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BAYESIAN ANALYSIS OF TIME-VARYING PARAMETER VECTOR AUTOREGRESSIVE MODEL FOR IRANIAN AGRICULTURAL ECONOMY AND MONETARY POLICY

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ABSTRACT

Monetary policies play a significant role in economic growth and development. This study analyzes the stochastic time-varying parameter vector autoregressive (TVP -VAR) model for the effect of monetary policy on Iranian agricultural economy variables. To achieve this purpose the time-varying parameters are estimated through the Markov chain Monte Carlo method and the posterior estimates for the time-varying parameters of monetary policy efficacy on the Iranian agricultural economic during the period from 1980 to 2013. The derived marginal likelihoods of the TVP-VAR model and other VAR models for Iranian agriculture economic data indicate that macroeconomic variables have dynamic interaction together.This means that decreasing the effective interest rate and increasing monetary base, increase the agricultural production and reducing the rate of inflation.

Keywords: Bayesian, Markov chain Monte Carlo, Monetary policy, Time-varying parameter.

1. INTRODUCTION

Monetary policy is one of the most important macroeconomic policies that play a significant role in economic growth and development. Governments by the application of monetary policy tools of their own affect the displacement of economics aggregate demand and cause the desired changes in investment and production. Monetary policy is of the economic policies of the demand side that is accomplished by changing in the bulk and growth of money, interest rates, changes in exchange rates and terms of financial facilities. Since agricultural sector has considerable capabilities and capacities as well as its role in supplying raw materials of industries and people's food is of paramount importance. In this study we estimate a time-varying parameter vector autoregressive (TVP-VAR) model for Iran's agricultural economic and monetary policy.

Time varying parameter (TVP) models have been comprehensively studied in the literature for instance Cooley and Prescott (1973, 1976). The TVP-VAR models have received considerable attention from the literature, the use of this estimation technique expansion by Cogly and Sargent (2005) and Primiceri (2005) derive its specification for the US economy data. Benati and Mumtaz (2005) provide empirical results for the TVP-VAR model for the UK economy and Baumeister et al. (2008) for the Euro economy. Nakajima et al. (2009, 2011, 2013) show significant relation among major macroeconomic variables in japan using time-varying parameter vector autoregressive (TVP-VAR) model. Also Ergün and Jun (2010), Maissant (2012), Giraitis et al (2013), Koopa and Korobilis (2013), Barnett et al (2014) applied time-varying parameter in their studies.

We apply their method to Iran's agricultural economy, in our empirical analysis using Iran's agricultural economy data that collected from Iranian central bank, a four-variable VAR system is estimated. The model includes the inflation rate, agricultural production, effective short-term interest rate, and monetary base. The stochastic volatilities performance and time-varying impulse responses of the macroeconomic variables are plotted over time, therefore marginal likelihoods of the TVP-VAR specification and other VAR models are derived.

2. Materials and Methods

Structural VAR models: We show a basic structural VAR model that Nakajima (2011) defined as:

$$Ay_t = F_1 y_{t-1} + ... + F_s y_{t-s} + u_t, \qquad t = s+1,...,n \text{ ....} \quad (1)$$

In this model y_t is an $K \times 1$ vector of observed variables, $A, F_1, \ldots, F_s$ are $K \times K$ matrices of coefficients, and u_t is a $K \times 1$ structural shock. Following Nakajima we have recursive identification for simultaneous relations of the structural shock, considering that A is lower-triangular,

$$A = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \cdots & a_{k,k-1} & 1 \end{pmatrix} \qquad (2)$$

That can express model (1) as the following autoregressive form VAR model:

$$y_t = B_1 y_{t-1} + \cdots + B_s y_{t-s} + A^{-1} \sum \varepsilon_t, \qquad \varepsilon_t \sim N(0, I_k) \qquad (3)$$

Which $B_i = A^{-1} F_i$, for $i = 1, \ldots, s$, also we have:

$$\sum = \begin{pmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_k \end{pmatrix} \qquad (4)$$

Where elements of $\delta_i \, (i = 1, \ldots, k)$ indicate the standard deviation of the structural shock in the main diagonal of the matrix. We can justify model by stating that $X_t = I_k \otimes (y_{t-1}, \ldots, y_{t-k})$, and have a backing of the elements in the rows of the B_i's to form β ($k^2 s \times 1$), as:

$$y_t = X_t \beta + A^{-1} \sum \varepsilon_t \qquad (5)$$

So far mentioned parameters was time-invariant, thus by dig more onto the literature in following we specify models by allowing these parameters change over time.

Time-Varying Parameter VAR: Nakajima (2009) consider random walk process for time-varying parameter VAR (TVP-VAR) model as following:

$$y_t = X_t \beta_t + A_t^{-1} \sum\nolimits_t \varepsilon_t, \qquad t = s+1, ..., n, \qquad (6)$$

In model (6) the coefficients β_t, and the parameters A_t, and $\sum_t$ are all time varying. There are many ways to illustrate the time-varying parameter technique, in the following we assume that a_t be a stacked vector of the lower-triangular elements in A_t and $h_t = (h_{1t}, \ldots, h_k)$ with $h_{jt} = \log \delta_{jt}^2$, for $j = 1, \ldots, k$, $t = s+1, \ldots, n$. As already mention and Following Primiceri (2005) and

Nakajima (2011), for random walk process in (6) we can write:

$$\begin{aligned}\beta_{t+1} &= \beta_t + u_{\beta t},\\ a_{t+1} &= a_t + u_{at},\\ h_{t+1} &= h_t + u_{ht},\end{aligned}\begin{pmatrix}\varepsilon_t\\ u_{\beta t}\\ u_{at}\\ u_{ht}\end{pmatrix} \sim N\left(0,\begin{pmatrix} I & 0 & 0 & 0\\ 0 & \sum_\beta & 0 & 0\\ 0 & 0 & \sum_a & 0\\ 0 & 0 & 0 & \sum_h\end{pmatrix}\right), \qquad (7)$$

Where

$t = s+1,\dots,n,\ \beta_{s+1} \sim N(\mu\beta_0, \sum \beta_0),\ a_{s+1} \sim (\mu_{a0}, \sum_{a0})$ and $h_{s+1} \sim N(\mu_{h0}, \sum_{h0})$, also denote that $\sum_\beta$, $\sum_a$ and $\sum_h$ are diagonal matrices. As Shephard (2005) estate that occurrence coefficients and parameters are designed such that derived shocks of the time-varying parameters can be uncorrelated among the β_t, a_t and h_t parameters and this design allows the log of variance (δ_t^2) to follow stochastic volatility with random walk process. In addition, Primiceri (2005) justify that structural of log volatility (h_t) has a stationary process with random walk process.

