1. Introduction

Production forecasting in high technology industries is important and difficult. The perspective of a high technology industry will deeply impact enormous investment plans from private sectors as well as industrial policies from the government. However, volatile wavering and abrupt growths are commonly observed in the development of high technology industries. Such a discrete growing path may be instigated by technological breakthrough, environmental change or an explosive market. So production forecasting in new technology industries, like IC (Integrated Circuit) manufacturing, is much more intricate than traditional industries, such as food manufacturing. These circumstances create efficient methods for production prediction, which are crucial for entrepreneurs, investors and governments in recent years. Meanwhile, time-series-based forecasting research for industrial production is burgeoning (e.g., Tseng et *al*, Marchetti and Parigi). These studies reveal the potential of the application of the time series model to the critical issue of industrial production prediction.

The vector autoregressive (VAR) by Sims is widely applied to macroeconomics, regional economics, exchange rate, and the consumption of one product. When first introduced, the VAR model aroused considerable attention from the fields of economics and statistics. Following the development of the VAR model, Doan et *al* and Litterman proposed a Bayesian VAR (BVAR) model to overcome over-parameterization of the original VAR and provide accurate forecasting. The Bayesian approach uses blurred coefficients in spite of its hard shape in classical statistics. Similar to the VAR model, the BVAR model is applicable in every field, but has proved to perform better according to the literature. Although there are many applications of the VAR and the BVAR model, production prediction for the high technology industry in an industrial cluster has not, to our knowledge, been addressed. In this study, we will show how BVAR models perform in forecasting industrial production of the high technology industry based on industrial cluster.

There are three reasons for us to utilize BVAR to forecast production of the high technology industry based on industrial cluster: first, the time series method has proved to perform well in time-dependent data series like macroeconomics indexes, consumptions and industrial production. Industrial production data is suited to time series form because the structure's nearby values of time parameters indicate closely related values of interest. Next, because of the fleeting development of high technology industries, the prediction work of high technology industries is destined to be based on a short-term sample period. So it is appropriate to consider the method most suitable to forecast on a small sample basis. For instance, it is not useful to take data over the previous ten years into our study in such a dynamic industry. As a result, we have good reason to use the Bayesian statistical methodology that is regarded as superior to classical statistics in a small-sized case. Lastly, industrial clusters are known as a crucial factor in supporting high technology industries. It is presupposed that relative industries can provide important information to forecast intended industry in the same industrial cluster. So multivariate vector autoregressive (VAR and BVAR) models may be more informative than a univariate autoregressive model.

This article is examines the forecasting performance expressed as follows. The result of our prediction is assessed in magnitude measure, directional measure and residual correlation. The rolling forecasting procedure is used and every predicted value one-step ahead is estimated by current actual values because we think the rolling forecasting procedure is much more reasonable and reactive than the multi-step forecasting procedure. In examining forecasting performance in two industries, it is found that the BVAR model outforecasts the VAR model and the naïve AR model in magnitude measures. This outcome corroborates that the BVAR model can provide an accurate prediction for industrial production based on industrial cluster. The remaining parts of this study are as follows: The review of literatures VAR, BVAR, power transformation forecasts are reviewed in Section 2. The methodology of VAR modeling, BVAR modeling and power transformation modeling are described in Section 3. Empirical prediction results of VAR and BVAR, for which we give of three Information technology industries, are compared and analyzed in Section 4 to Section 6. And some conclusions and further approaches directions are suggested in Section 7.

2. Literature Review

2.1 BVAR Forecasting Models

Since the autoregressive (AR) model was provided by Box and Jenkins in the 1970's, time series theory has developed rapidly in the past decades. The vector autoregressive (VAR) proposed by Sims (1980) has been widely applied in macroeconomics, regional economics and financial market. In reviewing the Bayesian time series approach, Litterman (1984) proposed a Bayesian autoregressive (Bayesian AR), and Doan *et al*., (1992) and Litterman (1986) proposed the Bayesian VAR (BVAR). Then Spencer (1993) developed a procedure of BVAR modeling that included eight-step jobs. In his procedure, BVAR modeling including two main parts: the VAR modeling part and the Bayesian part. In the literature, the BVAR model outperformed the VAR model in many studies. Holden (1995) concludes that the forecasts produced by BVAR are at least as accurate as forecasts from traditional economic models. The forecasting variables of these approaches have covered electricity consumption quantity and price, monthly GDP, steel consumption, sales of homes, and even marketing management. Dua and Ray (1995) developed a BVAR to predict Connecticut's economy, in competition with univariate ARIMA and unrestricted VAR. They found that the loose prior generally produces more accurate forecasts. Finally, it was verified again that the BVAR model produces the most accurate outcomes both short-term and long-term. Conclusions show that BVAR prediction is more precise than unrestricted VAR and best-fit ARIMA models. Sarantis and Stewart (1995) compared the out-of-sample forecasting accuracy of a wide class of structural, VAR, BVAR models for sterling exchange rates. They inspected the impact of lag length selection of VAR and of the hyper parameters setting of BVAR and noted that the forecasting performance of BVAR is sensitive to original hyper parameter settings. After the trial of a large class model, they concluded that the BVAR out predicts other models in the short term. Moreover, they verified that BVAR and VAR models in level form are much better than those in differentiated form in all prediction horizons. Their study also indicates that the loose prior produces more accurate forecasting.

Besides the macroeconomic series, several studies attempted to expand BVAR forecasting to other fields. For instance, Dua and Smyth (1995) used BVAR to examine whether the survey data on households' purchasing attitudes was helpful in predicting sales of homes. Similarly, Kumar, Leone, and Gaskins (1995) applied BVAR in evaluating the usefulness of Katona's "ability and willingness to buy" work frame for business forecasting. Curry *et al.*, (1995) applied BVAR to decide the best strategy in category management in marketing fields. They used state space in their BVAR setting. The parsimonious property (parsimonious in the use of degree of freedom) of BVAR, they assert, is very valuable in cases with large variables.

Three conclusions can be drawn from these previous studies. First, multivariate time series is useful in examining informative interaction between different economic series. Apparently, such an endeavor is usually worthy. Second, BVAR is verified to be better than VAR in most short-term horizons by multiple measures. As Holden's conclusion (1995) suggest "The evidence is that the forecasts produced by BVAR models are at least as accurate as forecasts from traditional economic models" (p. 162). Since the general-purposed BVAR is so advantageous in macroeconomic series foresight, we may reasonably expect the same performance in stock price prediction for high technology industries. Lastly, the related industries and related leading indicators in a specific industrial cluster are expected to provide important information to each other in prediction. So a dynamic and multivariate time series VAR model is preferred in forecasting.

2.2 Logarithmic Transformation and Power Transformation Forecasting Model

There are some arguments regarding logarithmic transformation that show the log-transformed forecasts are biased and inferior to level forecasts in both AR and VAR (e.g., Granger & Newbold, 1976; Ariño & Franses, 2000). Such a log-transformation is regarded to reduce the variance of data series for stationarity in VAR model. Furthermore, many researchers took difference after log-transformation to further stationarize the data series, but such a differentiation may destroy the inherent cointegration within the data and is discouraging (Sims, 1980; Doan, 1992; Enders, 1995, p. 301). It is noted that, because of the stationary limitation, VAR econometricians have to take differentiation or to take the growth rate to stabilize the data series (e.g., Litterman, 1986). But as pointed out by Enders (1995, p. 301), simply taking difference will throw out the co-movement information of series.

All of the above facts necessitate us that we consider another transformation — the Box-Cox power transformation. Nelson and Granger (1979) examined the power transformation in ARIMA models in twenty-one time series data and refuted the superiority of power transformation in forecasting. They proposed a recursive estimation process for ARIMA modeling and selected the best model on the basis of white noise and minimum mean square errors to forecast. The data under different power transformation are fitted into corresponding ARIMA models with the residuals under normal distribution assumption. Then the appropriate power is searched for the maximum likelihood value within these power-model combinations. However, their feedback estimation is less applicable for multivariate time series models because there are too many combinations of multiple powers which makes the estimation procedure quite complex. Guerrero (1993) proposed a two-stage procedure with model-independent power transformation that conducted power transformation before the modeling of time series. His data-based method is simple in estimation and efficient in implemention. Contrary to the debate on the effect of power transformation in univariate forecasts (e.g., Chatfield & Prothero, 1973; Nelson & Granger, 1979; Granger & Newbold, 1986, p. 119), the effect of power transformation in multivariate time series, VAR and BVAR models mainly, has never been examined in the literature.

With the above review, we are motivated to inspect power transformation in multivariate time series models for several reasons. First, when the data is cumulative and growing in trend, like GNP and investment, the power transformation can effectively stabilize the variance of series and then make better estimation. Second, power transformation can be applied to transform variables so as to satisfy model assumptions including stationary, stability and uncorrelated white noise disturbances. Besides, the power transformation includes the log-transformation as a special case, so it is applicable for VAR and BVAR models. Researchers can tackle many explosive time series data using appropriate power transformation and make better prediction. Third, Guerrero's (1993) two-stage procedure is more applicable than Nelson and Granger's (1979) recursive procedure in VAR and BVAR models.

3. Methodologies

3.1 The General VAR Model

Empirical analysis of the impact of monetary policy on macroeconomic variables is conducted by using vector autoregressive models. This is a tool that is widely used for this purpose. In its basic form, a vector autoregressive model of order *k* is described by

$$\boldsymbol{X}_t = \boldsymbol{u}_t + \sum_{i=1}^{k} \boldsymbol{A}_i \boldsymbol{X}_{t-i} + \boldsymbol{\mu}_t . \tag{1}$$

where $\boldsymbol{X}_t = (\boldsymbol{X}_{1t}, \boldsymbol{X}_{2t}, \ldots, \boldsymbol{X}_{pt})$ is a $(p \times 1)$ vector of endogenous variables, $\boldsymbol{\mu}_t \sim \boldsymbol{N}(\mathbf{0}, \Sigma_u)$ is a p-dimensional i.i.d. error process with mean vector 0 and covariance matrix Σ_u, $\boldsymbol{u}_t$ contains deterministic terms (which are ignored in the following) like a constant, a linear time trend and/or dummy variables. The coefficient matrices $\boldsymbol{A}_i$ and the covariance matrix Σ_u can be estimated using the ordinary least squares technique and the optimal lag length k can be determined by comparing information criteria like Akaike Information Criterion (AIC), Hannan-Quinn Criterion (HQ) or Schwarz Criterion (SC). Once the parameters of the model have been estimated, the structural information of the model can be summarized in different ways. One possibility is the inspection of the implied impulse response functions measuring the impact of single innovations on the endogenous variables. Forecast error impulse responses Φ_i are calculated from the moving average representation of the VAR

$$X_t = \sum_{i=0}^{\infty} \Phi_i \mu_{t-i} \,.$$

The underlying assumption that innovations in the different equations are uncorrelated (that Σ_u is diagonal) is in general not compatible with the observed data and with the theoretical background.

3.2 The BVAR Models

3.2.1 Litterman's BVAR Model

After the introduction of VAR model, Doan et *al* and Litterman proposed the BVAR model for providing a more flexible method by prior setting. According to Litterman, it is assumed that the *i*th equation in the VAR model as:

$$\begin{aligned} y_{i,t} &= C_i + \phi_{i1}^{(1)} y_{1,t-1} + \Lambda + \phi_{in}^{(1)} y_{n,t-1} \\ &\quad + \phi_{i1}^{(2)} y_{1,t-2} + \Lambda + \phi_{i,n}^{(2)} y_{n,t-2} + \Lambda + \phi_{i1}^{(p)} y_{1,t-p} + \Lambda + \phi_{i,n}^{(p)} y_{n,t-p} + \varepsilon_{it} \end{aligned} \quad (2)$$

The variable *j* refers to the *j*th variable listed in the equation. By Litterman's assumption, the $\phi_{ii}^{(1)} \sim N(1, \gamma^2)$ for i = 1,…,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 $\phi_{ii}^{(1)}$ The γ is also regarded as the overall tightness of the prior on the first own lag in each equation. Other coefficients are $\phi_{ij}^{(d)} \sim \boldsymbol{N}(0, \mathbf{S}(i, j, l))$ for $d \neq 1$, where each $\phi_{ij}^{(d)}$ gives the coefficient relating $y_{i,t}$ to $y_{i,t-d}$. Therefore, the meaning is one in the first own lag and zero in the others in each equation.

Under the above assumptions, we still require information about the standard deviation of the prior distribution. The standard deviation for the lag *l* of variables *j* in the *i*th equation, proposed by Litterman, is

$$\mathbf{S}(i, j, l) = [\gamma\, g(l)\, f(i, j)\, s_i] / s_j \tag{3}$$

here $f(i, i) = g(1) = 1$, and s_i is the standard error of the univariate autoregressive relation on the *i*th equation. The number in the square bracket includes tightness and weight of the prior on the coefficient *i, j, l*. The tightness on lag *l* relative to lag 1 is $g(l)$; also, the tightness on variable *j* in equation *i* relatives to variable *i* is $f(i, j)$. So the most important hyperparameter in the construction of BVAR is $f(i, j)$. Such a Bayesian prior system is known as "Litterman's BVAR (LBVAR)" or "Minnesota prior BVAR". There are many kinds of hyperparameter settings in BVAR and the most frequent one is the symmetric-type

$$f(i, j) = \begin{cases} 1 & \text{if } i = j \\ \omega & \text{otherwise} \end{cases} \tag{4}$$

The relative tightness (ω) applies to all off-diagonal variables in the system.

There are many combinations of γ and ω to set up the prior. The most frequently used prior is the standard prior (γ =0.2, ω =0.5) by the optimal experience of Litterman and Doan. However, the Litterman method is informative and researchers need to try numerous hyperparameters to decide the best model. Such a method is inefficient and time-consuming in practice.

3.2.2 Noninformative Prior BVAR Model

In general, the statistical tests of the hypothesis are based on the assumption that the underlying data series is stationary ergodic process. According to Engle and Grange (1987), unit root tests provide an easy method to test whether a series is non-stationary. Most studies showed that the rejection of the unit root hypothesis is the necessary condition to conclude that a series is stationary. In other words, if the unit root hypothesis is not rejected, we conclude that the series is non-stationary. Testing for unit root is conducted by performing the augmented Dickey-Fuller (ADF) (1981) regression, which may be written as：

$$\Delta y_t = a_0 + a_1 y_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta y_{t-i} + \varepsilon_t \, . \qquad (5)$$

where p is large enough to ensure that the residual series ε_t is white noise. For a sufficiently large value of p, the ADF test loses its power. If the t-statistic is negative and significantly different from zero, we reject the null hypothesis that the level of the series is I(1), and conclude that the series meets the necessary conditions for being stationary, i.e., the series is I(0). Once we find that each series contains a single unit root (i.e., I(1)), we can check the series for cointegration. Consider the multivariate time-series where x_t is a $p \times 1$ vector and I(1). Usually, any linear combination of x_t and $x_{t-1}, x_{t-2}, \Lambda\Lambda, x_{t-q}$ is I(1). If a linear combination $y_t = x_t - \beta_0 - \beta_1 x_{t-1} - \Lambda\Lambda - \beta_q x_{t-q}$ exits which is I(0), then, according to Engle and Granger (1987), x_t and $x_{t-1}, x_{t-2}, \Lambda\Lambda, x_{t-q}$ are co-integrated with cointegrating parameter $\beta_1, \beta_2, \Lambda\Lambda, \beta_q$. Cointegration conjoins the long-run relationship between integrated financial variables and the variables in the statistical model.

If the series exhibit a long-term relationship, then they are co-integrated. The empirical testing computes the test statistic from the residuals of the following co-integrating regression:

$$\boldsymbol{x_t = \beta_0 + \beta_1 x_{t-1} + \Lambda\Lambda + \beta_q x_{t-q} + \varepsilon_t} \quad . \tag{6}$$

From the regression model (6), we get the parameter estimation and the residual. Next, we compute estimates for each of the unknown parameters and for the prediction of future values.

Let $\boldsymbol{y_t}$ be the row vector of *p* variables of interest observed at time *t*. Then

VAR can be written as:

$$\boldsymbol{y}_t = \boldsymbol{\beta}_0 + \sum_{i=1}^{q} \boldsymbol{\beta}_i \boldsymbol{y}_{t-i} + \boldsymbol{\varepsilon}_t \,, \tag{7}$$

where β_i are parameter matrices of dimension $p \times p$ and $\boldsymbol{\varepsilon}_t$ are independent p-variate normal with mean vector $\underset{\sim}{\mathbf{0}}$ and common covariance matrix $\boldsymbol{\Sigma}$ which is a positive definite matrix.

For the technical discussion of the prior and posterior distributions, we need the following notation. Write equation (7) as:

$$\boldsymbol{y}_t = \boldsymbol{\beta} \boldsymbol{x}_t + \boldsymbol{\varepsilon}_t \quad , \tag{8}$$

where $\boldsymbol{x}_t = (1, \boldsymbol{y}_{t-1}, \boldsymbol{y}_{t-2}, \Lambda\Lambda, \boldsymbol{y}_{t-q})'$ and the matrix $\boldsymbol{\beta}$ is given by $(\boldsymbol{\beta}_0, \boldsymbol{\beta}_1, \Lambda\Lambda, \boldsymbol{\beta}_q)$. Performing the conventional stacking of the row vectors $\boldsymbol{y}_t$, $\boldsymbol{x}_t$ and $\boldsymbol{\varepsilon}_t$ for t = 1,2,…….,N into $\mathbf{Y}$，$\mathbf{X}$ and $\boldsymbol{\varepsilon}$, we have the multivariate regression model:

$$\mathbf{Y}_{p\times N} = \boldsymbol{\beta}_{p\times p(q+1)} \mathbf{X}_{p(q+1)\times N} + \boldsymbol{\varepsilon}_{p\times N} \,. \tag{9}$$

Throughout the paper, it is assumed that $\boldsymbol{\varepsilon} \sim N(0, \Sigma \otimes \mathrm{I})$, and we set $q^* = p(q+1)$. Then the likelihood function is given by:

$$\mathrm{L}(\boldsymbol{\beta}, \Sigma \mid \mathbf{Y}, \mathbf{X}) \;\propto\; |\Sigma|^{-\frac{N}{2}} \exp^{-\frac{1}{2} tr(\mathbf{Y}-\beta\mathbf{X})' \Sigma^{-1} (\mathbf{Y}-\beta\mathbf{X})}$$

$$= |\Sigma|^{-\frac{N}{2}} \exp^{-\frac{1}{2} tr[(\beta-\hat{\beta})' (\Sigma^{-1} \otimes \mathbf{X}\mathbf{X}')(\beta-\hat{\beta}) + (\mathbf{Y}-\hat{\beta}\mathbf{X})' \Sigma^{-1} (\mathbf{Y}-\hat{\beta}\mathbf{X})]}$$

$$=|\Sigma|^{-\frac{q^*}{2}} \exp^{-\frac{1}{2}(\beta-\hat{\beta})'(\Sigma^{-1}\otimes \mathbf{XX}')(\beta-\hat{\beta})} |\Sigma|^{-\frac{N-q^*}{2}} \exp^{-\frac{1}{2}tr(\mathbf{Y}-\hat{\beta}\mathbf{X})'\Sigma^{-1}(\mathbf{Y}-\hat{\beta}\mathbf{X})}$$

$$\propto \mathrm{N}(\beta \mid \hat{\beta}, \Sigma\otimes(\mathbf{XX}')^{-1}) \times \mathrm{IW}(\Sigma \mid (\mathbf{Y}-\hat{\beta}\mathbf{X})'(\mathbf{Y}-\hat{\beta}\mathbf{X}), \mathrm{N}\text{-}\mathrm{q}^*),$$

where N(.) denotes normal distribution and IW(.) denotes an inverse Wishart distribution.

