



Analysis on Energy Consumption Cost of Chinese Road Transportation (Physical Quantity)

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Abstract. Chinese economy entered New Normal development stage in 2014. The stock and increment of traffic infrastructure and transport equipment will be maintain at a large scale. The continuous increase in the demand of transportation has brought about the increase of transportation energy consumption and pollution emission. In this paper, we focus on road transportation energy consumption. Firstly, analyze the core influence factors of road transportation energy consumption, and establish a road transportation energy consumption BVAR model. Secondly, introduce the loss function when establishing BVAR model in order to explain the asymmetric effect. Therefore, combine the merits of the loss function and BVAR model, and compare difference in loss when the regression coefficient is too high or too low under normal-Wishart prior distribution. The results show that the response of road transportation energy consumption to total turnover volume (i.e. ZZ) and mileage (i.e. LC) are observably, the mileage is a caused demand. Contribution rate of road transportation energy consumption itself is the largest, about 93%, and it has stock (up-tail) effect. Contribution rate of total turnover volume and mileage to road transportation energy consumption keep at about 6% and 1% respectively. There is asymmetric effect between road transportation energy consumption and its influence factors, Value a will affect the estimated result. The deviation of estimated values when $a > 0$ are large than the estimated values when $a < 0$.

1. Introduction

Chinese economy still keeps developing at medium and high speed after entering the stage of 13th five-year. The processes of industrialization, urbanization, informatization and modernization will further accelerate. Transportation industry is a basic sector of national economy. Both stock and increment of transportation infrastructure and transportation equipment keep relatively large scales. In 2014, fixed

2010 Mathematics Subject Classification. Primary 62P20; Secondary 90B50

Keywords. road transportation energy consumption; VAR; BVAR; loss function; cost.

Received: 15 May 2015; Accepted: 15 April 2016

Communicated by Dr. Alex Maritz and Dr. Charles Xie

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Research supported by the National Natural Science Foundation of China (NSFC) under grants No. 71473155, the New Star of Youth Science and Technology Plan Project in Shaanxi Province, China No. 2016KJXX-14, Shaanxi Normal University College Basic Scientific Research Special Support Project No. 14SZTZ03 and 2015 Annual Silk Road Economic Belt Research Project of Xidian University No. 7215628803.

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investments of the transportation industry reached RMB 4,298,447,000,000, among which fulfilled amount of fixed assets investment of transportation industry was RMB 2,456,582,000,000, increased by 19.82% year on year. The highway mileage reached 4,463,900 km increased by 107,700 km compared with that of last year (*CEInet statistical database*) [1]. Continuous increase of transportation demand makes the energy consumption and GHG emission of China's transportation sector increased. According to World Bank statistics, China's road energy consumption increased from 21,008,000 tons of equivalent petroleum in 1990 to 58,027.99 ktoe in 2000 and further to 153,140.10 ktoe in 2010. The annual increase rate is 21.97%. Road transportation is the greatest part in China's transportation structure. 93% and 76% of passenger capacity and freight volume are undertaken by road transportation [2]. Therefore, analysis on the core influence factors of road transportation energy consumption (physical quantity) and research on energy conservation and emissions reduction path and strategy in road transportation are of great significance for reducing energy and environment pressure in China or even in the world.

Considering the proportion of transportation energy consumption in the social total energy consumption on the increase, more and more researchers at home and abroad research on the influence factors of transportation energy consumption, energy consumption prediction and analysis of energy saving and emission reduction.

Influence factors of energy consumption in the transportation sector. Kenworthy et al. (1999) [3] and Shim et al. (2006) [4] have the similar view. They all considered that transportation energy consumption is closely related to the urban form. Energy efficiency will be enhanced with increase in population until population size of the city reaches the optimal level; when population of the city exceeds the critical level, traffic jam will take place. Thus its energy efficiency will be reduced. Population density has strong negative correlation with transportation energy consumption. Al-Ghandoor et al. (2013) [5] confirmed main factors influencing transportation energy demand such as quantity of registered vehicle, income level and gasoline price by establishing a multiple regression model. Lindsey et al. (2011) [6] studied relations between residence and mileage and between energy consumption and CO₂ emission based on 2007–2008 data of Chicago. Skeer and Wang (2007) [7] used elastic coefficient method to analyze relations between passenger and freight turnover volumes of China, GDP and transportation energy consumption and predicted variation trend of transportation intensity and energy consumption of the transportation sector in the next few years.

