Production Forecasting of Taiwan's Technology Industrial Cluster: A Bayesian Autoregression Approach

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Abstract
This study proposes a forecasting method that combines the clustering effect and non-informative diffuse-prior Bayesian vector autoregression (NDBVAR) model to forecast the productions of technology industries. Two empirical cases are examined to verify the proposed method: the semiconductor industry and computer manufacturing industry in Taiwan. It is found that the NDBVAR model outperforms the other three conventional time series models including the autoregression (AR), vector autoregression (VAR), and Litterman Bayesian VAR (LBVAR) models. Moreover, the NDBVAR model also outperforms the forecast reports from leading market information providers over the past several years. The forecasting method proposed is therefore concluded to be a feasible approach for production prediction, especially for technology industries in volatile environments.

JEL Classification: C32, C53, E27

Keywords: industrial clusters, vector autoregression, Bayesian vector autoregression, forecasting, Taiwan.

Résumé
La présente étude propose une méthode prévisionnelle qui combine les effets de regroupement et le non-informative diffuse-prior Bayesian vector autoregression model (NDBVAR) pour prévoir les productions des industries de technologie. Pour évaluer la méthode proposée, l'étude examine deux cas empiriques : les industries taiwanaises du semiconducteur et de fabrication d'ordinateur. Elle révèle que le modèle NDBVAR est plus performant que les trois modèles conventionnels en série chronologique notamment le modèle d'autoregression (AR), le modèle de vecteur d'autoregression (VAR), et le modèle Litterman Bayesian (LBVAR). L'étude montre aussi qu'au cours des dernières années, les modèles NDBVAR ont été plus performants que les rapports prévisionnels des prestataires d'informations qui dominent le marché. Elle débouche sur la constatation que la méthode prévisionnelle proposée est une approche réalisable pour la prévision de la production, en particulier pour les industries de la technologie dans un environnement volatile.

Mots clés : grappes industrielles, vecteur d'autorégression, Bayesian vector autorégression, prévision, Taiwan.

The development of technology industries is one of the main subjects in contemporary business research. The perspective of a specific technology industry affects investment plans of private sectors and science and technology policies of governments. Production forecasting is a burgeoning topic in technology management, which aims to assist decision makers in technology industries that are exposed to numerous uncertainties including volatile fluctuations, sudden skyrocketing growth, and unexpected slumps in market. In the literature, the time series model class was 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., Chang, Lai, & Yu, 2005; Hsu, Wang, Shyu, & Yu, 2003;

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Tseng, Tzeng, & Yu, 1999). However, those prognostic techniques are still far from satisfactory at this time, 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 better features in handling the unstable dynamics and discrete shocks? Using that model, what variables could be considered to produce better prediction?

First, we observed that various time series models have been used to predict industrial productions (e.g., Hsu et al., 2003; Marchetti & Parigi, 2000; Simpson, Osborn, & Sensier, 2001; Tseng et al., 1999). Second, we looked for a Bayesian multivariate time series model that fits unsteady environments better than traditional frequency-based models, and found that the non-informative diffuse-prior Bayesian vector autoregression (NDBVAR) model has good features: its prior is flexible and its computation is efficient. It is therefore expected to provide more precise short-term forecasting for production of technology industries. Third, since industrial clustering has been regarded as a crucial driver in the development of technology industries (Bergeron, Lallich, & Bas, 1998; Gover, 1993; Mathews, 1997; Swann & Prevezer, 1996),[1] it can be presumed that the production values of different industries within a specific industrial cluster carry important information regarding the momentum and dynamics between those industries. We followed this rationale and took the production values within an industrial cluster as the endogenous variables in multivariate time series models. After considering all three questions, we were motivated to propose a new forecasting method that is a NDBVAR model based on industrial clustering.

We examined the feasibility of our method by considering two empirical cases of Taiwan's technology industries: the semiconductor industry and the computer manufacturing industry. We had good reasons for considering these two industries. First, in both industries, Taiwan's firms have been main players in global markets over the past 10 years, so our experiments will be meaningful to researchers and practitioners from other countries. Second, a review of the history of these two industries indicates that their prosperity can be attributed to a strong clustering effect within Taiwan (e.g., Chang & Hsu, 1998; Mathews, 1997). To validate our proposition, we checked the predictive abilities of a series of autoregression (AR) systems including univariate AR, vector autoregression (VAR), Litterman BVAR (LBVAR), and NDBVAR models. The results show that, in both industries, the NDBVAR model provides more accurate predictions than all of the other competitive models. Moreover, we found that NDBVAR forecasts offer favourable results in comparison with the forecast reports from leading market information providers in Taiwan: the Industrial Technology Research Institute (ITRI) in the semiconductor industry and the Institute for Information Industry (III) in the computer manufacturing industry. We therefore confirmed that the proposed forecasting method is of practical merit.

The remaining parts of this study are arranged as follows: the second section reviews the relevant literature of LBVAR and NDBVAR forecasts and provides the reasons that motivate us to propose the NDBVAR model as the main predictor in our method. The third section explains the structure and estimation of the NDBVAR model. The history and current circumstances of Taiwan's semiconductor industry and computer manufacturing industry are briefly depicted in the fourth section. Data collection, modeling process, and performance criteria are illustrated in the fifth section, the sixth includes discussions on forecasting results and a comparison between NDBVAR forecasts and the forecast reports from market information providers, and the seventh section concludes this paper.

Literature Review

Since proposed by Sims (1980), the VAR model has been widely utilized in macroeconomics, regional development, and financial economics and analysis. Subsequently, Litterman (1986) proposed a Bayesian VAR (LBVAR) that embeds the Bayesian approach into a VAR structure. His method is also called "Minnesota prior". The most common VAR and LBVAR application is macroeconomic analysis. There are also several studies that have attempted to expand LBVAR forecasting to other fields (e.g., Curry, Divakar, Mathur, & Whiteman, 1995; Dua & Smyth, 1995; Kumar, Leone, & Gaskins, 1995). Overall, it is widely accepted that LBVAR models possess a parsimonious property in parameterization and provide more accurate forecasts than VAR models do. However, the estimation and prediction of LBVAR models are determined using a prior form selection that is not efficient and highly restricted. Forecasters must achieve an optimal predictive model by searching the prior types and hyperparameter values (e.g., Sarantis & Stewart, 1995). This model is inefficient and not deterministic, and its practical value is therefore limited. Kadiyala and Karlsson (1997) considered several other priors that make the computation more efficient for optimal short-term forecasting, that is, forecasters need only consider the format of priors and then the optimization of priors is obtained by estimation process. They also found that the BVAR model of other priors, like NDBVAR, could provide better forecasts.

