

Summary

In sum, the output gap estimates of the different approaches are presented in Figure 11. The Cobb-Douglas and the SVAR have the most volatile output gaps, while the quadratic and the HP filter approaches records the highest output gaps. Unlike the output gap estimates in the quarter models, the output gap in the annual models varies greatly from each other.

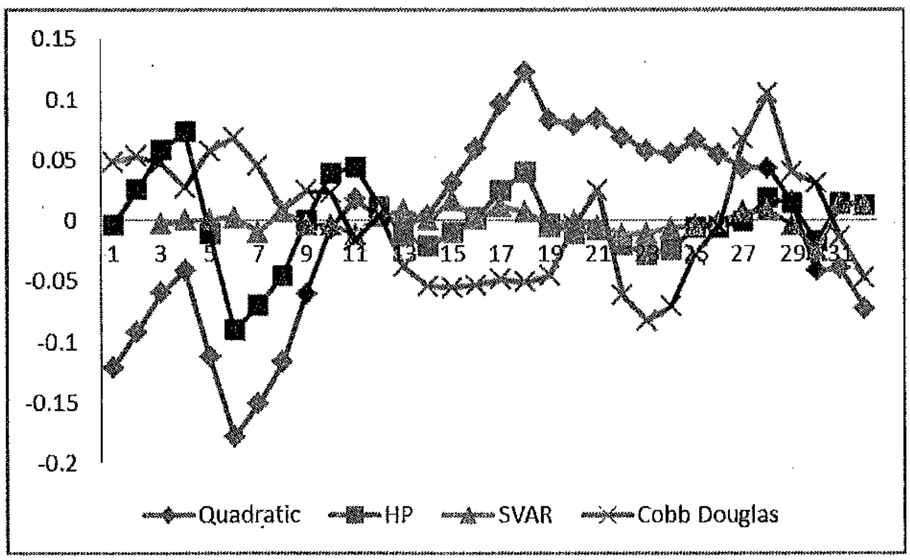


Figure 11. Output Gap Estimates of different Approaches

5. Output Gap Estimates in the Inflation Model

To determine the significance of the output gap in inflation targeting, the output gap estimates generated in the different approaches are tested in a general inflation model.

Again, the output gaps generated by the quadratic time and the Cobb-Douglas are significant in the inflation model. However, in the annual model of inflation, only the broad money appears a significant explanatory variable alongside the output gaps.

A. Quadratic

Dependent Variable: LOGCPI
Method: Least Squares
Date: 10/09/12 Time: 10:45
Sample: 1980 2011
Included observations: 32

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.415824	0.034983	40.47198	0.0000
M2	1.40E-13	1.41E-14	9.896401	0.0000
QOUTGAP	1.824520	0.321585	5.673520	0.0000
DUM95	0.063181	0.137262	0.460296	0.6489

R-squared	0.867665	Mean dependent var	1.655479
Adjusted R-squared	0.853486	S.D. dependent var	0.346372
S.E. of regression	0.132581	Akaike info criterion	-1.086777
Sum squared resid	0.492176	Schwarz criterion	-0.903560
Log likelihood	21.38843	F-statistic	61.19479
Durbin-Watson stat	0.404310	Prob(F-statistic)	0.000000

B. HP Filter

Dependent Variable: LOGCPI
Method: Least Squares
Date: 10/09/12 Time: 10:46
Sample: 1980 2011
Included observations: 32

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.359630	0.047737	28.48179	0.0000
M2	1.66E-13	1.91E-14	8.698149	0.0000
HPOUTGAP	-1.398864	1.015647	-1.377313	0.1793
DUM95	0.204785	0.191728	1.068102	0.2946

R-squared	0.733582	Mean dependent var	1.655479
Adjusted R-squared	0.705038	S.D. dependent var	0.346372
S.E. of regression	0.188116	Akaike info criterion	-0.387048
Sum squared resid	0.990853	Schwarz criterion	-0.203831
Log likelihood	10.19277	F-statistic	25.69939

Durbin-Watson stat	0.164807	Prob(F-statistic)	0.000000

C. SVAR

Dependent Variable: LOGCPI
Method: Least Squares
Date: 10/09/12 Time: 10:47
Sample (adjusted): 1982 2011
Included observations: 30 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.419922	0.043845	32.38509	0.0000
M2	1.49E-13	1.69E-14	8.789281	0.0000
SOUTGAP	0.094162	3.348654	0.028119	0.9778
DUM95	0.157831	0.165241	0.955156	0.3483

R-squared	0.748376	Mean dependent var	1.701485
Adjusted R-squared	0.719343	S.D. dependent var	0.305254
S.E. of regression	0.161715	Akaike info criterion	-0.682400
Sum squared resid	0.679943	Schwarz criterion	-0.495574
Log likelihood	14.23600	F-statistic	25.77631
Durbin-Watson stat	0.170094	Prob(F-statistic)	0.000000

D. Cobb-Douglas

Dependent Variable: LOGCPI
Method: Least Squares
Date: 10/09/12 Time: 10:48
Sample: 1980 2011
Included observations: 32

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.375508	0.040271	34.15590	0.0000
M2	1.59E-13	1.61E-14	9.899739	0.0000
COBBOUTGAP	-2.246787	0.593034	-3.788631	0.0007
DUM95	0.073173	0.164536	0.444719	0.6599

R-squared	0.811939	Mean dependent var	1.655479
Adjusted R-squared	0.791790	S.D. dependent var	0.346372
S.E. of regression	0.158050	Akaike info criterion	-0.735347
Sum squared resid	0.699431	Schwarz criterion	-0.552130
Log likelihood	15.76555	F-statistic	40.29595
Durbin-Watson stat	0.382413	Prob(F-statistic)	0.000000

Chapter V

Summary and Conclusion

Among the univariate models, the quadratic model's output gap is tested to be significant in inflation targeting, while the HP filter does not pose any influence on inflation. On the other hand, the output gap estimations of the Cobb-Douglas structural model appears to be significant in the inflation model as well, wherein potential output was derived using the total factor productivity derived from quadratic time trend. It is important to take note that different output gaps were derived from the Cobb-Douglass production function by using different estimates of total factor productivity derived from several methods (linear time trend, geometric time trend, cubic time trend, quadratic time trend and H-P filter).

In conclusion, the significance of output gap in inflation targeting appears to be weak. Although theory states that structural models (SVAR and Cobb-Douglas) can make the estimation of output gap more accurate, their use in the inflation model is still inconclusive. Given the inconsistency of results, that is, only the output gap estimated using quadratic and Cobb-Douglas models are shown to be significant in the BSP's inflation model, and output gap being based on past static data, the BSP should not be depending heavily on output gap as a tool for inflation targeting.

