Green Energy, Environment and Sustainable Development
C. Wang et al. (Eds.)

doi:10.3233/ATDE230365

Energy and Environment Constraints, Manufacturing Export Quality Margin and Export Growth Rate—Dynamic Analysis Based on TVP-VAR

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Abstract. This paper constructs a TVP-VAR model to identify the time-varying relationships among energy and environmental constraints, manufacturing export quality margin and export growth rate. The results show that: (1) The impact of energy and environmental constraints on the export growth rate of manufacturing industry is more significant than the marginal impact of export quality; in the short term, it will hinder the improvement of the export growth rate of manufacturing industry; in the long term, the innovation compensation effect cannot completely offset the crowding out effect, which makes the long-term negative effect of energy and environmental constraints on the marginal improvement of manufacturing export quality more significant, and the external impact will increase the crowding effect of energy and environmental constraints on the marginal improvement of manufacturing export quality. (2) There is no structural change in the impact of manufacturing export quality margin and export growth rate on energy and environmental constraints. Manufacturing export quality margin has a sustained negative impact on energy and environmental constraints, and manufacturing export growth rate has a sustained positive impact on energy and environmental constraints.

Keywords. TVB-VAR model, energy and environmental constraints, export quality margin, impulse response function

1. Introduction

As the marginal increase in resource supply decreases and environmental responsibility continues to strengthen, the opportunity cost of China's manufacturing exports continues to rise, and bottleneck constraints mainly represented by energy and environment gradually emerge. And the previous growth model of manufacturing exports often focused on the quantity expansion but ignores the quality improvement. This export growth model will lead to the unsustainability of various domestic factors of production, including energy, and will also lead to irreversible damage to the ecological environment. Once this situation exceeds the range of ecological carrying capacity of natural resources, energy, environment, and manufacturing export growth will be trapped in a vicious circle. The problem to be solved is to make China's manufacturing export growth change from focusing on quantitative expansion to qualitative improvement under the premise of fully

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considering the total energy and environmental carrying capacity constraints on manufacturing export growth.

This paper argues that only by dynamically identifying the time-varying relationships among energy and environmental constraints, manufacturing export quality margins and export growth rates can relevant policies be adjusted in a timely manner and reasonable expectations be made based on feedback mechanisms. This paper firstly expands the dimension of export growth margin analysis and introduces the quality margin to reveal the pattern of China's manufacturing export growth in a more comprehensive and realistic way. Then, by constructing a TVP-VAR model, the dynamic relationship characteristics of energy and environmental constraints, manufacturing export quality margins and export growth rate are fully captured. The paper provides empirical evidence to clarify the time-varying relationship of the interaction among them.

2. Model Construction and Variable Selection

2.1. Time-Varying Parametric Vector Autoregressive Model

TVP-VAR model is developed from the structural vector autoregressive model (SVAR) with time-varying covariance matrices of coefficients and shocks. The basic SVAR model can be defined as follows:

$$Ay_t = F_1 y_{t-1} + F_2 y_{t-2} + \cdots + F_p y_{t-p} + \mu_t, t = p + 1, \cdots, n \tag{1}$$

where y_t represents a $k \times 1$-dimensional vector composed of observed variables, A, F1, F2, …, Fp represents the $k \times k$ coefficient matrix, the random perturbation term μ_t represents a $k \times 1$-dimensional structural shock, and p denotes the lag of the model. Assuming that the random perturbation term $\mu_t \sim (0, SS)$, then

$$S = \begin{bmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_k \end{bmatrix} \tag{2}$$

$\sigma_j (j = 1,2, \cdots, k)$ in the above equation is the standard deviation of the structural shocks. The recursive identification method to determine the contemporaneous relationship between the structural shocks of the model requires the assumption that A is a lower triangular matrix [1]. The lower triangular matrix A can be expressed as

$$A = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \cdots & a_{k,k-1} & 1 \end{bmatrix} \tag{3}$$

Then, equation (1) can be rewritten into a simplified form of the SVAR model as follows:

$$y_t = B_1 y_{t-1} + B_2 y_{t-2} + \cdots + B_p y_{t-p} + A^{-1} S \varepsilon_t, \varepsilon_t \sim N(0, I_k) \tag{4}$$

where stacking of the row elements in the matrix B_i by $B_i = A^{-1} F_i, i = 1,2, \cdots, p$ can form $k^2 p \times 1$ the dimensional column vector b, and defining $X_t = I_k \otimes$