Our study aims to consider the model (9) from a Bayesian point of view in hope that a more practical solution can be furnished when the sample size is small. Therefore, we compute the Bayesian point estimates for every unknown parameter and prediction point. We use the convenient diffuse prior distribution (Geisser, 1965; Tiao & Zellner, 1964) as follows:

$$\boldsymbol{g}(\beta, \Sigma^{-1}) \propto |\Sigma|^{\frac{1}{2}(p+1)}. \tag{10}$$

Instead of deciding the values of priors, we only assume the $\boldsymbol{g}$ is proportional to the determinant of $\mathbf{\Sigma}$ in 1/2(p+1) power. This is a non-informative prior setting. By combining the prior setting given in equation (10) with the likelihood function of β, $\mathbf{\Sigma}$ given $\mathbf{Y}$, Geisser (1965) obtained following posterior distribution:

$$P(\Sigma \mid \mathbf{X},\mathbf{Y}) = \mathrm{IW}(\Sigma \mid (\mathbf{Y}-\hat{\beta}\mathbf{X})'(\mathbf{Y}-\hat{\beta}\mathbf{X}), \mathrm{N}\text{-}\mathrm{q}^*\text{-p-1}). \tag{11}$$

$$P(\beta \mid \mathbf{X},\mathbf{Y}) \propto \left|\mathbf{A} + (\beta-\hat{\beta})\mathbf{XX}'(\beta-\hat{\beta})'\right|^{-\frac{N}{2}}, \tag{12}$$

or
$$P(\beta \mid \mathbf{X},\mathbf{Y}) = \frac{C_{p,N-q}\pi^{-\frac{pq^*}{2}} \mid \mathbf{A} \mid^{\frac{1}{2}(N-q^*)} \mid \mathbf{XX}' \mid^{\frac{p}{2}}}{C_{p,N} \left| \mathbf{A} + (\beta - \hat{\beta})\mathbf{XX}'(\beta - \hat{\beta})' \right|^{\frac{N}{2}}}, \tag{13}$$

where
$$\begin{cases} \mathbf{A} = (\mathbf{Y} - \hat{\beta}\mathbf{X})(\mathbf{Y} - \hat{\beta}\mathbf{X})', \\ \hat{\beta} = \mathbf{YX}'(\mathbf{XX}')^{-1}, \\ C_{p,N} = \pi^{-\frac{1}{4}p(p-1)} \prod_{i=1}^{p} (\frac{n-1-i}{2})!, \\ q^* = p(q+1). \end{cases}$$

and this implies that the marginal posterior distribution of β in matricvariate $\boldsymbol{t}$ is:

$$\beta \mid \mathbf{Y} \sim D(\cdot;\ \hat{\beta}, \mathbf{XX}', \mathbf{A}, q^*, p, N - q^*).$$

For the prediction of the future value $\mathbf{V}$, which is $p \times K$, where K indicates the forecasting step (i.e., when K=1, we are doing 1-step ahead forecasting). We assume that

$$\mathbf{V}_{p\times K} = \beta_{p\times p(q+1)}\mathbf{X}^*{}_{p(q+1)\times K} + \varepsilon^*{}_{p\times K}\,. \tag{14}$$

where $\mathbf{X}^*$ is a known $p(q+1)\times K$ matrix, and the columns of $\boldsymbol{\varepsilon}^*$ are independent p-variate normal with the mean vector $\underset{\sim}{\mathbf{0}}$ and common covariance matrix $\boldsymbol{\Sigma}$. The likelihood function of all parameters and predictions is therefore given as follows:

$$\mathrm{L}(\mathbf{V}, \beta, \Sigma \mid \mathbf{Y}) \propto |\Sigma|^{-\frac{N+K}{2}} \exp^{-\frac{1}{2}tr[(\mathbf{Y}-\beta\mathbf{X})'\Sigma^{-1}(\mathbf{Y}-\beta\mathbf{X})+(\mathbf{V}-\beta\mathbf{X}^*)'\Sigma^{-1}(\mathbf{V}-\beta\mathbf{X}^*)]}$$

$$\propto |\Sigma|^{-\frac{N+K}{2}} \exp^{-\frac{1}{2}tr\Sigma^{-1}[(\mathbf{Y}-\hat{\beta}\mathbf{X})(\mathbf{Y}-\hat{\beta}\mathbf{X})'+(\mathbf{V}-\hat{\beta}\mathbf{X}^*)(\mathbf{I}-\mathbf{X}^{*}(\tilde{\mathbf{X}}\tilde{\mathbf{X}})^{-1}\mathbf{X}^{*'}(\mathbf{V}-\hat{\beta}\mathbf{X}^*)']}. \tag{15}$$

By integrating with respect to $\boldsymbol{\beta}$, $\boldsymbol{\Sigma}$, we obtained the following posterior distribution for the prediction value $\mathbf{V}_{p\times K} = (\mathbf{V}_1, \mathbf{V}_2, \Lambda\ \Lambda\ , \mathbf{V}_k)$:

$$P(\mathbf{V} \mid \mathbf{X}, \mathbf{Y}) \propto \left| (\mathbf{Y} - \hat{\beta}\mathbf{X})(Y - \hat{\beta}\mathbf{X})' + (\mathbf{V} - \hat{\beta}\mathbf{X}^*)(\mathbf{I} - \mathbf{X}^*(\tilde{\mathbf{X}}\tilde{\mathbf{X}})^{-1}\mathbf{X}^{*'})(\mathbf{V} - \hat{\beta}\mathbf{X}^*)' \right|^{-\frac{N}{2}},$$

where $\tilde{\mathbf{X}} = (\mathbf{X}, \mathbf{X}^*)$.

That implies that the marginal distribution of **V** in matricvariate *t* is:

$$\mathbf{V} \mid \mathbf{Y} \sim D(\cdot;\ \hat{\beta}\mathbf{X}^*, \mathbf{I} - \mathbf{X}^{*'}(\tilde{\mathbf{X}}\tilde{\mathbf{X}}')^{-1}\mathbf{X}^*, \mathbf{A}, K, p, N - q^*).$$

and thus, $E(\mathbf{V} \mid \mathbf{Y}) = \hat{\beta}\mathbf{X}^*$. Therefore, we get the *K*-step ahead predictions for conditional means. Note that, for making a prediction for time *t*, we re-estimate the model parameters $\hat{\beta}$ based on the sample in *t*-1 to *t*-*w*, where the *w* is called "look-back window size". Meanwhile, the covariance matrix $\mathbf{\Sigma}$ is also re-estimated by using equation (11). We estimate these parameters by maximum these posterior functions. This dynamic forecasting that inputs the forecasted data into the same model for next step forecasting brings new information, and parameters will be more "precision" than conventional ordinary least square (OLS) estimates that set covariance matrix is uncorrelated. And the Bayesian estimator tends to give more weight to the sample information when the prior information becomes vaguer.

3. 3 The Power Transformation BVAR Model

Using the Box-Cox power transformation to achieve normality and stable variance has no doubt occurred to data analysts from time to time. The applicability of statistical models can be enhanced through the use of the power transformations, and time-series models are no exception. It is noted that the Box-Cox power transformation will include the log transformation as a special case. For this reason, Chen and Lee (1997) applied the Box-Cox power transformation to the ARMA (p,q) model . More specifically, let Z_{ij} be a linear function of time at the *j*th time. The Box-Cox transformation of Z_{ij} is defined as

$$\mathbf{Z}_{\mathbf{ij}}^{(\lambda_i)} = \begin{cases} \dfrac{(\mathbf{Z}_{\mathbf{ij}} + \upsilon)^{\lambda_i} - \mathbf{1}}{\lambda} & \textbf{if } \lambda_i \neq \mathbf{0} \\ \log(\mathbf{Z}_{\mathbf{ij}} + \upsilon) & \textbf{if } \lambda_i = \mathbf{0} \end{cases} \tag{16}$$

where υ is a known constant such that $Z_{ij} + \upsilon > 0$.

Then $Z_i^{(\lambda_i)} = (Z_{i1}^{(\lambda_i)}, Z_{i2}^{(\lambda_i)}, \ldots, Z_{iN}^{(\lambda_i)})$, can be represented as the model defined below,

$$\mathbf{Z_i}^{(\lambda i)}{}_{1\times N} = \boldsymbol{\beta}_{i\ 1\times q} \mathbf{X_i}^{(\lambda i)}{}_{q\times N} + \boldsymbol{\varepsilon}_{\mathbf{i}\ 1\times N} \tag{17}$$

where β_i is unknown, and $X_i^{(\lambda_i)}$ is a known design matrix in general, and is a matrix of lagged values of $Z_i^{(\lambda_i)}$ in our study. Furthermore, the rows of ε_i are independent normal with mean vector **0** and common variance σ^2 which can be arbitrary.

Similar to Chen and Lee (1997), the AR model is considered and we have the likelihood of the following function,

$$\mathbf{L}(\sigma^2,\beta_i,\lambda_i \mid \mathbf{Z}_i) \propto \sigma^{-(N-p)}\exp\{-\frac{1}{2\sigma^2}(\mathbf{Z}_i^{(\lambda)} - \beta_i\mathbf{X}_i^{(\lambda)})(\mathbf{Z}_i^{(\lambda)} - \beta_i\mathbf{X}_i^{(\lambda)})'\}\lambda_i^{n-p}\prod_{j=p+1}^{N}\mathbf{Z}_{ij}^{\lambda_i-1} \quad (18)$$

By maximizing the likelihood function with respect to β_i, σ^2, we obtain

$$\begin{aligned} L(\lambda_i \mid Z_i) &\propto \max_{\sigma^2}\max_{\beta|\sigma^2} L(\sigma^2,\beta_i,\lambda_i \mid Z_i) \\ &\propto \hat{\sigma}^{-(N-p)}\exp\{-\frac{1}{2\sigma^2}(\mathbf{Z}_i^{(\lambda_i)} - \hat{\beta}_i\mathbf{X}_i^{(\lambda_i)})(\mathbf{Z}_i^{(\lambda_i)} - \hat{\beta}_i\mathbf{X}_i^{(\lambda_i)})'\}\lambda_i^{n-p}\prod_{j=p+1}^{N}\mathbf{Z}_{ij}^{\lambda_i-1} \end{aligned} \quad (19)$$

where $\hat{\beta}_i = Z_i^{(\lambda_i)}X_i^{(\lambda_i)'}(X_i^{(\lambda_i)}X_i^{(\lambda_i)'})^{-1}$, and

$\hat{\sigma}^2 = \frac{1}{\mathbf{N}-\mathbf{p}}(\mathbf{Z}_i^{(\lambda_i)} - \hat{\beta}_i\mathbf{X}_i^{(\lambda_i)})(\mathbf{Z}_i^{(\lambda_i)} - \hat{\beta}_i\mathbf{X}_i^{(\lambda_i)})'$.

The maximum likelihood estimate of λ_i is obtained by maximizing (19). We can express the full model $\mathbf{Z} = \beta\mathbf{X} + \varepsilon$,

Where $Z = (Z_1^{(\lambda_1)'}, Z_2^{(\lambda_2)'}, \Lambda\ \Lambda, Z_q^{(\lambda_q)'})'$, $\beta = (\beta_1', \beta_2', \Lambda\ \Lambda, \beta_l')'$ and

$X = (X_1^{(\lambda_1)}, X_2^{(\lambda_2)}, \Lambda\ \Lambda, X_l^{(\lambda_l)})$.

Turing to Bayesian treatment. For the model (18), we will study prediction of future values from a Bayesian point of view. The purpose of this article is to consider the model (19) from a Bayesian point of view hoping that a more practical solution can be furnished when the sample size is small. Therefore, we will compute Bayesian point estimates for each of the unknown parameters and for the prediction of future values.

For Bayesian point of view, we will use the following noninformative prior,

$$\mathbf{g}(\lambda_i, \sigma^{-2}, \beta_i) \propto \sigma^{-2} \tag{20}$$

By combining equation (20) with the likelihood of $\lambda_i, \beta, \sigma_i^{-2}$ and Z_i, we obtained following posterior distribution,

$$\mathbf{P}(\lambda_i \mid Z_i) \propto [(Z_i^{(\lambda_i)} - \hat{\beta}_i X_i^{(\lambda_i)})(Z_i^{(\lambda_i)} - \hat{\beta}_i X_i^{(\lambda_i)})']^{-\frac{1}{2}(N-p)} \left| X_i^{(\lambda_i)} X_i^{(\lambda_i)'} \right|^{-\frac{p}{2}} \lambda_i^{n-p} \prod_{j=p+1}^{N} Z_{ij}^{\lambda_i - 1} \tag{21}$$

where $\hat{\beta}_i = Z_i^{(\lambda_i)} X_i^{(\lambda_i)'} (X_i^{(\lambda_i)} X_i^{(\lambda_i)'})^{-1}$.

The posterior estimate of λ_i is obtained by maximizing (21).

For the prediction of future value V_i, which is $1 \times K$, we will assume that

$$V_i^{(\lambda)}{}_{1\times K} = \beta_{1\times q} X_i^{(\lambda)*}{}_{q\times K} + \varepsilon^*{}_{1\times K} \tag{22}$$

where $X^{(\lambda)*}$ is a known $q \times K$ matrix, and the rows of $\boldsymbol{\varepsilon}^*$ are independent normal with the mean $\mathbf{0}$ and common variance σ^2 which can be arbitrary. We will consider the following conditional expectation of $V_i^{(\lambda_i)}$ given $Z_i^{(\lambda_i)}$,

$$E(V_i^{(\lambda_i)}{}_{1\times K} \mid Z_i^{(\lambda_i)}{}_{1\times N}\ ,) = E(V_i^{(\lambda_i)}{}_{1\times K}) + \Sigma_{21}\Sigma_{11}^{-1}(Z_i^{(\lambda_i)}{}_{1\times N}\ ,-E(Z_i^{(\lambda_i)}{}_{1\times N}\ ,))$$

$$= \hat{\beta} X_i^{(\lambda)*}.$$

Therefore we can predict V_{ij} by the following approximation predictor,

when $\lambda \neq 0$, $\mathbf{V_{ij}} = (\hat{\lambda} \cdot \mathbf{V_{ij}^{(\hat{\lambda})}} + 1)^{\frac{1}{\hat{\lambda}}}$,

$\lambda = 0$, $\mathbf{V_{ij}} = \exp(V_{ij}^{(\lambda)})$.

Thus we can obtain the prediction V_{ij}.

3.4 Rolling Forecasting Procedures and Performance Criteria

3.4.1 Look Back & Look Ahead Span Procedures

Two issues in our forecasting experiment need to be further explicated: the look-back window size and the look-ahead span. The look-back window size w means that when we make a prediction for time t, we estimate the model parameters based on the sample t-1 to t-w. The w is, of course, less than the available sample size for our first prediction point. For example, if our data spans from 1994 Q1 to 2003 Q4, we set the look-back window w to 20 because we assumed that it was improper to take data from too long ago into account for technology industries. The look-ahead span size s indicates how far we looked forward. When s = 1, we made prediction for time t based on data t-1 to t-w and for t +1, based on data t to t-w+1, and so on. This is the so-called 1-step ahead forecasting. When $s \geq 2$, it becomes multi-step ahead forecasting, making prediction for time t+s using only t-1 to t-w. Here we used dynamic forecasting that inputs the forecasted data into the same model for next step forecasting. That means, when forecasting t+s from t (known period), we estimated the model parameters based on real data in t thru t-w+1 and then forecasted t+1 based on that model/parameters. Forecasting data point t+2 used the same model and parameters, but was based on the forecasted data of $t+1$, not the actual data of $t+1$ (This is because we were assumed to know nothing about time *t+1* when we were in time *t*. So, to predict for *t+2* or more, we had no choice but to use forecasted data of *t+1*). This process was to continue until we reached *t+s*. In this study, we checked 1-, 2-, 3- and 4-step ahead for the forecasting results. In the 1-step ahead forecasting situation, we assumed that the industrial practitioners updated their data quarterly. This is more plausible in real world. On the other hand, the 4-step ahead forecasting situation means that industrial practitioners predicted only once a year. Although this is not quite convincing, it serves as our 1-year ahead forecast to be compared with the annual forecast reports published annually by market information providers in every spring or early summer.

3.4.2 Performance Criteria

In this study, we use the following criteria to measurement the performance,

(a) RMSE (Root of mean square error)

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

$$\text{RMSE} = \sqrt{T^{-1}\sum_{t\in T}\left(Y_t - \hat{Y}_t\right)^2}$$

(b) Theil U

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

Hence, if U < 1 it means the estimated model performs better than random walk without a drift. On the other hand, if U > 1, it means the estimated model performs less well than the random walk case.

(c) MAE (Mean absolute error) MAE = $\dfrac{\sum_{t\in T}\left|Y_t - \hat{Y}_t\right|}{T}$

(d) FESD (Forecast error standard deviation)

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

(e) RMSPE (Root mean square percentage error) RMSPE = $\sqrt{T^{-1}\sum_{t\in T}\dfrac{\left(Y_t - \hat{Y}_t\right)^2}{\left|Y_t\right|}}$

(f) MARD (Mean absolute relative deviation) MARD = $\dfrac{\sum_{t\in T}\left|\dfrac{Y_t - \hat{Y}_t}{Y_t}\right|}{T}$

4. Using Four Forecasting Models to Forecast of Total Production Output of Taiwan's Photonic Industry

In this section, we will show how BVAR models perform in forecasting industrial production of high technology industry based on industrial clustering. The photonics industry is used to examine the performance of VAR and BVAR model as an empirical study. This industry is one of regarded as a very promising industry, and Taiwan's government has been making a big effort to develop this critical industry. The existing information and electronic industries are regarded as an important bolster for the development of other new industries. The result of our prediction is assessed in magnitude measure, directional measure and residual correlation. The rolling forecasting procedure is used and every predicted value one-step ahead is estimated by current actual values because we think the rolling forecasting procedure is much more reasonable and reactive than multi-step forecasting procedure. In examining forecasting performance in this industry, it is found that the BVAR model outperforms the VAR model and the naïve AR model in magnitude measures. This outcome corroborates that the BVAR model can provide an accurate prediction for industrial production based on industrial cluster.

4.1 Dependent and Independent Variables

In this Empirical case study, we use AR, VAR, Standard BVAR, and Low weight BVAR models to estimate the parameters and forecast the future value by the following procedures:

The production data were drawn from the Department of Statistics, Ministry of Economic Affairs (MOEA) of Taiwan. The quarterly data are used as basis of model fitting and forecasting. It is reasonable for us to take quarterly data instead of month data because monthly data cover a too short period of time to evaluate industrial production. In contrast, annual data carry a too long period of time to reflect the unstable and explosive development of high technology industries. There are up to seven relative industries, including most electronics and information industries, which probably contribute to the photonics industry development path according to our identification (Table 4.1). Like Joutz, Maddala and Trost, we use the production index to represent production value for modeling and forecasting. So data form seven industries have been collected from 1990 Q1 to 2000 Q1, for a total of 41 quarterly observations. The front 32 (1990 Q1 to 1997 Q4) are used to select variables (series) and specify model. The following nine observations are taken to assess the predictive capability of VAR and BVAR model. The out-of-sample ratio is 22.5 percent (9/41).

Table 4.1: Product Group Code and Detailed Product Items of Photonic Industry

Code	Group	Product Item
3173	Photonics Materials and Components	LED, LED display, Solar cell, Laser diode, LCD display, Other opto devices, Other displayers.
3141	Data Processing and Storage Equipments	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 Equipments	Tube monitor, LCD monitor, Terminal
3144	Data I/O Peripheral Equipments	Hard disc driver, Floppy disc driver, Compact disc driver, Printer, Plotter, Keyboard, Scanner, Mouse, Card reader, Other input/output peripherals.
3145	Computer Components	Internet-work, Server, Wiring concentrator, PC-LAN, Network card, Fax card, Memory extension card, Graphic card, Control card, ISDN card, Sound card, Other interface cards.
3179	Other Electronic Parts	PCB, Board, Copper-clad laminate, UPS, Filter, Electronic rectifier, other power supplier, others parts.

Note:

1. This table is based on definition provided by Department of Statistics, Ministry of Economic Affairs (MOEA), Taiwan, Republic of China, 2000.
2. The code 3173 (Photonics Materials and Components) is treated as dependent variable, others are treated as independent variables.

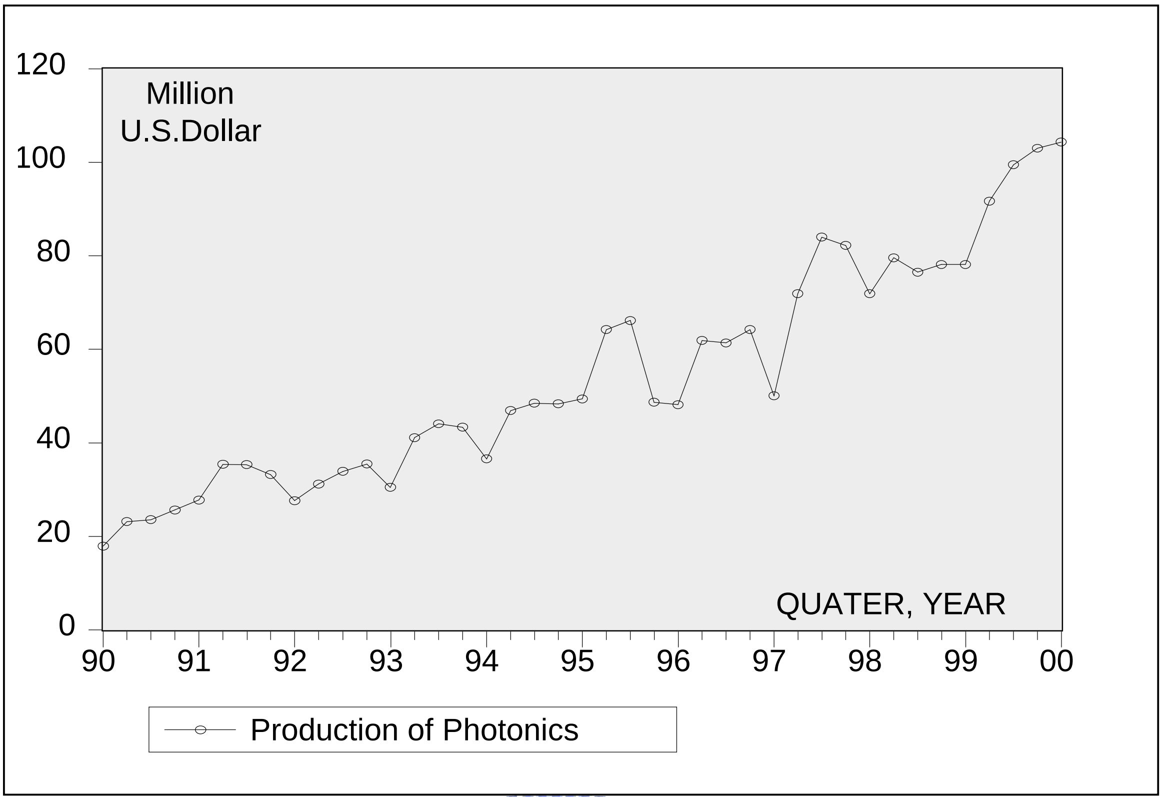

Figure 4.1: Production Value of Photonic Industry in Taiwan

4.2 Pre-processing of Dependent and Independent Variables

4.2.1 Logarithmic adjustment

As explained in the previous passage, the quarterly production indexes of all information and electronics industries in Taiwan are collected, then these production indexes are transformed into natural logarithmic numbers. We use the common procedure that turns nonlinear growth series into logarithmic series for stable volatility in AR, VAR and BVAR analysis.