Energy consumption prediction methods. Energy consumption prediction methods can mainly classified into typical prediction methods, traditional prediction methods and modern prediction methods. Typical prediction methods mainly include unit consumption method, elastic coefficient method and negative load density method. Traditional prediction methods include time series smoothing method, regression model method, trend extrapolation method and relevant analysis method. Modern prediction methods include grey prediction method, neural network prediction method, wavelet analysis method, fuzzy prediction method, state space and Kalman filtering method and optimized combined prediction method. Moreover, with continuous development of intelligent algorithm, the prediction methods improved from traditional methods to today's fuzzy sets, rough sets, support vector machine (SVM), genetic algorithm, etc. intelligent methods have been widely used in energy forecast. (Dai, Wen, Hu et al.) [8–14]

Transportation energy conservation potential and pollution analysis. He et al. [15] analyzed road transportation oil consumption and CO₂ emission from 1997 to 2002 by using a bottom-up mode. While taking change of fuel efficiency into full consideration, they designed three schemes to predict future energy consumption and CO₂ emission. The prediction result shows that in the future 20 years, road transportation sector will be the largest oil consuming sector in China. Timilsina et al. (2009) [16, 17] studied factors driving increase of CO₂ emission in the traffic sectors of Asian countries including China based on data of International Energy Agency. They thought that with continuous increase of motor vehicle amount in China, the trend of passenger capacity in the transportation sector transferring to road transportation will intensify. In the past 20 years, CO₂ emission in road transportation sector is on the rise. This process is the same as that of developed nations. Chung et al. (2013) [18] used LMDI decomposition method to analyze energy consumption and efficiency in Chinese transportation industry from 2003 to 2009 and found that energy conservation and efficiency policies are more effective in central and western China than in the eastern area. In addition, the effect of regional transfer shows that in eastern China, energy-saving effect of policy support is insignificant. Freitas and Kaneko (2011) [19] studied the unhook relationship between economic

growth of Brazil and CO₂ emission caused by energy consumption. They thought that energy structure optimization and improvement of energy intensity could help reduce emission of CO₂.

From the existing researches, we know that there are two difficulties in the study on Chinese transportation. The first is difficulty in data acquisition. As China has no segmentation on transportation research. There is no accurate statistical result in energy consumption. Jia (2010) [20] analyzed difference between statistical data of energy consumption in Chinese transportation sector and the international statistical caliber. They thought that in current China's statistics, there is no energy consumption data of public and private automobiles, motorcycles, low speed automobiles, agricultural vehicles, etc. therefore, they set up a transportation energy consumption calculating model based on car use and calculated relevant parameters. Moreover, they compared Chinese transportation energy consumption data with that of advanced countries and found that though energy consumption per capita and transportation energy consumption of China are relatively low, they increase rapidly in recent years. The second difficulty is about the modeling strategy. Existing research provides us a good theoretical basis and reference, but most of the existing research results could not fully consider or reflect the driving and limiting factors of transportation energy consumption. Prediction methods in the literatures interpret structural relationship among variables in light of economic theories. The advantage of these methods is having clear economic theoretical background. However, as it is necessary to separate endogenous variables from exogenous variables during modeling, and endogenous variables in each equation are relevant to disturbing terms, estimation of model parameters are quite complicated, and there might possibly be huge errors. As a result, dynamic relations among variables cannot be accurately reflected. Especially, when the sample data selected is relatively small, it cannot effectively estimate the model limited by the degree of freedom. VAR (vector auto regression) model is an effective prediction model for interrelated time series variable systems. Therefore, it is frequently used to analyze the dynamic influence of different kinds of random errors on system variables. However, when the number of samples selected is not enough, prediction of VAR model will result in decline of multicollinearity and degree of freedom. As a result, error of parameter estimation will enlarge. Therefore, BVAR (Bayes vector auto regression) model makes up deficiency of VAR model. Intrinsic features of Bayes theory make it show distinct advantages for small samples. In recent years, BVAR is widely recognized when being used in energy prediction. For example, Crompton and Wu (2005) [21] used BVAR to predict energy consumption of China and discuss the potential influences. Bayes prediction derives from minimization of loss of posterior parameter space.

In BVAR model, posterior means of regression coefficient and covariance matrix are calculated as Bayes estimation. Posterior means can be regarded as some appropriate loss functions. Therefore, selection of loss function decides the form of Bayes estimation, and also the estimated results. In decision making problems, the loss function is a bridge for the connection of economic benefit and decision. Overestimate and low estimate will cause economic losses. Policy makers want to avoid big loss, and seek small losses, even no loss. However, the posterior mean of the regression coefficient is often biased in the actual problem. Asymmetric loss function (LINEX loss function) will help to correct the deviation. At present, the application of the loss function in BVAR model is very few, especially in the study of energy consumption. Ni and Sun (2005) [22] discussed VAR model estimation's effect in different non-information priors and several common loss functions and used American macro-economic data for empirical analysis. The result shows that in prior distribution of constant, estimation of LINEX loss function is a little weaker than the estimated result obtained under squared loss function. Nevertheless, the LINEX loss is better in normal situations. We will introduce the loss function in the process of building BVAR model of transportation energy demand, and try to explain the economic loss under the asymmetric effect caused by estimated deviation of regression coefficient.

