Can CNY Internationalization Eliminate Overcapacity of Steel?

——Research Based on Data Mining

Shizhen Hua

School of Finance and Business, Shanghai Normal University, Shanghai, China

hsz0827@163.com

Abstract. In recent years, with the continuous improvement of China's comprehensive strength, the international circulation of CNY is accelerating day by day, and the internationalization of CNY is unstoppable. In this regard, this paper mainly discusses whether the internationalization of CNY can solve the problem of iron and steel overcapacity in China. The small /medium/large TVP-VAR model and TVP-VAR-dma/DMS are used to predict and compare China's iron and steel demand respectively. TVP-VAR-dma can quickly adapt to various changes in China's economic structure and has high accuracy. Based on the IMF's prediction of GDP growth rate of various countries and the prediction that China's steel production capacity will not increase, the results show that CNY internationalization can effectively resolve China's excess steel production capacity. In addition, in order to completely solve the problem of overcapacity in China's steel industry, the state should further expand the effective transformation of the steel industry under the background of CNY internationalization, strengthen the function of market resource allocation, and reduce the capacity expansion of low-end steel products.

Keywords: CNY Internationalization, Steel Overcapacity, Time Varying Parameter Vector Autoregressive Model

1 Introduction

Since the outbreak of the financial crisis, in order to cope with the sudden economic pressure, countries around the world have introduced and implemented a series of relevant policies to stimulate economic development in a short period of time. However, from the perspective of the response effect of the world, the economic demand of various countries is facing a second challenge. The contradiction between institutional and structural issues is becoming increasingly prominent, and overcapacity has gradually become a major global problem. According to the statistics of the International Iron and Steel Association, the capacity utilization rate of the global steel industry has rebounded briefly after the financial crisis. However, this recovery only lasted for more than two years, and then began to decline, with the capacity utilization

H. Wu et al. (Eds.): CSIEDE 2022, ACSR 103, pp. 792–799, 2022.
https://doi.org/10.2991/978-94-6463-108-1_88

rate dropping from 80% to 70%. In 2020, with the outbreak of the COVID-19, the economy of various countries will be more affected, and the fluctuation of the steel industry will be more intense.

With the continuous development of China's economy, China's international trade position is becoming more and more stable, the international competitiveness of CNY is becoming stronger and stronger, and the circulation scope of CNY in the world is gradually expanding. The internationalization of CNY can highly link China's development strategy after entering the new economic normal with the economic development of other countries in the world, and will also promote China to become a regional pillar of external radiation, prosperity and stability.

Based on the above background, this paper selects small TVP-VAR model, medium TVP-VAR model, large TVP-VAR model, time-varying parameter vector autoregression model (TVP-VAR dma) and time-varying parameter vector autoregression model (TVP-VAR dms) proposed by Koop et al. (2013) to scientifically and accurately forecast China's steel demand, Study whether CNY internationalization can alleviate China's steel overcapacity [1].

Finally, based on the analysis and conclusions of this paper, we propose policy recommendations to further resolve the problem of iron and steel overcapacity in China, with a view to making contributions to maintaining the balance of iron and steel supply and demand and industrial transformation and upgrading.

2 Method and Materials

2.1 Model Establishment

The single TVP-VAR model is writed as follows:

$$y_t = Z_t \beta_t + \varepsilon_t \text{ and } \beta_{t+1} = \beta_t + u_t \tag{1}$$

Among ε_t,N(0,Σ_t)and u_t is prior knowledge. N(0,Q_t),u_t and u_s is independent of each other for any s and t. y_t is a vector matrix of M×1, including the observation vector of M time series variables. Z_t is the matrix of M×K. In the equation of each TVP-VAR model, Z_t includes constant term and p-order hysteretic term, that is, K=M(1+p*M).

The observation value of time s is represented by$y^s = (y_1, \cdots, y_s)'$. Bayesian derived ε_t involves Kalman filtering, and the key steps are:

$$\beta_{t-1} | y^{t-1} \sim N(\beta_{t-1|t-1}, V_{t-1|t-1}) \tag{2}$$

Then use Kalman filtering:

$$\beta_t | y^{t-1} \sim N(\beta_{t|t-1}, V_{t|t-1}) \tag{3}$$

$$V_{t-1} \big| V_{t-1|t-1} + Q_t \tag{4}$$

This is the only place where Q_t enters the Kalman filtering formula. Therefore, if we replace the previous equation with:

$$V_{t|t-1} = \frac{1}{\lambda} V_{t-1|t-1} \tag{5}$$

Where it is no longer necessary to estimate or simulate Q_t. λ It is called forgetting factor, and 0<λ≤1. Formula (5) indicates that the past j observation periods have a weight of λ^j in the filter estimation of β_t. Note also that (4) and (5) mean $Q_t = (\lambda^{-1} - 1)V_{t-1|t-1}$, from which it can be seen that when λ= At 1, constant coefficient occurs.

