

The Role of Oil Revenue Shocks in Iranian Economy, A TVP-VAR Approach

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Abstract

In this paper, we analyze the effects of oil revenue shocks on different sectors of Iranian economy. We use quarterly data of Iranian economy from 1988:2 to 2011:1 to analyze a time varying parameter VAR model with Bayesian method. The results show that in late 1980s and early 1990s, the positive effects of oil revenue were mostly emerged in industrial and oil sectors, having almost no effect on services sector and negative effect on agricultural sector. In 2000s, oil revenue is relatively less effective in industrial sector, while more effective in agricultural and services sectors.

Keywords: Oil, Shock, Output, VAR, Bayesian

1- Introduction

In this paper, we analyze the effect of oil revenue shocks on Iranian economy. This is not a new subject and many papers have dealt with it. (see Frazanegan and Marqwardt (2009), Frazanegan (2011), Mojab and Barakchian (2011) and Esfahani and et. al. (2012) among others). This paper contributes to the existing literature in two main ways: First, we estimate a Time-Varying Parameter VAR model and second, we disaggregate output into value-added of different sectors of economy.

Time-varying parameters models become more and more important as the length of the observed time series increases and the series itself is subject to changes in the dynamic structure (see Canova (1993), Sims (1993) and

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Stock and Watson (1996) for some discussions). There are at least four major changes in Iranian economy after Iran-Iraq war, which might have an effect on the parameters of a macro model. First, late years of 1980s and the early years of 1990s are known to be the reconstruction period. Due to the diminishing marginal productivity law, the marginal productivity of capital is higher in those years. Since oil revenues finance most of capital import, we expect that oil play a more important role in that period.

Second, there level of oil revenue changed from 1990s to 2000s. Non-linear effects of oil revenue in an economy are discussed in the literature since mid-1980s, when the decrease of the oil price did not affect output positively (see Hamilton (1996) or Jimenez-Rodriguez and Sanchez (2005) among others). Adapting these theories for oil exporting countries (see Farznegan and Markwardt (2009)), this means that an increase in oil revenue does not have exactly the opposite effect of a decrease in oil revenue. As a result, there is a possibility that the role of oil in Iranian economy changes from 1990s to 2000s. The formation of the exchange reserve fund and exchange rate unification policy in early 2000s, are two other changes that might have changed the parameters of a macro-model in Iranian economy. As a result, in this study we estimate a TVP-VAR model of Iranian economy.

The second contribution of this paper is about decomposing GDP into the value added of agricultural, Industrial, oil and services sectors. Degree of freedom consideration does not allow the researchers to estimate large VAR models with conventional approaches like maximum likelihood. This can explain why none of the previous studies used a decomposed GDP.

There are many good reasons why decomposition is important. First, Simple correlation analysis shows that value added of different sectors of economy are not highly positively correlated. In fact, as the results in table (1) shows, the agricultural and industrial sectors are negatively correlated, which is significant in quarterly data. Only the industrial and services sectors are positively and significantly correlated. This means that aggregation eliminates many of the variation. Second, disaggregation of output is not a new discussion. According to Dutch disease theory (see Rosser (2006)), the oil revenue shocks will have different effects on tradable and non-tradable sectors of economy.

In this paper, we decompose GDP to value added of different sectors of economy. Although we can divide different sectors to tradable and non-tradable, but in addition to the tradability of output, the nature of production differs in different sectors. Production in oil sector is mostly related to the pressure of oil wells and foreign investment and therefore is more exogenous than production in other sectors. In other words, we should not expect monetary policy to affect production in this sector. Production in agricultural sector is more traditional and therefore uses a lower level of technology. Since oil revenue is the main determinant of technology level (see Esfahani and et. al (2012) and Mojab and Barakchian (2011)), this implies that agricultural sector is less dependent to oil revenues. On the other hand, Services and agricultural sectors are more labor intensive, which again implies different dependencies to oil.

The remainder of this paper is organized as follows. Section 2 describes the basic statistical model that we used to develop empirical evidence. Section 3 reports our results and section 4 concludes.

Table 1: The Correlation Coefficients between Growth Rates in Different Sectors of Economy

Industrial s.	Oil s.	Services s.	Agricultural s.	
-0.04(0.85)	0.52(0.01)	0.15(0.51)		Agricultural s.
0.72(0.00)	0.27(0.24)		-0.27(0.01)	Services s.
0.07(0.75)		-0.15(0.16)	0.29(0.00)	Oil s.
	-0.08(0.41)	0.72(0.00)	-0.48(0.00)	Industrial s.

This is NOT a correlation matrix. The numbers in the lower triangular is the correlation coefficients calculated using *quarterly* data and the higher triangular shows the correlation coefficients calculated using *yearly* data. The numbers in the parenthesis are the p. value in zero correlation tests. The data are discrete growth rate. They have been deseasonalized using X-12-ARIMA Filter.

