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A Litterman BVAR approach for production forecasting of technology industries

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Abstract

Forecasting the production of technology industries is important to entrepreneurs and governments, but usually suffers from market fluctuation and explosion. This paper aims to propose a Litterman Bayesian vector autoregression (LBVAR) model for production prediction based on the interaction of industrial clusters. Related industries within industrial clusters are included into the LBVAR model to provide more accurate predictions. The LBVAR model possesses the superiority of Bayesian statistics in small sample forecasting and holds the dynamic property of the vector autoregression (VAR) model. Two technology industries in Taiwan, the photonics industry and semiconductor industry are used to examine the LBVAR model using a rolling forecasting procedure. As a result, the LBVAR model was found to be capable of providing outstanding predictions for these two technology industries in comparison to the autoregression (AR) model and VAR model.

Keywords: Production forecasting; Autoregression (AR); Vector autoregression (VAR); Bayesian vector autoregression (BVAR); Industrial clusters

1. Introduction

The production forecasting in technology industries is an important job in practice because the perspective of a technology industry deeply impacts enormous investment plans from private sectors and industrial policies from government. However, volatile waver and

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explosive growth are commonly observed in the development of technology industries. The discontinuous path may be instigated by technological breakthrough, environmental change, or explosive demand. Therefore, the production forecasting in technology industries is much more intricate than in traditional industries such as food manufacturing. Such circumstances necessitate efficient methods for production forecasting for entrepreneurs, investors, and governments. Researches of time series forecasting for industrial production have been burgeoning in recent years (e.g., Tseng et al. [29], Marchetti and Parigi [31]). Some studies already revealed the applicability of time series models on industrial production prediction.

The VAR model developed by Sims [1], which is a dynamic multivariate time series model, has been widely applied to macroeconomics, regional economics, exchange rate, and even consumption. After being first introduced, the VAR model aroused considerable attention in both economics and statistics fields. Following Sims, Doan et al. [2] and Litterman [3] proposed a Litterman Bayesian VAR (LBVAR) model to overcome the pitfall of over-parameterizations in VAR and provide accurate forecasting in small samples. The Bayesian approach uses flexible coefficients in spite of a hard shape in classical statistics. Although there exist many applications of the VAR and the LBVAR model, the production prediction of the technology industry has not, to our knowledge, been addressed. In this paper, we present two samples — Taiwan's photonics industry and semiconductor industry — to examine the forecasting ability of AR, VAR, and LBVAR models for industrial production.

There are three reasons for us to recommend the LBVAR model, a model that covers clustering industries to forecast production: first of all, the multivariate time series model has been proved to be valid in forecasting dependent time series like macroeconomics indexes, consumption, and industrial production. Next, in the fleeting development of technology industries, the prediction model is destined to be a short-term sample method. For instance, it is obviously improper to consider old data from over 10 years ago for the dynamic circumstance of technology industries. As a result, we have a good reason to use the Bayesian statistical methodology, which is regarded as superior to classical statistics in a small-sized case, as in this study. Lastly, industrial clusters are known as a crucial factor in supporting technology industries [38], and the relative industries can provide important information to make predictions. Therefore, the LBVAR model is believed to provide better prediction than the univariate AR model and conventional VAR model.

In examining the forecasting performance in two industries, it is found that the LBVAR model outforecasts the VAR model and the naive AR model in magnitude measures. This outcome corroborates that the LBVAR model that covers clustering industries can provide an accurate prediction for industrial production. The remaining parts of this study are as follows: Literature and methodology of LBVAR forecasts are reviewed in Section 2. Then an overview of Taiwan's photonics industry and semiconductor industry is provided in Section 3. The detailed procedure of modeling and estimating of VAR and LBVAR models is described in Section 4. Empirical results of VAR and LBVAR forecasts for two technology industries are compared and analyzed in Section 5, and some conclusions are drawn in Section 6.