$(y_{t-1}^{'}, y_{t-2}^{'}, \cdots, y_{t-p}^{'})$, $\otimes$ which represents the Kronecker product, thus transforming equation (4) into

$$y_t = X_t b + A^{-1} S \varepsilon_t \tag{5}$$

By introducing the time-varying variance into the variance covariance matrix of the original SVAR model, we can obtain a multivariate nonlinear time-varying parameter vector autoregressive model (TVP-VAR) as follows:

$$y_t = X_t b_t + A_t^{-1} S_t \varepsilon_t \tag{6}$$

where both the coefficient matrix b_t and the parameter matrix A_t^{-1} and S_t can vary with time. In order to obtain more efficient parameter estimation results, the vectors that are not 0 and 1 in the lower triangular matrix A_t are now stacked as column vectors, and we have $a_t = (a_{21}, a_{31}, a_{32}, a_{41}, \cdots, a_{k,k-1})'$.

Assume that the parameters in equation (6) obey the random wandering process, which is $b_{t+1} = b_t + \mu_{bt}, \alpha_{t+1} = \alpha_t + \mu_{\alpha t}, h_{t+1} = h_t + \mu_{ht}$. Let the logarithmic random rate fluctuation matrix be $h_t = (h_{1t}, h_{2t}, \cdots, h_{kt})'$, and $h_{jt} = log\, \sigma_{jt}^2$, $j = 1, \cdots, k,\ t = p+1, \cdots, n.$ μ_{bt}, $\mu_{\alpha t}$, μ_{ht} are perturbation terms, then

$$\begin{bmatrix} \varepsilon_t \\ \mu_{bt} \\ \mu_{\alpha t} \\ \mu_{ht} \end{bmatrix} \sim N\left[0, \begin{bmatrix} I & O & O & O \\ O & S_b & O & O \\ O & O & S_\alpha & O \\ O & O & O & S_h \end{bmatrix}\right], t = p+1, \cdots, n \tag{7}$$

Among them, $b_{p+1} \sim N(\mu_{b0}, S_{b0}), \alpha_{p+1} \sim N(\mu_{\alpha 0}, S_{\alpha 0}), h_{p+1} \sim N(\mu_{h0}, S_{h0})$. This indicates that the perturbations of structural shocks on the time-varying parameters b_t, α_t and h_t are uncorrelated with each other. In addition, I is the unit matrix, S_b, S_α and S_h are positive definite diagonal matrixes. The initial values of time-varying parameters can first be set as: $\mu_{\alpha_0} = \mu_{b_0} = \mu_{h_0} = 0$, and the covariance matrix is $S_{\alpha_0} = S_{b_0} = S_{h_0} = 10 \times I$ [2]. And assume that the prior distribution of the I-th diagonal parameter of the covariance matrix is $(S_b)_i^{-2} \sim Gamma(40{,}0.02)$, $(S_\alpha)_i^{-2} \sim Gamma(4{,}0.02)$, $(S_h)_i^{-2} \sim Gamma(4{,}0.02)$.

2.2. Variable Selection and Data Processing

The following TVP-VAR model needs to be developed based on the above equation.

$$y_t = (EEC_t, GW_{t,} MRZ_t) \tag{8}$$

EEC_t is the energy and environment constraint index, GW_t is the manufacturing export growth rate, and MRZ_t is the manufacturing export quality margin. The model selects quarterly data of the Chinese manufacturing industry from the first quarter of 2002 to the second quarter of 2018 as the sample interval.

(1) Energy and environmental constraint index. In this paper, the energy and environmental constraint index is formed by combining energy consumption intensity, energy consumption elasticity coefficient, coal consumption intensity, single-value CO_2 and SO_2 emissions and green total factor energy efficiency [3] of manufacturing export industries by using factor analysis method. The change of the energy and environment constraint index can reflect the increase or decrease of the domestic energy and environment constraint degree. The higher the value of the index, the greater the degree

of energy and environmental constraints. The smaller the value is, the weaker the degree of energy and environmental constraints are.

(2) Manufacturing export quality margin (MRZ). The paper defines the quality margin as the factors that affect the quantity demanded other than product type, product price and expenditure. Therefore, this paper refers to Bing-Zhan Shi et al. (2013) [4] to derive the quality margin by inferring product quality with demand information.