4.2.2 Seasonal adjustment

To deal with conspicuous seasonality within small-sample data, we decide to take seasonal adjustment before modeling in spite of seasonal dummy variables in model setting. Besides, such a deseasonalization is much preferable in BVAR estimation because a series with season factor makes large coefficients in high-order lag which in turn makes inefficient parameterization. The census X-11 method is applied in multiplicative and half-weighted endpoint ways to provide deseasonalized series.

4.2.3 The First-order difference adjustment

From the two procedures mentioned, we can reach the conclusion that level (Only Log transformation) and differenced data series (Log transformation and difference) models are simultaneously the comprehensive comparison. Many researchers recommend level VAR and appose the differentiation of series that present a unit root or trend factors. Based on Enders, taking difference will throw out the co-movement information of series. On the other hand, some researchers consider VAR model in differenced as well as level data forms in their studies. We used both models in this study to find possible dynamic interaction of an industrial cluster. The result of the Augmented Dickey-Fuller test (ADF test) and the nonparametric Phillips-Perron test (PP test) also corroborate the existence of a unit root (Table 4.2). So two typical VAR models, one in level and another in first-order differentiation, are produced and will be compared. To produce the differentiated VAR model, we take first-order upon the seven seasonal-adjusted logarithmic series. We illustrate our preliminary transformation process of production index in our main example: the photonics industry (Figure 4.2).

Table 4.2: The result of Unit Root Test

Code #	Groups	Phillips-Perron Test		Augmented Dickey-Fuller Test	
		In level	First Order Differentiation	In level	First Order Differentiation
3141	Data Processing and Storage Equipments	0.7642	-6.4369*	0.4305	-5.6890*
3142	Data Storage Media Units	-1.1758	-5.9600*	-0.7375	-5.0291*
3143	Data terminal Equipments	-0.3581	-6.3270*	-0.2884	-5.1094*
3144	Data I/O Peripheral Equipments	2.9191	-4.7493*	2.1923	-2.9605
3145	Computer Components	0.5178	-7.9533*	1.1648	-3.6910*
3173	Photonics Materials and Components	-0.9539	-5.8102*	-0.8522	-3.9377*
3179	Other Electronic Parts	1.0398	-5.7495*	1.7310	-2.6541
Hypothesis Testing under α=0.05		All not reject	All reject	All not reject	All reject but 3144 and 3179

Note:

1. Nonparametric Phillips-Perron Unit Root Test is used here with intercept and truncation lag 3 (by Newey-West suggestion). The null hypothesis is a unit root existing in one series under α=0.05 by Mackinnon Critical Value.
2. Augmented Dickey-Fuller Unite Root Test is used here with intercept and presupposed lag 1. The null hypothesis is a unit root existing in one series under α=0.05 by Mackinnon Critical Value.

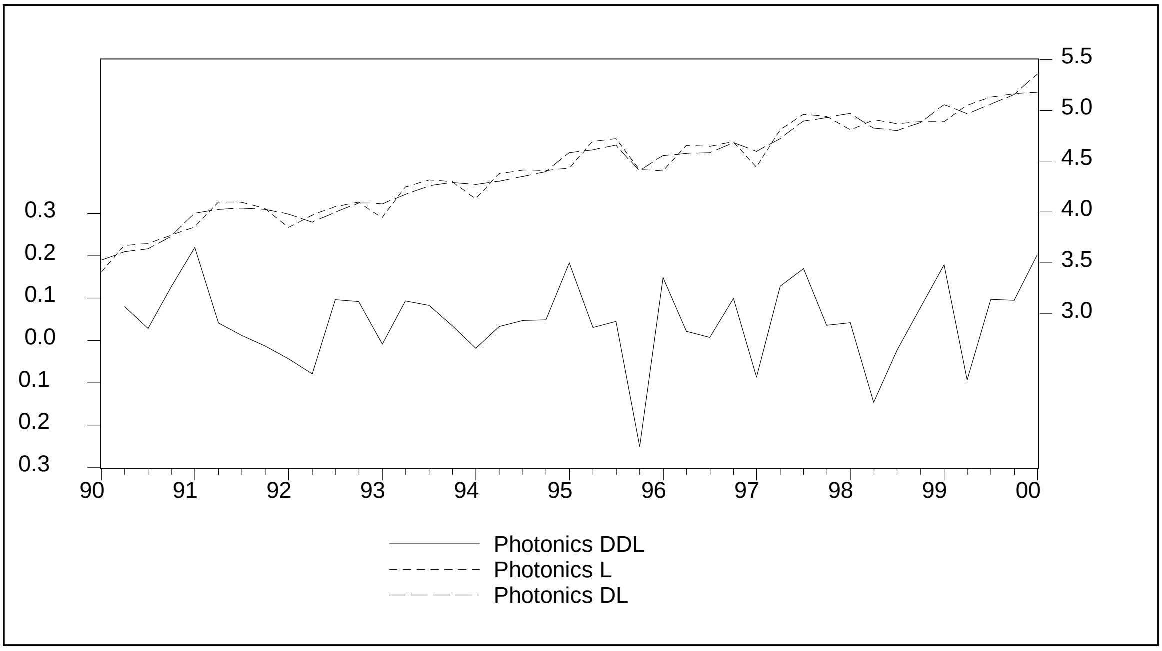

Figure 4.2: Transformations of Photonics Production Value (Code 3173)

1. The dashed line (Photonics L) is the logarithmic production index.
2. The dotted line (Photonics DL) is the deseasonalized logarithmic production index.
3. The thick line (Photonics DDL) is the first-order differenced deseasonalized logarithmic production index

4.3 The Selection of Dependent Variables

Here we set models for photonics industry. The industrial cluster structure and Granger Causality test are used to find out effective variables (series) in model. Although there are seven adjusted series collected in preliminary adjustments, we have to cull appropriate variables (series) for VAR and BVAR forecasting model; otherwise, we will waste the degrees of freedom in inefficient endogenous variables. The concept of industrial cluster is used to filter-off series. That means we select the series of directly related industries into model. So the downstream, upstream and peripheral industries of Taiwan's photonics industry are put into

VAR model. There are six candidates for photonics industry: code 3141, 3142, 3143, 3144, 3145 and 3179. A test of Granger-Causality is used to verify whether the explanatory degree is improved by adding one variable into the univariate equation. We experiment with two sets in the causality test: level data series and differenced data series (Table 4.3). Because Granger Causality Test is sensitive to the number of lag, we execute this test in lags that span from 1 to 4 to cover possible model order. The main results of Granger's Causality Test from lag 1 to 4 are reported in Table 4.3 and Table 4.4. In the photonics industry, six candidates are found to be informative in a level VAR model under $\alpha = 0.05$. However, when we consider a differenced VAR model, we need only to contain the Data Processing and Storage Equipments (the so-called "Computer Manufacturing Industry, code 3141) and Data terminal Equipments (code 3143). Our outcome is harmonic with our presupposition that the future development potential of Taiwan photonics industry is highly dependent on the pull power from local downstream demand.

Table 4.3: Granger Causality Test of Candidate Independent Variables for forecast of the Production of Photonics Industry

	Independent Variables / Dependent Variable	P-value	Data Processing and Storage Equipments # 3141	Data Storage Media Units # 3142	Data terminal Equipments # 3143	Data I/O Peripheral Equipments # 3144	Computer Components # 3145	Other Electronic Parts # 3179
Level (log trans-formation)	Photonics Materials and Components #3173	Lag 1	0.0112*	0.0310*	0.3846	0.0407*	0.0244*	0.0152*
		Lag 2	0.0437*	0.0383*	0.0368*	0.1238	0.0833	0.0289*
		Lag 3	0.0067*	0.1050	0.0475*	0.0432*	0.0642	0.0168*
		Lag 4	0.00327*	0.2245	0.1653	0.1131	0.1305	0.0059*
Differenced (log trans-formation and difference))	Photonics Materials and Components #3173	Lag 1	0.30813	0.7725	0.0163*	0.4803	0.7104	0.5343
		Lag 2	0.03325*	0.1604	0.0454*	0.6059	0.8599	0.5621
		Lag 3	0.00769*	0.2248	0.0928	0.7297	0.8322	0.8292
		Lag 4	0.00815*	0.5471	0.2140	0.7183	0.9266	0.5477

Note:

1. The dependent variable is photonics industry and code #3177
2. All series are considered in level.
3. Null hypothesis: the suspicious series does not Granger Cause the production series of photonics.
4. The mark * point the rejection under significant level α=0.05

4.4 The Lag Order Selection Procedures

4.4.1 The Order Selection of the VAR Model

In this stage, we have to decide appropriate lag-length of VAR model. Otherwise we will also waste the degrees of freedom in inefficient lag orders in estimation. The comparison criteria are listed in Table 4.4. To decide the appropriate order of VAR and BVAR, we focus on three criteria including AIC (Akaike Information Criterion), Hannan-Quinn Criterion (HQ) and Schwarz

Criterion (SC) to specify the appropriate lag-length.

By criteria outcomes in Table 4.4, it is obvious to accept differenced VAR with order 1 as a qualified forecasting model. As to level VAR, the criteria of level VAR model decline simultaneously because the determinant slumps with the number of modeling lag. So we decide to fit level VAR with order 1 as the general model. We select three models to make production forecasting for the photonics industry: AR (1), VAR (1) for the seven series model, and VAR (1) for the three differenced series model.

Table 4.4: Order Selection in VAR Model for Photonics Production Forecasting

	Criteria	Lag 4	Lag 3	Lag 2	Lag 1
VAR 7 series (Log Trans-formation)	Determinant of Residual Covariance	≒ 0*	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
VAR 3 series (Log Trans-formation and Differenced)	Determinant of Residual Covariance	1.56E-8	4.30E-8	1.16E-7	1.48E-7
	Log Likelihood	127.7346	118.2721	108.0980	108.1987
	HQ	8.4723	4.7920	1.3368	-2.6432
	SC	-4.7012	-4.8778	-5.0166	-5.8528
	AIC	-6.5730	-6.3051	-6.0068	-6.4132

Note:

1. The number in the square bracket presents the endogenous variables to be considered (equations) in our VAR estimation according to last stage
2. In the level VAR (4) model, the determinant of residual covariance tends to 0. (Precisely speaking, the number is less than E-30 in computation) As the result, the HQ, SC, AIC values in level VAR (4) can not be presented, but they obviously tend to be less than those of level VAR (3).

4.4.2 The Order Selection of the BVAR Model

According to Spencer, the specification of BVAR model is based on VAR modeling. But there is still some argument among researchers: it is argued that whether the stationarization is necessary in preliminary transformation. Some researchers set BVAR only in level data series on the basis of Sims et *al*'s statement, "…the Bayesian approach is entirely based on the likelihood function, which has the same Gaussian shape regardless of the presence of nonstationarity, and Bayesian inference needs to take no special account of nonstationarity" (p. 136). It seems trivial to consider preliminary transformation before BVAR model. But in this study, we set BVAR in both level and differenced forms when possible to challenge the VAR model because the BVAR model is often thought of as able to outperform the VAR model. In order of selection, the BVAR is usually in lag one and is seldom in lag over three. We follow the parsimonious parameterization principle of BVAR model, and consider the BVAR model with lag number that does not exceed the lag number of the VAR model. So, we set BVAR in order 1 for photonics industry. Then, we use the symmetric prior form in two values: the standard symmetric prior and the low-weighted prior. The standard prior is 0.2 in tightness and 0.5 in weight (γ =0.2, ω=0.5) according to the optimal experience cited by Litterman and Doan. We term it as the "Standard prior BVAR". In the low-weighted prior, we let the weight approximate to zero (set γ =0.2, ω=0.001) to get a "Low-weighted prior BVAR" for better prediction for the seemingly univariate system. In Spencer's study, it is found that the "Low-weighted prior BVAR" is the optimal prior in one-step ahead forecasting.

4.5 Assessment of Forecast Results

As explained in Section 4.1, we divide a 10-year sample (1990:Q1-2000:Q1) into two parts. The first part is used to build the models, and the second is used to assess the performance of the forecast models, also called the cross-validation process. The quarterly data from 1990 to 1997 are used as model specification and the following data are used as prediction assessment. We use the rolling forecasting procedure in this study. Researchers re-estimate the model whenever new real data are available and then forecast for the next period. Consequentially, one-step-ahead predictions and model estimations are repeating as rolling. The result of our prediction is assessed in magnitude measure, directional measure and residual correlation. Here we use six criteria in magnitude measure: RMSE (Root of mean square error), Theil U, MAE (Mean absolute error), FESD (Forecast error standard deviation), RMSPE (Root mean square percentage error) and MARD (Mean absolute relative deviation). Besides the magnitude measures, the directional measure is another important measurement for evaluating the accuracy in direction prediction. In practice, the accuracy in direction is sometimes more important than in magnitude for forecasting models. We use the accuracy ratio in directional, with two alternatives: “up” or “down”, as the assessment criterion for directional measure. When discussing the differenced data, we modify the accuracy ratio in two alternatives: “positive” and “negative”. As indicated by Curry et *al*, the criteria of model fit and residual correlation can give some indication as model specification and forecasting. Therefore, the model without forecasting residuals without serial correlations is expected to be better in dealing with external uncertainties.

The performance on rolling forecasting is used for verifying whether the proposed method is helpful to production prediction. The detail findings of level model in photonics industry are illustrated in Figure 4.3 and Table 4.5. The BVAR model significantly outperforms the other models. If we compare the VAR model and AR model, our endeavor in variable selection seems in vain because the VAR model is less accurate than AR model. But when we consider the BVAR, it is encouraging to find that both BVAR models (standard prior and low-weighted prior) show excellent precision. The low-weighted prior BVAR model, which hardly accounts for cross impact, is less accurate than standard prior BVAR, as we anticipated. Such an outcome validates that a specific industrial cluster indeed impacts the photonics industry. So the related industry can provide useful information for forecasting Taiwan's photonics industry. If we only consider VAR and AR in analysis, we may lose that implication because the AR performs beyond VAR. In the differenced series of the photonics industry cases as shown in Table 4.6, the standard prior BVAR also overwhelms VAR in prediction. The statement is re-confirmed that BVAR model is at least as good as VAR model, no matter whether it is in level or in difference.

Table 4.5 The Performance Comparison of AR, VAR, Standard BVAR and Low-weighted BVAR for Photonics Production Value (Seven Independent Variables, Log Transformation)

	Criteria	VAR (1)	AR (1)	Standard Prior BVAR (1)	Low-weighted Prior BVAR (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

Note:

1. "Accuracy in direction ratio" the ratio that the model predicts accurate direction in two alternatives: "up" or "down".
2. The Serial correlation of residual is verified by Ljung-Box Q statistics of every lag under α=0.05.

Table 4.6: The Performance Comparison of VAR, Standard BVAR and Low-weighted BVAR for Photonics Production Value (Three Independent Variables, Log Transformation differenced)

	Criteria	VAR (1)	Standard Prior BVAR (1)
Magnitude	RMSE	0.1437	0.1229
	Theil U	0.9819	0.8397
	MAE	0.1078	0.1014
	RMSPE	0.4688	0.3553
	MARD	1.3618	0.9498
	FESD	0.1393	0.1225
Direction	Accuracy in direction (%)	62.5%	50%
Residual	Serial correlation of Residual(Q-statistics)	No serial correlation	No serial correlation

Note:

1. "Accuracy in direction ratio" in this table shows the accuracy ratio in two alternatives: "positive" and "negative".
2. The Serial correlation of residual is verified by Ljung-Box Q statistics of every lag under α =0.05

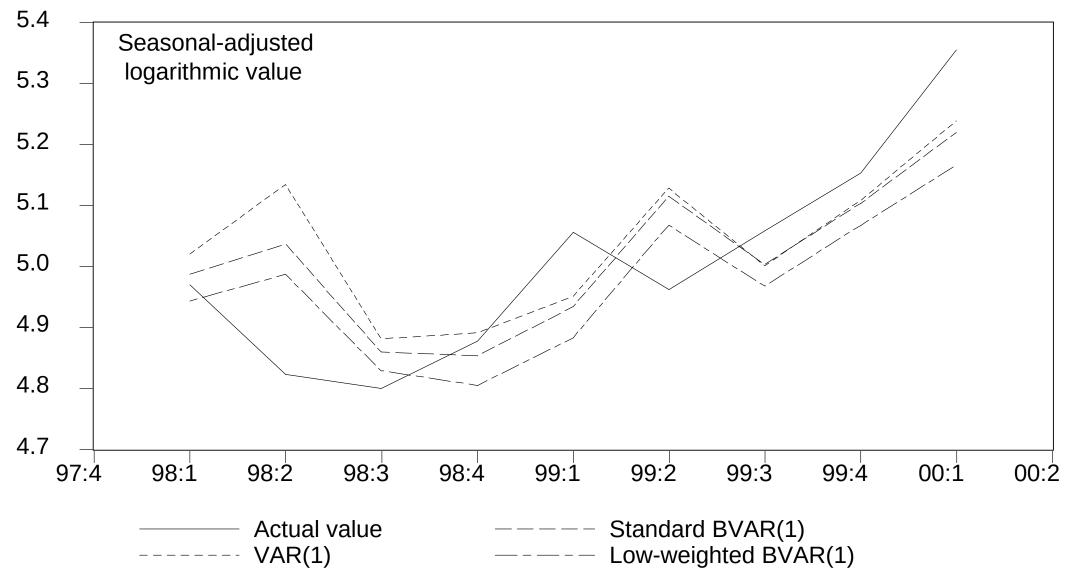

Figure 4.3: The Actual Value and the Forecast Values of Photonics Production Values (1998:Q1-2000:Q1)

4.6 Finding and Discussion

In this section, we utilize the BVAR model to predict industrial production of high technology industries based on industrial clusters. In our experiment, the development of Taiwan's photonics industry proved to heavily rely on downstream and peripheral industries. The downstream sectors include computer manufacturing and data terminal equipment (ex, LCD monitor); the peripheral sector is the data media industry (ex, compact disc). So the industrial cluster in Taiwan has substantially contributed to the prosperity of the photonics industry for the past decade. The result shows that the BVAR model transcends the VAR and AR models in its performance in rolling forecasting procedure. We may therefore conclude that when the intended series is dependent on other series, the standard prior BVAR model is recommened. Otherwise, lower-weighted prior BVAR is preferable in production prediction.

Overall, BVAR forecasts surpass corresponding VAR and AR forecasts. The superiority of Bayesian statistics is confirmed in small-sized samples forecasting again. Furthermore, the BVAR model is capable of dynamic analysis in industrial clusters and performs superior production prediction in magnitude. As a result, we have confidence in BVAR forecasts of industrial production based on industrial clusters, especially for high technology industries.

5. Using Four Forecasting Models to Forecast Total Production Output of Taiwan's Semiconductor Industry

In the literature, the time series model class has been one of the most popular prediction methodologies in previous decades. Some pioneer studies have attempted to provide predictive methods for production forecasting of technology industries (e.g., Tseng et *al*., 1999; Hsu et *al*., 2003; Chang et *al*., 2004). However, those prognostic techniques are still far from satisfactory in practice, and more exploration is needed.

We start our exploration in developing a new forecasting method for technology industries by meditating on the following questions: which models have been studied in the literature? Can we propose a model with features that better handle the unstable dynamics and discrete shocks? By using that model, what variables could be considered to produce better prediction? In this section, we examine the performance of time series models by considering the semiconductor industry. And we show how BVAR models perform in forecasting industrial production of high technology industry based on industrial clustering.

5.1 Dependent and Independent Variables

In this Empirical case study, we use AR, VAR, Standard BVAR, and Low weight BVAR models to estimate the parameters and forecast the future value by the following procedures:

The production data is drawn from the Department of Statistics, Ministry of Economic Affairs (MOEA) of Taiwan. The quarterly data are used as the basis of model fitting and forecasting. As in section 4.1, the quarterly data are used as the basis of model fitting and forecasting. There are up to three relative industries, including most electronics and information industries, which probably contribute to the semiconductor industry is development path according to findings (Table 5.1). Like Joutz, Maddala and Trost, the production index is used to represent production value for modeling and forecasting. So data form these four industries have been collected from 1990 Q1 to 2000 Q1, for a total of 41 quarterly observations. The front 32 (1990 Q1 to 1997 Q4) are used to select variables (series) and specify model. The following nine observations are taken to assess the predictive capability of VAR and BVAR model. The out-of-sample ratio is 22.5 percent (9/41).