2. Review of LBVAR forecasts

Since first proposed by Box and Jenkins in the 1970s, the time series model has experienced fast development throughout the past decades. The vector autoregression (VAR) model proposed by Sims [1] has been widely applied in macroeconomics, regional economics, and finance. In the Bayesian approach, Litterman proposed a Bayesian autoregression (BAR) [4] and a Bayesian vector autoregression that is known as Litterman BVAR (LBVAR) model [3]. Spencer [5] developed an eight-step procedure including VAR modeling and Bayesian prior estimating for establishing a LBVAR model. In literature, the forecasting application of LBVAR model covers electricity consumption quantity and price, monthly GDP, steel consumption, sales of homes, and marketing management. Dua and Ray [7] developed a LBVAR to predict Connecticut's economy in competition with univariate ARIMA and an unrestricted VAR. They found that the loose prior generally produces more accurate forecasts. Finally, it was verified again that the LBVAR model produces the most accurate outcomes in both short-term and long-term and also predicts the change in direction. Their conclusion presents that LBVAR prediction is more precise than unrestricted VAR and best-fit ARIMA models, and the best LBVAR model in Connecticut economy forecasting is LBVAR(1). Sarantis and Stewart [8] compared the out-of-sample forecasting accuracy of a wide class of structural, VAR, and LBVAR models for sterling exchange rates. They observed the impacts of lag-length selection in VAR models and the impacts of the hyperparameters setting in LBVAR models. After the trial of a large class of models, they concluded that the LBVAR outpredicts other models in the short term and, with loose priors, produces more accurate forecasts. Besides macroeconomic data, several researchers attempted to expand LBVAR forecasting to other fields. For instance, Dua and Smyth [9] used LBVAR to examine whether the survey data on households' purchasing attitudes was helpful in predicting the sales of homes. Similarly, Kumar et al. [10] applied LBVAR in evaluating the usefulness of Katona's "ability and willingness to buy" framework for business forecasting. Curry et al. [11] applied LBVAR to decide the best strategy in category management in marketing fields.

Three conclusions can be drawn from these previous studies. First, a multivariate time series model is useful in examining the informative interaction between different data series. Second, LBVAR is verified to be better than VAR in most short-term horizons by multiple measures. As Holden's conclusion [6]: "The evidence is that the forecasts produced by LBVAR models are at least as accurate as forecasts from traditional economic models" (p. 162). Since the LBVAR is of much advantage in macroeconomic foresight, it is expected to be helpful in production prediction of industrial clusters.

In the model establishment of the LBVAR model, Litterman [3] assumed that the ith equation in the VAR model is as follows:

$$Y_{i,t} = C_i + \phi_{i1}^{(1)} y_{1,t-1} + \ldots + \phi_{in}^{(1)} y_{n,t-1} + \phi_{il}^{(2)} Y_{l,t-2} + \ldots + \phi_{i,n}^{(2)} y_{n,t-2} + \ldots + \phi_{il}^{(p)} y_{1,t-p} + \ldots + \phi_{i,n}^{p} Y_{n,t-p} + \varepsilon_{it}, \quad (1)$$

variable j refers to the jth variable listed in (Eq. (1)). By Litterman's assumption, the $\phi_{ij}^{(1)} \sim N(1,\gamma^2)$ for $i = 1,\ldots,n$ because the covariance matrix for the prior distribution is set to be diagonal, with γ denoting the standard deviation of the prior distribution for $\phi_{ij}{}^{(1)}$. The γ is also regarded as the overall tightness of the prior on the first own lag in each equation. Other coefficients are $\phi_{ij}^{(d)} \sim N\,(0, \boldsymbol{S}\,(i, j, l))$ for $d \neq 1$, where each $\phi_{ij}^{(d)}$ gives the coefficient relating $y_{i,t}$ to $y_{i,t-d}$. Therefore, the mean is one in the first own lag and zero in others in each equation. The standard deviation for the lag l of variables j in the ith equation, proposed by Litterman, is

$$S(i,j,l) = [\gamma g(l) f(i,j) s_i]/s_j, \tag{2}$$

here $f(i,i) = g(1) = 1$, and s_i is the standard error of the univariate AR on the ith equation (Eq. (2)). The number in the square bracket includes tightness and weight of the prior on coefficient i, j, l. The tightness on lag l relative to lag 1 is $g(l)$; the tightness on variable j in equation i relative to variable i is $f(i,j)$. Therefore, the most important hyperparameter in the construction of the LBVAR model is $f(i,j)$. Such a Bayesian prior system is known as "Litterman's BVAR (LBVAR)" or "Minnesota prior BVAR." There are many types of hyperparameter in LBVAR, and the most frequent one is the symmetric type as:

$$f(i,j) = \begin{cases} 1 & \text{if } i = j, \\ \omega & \text{otherwise,} \end{cases} \tag{3}$$

here Eq. (3) gives the relative tightness (ω) applied to all off-diagonal variables in the system.

As one reviewer pointed out, considering the cointegration and error-correction model (ECM) is important. We know that there are two main streams of the development of the VAR model: the Bayesian VAR (BVAR) and the cointegration. In literature, the BVAR model and cointegration are two separable issues because some studies focused on BVAR without cointegration (e.g., Ref. [8]). Three recent papers combined these two streams to discuss the Bayesian error-correction (BECM) model [13,35,37]. Though some studies revealed that the cointegration within a data series requires ECM to provide better forecasting than BVAR (e.g., Ref. [36]), it is still arguable whether to consider cointegration or not. Some studies discovered that the ECM and BECM are not necessarily better than the BVAR model. For instance, Joutz et al. [13] regarded the LBVAR model as good as the ECM and BECM. After these reviews, we concluded that considering the ECM or not is selective and not necessary. Since the goal of our article is to propose a forecasting application of VAR and LBVAR to technology industries, the ECM is not considered in this study.