Chapter VI

Recommendation

Given the inferred results of this study, the authors would like to recommend the following for future researches: (1) employ other univariate and multivariate models in estimating the Philippine output gap. This may improve the output gap estimates which will be afterwards incorporated in the inflation model. It is to be expected however, that the different approaches would in turn approximate different output gap. Still, a greater number of estimations, consequently a greater number of inflation model would make the observations more conclusive. (2) Dividing the observations into (a) prior 1997 and (b) post 1997 is also ideal. Since the output gap of the Philippines is significantly negative before 1997, the models which were generated may be biased. Although this appears to be insignificant on the Cobb-Douglas production model (as shown in the paper), the importance of this division on the other approaches and models was not observed in the paper. Lastly, (3) the inflation model which tests the impact of output gap in inflation targeting regime of the BSP, can also be remodeled. The paper used the 2007 BSP inflation model. Future studies can therefore acquire the latest BSP inflation targeting model in which they can retest the significance of output gaps.

References

Abat, C. 2006. "GDP Growth, Potential Output and Output Gaps in the Philippines." University of Asia and the Pacific. Pasig City.

Ghazanfar, S. M. and Candelaria L. Sevcik. 2008. "Inflation Targeting Policies in Less-Developed Countries: Some Evidence and Potential." *The Journal of Social, Political, and Economic Studies* 33 (1): 71-83. http://search.proquest.com/docview/216800903?accountid=28547.

McNells, Paul D., and Cristeta B. Bagsic. "Output Gap Estimation for Inflation Forecasting: The Case of the Philippines." *BSP Working Paper Series* no. 1 (August 2007): 1-27.

Sek, Siok Kun. 2009. "Interactions between Monetary Policy and Exchange Rate in Inflation Targeting Emerging Countries: The Case of Three East Asian Countries." *International Journal of Economics and Finance* 1 (2): 27-44. http://search.proquest.com/docview/820912151?accountid=28547.

Yap, Josef T. "The Output Gap and Its Role in Inflation-Targeting in the Philippines." *Philippine Institute of Development Studies*

Appendix A-Quarter

1. Quadratic Model

Dependent Variable: RGDPSA
Method: Least Squares
Date: 10/09/12 Time: 08:47
Sample: 1994Q1 2011Q4
Included observations: 72

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	875953.1	12797.07	68.44949	0.0000
QUADTIME	0.029478	0.001385	21.28146	0.0000

R-squared	0.866131	Mean dependent var	1039945.
Adjusted R-squared	0.864219	S.D. dependent var	235269.7
S.E. of regression	86693.33	Akaike info criterion	25.60553
Sum squared resid	5.26E+11	Schwarz criterion	25.66877
Log likelihood	-919.7989	F-statistic	452.9005
Durbin-Watson stat	0.024418	Prob(F-statistic)	0.000000

Period	Actual	Potential	Output Gap
1994Q1	704684.7	875953.1749	-0.195522409
1994Q2	712955.57	875953.6171	-0.186080683
1994Q3	716718.4	875955.5332	-0.181786777
1994Q4	733578.1	875960.6919	-0.162544499
1995Q1	739003.57	875971.5694	-0.156361238
1995Q2	742988.98	875991.3493	-0.151830688
1995Q3	757542.3	876023.9229	-0.135249301
1995Q4	763830.81	876073.8886	-0.128120562
1996Q1	778956.53	876146.5526	-0.110928956
1996Q2	789857.46	876247.9285	-0.098591353
1996Q3	800753.98	876384.7373	-0.086298579
1996Q4	808620.37	876564.4076	-0.077511746

1997Q1	821011.24	876795.0753	-0.063622432
1997Q2	836559.42	877085.584	-0.046205484
1997Q3	835512.72	877445.4847	-0.047789595
1997Q4	849747.91	877885.0357	-0.032051037
1998Q1	837524.77	878415.203	-0.046550234
1998Q2	829055.65	879047.66	-0.056870648
1998Q3	834225.42	879794.7877	-0.051795451
1998Q4	827475.68	880669.6743	-0.060401755
1999Q1	843794.62	881686.1157	-0.042976174
1999Q2	853038.55	882858.6153	-0.033776717
1999Q3	859710.1	884202.3839	-0.027699862
1999Q4	870220.68	885733.3397	-0.017513916
2000Q1	881743.81	887468.1085	-0.006450146
2000Q2	889499.03	889424.0235	8.43316E-05
2000Q3	903835.44	891619.1255	0.01370127
2000Q4	902313.48	894072.1627	0.009217732
2001Q1	906949.26	896802.5907	0.011314273
2001Q2	915022.76	899830.5727	0.016883386
2001Q3	928395.56	903176.9794	0.027922081
2001Q4	931333.78	906863.3889	0.026983547
2002Q1	936716.52	910912.0867	0.028328127
2002Q2	949166.46	915346.066	0.036948205
2002Q3	956642.98	920189.0273	0.039615722
2002Q4	974100.32	925465.3787	0.052551875
2003Q1	980184.1	931200.2356	0.052602934
2003Q2	991639.84	937419.421	0.057840085
2003Q3	1011628.8	944149.4655	0.07147103
2003Q4	1024105.6	951417.607	0.076399672
2004Q1	1050269.2	959251.7909	0.094883752
2004Q2	1063078.6	967680.6701	0.098584102
2004Q3	1074350.7	976733.605	0.099942394
2004Q4	1087165.7	986440.6636	0.102109575
2005Q1	1097414	996832.621	0.100900971
2005Q2	1113350.6	1007940.96	0.104579181
2005Q3	1125179.5	1019797.872	0.103335799
2005Q4	1142499.6	1032436.253	0.106605465
2006Q1	1156933.7	1045889.709	0.106171798
2006Q2	1167542.8	1060192.553	0.101255424
2006Q3	1183716.4	1075379.806	0.100742634
2006Q4	1205122.9	1091487.194	0.104110893
2007Q1	1232388.5	1108551.153	0.11171099