In this paper, we take road transportation as the object of study. Firstly, select core factors influencing road transportation energy consumption by VAR model. Secondly, introduce in loss function when setting up BVAR model and compare the estimated values of regression coefficients under asymmetric loss function (LINEX loss function) and squared coefficient. Lastly, compare different economic loss situations caused by too high or too low of the regression coefficient under Normal-Wishart prior distribution.

2. Methodology

2.1. VAR model

The general VAR model can be expressed as the following equation:

$$y_t = c + A_1 y_{t-1} + \dots + A_p y_{t-p} + \mu_t, \quad t = 1, 2, \dots, n \tag{1}$$

Hereinto, $y_t = (y_{1t} \dots y_{kt})$ is a $k \times 1$ random vector, A_1 to A_p represents $m \times m$ coefficient matrix. c is a m dimensional vector. It assumes that μ_t is a white noise sequence. $E(\mu_t) = 0$, $E(\mu_t \mu_s') = \Sigma$, Σ is a $m \times m$ positive definite matrix, $E(\mu_t \mu_t') = 0$, ($t \neq s$).

When using nonstationary time series to build the econometric model, you need to prevent spurious regression. Moreover, long-term relations among variables can be maintained though there are difference sequences. Therefore, before building VAR model, co-integration test of variables should be made. There is more than one co-integration test method. But the most extensively used one is the maximum likelihood method proposed by Johansen and Juselius respectively in 1988 and 1990. It is called Johansen test. The maximum likelihood estimation of the co-integration system makes general analysis on all independent co-integration relations in the co-integration system. There is no assumption on the number of co-integration in the system. There is no need to specify on the coefficient of the vector. When making Johansen test, it is necessary to make unit root test for each variable. After passing the unit root test, build VAR system composed by different variables. After building VAR system, you need to test its stability.

VAR model is the effective forecasting model for related time series variable system. Meanwhile, the VAR model is used to analyze dynamic effect of the different types of random error term to system variables frequently. But when a few samples are selected, VAR model estimation will result in decline of multicollinearity and degree of freedom. Hence, the parameter estimation error will be large. Superiority of BVAR model is that parameter estimation is made after constraint of prior information is added. Thus, accuracy of the model can be enhanced. Deficiency of VAR can be complemented.

2.2. BVAR model

BVAR model regards all coefficients of variables as a certain prior distribution function of random variable. So far, many prior distributions have been developed such as conjugate prior distribution, maximum entropy prior distribution, ML-II prior distribution and multi-layer prior distribution. Different BVAR prior distribution modes selected have different and significant influences on the prediction results because selection of the prior distribution model has decisive impact on enhancement of prediction accuracy of BVAR model. Theoretically, there are many optional prior distribution models for BVAR model, but some prior distribution models may not make perdition or result in large prediction deviation under restriction of the data structures. In this study, we adopt the common Normal-Wishart prior distribution.

The general VAR equation can be expressed as the following equation:

$$y_t = Z_t B' + \mu, \quad t = 1, 2, \dots, n \tag{2}$$

If $y_t, Z_t B', \mu_t$ ($t = 1, 2, \dots, n$) are arranged according to their transpose, then each of them is a $n \times m$ matrix. Thus, the above formula can be written into:

$$Y = ZB + U, U \sim N_{nm}(0, \Sigma \otimes I_n) \tag{3}$$

where, $Y = [y_1^T, y_2^T, \dots, y_n^T]_{n \times m}^T$, $Z = [z_1^T, z_2^T, \dots, z_n^T]_{n \times (mp+1)}^T$, $U = [u_1^T, u_2^T, \dots, u_n^T]_{n \times m}^T$, $B = [c^T, A_1^T, \dots, A_p^T]_{(mp+1) \times m}^T$, $Z_t = [1, y_{t-1}, \dots, y_{t-p}]_{(mp+1) \times 1}^T$.