It is assumed that the utility function of representative consumers in Country m to the manufactured products in China in the form of constant elasticity of substitution is a nested CES utility function, which increases with the increase of product consumption quantity, product type and product quality.

$$U = \left[\int_{i\in I_{cm}} (\lambda_{cmi} q_{cmi})^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{9}$$

where λ_{cmi} is the quality index reflecting the preference of consumers in country m for manufacturing product variety i, q_{cmi} is the quantity of exports of variety i to country m, and the elasticity of demand between any variety pair $\sigma > 1$ [5]. And under the utility maximization condition, the demand function of consumers in country m for manufacturing product i is as follows:

$$q_{cmi} = \lambda_{cmi}^{\sigma_i - 1} p_{cmi}^{-\sigma_i} \frac{E_{cmi}}{P_{cmi}} \tag{10}$$

where E_{cmi} denotes the level of total consumer spending on product i in country m, P_{mi} is the composite price index in country m, and p_{mi} denotes the price of product i. $\frac{E_{cmi}}{P_{cmi}}$ can represent the size of the market in country m, so equation (10) then shows that consumer demand for manufacturing product i in country m depends on price, quality, and market size at the same time.

Drawing on the derivation of Hummels & Klenow (2005) [6] and Liu Xuemei & Dong yinguo (2019) [7] for the price margin and quantity margin, this paper needs to define the quality margin of China's manufacturing exports to country m. The quality margin of manufacturing exports to country m is defined as

$$\lambda_{cm} = \prod_{i\in I_{cm}} \left[\left(\frac{q_{cmi}}{q_{wmi}}\right)^{\frac{1}{\sigma_i - 1}} * \left(\frac{p_{cmi}}{p_{wmi}}\right)^{\frac{\sigma_i}{\sigma_i - 1}}\right]^{w_{cmi}} \tag{11}$$

The weights w_{cmi} in equation (11) are calculated as follows:

$$w_{cmi} = \frac{\frac{S_{cmi} - S_{wmi}}{\ln S_{cmi} - \ln S_{wmi}}}{\sum_{i\in I_{cm}} \frac{S_{cmi} - S_{wmi}}{\ln S_{cmi} - \ln S_{wmi}}}, \quad S_{cmi} = \frac{p_{cmi} q_{cmi}}{\sum_{i\in I_{cm}} p_{cmi} q_{cmi}}, \quad S_{wmi} = \frac{p_{wmi} q_{wmi}}{\sum_{i\in I_{cm}} p_{wmi} q_{wmi}}$$

In order to further analyze the overall export quality of China's manufacturing industry, the export quality margins of China's manufacturing industry to different markets need to be summed up by the following formula.

$$\lambda_c = \prod_{m\in M_c} (\lambda_{cm})^{a_{cm}} \tag{12}$$

where M_c denotes the set of all countries and regions of China's manufacturing exports, and a_{cm} denotes the proportion of manufacturing exports to country m in China's total manufacturing exports.

2.3. Parameter Estimation Results and Model Diagnosis

In the ADF unit root test after first-order differencing of all-time series, it is found that each variable in equation (8) shows a smooth series without unit root at 5% significance level. Therefore, there is no pseudo-regression in the subsequent model analysis.

According to the optimal lag diagnosis, the setting of the lag is 1. The number of Markov Monte Carlo iterations is set to 10,000, and the first 1,000 instabilities are discarded to test the validity and stability of the parameter estimates. The specific parameter results are estimated in Table 1.

Table 1. Parameter estimation results and model diagnosis.

Parameter	Mean value	Standard deviation	95% Confidence interval	CD statistics	Invalid factor
s_{b_1}	0.0225	0.0027	[0.0180, 0.0287]	0.940	35.20
s_{b_2}	0.0228	0.0026	[0.0183, 0.0284]	0.843	5.06
s_{α_1}	0.0522	0.0113	[0.0347, 0.0778]	0.944	33.00
s_{α_2}	0.1377	0.0541	[0.0546, 0.2649]	0.001	41.77
s_{h_1}	1.1200	0.3924	[0.5269, 2.0886]	0.176	74.46
s_{h_2}	0.8575	0.1727	[0.5769, 1.2349]	0.003	73.12

From the estimation results in Table 1, the CD statistic for each parameter is more than the critical value at the 5% significance level (the critical value is 1.96), and none of them can reject the original hypothesis that the MCMC sampling results converge to a smooth distribution (i.e., the posterior distribution of the parameter), indicating that its overall convergence is good [8]. From the invalid factors in the table, the values of invalid factors for each parameter are less than 100, indicating that the MCMC estimation method has effectively sampled the posterior distributions of the parameters in the model.