2007Q2	1250526.6	1126608.826	0.109991837
2007Q3	1258069.6	1145698.063	0.098081284
2007Q4	1281824.3	1165857.421	0.099469178
2008Q1	1286729.1	1187126.165	0.083902569
2008Q2	1300715.1	1209544.269	0.075376183
2008Q3	1322519.9	1233152.412	0.072470756
2008Q4	1324897.4	1257991.982	0.053184296
2009Q1	1298698.2	1284105.073	0.011364433
2009Q2	1317132.1	1311534.489	0.004267986
2009Q3	1333733.5	1340323.739	-0.004916901
2009Q4	1353026.7	1370517.04	-0.012761856
2010Q1	1400313.3	1402159.319	-0.001316554
2010Q2	1426169.6	1435296.206	-0.006358692
2010Q3	1434066.9	1469974.042	-0.024427059
2010Q4	1442806.3	1506239.874	-0.04211386
2011Q1	1464694	1544141.458	-0.051450894
2011Q2	1472215.7	1583727.255	-0.070410833
2011Q3	1481201.6	1625046.436	-0.088517369
2011Q4	1497013	1668148.877	-0.10259029

2. HP Filter

Period	Actual Output	Potential Output	Output Gap
1994Q1	704684.7	711540.1	-0.00963
1994Q2	712955.6	719468.3	-0.00905
1994Q3	716718.4	727392.1	-0.01467
1994Q4	733578.1	735303.4	-0.00235
1995Q1	739003.6	743186.9	-0.00563
1995Q2	742989.0	751026.7	-0.0107
1995Q3	757542.3	758804.0	-0.00166
1995Q4	763830.8	766495.1	-0.00348
1996Q1	778956.5	774075.4	0.006306
1996Q2	789857.5	781518.7	0.01067
1996Q3	800754.0	788802.0	0.015152
1996Q4	808620.4	795907.2	0.015973
1997Q1	821011.2	802823.9	0.022654
1997Q2	836559.4	809549.5	0.033364
1997Q3	835512.7	816093.0	0.023796

1997Q4	849747.9	822480.1	0.033153
1998Q1	837524.8	828748.6	0.01059
1998Q2	829055.7	834953.4	-0.00706
1998Q3	834225.4	841155.0	-0.00824
1998Q4	827475.7	847410.0	-0.02352
1999Q1	843794.6	853770.8	-0.01168
1999Q2	853038.6	860277.3	-0.00841
1999Q3	859710.1	866963.3	-0.00837
1999Q4	870220.7	873857.8	-0.00416
2000Q1	881743.8	880985.6	0.000861
2000Q2	889499.0	888368.9	0.001272
2000Q3	903835.4	896030.6	0.00871
2000Q4	902313.5	903994.2	-0.00186
2001Q1	906949.3	912288.1	-0.00585
2001Q2	915022.8	920939.8	-0.00642
2001Q3	928395.6	929973.1	-0.0017
2001Q4	931333.8	939408.5	-0.0086
2002Q1	936716.5	949265.3	-0.01322
2002Q2	949166.5	959557.8	-0.01083
2002Q3	956643.0	970292.4	-0.01407
2002Q4	974100.3	981469.0	-0.00751
2003Q1	980184.1	993079.2	-0.01298
2003Q2	991639.8	1005110.	-0.0134
2003Q3	1011629.	1017539.	-0.00581
2003Q4	1024106.	1030338.	-0.00605
2004Q1	1050269.	1043473.	0.006513
2004Q2	1063079.	1056907.	0.00584
2004Q3	1074351.	1070607.	0.003497
2004Q4	1087166.	1084543.	0.002419
2005Q1	1097414.	1098690.	-0.00116
2005Q2	1113351.	1113021.	0.000296
2005Q3	1125180.	1127511.	-0.00207
2005Q4	1142500.	1142133.	0.000321
2006Q1	1156934.	1156862.	6.22E-05
2006Q2	1167543.	1171669.	-0.00352
2006Q3	1183716.	1186528.	-0.00237
2006Q4	1205123.	1201410.	0.003091
2007Q1	1232389.	1216283.	0.013242
2007Q2	1250527.	1231117.	0.015766
2007Q3	1258070.	1245895.	0.009772
2007Q4	1281824.	1260610.	0.016828
2008Q1	1286729.	1275261.	0.008993
2008Q2	1300715.	1289865.	0.008412
2008Q3	1322520.	1304440.	0.01386
2008Q4	1324897.	1319017.	0.004458

2009Q1	1298698.	1333634.	-0.0262
2009Q2	1317132.	1348334.	-0.02314
2009Q3	1333734.	1363138.	-0.02157
2009Q4	1353027.	1378048.	-0.01816
2010Q1	1400313.	1393048.	0.005215
2010Q2	1426170.	1408104.	0.01283
2010Q3	1434067.	1423190.	0.007643
2010Q4	1442806.	1438289.	0.003141
2011Q1	1464694.	1453391.	0.007777
2011Q2	1472216.	1468489.	0.002538
2011Q3	1481202.	1483583.	-0.0016
2011Q4	1497013	1498677	-0.00111

3. SVAR

Vector Autoregression Estimates
Date: 10/09/12 Time: 07:45
Sample (adjusted): 1994Q3 2001Q4
Included observations: 30 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	LOGRGDPCHANGE_SA	LOGLFORCE_SA	LOGREER	TBILLRATE	FDEFGDP
LOGRGDPCHANGE_SA(-1)	0.344197	-0.062717	-0.283307	43.06027	-1.284586
	(0.24203)	(0.18176)	(0.81441)	(86.2770)	(0.66823)
	[1.42211]	[-0.34506]	[-0.34787]	[0.49909]	[-1.92238]
LOGRGDPCHANGE_SA(-2)	0.447042	0.026537	-0.340144	2.146916	1.139619
	(0.21469)	(0.16123)	(0.72241)	(76.5308)	(0.59274)
	[2.08225]	[0.16459]	[-0.47085]	[0.02805]	[1.92262]
LOGLFORCE_SA(-1)	0.308925	0.927449	0.709983	-119.8936	1.517075
	(0.38890)	(0.29205)	(1.30858)	(138.629)	(1.07370)
	[0.79437]	[3.17570]	[0.54256]	[-0.86485]	[1.41294]
LOGLFORCE_SA(-2)	0.140843	0.026979	0.795440	-98.08206	-2.611393
	(0.42089)	(0.31607)	(1.41622)	(150.032)	(1.16202)
	[0.33463]	[0.08536]	[0.56166]	[-0.65374]	[-2.24728]
LOGREER(-1)	0.130100	-0.064223	0.339787	17.63212	0.037032
	(0.08121)	(0.06099)	(0.27326)	(28.9488)	(0.22421)
	[1.60202]	[-1.05309]	[1.24346]	[0.60908]	[0.16517]