3. Overview of Taiwan's photonics industry and semiconductor industry

The clustering effect is a critical factor in developing the information industry in Taiwan. In the 1980s, the success of the electronic calculator industry promoted the following semiconductors and desktop personal computer (PC) industries. Subsequently, the PC peripherals and key components industries grew quickly and prospered over the past 10 years. Today, emerging industries like photonics, telecommunications, and software have largely benefited from existing industrial clusters in Taiwan. These phenomena suggest that the clustering effect of technology industries plays a crucial role and requires more inspection and discussion.

3.1. Photonics industry

Taiwan's photonics industry has become one of the fastest growing sectors in recent years and is regarded as a high potential technology industry for the next century. The photonics industry includes light-emitting diode dice (LED dice), LED display, solar cell, laser diode, semiconductor laser diode, laser diode indicator, liquid crystal display (LCD), and other opto devices. The production value of Taiwan's photonics industry, shown in Fig. 1, has grown from US$235.5 million in 1996 to US$367.7 million in 1999, a 16% compound average growth rate. It is predictable that the scale of Taiwan's photonics industry will keep escalating due to the mushrooming investments. For instance, there are up to seven large plants of Thin Film Transistor-Liquid Crystal Displayer (TFT-LCD) that had trial productions or runs up this year (2000). Moreover, another seven plants are going into the TFT-LCD industry with capital of over 6 billion US dollars.

The clustering effect is a main propelling factor for Taiwan's photonics industry because the existing industries have formed strong cornerstones. Like other technology industries in Taiwan, the photonics industry is demand-driven, and most photonics products are combined in downstream industries to finally be exported. The well-developed industrial cluster performs as a strong bolster for the emerging photonics industry in human resource, raising capital, technology transfer, and other fields. As a result, when forecasters make predictions on the photonics production value, the production value of related sectors, like peripheral and downstream industries, are believed to contribute as leading indicators.

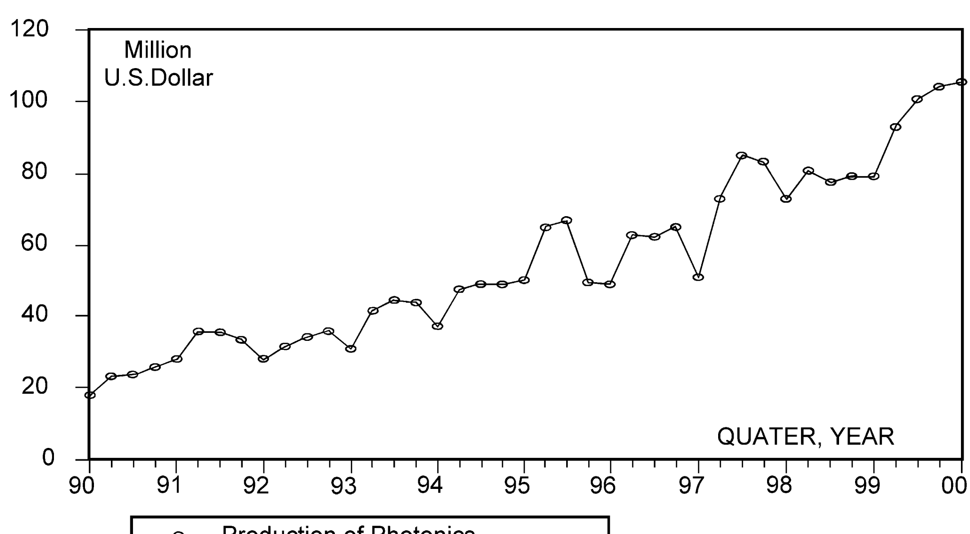

Fig. 1. Production value of photonics industry in Taiwan.

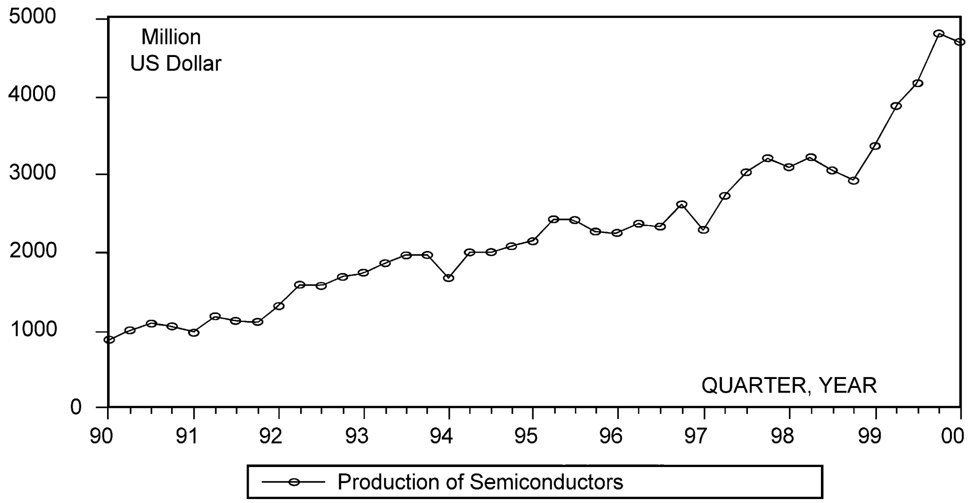

Fig. 2. Production value of semiconductor industry in Taiwan.