From Bayesian technique viewpoint, Chib (2001) describe that MCMC procedure estimate parameters in the TVP-VAR models under certain prior probability and sample drawn from high-dimensional posterior distribution of parameters including unobserved latent variables and state space particularity.

For sampling draw, de Jong and Shephard (1995), Durbin and Koopman (2002)) state a shortcut for sampling of $\beta = \{\beta_t\}_{t=s+1}^n$ (also, $a = \{a_t\}_{t=s+1}^n$, $h = \{h_t\}_{t=s+1}^n 1$) which in this sense, this sampling method does not rely on the one-at-a-time is better since written as linear Gaussian state space form, the simulation smoother proper for sampling the time-varying coefficient β and parameter.

Kim et al. (1998),Given that h has the stochastic volatility structure and follow the non-linear non-Gaussian state space form, expansion mixture sampler and multi-move sampler technique that has been comprehensively employed in the literature, for instance Omori et al. (2004, 2007), Primiceri (2005), Shephard and Pitt (1997).

MCMC algorithm: We apply the MCMC algorithm that Nakajima verify in seven steps and with this appendix that $y = \{y_t\}_{t=1}^n$ and $\omega = (\sum_\beta, \sum_a, \sum_h)$, we classify the prior probability density as $\pi(\omega)$ for ω. In the first step by the MCMC method derived the posterior distribution for y sample from the, $\pi(\beta, a, h, \omega | y)$, and continues affairs as:

1-Initialize β, a, h, ω

Repeat the following:

2-Sample $\beta|a,h,\sum_{\beta},y$ that steer by simulation smoother.

3-Sample $\sum_{\beta}|\beta,$ derivingsample from a Wishart or Gamma distribution under conjugate priors.

4-Sample $a|\beta,h,\sum_{a},y,$ its operations similar step 2.

5-Sample $\sum_{a}|a,$ its operations similar the step 3.

6-Sample $h|\beta,a,\sum_{h},y,$ the multi-move sampler for the stochastic volatility is necessity.

7-Sample $\sum_{h}h,$ its operations similar the step 3.

Denote that since the conditional posterior distribution of $\{h_{jt}\}_{t=s+1}^{n},(j=1,\ldots,k)$ is independent in the diagonal matrix of $\sum h$, sampling for h is relatively easier.

Sampling β: The conditional posterior distribution $\pi(\beta|a,h,\sum_{\beta},\ y)$ in the state space model verify sample β as following:

$$y_t = X_t\beta_t + A_t^{-1}\sum_t \varepsilon_t, \qquad t=s+1,\ldots,n,$$
$$\beta_{t+1} = \beta_t + u_{\beta t}, \qquad t=s,\ldots,n-1, \qquad \ldots\ldots\ldots\ldots\ldots\ldots(8)$$

In this models $\beta_s = \mu_{\beta 0}$, and $u_{\beta s} \sim N(0,\sum_{\beta 0})$ and we can derive sample from the joint posterior distribution $\pi(\beta_{s+1},\ldots,\beta_n|a,h\sum\beta,y)$. De Jong and Shephard (1995), expansion the state space model in order to simulation smoother as:

$$y_t = Z_t\alpha_t + G_t u_t, \qquad t=s+1,\ldots,n,$$
$$\alpha_{t+1} = T_t\alpha_t + H_t u_t, \qquad t=s,\ldots,n-1 \qquad (9)$$

That $u_t \sim N(0,1)$ and $G_t H_t = 0$ and simulation smoother shows $\eta = (\eta_s,\ldots,\eta_{n-1}) \sim \pi(\eta|y,\theta)$, in this case $\eta_t = H_t u_t$ for $t=s,\ldots,n-1$, and θ indicate other parameters in the model. So we can present Kalman filter as:

$$e_t = y_t - Z_t a_t, \qquad D_t = Z_t P_t Z_t' + G_t G_t', \qquad K_t = T_t P_t Z_t' D_t^{-1},$$
$$L_t = T_t - k_t Z_t, \qquad a_{t+1} = T_t a_t + K_t e_t, \qquad P_{t+1} = T_t P_t L_t' + H_t H_t', \qquad (10)$$

In the models $t=s+1,\ldots,n,$ and $a_{s+1} = T_s\alpha_s$, also $P_{s+1} = H_s H_s$. With assume that $\Lambda_t = H_t H_t$, we have for simulation smoother:

$$C_t = \Lambda_t - \Lambda_t U_t \Lambda_t, \qquad \eta_t = \Lambda_t r_t + \varepsilon_t, \qquad \varepsilon_t \approx N(0,C_t), \qquad V_t = \Lambda_t U_t L_t,$$
$$r_{t-1} = Z_t' D_t^{-1} e_t + L_t' r_t - V_t' C_t^{-1}\varepsilon_t, \qquad U_{t-1} = Z_t' D_t^{-1} Z_t + L_t' U_t L_t + V_t' C_t^{-1} V_t \qquad (11)$$

That $t=n,n-1,\ldots,s+1,$ and $r_n = U_n = 0$. We have $\eta_s = \Lambda_s r_s + \varepsilon_s, \varepsilon_s \sim N(0,C_s)$, with $C_s = \Lambda_s - \Lambda_s U_s \Lambda_s$. The simulation smoother figurate sample of $\{\alpha_t\}_{t=s+1}^{n}$ with the state equation using $\{\eta_t\}_{t=s}^{n-1}$ and for sampling β, we satisfy that $Z_t = X_t, T_t = I, G_t = (A_t^{-1}\sum_t,0), H_t = (O,\sum_{\beta}^{1/2})$, for $t=s+1,\ldots,n, T_s\alpha_s = \mu_{\beta 0}$, and $H_s = (O,\sum_{\beta 0}^{1/2})$ for parameters.

Sampling a: With have state space form, we can derive sampling a from its conditional posterior distribution $\pi(a|\beta,h,\sum_{a},y)$, as:

$$\hat{y}_t = \hat{X}_t a_t + \sum_t \varepsilon_t, \qquad t = s+1,\ldots,n, \qquad (12)$$
$$a_{t+1} = a_t + u_{at}, \qquad t = s,\ldots n-1,$$

Where $a_s = \mu_{a0}$, $u_{as} \sim N(0,\sum_{a0}), \hat{y} = y_t - X_t\beta_t,$ so we have:

$$\hat{X}_t = \begin{pmatrix} 0 & \cdots & & & & & 0 \\ -\hat{y}_{1,t} & 0 & 0 & \cdots & & & \vdots \\ 0 & -\hat{y}_{1,t} & -\hat{y}_{2,t} & 0 & \cdots & & \\ 0 & 0 & 0 & -\hat{y}_{1,t} & \cdots & & \\ \vdots & & & & \ddots & 0 & 0 \\ 0 & \cdots & & & 0 & -\hat{y}_{1,t} & \cdots & -\hat{y}_{t-1,t} \end{pmatrix}, \qquad (13)$$

That $t = s+1,\ldots,n$. As shown for sampling β, we can employ simulation smoother with $Z_t = \hat{X}_t, T_t = I, G_t = (\sum_t, O), H_t = (O,\sum_a^{1/2})$, where $t = s+1,\ldots,n, T_s\alpha_s = \mu_{a0}$, and $H_s = (O,\sum_{a0}^{1/2})$.