2- Bayesian estimation of a TVP-VAR model

The statistical model of this paper is a State-Space model, which is a transformation of a VAR model with time varying parameters:

$$\begin{aligned}
 y_t &= X_t s_t + s_{\epsilon t}, & t &= 1, \dots, T \\
 s_{t+1} &= s_t + u_{t+1}, & t &= 0, 1, \dots, T \\
 s_0 &\sim N(\alpha, P)
 \end{aligned}
 \tag{1}$$

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In this mode $\mathbf{y}_t: n \times 1$ is the vector of endogenous variables. $\mathbf{X}_t: n \times k$ consists of the exogenous or lags of endogenous variables. $\mathbf{s}_t: k \times 1$ is the state variables and consists of the parameters of the VAR model. The first equation is the observation equation and the second one is the State equation. We assume that $\mathbf{s}_t \sim N(\mathbf{0}, \mathbf{\Omega})$ and $\mathbf{\Omega}: n \times n$ is a positive definite matrix. We assume that $\mathbf{u}_t \sim N(\mathbf{0}, \mathbf{\Sigma})$ and $\mathbf{\Sigma}: k \times k$ is also a positive definite matrix. We assume that \mathbf{s}_t and \mathbf{u}_t are uncorrelated in all times. $\mathbf{a}: k \times 1$ and $\mathbf{P}: k \times k$ determines the first value of the states and needs to be calibrated. $\mathbf{\Omega}$ and $\mathbf{\Sigma}$ are named the hyper-parameters of the model.

Gibbs sampling is a common numerical approach to generate posterior joint distribution of states and hyper-parameters. To use this approach, one needs the conditional distributions. It is common to assume that the prior joint probability distribution of state variables and hyper-parameters is an independent Normal-Inverse Wishart distribution. As a result, we assume that $\mathbf{\Omega} \sim \mathcal{W}^{-1}(\mathbf{A}, \mathbf{v})$ and $\mathbf{\Sigma} \sim \mathcal{W}^{-1}(\mathbf{B}, w)$. The matrices $\mathbf{A}: n \times n$ and $\mathbf{B}: k \times k$ are positive definite and are proportional to the expected value of $\mathbf{\Omega}$ or $\mathbf{\Sigma}$. An increase in \mathbf{v} and w can be interpreted as a decrease in the variance of $\mathbf{\Omega}$ and $\mathbf{\Sigma}$, respectively. These parameters should be larger than the rows of $\mathbf{\Omega}$ and $\mathbf{\Sigma}$. That's why the values $\mathbf{v} = n + 1$ and $w = k + 1$ means the largest possible variance of $\mathbf{\Omega}$ and $\mathbf{\Sigma}$. The posterior distributions of hyper-parameters can be calculated using normal regression model theories:

$$\begin{aligned} \mathbf{\Omega} | \mathbf{y}, \mathbf{x}, \mathbf{s}, \mathbf{\Sigma} &\sim \mathcal{W}^{-1}(\bar{\mathbf{A}}, \bar{\mathbf{v}}) \\ \bar{\mathbf{v}} &= T + \mathbf{v} \\ \bar{\mathbf{A}} &= \mathbf{A} + \sum (\mathbf{y}_t - \mathbf{X}_t \mathbf{s}_t)(\mathbf{y}_t - \mathbf{X}_t \mathbf{s}_t)' \quad (2) \\ \mathbf{\Sigma} | \mathbf{y}, \mathbf{x}, \mathbf{s}, \mathbf{\Omega} &\sim \mathcal{W}^{-1}(\bar{\mathbf{B}}, \bar{w}) \\ \bar{w} &= T + w \\ \bar{\mathbf{B}} &= \mathbf{B} + \sum (\mathbf{s}_{t+1} - \mathbf{s}_t)(\mathbf{s}_{t+1} - \mathbf{s}_t)' \end{aligned}$$

We can use these results to generate random samples from conditional distribution of hyper-parameters. To use Gibbs sampling approach, one needs samples from conditional distribution of the state variables. To this regard, we use De Jong and Shepard (1995) algorithm.