3.2. Semiconductor industry

Since the foundation of Taiwan Semiconductor Manufacturing Company and United Microelectronics in the late 1980s, Taiwan's semiconductor industry has experienced a big boom. There are four main components in Taiwan's semiconductor industry: integrated circuit (IC) design, IC manufacturing (including IC foundry), packaging, and testing. The main products of Taiwan's semiconductor industry include IC materials, memory (DRAM, SRAM), logic IC, analog IC, lead frame, and foundry. The IC Manufacturing, especially in foundry and DRAM, brings up whole semiconductor clusters in Taiwan.[1] In recent years, the IC design part jumped up and ranked second globally in both number and revenue in 1998 [12]. There are three characteristics in Taiwan's semiconductor industry: First, Taiwan's semiconductor industry operates in a disintegrated but tight-linked structure that is unique worldwide. Second, vast capital is continuously invested in this industry, which maintains the advantage of massive production. Finally, the Taiwanese quick-to-respond entrepreneurship forms the excellence in manufacturing capability and flexibility.

The production value of Taiwan's semiconductor industry from 1990 to 1999 is plotted in Fig. 2. In 1995, the monthly revenue continued to rise from January and finally reached the zenith of the year in November. From June 1996 to May 1997, world semiconductor industry experienced a 12-month long recession. Moreover, the semiconductor industry worldwide suffered from the most severe downturn in history in 1998. Taiwan's semiconductor industry, inevitably, fluctuated accordingly with the global

[1] For instance, wafer foundry and memory comprised 59.77% of the local fabrication business in 1998 [23].

industry in this period. Though rocked by the great Chichi earthquake in 1999, Taiwan's semiconductor industry still showed strong recovery that year. Consequently, Taiwan's semiconductor industry generated a total revenue of US$12.5 billion in 1999 and a 48.1% growth rate.

4. Methodology

4.1. Step 1: data collection

In this study, production data were drawn from the Department of Statistics, Ministry of Economic Affairs of Taiwan. We consider the quarterly data in estimating, model fitting, and forecasting for the following reasons: The quarterly data are usually used in national, local, and industrial productions in literature (ex. Ref. [7,25,29,32–34]). The monthly data covers too short a period of time in evaluating industrial production and is very inappropriate in Chinese society.[2] On the other hand, the annual data carries too long a period of time to reflect the unstable and explosive development of technology industries. In collected data, there are up to 10 related industries as candidates that probably contribute to the photonics industrial and the semiconductor industry (see Table 1). As in Joutz et al. [13], the production index is used to substitute the production value in modeling and forecasting.[3] Data of these 10 industries were collected from 1990 Q1 to 2000 Q1, a total of 41 quarterly observations. The front 32 observations (1990 Q1 to 1997 Q4) are used in variables selection and model specification, and the following nine observations are used to assess the predictive capability of AR, VAR, and LBVAR models as the out-of-sample. The out-of-sample ratio is 22.5% (9/41).

4.2. Step 2: preliminary transformation of data series

Quarterly production indexes of all information and electronics industries in Taiwan were collected and transformed into natural logarithmic numbers as shown in Refs. [13,30], which is a common procedure that transforms exponentially growing data into linear data to stabilize the volatility for VAR and LBVAR modeling.[4]

To factor out the seasonality within small-sample data, we decided to make seasonal adjustment before modeling in spite of seasonal dummy variables in the model setting.[5]

[2] The Chinese (Lunar) New Year vacation may occur in January, February, and March on occasion. Such uncertainty and irregularity prompts us to discard monthly data into our consideration.

[3] The production index means the percentile of production value per year divided by the production value of the base year 1996. The reason we consider production indexes in substitution of production value is that the indexes can reduce enormous numbers in monetary unit and can keep equivalence in arithmetic operation.

[4] The graphics of original production index are not shown here due to limited space.

[5] Such preliminary deseasonalization is also found in papers by Doan et al. [2], Dua and Ray [7], Kumar et al. [10], Salazar and Weale [24], and Marchetti and Parigi [31].