Sampling h: Since sample h classify in to a non-linear state space model and already assumed that $\sum_h$ and $\sum_{h0}$ are diagonal matrices, and so expressed $\{h_{jt}\}_{t=s+1}^{n}, (j = 1,\ldots,k)$. Considering that y_{it}^* show the i-th element of $A_t\hat{y}_t$, in turn we have:

$$y_{it}^* = \exp(h_{it}/2)\varepsilon_{it}, \qquad t = s+1,\ldots,n, \qquad (14)$$
$$h_{i,t+1} = h_{it} + \eta_{it}, \qquad t = s,\ldots,n-1,$$
$$\begin{pmatrix}\varepsilon_{it} \\ \eta_{it}\end{pmatrix} \approx N\left(0, \begin{pmatrix} 1 & 0 \\ 0 & v_i^2 \end{pmatrix}\right),$$

Each $\eta_{is} \sim N(0,V_{i0}^2)$, and V_i^2 and V_{i0}^2 are the i-th diagonal elements of $\sum_h$ and $\sum_{h0}$, respectively, and η_{it} is the i-th element of u_{ht}. For this object, Shephard and Pitt (1997) and Watanabe and Omori (2004) expansion the sample $(h_{i,s+1},\ldots,h_{in})$ from its conditional posterior density for the non-linear Gaussian state space model, by running their achievement we can get multi-move sampler.

Following Nakajima (2011) procedure, we divide $(h_{i,s+1},\ldots,h_{in})$ into $K+1$ cell and sample, where each of them relate to the other posterior density condition, cells and parameters. So we have multi move sampling in cells $(h_{ir},\ldots,h_{i,r+d})$ from its joint posterior density, (note that $r \geq s+1, d \geq 1, r+d \leq n$). Generally the conditional posterior distribution is verifi as:

$$\pi(\eta_{i,r-1},\ldots,\eta_{i,r+d-1} \Big| \theta_i)\alpha \prod_{t=r}^{r+d} \frac{1}{e^{h_{it}/2}} \exp(-\frac{y_{it}^{*2}}{2e^{h_{it}}}) \times \prod_{t=r-1}^{r+d-1} f(\eta_{it}) \times f(h_{i,r+d}) \qquad (15)$$

Where

$$f(\eta_{it}) = \begin{cases} \exp(-\frac{\eta_{is}^2}{2v_{i0}^2}) & (if \ \ t = s), \\ \exp(-\frac{\eta_{it}^2}{2v_i^2}) & (if \ \ t \geq s+1), \end{cases} \qquad (16)$$

$$f(h_{i,r+d}) = \begin{cases} \exp\left\{-\frac{(h_{i,r+d+1} - h_{i,r+d})^2}{2v_i^2}\right\} & (if \ \ r+d \geq n), \\ 1 & (if \ \ r+d = n), \end{cases}$$

Where $\theta_i = (h_{i.r-1}, h_{i,r+d+1}, y_{ir}^*, \ldots, y_{i,r+d}^*, v_i, v_{i0})$ and the posterior show $(h_{ir}, \ldots, h_{i,r+d})$. We expect that running the state equation with its draw of $(h_{ir}, \ldots, h_{i,r+d})$ given the $h_{i,r-1}$.

The sample $(\eta_{i,r-1}, \ldots, \eta_{i,r+d-1})$ from (15) following the proposal density in AR-MH algorithm that presented by Tierney (1994), Chib and Greenberg (1995). Taylor justifies the proposal density begins with the second-order as:

$$g(h_{it}) \equiv -\frac{h_{it}}{2} - \frac{y_{it}^{*2}}{2e^{h_{it}}} \tag{17}$$

From other view $\hat{h}_t$ can expand as:

$$\begin{aligned} g(h_{it}) \approx\ & g(\hat{h}_{it}) + g'(\hat{h}_{it})(h_{it} - \hat{h}_{it}) + \frac{1}{2} g''(\hat{h}_{it})(h_{it} - \hat{h}_{it})^2 \\ \propto\ & \frac{1}{2} g''(\hat{h}_{it}) \left\{ h_{it} - \frac{g'(h'_{it}}{g''(\hat{h}_{it})} \right\}^2 \end{aligned} \tag{18}$$

Where

$$g'(\hat{h}_{it}) = -\frac{1}{2} + \frac{y_{it}^{*2}}{2e^{h_{it}}}, \quad g''(\hat{h}_{it}) = -\frac{y_{it}^{*2}}{2e^{h_{it}}}. \tag{19}$$

For proposal density we have:

$$q(\eta_{i,r-1,\ldots,}\eta_{i,r+d-1|\theta_i}) \ \propto \ \prod_{t=r}^{r+d} \exp\left\{ -\frac{(h_{it}^* - h_{it})^2}{2\sigma_{it}^{*2}} \right\} \times \prod_{t=r-1}^{r+d-1} f(\eta_{it}), \tag{20}$$

Where

$$\sigma_{it}^{*2} = -\frac{1}{g''(\hat{h}_{it})}, \quad h_{it}^* = \hat{h}_{it}^* + \sigma_{it}^{*2} g'(\hat{h}_{it}), \tag{21}$$

That $t = r, \ldots, r+d-1$ and $t = r, \ldots, r+d$ (when $r+d=n$). Also $t = r+d$ (when $r+d \prec n$),

$$\sigma_{i,r+d}^{*2} = \frac{1}{-g''(\hat{h}_{i,r+d)} + 1/v_i^2)} \tag{22}$$

$$h_{i,r+d}^* = \sigma_{i,r+d}^{*2} \left\{ g'(\hat{h}_{i,r+d}) - g''(\hat{h}_{i,r+d}) \hat{h}_{i,r+d} + h_{i,r+d+1} / v_i^2 \right\} \tag{23}$$

The proposal density is selected with respect with its corresponding state space model:

$$\begin{aligned} & h_{it}^* = h_{it} + \zeta_{it}, \quad t = r, \ldots, r+d, \\ & h_{i,t+1} = h_{it} + \eta_{it}, \quad t = r-1, \ldots, r+d-1, \\ & \begin{pmatrix} \zeta_{it} \\ \eta_{it} \end{pmatrix} \approx N\left(0, \begin{pmatrix} \sigma_{it}^{*2} & 0 \\ 0 & v_i^2 \end{pmatrix} \right), \quad t = r, \ldots, r+d, \end{aligned} \tag{24}$$

Where $\eta_{i,r-1} \sim N(0, v_i^2)$ when $r \geq 2$ and $\eta_{is} \sim N(0, v_{i0}^2)$. The simulations smoother provide drawing of $(\eta_{i,r-1}, \ldots, \eta_{i,r+d-1})$ for the AR-MH algorithm with respect to θ_i.