Table 5.1: Product Group Code and Detailed Product Items of Semiconductor Industry

Code	Group	Product Item
3172	Semiconductors	Wafer, Mask, IC package, Foundry, IC manufacturing, Diode, Transistor, Lead frame.
3144	Data I/O Peripheral Equipments	Hard disc driver, Floppy disc driver, Compact disc driver, Printer, Plotter, Keyboard, Scanner, Mouse, Card reader, Other input/output peripherals.
3145	Computer Components	Internet-work, 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 Equipments	Numerical controller, Word processor, ROM programmer, Network operating system, Case, Other computer equipments.

Note:

1. This table is based on definition provided by Department of Statistics, Ministry of Economic Affairs (MOEA), Taiwan, Republic of China, 2000.
2. The code 3172 (Semiconductors) is treated as dependent variable, others are treated as independent variables.

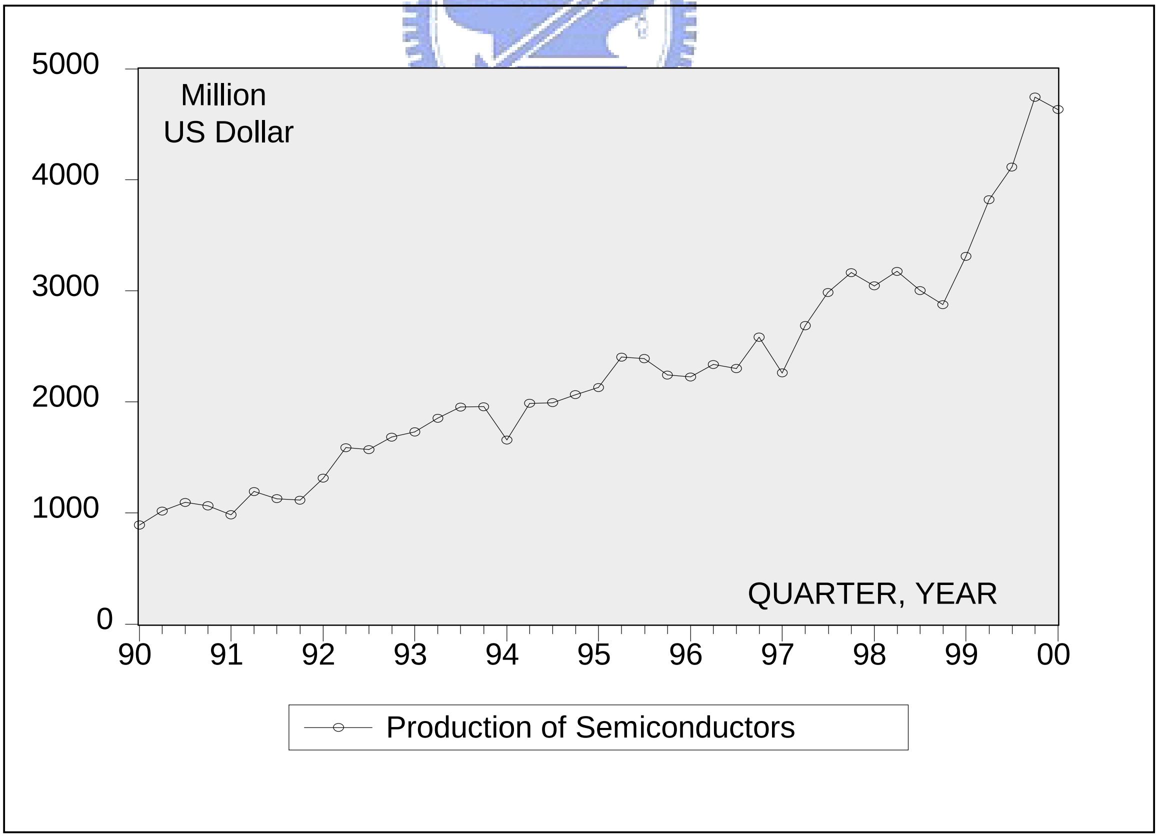

Figure 5.1: Production Value of Semiconductors Industry in Taiwan

5.2 Pre-processing of Dependent and Independent Variables

5.2.1 Logarithmic adjustment

As explained in the previous section passage, the quarterly production indexes of all information and electronics industries in Taiwan are collected, then these production indexes are transformed into natural logarithmic numbers. We use the common procedure that turns nonlinear growth series into logarithmic series for stable volatility in AR, VAR and BVAR analysis.

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To deal with conspicuous seasonality within small-sample data, we decide to take seasonal adjustment before modeling in spite of seasonal dummy variables in model setting. Besides, such a deseasonalization is much preferable in BVAR estimation because a series with season factor makes large coefficients in high-order lag which in turn makes inefficient parameterization. The census X-11 method is applied in multiplicative and half-weighted endpoint ways to provide deseasonalized series.

5.2.3 The First-order difference adjustment

From the two procedures mentioned, we can reach the conclusion that level and differenced data series models are simultaneously a comprehensive comparison. Many researchers recommend level VAR and appose the differentiation of series that present a unit root or trend factors. Based on Enders, taking difference will throw out the co-movement information of series. On the other hand, some researchers consider VAR model in differenced as well as level data forms in their studies. We used both models in this study to find possible dynamic interaction of an industrial cluster. The result of the Augmented Dickey-Fuller test (ADF test) and the nonparametric Phillips-Perron test (PP test) also corroborate the existence of a unit root (Table 5.2). So two typical VAR models, one in level and another in first-order differentiation, will be produced and compared. To produce the differentiated VAR model, we take first-order upon the four seasonal-adjusted logarithmic series. We illustrate our preliminary transformation process of production index in our main example: the semiconductor industry (Figure 5.2).

Table 5.2: The result of Unit Root Test

Code #	Groups	Phillips-Perron Test		Augmented Dickey-Fuller Test	
		In level	First Order Differentiation	In level	First Order Differentiation
3144	Data I/O Peripheral Equipments	2.9191	-4.7493*	2.1923	-2.9605
3145	Computer Components	0.5178	-7.9533*	1.1648	-3.6910*
3149	Other Computer Equipments	0.4275	-5.4122*	0.1979	-4.3237*
3172	Semiconductors	-0.7450	-6.1982*	-0.7419	-5.1024*
Hypothesis Testing under α=0.05		All not reject	All reject	All not reject	All reject but 3144 and 3179

Note:

1. Nonparametric Phillips-Perron Unit Root Test is used here with intercept and truncation lag 3 (by Newey-West suggestion). The null hypothesis is a unit root existing in one series under α=0.05 by Mackinnon Critical Value.
2. Augmented Dickey-Fuller Unite Root Test is used here with intercept and presupposed lag 1. The null hypothesis is a unit root existing in one series under α=0.05 by Mackinnon Critical Value.

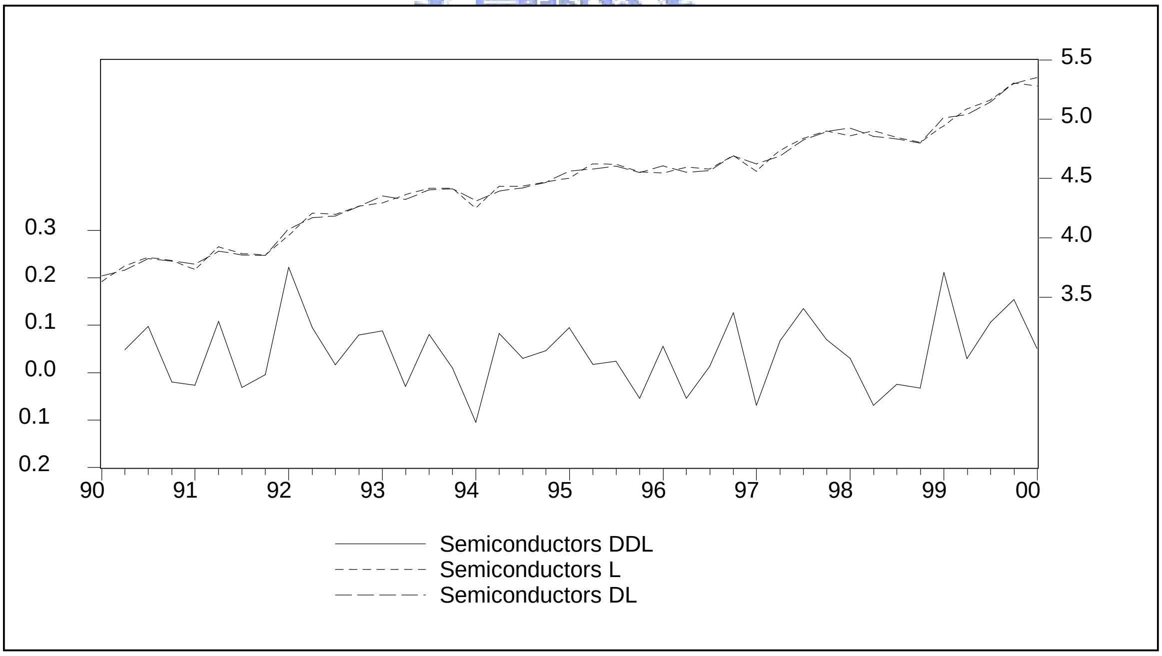

Figure 5.2: Transformations of Semiconductors Production Value (Code 3172)

1. The dashed line (Photonics L) is the logarithmic production index.
2. The dotted line (Photonics DL) is the deseasonalized logarithmic production index.
3. The thick line (Photonics DDL) is the first-order differenced deseasonalized logarithmic production index.

5.3 The Selection of Dependent Variables

Here we set models for the semiconductor industry. The industrial cluster structure and Granger Causality test are used to determine effective variables (series) in model. Although there are four adjusted series collected in preliminary adjustments, we have to cull appropriate variables (series) for VAR and BVAR forecasting model; otherwise, we will waste the degrees of freedom in inefficient endogenous variables. The concept of industrial cluster is used to filter-off series. That means we select the series of directly related industries into model. So the downstream, upstream and peripheral industries of Taiwan's semiconductor industry are put into VAR model. There are three candidates for the semiconductor industry: code 3144, 3145 and 3149. A test of Granger-Causality is used to verify whether the explanatory degree is improved by adding one variable into the univariate equation. We experiment with two sets in the causality test: level data series (Only Log transformation) and differenced data series (Log transformation and difference) (Table 5.3). Because Granger Causality Test is sensitive to the number of lag, we execute this test in lags that span from 1 to 4 to cover possible model order. The main results of Granger's Causality Test from lag 1 to 4 are reported in Table 5.3. From Table 5.3, only one of the three candidates manifest causality in production in the semiconductor sector: the Data I/O Peripheral

Equipments (code 3144) (Table 5.3). As a result we decide to consider two level VAR models: VAR with four variables (including code 3144, 3145, 3149, 3172) and VAR with two variables (including code 3144 and 3172). On the other hand, the result in Table 5.3 indicates that no differenced data series significantly (Granger) causes the differenced semiconductors production. So we discarded the differenced VAR in production forecasting here.

Table 5.3: Granger Causality Test of Candidate Independent Variables for Forecast of the Production of Semiconductor Industry

	Dependent variables \ Independent Variables	P-value	Data I/O Peripheral Equipments # 3144	Computer Components # 3145	Other Computer Equipments # 3149
Level (Log Trans-formation)	Semiconductors # 3172	Lag 1	0.0560	0.0975	0.0912
		Lag 2	0.1362	0.2393	0.0994
		Lag 3	0.0731	0.5735	0.2524
		Lag 4	0.0448*	0.2605	0.2232
Differenced (Log Trans-formation and difference)	Semiconductors # 3172	Lag 1	0.2021	0.8568	0.5340
		Lag 2	0.2891	0.8090	0.4694
		Lag 3	0.6554	0.6879	0.2310
		Lag 4	0.6479	0.8997	0.1160

Note:

1. All series are in differentiation.
2. Null hypothesis: the suspicious series does not Granger Cause the production series of photonics.
3. The mark * point the rejection under significant level α=0.05

5.4 The Lag Order Selection Procedures

5.4.1 The Order Selection of the VAR Model

In this stage, we have to decide appropriate lag-length of VAR model. Otherwise we will also waste the degrees of freedom in inefficient lag orders in estimation. The comparison criteria are listed in Table 5.4. To decide the appropriate order of VAR and BVAR, we focus on three criteria including AIC (Akaike Information Criterion), Hannan-Quinn Criterion (HQ) and Schwarz Criterion (SC) to specify the appropriate lag-length.

By criteria outcomes in Table 5.4, it is obvious to accept differenced VAR with order 1 as a qualified forecasting model. As to level VAR, the criteria of level VAR model declines simultaneously because the determinant slumps with the number of modeling lag. So we decide to fit level VAR with order 1 as the general model. We select three models to make production forecasting for the photonics industry: AR (1), VAR (1) for the seven series model, and VAR (1) for the three differenced series model.

Table 5.4: Order Selection in VAR Model for Semiconductor Production Forecasting

	Criteria	Lag 4	Lag 3	Lag 2	Lag 1
VAR 4 series (Log Trans-formation)	Determinant of Residual Covariance	7.10E-11	6.92E-10	3.52E-09	7.96E-09
	Log Likelihood	168.2299	141.2368	121.7096	113.1106
	HQ	-6.1703	-5.3864	-5.1761	-5.7056
	SC	-3.9239	-3.7026	-4.0325	-5.0820
	AIC	-7.1593	-6.1543	-5.7140	-6.0072
VAR 2 series (Log Trans-formation and difference)	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

Note: The number in the square bracket presents the endogenous

5.4.2 The order Selection of the BVAR Model

According to Spencer, the specification of BVAR model is based on VAR modeling. But there is still some argument among researchers: it is argued whether the stationarization is necessary in preliminary transformation. Some researchers set BVAR only in level data series on the basis of Sims et *al*'s statement, "…the Bayesian approach is entirely based on the likelihood function, which has the same Gaussian shape regardless of the presence of nonstationarity, and Bayesian inference needs to take no special account of nonstationarity" (p. 136). It seems trivial to consider preliminary transformation before BVAR model. But in this study, we set BVAR in both level and differenced forms, which possible, in to challenge with the VAR model because the BVAR model is often believed to be able to outperform the VAR model. In order of selection, the BVAR is usually in lag one and is seldom in lag over three. We follow the parsimonious parameterization principle of BVAR model, and consider the BVAR model with lag number that does not exceed the lag number of the VAR model. So, we set BVAR in order 1 forsemiconductor industry. Then, we use the symmetric prior form in two values: the standard symmetric prior and the low-weighted prior. The standard prior is 0.2 in tightness and 0.5 in weight (γ =0.2, ω=0.5) according to the optimal experience cited by Litterman and Doan. We term it as the "Standard prior BVAR". In the low-weighted prior, we let the weight approximate to zero (set γ =0.2, ω=0.001) to get a "Low-weighted prior BVAR" for better prediction for the seemingly univariate system. In Spencer's study, it is found that the "Low-weighted prior BVAR" is the optimal prior in one-step ahead forecasting.

5.5 Assessment of Forecast Results

As explained in Section 5.1, we divide a 10-year sample (1990:Q1-2000:Q1) into two parts. The first part is used to build up models, and the second is used to assess forecasting performance of models also called the cross-validation process. The quarterly data from 1990 to 1997 are used as model specification and the following data are used as prediction assessment. We use the rolling forecasting procedure in this study. Researchers re-estimate the model whenever new real data are available and then forecast for the next period. Consequentially, one-step-ahead predictions and model estimations are repeating as rolling. The result of our prediction is assessed in magnitude measure, directional measure and residual correlation. Here we use six criteria in magnitude measure: RMSE (Root of mean square error), Theil U, MAE (Mean absolute error), FESD (Forecast error standard deviation), RMSPE (Root mean square percentage error) and MARD (Mean absolute relative deviation). Besides the magnitude measures, the directional measure is another important measurement for evaluating the accuracy in direction prediction. In practice, the accuracy in direction is sometimes more important than in magnitude for forecasting models. We use the accuracy ratio in directional, with two alternatives: “up” or “down”, as the assessment criterion for directional measure. When discussing the differenced data, we modify the accuracy ratio in two alternatives: “positive” and “negative”. As indicated by Curry et *al*, the criteria of model fit and residual correlation can give some indication as model specification and forecasting. Therefore, the model without forecasting residuals without serial correlations is expected to be better in dealing with external uncertainties.

The performance on rolling forecasting is used for verifying whether the proposed method is helpful to production prediction. The detailedindings of level model in semiconductor industry, the problem is different from the photonics industry (see Figure 5.3 and Table 5.4). In this case, it is noticeable that standard prior BVAR outperforms VAR but significantly underperforms AR. This outcome is consistent with previous results of causality test. Such a result can be explained as follows: Use of inappropriate hyperparameters or misspecification in the causality relationship by Granger Causality Test. The first reason may be that we use inappropriate hyperparameters (γ and ω) in BVAR estimation and need more hyperparameter settings for the estimation. However, the Litterman method is inherently informative and researchers need to try numerous hyper-parameterizations to get the best model. The latter reason means the causality between the semiconductor industry and other industries, provided by Granger Causality Test, is useless unhelpful in our forecasting. We attribute the latter reason to market globalization: The IC business cycle worldwide and the over 40% direct export of total production. Then we find that low-weighted prior BVAR produces amore satisfactory outcome than AR (1). Accordingly, Bayesian statistics still ensure a better forecasting result in the semiconductor industry.

Table 5.5: The Performance Comparison of AR, VAR, Standard BVAR and Low-weighted BVAR for Semiconductor Production Value (Four & Two Independent Variables, Log Transformation)

	Criteria	4-variable VAR (1)	2-variable VAR (1)	AR (1)	4-variable Standard Prior BVAR (2)	2-variable Standard Prior BVAR (1)	Low-weighted Prior BVAR (1)
Magnitude	RMSE	0.1029	0.1073	0.0929	0.0963	0.0975	0.0928
	Theil U	1.0272	0.8980	0.7775	0.8059	0.8159	0.7764
	MAE	0.0903	0.0926	0.0702	0.0796	0.0783	0.0701
	RMSPE	0.0459	0.0478	0.0413	0.0429	0.0434	0.0413
	MARD	0.0180	0.0184	0.0139	0.0159	0.0155	0.0139
	FESD	0.1027	0.1068	0.0873	0.0951	0.0953	0.0873
Direction	Accuracy in direction (%)	62.5%	75%	62.5%	75%	75%	75%
Residual	Serial correlation of Residual (Q-statistics)	No serial correlation	No serial correlation	No serial correlation	No serial correlation	No serial correlation	No serial correlation

Note:

1. "Accuracy in direction ratio" the ratio that the model predicts accurate direction in two alternatives: "up" or "down".
2. The Serial correlation of residual is verified by Ljung-Box Q statistics of every lag under α=0.05.
3. There is seldom difference between 4-variable model and 2-variable model Low-weighted BVAR estimation. So we put the 2-variable Low-weighted BVAR as a representative of both.

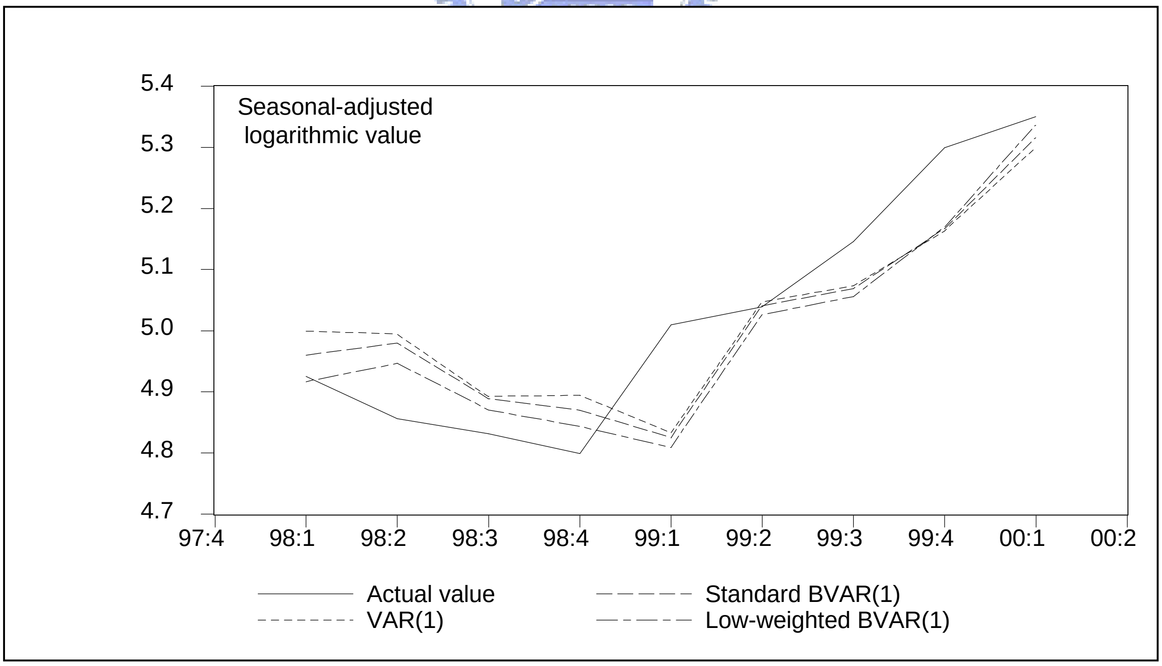

Figure 5.3: The Actual Values and Forecasting Values of Semiconductors Industry (1998:Q1-2000:Q1)

5.6 Another Approach for Semiconductor Industry

5.6.1. Dependent and Independent Variables Collection

As a result of Section 5.5, we consider another prior to the BVAR model and other appropriate candidates to modify our model**.**

The production values of these three Taiwan's industries are shown in Figures 5.4, 5.5 and 5.6. The definitions of these three industries are as follows (MOEA, 2000a): The computer manufacturing industry covers desktop computers, portable computers (including laptops, PDAs). The computer components industry includes network equipment, servers, wiring concentrators, PC-LAN, network cards, fax cards, memory extension cards, graphic cards, control cards, ISDN cards, sound cards, and other interface cards. The semiconductor industry includes wafers, masks, IC packages, IC foundry, IC manufacturing, diodes, transistors, and lead frames.