LOGREER(-2)	-0.028927	0.056062	0.372034	-3.923771	0.565409
	(0.07424)	(0.05575)	(0.24979)	(26.4628)	(0.20496)
	[-0.38966]	[1.00562]	[1.48937]	[-0.14828]	[2.75866]
TBILLRATE(-1)	3.34E-05	3.82E-05	-0.001159	0.331673	-0.001899
	(0.00059)	(0.00044)	(0.00199)	(0.21116)	(0.00164)
	[0.05630]	[0.08589]	[-0.58165]	[1.57074]	[-1.16089]
TBILLRATE(-2)	0.001115	0.000378	0.001783	0.150242	-4.53E-05
	(0.00059)	(0.00045)	(0.00200)	(0.21140)	(0.00164)
	[1.88034]	[0.84771]	[0.89377]	[0.71071]	[-0.02770]
FDEFGDP(-1)	-0.017169	-0.045896	0.070485	-29.43629	0.243345
	(0.06309)	(0.04738)	(0.21227)	(22.4880)	(0.17417)
	[-0.27215]	[-0.96877]	[0.33205]	[-1.30898]	[1.39714]
FDEFGDP(-2)	-0.062691	-0.012329	-0.199994	-37.42427	-0.280245
	(0.07126)	(0.05351)	(0.23978)	(25.4014)	(0.19674)
	[-0.87976]	[-0.23039]	[-0.83409]	[-1.47331]	[-1.42446]
C	0.632469	0.706811	2.278942	340.8977	5.739311
	(0.62016)	(0.46572)	(2.08674)	(221.066)	(1.71219)
	[1.01985]	[1.51769]	[1.09210]	[1.54206]	[3.35203]
R-squared	0.991566	0.939509	0.721033	0.740606	0.871511
Adj. R-squared	0.987127	0.907671	0.574208	0.604083	0.803885
Sum sq. resids	0.001330	0.000750	0.015060	169.0233	0.010139
S.E. equation	0.008367	0.006283	0.028154	2.982610	0.023101
F-statistic	223.3831	29.50947	4.910843	5.424763	12.88721
Log likelihood	107.7865	116.3786	71.38500	-68.50075	77.31994
Akaike AIC	-6.452436	-7.025239	-4.025667	5.300050	-4.421329
Schwarz SC	-5.938663	-6.511466	-3.511895	5.813822	-3.907557
Mean dependent	13.62899	4.479383	1.879893	16.49256	-0.035649
S.D. dependent	0.073747	0.020679	0.043146	4.740174	0.052164

Determinant resid covariance (dof adj.)	4.28E-15
Determinant resid covariance	4.36E-16
Log likelihood	317.6901
Akaike information criterion	-17.51267
Schwarz criterion	-14.94381

Structural VAR Estimates
Date: 10/09/12 Time: 07:45

Sample (adjusted): 1994Q3 2001Q4
Included observations: 30 after adjustments
Estimation method: method of scoring (analytic derivatives)
Convergence achieved after 14 iterations
Structural VAR is just-identified

Model: Ae = Bu where E[uu']=I
Restriction Type: short-run text form
@e1 = C(1)*@u1
@e2 = C(2)*@e1 + C(3)*@u2
@e3 = C(4)*@e1 + C(5)*@e2 + C(6)*@u3
@e4 = C(7)*@e1 + C(8)*@e2 + C(9)*@e3 + C(10)*@u4
@e5 = C(11)*@e1 + C(12)*@e2 + C(13)*@e3 + C(14)*@e4 + C(15)*@u5
where
@e1 represents LOGRGDPCHANGE_SA residuals
@e2 represents LOGLFORCE_SA residuals
@e3 represents LOGREER residuals
@e4 represents TBILLRATE residuals
@e5 represents FDEFGDP residuals

	Coefficient	Std. Error	z-Statistic	Prob.
C(2)	0.296092	0.125999	2.349955	0.0188
C(4)	1.636937	0.470577	3.478572	0.0005
C(5)	1.613452	0.626634	2.574793	0.0100
C(7)	13.38672	83.69205	0.159952	0.8729
C(8)	11.37323	103.9536	0.109407	0.9129
C(9)	-10.14602	27.41004	-0.370157	0.7113
C(11)	0.003876	0.646103	0.006000	0.9952
C(12)	0.382780	0.802340	0.477080	0.6333
C(13)	-0.097224	0.211998	-0.458607	0.6465
C(14)	0.000194	0.001409	0.137890	0.8903
C(1)	0.008367	0.001080	7.745967	0.0000
C(3)	0.005774	0.000745	7.745967	0.0000
C(6)	0.019819	0.002559	7.745967	0.0000
C(10)	2.975424	0.384126	7.745967	0.0000
C(15)	0.022960	0.002964	7.745967	0.0000
Log likelihood	283.4332			