To obtain an efficient sampling ($\hat{h}_{ir},\ldots,\hat{h}_{i,r+d}$) which is near the mode of the posterior density by replicate the following steps can to reach it as:

1-Initialize ($\hat{h}_{ir},\ldots,\hat{h}_{i,r+d}$).

Repeat the following:

2-Compute ($h^*_{ir},\ldots,h^*_{i,r+d}$), ($\sigma^*_{ir},\ldots,\sigma^*_{i,r+d}$) by (21) and (23).

3-Run the simulation smoother using current ($h^*_{ir},\ldots,h^*_{i,r+d}$), ($\sigma^{2*}_{ir},\ldots,\sigma^{2*}_{i,r+d}$) on (24) and obtain $\hat{h}^*_{it} \equiv E(h_{it}|\theta_i)$, for $t = r,\ldots,r+d-1$.

4-Replace ($\hat{h}_{ir},\ldots,\hat{h}_{i,r+d}$) by ($\hat{h}^*_{ir},\ldots,\hat{h}^*_{i,r+d}$).

With respect that $E(h_{it}|\theta_i)$, the multiply result as $\Lambda_t r_t$ with $\varepsilon_t = 0$ in the simulation smoother. For determining an efficient sampling Nakajima (2009) design the following cells as $(h_i, k_{j-1}+1,\ldots,h_i,k_j)$ for $j = 1,\ldots,K+1$ with $K_0 = s$ and $k_{k+1} = n$, also Shephard and Pitt (1997) justified stochastic knots $(k_1,\ldots,k_K)$, given that:

$$k_j = \mathrm{int}\left[\frac{n(j+U_j)}{K+2}\right], \qquad (25)$$

where U_j has uniform distribution $U[0,1]$ for $j = 1,\ldots,K$. With stochastic selecting $(k_1,\ldots,k_k)$ for each simulation step of MCMC sampling, can derive a supple draw of $(h_{i,s+1},\ldots,h_{in})$.

Sampling ω: Considering that $\delta_{\beta i}$ identify the i-th diagonal element of $\sum_\beta$ and according to sample β, deriving the conditional posterior density of $\sum_\beta$ is easy. Already mentioned that Σ_β is a diagonal matrix, and sample $\delta_{\beta i}$ is independently for $i = 1,\ldots,K$. By defining the prior as $\sigma^{-2}_{\beta i}$ ~ Gamma($(s_{\beta 0}/2, S_{\beta 0}/2)$, given the conditional posterior distribution as $\delta^{-2}_{\beta i}|\beta \sim$ Gamma($\hat{s}_{\beta i}/2$, $\hat{S}_{\beta i}/2$) in turn:

$$\hat{s}_{\beta i} = s_{\beta 0} + n - s - 1, \qquad \hat{S}_{\beta i} + \sum_{t=s+1}^{n-1}(\beta_{i,t+1} - \beta_{it})^2, \qquad (26)$$

Where β_{it} is the i-th element of β_i. In above the gamma prior is embedded and the posterior shown is directly. With the same procedure for sampling the diagonal elements of $\sum_a|a$ and $\sum_h h$ can be derived.

As regards that TVP-VAR nature has non-stationary random walk process, thus for selecting the priors should be expertly act, so that for the tight prior for the covariance matrix of the noise in the random walk process prevents the implausible behaviors of the time-varying parameters (Primiceri, 2005). To derive the correct results the simultaneous relations (a) and the volatility of thestructural shock (h) needs a loose prior than the time-varying coefficient (β), $\sum\beta$ and derived prior for $\sum a$ and $\sum h$. Since the time-varying parameters modeled as a stationary process and derived parametersare random walks, following Primiceri (2005) and Nakajima (2009), we estatethe prior of normal distribution for the initial state of each time-varying parameter.

Marginal likelihood: Based posterior probabilities criteria in a Bayesian derivation we can compare model fit given data. The posterior probability of respect model comes the ratio of prior probability and marginal likelihood and considering the prior probabilities equality, the model containing maximum marginal likelihood has been chosen. Achieve the integral of the likelihood according to the prior density of the parameter given the marginal likelihood. Geweke (1999) present a traditional way to estimate the marginal likelihood is simulation based harmonic mean estimator of the marginal likelihood. That remarked by ˆm(y) and obtained as:

$$\frac{1}{\hat{m}(y)} = \frac{1}{M}\sum_{j=1}^{M}\frac{g(\omega^{(j)})}{f(y|\omega^{(j)},\vartheta^{(j)})\pi(\omega^{(j)})} \quad \text{……………..(27)}$$

In this estimator the $\vartheta = (\beta, a, h)$, $f(y|\omega^{(j)},\vartheta^{(j)})$ indicate the likelihood function and $\pi(\omega^{(j)})$ verify the prior density also M is the iteration measure of the MCMC. With assume that measure of $g(\omega)/f(y|\omega,\vartheta)\pi(\omega)$ ratios has interval, its convergence rate is feasible and can be simulated to approximate, denote that g(ω) can be related any p.d.f of model's parameter space. Geweke (1999), considering the normal density with the tails truncated, justify the bounded g(ω) for the harmonic mean estimator fraction as:

$$g(\omega^{(j)}) = \frac{1}{\tau(2\pi)^{p/2}|\hat{V}|^{1/2}}\exp\left\{-\frac{1}{2}(\omega^{(j)}-\hat{\omega})'\hat{V}^{-1}(\omega^{(j)}-\hat{\omega})\right\}\times I\left[(\omega^{(j)}-\hat{\omega})'\hat{V}^{-1}(\omega^{(j)}-\hat{\omega}) \le \chi^2_\tau(p)\right] \quad (28)$$

In mentioned measurement the $I[\Omega]$ is an indicator function that takes two value if Ω is satisfied give one and zero otherwise, p is the number of elements in ω, and $\chi^2_\tau(P)$ verify the τ percentile of the Chi-square distribution with p degrees of freedom. As Nakajima (2011), can reaching to posterior draws $\{\omega^{(j)}\}_{j=1}^{M}$ with $\tau = 0.99$ (τ can get $0.99, 0.95, 0.90$ values) by setting $\hat{\omega}$ and $\hat{V}$ equal to the sample mean and covariance matrix. As we can find in literature and mentioned by Schorfheide (2000), the derived marginal likelihood hasn't serial correlation with τ, thus in TVP-VAR model the derived marginal likelihood has little sensitivity to the value of τ.