We should calibrate prior distributions. A common approach is to use a training sample (with T observations) and estimate a time-constant parameter model. If \mathbf{b}_{MLT} , \mathbf{P}_{MLT} and \mathbf{V}_{MLT} are respectively estimated coefficients,

estimated variance of the coefficients and estimated variance of residuals, priors will be calibrated by:

$$\begin{aligned} s_0 &\sim \mathcal{N}(b_{MLT}, P_{MLT}) \\ \Omega &\sim \mathcal{W}^{-1}(V_{MLT}, n + 1) \\ \Sigma &\sim \mathcal{W}^{-1}(\lambda^2 P_{MLT}, k + 1) \end{aligned} \quad (3)$$

As I discussed, $n + 1$ and $k + 1$ means we set the least possible probability to the priors. Since the hyper-parameters are not time varying, we calibrate them using all sample data (that's why they get subscript T). In a conservative approach, Cogley and Sargent (2005) suggest to use a small value for λ^2 . they use 0.00035. This is called a "Business-as-Usual" prior, which means we do not expect the parameters to change severely. Larger values for λ^2 will result in larger variations of the parameters and larger posterior variances. In other words, there is a tradeoff between uncertainty of the results and their time variations. Since there are no other bases for choosing this parameter, we follow the conservative approach of Cogley and Sargent (2005). This makes the posterior variances small, which means, in reporting the results we can only rely on posterior means. We executed 100,000 replications of a Gibbs sampler and discarded the first 50,000. We saved every 5th draw from Markov chain.

3- Empirical Results

Based on previous studies like Frazanegan and Marquardt (2009), Esfahani and et. al. (2012) and Mojab and Barakchian (2011) and the discussion of this paper about the importance of decomposing GDP to the value added of different sectors (see the introduction), we choose the following vector of endogenous variables for the VAR model:

$$y_t = (r_t, ag_t, in_t, ss_t, ol_t, e_t, p_t, m_t)' \quad (4)$$

in which y_t is the vector of endogenous variables in (1). r_t is real oil revenue, ag_t , in_t , ss_t and ol_t are real value added of the agriculture, industrial, services and oil sectors respectively, e_t is the real exchange rate, p_t is the price index and m_t is the monetary base. The oil revenue series is calculated by multiplying Iranian oil exports per barrel and crude oil price in

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Dubai market. The oil price is from IFS (64...ZF). Other data are from central bank of Iran database. We used quarterly data of 1988:2-2011:1.

We decompose shocks using Cholesky decomposition. The order of the variables in this decomposition is the same as (4). Oil revenue is the most exogenous variable, which is a common choice in the literature and since we only report the results of oil revenue shock, a change in the order of other variables does not change the results empirically and theoretically (see Sims and et. al. (1990)).

The early results showed that Impulse Response Functions (IRF) graphs could be best displayed in contour plots. The IRF of the value-added of oil, agricultural, industrial and services sectors to a positive shock to oil revenue are reported in figures 1 to 4 respectively. The horizontal axis represents the time; the vertical axis represents the number of periods after shock. Different colors represent different values of IRF. The color-bar at the right side of each graph represents the magnitude of values. Darker regions are related to higher values.

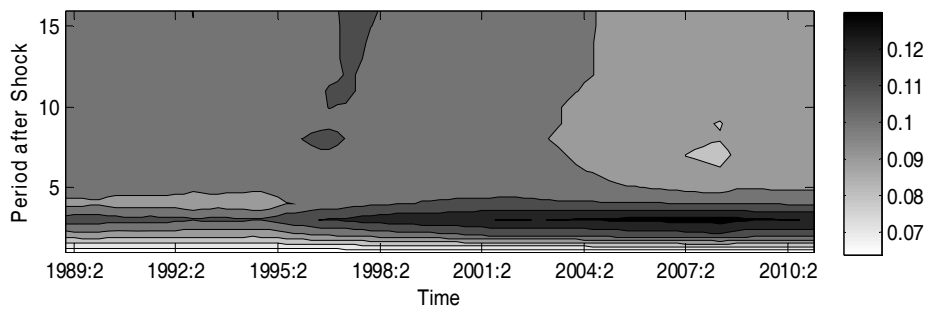


Figure 1: Response of Value Added of Oil Sector to a Positive Shock to Oil Revenue.

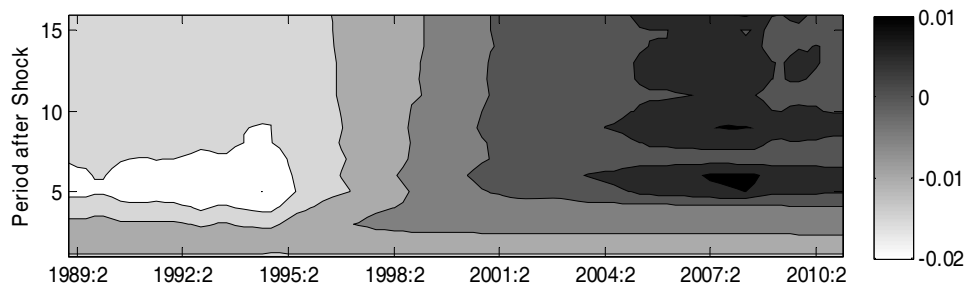


Figure (2): Response of Value Added of Agricultural Sector to a Positive Shock to Oil Revenue.