Table 1
Data code and product items of collected industrial production value

Code	Groups	Product items
3141	Data processing and storage equipment	Desktop computer, portable computer, work station, electric counter
3142	Data storage media units	Hard disk, floppy disk, compact disc, video disc, IC card
3143	Data terminal equipment	Tube monitor, LCD monitor, terminal
3144	Data I/O peripheral equipment	Hard disc driver, floppy disc driver, compact disc driver, printer, plotter, keyboard, scanner, mouse, card reader, other input/output peripherals
3145	Computer components	Internetwork, server, wiring concentrator, PC-LAN, network card, fax card, memory extension card, graphic card, control card, ISDN card, sound card, other interface cards
3149	Other computer equipment	Numerical controller, word processor, ROM programmer, network operating system, case, other computer equipment
3172	Semiconductors	Wafer, mask, IC package, foundry, IC manufacturing, diode, transistor, lead frame
3173	Photonics materials and components	LED, LED display, solar cell, laser diode, LCD display, other opto devices, other displayers.
3179	Other electronic parts	PCB, board, copper-clad laminate, UPS, filter, electronic rectifier, other power suppliers, others parts
3190	Other electrical and electronic machinery	Switch, coil, socket, and others

This table is based on definition provided by Department of Statistics, Ministry of Economic Affairs, Taiwan, Republic of China, 2000.

Besides, such a deseasonalization is much preferable in LBVAR estimation because a series with a season factor will make large coefficients in high-order lag that makes inefficient parameterization (e.g., Ref. [14,15,28,34]). The census X-11 method was applied in multiplicative and half-weighted endpoints.[6]

4.3. Step 3: variables (series) selection

The models for the photonics industry and semiconductor industry are established individually. The industrial relation and pairwise Granger causality test are two filters to cull effective variables (series) into VAR and LBVAR models. According to the industrial relation, we first select the directly dependent industries of the photonics industry or semiconductor industry into the model and filter off others.[7] Six candidates were selected for the photonics industry (codes 3141, 3142, 3143, 3144, 3145, and 3179) and three candidates were selected for the semiconductor industry (codes 3144, 3145, and 3149). Then, the pairwise Granger causality test, which examines whether the explanatory degree is improved by adding one variable into the univariate equation, is used in further filtering.

[6] Census X-11 methods, including multiplicative and additive methods, are standard methods used by the US Bureau of Census to make seasonal adjustments.

[7] Here the "directly dependent industries" mean downstream, upstream, and peripheral industries.

Table 2
Results of pairwise Granger causality test

	P value	Data processing and storage equipment, # 3141	Data storage media units, # 3142	Data terminal equipment, # 3143	Data I/O peripheral equipment, # 3144	Computer components, # 3145	Other electronic parts, # 3179
Photonics materials and components # 3173	Lag 1	.0112[a]	.0310[a]	.3846	.0407[a]	.0244[a]	.0152[a]
	Lag 2	.0437[a]	.0383[a]	.0368[a]	.1238	.0833	.0289[a]
	Lag 3	.0067[a]	.1050	.0475[a]	.0432[a]	.0642	.0168[a]
	Lag 4	.00327[a]	.2245	.1653	.1131	.1305	.0059[a]
	P value	Data I/O peripheral equipment, # 3144	Computer components, # 3145	Other computer equipment, # 3149			
Semiconductors # 3172	Lag 1	.0560	.0975	.0912			
	Lag 2	.1362	.2393	.0994			
	Lag 3	.0731	.5735	.2524			
	Lag 4	.0448[a]	.2605	.2232			

All series are considered in level.
Null hypothesis: the suspicious series does not Granger Cause the production series of the photonics industry or semiconductor industry.
[a] Points out the rejection under significant level α=.05.

Since the pairwise Granger causality test is sensitive to the number of lag [17], we execute it from lag 1 to lag 4 to cover the possible model order,[8] and the main results of the causality test are reported in Table 2. In the photonics industry all six candidates were found to be of pairwise causality under α=.05. This outcome is harmonic with our presupposition that the development of Taiwan's photonics industry is highly dependent on the pull power from local clusters. In the semiconductor industry, only one of three candidates manifested causality in semiconductors production: the Data I/O Peripheral Equipment (code 3144). Based on the industrial relation and pairwise Granger causality test, we considered seven variables (codes 3142, 3142, 3143, 3144, 3145, 3173, and 3179) in the model for the photonics industry and two variables (codes 3144 and 3172) in the model for the semiconductor industry.

4.4. Step 4: order selection

4.4.1. VAR model

At this stage, we had to decide the appropriate lag-length of the VAR model. To decide the appropriate order of VAR and LBVAR, we focused on three criteria, including Akaike Information Criterion (AIC), Hannan–Quinn Criterion (HQ) [18,19], and Schwarz Criterion

[8] We start the pairwise Granger Causality Test from lag 4 as 1-year-long because we have made seasonal adjustment in quarters. Moreover, 1 year is long enough for information diffusion in technology industry. According to Lütkepohi [26], reasonable lags used in the pairwise Granger causality test corresponding to the longest time over which one of the variables could help to predict the other.