RESULTS AND DISCUSSION FOR IRAN'S AGRICULTURAL ECONOMIC AND MONETARY POLICY

Data and estimation procedure: In following we estimate the TVP-VAR model for the Iran's agricultural Economy based on quarterly dataset includes four macroeconomic variables: inflation rate[1], agricultural production, effective short-term interest rate[2], and monetary base and the period is from 1980/1Q to 2013/4Q. These variables are used for a standard VAR model of Iranian agricultural sector, analyzed by several papers (Miyao (2000, 2002), Fujiwara (2006), Inoue and Okimoto (2008), Yano and Yoshino (2008), Nakajima (2009, 2011)).

With dig onto the literature, we can find that most of these studies have used monthly data on their computation. As mentioned by Nakajima (2009) and literature, the VAR estimation with monthly data often needs many lags, such as Miyao (2000, order 10 lags)). To cope with this problem following Nakajima we use quarterly data to reduces the number of parameters in our computation, since the TVP-VAR model consider the changes, shocks and affect the of other variables with their lags, as shown in the following this technique and methodological give our strong proficiency.

We estimate our models based on different lags and chosen the lags whose marginal likelihood is the highest among them as optimum lags. Accordingly the estimation results will go ahead based on two lags in following.

Figure 1 plots the term of variables and dynamics series for estimated stochastic volatility of the structural shock on four variables, based on the posterior mean, and quantile intervals of the standard deviation of the shock, $\delta_{it} = \exp(h_{it}/2)$.

[1]The inflation rate is taken from seasonally price index (CPI)

[2]Effective interest rate is taken from $i_e = (1+\frac{r}{t})^t - 1$,that r is nominal interest rate and t is number of composed in period

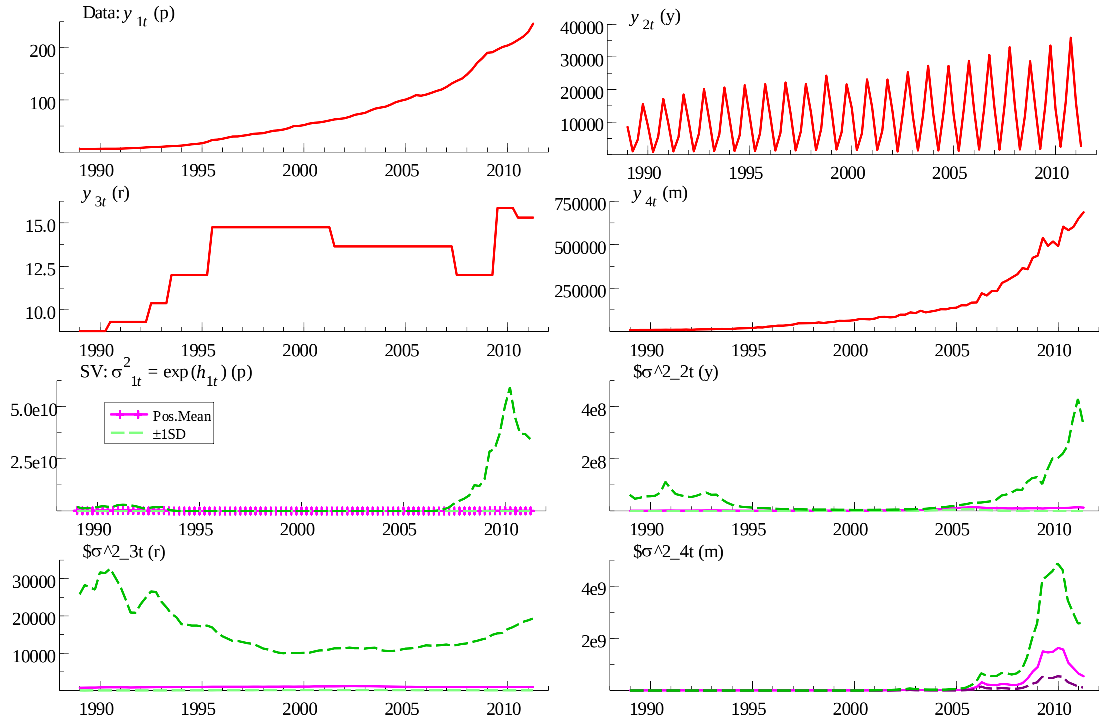

Figure 1: Posterior Estimates $\delta_{it} = \exp(h_{it}/2)$, posterior means and one standard deviation bands

The fluctuation in the plotted of variables' shock and stochastic volatility are observed. The TVP-VAR models not sensitive to change of the structural and we haven't divide data based on structural to subsample.

Parameter Estimates: By justifying the following prior for the i-th diagonals of the covariance matrices, the estimating of TVP regression model based on simulated data is possible,

$$(\Sigma_\beta)_i^{-2} \sim Gamma(10,0.01),\quad ((\Sigma_a)_i^{-2} \sim Gamma(2,0.01),\quad (\Sigma_h)_i^{-2} \sim Gamma(2,0.01)$$

Denote that for time-varying parameters, $\mu_{\beta 0} = \hat{\beta}_0$, $\mu_{a0} = \hat{a}_0$, $\mu_{h0} = \log \hat{\sigma}_2$, and $\Sigma_{\beta 0} = \Sigma_{a0} = \Sigma_{h0} = 4 \times I$, as well the OLS estimators as $\hat{\beta}_0, \hat{a}_0$ and $\hat{\sigma}_0$ are generate using the pre-sample period. Our numerical results after draw M = 10, 000 sample and the initial 1,000 sample are derived from using Ox version 6.0 (Doornik, 2006) and Nakajima (2013) TVP-VAR package.

Figure 2 shows the sample autocorrelation function, the sample paths and the posterior densities for selected parameters and gives the estimates for posterior means, standard deviations, the 95% credible intervals, the convergence diagnostics (CD) of Geweke (1992) and inefficiency factors. For comparison between the first n_0 draws and the last n_1 draws, Geweke (1992) verify the CD statistics as:

$$CD = (\bar{x}_0 - \bar{x}_1) / \sqrt{\hat{\sigma}_0^2 / n_0 + \hat{\sigma}_1^2 / n_1} \quad ,$$

In this statistic $\bar{x}_j = \frac{1}{n_j}\sum_{i=m_j}^{m_j+n_j-1} x^{(i)}, x^{(i)}$ is the i-th draw, and $\sqrt{\hat{\sigma}_j^2 / n_j}$ is the standard error of $\bar{x}_j$, that $j = 0,1$. When convergence has standard normal distribution, the stationary in sequence of the MCMC sampling should be established. By setting $m_0 = 1,\ n_0 = 1,000,\ m_1 = 5,001,$ and $n_1 = 5,000$ and deriving the $\hat{\delta}_j^2$ from Parzen window with bandwidth, $B_m = 500$.