When prior distribution of the regression coefficient is normal distribution, and covariance prior distribution is Wishart distribution, make prior condition distribution of the coefficient vector into $g(b|\Sigma) \sim N(\bar{b}, \Sigma \otimes \bar{\Omega})$, $g(\Sigma^{-1}) \sim W(\bar{\Sigma}, \bar{\nu})$, $\bar{b}, \bar{\Sigma}, \bar{\nu}$ is fixed. After being proved, posterior distribution of coefficient vector and covariance matrix is also Normal-Wishart distribution.

$$g(\Sigma^{-1} | y) \propto |\Sigma^{-1}|^{-(n+\bar{\nu}+m+1)/2} \exp\{-\frac{1}{2}trD\Sigma^{-1}\} \propto W_m(D^{-1}, n + \bar{\nu}) \tag{4}$$

Bayes estimation derives from loss minimization of posterior parameter space. In BVAR model, posterior means of the regression coefficient and the covariance matrix are calculated as Bayes estimation. Posterior means can be regarded as some proper loss functions. In actual problems, overestimated and low estimate will cause economic losses. The Regression coefficients of the posterior mean value is often biased. Asymmetric loss function (LINEX loss function) can correct the deviation. Considering the regression coefficients of VAR equations of road energy consumption might have asymmetric effect, we introduce asymmetric LINEX loss function for estimation. Therefore, decision makers can estimate the elasticity of the influence factors more accurately. We also compare the estimated results of regression coefficients under symmetric effect (squared loss) and asymmetric effect (LINEX loss).

2.3. Loss function

Facing a decision problem, we assume that the state set is $\Theta = \{\theta\}$ and the action set is $A = \{a\}$. The function of two variables $L = \{\theta, a\}$ defined on $\Theta \times A$ is called loss function. We assume that it keeps the state θ in nature (or society). When people take the action a , (economic) loss will be caused for people. In statistical experiment, if different loss functions are selected, quality of the statistics varies. Common loss functions include squared loss function, entropy loss function and 0-1 loss function. But, in practical use, they have a common defect. They all have symmetry. As a result, when making risk assessment of parameter estimation, impact of too high or too low estimation of the parameters cannot be effectively distinguished. It means that losses brought by too high or too low estimation of parameters cannot be reflected effectively. Thus, it is not applicable to some special problems. Therefore, after realizing this defect, many scholars have started to find a new loss functions having asymmetry among the statistical decisions. Varian (1975) [23] proposed LINEX loss. Then, Zenller (1986) [24] made in-depth discussion and used it in Bayes analysis on the estimation problems. As there might be asymmetry between road transportation energy consumption and its influence factors, we introduce LINEX loss function into estimation of regression coefficient of BVAR model.

The general LINEX loss function can be expressed as the following equation:

$$L(\hat{\theta}, \theta) = e^{a(\hat{\theta}-\theta)} - a(\hat{\theta} - \theta) - 1 \tag{5}$$

$\hat{\theta}$ is the estimation of θ . If $a \neq 0$, the formula is a convex loss function. If $a = 1$, the function is asymmetric. Loss of too high estimation is larger than that of too low estimation; when $a < 0$, $\Delta = \hat{\theta} - \theta < 0$ approximates exponential form. $\Delta = \hat{\theta} - \theta > 0$ approximates linear form. When $a > 0$, the situation is the contrary. When $a = 0$, LINEX loss function can be regarded as a special form of squared loss function. The smaller $|a|$ is, the more symmetric the function form will be. And the LINEX loss function will be more approximate to the squared loss function.

LINEX loss function formula of VAR equation regression coefficient worked out from the general form is as follows:

$$L(\hat{\Phi}, \Phi) = \sum_{i=1}^{1+Lp} \sum_{j=1}^p \left[\exp \{ a_{ij} (\hat{\phi}_{ij} - \phi_{ij}) \} - a_{ij} (\hat{\phi}_{ij} - \phi_{ij}) - 1 \right] \tag{6}$$

Under LINEX loss function, Bayes estimated value $\hat{\Phi}_n$ of each element of Φ is as follows:

$$\hat{\phi}_{ij} = -\frac{1}{a_{ij}} \log \left[E \left\{ \exp \left(-a_{ij} \phi_{ij} \right) | Y \right\} \right] \tag{7}$$

Formula of squared loss function of VAR equation regression coefficient is as follows:

$$L(\hat{\Phi}, \Phi) = \text{trace} \left\{ (\hat{\Phi} - \Phi)' W (\hat{\Phi} - \Phi) \right\} \tag{8}$$

Under square loss function, Bayes estimated value $\hat{\Phi}_n$ of each element of Φ is as follows:

$$\hat{\Phi} = E(\Phi | Y) \tag{9}$$

Formula (8) is a constant weighting matrix. W can be regarded as a unit matrix. According to Formula (8) and (9), in squared loss, Bayes estimated value $\hat{\Phi}_n$ of Φ is a posterior distributed mean. In LINEX loss, posterior estimated value $\hat{\Phi}_n$ of Φ might be larger or smaller than the posterior mean. It depends on value of the constant a_{ij} .