Figure 1 gives the autocorrelation coefficients, convergence trajectories and posterior distribution density functions of the MCMC sampling estimated parameters of model [9]. In the first row, it can be seen that the autocorrelation coefficients of the estimated parameters after 10,000 iterations of sampling decay rapidly and converge to 0 gradually, indicating that the MCMC estimation method effectively eliminates the autocorrelation generated by sampling. In the second row, it can be seen that the parameter sequences basically present fluctuating clustering motion trajectories around the posterior mean, indicating that the parameters obtained from the sampling obey a smooth process and the parameters are independent of each other. In the third row, it can be seen that the posterior distribution density function of each parameter is similar to the normal distribution, so the sampling of values in this paper is valid.

3. Analysis of Empirical Results

This section presents the equally spaced impulse response plots for the three variables: energy and environmental constraints, manufacturing export quality margin, and export growth rate (Figure 2). Where the y axis is the impulse response value and the x axis is the different time points. The three fluctuation lines in the figure represent the impulse responses formed by a standard positive shock of one unit of other variables for each variable one quarter (short term), four quarters (medium term) and eight quarters (long term) earlier in the sample period, respectively.

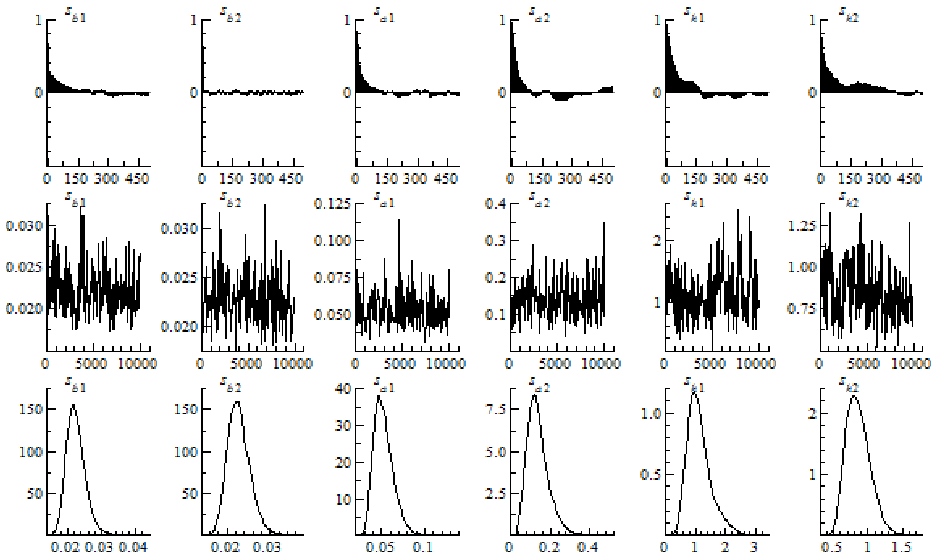

Figure 1. Figure of sample autocorrelation coefficient, simulation path and posterior distribution density function.

Figure 2 ($\varepsilon_{EEC\uparrow} \rightarrow MRZ$) plots the shock of the energy and environmental constraint to the manufacturing export quality margin. The responses at the three different lags are mostly negative, and this negative effect shows a diminishing trend over time after 2012. This indicates that the crowding-out effect of energy and environmental constraints is more obvious, thus inhibiting the improvement of China's manufacturing export quality; on the other hand, it also indicates that the innovation compensation effect of energy and environmental constraints on the improvement of manufacturing export quality begins to appear as time passes. Meanwhile, from the impulse response values of the three different lags, the peak in the medium and long term appears slightly earlier than in the short term, and the absolute value of the impulse response increases gradually with the increase of the lag period, reflecting that the long-term effect of energy and environmental constraints on the marginal effect of manufacturing export quality is more obvious than the short-term effect.

Figure 2 ($\varepsilon_{EEC\uparrow} \rightarrow GW$) plots the shock of the energy and environmental constraint to the manufacturing export growth rate, which is higher than its shock to the manufacturing export quality margin. Given a positive shock of energy and environmental constraint, the responses of lag 1 and lag 4 are mostly negative, and the absolute values of the impulse responses of lag 1 are mostly higher than those of lag 4 and lag 8. This indicates that the increased degree of energy and environmental constraints will hinder the increase of manufacturing export growth rate in the short term, and the short-term effect of energy and environmental constraints affecting manufacturing export growth rate is more obvious than the long-term effect.