Chib (2001) expansion the inefficiency factor for compute to how well the MCMC chain mixes, as $1 + 2\sum_{s=1}^{B_m} \rho_s$, denote that ρ_s is the sample autocorrelation at lag s. The derived numerical efficiency and Geweke (1992) defined it as inverse of the inefficiency factor and comes from the ratio of the numerical variance of the posterior sample mean to the variance of the sample mean from uncorrelated draws. For have uncorrelated sample the inefficiency factor and times as MCMC sample should be equal, Nakajima (2009).

So the null hypothesis of the convergence to the posterior distribution is not rejected for the parameters at the 5% significance level based on the CD statistics, and the inefficiency factors are very low, according to the results of our computation have been show an efficient sampling for the parameters and state variables.

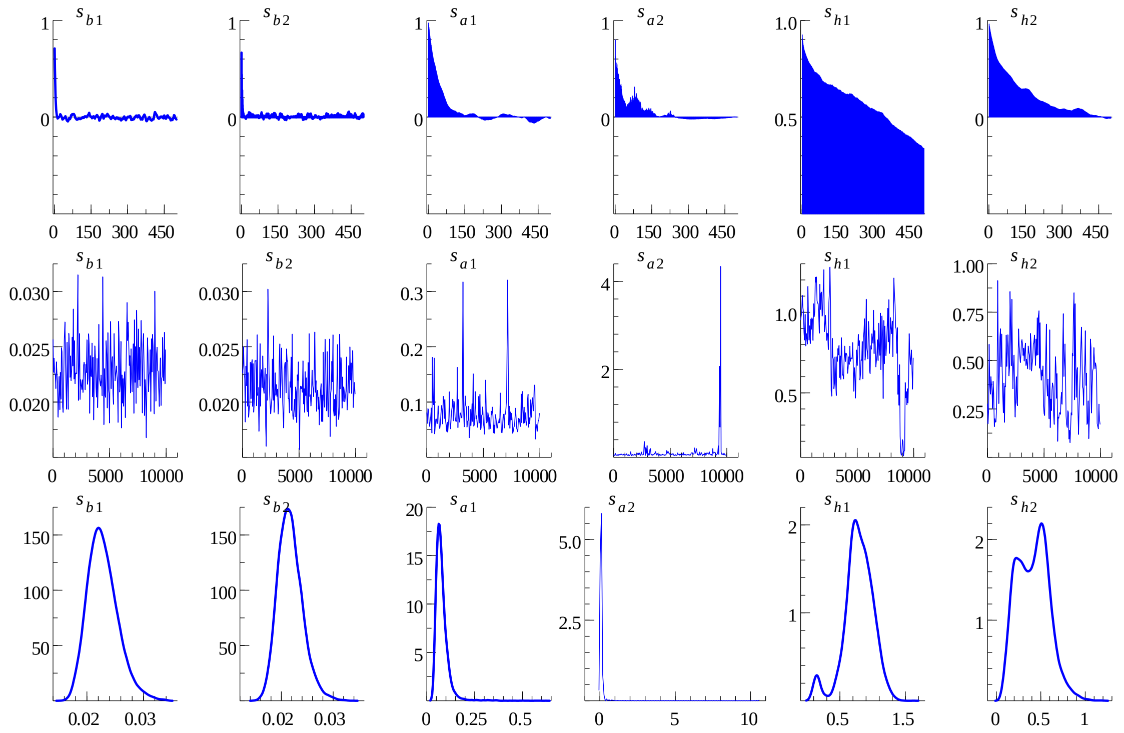

Figure2. Estimation Results of Selected Parameters in the TVP-VAR Model,Sample autocorrelations (top), sample paths (middle), and posterior densities (bottom)

Table 1: Estimated marginal likelihood for time-varying parameter

parameter	Mean	Stdev	95%L	95%U	Geweke	Inefficiency
$(\sum_{\beta})1$	**0.0228**	**0.0027**	**0.0183**	**0.0290**	**0.427**	**5.04**
$(\sum_{\beta})2$	**0.0217**	**0.0024**	**0.0176**	**0.0271**	**0.416**	**8.82**
$(\sum_{a})1$	**0.0793**	**0.0398**	**0.0417**	**0.1603**	**0.910**	**77.11**
$(\sum_{a})2$	**0.1027**	**0.2762**	**0.0388**	**0.2933**	**0.124**	**54.51**
$(\sum_{h})1$	**0.7861**	**0.2236**	**0.1603**	**0.1816**	**0.000**	**255.53**
$(\sum_{h})2$	**0.4137**	**0.1769**	**0.1211**	**0.7721**	**0.646**	**151.31**

In table 1 show the derived estimates for posterior means, standard deviations, the 5 percent significant level, the convergence diagnostics (CD) of Geweke (1992), and inefficiency factors, for the MCMC simulation. Acceptable results reflect the efficient sampling for parameter and state that null hypothesis of the convergence to the posterior distribution is not rejected for the parameters at the 5 percent significance level based on the CD statistics, and the inefficiency factors are around zero for $(\sum h)1$.

The Role of Stochastic Volatility: Based on Nakajima (2013) procedure for stochastic volatility in the TVP regression model and same data, the simulation TVP regressions with constant volatility model have been derived. exact results push our to discussion that how stochastic volatility misspecification affect the estimation results. Considering the prior as $\sigma^2 \sim IG(s_0/2, S_0/2)$ so that for simulation $\sigma^2 \sim IG(2, 0.02)$ and $\sigma^2 | \beta, \alpha, y \sim IG(\hat{s}/2, \hat{S}/2)$ as conditional posterior distribution the constant volatility can verify by $\sigma_t^2 = \sigma^2$ that $t = 1, \ldots, n,$ denote that $\hat{s} = s_0 + n$ where $\hat{S} = S_0 + \sum_{t=1}^{n} (y_t - x_t'\beta - z_t'\alpha_t)^2$, and the estimation procedure is similar the TVP regression model with stochastic volatility as already discussed.

In table 1 showed the simulation results of the TVP regression model, thus following is shown how the time-varying coefficients are estimated. The posterior estimates are plotted in Figure 3. Where shows the time variation of the coefficients, and the posterior mean for the TVP regression with stochastic volatility. The posterior meansgreatly cover thespecified time-varying coefficients. This means that for all α_{it} the true values falls in the 5 percent significant level. As discussed, in figure 3 the derived TVP regression with stochastic volatility is plotted.