We observed the following details in the literature. First, the LBVAR model is accredited as advantageous over the AR and VAR models in short-term horizons with several performance measures. Here the short-term horizon means the available sample length is shorter (i.e., small sample). This is consistent with Holden's (1995) induction: "The evidence is that the forecasts produced by BVAR models are at least as accurate as forecasts from traditional economic models" (p. 162) (Curry et al., 1995; Dua & Ray, 1995; Dua & Smyth, 1995; McNees, 1986; Sarantis & Stewart, 1995). This finding is intuitively convincing because the Bayesian method allows us to modify our beliefs in model estimating using updated information. This is a significant edge over the classical models (AR and VAR) in unstable environments. Second, the LBVAR model has been utilized frequently in economic forecasting for GDP, consumption quantity, and unemployment. In a recent study by Hsu et al. (2003), the LBVAR model also performs well in production forecasting for technology industries. We are motivated to search for other BVAR models to make better production prediction in a more efficient way. Third, most of the past studies focused on LBVAR models. In our view, the NDBVAR model has high potential for practical application because it requires fewer restrictions in variance-covariance matrix structure and is computationally more efficient, thereby producing better prediction.

Due to space limits, we are not able to provide a theoretical discussion on the comparison between the VAR, LBVAR, and NDBVAR models. For a comparison between the VAR and LBVAR models, please see a series of studies in a special issue of the Journal of Forecasting (Curry et al., 1995; Dua & Ray, 1995; Dua & Smyth, 1995; Sarantis & Stewart, 1995) as well as other references in this article. For comparison between the LBVAR and NDBVAR models, please refer to Kadiyala and Karlsson (1997). We would like to remind readers that the predictive ability of BVAR models could be sensitive to the selection of priors.

Non-informative Diffuse-prior BVAR (NDBVAR) Model and Forecast

Let y_t be the row vector of p variables of interest observed at time t. Then VAR can be written as:

$$y_t = \beta_0 + \sum_{i=1}^{q} \beta_i y_{t-i} + \epsilon_t\,, \qquad (1)$$

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

For the technical discussion of the prior and posterior distributions, we need the following notation. Write Equation 1 as:

$$y_t = \beta x_t + \epsilon_t\,, \qquad (2)$$

where $x_t = (1, y_{t-1}, y_{t-2}, \cdots\cdots y_{t-q})'$ and the matrix β is given by $(\beta_0, \beta_1, \cdots\cdots \beta_q)$. Performing the conventional stacking of the row vectors y_t, x_t, and ϵ_t for t = 1,2,.......,N into Y, X and ϵ we have the multivariate regression model:

$$Y_{p\times N} = \beta_{p\times p(q+1)}\, X_{p(q+1)\times N} + \epsilon_{p\times N}\,. \qquad (3)$$

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

$$\begin{aligned} L(\beta,\Sigma|Y, X) &\propto |\Sigma|^{-N/2} \exp^{-1/2\, \mathrm{tr}(Y-\beta X)'\Sigma^{-1}(Y-\beta X)} \\ &= |\Sigma|^{-N/2} \exp^{-1/2\, \mathrm{tr}[(\beta-\hat\beta)'(\Sigma^{-1}\otimes XX')(\beta-\hat\beta)+(Y-\hat\beta X)'\Sigma^{-1}(Y-\hat\beta X)]} \\ &= |\Sigma|^{-q^*/2} \exp^{-1/2(\beta-\hat\beta)'(\Sigma^{-1}\otimes XX')(\beta-\hat\beta)} |\Sigma|^{-(N-q^*)/2} \exp^{-1/2\,\mathrm{tr}(Y-\hat\beta X)'\Sigma^{-1}(Y-\hat\beta X)} \\ &\propto N(\beta|\, \hat\beta, \Sigma\otimes(XX')^{-1}) \times IW(\Sigma|\, (Y-\hat\beta X)'(Y-\hat\beta X), N-q^*), \end{aligned}$$

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

Our study aims to consider the model in Equation 3 from a Bayesian point of view in the hope that a more accurate prediction can be obtained 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:

$$g(\beta, \Sigma^{-1}) \propto |\Sigma|^{1/2\,(p+1)}. \qquad (4)$$

Instead of deciding the values of priors, we assume only that the prior distribution g is proportional to the determinant of Σ in 1/2 (p+1) power. This is a non-informative prior setting. By combining the prior setting given in Equation 4 with the likelihood function of β, Σ given Y, Geisser (1965) obtained the following posterior distribution:

$$P(\Sigma \mid X,Y) = IW(\Sigma \mid (Y-\hat\beta X)'(Y-\hat\beta X), N-q^*-p-1). \qquad (5)$$

$$P(\beta \mid X,Y) \propto | A+(\beta-\hat\beta)XX'(\beta-\hat\beta)' |^{-N/2}, \qquad (6)$$

$$\text{or} \quad P(\beta \mid X,Y) = \frac{C_{p,\,N-q}\, \pi^{-(pq^*)/2}\, |A|^{1/2(N-q^*)}\, |XX'|^{p/2}}{C_{p,\,N}\, | A+(\beta-\hat\beta)XX'(\beta-\hat\beta)' |^{-N/2}}\,, \qquad (7)$$

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

and this implies that the marginal posterior distribution of β in matricvariate t is:

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

For the prediction of the future value 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

$$\mathrm{V}_{p\times K} = \beta_{p\times p(q+1)}\, \mathrm{X}^*_{p(q+1)\times K} + \epsilon^*_{p\times K}\,, \tag{8}$$

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

$$\mathrm{L}(\mathrm{V},\beta,\Sigma|\mathrm{Y}) \propto |\Sigma|^{-(N+K)/2} \exp^{-1/2\; tr[(\mathrm{Y}-\beta\mathrm{X})'\Sigma^{-1}(\mathrm{Y}-\beta\mathrm{X})+(\mathrm{V}-\beta\mathrm{X}^*)'\Sigma^{-1}(\mathrm{V}-\hat{\beta}\mathrm{X})}$$
$$\propto |\Sigma|^{-(N+K)/2} \exp^{-1/2\; tr[(\mathrm{Y}-\hat{\beta}\mathrm{X})(\mathrm{Y}-\hat{\beta}\mathrm{X})'+(\mathrm{V}-\hat{\beta}\mathrm{X}^*)(\mathrm{I}-\mathrm{X}^*(\tilde{\mathrm{X}}\tilde{\mathrm{X}})^{-1}\mathrm{X}^{*\prime})(\mathrm{V}-\hat{\beta}\mathrm{X}^*)']}. \tag{9}$$

By integrating with respect to β, Σ, we obtained the following posterior distribution for the prediction value $\mathrm{V}_{p\times K} = (\mathrm{V}_1, \mathrm{V}_2, \cdots\cdots, \mathrm{V}_k)$:

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

where $\tilde{\mathrm{X}} = (\mathrm{X},\mathrm{X}^*)$. That implies that the marginal distribution of V in matricvariate t is:

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

and thus, $E(\mathrm{V} \mid \mathrm{Y}) = \hat{\beta}\mathrm{X}^*$. 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" and is set as 20 in this study. Meanwhile, the covariance matrix Σ is also re-estimated by using Equation 5. We estimate these parameters by maximizing these posterior functions. This dynamic forecasting that inputs the forecast data into the same model for next step forecasting brings new information. Moreover, the Bayes estimator tends to give more weight to the sample information when the prior information becomes more vague. More details can be found in a subsequent section.