3. Empirical Analysis

3.1. Data and core factors

According to existing research conclusions, the influence factors of road transportation energy consumption are mainly divided into driving factors and limiting factors. Driving factors include: GDP, income level, population, urbanization, the highway mileage, turnover volume, car ownership, etc. Limiting factors include: carbon dioxide emissions, oil, etc. We find that there are many factors influencing road transportation energy consumption and many fields are involved. Moreover, interrelations among these factors are complicated. There are few existing literature considering driving factors and limiting factors synthetically. Based on literature review, we divide all factors into driving factors and limiting factors, and select GDP, population, urbanization rate, total road turnover volume (According to China Road Transportation Statistics Index and Calculation Method, Total road turnover = passenger turnover + 10 * freight turnover [25]), road mileage and quantity of private vehicles after making comprehensive consideration from the perspectives of demand and supply, alternative energy resources, cost factor and national policies. When building VAR model, the core influence factors can be confirmed. Data used in this paper come from World Bank and China Statistical Yearbook (1987–2011) [26]. Based on data availability, we calculate energy consumption of road transportation of China.

3.2. Model estimation

As we know, VAR model is an integrated system. When considering the influence factors, we need to make clear which are internal factors of the system. It means that every two variables have mutual effect. We also need to learn which factors have mutual monomial influence relations. They can only be regarded as external influence factors of the system. For the system of road energy consumption, internal influence factors are mainly demand and cost. Demand indicators mainly include total road turnover volume, road mileage and quantity of private vehicles; cost indicators mainly refer to diesel and gasoline process. Influences of income and populations structure (GDP and urbanization rate) on road transportation energy consumption are external influence factors of the system. By making comparison, we find that VAR model system with total turnover volume, road mileage (LNZZ and LNLC) and road transportation energy consumption (LNY) as endogenous variables and urbanization rate and LNCZ as exogenous variables is the most stable. It meets integrated order of the original series. (See Table 1, Table 2 and Fig. 1)

Road transportation energy consumption VAR system model is as follows:

$$LNY = 0.7478LNY(-1) + 0.0279LNZZ(-1) - 0.0411LNLC(-1) + 0.7770LNCZ - 0.0612 \tag{10}$$

$$LNZZ = 0.0535LNY(-1) + 0.7974LNZZ(-1) + 0.5800LNLC(-1) - 0.4945LNCZ + 0.6209 \tag{11}$$

$$LNLC = 0.0166LNY(-1) - 0.0416LNZZ(-1) + 0.7225LNLC(-1) + 0.7494LNCZ - 0.9098 \tag{12}$$

Estimation result of the model (Table 2) shows that AIC of the whole model is -4.4589 , which is small enough. Log likelihood is 70.7365 , which is large enough. Integrated effect of the model is relatively good. After building the model, we need to make validity check of the model. From test value of the output JB statistic, we find that accepting the original assumption, namely the residual obeys normal distribution. According to the stability test result, all units are within the unit circle. It shows that VAR model system is stable.

Fig. 2 shows the impulse response function of each variable on road energy consumption. The horizontal axis represents periods (years) the impact effect lasts. The ordinate axis represents the contribution rate from the economic variables to the road energy consumption. The curve is the impulse response function representing dynamic effect of the response variable impact. The figure shows that when positive impact

is given to the current total road turnover volume and the mileage, possible influence on road energy consumption will be produced. When positive impact of one standard deviation is given to the current total road turnover volume (ZZ increases), road energy consumption will increase. After reaching the climax in the fifth period, it will become stable. It shows that total road turnover volume will increase in a short term and road energy consumption will also increase. Total road turnover volume reflects the social and economic development of road transportation demand. With the development of economic, people's demand for quality of life is growing higher. Purchasing power increases, freight turnover volume increases. Meanwhile, people's increased travel intensity causes passenger turnover volume increased. As a result, road total turnover volume increased. We can see, total turnover volume has been a positive impact on the road transportation energy consumption, and it connected with the level of economic development closely.

When positive impact of one standard deviation is given to the mileage (LC increases), road energy consumption will start to rise perpendicularly after reaching the bottom in the third period and will restrain itself after reaching the maximum in the ninth year. It shows that if a positive impact is given to mileage, road energy consumption will decrease first and then increase, because the mileage is a caused demand of road transportation, travel and car ownership increased lead to highway mileage increases, and the traffic demand increases. In order to meet people's traffic demand, the country will strengthen road infrastructure construction. When the mileage increases, road supply will increase. The roads will be clear. Energy consumption of motor vehicles will be smaller than that during traffic jam. However, when the traffic condition is favorable, people's travelling demand and intensity will increase, and people's intention of car purchase and driving will increase. Speaking of logistics, we take a comprehensive consideration of time and cost factors. Road transportation will take over market share of air transportation. Therefore, the influence of mileage on road transportation energy consumption will be negative first and then become positive.