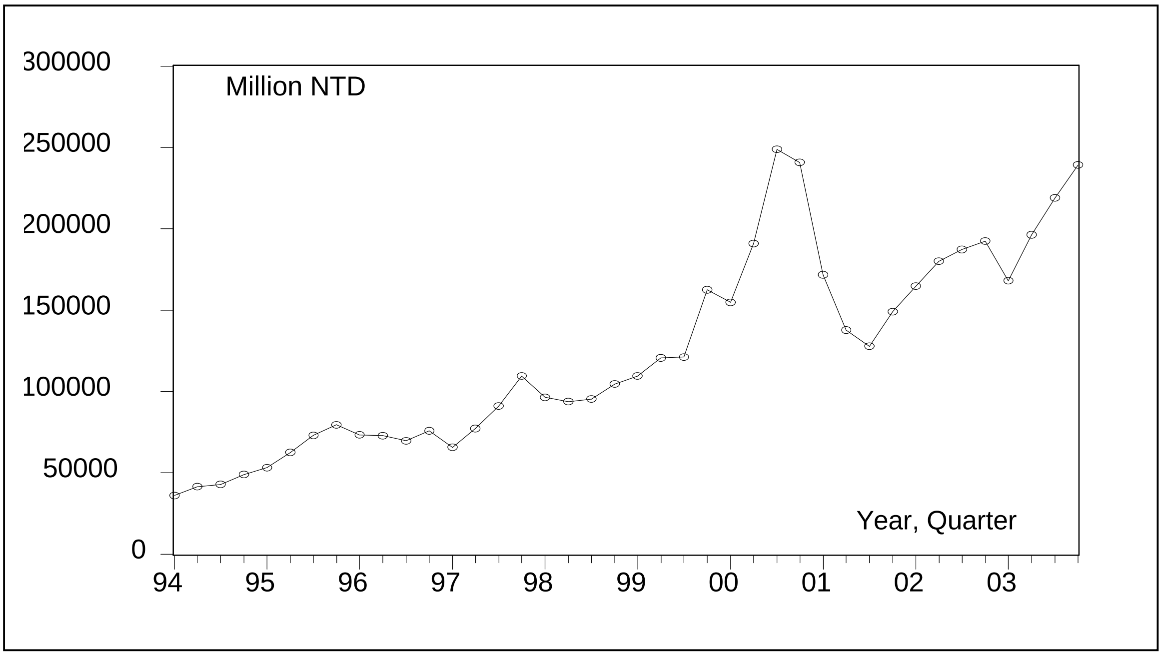

Figure5.4. Production Value of Taiwan's Semiconductor Industry

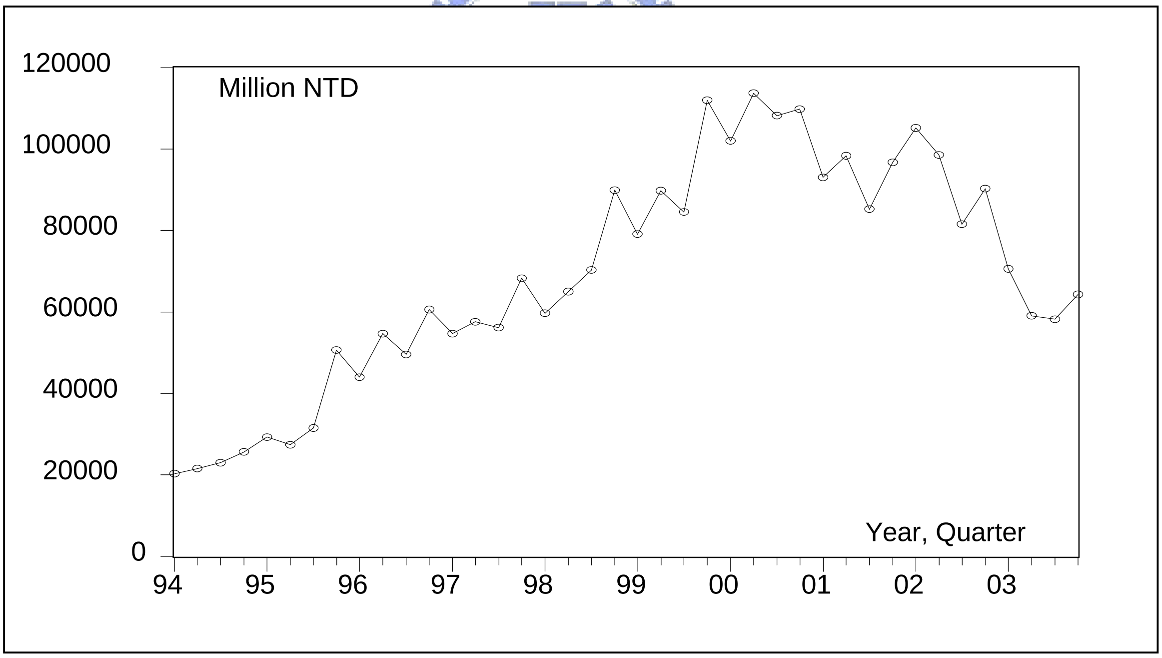

Figure5.5. Production Value of Taiwan's Computer Manufacturing Industry

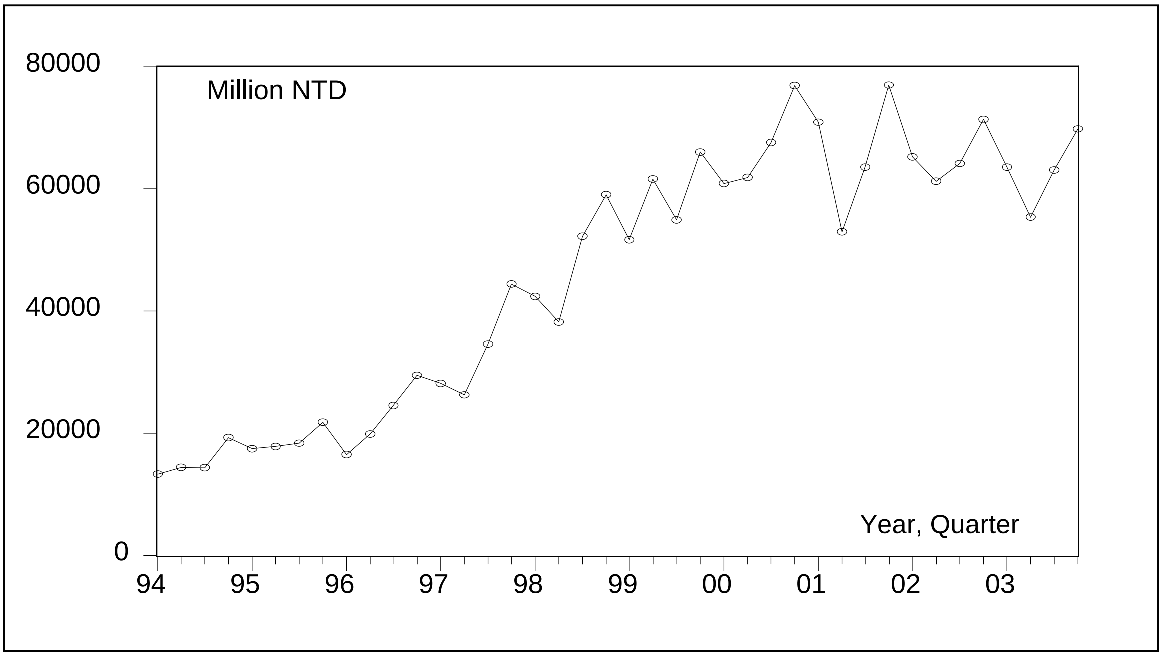

Figure5.6. Production Value of Taiwan's Computer Components Industry

The pre-processing as same as section 5.2, transforms all production values into natural-log values. This procedure aims to make the time series more stationary in variance and trend. Subsequently, we observed the evident seasonality in the three logarithmic series. We took X-11 seasonal adjustment before modeling instead of using seasonal dummy variables in these models. Such a pre-deseasonalization is preferable in the BVAR models because a series with a seasonal factor will produce significance in high-lag coefficients that makes inefficient parameterization (e.g., Doan, 1992; Hamilton, 1994; Ravishanker & Ray, 1997).

After being adjusted as above, production from Taiwan's semiconductor and computer manufacturing industries were estimated and predicted by using the AR, VAR, LBVAR, and DBVAR models. For VAR, LBVAR and DBVAR models, three production series were used together. We considered 4-lag (one year), 2-lag (half year) and 1-lag (1 quarter) in our model setting. This means that we estimated the parameters and then performed prediction in the AR(1), AR(2), AR(4), VAR(1), VAR(2), VAR(4), and so on. This is because a one-year model is presumably long enough to describe the interactions between industries. For the same reason, one half-year and one quarter are also possible and were considered in our model settings as well. In LBVAR model, we used the standard prior (γ =0.2, ω=0.5) according to the experience of Litterman (1986) and Doan (1992). In DBVAR model, we used the non-informative diffuse-prior proposed by Tiao and Zellner (1964) and Geisser (1965).

The forecasting performance of all models is summarized in Table 5.6. Here we provided only the performance of 1-step ahead and 4-step ahead forecasts. The 2- and 3-step ahead forecasts are similar, eliminating the need to address them. To examine the model forecasting performance, we considered all of the criteria in 1-step ahead forecasting, but used only the RMSE and MAE in 4-step ahead forecasting. This is because the Theil U and directional accuracy is inappropriate in multi-step ahead forecasting. Note that, in this part, all these results are based on the performance measure between model predictions and adjusted real data, not unadjusted real data.

We first checked the results in semiconductor industry case: In 1-step ahead forecasting, the DBVAR class provides significantly better predictions than all of the other model classes. It is noteworthy that all DBVAR models produce less-than-one statistics in Theil U, but the LBVAR(2) and LBVAR(4) models barely beat the random walk with 0.961 and 0.959 Theil U statistics, respectively. The directional accuracy basically describes the same outcome. In 4-step ahead forecasting, the DBVAR class also significantly outperforms the other model classes. Among the three DBVAR models, the DBVAR(4) model is the best in 1-step ahead forecasting, and the DBVAR(1) is superior to the others in 4-step ahead forecasting.

Table 5.6. Summary of Model Forecasting Performance

	Semiconductor Industry					
	1-step ahead				4-step ahead	
	RMSE	Theil U	MAE	Directional accuracy	RMSE	MAE
AR(1)	0.153	1.089	0.121	50%	0.599	0.427
AR(2)	0.142	1.008	0.108	60%	0.630	0.480
AR(4)	0.151	1.077	0.118	60%	0.593	0.441
VAR(1)	0.173	1.235	0.148	50%	0.494	0.353
VAR(2)	0.189	1.348	0.143	70%	0.472	0.355
VAR(4)	0.306	2.183	0.234	55%	1.983	0.826
LBVAR(1)	0.148	1.052	0.116	55%	0.516	0.375
LBVAR(2)	0.135	0.961	0.105	65%	0.482	0.361
LBVAR(4)	0.135	0.959	0.103	70%	0.472	0.357
DBVAR(1)	0.101	0.817	0.093	75%	0.268	0.209
DBVAR(2)	0.098	0.782	0.084	75%	0.282	0.216
DBVAR(4)	0.094	0.758	0.083	80%	0.402	0.327

Here we summarize findings from Table 5.6 as follows: First, the VAR class performs badly under Theil U criterion, which implies that VAR models cannot beat the random walk. We explained this result as evidence of the inability of the VAR class in unstable dynamics. Second, if the DBVAR class were neglected, we would find that the LBVAR class provides better prediction than the AR and VAR classes. This is consistent with a previous study that presented the advantage of LBVAR models in comparison with the classical AR and VAR models (Hsu et *al*., 2003). The outcome that both Bayesian classes are better than AR and VAR classes in forecasting validates our proposition that the Bayesian forecasts are good in volatile dynamics. Third, the LBVAR models perform almost as badly as random walks in Theil U criterion in our sample, making it an unsatisfactory approach. This outcome confirms the merit of the DBVAR models in producing good predictions, even in the turbulent 2001 and 2002 years. Finally, we found that it was difficult to identify the best among three DBVAR models. For example, DBVAR(4) performs best in 1-step ahead forecasting but performs worse in 4-step forecasting for the semiconductor industry. We will consider all three DBVAR models in comparison with forecast reports from leading market information providers.

5.6.2 Some Comparisons with the Industrial Technology Research Institute's (ITRI) Prediction on Semiconductor Production

In Section 5.6.1, we showed that the DBVAR models outperform parallel models. However, those results will be pointless if all competitive models are poor predictors. To validate the feasibility of our method, we conducted a comparison between our NDBVAR forecasts and popular forecasting reports. The leading market information provider in the semiconductor market in Taiwan is the Industrial Technology Research Institute (ITRI). ITRI has several divisions pertaining different industries and publishes a series of market and technology reports. ITRI provides production predictions for the semiconductor industry and other electronic industries in the second quarter of each year. Its report is one of the most authoritative indicators for industry people. ITRI's forecasting methodology is based on two sources: global market reports by international market research institutes, like the Semiconductor Industry Association (SIA), and expert surveys within Taiwan.

Here we use ITRI's annual growth rate forecasts as the benchmark in assessing our predictive method. The growth rate of realized data, ITRI's prediction, and DBVAR 1-year ahead predictions are presented in Table 5.7 and Figures 5.7, 5.8 & 5.9. Note here that our 1-year ahead predictions are based on previous data only and then make 1-, 2-, 3-, and 4-step ahead forecasts for the next year. For example, to make 1-year ahead predictions for 2001, we use data from 1996 Q1 to 2000 Q4 to make 1-, 2-, 3-, and 4-step ahead forecasts for Q1, Q2, Q3, and Q4 of 2001 respectively. Summing these numbers and adjusting them by seasonal factors and exponential transformation, we make forecasts for 2001 annual production and growth rate. It is appropriate to say that the DBVAR's 1-year ahead predictions are competitive with ITRI's reports in several aspects: First, the MAEs of DBVAR(1), DBVAR(2) and DBVAR(4) are significantly less than ITRI's prediction (we use MAE only because RMSE is not an appropriate measure for annual growth rate). Second, ITRI's predictions tend to overshoot because of that suffer from market atmosphere (i.e., when there was a market surge in 1997, ITRI analysts tended to be more optimistic in the following year. 1998 is an example). Instead, our method is not or is less affected by market emotion and optimism. Third, in grabbing the tipping points, like 1998 and 2001, our method is as good as ITRI. Finally, our 1-year ahead forecasting was actually better because ITRI's forecasts include information from the first quarter. However, that is not a claim that our method beats ITRI's professional judgment. Instead, we would declare that we provide a quantitative forecasting approach to complement ITRI's reports.

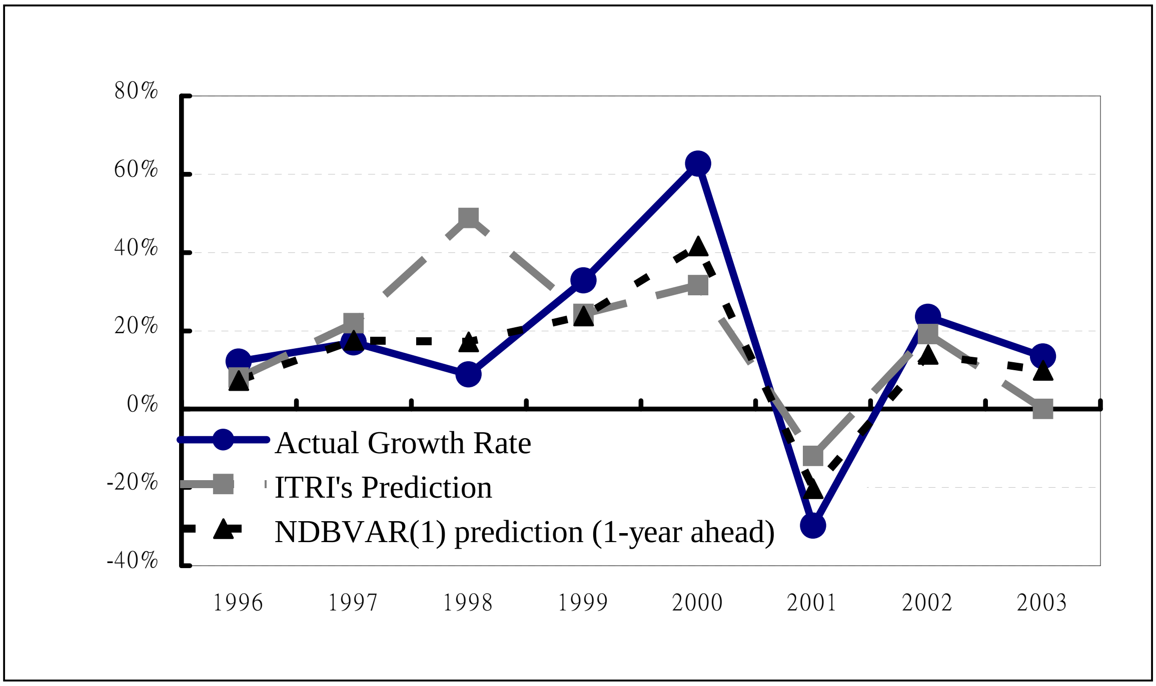

Figure5.7. DBVAR(1) vs. ITRI's Predictions for Taiwan's Semiconductor Industry

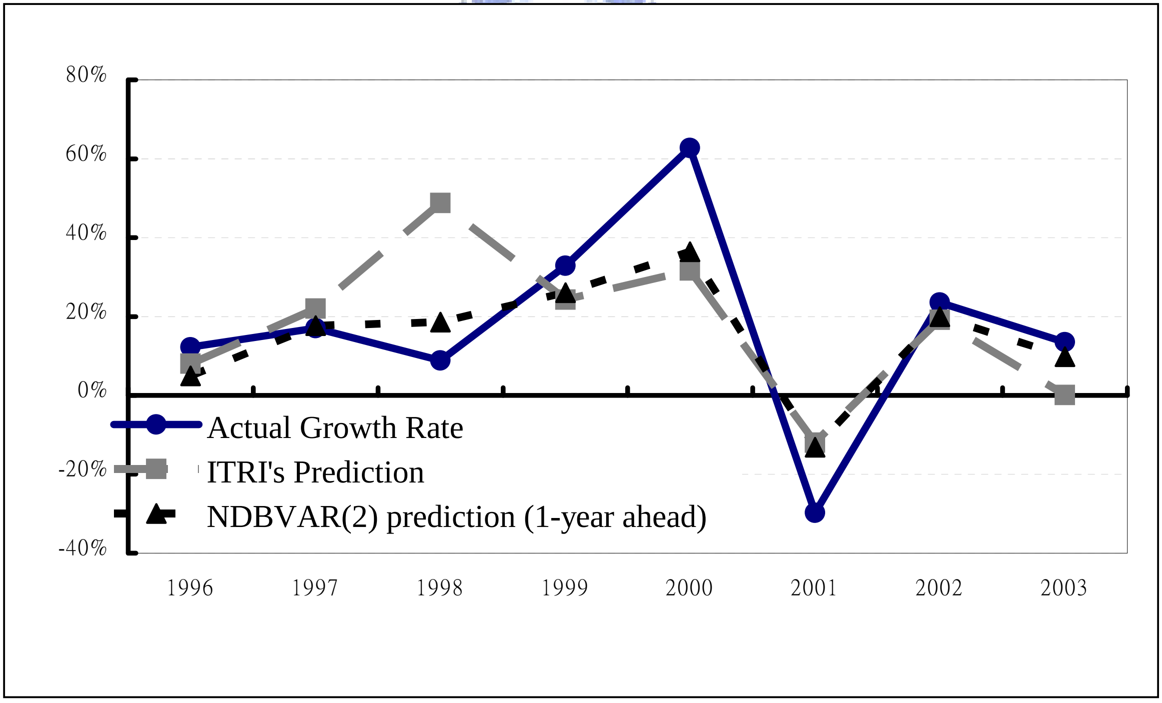

Figure5.8. DBVAR(2) vs. ITRI's Predictions for Taiwan's Semiconductor Industry

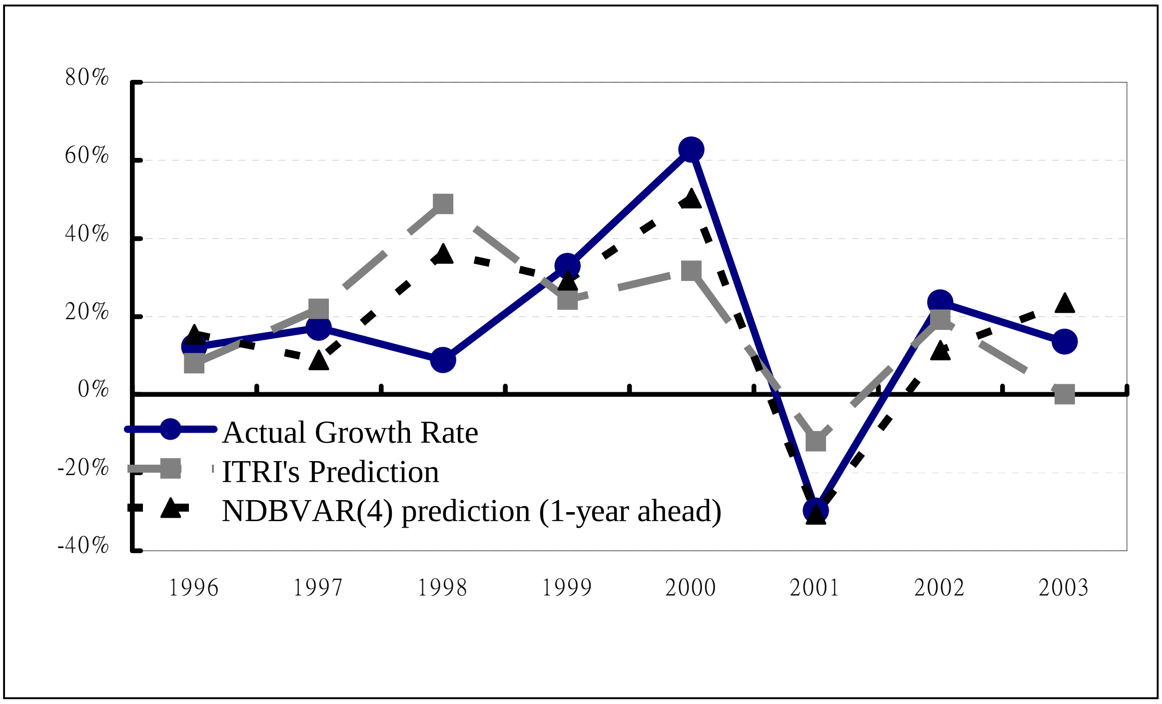

Figure5.9. DBVAR(4) vs. ITRI’s Predictions for Taiwan’s Semiconductor Industry

Table5.7. Growth Rate in Semiconductor Industry Production: Real Data, ITRI's Prediction, and DBVAR's Prediction