Empirical Cases

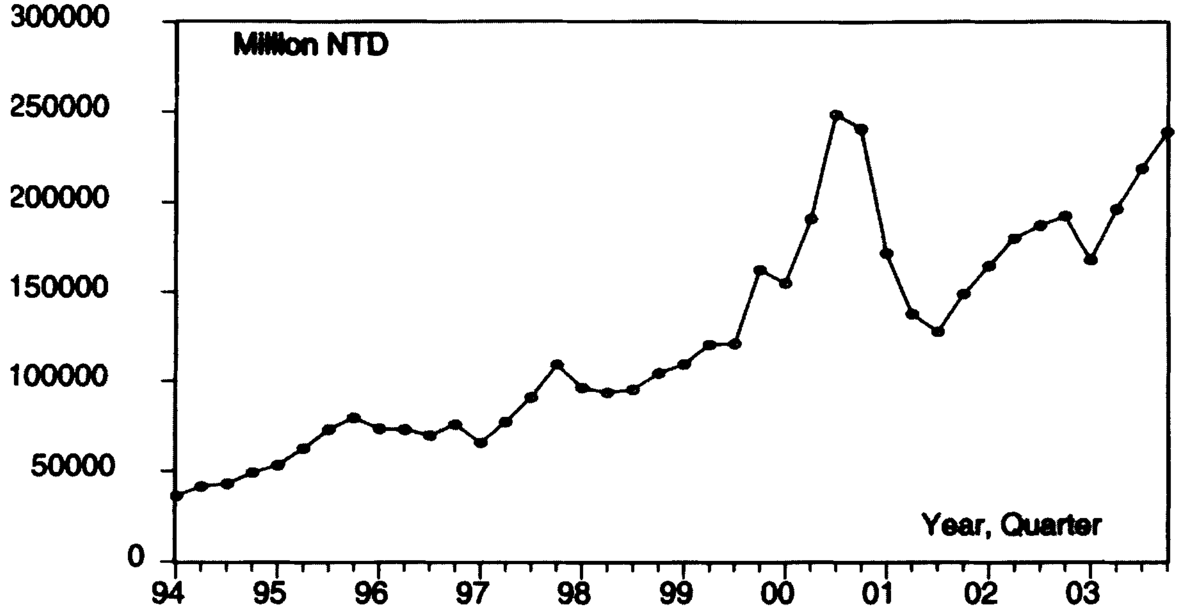
A Brief History of Taiwan's Semiconductor Industry

The start of Taiwan's semiconductor industry can be traced back to 1976. The Taiwan government obtained RCA's assistance to transfer its 7.0μm complementary metal-oxide semiconductor to the Industrial Technology Research Institute (ITRI), a government-sponsored research institute in charge of disseminating the technology to private firms (Liu, 1993). Two leading firms, the United Microelectronics Corporation (UMC) and Taiwan Semiconductor Manufacturing Company (TSMC) were established in 1980 and 1987, respectively. Since then, Taiwan's semiconductor industry has emerged into the global market and attained stunning prosperity. Interested readers should refer to Liu (1993) and Mathews (1997).

Taiwan's semiconductor industry can be divided into three sectors: IC design, IC manufacturing (including IC foundry), and IC packaging and testing. The main products are: IC materials, memory (DRAM, SRAM), logic IC, analog IC, lead frame, and foundry. In IC manufacturing, foundry and DRAM have been the key product drivers for Taiwan's semiconductor industry. TSMC and UMC are the top two IC foundry players in the world, with 2003 revenues of US$5.98 billion and US$2.74 billion, respectively (IEK, 2004). Taiwan's IC design sector quickly became the second largest IC design area in the world in 1998 and remains in that position. In 2003, over 51% of the total IC production was exported.

The production value of Taiwan's semiconductor industry from 1994 to 2003 is shown in Figure 1. In 1995, the revenue continued to rise from the first quarter (Q1), reaching its first peak in Q4. Then, Taiwan's semiconductor industry experienced its first recession, which lasted for an entire 12 months (1996 Q1–1997 Q1), and suffered from a worldwide downturn in 1998 Q1. In spite of the great Chichi earthquake in 1999, Taiwan's semiconductor industry showed a strong recovery in the global semiconductor industry. This rapid growth reached its second peak in 2000 with a 62.7% annual growth rate. Suddenly, the industry experienced the worst situation in 2001: over-capacity, intense price competition, and a downturn in information technology (IT) sales resulted in a severe industry recession. Nevertheless, in 2002 and 2003, Taiwan's semiconductor industry presented another strong recovery and continued steady development. By 2003, Taiwan's semiconductor industry produced US$24 billion and grew by 26.3% from 2002.