Figure 2 ($\varepsilon_{MRZ\uparrow} \rightarrow EEC$) and Figure 2 ($\varepsilon_{GW\uparrow} \rightarrow EEC$) respectively show the shock of the manufacturing export quality margin and the manufacturing exports growth rate to the energy and environmental constraints. There is no structural shift in the impact paths of manufacturing export quality margin and export growth rate on energy and environmental constraints. The manufacturing export quality margin has a persistent negative effect on the energy and environmental constraint, while the manufacturing export growth rate has a persistent positive effect on the energy and environmental constraint.

Figure 2 ($\varepsilon_{MRZ\uparrow} \rightarrow GW$) plots the shock of the manufacturing export quality margin to the manufacturing exports growth rate. Given a positive shock to the manufacturing exports quality margin of all three different lags show a persistent negative response.

Figure 2 ($\varepsilon_{GW\uparrow} \rightarrow MRZ$) plots the shock of the manufacturing export growth rate to the manufacturing export quality margin. In terms of the absolute value of the impulse effect, the positive impact of the growth rate of manufacturing exports on the quality margin of manufacturing exports is negligible.

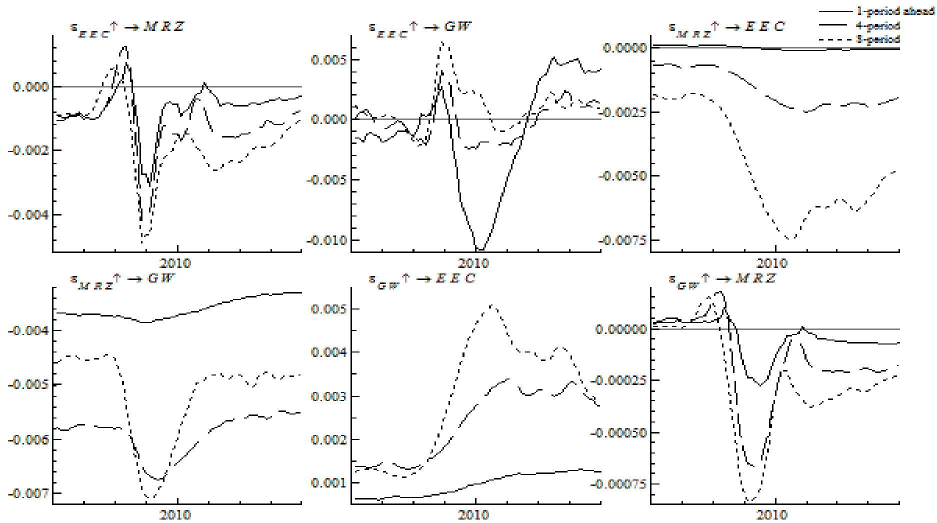

Figure 2. Equal-interval impulse response of energy environment constraints, export quality margin and export growth rate.

4. Conclusions and Recommendations

According to the above empirical results, it can be seen that the impact of energy and environmental constraints on manufacturing export quality margins and export growth rate has certain time-varying characteristics in terms of direction and magnitude of impact. The conclusions are as follows:

(1) There is an asymmetric impact of energy and environmental constraints on the manufacturing exports quality margin, and the effect of the impact varies from period to period. Whether in the short, medium, or long term, energy and environmental constraints have mainly had a negative impact on the marginal improvement of

manufacturing export quality, while external shocks can increase the crowding-out effect of energy constraints on the marginal improvement of manufacturing export quality.

(2) The impact of energy and environmental constraints on the manufacturing export growth rate is higher than its impact on the manufacturing exports quality margin. The increased degree of energy and environmental constraints will hinder the manufacturing exports growth rate in the short term, and the short-term effect of energy and environmental constraints affecting the manufacturing exports growth rate is more significant than the long-term effect.

(3) The impact paths of both the marginal quality of manufacturing exports and the export growth rate on energy and environmental constraints have not changed structurally. Improving the quality of manufacturing exports will help improve energy efficiency and environmental conditions in the long run, while focusing on the growth rate of manufacturing exports will reduce energy use efficiency and lead to increased environmental pollution emissions.

(4) The current export product quality upgrade will be more helpful to promote terms of trade improvement rather than export quantity expansion, and the pursuit of quality is bound to change the original export quantity-led discovery model to a certain extent, thus making the growth rate of manufacturing exports will be subject to the negative impact of the export quality margin. The increase in the manufacturing exports growth rate will have a minimal impact on the manufacturing exports quality margin.

Acknowledgement

This research was financially supported by Doctoral Fund Project, University of Jinan (Grant No. B1616).

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