	1996	1997	1998	1999	2000	2001	2002	2003	MAE
Actual Growth Rate1	12.2 %	17.1 %	8.8 %	32.9 %	62.7%	-29.8%	23.6%	13.5%	-
ITRI's Prediction2	8.0 %	22 .0%	48.8 %	24.3 %	31.7%	-12.0%	19.2%	0.02%	0.155
DBVAR(1)3	7.3 %	17.6 %	17.2 %	23.8%	41.7%	-20.3%	14.0%	9.9%	0.082
DBVAR(2)3	4.9 %	17.7 %	18.6 %	26.1%	36.5%	-13.2%	20.0%	9.8%	0.092
DBVAR(4)3	15.5 %	8.9 %	36.2 %	29.3%	50.4%	-30.7%	11.4%	18.6%	0.096

Note:

1. The actual growth rate of production value is from AREMOS database based on the official publications of Ministry of Economic Affairs (MOEA), Taiwan.
2. The forecasts are from ITRI's publications (1997, 1998, 1999), ITRI analysts' reports (Wang, 1996; IEK, 2001; Chang, 2002; Hsieh, 2003), and other government publication that includes ITRI's forecasts (MOEA, 2000b).
3. All listed DBVAR forecasts are 1-year ahead prediction.

5.7 Power Transformation Approach for Semiconductor Industry

Form Section 5.5 and 5.6, we see that the BVAR model is superior to the other time series model. It is not only more precise in forecasting, but it can also catch the inflection time point. In this section, we consider another transformation which is different form Log transformation and moving average. This method is called power transformation, and it can stabilize variance.

Box, Jenkins and Reinsel (pp. 99 & 358-359, 1994) suggested using the Box-Cox power transformation (Box & Cox, 1964) for establishing an appropriate time series model. Power transformation's effect in univariate time series forecasts has been widely examined for decades (e.g., Nelson & Granger, 1979; Hopwood et *al*., 1984; Nazmi & Leuthold, 1988; Lee & Tsao, 1993; Guerrero, 1993; Chen & Lee, 1997; McKenzie, 1999). However, power transformation's effect in multivariate time series is still untouched in the literature. Therefore, in this article, we examine the predictive capabilities of power transformation and log-transformation in vector autoregressive (VAR) and Bayesian VAR (BVAR) forecasts, with a view to validating power transformation's advantage in practice.

We examine a technology industrial cluster in Taiwan which includes four close dependent industries with high growth is another noteworthy case of BVAR forecasting (Lee et *al.*, 2000; Hsu et *al.*, 2000). In this study, Taiwan's technology industrial cluster includes four industries: semiconductor industry, personal computer (PC) manufacturing industry, computer components industry, and other electronics parts industry. The production values of these four industries are collected from the Department of Statistics, Ministry of Economic Affairs (MOEA), and Taiwan. The production data are collected from 1990 Q1 to 2000 Q1, for a total of 43 quarterly observations. The quarterly data are season-adjusted through X-11 method. To set up a stable power in comparison to log-transformation, we estimate the power using all 43 observations. The lag number of power transformation, VAR, and BVAR models are set to be 1 according to our experience (Lee et *al.*, 2000; Hsu et *al.*, 2000). That implies we estimate the power of each data series separately by using AR(1). Then the transformed data is utilized for VAR(1) and BVAR(1) modeling and forecasts. The constant term is also included.

We compare the predictive performance of the log-transformation and the power transformation based on one-step ahead rolling forecast. We found our comparison on one-step ahead forecasts feasible for the reason that rational predictors will adaptively adjust the forecasting based on the newest information. The parameters of VAR and BVAR models are re-estimated to forecast the *i*th forecasts based on data available in *(i-1)*-th the period. In Taiwan's technology industrial cluster case, we examine the performance of the latest 19 observations (1996 Q1 to 2000 Q1). Each one-step ahead forecast is obtained by re-estimating the parameters of VAR and BVAR models by using previous 20 observations (5-year). The magnitude measures for gauging the performance include the root of mean square error (RMSE), the Theil U statistic, and the mean absolute error (MAE).

In the case of Taiwan's technology industrial cluster, we estimated the power to be as **0.64** for semiconductors. Predictive results are shown in Table 5.8. The predictive performance of the power transformation is better than the log-transformation. In semiconductors, the performance of the power transformation overwhelms the log-transformation in all three models.

Table 5.8: Comparing Box-Cox Power Transformation with Log-Transformation in Taiwan Technology Industrial Cluster Production: VAR and BVAR forecasts

Semiconductors				
	Transformation	**RMSE**	**Theil U**	**MAE**
VAR(1)	Log	16171.55	0.87	10861.42
	Power	14549.35	0.78	10198.37
BVAR(1) (Litterman)	Log	15061.35	0.81	10842.67
	Power	14905.70	0.80	10761.85
BVAR(1) (Non-informative)	Log	13127.25	0.71	9605.21
	Power	10018.24	0.54	8021.98

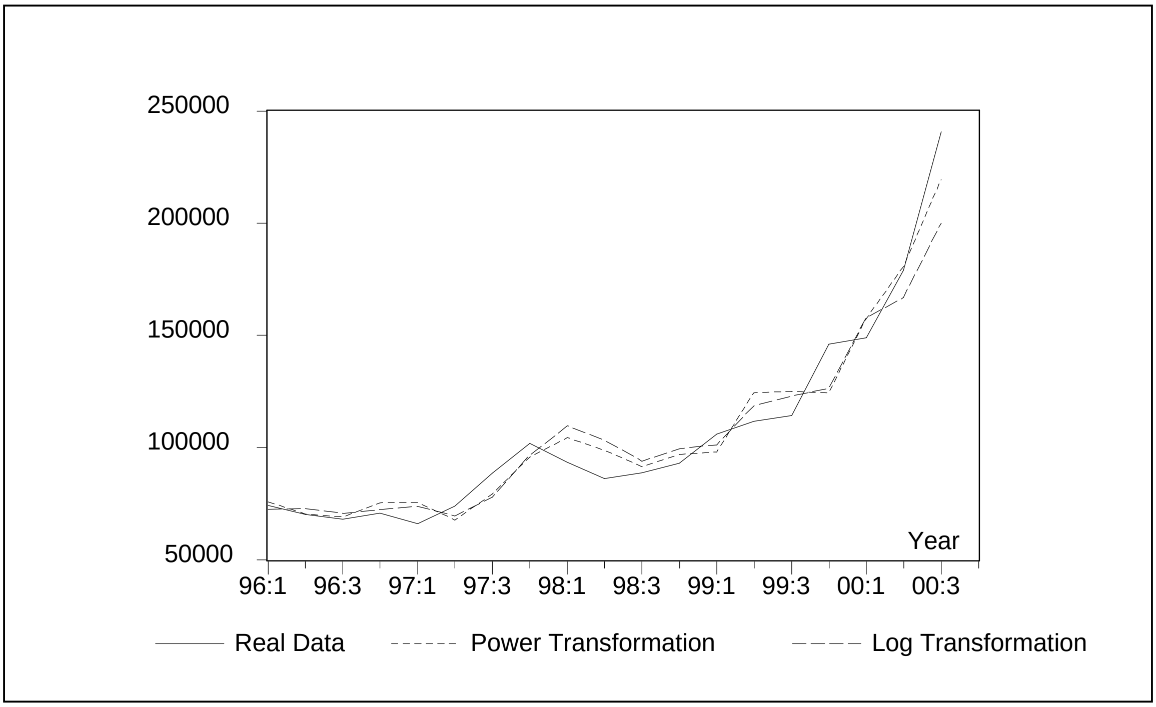

Figure 5.10: One-Step Ahead Non-Informative BVAR Forecasts for Semiconductors Production.

5.8 Finding and Discussion

In this section, we utilized the BVAR model with two different transformations to predict industrial production of high technology industries based on industrial clusters. In our experiment, the semiconductor industry's development seems unaffected by other local industries in Taiwan from our first study. The results of the first forecasting experiment show that in the semiconductor industry case the VAR prediction may underperform the naive AR model if its covered series are less effective. We may therefore conclude that when the intended series is dependent on other series, the standard prior BVAR model is recommendable. Otherwise, lower-weighted prior BVAR is preferable in production prediction. In the second forecasting experiment, we find more appropriate candidates, which position downstream to the semiconductor industry, and other prior distribution to modify our model. It was shown that the DBVAR model could outperform other time series models including LBVAR, VAR and AR models in production forecasting for technology industries. In the other words, we developed a better forecasting method than the one we discussed in the previous section, which is constructive to relevant studies like forecasting research and technology management. Moreover, our method provided better or as good prediction in compared to authoritative forecasts from leading market information providers. In the third forecasting experiment, we also show that the non-informative prior BAVR model generates better forecasts than Litterman prior BVAR model and VAR model, either in log-transformation or in power transformation. The superior performance of non-informative prior BAVR forecasting method is further confirmed in this study.

Overall, the newly proposed model approach is more efficient accurate proposed which contributes the following advantages. We find that the DBVAR model, with its short lag order, provides striking performance. Furthermore, the BVAR model is capable of dynamic analysis in industrial clusters and performs superior production prediction in magnitude. Our results provide a successful exploration of the semiconductor industry by multivariate time series models.

6. Using Four Forecasting Models to Forecast of Total Production Output of Taiwan's Computer manufacturing

Form section 4 and section 5, we find BVAR model provide more precision to forecast two industries which are photonic and semiconductor. In this section, we examined the feasibility of our method by considering empirical case of Taiwan's technology industries "computer manufacturing industry". We have good reasons for considering this industry. First, it has been main players in global markets over the previous 10 years, so our experiment will be meaningful to researchers and practitioners from other countries. Second, while reviewing the history of this industry, its prosperity can be attributed to a strong clustering effect within Taiwan (e.g., Mathews, 1997; Chang & Hsu, 1998). To validate our proposition, we checked the predictive abilities of a series of autoregressive (AR) systems including univariate AR, vector autoregressive (VAR), Litterman BVAR (LBVAR), and DBVAR models. The result shows that, the DBVAR models provide more accurate predictions than all of the other competitive models. Moreover, we find that DBVAR forecasts offer favorable results in comparison with the forecast reports from leading market information providers in Taiwan: the Institute for Information Industry (III) in computer manufacturing industry. We therefore confirmed that the proposed forecasting method is of practical merit in this case.

6.1 Dependent and Independent Variables

Our empirical study aims to examine the predictive performance of our proposed method by using two benchmarks. The first benchmark is the predictability of other time series models (AR, VAR, and LBVAR) used in Hsu et *al*. (2003). The second benchmark is the forecast reports from the leading market information provider, the III, in Taiwan.

The production values from all industries are available in the AREMOS database that collects data from the Department of Statistics, Ministry of Economic Affairs (MOEA) publications in Taiwan. These values are presented in monetary units (New Taiwan Dollars, NTD$). The data frequency is the yearly quarter as used in Tseng et *al*. (1999), Hsu et *al*. (2003), and Chang et *al*. (2003). Our reason is that the monthly data are too short for evaluating industrial production and the annual data are too long to appropriately describe the unstable dynamics and explosive growth of technology industries. We collected the production values for each industry for the past 10 years (1994 Q1-2003 Q4), with a total of 40 sample points for each industry.

When considering multivariate time series models including VAR, LBVAR and DBVAR models, we had to determine which variables are beside computer manufacturing industry. Based on the industrial clustering argument, we suggested that the computer components industry, positions downstream to the semiconductor industry and upstream from computer manufacturing industry, would be an appropriate candidate. When checking the supply chain of Taiwan's technology industries, one can find that the entire chain is demand-driven: Taiwan's computer manufacturers obtain OEM or ODM orders from big brands like Dell and IBM, and then purchase components like the chip sets and cards from component manufacturers. The main materials used in fabricating computer components are ICs that are supplied by the semiconductor industry. Although there are still some industries related to semiconductor and computer manufacturing industries, we did not cover them in this study for simplicity and parsimonious principle in parameter usage. As a result, there will be three time series included in VAR, LBVAR, and DBVAR models and forecasts the production values of Taiwan's semiconductor, computer manufacturing, and computer components industries simultaneously.

The production values of these three Taiwan's industries are shown in Figures 6.1, 6.2 and 6.3. The definitions of these three industries are as follows (MOEA, 2000a): The computer manufacturing industry covers desktop computers, portable computers (including laptops, PDAs). The computer components industry includes network equipment, servers, wiring concentrators, PC-LAN, network cards, fax cards, memory extension cards, graphic cards, control cards, ISDN cards, sound cards, and other interface cards. The semiconductor industry includes wafers, masks, IC packages, IC foundry, IC manufacturing, diodes, transistors, and lead frames.

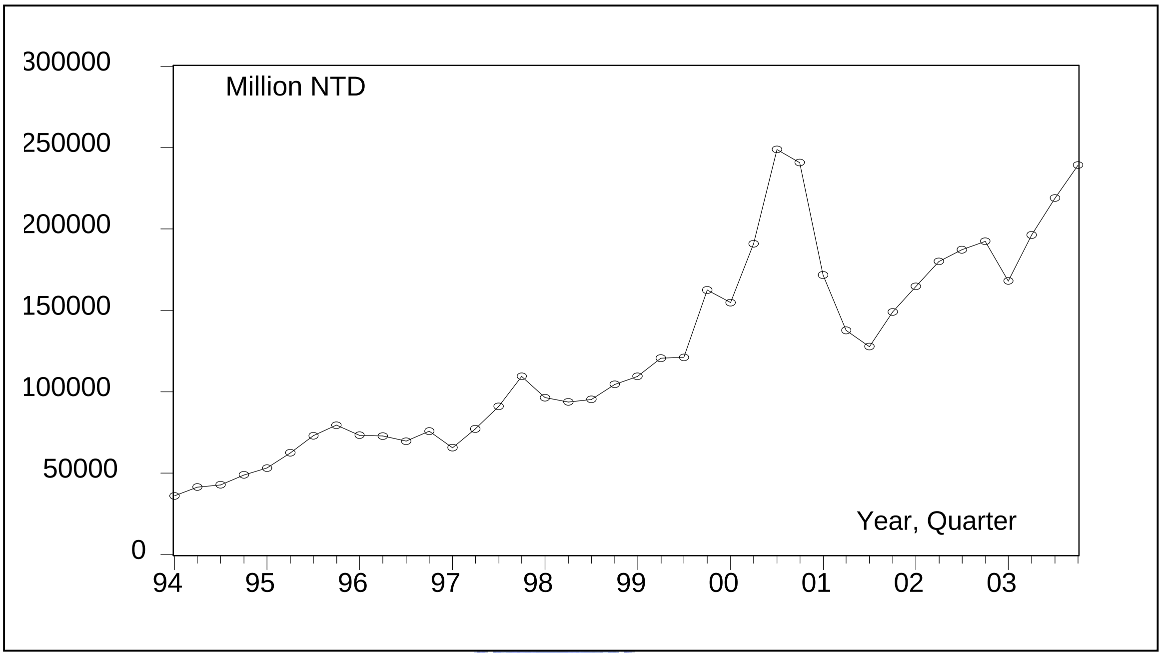

Figure 6.1. Production Value of Taiwan's Semiconductor Industry

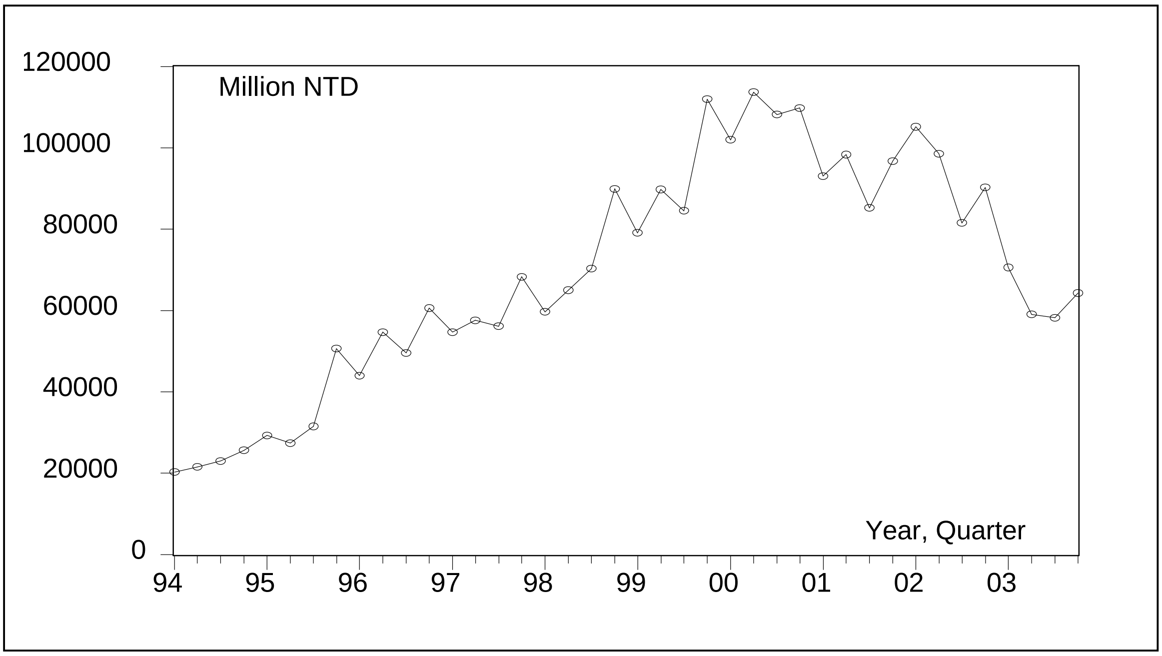

Figure 6.2. Production Value of Taiwan's Computer Manufacturing Industry

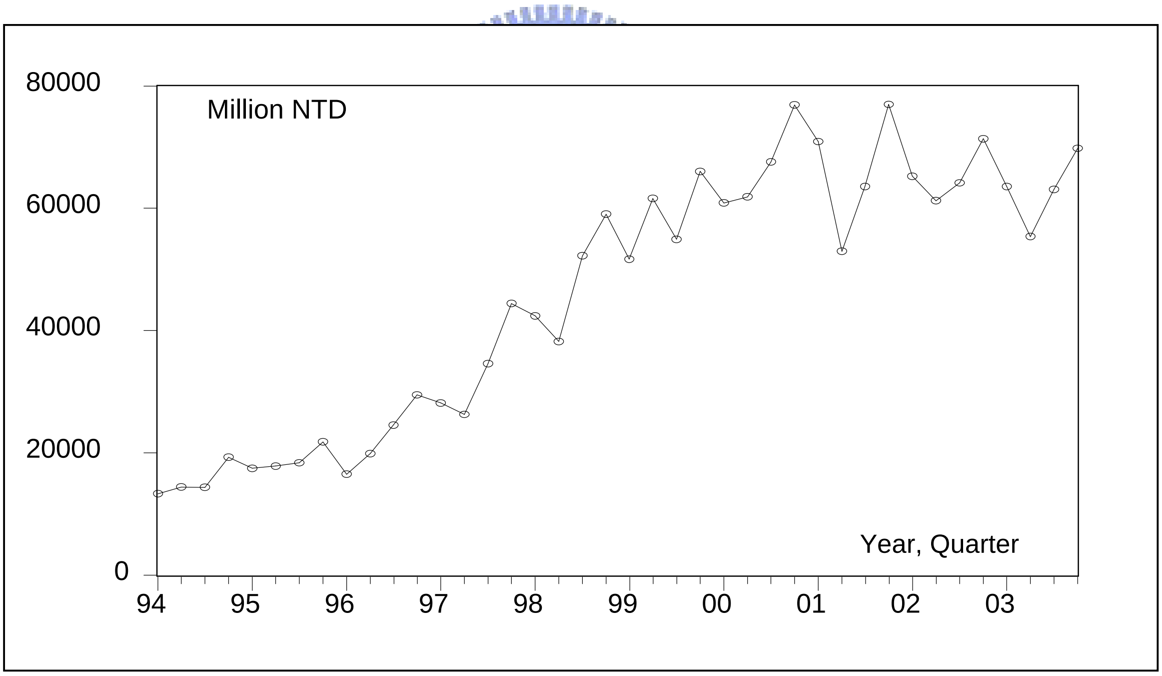

Figure 6.3. Production Value of Taiwan's Computer Components Industry

6.2 Pre-processing of Dependent and Independent Variables

The production values were adjusted by using two procedures before being put into estimation and forecasting: logarithmic transformation and seasonal adjustment. Both procedures were commonly used in relevant studies. First, we observed the exponential growth trend in Figures 6.1, 6.2, & 6.3, and then transform all production values into natural-log values. This procedure aims to make the time series more stationary in variance and trend. Subsequently, we observed the evident seasonality in the three logarithmic series. For example, because of customers' shopping behavior, the production value of computer manufacturing industry in Q4 is always better than the coming Q1. We took X-11 seasonal adjustment before modeling instead of using seasonal dummy variables in these models. This means that we use the census X-11 additive method first to produce deseasonalized series. Such a pre-deseasonalization is preferable in the BVAR models because a series with a seasonal factor will produce significance in high-lag coefficients that makes inefficient parameterization (e.g., Doan, 1992; Hamilton, 1994; Ravishanker & Ray, 1997).