Figure 1
Production Value of Taiwan's Semiconductor Industry

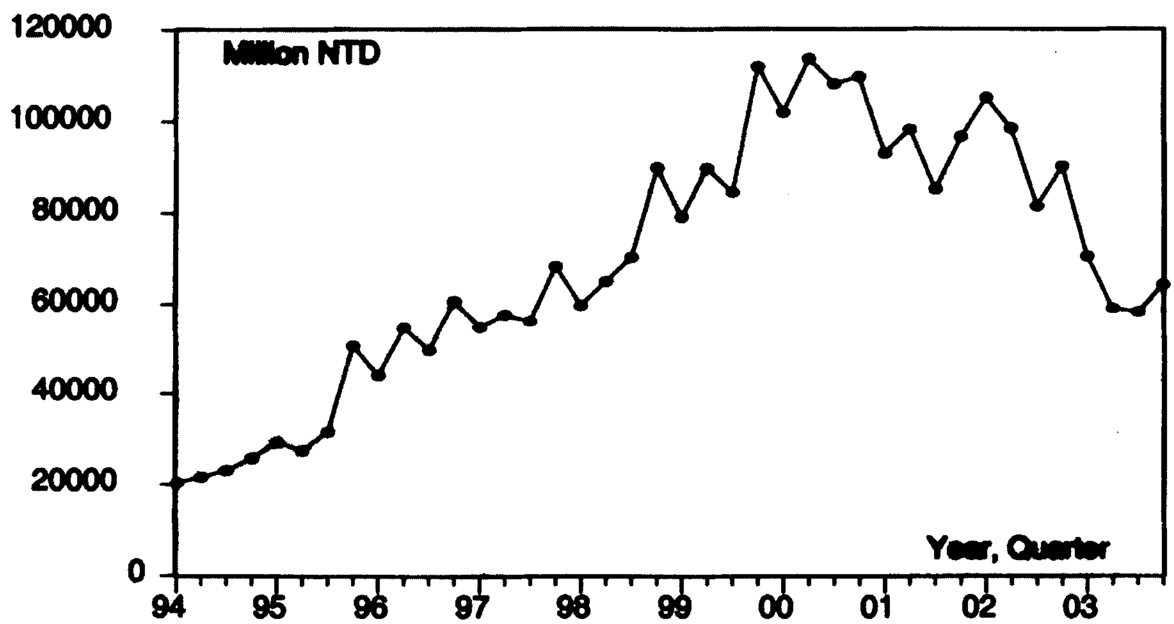


A Brief History of Taiwan's Computer Manufacturing Industry

In 1978, the Taiwanese government launched the First National Science and Technology Research Conference. At that conference, the government was advised to determine several industrial policies. One critical policy among them was to develop small computer manufacturing and assembly industries as the foundation of higher technologies for the future. The Taiwan government then started a series of plans including tax deductions, subsidizing industry R&D expenses, recruiting staff from abroad, introducing venture capital, and so on. At the same time, ITRI, the leading government-supported institute, initiated many research projects and supported sentrepreneurs. After several years, many international companies, such as IBM and HP, began to set up branches in Taiwan and release OEM orders to Taiwan's computer manufacturers. In this way, Taiwan's computer manufacturing industry gained a foothold in the global market in the mid-80s. The production values of Taiwan's computer manufacturing industry from 1994 to 2003 are shown in Figure 2.

From 1984 to 1990, Taiwan's computer industry increased its growth by maintaining low prices and improving quality. Since the '90s, Taiwan's computer manufacturing industry has used three strategies to cope with fierce competition in the global market: vertically upgrading, expanding/diversifying product lines, and branding. In the first strategy, manufacturers conducted joint research and strategic alliances to enter workstation and industrial computer markets. In the second strategy, Taiwan's manufacturers expanded product lines to multimedia computers, laptop computers, and communication technology products (personal digital assistants, cellular phones). The third strategy involved global marketing to seize the value of brand names. Acer and ASUS are two successful cases. It was also in this period that Taiwan's computer manufacturing achieved a critical position in the global personal computer (PC) market. In recent years, because of the lower cost employees available in China, most manufacturers set up factories in China and transferred most of their product lines there. This is why we observed a continual decrease since 2000 in Figure 2. By 2003, Taiwan's laptop computer sector produced US$16.2 billion, taking 61.5% of the global market. The desktop computer sector produced US$8.2 billion, taking 30.0% of the global market. If the production values of Taiwan's manufacturers in China were included, the market portion would become even bigger (III, 2004).

Figure 2
Production Value of Taiwan's Computer Manufacturing Industry



Empirical Studies

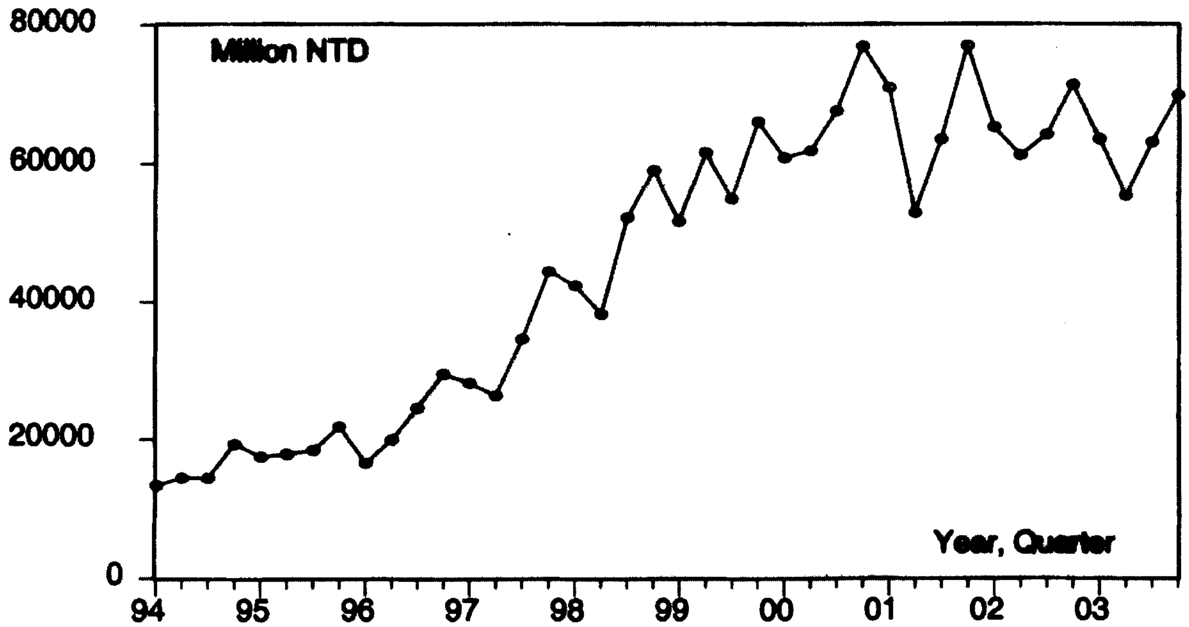
In this study, we consider two real cases: Taiwan's semiconductor and computer manufacturing industries. Our empirical study aims to examine the predictive performance of our proposed method using two benchmarks. The first is the predictability of other time series models (AR, VAR, and LBVAR) used in Hsu et al. (2003). The second is the forecast reports from two leading market information providers, the ITRI and III, in Taiwan.

Data

Since VAR models are applicable in explaining the relationship between investments and production in monetary units (e.g., Sturm, Jacobs, & Groote, 1999), we used the industrial production values as the endogenous variable in our time series models. This is because we treat the industrial production as the proxy for industrial development and dynamics. The production values from all industries are available in the AREMOS database, which 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. (2005). Our reason is that the length of monthly data is too short for evaluating industrial production and the annual data is 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 NDBVAR models, we had to determine the variables besides the semiconductor and computer manufacturing industries. Based on the industrial clustering argument, we suggested that the computer components industry, positioned downstream from 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 supplied by the semiconductor industry. Although there are still some industries related to semiconductor

Figure 3
Production Value of Taiwan's Computer Components Industry



and computer manufacturing industries, we did not cover them in this study for simplicity and the parsimonious principle in parameter usage. As a result, there will be three time series included in VAR, LBVAR, and NDB-VAR models and forecasts throughout this study: the production values of Taiwan's semiconductor, computer manufacturing, and computer components industries.[2]

The production values of these three Taiwanese industries are shown in Figures 1, 2, and 3. The definitions of these three industries are as follows (MOEA, 2000a): the computer manufacturing industry covers desktop computers and 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; and the semiconductor industry includes wafers, masks, IC packages, IC foundry, IC manufacturing, diodes, transistors, and lead frames.