From the variance decomposition diagram (Fig. 3), we find that contribution rate of road energy consumption itself is the largest, maintaining at about 93%. It is stock (up-tail) effect. Contribution rate of the total turnover volume keeps a rising trend and becomes stable from the ninth period at about 6%. Contribution rate of the mileage also increases constantly and now keeps at about 1%, this is because derived demand.

In this paper, after estimating all parameters of VAR model by using given data, we use MCMC algorithm to make Bayes estimation. Thus, $\hat{\Phi}_n$ under squared loss can be worked out. See Table 3 for the result. Similarly, by using Formula (7), Bayes estimated value of the regression coefficient under LINEX loss function can be obtained. Value of a_{ij} will directly affect the estimation result. In the road energy consumption system, value of a directly reflects economic and environmental influences brought by different strategic decisions in future under economic restraints and environmental restraints. Considering economic constraint, the total turnover volume reflects to GDP; as for environmental constraint, road energy consumption is the most direct cause of CO₂. Refer to the thesis of Zeller (1986) and Shawn Ni (2003). In this paper, value range of a_{ij} is -4 to 4 . We compare variation of the estimated result when a_{ij} changes for each unit. Table 4 shows the specific results.

From Table 4, we can find that there is asymmetric effect between road transportation energy consumption and its influence factors. When $a = 0$, the estimated results of regression coefficients under LINEX loss function equal to the estimated results under squared loss function. It shows that the squared loss is a special form of asymmetric loss. The smaller $|a|$ is, the more symmetric the function form will be. And the LINEX loss function will be more approximate to the squared loss function. When $a < 0$, with the increase of a , the estimated value under asymmetric loss function are more closer to the estimated values under squared loss function; When $a > 0$, with the increase of a , the estimated values under asymmetric loss function are further from the estimated value under squared loss function; and the deviation of estimated values when $a > 0$ are large than the estimated values when $a < 0$.

When the elastic coefficient of total turnover volume and the road mileage on road energy consumption is larger than the actual elastic coefficient, the estimated road energy consumption will be larger than the actual energy consumption. The national policy makers will consider that high energy consumption may bring pollution, so they will formulate relevant policies to control traffic demand, reduce investment in

transportation infrastructure, which might possibly leads to the traffic quantity supplied smaller than the actual demand. Actually, the goal of energy conservation and emission reduction will not be realized. Such results as traffic jam, increase of CO₂ emission and worsening environment pollution will be caused. On the contrary, when the elastic coefficient of total turnover volume and the road mileage on road energy consumption is smaller than the actual elastic coefficient, the estimated road energy consumption will be smaller than the actual energy consumption. The policy makers will think that the environment constraint reduces. In order to guarantee high economic development level, they will increase investment in traffic infrastructure to make supply larger than demand. Potential traffic demand will be caused. When road supply increases, convenient traffic will promote increase of people's travelling intensity. Thus, environmental pressure might be increased. It shows that when a country is making future strategic planning, it must take the asymmetric effect between economic development, traffic construction and environment into full consideration. It is not wise to promote economic development at the cost of environment, or ignore people's basic need on traffic infrastructure in order to save energy and reduce emission. In road traffic strategy formulating or policy adjusting process, it is not enough to focus only on static influence of several factors. A comprehensive consideration from a dynamic perspective is necessary.

4. Conclusions

With acceleration of Chinese urbanization process and constant enhancement of people's livelihood, the proportion of urban residents per capital's traffic expense in nonproductive expenses increases continuously. Meanwhile, the residents' travelling demand and intensity keep increasing. The increase rate of the quantity of private vehicles keeps high. As a result, energy consumption and CO₂ emission increases rapidly in spite of acceleration of economic development. In this paper, we take energy consumption of road transportation as the object of study and analyzes the dynamic mechanism of the road transportation energy consumption system from the perspective of cost. The result shows that in the VAR system of road transportation energy consumption, when positive impact of one standard deviation is given to the current total road turnover volume (ZZ increases), road energy consumption will increase. After reaching the climax in the fifth period, it will become stable. When positive impact of one standard deviation is given to the mileage (LC increases), road energy consumption will start to rise perpendicularly after reaching the bottom in the third period and will restrain itself after reaching the maximum in the ninth year. The mileage is a caused demand. Contribution rate of road energy consumption itself is the largest, about 93%, and it has stock (up-tail) effect. Contribution rate of total turnover volume and mileage to road energy consumption keep at about 6% and 1% respectively. When comparing estimated results of VAR equation regression coefficient under the squared loss function and the LINEX loss function, we find that there is asymmetric effect between road energy consumption with its influence factors. Value a will affect the estimated result. The smaller $|a|$ is, the more symmetric the function form will be and the LINEX loss function will be more approximate to the squared loss function. The deviation of estimated values when $a > 0$ are large than the estimated values when $a < 0$. When making road traffic strategic planning, the government should take this asymmetric effect into full consideration. Not only focus on the static effects among factors in the system of road transportation energy consumption cost, but also the dynamic effects. On the premise of guaranteeing economic development and environment constraint, the government should try to minimize the loss.