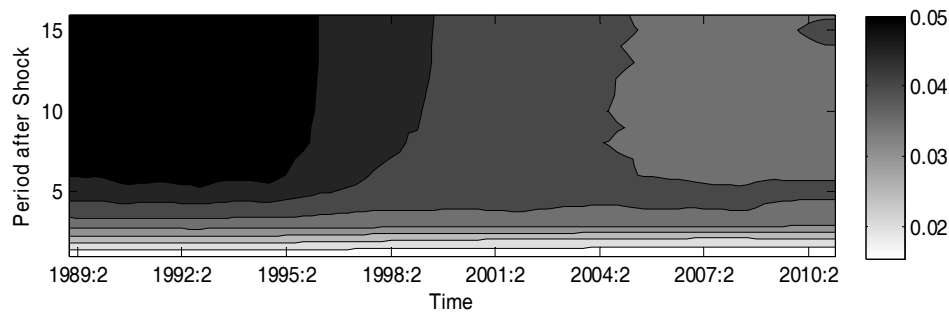


Figure 3: Response of Value Added of Industrial Sector to a Positive Shock to Oil Revenue.

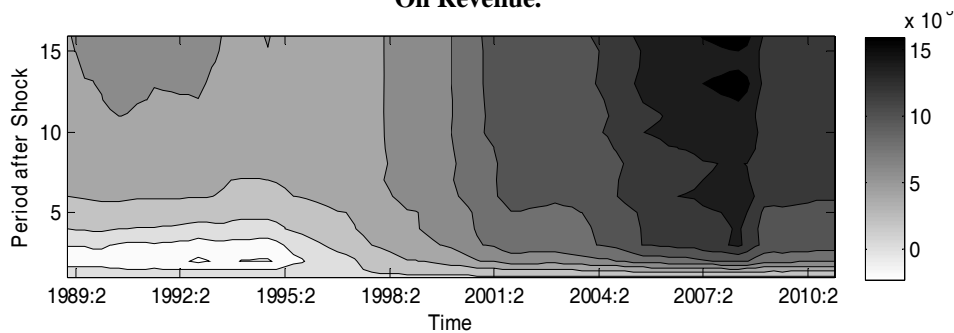


Figure 4: Response of Value added of Services Sector to a Positive Shock to Oil Revenue.

The results show that oil revenue shock has a positive impact on the value added of oil sector (Figure 1). The effect is humped shape. It increases in the first 2 or 3 periods and decreases after 5 periods. After more than 12 quarters, the new level is positive and is about 0.07.

The effect of oil revenue shock on industrial sector is also positive, but more time-dependent than oil sector (Figure 3). In 1990s, in contrast with oil sector, the effect in longer periods is larger than shorter periods, while in 2000s, the positive effect increases in the first 2 or 3 periods and decreases after 5 periods. The effects are positive in longer periods.

The effect of oil revenue shock in services sector is almost positive in all times, but are rather small, compared with industrial and oil sectors (Figure 4). The results are relatively small, but they are time dependent. In 2000s the effects are larger than 1990s. In agricultural sector, the responses are time dependent, negative before 2000 and positive after that.

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Comparing the results of different variables shows that oil revenue shocks has been more effective in oil and industrial sectors. The magnitude of responses in oil (Figure 1) and industrial sectors (Figure 3) are between 0.6 to 0.13 and 0.1 to 0.5, respectively, which is higher than the range of values in two other sectors. The magnitude of responses in agricultural (Figure 2) and services sectors (Figure 4) are between -0.02 to 0.01 and 0.00 to 0.015, respectively.

There exists some periods in which oil revenue shocks have decreased the value-added of agricultural sector. Figure 2 shows that these periods are mostly after the war and before 1995, the period we called the reconstruction period. Figure 4 shows that in this period, oil revenue is almost ineffective on the services sector, but changes the value-added of industrial and oil sectors more than any other time. Of course, this effect is more significant in industrial sector.

4- Conclusion

The results show the time-dependency of responses of output in different sectors of the economy to an oil revenue shock, while they also show the importance of decomposing output into different sectors of the economy.

The economic interpretation of the empirical results is not easy, because as we discussed in the introduction, we should consider at least four events: war reconstruction period of late 1980s and early 1990s, oil revenue boom of 2000-2008, exchange reserve fund formation and exchange rate unification policy of early 2000s. In addition, we should consider the fact that the positive or negative effect of oil in economy is still a debatable issue in the theoretical literature (see Rosser (2006)).

It seems that in the war reconstruction period, whether because of government policies or because of the economic conditions, the positive effects of oil revenue were mostly emerged in industrial and oil sectors, having almost no effect on services sectors and negative effect on agricultural sectors. In 2000s, the war reconstructions are almost over and the economy enters a high oil revenue period. In this period, oil revenue is less effective in industrial sector, while more effective in agricultural and services sectors.

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