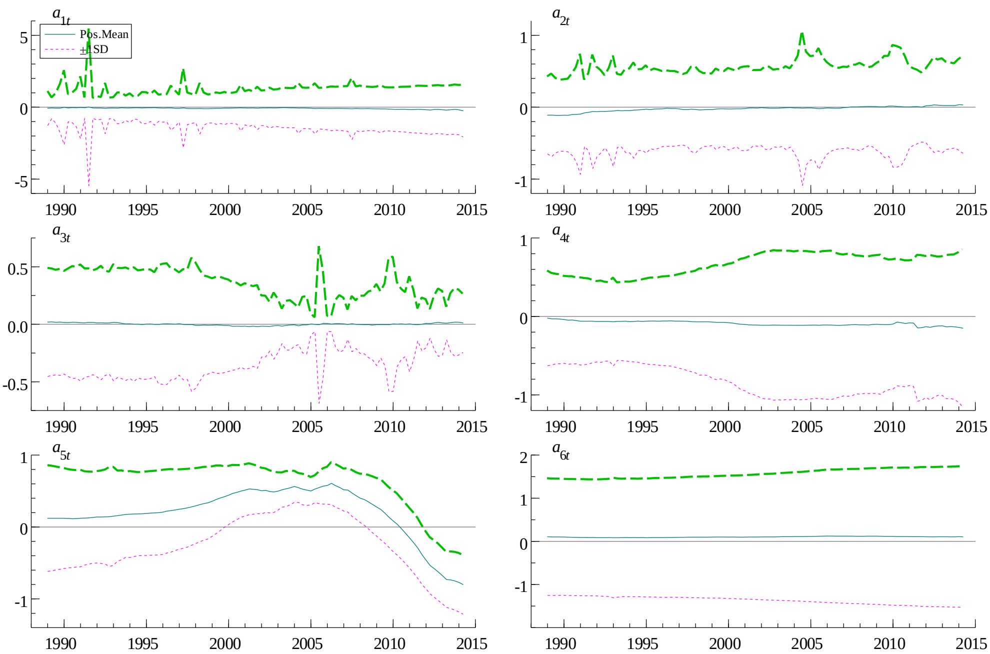

Figure 3: Posterior Estimates of α_{it} , posterior mean traceand one standard deviation bands

Note: Posterior mean (solid line) and 95 percent credible intervals (dotted line)

Estimation result for macroeconomic dynamic: The MCMC procedure estimates parameter under uncertainty, thus in figure 4 plotted the posterior means of stochastic volatility $\sigma_{it} = \exp(h_{it}/2)$ and the simultaneous relation for the main variables (y, m, p, r). Forasmuch as the lower triangular matrix A_t for simultaneous relation and posterior estimates of the free elements in A_t^{-1}, plotted $\tilde{a}_{it}$ based on recursive attributes reveals the intensity simultaneous reaction of variables to one unit of the structural shock.

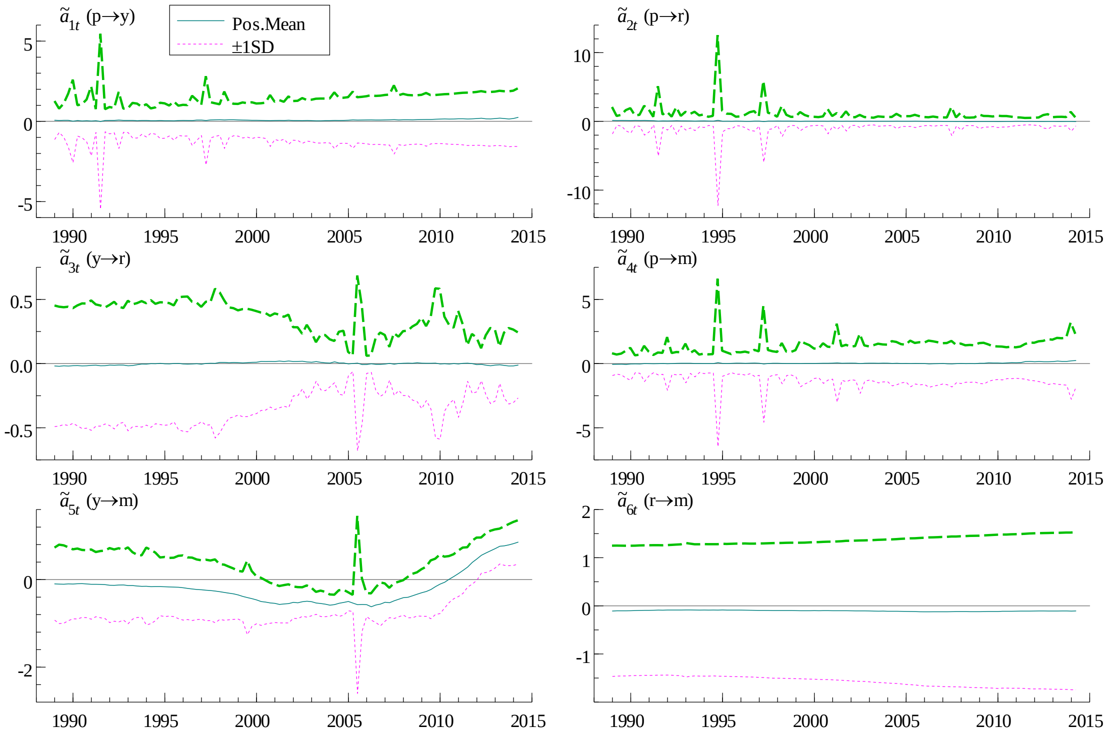

Figure 4 Posterior Estimates of free element A_t^{-1} for Simultaneous Relation $\tilde{a}_{it}$ of variables
Note: Posterior mean (solid line) and 95 percent credible intervals (dotted line).

The monetary bases stochastic volatility shows a general trend ofposterior mean and remains stable during the time period, when Iran's economy experiences inflation. As well as, the stochastic volatility of other variables are awhile stable.

One of the main characteristics in the TVPVAR model is time-varying simultaneous relation. The simultaneous relation of the inflation to the agricultural production shock $p \rightarrow y$ stays negative, and remains almost stable over the time period. Also, the simultaneous relations of the inflation to the effective interest rate shock $p \rightarrow r$ and MB shock $p \rightarrow m$ over time are negative, denote that from direct relationship betweeninflation and effective interest ratecan be seen the Fisher's relation (1986).

The impulse response is an obvious application to see the macroeconomic dynamics efficacy for each set of two variables by the estimated VAR collection. Figure 5 and 6 shows the impulse responses of the VAR model and the time-varying responses for the TVP-VAR model.