Acknowledgments

This research is supported by the National Natural Science Foundation of China (NSFC) under grants No. 71473155, the New Star of Youth Science and Technology Plan Project in Shaanxi Province, China No. 2016KJXX-14, Shaanxi Normal University College Basic Scientific Research Special Support Project No. 14SZTZ03 and 2015 Annual Silk Road Economic Belt Research Project of Xidian University No. 7215628803. The authors would like to thank the anonymous referees as well as the editors.

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Appendices

Table 1: VAR Lag order selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	28.74350	NA	3.26e-05	-1.819480	-1.526949	-1.738344
1	70.73652	67.18884*	2.36e-06*	-4.458922*	-3.727596*	-4.256083*
2	77.02756	8.555809	3.09e-06	-4.242205	-3.072084	-3.917663

Table 2: The estimation results of VAR model

	LNy	LNZZ	LNLC
R-squared	0.993513	0.964693	0.964990
Adj. R-squared	0.992216	0.957631	0.957988
Sum sq. resid	0.080463	0.588973	0.238124
S.E. equation	0.063428	0.171606	0.109116
F-statistic	765.7929	136.6144	137.8151
Log likelihood	36.26190	11.37967	22.69952
Akaike AIC	-2.500952	-0.510374	-1.415961
Schwarz SC	-2.257177	-0.266599	-1.172186
Mean dependent	10.82368	11.27772	5.141434
S.D. dependent	0.718915	0.833702	0.532351
Determinant resid covariance (dof adj.)		1.37E-06	
Determinant resid covariance		7.00E-07	
Log likelihood		70.73652	
Akaike information criterion		-4.458922	
Schwarz criterion		-3.727596	

Table 3: The regression coefficient under Normal-Wishart prior distribution under quadratic loss function

coefficient	Mean	sd	MC_error	val2.5pc	median	val97.5pc	start	sample
b[1,1]	0.7714	0.7608	0.02484	-0.7218	0.7589	2.279	5000	10001
b[1,2]	0.011	0.7578	0.02579	-1.494	0.02083	1.461	5000	10001
b[1,3]	-0.0791	0.9532	0.01922	-1.925	-0.07399	1.76	5000	10001
b[1,4]	0.8014	0.9938	0.01619	-1.087	0.7982	2.729	5000	10001
b[1,5]	-0.0637	0.9924	0.009687	-1.996	-0.05449	1.869	5000	10001
b[2,1]	0.44	0.2654	0.02659	-0.01286	0.4579	0.7941	5000	10001
b[2,2]	0.8114	0.1261	0.01251	0.5616	0.8161	1.039	5000	10001
b[2,3]	0.5571	0.1249	0.01184	0.3016	0.5582	0.8054	5000	10001
b[2,4]	-1.612	0.5811	0.05806	-2.546	-1.664	-0.4607	5000	10001
b[2,5]	0.4032	0.5463	0.05082	-0.7999	0.437	1.384	5000	10001
b[3,1]	0.0003	0.7617	0.03651	-1.437	-0.01449	1.515	5000	10001
b[3,2]	-0.0032	0.7386	0.03363	-1.468	0.004807	1.413	5000	10001
b[3,3]	0.6595	0.9489	0.03208	-1.183	0.6503	2.554	5000	10001
b[3,4]	0.7787	0.9624	0.02391	-1.094	0.7654	2.667	5000	10001
b[3,5]	-0.9336	0.9994	0.01099	-2.921	-0.9252	1.001	5000	10001