One of the contributions of this model is to explore the use of forgetting factors in large TVP-VARs [2]. A similar approximation method is used to replace the posterior simulation algorithm for multivariate random volatility in the measurement equation. We use exponential weighted moving average (EWMA) to model volatility and EWMA estimation to measure the error covariance matrix:

$$\Sigma_t = k\,\Sigma_{t-1} + (1-k)\hat{\varepsilon}_t \hat{\varepsilon}_t \tag{6}$$

Where $\hat{\varepsilon}_t = y_t - \beta_{t|t} Z_t$ is provided by Kalman filter. The EWMA estimator also needs to select the attenuation factor, Κ. This estimator needs to select an initial condition $\hat{\Sigma}_0$. For this purpose, we use the sample covariance matrix y^τ, among τ+ 1 is the time when we began to predict and evaluate.

DMS is a recursive algorithm, and the necessary recursion is similar to the prediction and update equation of Kalman filter. Given the initial condition $\pi_{0|0,j}$ (where j=1, ..., J), Raftery et al. (2010) deduced a model prediction equation using forgetting factor α[3]:

$$\pi_{t|t-1,j} = \frac{\pi_{t-1|t-1,j}^{\alpha}}{\sum_{l=1}^{j} \pi_{t-1|t-1,l}^{\alpha}} \tag{7}$$

The model correction equation is:

$$\pi_{t|t,j} = \frac{\pi_{t|t-1,j}\, p_j(y_t|y^{t-1})}{\sum_{l=1}^{j} \pi_{t|t-1,l}\, p_l(y_t|y^{t-1})}, \tag{8}$$

Where $p_j(y_t|y^{t-1})$ represents the probability of prediction (i.e. the prediction density of model j at y_t). It should be noted that this prediction density is generated by the Kalman filter, and there is a standard textbook formula. Forecast possibility is a measure of forecast performance.

To help understand the forgetting factor method, $\pi_{t|t-1,j}$ (used to select the key probability of the model) can be written as:

$$\pi_{t|t-1,j} \propto \prod_{i=1}^{t-1} \left[p_j(y_{t-i}|y^{t-i-1})\right]^{\alpha^i}$$

As mentioned above, DMS needs to select forgetting factors α and λ, as well as the attenuation factor K. They are usually set to fixed constants [4]. However, we now use DMS methods to estimate b and c. For this reason, we interpret the different values of forgetting factor as defining different models, and then use DMS to choose between them [5]. For this reason, we interpret the different values of forgetting factor as defining different models, and then use DMS to choose between them.

For TVP-VAR of a specific dimension β_0 uses a Normal prior, similar to the previous Minnesota prior. Our experience part uses a data set, in which all variables are converted into stationarity [6], so we choose a priori mean of E (β_0)=0.

Minnesota prior covariance matrix E (β_0)=0 is usually assumed to be diagonal, and var is assumed $\mathrm{var}\,(\beta_0)$=V and V_i is the diagonal element, then the prior covariance matrix is defined as:

$$V_t = \begin{cases} \frac{\gamma}{r^2} Coefficient\ of\ the\ r-th\ order\ lag\ term, r = 1, \cdots, p \\ \alpha\ Intercept\ term\ coefficient \end{cases}$$

Where p is the lag length. The key super parameter γ in V is the super parameter that controls the shrinkage of VAR coefficient. We will estimate γ based on the data. Note that this is different from the previous Minnesota, which contains two shrinkage parameters (corresponding to its own hysteresis and other hysteresis) [7], which are set to a fixed value. Theoretically, it is simple to consider two shrinkage parameters in our method. To simplify the calculation, we only have one shrinkage parameter. Finally, we set a=102 to intercept without providing any information.

2.2 Description of Forecast Indicators and Variables

This paper empirically studies 13 variables that affect the main factors of China's steel demand through three TVP-VAR models. The time range of data selection is from 2007Q1 to 2021Q4. The first type is the Small TVP-VAR model, which includes the three core elements in the principle of supply and demand, namely the apparent consumption of crude steel, the composite index of steel price and the output of crude steel. The second type is the Medium TVP-VAR model. In addition to the factors of the first type TVP-VAR model, the model also includes the cumulative year-on-year GDP, the cumulative year-on-year fixed asset investment completion, the broad money supply and the sum of the quarterly GDP of the United States, Japan and the United Kingdom. The third type is the Large TVP-VAR model. In addition to the factors of the second type of TVP-VAR model, it also includes iron ore price, benchmark interest rate of CNY loans, Baltic Sea dry goods index, weighted exchange rate of CNY against USD, real crude oil price index and CNY internationalization factors. Table 1 includes the variables, stationarity processing and data sources used in the above three TVP-VAR models.