Table 3
Order selection in VAR model for production forecasting

	Criteria	Lag 4	Lag 3	Lag 2	Lag 1
Photonics industry					
VAR, 7 variables	Determinant of residual covariance	≑	4.63E − 26	1.38E − 19	1.09E − 17
	Log likelihood	NA	557.8052	353.4566	297.4897
	HQ	NA	− 25.5746	− 14.9949	− 7.3678
	SC	NA	− 20.5878	− 11.6596	− 12.9896
	AIC	NA	− 27.84863	− 16.56377	− 15.57998
Semiconductor industry					
VAR, 2 variables	Determinant of residual covariance	3.27E − 05	4.32E − 05	5.72E − 05	6.10E − 05
	Log likelihood	65.1415	63.4234	61.3963	62.4395
	HQ	− 3.1054	− 3.2018	− 3.27700	− 3.5508
	SC	− 2.5108	− 2.7484	− 2.9594	− 3.6413
	AIC	− 3.3672	− 3.4085	− 3.4264	− 3.3637

The number in the square bracket presents the endogenous variables to be considered (equations) in our VAR estimation according to last stage because the determinant in lag 4 approximates zero in photonics industry, the log likelihood, HQ, SC and A1C are unavailable (“NA”).

(SC) [20] to specify the appropriate lag-length.[9] According to criteria outcomes in Table 3, the criteria of VAR model for the photonics industry decline simultaneously because the determinant slumps with the number of lag. Consequently, we decided to fit the VAR model with lag 1 for the photonics industry. In the semiconductor industry, we accept the VAR model in lag 1 (VAR(1)) as a qualified model.

4.4.2. LBVAR model

In order selection, the LBVAR is usually in lag one and is seldom in lag over three [8,13]. We followed the parsimonious parameterization principle of the LBVAR model [21] and considered the LBVAR model with a lag number that does not exceed the lag number of the VAR model [5]. Therefore, we set the LBVAR in order 1 for both the photonics industry and semiconductor industry. Then, we considered two symmetric priors: the standard symmetric prior and the low-weighted prior. The standard prior is 0.2 in tightness and 0.5 in weight ($\gamma = 0.2$, $\omega = 0.5$) by the optimal experience of Litterman [3] and Doan [22]. We term it as the “Standard prior LBVAR.” For the “Low-weighted prior LBVAR,” we follow [5] and let the weight approximate to zero (set $\gamma = 0.2$, $\omega = 0.001$) as a low-weighted prior for better prediction once a seemingly univariate system occurs in our modeling.[10]

[9] Generally speaking, the methods for order selection include: Likelihood Ratio Test (LR test), Final Prediction Error Criterion (FPE), AIC, HQ, and SC. According to Lütkepohi [27], the LR, FPE, and AIC are not suitable to process small sample problems. Therefore, HQ and SC are used to decide the VAR order in this study. See Lütkepohi [27].

[10] It is known that if the ω of the LBVAR model approximates zero, then the LBVAR is going close to a univariate AR model.

4.5. Step 5: estimation and forecasting

The estimation and forecasting procedure in this study, following Refs. [5,16,32], was conducted out using the RATS software package which was set up to accommodate BVAR models with Litterman priors. The model is reestimated whenever new real data is available and does forecasting for the next period. Therefore, one-step-ahead prediction and model reestimation are repeated alternatively as a rolling procedure. This procedure reflects the empirical rationalism: Practitioners always react promptly to the latest information.

The results of model prediction are assessed by magnitude measures, directional measures, and residual correlation patterns. We used six magnitude measures: Root of mean square error (RMSE), Theil U, mean absolute error (MAE), forecast error standard deviation (FESD), root mean square percentage error (RMSPE), and mean absolute relative deviation (MARD).[11]

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[11] (1) RMSE

Set T to be the total number of observations in the prediction period; Y is the actual value in the prediction period; $\hat{Y}$ is the estimated value in the prediction period.

$$\mathrm{RMSE} = \sqrt{T^{-1}\sum_{t\in T}(Y_t - Y_t)^2}$$

(2) Theil U

$$U = \frac{\mathrm{RMSE\ (Model)}}{\mathrm{RMSE\ (Random\ Walk)}} = \left[\frac{\sum_{t\in T}(Y_t - \hat{Y}_t)^2}{\sum_{t\in T}(Y_t - Y_{t-1})^2}\right]^{\frac{1}{2}}$$

Hence, if $U < 1$ means the estimated model performs better than random walk without a drift. On the other hand, if $U > 1$, that means the estimated model underperforms random walk.(3) MAE

$$\mathrm{MAE} = \frac{\sum_{t\in T}|Y_t - \hat{Y}_t|}{T}$$

(4) FESD

$$\mathrm{FESD} = \sqrt{\left[T^{-1}\sum_{t\in T}e_t^2\right] - e^{-2}}$$ here $e_t = Y_t - Y_t$ is the forecasting error

(5) RMSPE

$$\mathrm{RMSPE} = \sqrt{T^{-1}\sum_{t\in T}\frac{(Y_t - \hat{Y}_t)^2}{|Y_t|}}$$

(6) MARD

Besides magnitude measures, the directional measure is another important measurement for evaluating the accuracy in direction prediction. In practice, the accuracy in direction is even more important than in magnitude. We used the accuracy ratio in direction in two alternatives (up or down) as the directional measure. As indicated by Curry et al. [11], the residual correlation pattern is also an assessment for the forecasting ability of a model because a model without serial correlation residuals in forecasting implies it performs better in tolerating external disturbs. The Q statistic is considered to examine the existence of serial correlation in forecasting residuals.