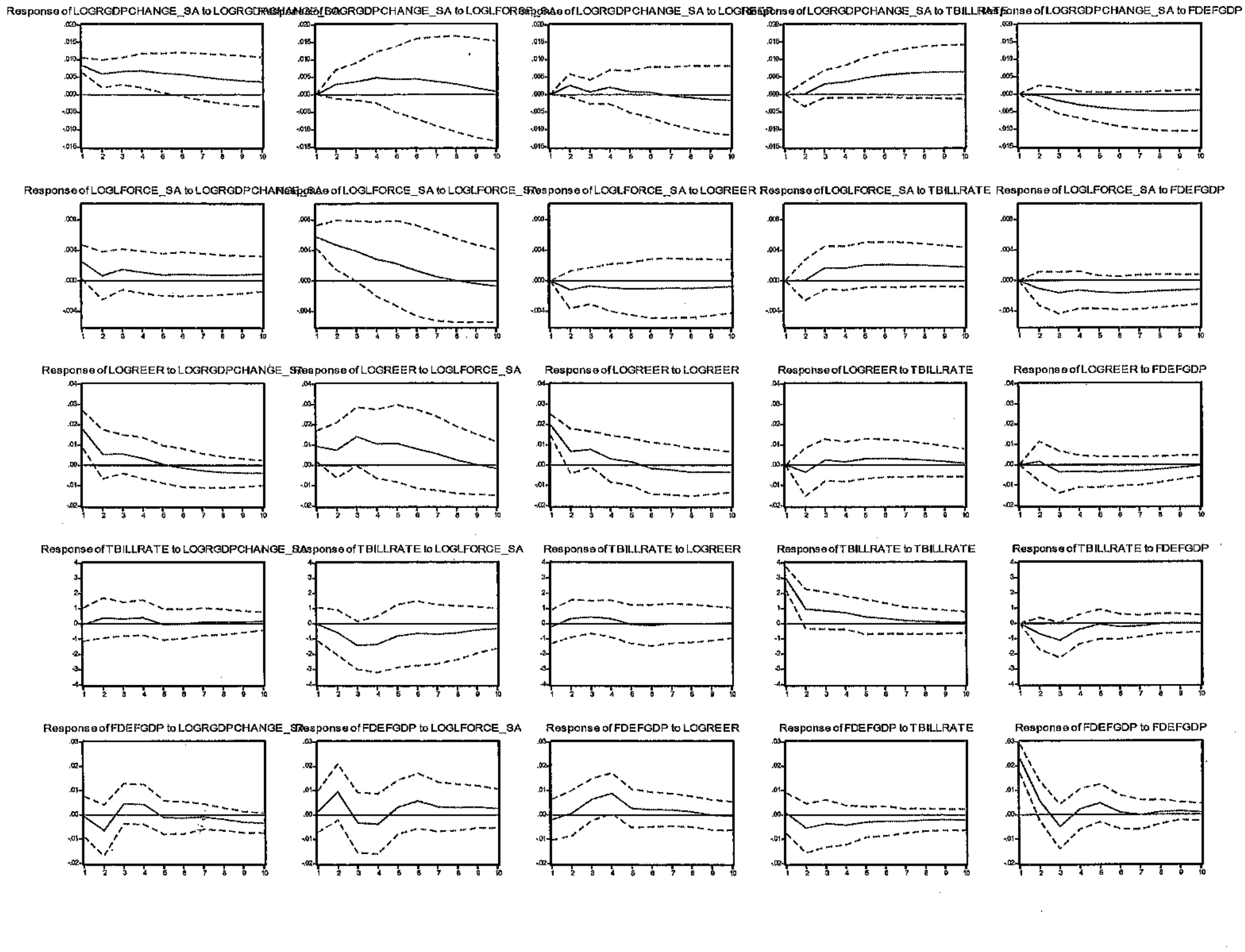
Estimated A matrix:

1.000000	0.000000	0.000000	0.000000	0.000000
-0.296092	1.000000	0.000000	0.000000	0.000000
-1.636937	-1.613452	1.000000	0.000000	0.000000
-13.38672	-11.37323	10.14602	1.000000	0.000000
-0.003876	-0.382780	0.097224	-0.000194	1.000000

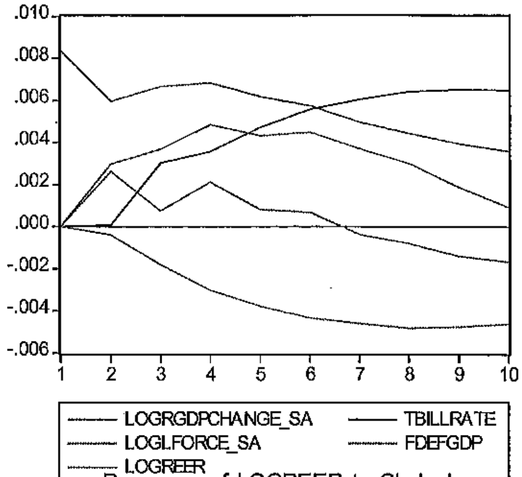
Estimated B matrix:

0.008367	0.000000	0.000000	0.000000	0.000000
0.000000	0.005774	0.000000	0.000000	0.000000
0.000000	0.000000	0.019819	0.000000	0.000000
0.000000	0.000000	0.000000	2.975424	0.000000
0.000000	0.000000	0.000000	0.000000	0.022960

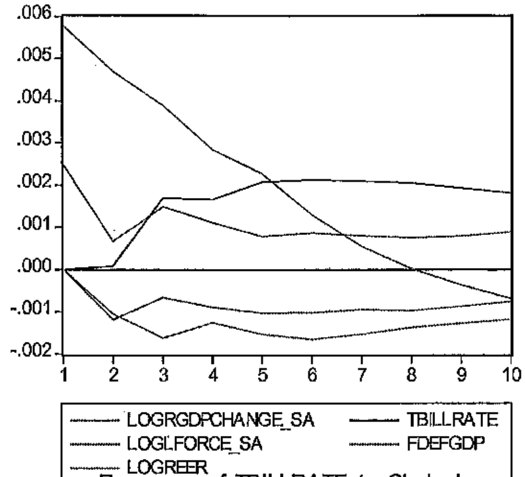
Response to Cholesky One S.D. Innovations ± 2 S.E.



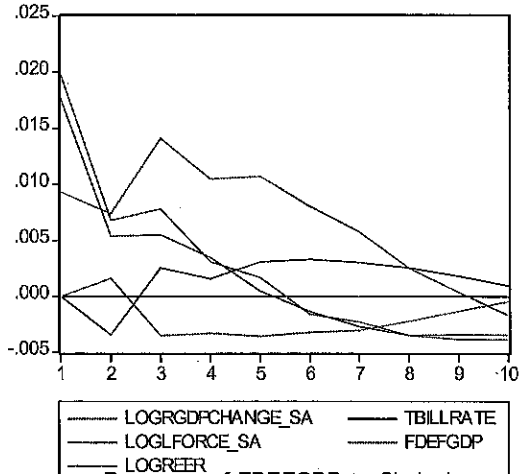
Response of LOGRGDPCHANGE_SA to Cholesky
One S.D. Innovations



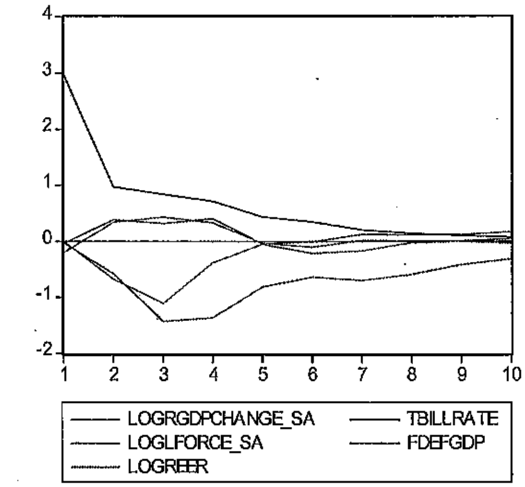
Response of LOGLFORCE_SA to Cholesky
One S.D. Innovations