Table 1. Variables Description[owner-draw]

Variable Classification	Agent Variable	Conversion Code
Apparent consumption of crude steel	AD	2
Composite index of steel price	P	2
Crude steel output	AS	2
Cumulative year-on-year GDP	GDP	2
Year on year accumulative completed amount of fixed assets investment	FAI	2
Broad money supply	M2	1
Total quarterly GDP of the United States, Japan and the United Kingdom	SumGDP	3
Iron ore price	ST	3
Benchmark interest rate of CNY loans	r	1
Baltic Dry Index	BDI	2
Weighted exchange rate of CNY against USD	ER	1
Crude oil real price index	OP	2
Factors of CNY internationalization	BeltRoad	2

Note: The variables are stable after the corresponding conversion code transformation. Conversion codes 1, 2 and 3 in the table represent first-order difference, logarithmic first-order difference and logarithmic second-order difference respectively.

3 Results

All variables in the empirical part of this paper have undergone approximate standardization after being stabilized, that is, after being stabilized, the data mean value between 2005 and 2021 is subtracted and divided by the standard deviation of the data in this interval, the lag length of all dependent variables p=2, the parameter β The prior distribution of 0 is Koop type Minnesota prior. Attenuation factorK= 0.96, forgetting factor α= 0.99, which means that the observed value five years ago is equivalent to 80% of the observed value in the previous period when making predictions.

We use MAFE and MSFE to compare the prediction ability of different models. Kappa and alpha in Tables 2 to 5 are the attenuation factor and forgetting factor in the model introduction respectively.

Table 2. Prediction Results of Four Models[owner-draw]

	Step h prediction in advance	h=1		h=2		h=4	
	Evaluation criteria	MAFE	MSFE	MAFE	MSFE	MAFE	MSFE
Small TVP-VAR	TVP-VAR (kappa=0.98, alpha=0.95)	0.974	1.312	0.975	1.313	0.953	1.245
	TVP-VAR (kappa=0.98, alpha=0.99)	0.989	1.396	0.953	1.278	0.974	1.286

	TVP-VAR (kappa=0.98, alpha=1)	0.956	1.256	0.966	1.296	0.928	1.227
Medium TVP-VAR	TVP-VAR (kappa=0.98, alpha=0.95)	0.974	1.343	0.974	1.348	0.976	1.332
	TVP-VAR (kappa=0.98, alpha=0.99)	1.000	1.378	0.996	1.302	0.946	1.286
	TVP-VAR (kappa=0.98, alpha=1)	0.946	1.304	0.974	1.348	0.975	1.347
Large TVP-VAR	TVP-VAR (kappa=0.98, alpha=0.95)	1.07	1.447	1.012	1.425	0.992	1.355
	TVP-VAR (kappa=0.98, alpha=0.99)	1.049	1.503	1.006	1.387	0.993	1.357
	TVP-VAR (kappa=0.98, alpha=1)	1.058	1.428	1.007	1.446	0.99	1.37
TVP-VAR-DMA/S	DMA (kappa=0.98, alpha=0.95)	0.972	1.352	0.943	1.275	0.935	1.303
	DMS (kappa=0.98, alpha=0.95)	1.031	1.510	0.963	1.33	0.942	1.316
	DMA (kappa=0.98, alpha=0.99)	0.966	1.381	0.953	1.347	0.933	1.301
	DMS (kappa=0.98, alpha=0.99)	1.015	1.465	0.97	1.376	0.948	1.327
	DMA (kappa=0.98 alpha=1),	0.983	1.39	0.953	1.336	0.901	1.236
	DMS (kappa=0.98, alpha=1)	1.028	1.477	0.962	1.346	0.941	1.312

Table 2 shows that Small TVP-VAR (Kappa=0.98, alpha=1) has the best prediction effect in short-term prediction (h=1 and h=2), but TVP-VAR-DMA (Kappa=0.98, alpha=1) has the best prediction effect in long-term prediction (h=4). In addition, we can also find the following characteristics: Firstly, under different prediction evaluation criteria, the Small TVP-VAR model has the best prediction effect under the same advance prediction step size for the same forgetting factor and attenuation factor, followed by the Medium TVP-VAR model, and the Large TVP-VAR model is the worst. This shows that the simplicity of the model will greatly affect the accuracy of the forecast, and also verifies the adaptability of the supply and demand principle in the steel industry, that is, the demand, price and supply of steel can interact to effectively forecast. Secondly, the prediction effect of TVP-VAR-DMA is better than that of the corresponding TVP-VAR-DMS under the same advance prediction steps for the same forgetting factor and attenuation factor, which indicates that TVP-VAR-DMS gives the weight of 1 to the optimal model and 0 to other models in each period. Because it does not take into account the information contained in other smaller posterior inclusion probability models, its prediction accuracy is not high. TVP-VAR-DMA considers the information contained in all models in each period, gives corresponding weights to different models, and averages the prediction results of each model, thus greatly improving the accuracy of prediction. Thirdly, it can be found that when h=4, TVP-VAR-DMA (Kappa=0.98, Alpha=1) model has the best prediction effect. This shows that three TVP-VAR models with different dimensions only consider the time variation of parameters, but do not consider the uncertainty of model dimensions, so the prediction accuracy is not good. At the same time, it also shows that in the long-term forecast, due to the increase of economic uncertainty, it is necessary to consider the changes in model dimensions. Fourthly, with the change of prediction step h, it is necessary to adjust the forgetting factor and attenuation factor to achieve higher prediction accuracy. When h=1, 2 and 4, the best prediction models selected in this paper are Small TVP-VAR (Kappa=0.98, alpha=1) model, Small TVP-VAR (Kappa=0.98, alpha=1) model, alpha=1) model and TVP-VAR-DMA (Kappa=0.98, alpha=1) model.