5. Empirical results

According to the modeling procedure just described, the AR(1), VAR(1), and LBVAR(1) models are considered most effective for forecasting Taiwan's photonics and semiconductor industry. Seven variables are included in the VAR(1) and LBVAR(1) models for the photonics industry, and two variables are covered in the VAR(1) and LBVAR(1) models for the semiconductor industry. Detailed findings of the photonics industry in the AR, VAR, and LBVAR models are illustrated in Fig. 3 and Table 4. Comparing the VAR(1) model and AR(1) model, multivariate times series does not seem able to provide better prediction because the VAR(1) model is less accurate than the AR(1) model. However, when we consider the LBVAR models, both models (standard prior and low-weighted prior) show excellent precision. The low-weighted prior LBVAR model, which hardly accounts for cross impact, is less accurate than the standard prior LBVAR model as we anticipated. Such an outcome validates that the existing industrial cluster indeed impacts Taiwan's photonics industry, and the related industries provide useful information for forecasting.

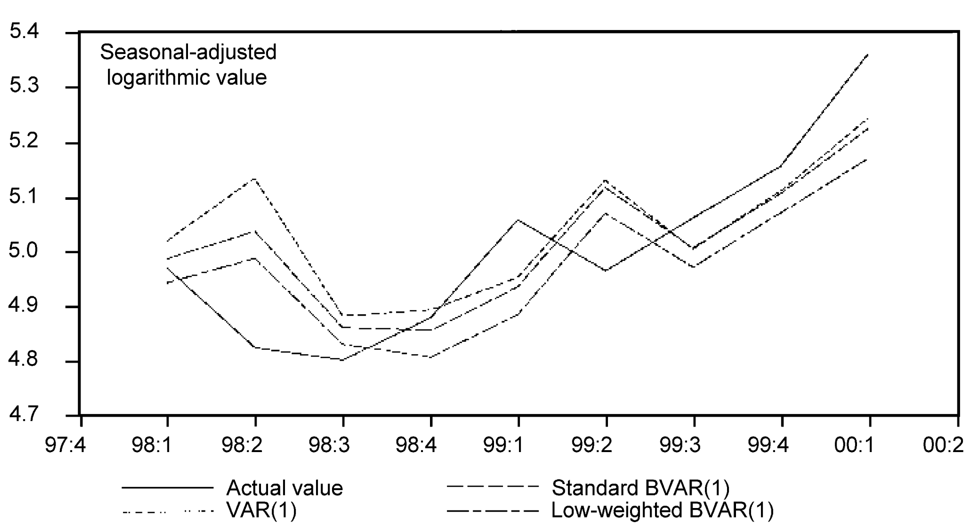

Fig. 3. The actual value and forecasting values of photonics Industry (1998:1–2000:1).

Table 4
The performance of AR, VAR, standard LBVAR, and low-weighted LBVAR models for photonics industry

	Criteria	VAR(1)	AR(1)	Standard prior LBVAR(1)	Low-weighted prior LBVAR(1)
Magnitude	RMSE	0.1348	0.1203	0.1116	0.1184
	Theil U	1.1241	1.0034	0.9309	0.9875
	MAE	0.1051	0.1054	0.0922	0.1041
	RMSPE	0.0608	0.0533	0.0500	0.0525
	MARD	0.0211	0.0208	0.0184	0.0206
	FESD	0.1306	0.1134	0.1114	0.1121
Direction	Accuracy in direction (%)	62.5%	50%	50%	50%
Residual	Serial correlation of residual (Q statistics)	No serial correlation	No serial correlation	No serial correlation	No serial correlation

"Accuracy in direction ratio" indicates the ratio that the model predicts accurate direction in "up" or "down." The serial correlation of residual is verified by Ljung–Box Q statistics of every lag under α=.05.