Table 4: The regression coefficient under quadratic loss function and LINEX loss function

coefficient	quadratic loss		LINEX loss							
	Mean	-4	-3	-2	-1	a = 0	1	2	3	4
b[1,1]	0.7714	1.929	1.6396	1.3502	1.0608	0.7714	0.482	0.1926	-0.0968	-0.3862
b[1,2]	0.011	1.1595	0.8724	0.5853	0.2981	0.011	-0.2761	-0.5633	-0.8504	-1.1375
b[1,3]	-0.0791	1.7381	1.2838	0.8295	0.3752	-0.0791	-0.5334	-0.9877	-1.442	-1.8963
b[1,4]	0.8014	2.7767	2.2829	1.789	1.2952	0.8014	0.3076	-0.1862	-0.6801	-1.1739
b[1,5]	-0.0637	1.906	1.4136	0.9211	0.4287	-0.0637	-0.5562	-1.0486	-1.541	-2.0334
b[2,1]	0.44	0.5809	0.5457	0.5104	0.4752	0.44	0.4048	0.3696	0.3343	0.2991
b[2,2]	0.8114	0.8432	0.8353	0.8273	0.8194	0.8114	0.8034	0.7955	0.7875	0.7796
b[2,3]	0.5571	0.5883	0.5805	0.5727	0.5649	0.5571	0.5493	0.5415	0.5337	0.5259
b[2,4]	-1.612	-0.9366	-1.1055	-1.2743	-1.4432	-1.612	-1.7808	-1.9497	-2.1185	-2.2874
b[2,5]	0.4032	1.0001	0.8509	0.7016	0.5524	0.4032	0.254	0.1048	-0.0445	-0.1937
b[3,1]	0.0003	1.1607	0.8706	0.5805	0.2904	0.0003	-0.2898	-0.5799	-0.87	-1.1601
b[3,2]	-0.0032	1.0878	0.8151	0.5423	0.2695	-0.0032	-0.276	-0.5488	-0.8215	-1.0943
b[3,3]	0.6595	2.4603	2.0101	1.5599	1.1097	0.6595	0.2093	-0.2409	-0.6911	-1.1413
b[3,4]	0.7787	2.6311	2.168	1.7049	1.2418	0.7787	0.3156	-0.1475	-0.6106	-1.0737
b[3,5]	-0.9336	1.064	0.5646	0.0652	-0.4342	-0.9336	-1.433	-1.9324	-2.4318	-2.9312

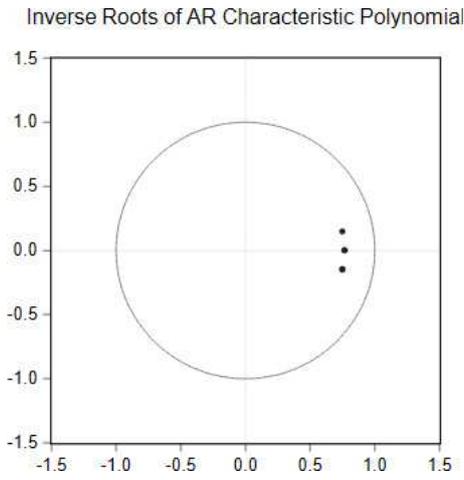


Figure 1: Unit root graph

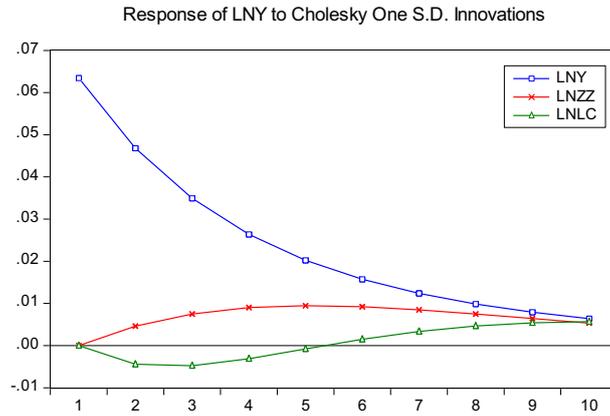


Figure 2: Impulse response

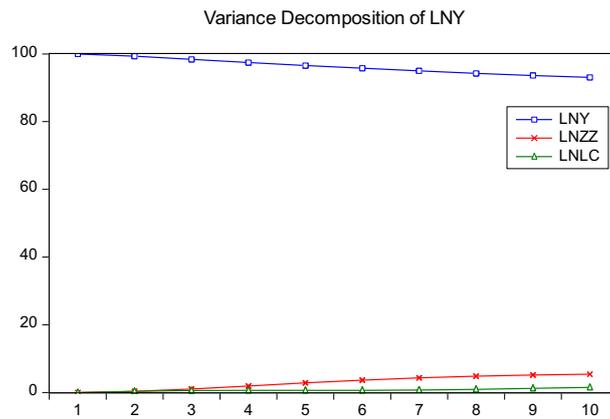


Figure 3: Variance decomposition