6.3 The Lag Order Selection Procedures

After being adjusted as above, the productions from Taiwan's semiconductor and computer manufacturing industries were estimated and predicted by using the

AR, VAR, LBVAR, and DBVAR models. For AR, the univariate time series model, we performed individual estimating and forecasting of each series. For VAR, LBVAR and DBVAR models, three production series were used together. We considered 4-lag (one year), 2-lag (half year) and 1-lag (1 quarter) in our model setting. This means that we estimated the parameters and then performed prediction in the AR(1), AR(2), AR(4), VAR(1), VAR(2), VAR(4), and so on. This is because that a one-year model is presumably long enough to describe the interactions between industries. For the same reason, one half-year and one quarter are also possible and were considered in our model settings as well. In LBVAR model, we used the standard prior (γ =0.2, ω=0.5) according to the experience of Litterman (1986) and Doan (1992). In DBVAR model, we used the non-informative diffuse-prior proposed by Tiao and Zellner (1964) and Geisser (1965). The implementation of AR, VAR, and LBVAR models is simple and ready in several software packages, like RATS. Doan's (1992) guide for RATS is ready and complete. The codes to implement DBVAR model are available upon request.

In evaluating the model forecasting performance, we checked both the magnitude and directional measures. The magnitude measures include the root mean square error (RMSE), Theil U statistics, and mean absolute error (MAE) as Hsu et *al*. (2003). We examined the prediction performance in 1-, 2-, 3- and 4-step ahead situation. In multi-step ahead situations (2-step ahead to 4-step ahead), we used dynamic forecasting and recorded the error measures in terms of the end forecasts. For example, we made 4-step ahead forecasting based on the known data in 2001 Q4, and collected forecasting errors in the 2002 Q4 (i.e., the 1-, 2-, and 3-step ahead forecasts are neglected). The directional measure is another important measurement for evaluating the prediction accuracy. Actually, in practice, the capability for predicting the tipping point is sometimes more crucial than providing a smaller error magnitude. We used a measure named "directional accuracy" that indicates the percentile of correct model prediction regarding whether the future movement will be up or down. We believe this criterion serves as a good complementary for traditional magnitude-measured criteria in justifying how good the predictive models are.

6.4 Assessment of Forecast Results

The forecasting performance of all models is summarized in Table 6.1. Here we provided only the performance of 1-step ahead and 4-step ahead forecasts. The 2- and 3-step ahead forecasts are similar eliminating the need to address them. To examine the model forecasting performance, we considered all of the criteria in 1-step ahead forecasting, but used only the RMSE and MAE in 4-step ahead forecasting. This is because the Theil U and directional accuracy is inappropriate in multi-step ahead forecasting. Note that, in this part, all these results are based on the performance measure between model predictions and adjusted real data, not unadjusted real data.

We checked the results in the computer manufacturing industry: In 1-step ahead forecasting, the DBVAR class surpasses all of the other model classes, and is the only one model class to provide less-than-one Theil U statistics. In 4-step ahead forecasting, the DBVAR class marginally outperforms the LBVAR and AR classes.

Here we summarize findings from Table 6.1 as follows: First, the VAR class performs badly under Theil U criterion, which implies that VAR models cannot beat the random walk. We explained this result as evidence of the inability of the VAR class in unstable dynamics. Second, if the DBVAR class were neglected, we would find that the LBVAR class provides better prediction than the AR and VAR classes. This is consistent with a previous study that presented the advantage of LBVAR models in comparison with the classical AR and VAR models (Hsu et *al*., 2003). The outcome that both Bayesian classes are better than AR and VAR classes in forecasting validates our proposition that the Bayesian forecasts are good in volatile dynamics. Third, the LBVAR models perform almost as bad as random walks in Theil U criterion in our sample, making it an unsatisfactory approach. This outcome confirms the merit of the DBVAR models in producing good predictions, even in the turbulent 2001 and 2002 years. Finally, we found that it was difficult to identify the best among three DBVAR models. For example, DBVAR(4) performs best in 1-step ahead forecasting but performs worst in 4-step forecasting for the semiconductor industry. We will consider all three DBVAR models in comparison with forecast reports from leading market information providers.

Table 6.1. Summary of Model Forecasting Performance

	Computer Manufacturing Industry					
	1-step ahead				**4-step ahead**	
	RMSE	Theil U	MAE	Directional accuracy	RMSE	MAE
AR(1)	0.116	1.165	0.093	35%	0.268	0.221
AR(2)	0.120	1.211	0.101	35%	0.286	0.232
AR(4)	0.125	1.257	0.101	45%	0.329	0.288
VAR(1)	0.119	1.200	0.099	70%	0.323	0.261
VAR(2)	0.163	1.642	0.129	55%	0.404	0.301
VAR(4)	0.229	2.299	0.186	40%	0.383	0.322
LBVAR(1)	0.107	1.075	0.091	40%	0.276	0.229
LBVAR(2)	0.104	1.048	0.088	50%	0.280	0.225
LBVAR(4)	0.107	1.073	0.091	50%	0.284	0.235
DBVAR(1)	0.088	0.880	0.075	65%	0.240	0.192
DBVAR(2)	0.079	0.832	0.068	70%	0.260	0.210
DBVAR(4)	0.058	0.726	0.050	75%	0.253	0.218

6.4 Some Comparisons with the Institute for Information Industry's (III) Prediction on Computer Manufacturing Production

The leading market information provider of Taiwan's computer manufacturing industry is the Institute for Information Industry (III), which plays a pivotal role in Taiwan's information technology (IT) industries. III publishes production predictions for all information technology (IT) industries including the computer manufacturing industry every second quarter. This report is important references for industry people. III's forecasts are based on two sources: international market research institutes like IDC, and expert surveys within Taiwan as well.

Here we use III's forecasts on the annual growth rate as the benchmark to examine our predictive method. The growth rate for realized data, III's prediction, and DBVAR 1-year ahead predictions are presented in Table 6.2 and Figure 6.4, 6.5 &6.6. The DBVAR forecasts were obtained following the same procedure in the semiconductor case. Again, it is appropriate to say that the DBVAR's 1-year ahead predictions compare favorably to III's reports in three aspects: First, the MAEs of DBVAR(1), DBVAR(2), and DBVAR(4) are much less than III's prediction. Second, in catching the temporary bump in 2001-2002, DBVAR(1) and NDBVAR(2) forecasts are as good as III's. The DBVAR (4) forecast is even better than III's. Finally, our 1-year ahead forecasting is actually better because III's forecasts include first quarter information. Therefore, it is fair to say that our method has been confirmed as a valid approach, not only in forecasting research but also in practice as this case.

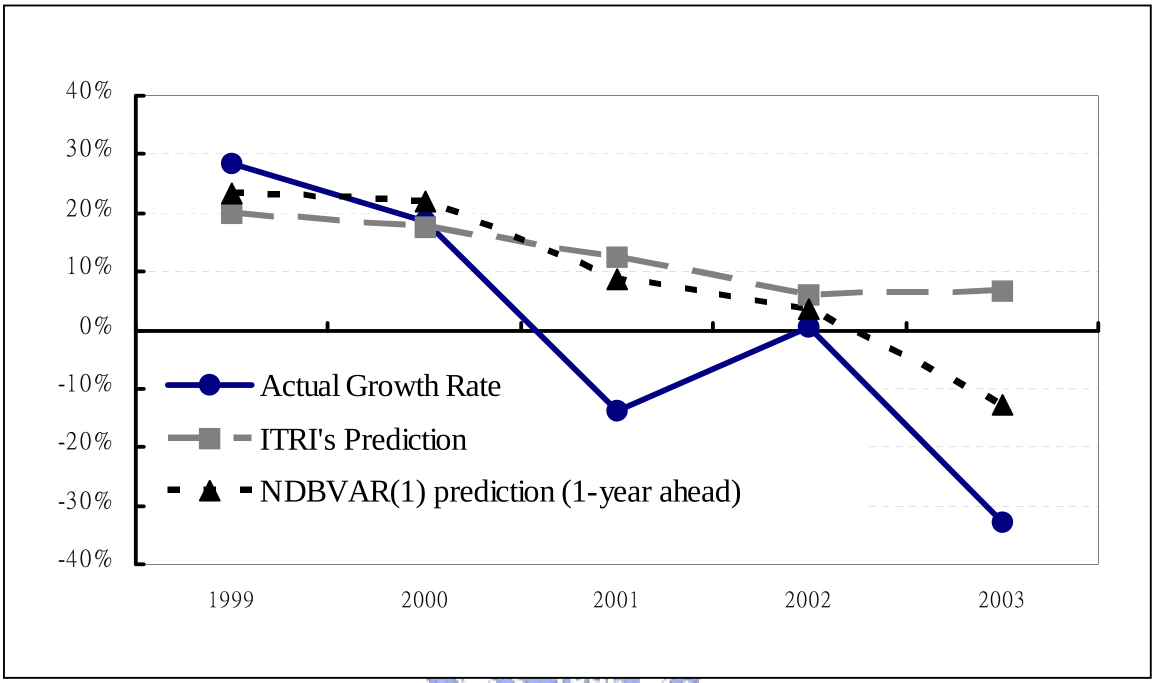

Figure6.4. DBVAR(1) vs. III's Predictions for Taiwan's Computer Manufacturing Industry

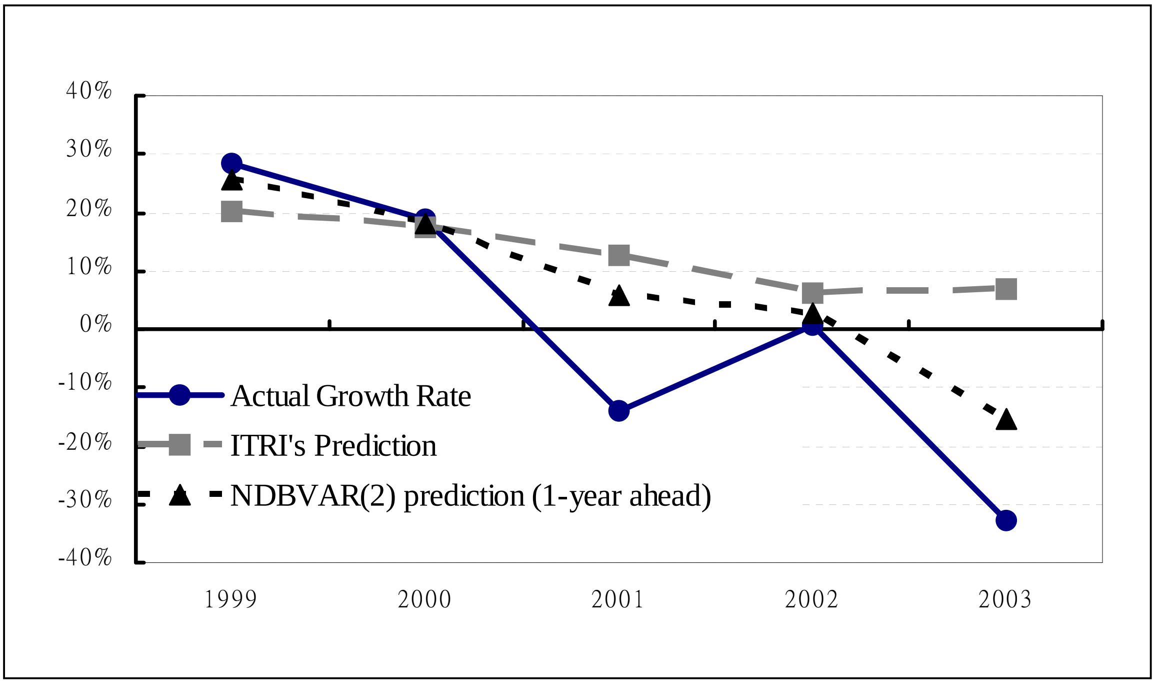

Figure 6.5. DBVAR(2) vs. III's Predictions for Taiwan's Computer Manufacturing Industry

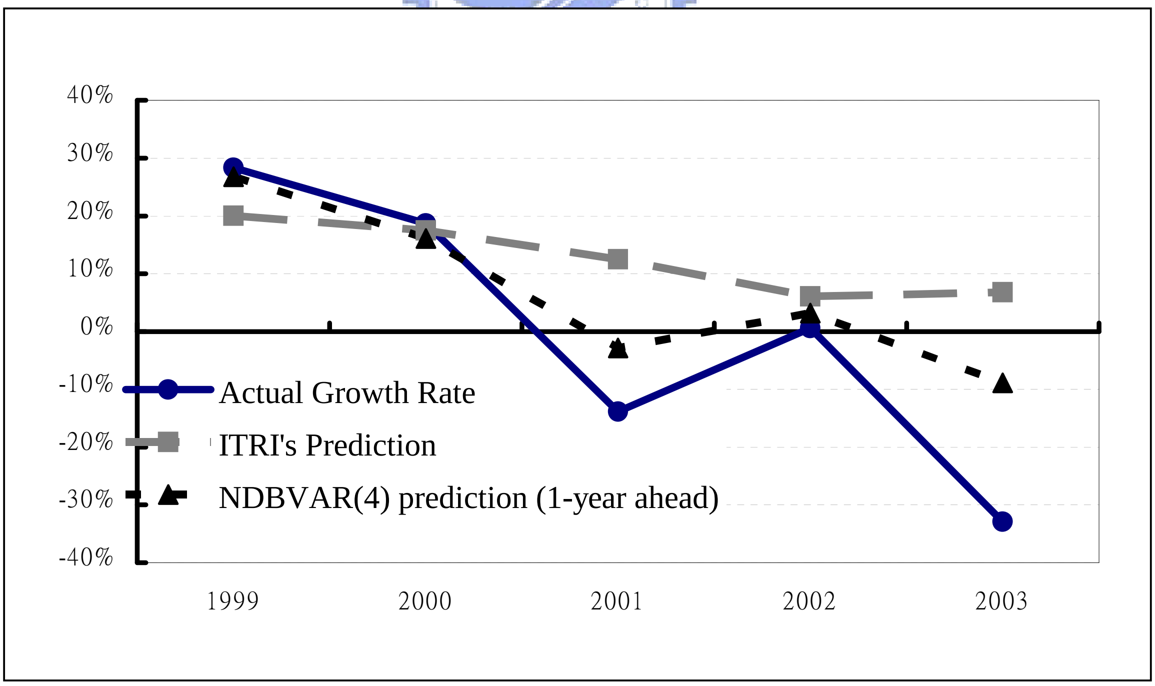

Figure 6.6. DBVAR (4) vs. III's Predictions for Taiwan's Computer Manufacturing Industry

Table 6.2 Growth Rate in Computer Manufacturing Industry Production: Real Data, ITRI's Prediction, and NDBVAR's Prediction

	1999	2000	2001	2002	2003	**MAE**
Actual Growth Rate[1]	28.3%	18.7%	-13.9%	0.6%	-32.9%	-
III's Prediction[2]	20.0%	17.5%	12.5%	6.1%	6.8%	**0.162**
DBVAR(1)[3]	23.2%	21.8%	8.7%	3.5%	-12.9%	**0.107**
DBVAR(2)[3]	25.6%	18.0%	5.9%	2.6%	-15.3%	**0.085**
DBVAR(4)[3]	26.8%	16.1%	-2.8%	3.2%	-8.9%	**0.083**

Note:

1. The actual growth rate in production value is from AREMOS database based on the official publications of Ministry of Economic Affairs (MOEA), Taiwan.
2. The forecasts are from III's publications (1999, 2000, 2001 & 2002), and III analysts' report (Chen, 2002).
3. All listed DBVAR forecasts are 1-year ahead prediction.

6.5 Power Transformation Approach for Taiwan's Computer Manufacturing

Form section 6.3 and section 6.4, we obtain the BVAR model is superior to the other time series model. It is not only more precise on forecasting, but also can catching the inflection time point. In this section, we will consider another transformation which is different form Log transformation and moving average. This method is called power transformation that can be stabilizing variance.

Box, Jenkins and Reinsel (pp. 99 & 358-359, 1994) suggested using the Box-Cox power transformation (Box & Cox, 1964) for establishing an appropriate time series model. Then, the power transformation's effect in univariate time series forecasts has been widely examined for decades (e.g., Nelson & Granger, 1979; Hopwood et *al*., 1984; Nazmi & Leuthold, 1988; Lee & Tsao, 1993; Guerrero, 1993; Chen & Lee, 1997; McKenzie, 1999). However, the power transformation's effect in multivariate time series is still untouched in the literature. Therefore in the article, we are devoted to examining the predictive capabilities of power transformation and log-transformation in vector autoregressive (VAR) and Bayesian VAR (BVAR) forecasts, and to validating the power transformation's advantage in practice.

We examine the Taiwan's technology industrial cluster including four close dependent industries with high growth is another noteworthy case of BVAR forecasting (Lee et *al.*, 2000; Hsu et *al.*, 2000). In this study, Taiwan's technology industrial cluster includes four industries: semiconductor industry, personal computer (PC) manufacturing industry, computer components industry, and other electronics parts industry. The production values of those four industries are collected from the Department of Statistics, Ministry of Economic Affairs (MOEA), and Taiwan. The production data are collected from 1990 Q1 to 2000 Q1, for a total of 43 quarterly observations. The quarterly data are season-adjusted through X-11 method. To set up a stable power in comparison to log-transformation, we estimate the power using all 43 observations. The lag number of power transformation, VAR, and BVAR models are set to be 1 according to our experience (Lee et *al.*, 2000; Hsu et *al.*, 2000). That implies we estimate the power of each data series separately by using AR(1). Then the transformed data is utilized to VAR(1) and BVAR(1) modeling and forecasts. The constant term is also included.

We compare the predictive performance of the log-transformation and the power transformation based on one-step ahead rolling forecast. We found our comparison on one-step head forecasts for the feasible reason that rational predictors will adaptively adjust the forecasting based on newest information. The parameters of VAR and BVAR models are re-estimated to forecast the *i*th forecasts based on data available in *(i-1)*-th the period. In Taiwan's technology industrial cluster case, we examine the performance of the latest 19 observations (1996 Q1 to 2000 Q1). Each one-step ahead forecast is obtained by re-estimating the parameters of VAR and BVAR models by using previous 20 observations (5-year). The magnitude measures for gauging the performance include the root of mean square error (RMSE), the Theil U statistic, and the mean absolute error (MAE).