Preliminary Adjustment

The production values were adjusted using two procedures before being put into estimation and forecasting: logarithmic transformation and seasonal adjustment. Both were commonly used procedures in relevant studies.[3] First, we observed the exponential growth trend in Figures 1, 2, and 3, and then transformed all production values into natural-log values. This procedure aimed 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 behaviour, the production values of the computer manufacturing industry in Q4 are 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 used the census X-11 additive method first to produce deseasonalized series. Such a predeseasonalization is preferable in the BVAR model structure 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).

Model Estimating and Forecasting

After being adjusted as above, the productions from Taiwan's semiconductor and computer manufacturing industries were estimated and predicted using the AR, VAR, LBVAR, and NDBVAR models. For AR, the univariate time series model, we performed individual estimating and forecasting of each series. For the VAR, LBVAR and NDBVAR models, three production series were used together. We considered four-lag (one year), two-lag (half year), and one-lag (one 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 the LBVAR model, we used the standard prior ($\gamma = 0.2$, $\omega = 0.5$) according to the experience of Litterman (1986) and Doan (1992). In the NDBVAR 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 guide for RATS is ready and complete. The codes to implement NDBVAR model are available upon request.

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 size of w is, of course, less than the available sample size for our first prediction point. We set the look-back window w to be 20 (5 years) because we assumed that it was improper to take data from the remote past into account for technology industries. Our data set spans 1994 Q1 to 2003 Q4. Because we set w to be 20, the forecasts start from 1999 Q1 thru 2003 Q4. 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 one-step ahead forecasting. When s = 2, it becomes multi-step ahead forecasting, making predictions for time t+s using only data from time t-1 to t-w. Here we used dynamic forecasting that inputs the forecast data into the same model for next step forecasting.[4] That means, when forecasting t+s from t (known period), we estimated the model parameters based on real data from time t thru t-w+1 and then forecast t+1 based on that model/parameter. Forecasting data point t+2 used the same model and parameters, but based on the forecast data of t+1, not the actual data of t+1. (This is because we 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 the forecast data of t+1.). This process was continued until we reached t+s. In this study, we checked one-, two-, three-, and four-step ahead for the forecasting results. In the one-step ahead forecasting situation, we assumed that the industrial practitioners updated their data quarterly. This is more plausible in the real world. On the other hand, the four-step ahead forecasting situation means that industrial practitioners predicted only once a year. Although this is not quite convincing, it serves as our one-year ahead forecast to be compared with the annual forecast reports published annually by market information providers every spring or early summer.

Forecasting Performance Criteria

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 in Hsu et al. (2003). We examined the prediction performance in one-, two-, three-, and four-step ahead situation. In multi-step ahead situations (two-step ahead to four-step ahead), we used dynamic forecasting and recorded the error measures in terms of the end forecasts. For example, we made four-step ahead forecasting based on known data in 2001 Q4, and computed forecasting errors in the 2002 Q4 (i.e., the one-, two-, and three-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 called directional accuracy, which indicates the percentage of correct model prediction regarding whether the future movement will be up or down. We believe this criterion serves as a good complementary measure to the traditional magnitude-based measure criteria in justifying how good the predictive models are.

Results and Discussions

Forecasting Performance of Time Series Models

The forecasting performance of all models is summarized in Table 1. Here we provided only the performance of one-step ahead and four-step ahead forecasts. The results of two- and three-step ahead forecasts are similar, eliminating the need to address them. To examine the model forecasting performance, we considered all of the criteria in one-step ahead forecasting, but used only the RMSE and MAE in four-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.

Table 1
Summary of Model Forecasting Performance

	Semiconductor Industry						Computer Manufacturing Industry					
	1-step ahead				4-step ahead		1-step ahead				4-step ahead	
	RMSE	Theil U	MAE	Directional accuracy	RMSE	MAE	RMSE	Theil U	MAE	Directional accuracy	RMSE	MAE
AR(1)	0.153	1.089	0.121	50%	0.599	0.427	0.116	1.165	0.093	35%	0.268	0.221
AR(2)	0.142	1.008	0.108	60%	0.630	0.480	0.120	1.211	0.101	35%	0.286	0.232
AR(4)	0.151	1.077	0.118	60%	0.593	0.441	0.125	1.257	0.101	45%	0.329	0.288
VAR(1)	0.173	1.235	0.148	50%	0.494	0.353	0.119	1.200	0.099	70%	0.323	0.261
VAR(2)	0.189	1.348	0.143	70%	0.472	0.355	0.163	1.642	0.129	55%	0.404	0.301
VAR(4)	0.306	2.183	0.234	55%	1.983	0.826	0.229	2.299	0.186	40%	0.383	0.322
LBVAR(1)	0.148	1.052	0.116	55%	0.516	0.375	0.107	1.075	0.091	40%	0.276	0.229
LBVAR(2)	0.135	0.961	0.105	65%	0.482	0.361	0.104	1.048	0.088	50%	0.280	0.225
LBVAR(4)	0.135	0.959	0.103	70%	0.472	0.357	0.107	1.073	0.091	50%	0.284	0.235
NDBVAR(1)	0.101	0.817	0.093	75%	0.268	0.209	0.088	0.880	0.075	65%	0.240	0.192
NDBVAR(2)	0.098	0.782	0.084	75%	0.282	0.216	0.079	0.832	0.068	70%	0.260	0.210
NDBVAR(4)	0.094	0.758	0.083	80%	0.402	0.327	0.058	0.726	0.050	75%	0.253	0.218

We first checked the results in the semiconductor industry case: in one-step ahead forecasting, the NDBVAR class provides significantly better predictions than all of the other model classes. It is noteworthy that all NDBVAR 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 four-step ahead forecasting, the NDBVAR class also significantly outperforms the other model classes. Among the three NDBVAR models, the NDBVAR(4) model is the best in one-step ahead forecasting, and the NDBVAR(1) is superior to the others in four-step ahead forecasting. We then turned to the computer manufacturing industry: In one-step ahead forecasting, the NDBVAR class surpasses all of the other model classes, and is the only one-model class to provide less-than-one Theil U statistics. In four-step ahead forecasting, the NDBVAR class marginally outperforms the LBVAR and AR classes.

Here we summarize findings from Table 1. 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 NDBVAR 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.[5] This outcome confirms the merit of the NDBVAR 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 NDBVAR models. For example, NDBVAR(4) performs best in one-step ahead forecasting but performs worst in four-step forecasting for the semiconductor industry. We will consider all three NDBVAR models in comparison with forecast reports from leading market information providers.