4 Discussion

TVP-VAR-DMA allows the model to select the best Minnesota shrinkage prior and best coefficient for each period β, assigns corresponding weights to different models, and then weighted average the prediction results of each model. It contains the information contained in all models, and can quickly adapt to the gradual changes and sudden changes in China's economic structure. Thus, the prediction accuracy is greatly improved. The forecast results show that the internationalization of CNY will reduce China's excess steel production capacity year by year. Finally, by 2025, China will have only about 18 million tons of excess crude steel production capacity. It can be seen that CNY internationalization is conducive to maintaining the stable growth of China's steel demand in the future and solving the problem of domestic steel overcapacity.

However, the internationalization of CNY alone cannot completely solve the problem of overcapacity in China's steel industry. There are three main reasons for overcapacity in China's steel industry: cyclical overcapacity, long-term overcapacity in different industries caused by the imbalance of economic structure, and institutional overcapacity caused by the Chinese government led growth model.

Based on the analysis and conclusion of this paper, in order to solve the problem of overcapacity in China's iron and steel industry, this paper puts forward the following policy recommendations.(1)Actively change the mode of economic development, encourage steel enterprises to increase investment in R&D and product innovation, achieve economic growth with scientific and technological progress, and realize the greening and modernization of the steel industry.(2)Encourage iron and steel enterprises to expand the scale of foreign investment, attract more foreign direct investment, and absorb domestic overcapacity through international small cycle and domestic large cycle, so as to optimize and upgrade the economic structure. (3) Slow down the expansion of the iron and steel industry, appropriately reduce government control, strengthen the function of market allocation of resources, improve the market system of production factors, and reduce the unreasonable capacity expansion disorder of terminal iron and steel enterprises. (4) Financial institutions help steel enterprises to "go global", provide convenient financing and investment for steel enterprises, and promote the vigorous development of the steel industry.

5 Conclusions

This paper studied the main influencing factors of China's steel demand. We used three different dimensions of TVP-VAR model and TVP-VAR DMA/S to forecast China's steel demand, and compared the prediction accuracy. The results showed that in the short-term prediction, i.e. h=1 and h=2, Small TVP-VAR (Kappa=0.98, alpha=1) model had the best prediction effect. When h=4, TVP-VAR-DMA (Kappa=0.98, alpha=1) model had the best prediction effect. In order to completely solve the problem of overcapacity in China's steel industry, the country should further expand the effective transformation of the steel industry under the background of CNY internationalization, strengthen the function of market resource allocation, and reduce the capacity expansion of low-end steel products.

References

1. Gary Koop, Dimitris Korobilis. Large time-VARying parameter VARs[J]. Journal of Econometrics,2013,177(2).
2. Banbura M, Giannone D, Reichlin L , et al. Large Bayesian vector auto regressions[J]. ULB Institutional Repository.
3. Raftery A E, M Kárny, Ettler P. Online Prediction Under Model Uncertainty via Dynamic Model Averaging: Application to a Cold Rolling Mill[J]. Technometrics, 2010, 52(1):52-66.
4. Joshua C.C. Chan, Eric Eisenstat, Rodney W. Strachan. Reducing the state space dimension in a large TVP-VAR[J]. Journal of Econometrics,2020,218(1).
5. Cogley T, Sargent T J. Drifts and volatilities: monetary policies and outcomes in the post WWII U.S.[J]. Review of Economic Dynamics, 2005, 8(2):262-302.
6. Diebold F X , Mariano R S . Comparing Predictive Accuracy[J]. Journal of Business and Economic Statistics, 1995, 13(3):134-144.
7. Laura Coroneo, Fabrizio Iacone. Comparing predictive accuracy in small samples using fixed-smoothing asymptotics [J]. Journal of Applied Econometrics,2020,35(4):