In the semiconductor industry, the forecasting results are illustrated in Fig. 4 and Table 5. It is noticeable that the standard prior LBVAR model outperforms the VAR model but significantly underperforms the AR model. Two reasons explain this result: setting inappropriate hyperparameters or covering helpless variables in VAR and LBVAR models. Regarding the first reason, we may use inappropriate hyperparameters (γ and ω) in an LBVAR estimation but need to experiment more hyperparameters. However, the Litterman method is inherently informative, and researchers need to try numerous hyperparameters to get the best model. The latter reason means the causality between the semiconductor industry and

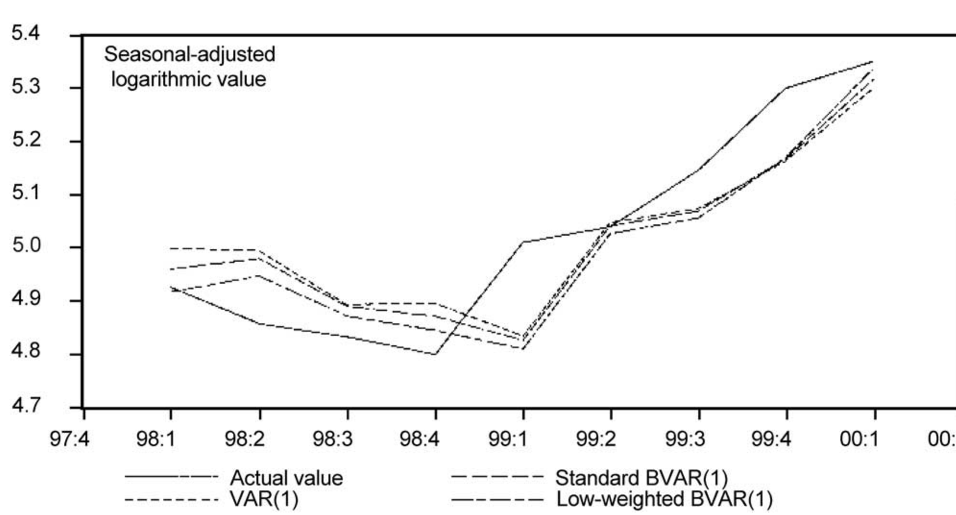

Fig. 4. The actual values and forecasting values of semiconductor industry (1998:1–2000:1).

Table 5
The performance of AR, VAR, standard LBVAR and Low-weighted LBVAR models for semiconductor industry

	Criteria	VAR(1)	AR(1)	Standard prior BVAR(1)	Low-weighted prior BVAR(1)
Magnitude	RMSE	0.1073	0.0929	0.0975	0.0928
	Theil U	0.8980	0.7775	0.8159	0.7764
	MAE	0.0926	0.0702	0.0783	0.0701
	RMSPE	0.0478	0.0413	0.0434	0.0413
	MARD	0.0184	0.0139	0.0155	0.0139
	FESD	0.1068	0.0873	0.0953	0.0873
Direction	Accuracy in direction (%)	75%	62.5%	75%	75%
Residual	Serial correlation of residual (Q statistics)	No serial correlation	No serial correlation	No serial correlation	No serial correlation

"Accuracy in direction ratio" indicates the ratio that the model predicts accurate direction in "up" or "down." The serial correlation of residual is verified by Ljung–Box Q statistics of every lag under α=.05.

other industries, provided by the pairwise Granger causality test, is ineffective for forecasting. We attributed the latter reason to market globalization: over 40% of the total production of Taiwan's semiconductor industry is directly exported. However, the low-weighted prior LBVAR model produces a more satisfactory outcome than the AR(1), so the LBVAR model still ensures a better forecasting result.

Overall, the LBVAR model outforecasts corresponding VAR and AR models in both industries. The Bayesian method is corroborated to be appropriate in small sample forecasting, and the LBVAR forecasting method for technology industries is validated to be better. However, the results of directional measure are similar in AR, VAR, and LBVAR models, so there is no evidence for us to proclaim that the LBVAR model can foretell future direction.

6. Conclusions

In this paper, we utilized the LBVAR model to predict industrial production of technology industries based on industrial clusters. In our two experiments, the development of Taiwan's photonics industry is proved to heavily rely on downstream and peripheral industries. The downstream sectors include computer manufacturing and data terminal equipment industries (ex. LCD monitor), and the peripheral sector is the data media industry (ex. compact disc). Therefore, the industrial cluster in Taiwan has substantially contributed to the prosperity of the photonics industry for the past decade. On the other hand, the semiconductor industry's development seems unaffected by other local industries in Taiwan. Such a circumstance may be explicated by the worldwide market and specific business cycles. The predictive results of the two industries show that the LBVAR model transcends the VAR and AR models in magnitude measure using a rolling forecasting procedure. It was also found in the semiconductor industry that the VAR prediction might underperform the naive AR model if it covers helpless variables. It is concluded that when the main industry is dependent on others, the standard prior LBVAR model is recommendable. Otherwise, lower-weighted prior LBVAR model is preferable when the intended industry is independent of others.

Overall, the proposed LBVAR forecasts surpass VAR and AR forecasts. Furthermore, the LBVAR model is capable of dynamic analysis in industrial clusters and performs superior production prediction in magnitude. As a result, we have confidence in LBVAR forecasts for industrial production based on industrial clusters, especially for technology industries.

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