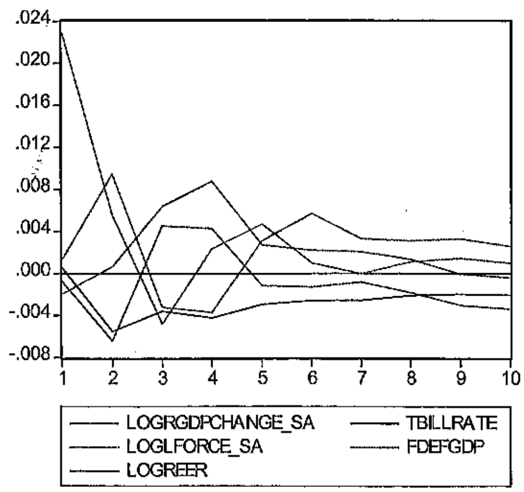
Response of LOGREER to Cholesky
One S.D. Innovations



Response of TBILLRATE to Cholesky
One S.D. Innovations



Response of FDEFGDP to Cholesky
One S.D. Innovations



Appendix B- Annual

1. Quadratic Mode

Dependent Variable: RGDP00
Method: Least Squares
Date: 10/09/12 Time: 08:51
Sample: 1980 2011
Included observations: 32

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2601567.	55817.29	46.60862	0.0000
QUADTIME	3.609211	0.149144	24.19945	0.0000

R-squared	0.951268	Mean dependent var	3418839.
Adjusted R-squared	0.949644	S.D. dependent var	1120293.
S.E. of regression	251396.1	Akaike info criterion	27.76791
Sum squared resid	1.90E+12	Schwarz criterion	27.85952
Log likelihood	-442.2865	F-statistic	585.6133
Durbin-Watson stat	0.188282	Prob(F-statistic)	0.000000

Period	Actual	Potential	Output Gap
1980	2284502.65	2601570.762	-0.121875644
1981	2362707.325	2601624.9	-0.091833982
1982	2448221.444	2601859.499	-0.059049328
1983	2494116.206	2602491.111	-0.041642757
1984	2311455.052	2603822.91	-0.112284079
1985	2142566.073	2606244.691	-0.177910623
1986	2215772.902	2610232.869	-0.151120604
1987	2311308.938	2616350.481	-0.116590474
1988	2467381.102	2625247.187	-0.060133798
1989	2620489.776	2637659.263	-0.006509365
1990	2700073.167	2654409.612	0.017202905
1991	2684457.709	2676407.753	0.003007747
1992	2693520.519	2704649.829	-0.00411488
1993	2750523.687	2740218.603	0.003760679
1994	2871206.307	2784283.461	0.031219108

1995	3005541.213	2838100.406	0.058997492
1996	3181241.349	2903012.066	0.095841587
1997	3346200.238	2980447.688	0.122717319
1998	3326901.959	3071923.142	0.083002994
1999	3429434.298	3179040.915	0.078763813
2000	3580714.263	3303490.12	0.083918563
2001	3684339.671	3447046.488	0.068839566
2002	3818667.133	3611572.372	0.057341994
2003	4008468.969	3799016.746	0.055133272
2004	4276941.133	4011415.205	0.066192581
2005	4481279.173	4250889.965	0.054197876
2006	4716230.864	4519649.864	0.043494741
2007	5028287.933	4819990.358	0.043215351
2008	5237100.502	5154293.528	0.01606563
2009	5297239.816	5525028.074	-0.041228435
2010	5701539.019	5934749.318	-0.039295729
2011	5924408	6386099.201	-0.072296278

2. HP Filter

Period	Actual	Potential	Output Gap
1980	2284502.65	2293799.658	-0.004053104
1981	2362707.325	2303770.913	0.025582584
1982	2448221.444	2313649.197	0.058164499
1983	2494116.206	2323930.905	0.073231653
1984	2311455.052	2336458.153	-0.010701283
1985	2142566.073	2354774.911	-0.090118524
1986	2215772.902	2382175.118	-0.069853058
1987	2311308.938	2419830.624	-0.044846811
1988	2467381.102	2467249.256	5.34384E-05
1989	2620489.776	2522853.626	0.03870068
1990	2700073.167	2585067.663	0.044488392
1991	2684457.709	2653291.659	0.011746183
1992	2693520.519	2728075.959	-0.012666597
1993	2750523.687	2810282.57	-0.021264368
1994	2871206.307	2900427.944	-0.01007494

1995	3005541.213	2998430.945	0.002371329
1996	3181241.349	3103918.22	0.024911458
1997	3346200.238	3216587.518	0.040295101
1998	3326901.959	3336909.82	-0.00299914
1999	3429434.298	3466652.235	-0.010735988
2000	3580714.263	3607481.791	-0.007420004
2001	3684339.671	3760693.34	-0.020303083
2002	3818667.133	3927314.056	-0.027664435
2003	4008468.969	4107607.577	-0.024135365
2004	4276941.133	4300751.073	-0.005536228
2005	4481279.173	4504930.326	-0.00525006
2006	4716230.864	4718093.019	-0.000394684
2007	5028287.933	4937950.326	0.018294556
2008	5237100.502	5162194.795	0.014510438
2009	5297239.816	5389422.355	-0.017104345
2010	5701539.019	5618977.987	0.014693247
2011	5924408	5849284.851	0.012843134

3. SVAR

Vector Autoregression Estimates
Date: 10/06/12 Time: 22:16
Sample (adjusted): 1982 2011
Included observations: 27 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	LOGRGDPCHANGE	LOGREER	LOGTLFORCE	TBILLRATE	FDEFICITGDP
LOGRGDPCHANGE(-1)	1.136281	0.126411	-0.044439	75.07302	0.160393
	(0.28020)	(0.43253)	(0.05893)	(15.7691)	(0.12448)
	[4.05523]	[0.29226]	[-0.75411]	[4.76078]	[1.28846]
LOGRGDPCHANGE(-2)	-0.289287	0.218913	-0.003800	-93.41275	-0.160308
	(0.25403)	(0.39213)	(0.05343)	(14.2962)	(0.11286)
	[-1.13879]	[0.55827]	[-0.07112]	[-6.53411]	[-1.42046]
LOGREER(-1)	0.385930	0.532728	0.042378	7.378432	-0.028961
	(0.19590)	(0.30240)	(0.04120)	(11.0249)	(0.08703)
	[1.97001]	[1.76166]	[1.02858]	[0.66925]	[-0.33276]
LOGREER(-2)	-0.515614	-0.280324	0.063595	-8.731246	-0.006520