In the case of Taiwan's technology industrial cluster, we estimated the power to be as **0.81** for computer system, **0.87** for computer components, **0.64** for semiconductors, and **0.79** for other components. Predictive results are shown in Table 6.3. The predictive performance of the power transformation is better than the log-transformation. In computer system and semiconductors, the performance of the power transformation overwhelms the log-transformation in all three models. In computer components, the power transformation provides better predictions in VAR model. In other components, the power transformation produces better predictions in Litterman prior BVAR model. The non-informative prior BVAR with power transformation provides the best forecasts in Taiwan's technology industrial cluster. With this case, we confirm the power transformation is a better forecasting approach than the conventional log-transformation.

Table 6.3: Comparing Box-Cox Power Transformation with Log-Transformation in Taiwan Technology Industrial Cluster Production: VAR and BVAR forecasts

	Transformation	RMSE	Theil U	MAE
Panel A: Computer System				
VAR(1)	Log	7145.76	1.12	6136.50
	Power	6429.89	1.01	5181.51
BVAR(1) (Litterman)	Log	6163.74	0.97	4849.92
	Power	5680.28	0.89	4376.13
BVAR(1) (Non-informative)	Log	4938.44	0.78	3819.63
	Power	4264.01	0.67	3449.91
Panel B: Computer Components				
VAR(1)	Log	4688.96	0.95	3766.81
	Power	4946.07	1.00	3955.69
BVAR(1) (Litterman)	Log	4995.77	1.01	4076.28
	Power	5012.12	1.01	4104.91
BVAR(1) (Non-informative)	Log	3890.35	0.79	2905.41
	Power	3833.77	0.77	2888.23
Panel C: Semiconductors				
VAR(1)	Log	16171.55	0.87	10861.42
	Power	14549.35	0.78	10198.37
BVAR(1) (Litterman)	Log	15061.35	0.81	10842.67
	Power	14905.70	0.80	10761.85
BVAR(1) (Non-informative)	Log	13127.25	0.71	9605.21
	Power	10018.24	0.54	8021.98
Panel D: Other Components				
VAR(1)	Log	7017.10	0.89	5241.38
	Power	7824.71	1.00	6044.97
BVAR(1) (Litterman)	Log	7378.48	0.94	5722.62
	Power	7293.89	0.93	5670.60
BVAR(1) (Non-informative)	Log	5745.40	0.73	4449.04
	Power	5851.64	0.74	4431.94

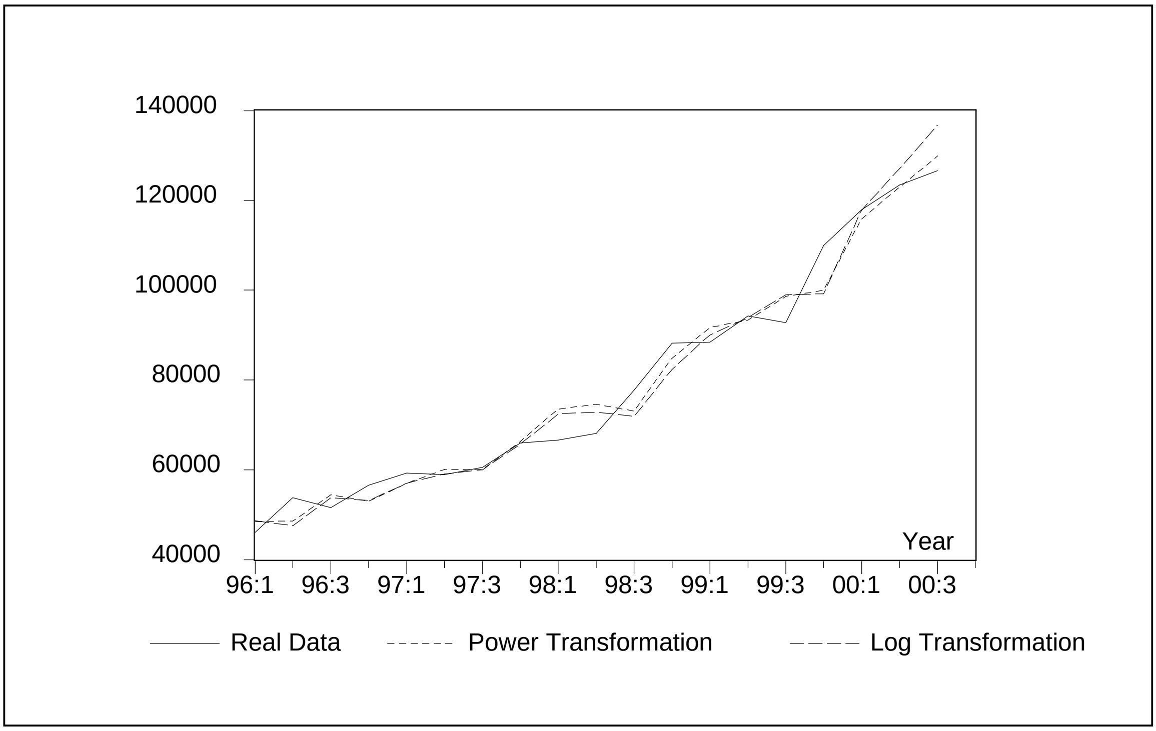

Figure 6.7: One-Step Ahead Non-Informative BVAR Forecasts for Computer System Production.

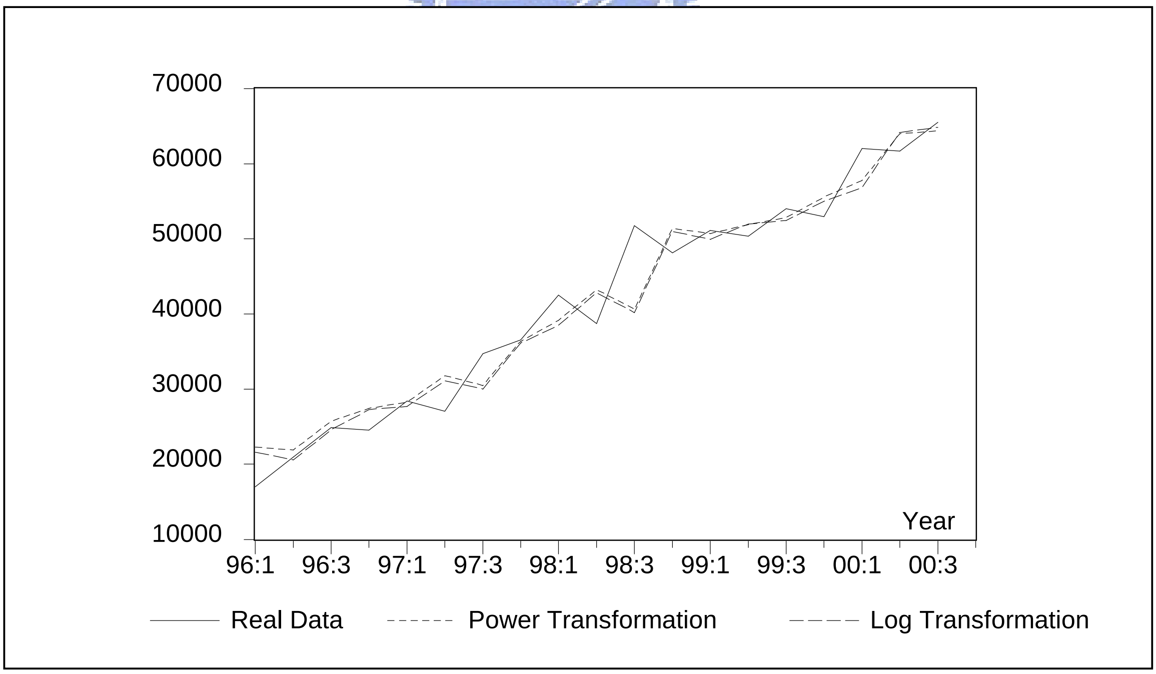

Figure 6.8: One-Step Ahead Non-Informative BVAR Forecasts for Computer Components Production.

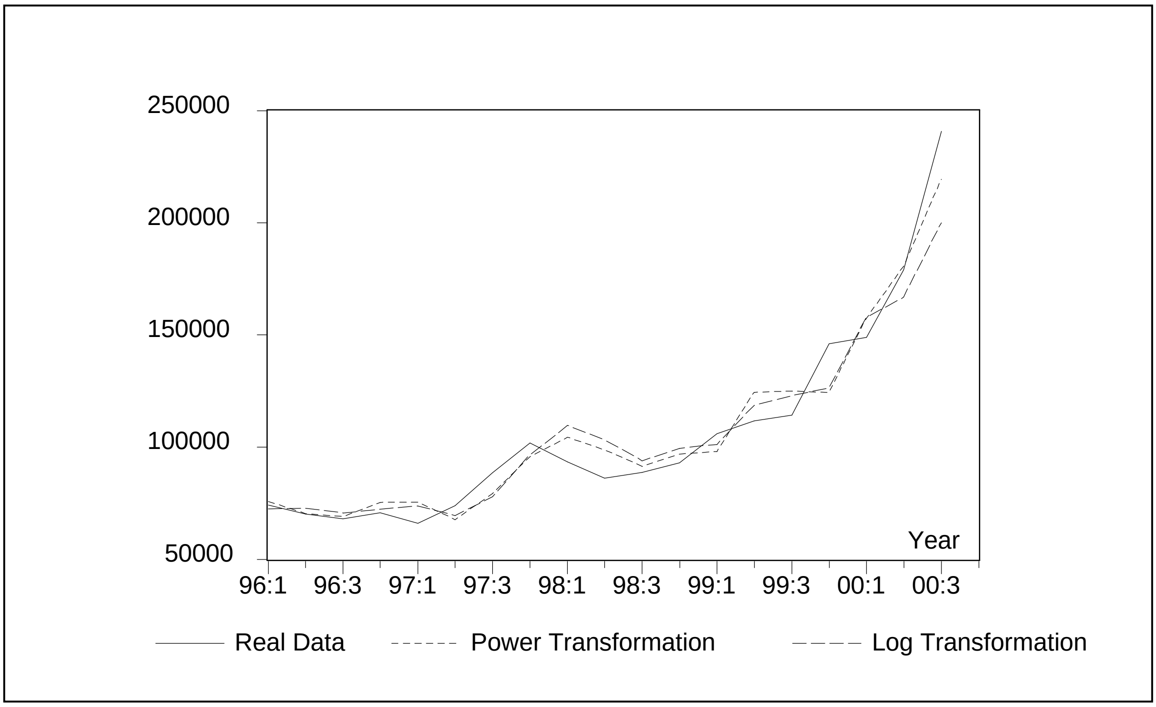

Figure 6.9: One-Step Ahead Non-Informative BVAR Forecasts for Semiconductors Production.

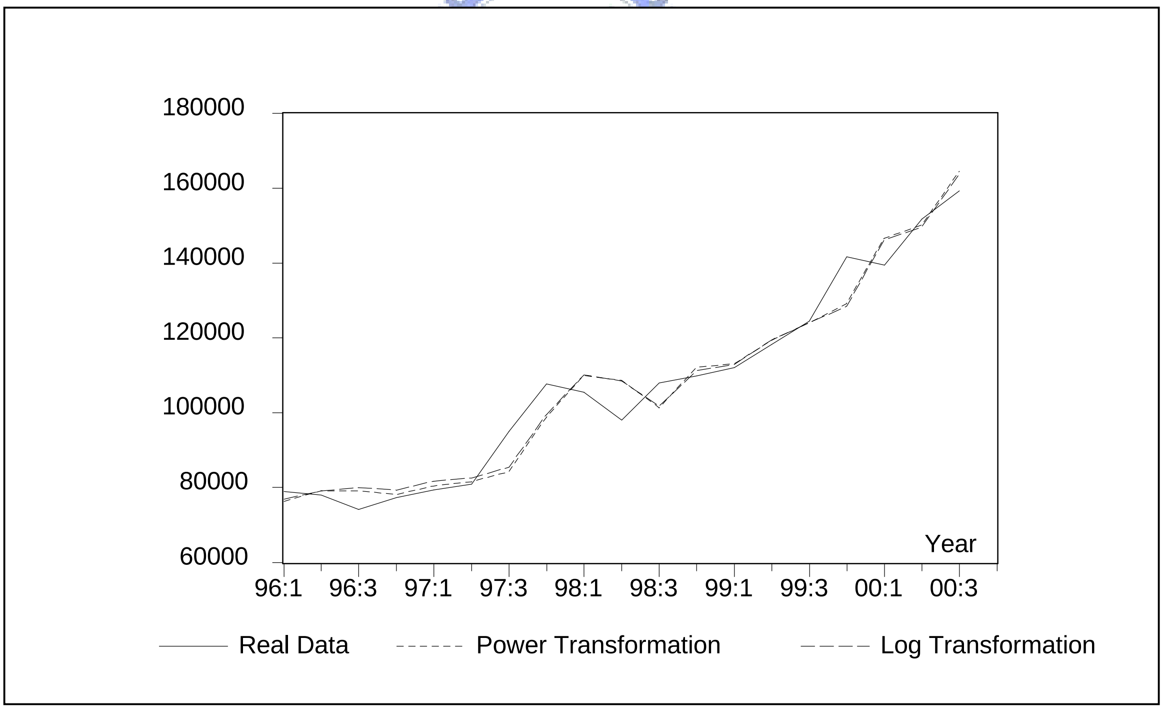

Figure 6.10: One-Step Ahead Non-Informative BVAR Forecasts for Other Components Production.

6.6 Finding and Discussion

This study makes two contributions: First, we have proposed a new forecasting method that combines the industrial clustering effect and DBVAR model to forecast industrial productions. It was shown that the DBVAR model could outperform other time series models including LBVAR, VAR and AR models in production forecasting for technology industries. In the other word, we developed a better forecasting method than previous studies, and that is constructive to relevant studies like forecasting research and technology management. Second, our method provided better or as good prediction in comparison with the authoritative forecasts from leading market information providers. The DBVAR model's good performance in both cases and updated data (2000-2003) makes it appropriate to say that our outcome is robust. These results also prove the feasibility of our method, and shed a light on the potential of quantitative techniques in improving forecasting, especially for technology industries.

Based on the results of this study and previous literature, we summarize following suggestions in predictive practices: first, the non-informative prior functions well and efficiently in Bayesian forecasting. Second, although the best prior form is unknown to us ex ante, the best one in in-sample usually works well in out-of-sample due to the weak stationarity of multivariate data generating process. Finally, a real-time forecasting adjustment is strongly advocated. That is, under acceptable budget constraint, practitioners should modify their forecasts frequently to match the change path of environment.

Of course, our results are based on experiments on the case and may not be generally applicable. However, we do believe that our results from deliberately examining this case is credible; making it fair to say that our forecasting method has merit in at least some circumstances. Although the variables used in this study are based on clustering effect, other variables selection, like macroeconomic variables, could be also helpful in BVAR structure. We left this issue to future study. Forecasting is always difficult, and even tougher in volatile and highly dynamic environments. The exploration of quantitative techniques for forecasting is just in the beginning stage, and we expect to see more advanced methodologies being developed in the immediate future.

7. Conclusion and Future direction

7.1 Conclusion

In this study of three industries in Taiwan, we use difference time series models and related industries, which provide more information for these industries. The results are summarized as follows: First, in the photonics industry, the BVAR model significantly outperforms the other models. If we compare the VAR model and AR model, our endeavor in variable selection seems in vain because the VAR model is less accurate than AR model. But when we consider the BVAR, we are encouraged to find that both BVAR models (standard prior and low-weighted prior) show excellent precision. The low-weighted prior BVAR model, which hardly accounts for cross impact, is less accurate than standard prior BVAR, as we anticipated. So the related industry can provide useful information for forecasting Taiwan's photonics industry. Second, in the semiconductor industry, the problem is different from the photonics industry. In its case, it is noticeable that standard prior BVAR outperforms VAR but significantly underperforms AR. This outcome is consistent with the results of causality test. Such a result can be explained as follows: Inappropriate hyperparameters use or misspecification in causality relationship by Granger Causality Test. Regarding the first reason, we may use inappropriate hyperparameters (γ and ω) in BVAR estimation and need more hyperparameters setting for the estimation. However, the Litterman method is informative inherently and researchers need to try numerous hyper-parameterizations to get the best model. The latter reason means the causality between the semiconductor industry and other industries, provided by Granger Causality Test, is unless unhelpful in our forecasting. So we must consider another prior distribution to the BVAR model and other appropriate candidates to modify our model**.** After doing these steps, which we obtain in 1-step ahead forecasting, the DBVAR class provides significantly better predictions than all other model classes. In 4-step ahead forecasting, the DBVAR class also significantly outperforms other model classes. Among the three DBVAR models, the DBVAR(4) model is the best in 1-step ahead forecasting, and the DBVAR(1) is superior to the others in 4-step ahead forecasting. Next, we also consider power transformation which is different from Log transformation, and which can better stabilize variance. Predictive results are shown in the performance: The power transformation overwhelms the log-transformation in all three models. Third, in the computer manufacturing industry, for 1-step ahead forecasting, the DBVAR class surpasses all of the other model classes and is the only model class to provide less-than-one Theil U statistics. In 4-step ahead forecasting, the DBVAR class marginally outperforms the LBVAR and AR classes.

This outcome confirms the merit of the DBVAR models in producing good predictions, even in the turbulent 2001 and 2002 years.

Based on the results of this study and previous literature, the newly proposed model approach is more efficient accurate proposed which contributes the following advantages. First, we find that the BVAR model with non-informative prior functions and with its short lag order provides efficient performance. Second, although the best prior form is unknown to us ex ante, the best one in in-sample usually works well in out-of-sample due to the weak stationarity of the multivariate data generating process. Third, the BVAR model is capable of dynamic analysis in related industries and performs superior production prediction in magnitude. Finally, the variables used in this study are based on related industries and could provide other researchers more forecast precision by using multivariate time series structure. Overall, the results are based on empirical results of three industries which make a successful exploration for high-tech industries by multivariate time series models. So we have confidence in the BVAR forecasts of industrial production based on related industries, especially for high-tech industries.

7.2 Future research

In Bayesian analysis of MVAR-models, and especially in forecasting applications, there are five prior distributions that have been used. In this dissertation, The Minnesota prior of Litterman and Diffuse prior distribution are used in the research and compared to other multiple time series models. In other cases, there are other prior distributions, such as Normal-Wishart, the Normal-Diffuse and Extended Natural Conjugate priors, which have nice properties and predictive power from the theoretical viewpoint. With these, more general prior distributions and, numerical methods are required in order to evaluate the posterior distributions.

It is straightforward to implement Monte Carlo methods with the Normal-Wishart and Diffuse priors. For these prior distributions we can sample directly from the posterior and Monte Carlo methods are practical even for large MVAR models.

The Normal-Diffuse and ENC priors, on the other hand, require importance or Gibbs sampling. The numerical performance of the importance functions considered is unsatisfactory with the large Litterman model. The Gibbs sampling algorithms, while being slow with models this size, proved to be reliable and to give precise estimates.

For smaller models, importance sampling is a viable alternative to Gibbs sampling and is sometimes faster when the precision of the estimate is accounted for. The saving in computational time in importance sampling compared to Gibbs sampling, however, is modest. Given the greater robustness in relation to the size of the model of the Gibbs sampler, we prefer Gibbs sampling over importance sampling.

Different prior distributions applied into the same data will give another perspective and some different viewpoints. From the empirical point of view, the choice of a distribution to embody a set of prior beliefs is not an easy one. All the priors considered here are easy to specify if the prior beliefs are of the type suggested by Litterman. The Normal-Wishart is less suitable if the prior beliefs contain more specific information, and the ENC prior require prior independence between equations to be easy to specify. In addition, the Normal-Wishart and ENC priors require that the user specify the prior degrees of freedom or, equivalently, the existence of prior moments. All prior moments of the parameters exist for the other informative priors.

In terms of analyzing the posterior distribution, the Minnesota prior has a slight edge over the Diffuse and Normal-Wishart priors in that expressions for all posterior moments are readily available. For more complicated functions of the parameters, Monte Carlo procedures are easy to implement and efficient for these priors. The Normal-Diffuse and ENC priors require numerical evaluation of the posterior distribution and this can, while feasible, be quite expensive for large models.

Finally, or perhaps first, the credibility of the model specification must be considered. The Minnesota prior is at a disadvantage here since it comes with quite severe restrictions on the likelihood in the form of the fixed and diagonal residual variance-covariance matrix. Taking this into consideration our preferred choice is the Normal-Wishart when the prior beliefs are of the Litterman type. For more general prior beliefs or when the computational effort is of minor importance, the Normal-Diffuse and ENC priors are strong alternatives to the Normal-Wishart. The Bayesian method, compared with the traditional statistical method, is thought to be much more reliable and efficient when we incorporate the latest information at hand. That is the spirit of Bayesian philosophy, especially for multivariate cases. In multivariate VAR models, the Bayesian method could even be treated as a better way for parameter estimation and model forecasting. Even for mild sample points, the Bayesian model is considered to be robust compared to the traditional one. That is the main reason why the Bayesian method is used. Easy implementation and good empirical explanations are also reasons for the method used.

In conclusion, using different priors is supported on the empirical and theoretical grounds, but it still needs to be implemented and verified carefully in the future.

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