Comparison with the Industrial Technology Research Institute's (ITRI) Prediction for Semiconductor Production

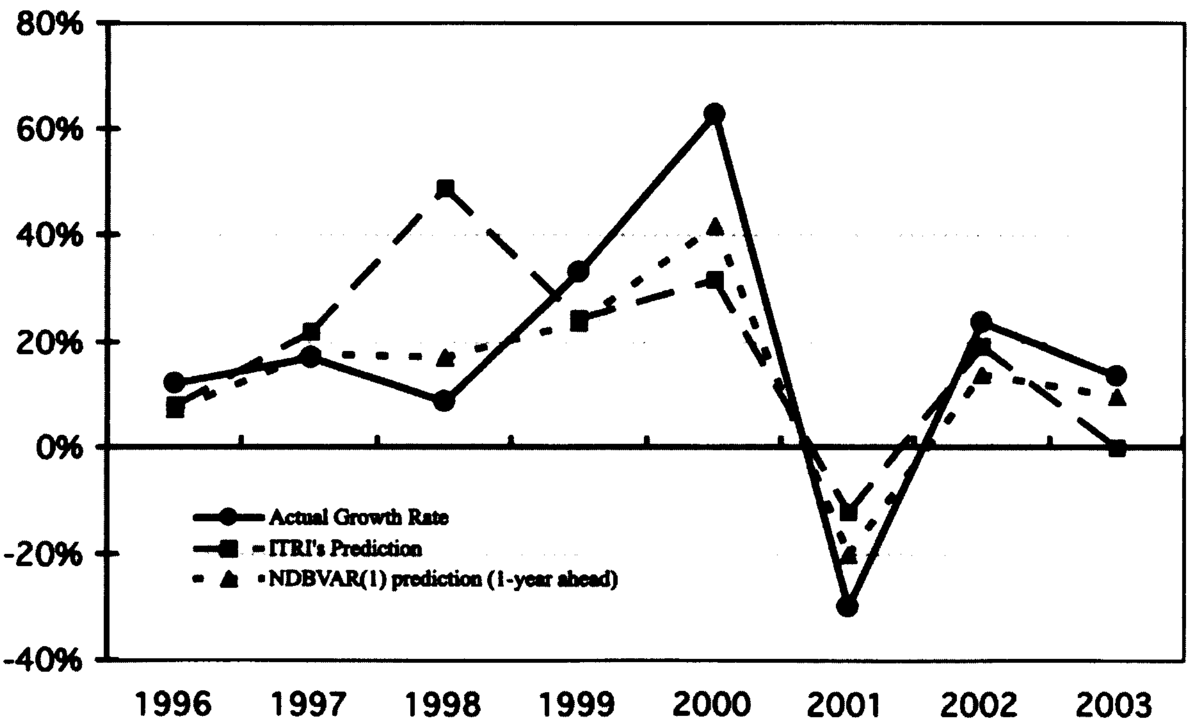
In the previous section, we showed that the NDBVAR models outperform parallel models; however, those results will be pointless if all competitive models are poor predictors. To validate the feasibility of our method, we conducted a comparison between our NDBVAR forecasts and popular forecasting reports.[6] The

Table 2
Growth Rate in Semiconductor Industry Production: Real Data, ITRI's Prediction, and NDBVAR's Prediction

	1996	1997	1998	1999	2000	2001	2002	2003	MAE
Actual Growth Rate[1]	12.2 %	17.1 %	8.8 %	32.9 %	62.7%	-29.8%	23.6%	13.5%	-
ITRI's Prediction[2]	8.0 %	22 .0%	48.8 %	24.3 %	31.7%	-12.0%	19.2%	0.02%	**0.155**
NDBVAR(1)[3]	7.3 %	17.6 %	17.2 %	23.8%	41.7%	-20.3%	14.0%	9.9%	**0.082**
NDBVAR(2)[3]	4.9 %	17.7 %	18.6 %	26.1%	36.5%	-13.2%	20.0%	9.8%	**0.092**
NDBVAR(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 MOEA, Taiwan.
2. The forecasts are from ITRI's publications (1997, 1998, 1999), ITRI analysts' reports (Chang, 2002; Hsieh, 2003; IEK, 2001; Wang, 1996), and other government publication that includes ITRI's forecasts (MOEA, 2000b).
3. All listed DBVAR forecasts are one-year ahead prediction.
4. The NDBVAR forecasts for 1996-1998 are from the earlier version of this paper.

Figure 4
NDBVAR(1) vs. ITRI's Predictions for Taiwan's Semiconductor Industry



leading market information provider in the semiconductor market in Taiwan is the ITRI,[7] which has several divisions pertaining to different industries and publishes a series of market and technology reports. ITRI provides production predictions for the semiconductor industry and other electronics 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