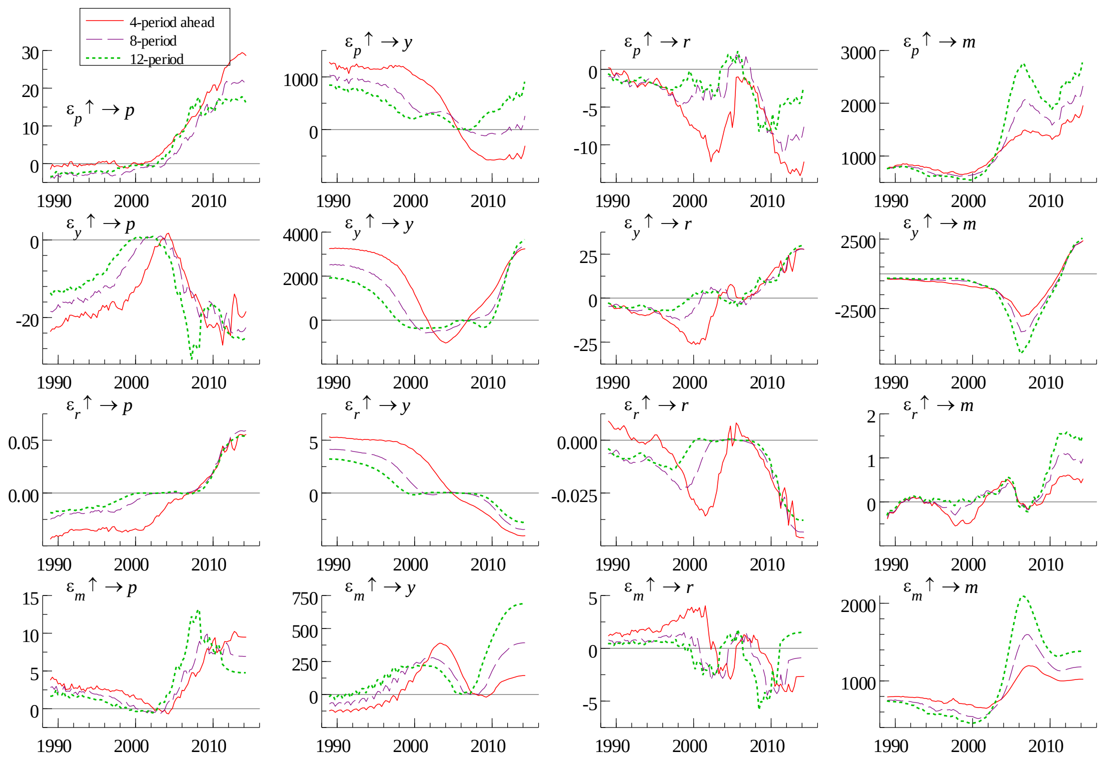

Figure5. Posterior mean of TVP-VAR Models Impulse Responses
Note: Posterior mean (solid line) and 95 percent intervals (dotted line) for the time-varying responses for one-quarter (dotted line), one-year (dashed line), two-year (solid line), and three-year (bold line) horizons for the TVP-VAR model.

The impulse responses of agricultural production to a positive inflation shock $\varepsilon_p \rightarrow y$ are estimated as being insignificantly different from zero, although it should be noted that impulse responses vary significantly over time and the stay negativewith increasing downward all over the time period. This is remind that relying to the economic theory, inflation shock affects output negatively in the medium to long term, which is consistent with the negative impulse responses observed that shows the aspect of augment Philips curve, also the impulsive response of agriculture production to a positive MB shocks $\varepsilon_y \to m$ is increasing in the early 2005.

The impulse responses of inflation to a positive agricultural production shock $\varepsilon_y \to p$ increasing in time period and impulse responses of agricultural production to a positive interest rate shock $\varepsilon_r \to y$ stay negative in during 1980-2013 period.

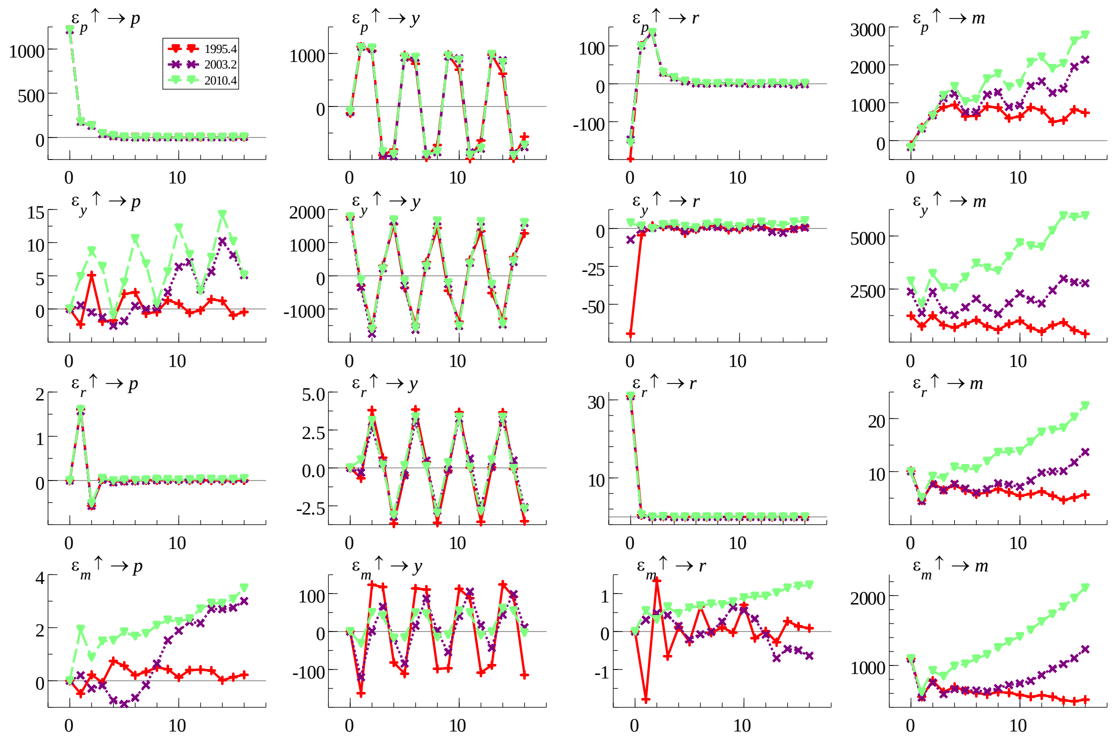

Figure 6: Impulse Responses of posterior mean Constant VAR Models
Note: Posterior mean (solid line) and 95 percent intervals (dotted line) for the constant VAR model.

CONCLUDING REMARKS

This paper analyzes the TVP-VAR models of the Iranian agricultural sector and monetary policy. The time-varying parameters are estimated via the Markov chain Monte Carlo method and the posterior estimates of parameters reveal the time-varying structure of the Iranian agricultural economy and monetary policy during the period from 1980 to 2013.

To solve this problem, Nakajima (2013) proposes an OX package for TVP-VAR model and wepresents empirical findings using Iranian economic data. The marginal likelihoods of the TVP-VAR model and simulation of the TVP regression model revealed the importance of incorporating volatility into the TVP regression models. The empirical applications using the Iranian data showed the time-varying nature of the dynamic relationships between macroeconomic variables and we can defined that with decreasing the effective interest rate and increasing monetary base can improve the agricultural production and reducing the rate of inflation.

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