	(0.16993)	(0.26231)	(0.03574)	(9.56325)	(0.07549)
	[-3.03427]	[-1.06868]	[1.77946]	[-0.91300]	[-0.08637]
LOGTLFORCE(-1)	0.731423	0.703789	0.626004	-43.33384	-0.575503
	(0.96349)	(1.48728)	(0.20263)	(54.2232)	(0.42805)
	[0.75914]	[0.47321]	[3.08933]	[-0.79918]	[-1.34448]
LOGTLFORCE(-2)	-0.385527	-1.590013	0.525773	65.75481	0.480433
	(1.04253)	(1.60929)	(0.21926)	(58.6713)	(0.46316)
	[-0.36980]	[-0.98802]	[2.39798]	[1.12073]	[1.03729]
TBILLRATE(-1)	0.001260	0.002863	-0.000145	0.438598	-0.001132
	(0.00288)	(0.00445)	(0.00061)	(0.16216)	(0.00128)
	[0.43742]	[0.64368]	[-0.23892]	[2.70472]	[-0.88419]
TBILLRATE(-2)	-0.004139	0.000644	-0.000387	-0.107074	0.001131
	(0.00267)	(0.00412)	(0.00056)	(0.15014)	(0.00119)
	[-1.55152]	[0.15642]	[-0.68969]	[-0.71314]	[0.95446]
FDEFICITGDP(-1)	-1.034413	0.092933	0.080016	-76.98735	0.861687
	(0.51341)	(0.79252)	(0.10798)	(28.8937)	(0.22809)
	[-2.01477]	[0.11726]	[0.74104]	[-2.66450]	[3.77778]
FDEFICITGDP(-2)	0.779314	0.725079	-0.048535	128.2162	-0.298967
	(0.58155)	(0.89771)	(0.12231)	(32.7285)	(0.25837)
	[1.34006]	[0.80770]	[-0.39683]	[3.91758]	[-1.15715]
C	0.008915	2.784948	-0.582656	115.3515	0.764189
	(1.13185)	(1.74716)	(0.23804)	(63.6977)	(0.50284)
	[0.00788]	[1.59399]	[-2.44772]	[1.81092]	[1.51974]
R-squared	0.996053	0.763419	0.998388	0.948184	0.811406
Adj. R-squared	0.993586	0.615555	0.997381	0.915800	0.693534
Sum sq. resids	0.010105	0.024079	0.000447	32.00476	0.001994
S.E. equation	0.025131	0.038793	0.005285	1.414319	0.011165
F-statistic	403.7581	5.163002	991.1766	29.27870	6.883820
Log likelihood	68.21102	56.48928	110.3085	-40.60698	90.11690
Akaike AIC	-4.237853	-3.369577	-7.356186	3.822739	-5.860511
Schwarz SC	-3.709920	-2.841643	-6.828252	4.350673	-5.332578
Mean dependent	15.04313	1.873308	7.455324	8.830175	-0.019743
S.D. dependent	0.313794	0.062566	0.103279	4.874051	0.020168

Determinant resid covariance (dof adj.)	1.28E-15
Determinant resid covariance	9.33E-17
Log likelihood	306.7417
Akaike information criterion	-18.64753
Schwarz criterion	-16.00786

Structural VAR Estimates
Date: 10/06/12 Time: 22:16
Sample (adjusted): 1982 2011
Included observations: 27 after adjustments
Estimation method: method of scoring (analytic derivatives)
Convergence achieved after 13 iterations
Structural VAR is just-identified

Model: Ae = Bu where E[uu']=I
Restriction Type: short-run text form
@e1 = C(1)*@u1
@e2 = C(2)*@e1 + C(3)*@u2
@e3 = C(4)*@e1 + C(5)*@e2 + C(6)*@u3
@e4 = C(7)*@e1 + C(8)*@e2 + C(9)*@e3 + C(10)*@u4
@e5 = C(11)*@e1 + C(12)*@e2 + C(13)*@e3 + C(14)*@e4 + C(15)*@u5
where
@e1 represents LOGRGDPCHANGE residuals
@e2 represents LOGREER residuals
@e3 represents LOGTLFORCE residuals
@e4 represents TBILLRATE residuals
@e5 represents FDEFICITGDP residuals

	Coefficient	Std. Error	z-Statistic	Prob.
C(2)	0.559592	0.276865	2.021176	0.0433
C(4)	0.006857	0.043357	0.158149	0.8743
C(5)	0.005007	0.028088	0.178277	0.8585
C(7)	37.93224	7.050063	5.380411	0.0000
C(8)	-26.10287	4.567763	-5.714586	0.0000
C(9)	34.10580	31.27870	1.090384	0.2755
C(11)	0.035067	0.102818	0.341060	0.7331
C(12)	0.178577	0.068788	2.596043	0.0094
C(13)	-0.462083	0.323794	-1.427089	0.1536
C(14)	0.001283	0.001950	0.657803	0.5107
C(1)	0.025131	0.003420	7.348469	0.0000
C(3)	0.036154	0.004920	7.348469	0.0000
C(6)	0.005277	0.000718	7.348469	0.0000
C(10)	0.857612	0.116706	7.348469	0.0000
C(15)	0.008689	0.001182	7.348469	0.0000