Figure 5
NDBVAR(2) vs. ITRI's Predictions for Taiwan's Semiconductor Industry

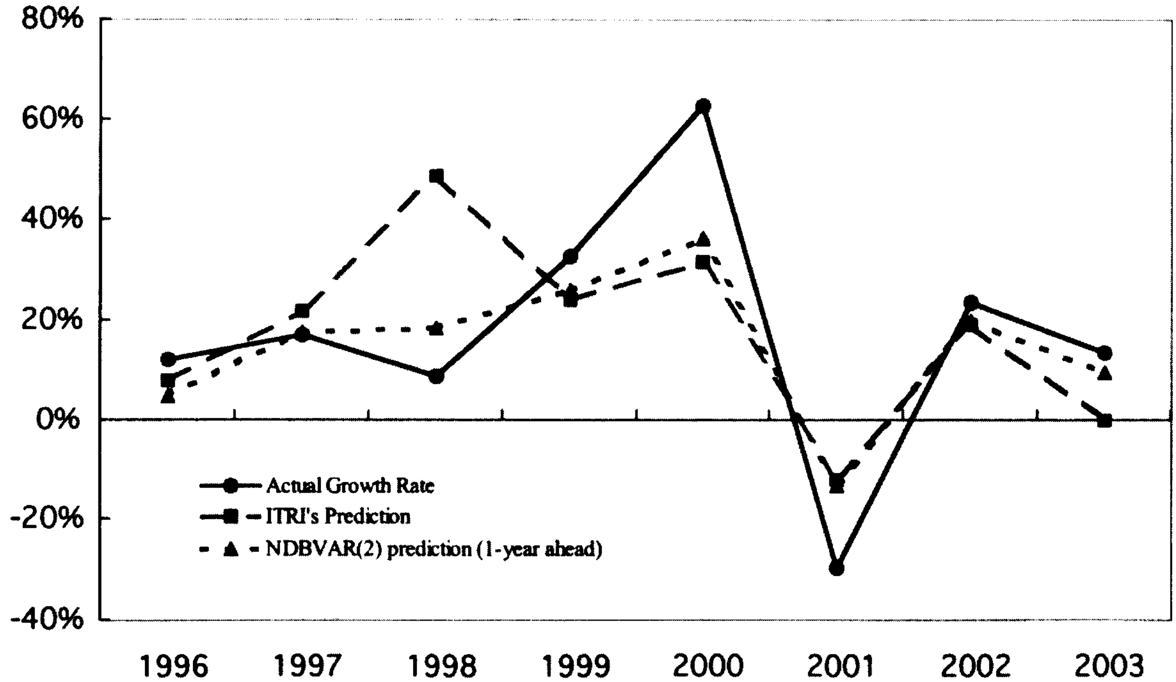


Figure 6
NDBVAR(4) vs. ITRI's Predictions for Taiwan's Semiconductor Industry

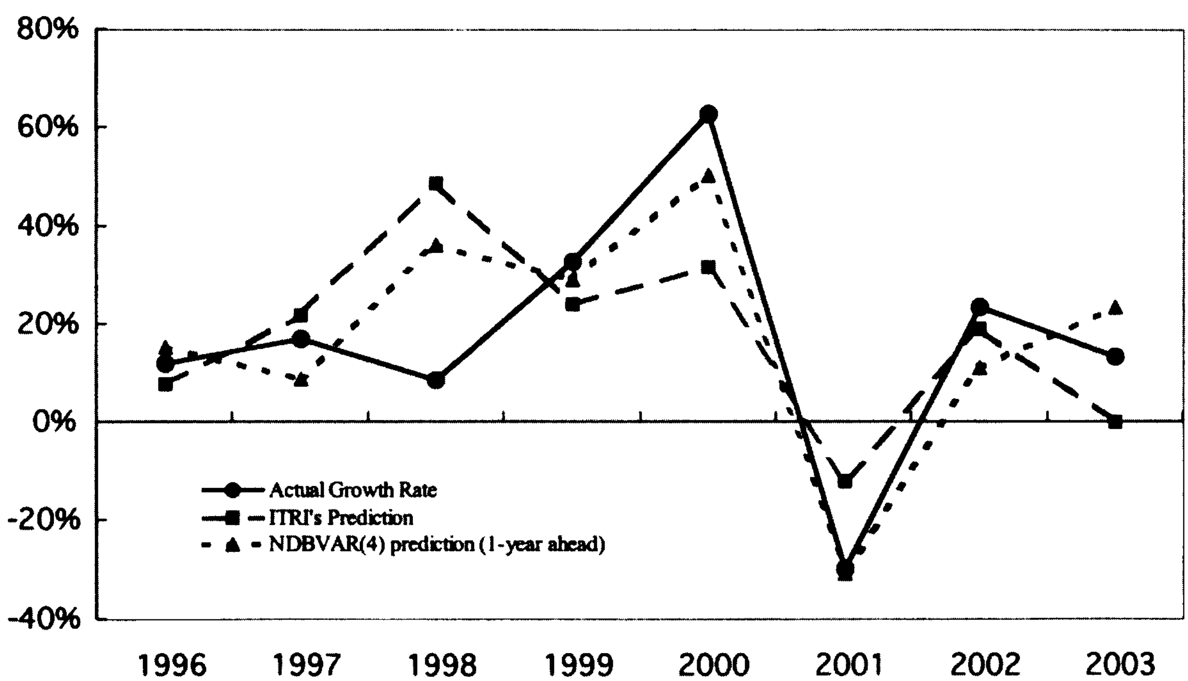


Table 3
Growth Rate in Computer Manufacturing Industry Production: Real Data, ITRI's Prediction, and NDBVAR's Prediction

	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**
NDBVAR(1)[3]	23.2%	21.8%	8.7%	3.5%	-12.9%	**0.107**
NDBVAR(2)[3]	25.6%	18.0%	5.9%	2.6%	-15.3%	**0.085**
NDBVAR(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 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.

the Semiconductor Industry Association, and expert surveys within Taiwan.

We used ITRI's annual growth rate forecasts as the benchmark in assessing our predictive method. The growth rate of realized data, ITRI's prediction, and NDBVAR one-year ahead predictions are presented in Table 2 and Figures 4-6. Note that our one-year ahead predictions are based on previous data only and then make one-, two-, three-, and four-step ahead forecasts for the next year. For example, to make one-year ahead predictions for 2001, we used data from 1996 Q1 to 2000 Q4 to make one-, two-, three-, and four-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 got forecasts for 2001 annual production and growth rate also. It is appropriate to say that the NDBVAR's one-year ahead predictions are competitive with ITRI's reports in several aspects. First, the MAEs of NDBVAR(1), NDBVAR(2), and NDBVAR(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 suffering from market atmosphere (i.e., when there was a market surge in the previous year, ITRI analysts tended to be more optimistic in the current 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 one-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.

Comparison with the Institute for Information Industry's Prediction for 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 IT industries. III publishes production predictions for all IT industries, including the computer manufacturing industry, every second quarter. Those reports are important references for industry people. III's forecasts are based on two sources: international market research institutes like IDC, and expert surveys within Taiwan.

We used III's forecasts on the annual growth rate as the benchmark to examine our predictive method.[8] The growth rate for realized data, III's prediction, and NDBVAR one-year ahead predictions are presented in Table 3 and Figures 7-9. The NDBVAR forecasts were obtained following the same procedure in the semiconductor case. Again, it is appropriate to say that the NDBVAR's one-year ahead predictions compare favourably to III's reports in three aspects. First, the MAEs of NDBVAR(1), NDBVAR(2), and NDBVAR(4) are much less than III's prediction. Second, in catching the temporary bump in 2001-2002, NDBVAR(1) and NDBVAR(2) forecasts are as good as III's. The NDBVAR(4) forecast is even better than III's. Finally, our one-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.

Figure 7
NDBVAR(1) vs. III's Predictions for Taiwan's Computer Manufacturing Industry