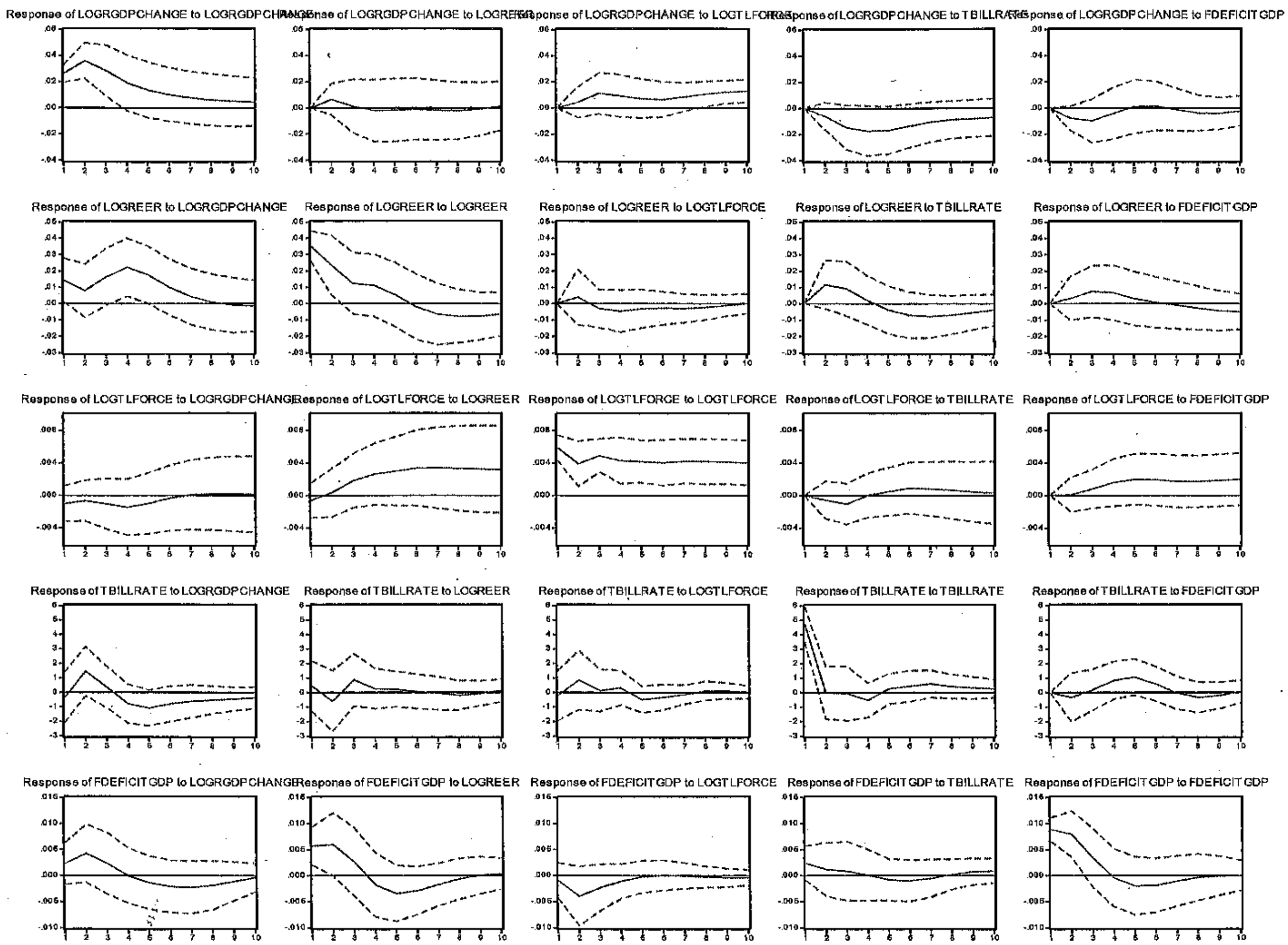
Log likelihood 271.4224

Estimated A matrix:

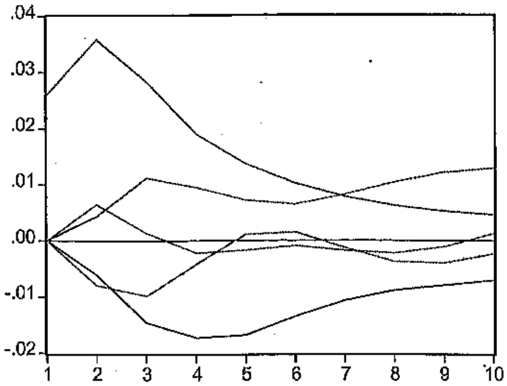
1.000000	0.000000	0.000000	0.000000	0.000000
-0.559592	1.000000	0.000000	0.000000	0.000000

-0.006857	-0.005007	1.000000	0.000000	0.000000
-37.93224	26.10287	-34.10580	1.000000	0.000000
-0.035067	-0.178577	0.462083	-0.001283	1.000000
Estimated B matrix:				
0.025131	0.000000	0.000000	0.000000	0.000000
0.000000	0.036154	0.000000	0.000000	0.000000
0.000000	0.000000	0.005277	0.000000	0.000000
0.000000	0.000000	0.000000	0.857612	0.000000
0.000000	0.000000	0.000000	0.000000	0.008689

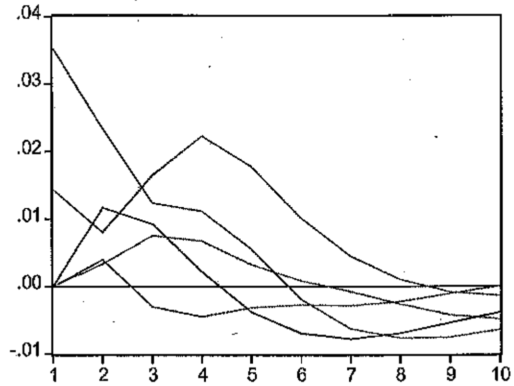
Response to Cholesky One S.D. Innovations ± 2 S.E.



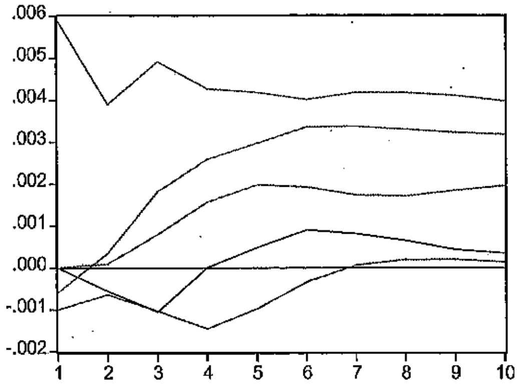
Response of LOGRGDPCHANGE to Cholesky
One S.D. Innovations



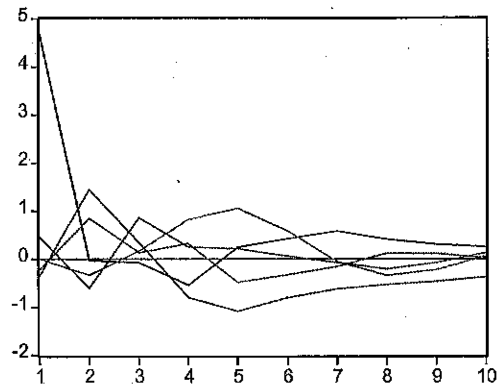
Response of LOGREER to Cholesky
One S.D. Innovations



Response of LOGTLFORCE to Cholesky
One S.D. Innovations



Response of TBILLRATE to Cholesky
One S.D. Innovations



Response of FDEFICITGDP to Cholesky
One S.D. Innovations