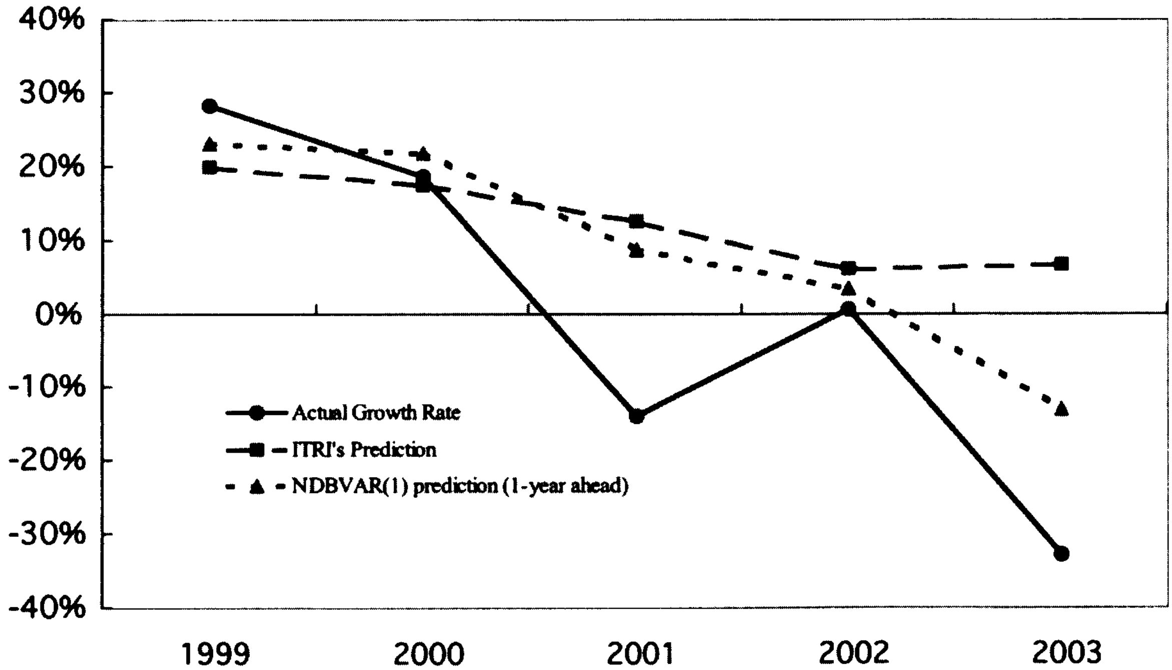


Figure 8
NDBVAR(2) vs. III's Predictions for Taiwan's Computer Manufacturing Industry

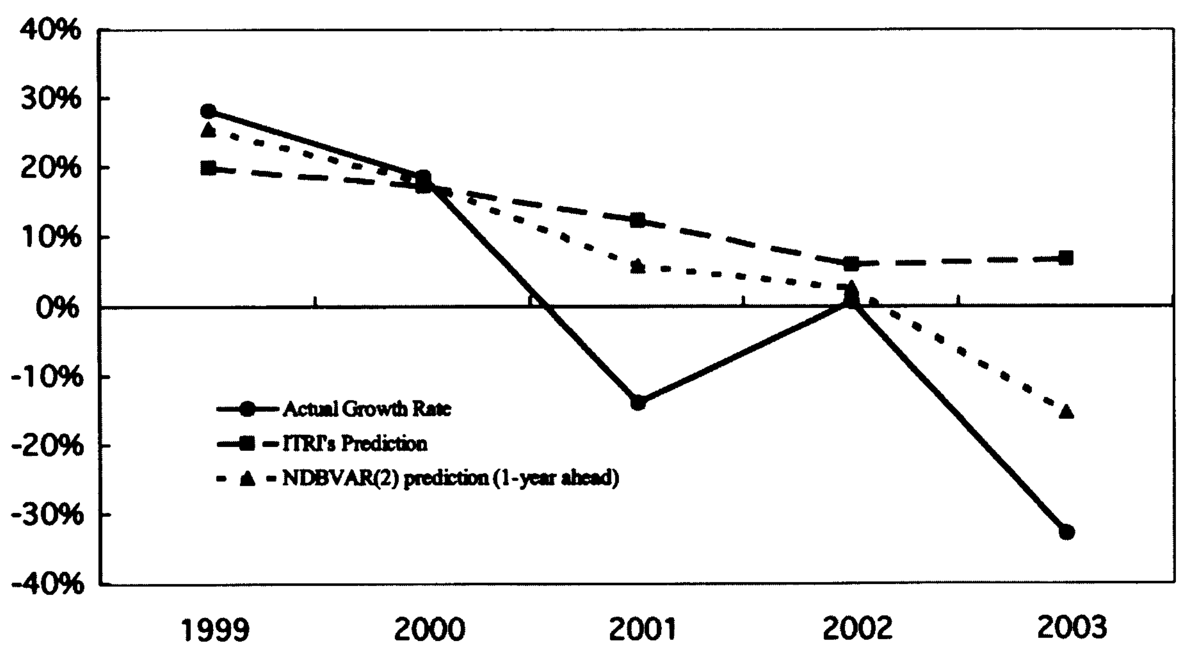
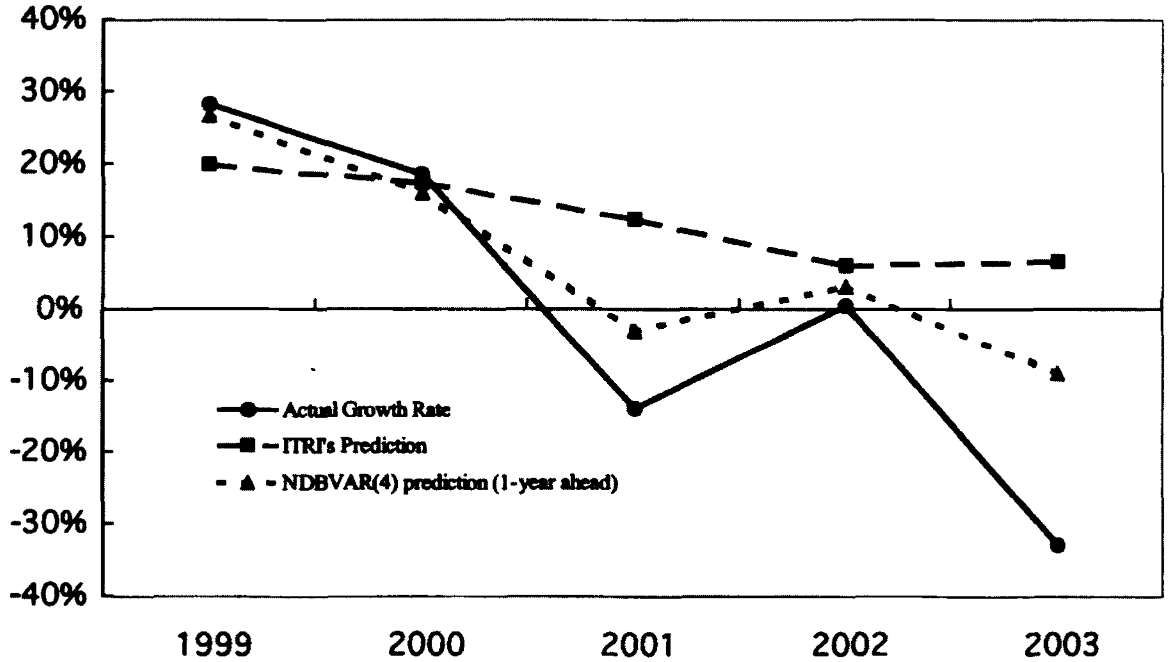


Figure 9
NDBVAR(4) vs. III's Predictions for Taiwan's Computer Manufacturing Industry



Concluding Remarks

This study makes two contributions. First, we propose a new forecasting method that combines the industrial clustering effect and the NDBVAR model to forecast industrial productions. We show that the NDBVAR model outperforms other time series models including LBVAR, VAR, and AR models in production forecasting for technology industries. In other words, we develop a better forecasting method than previous studies, and that is constructive to relevant studies like forecasting research and technology management. Second, our method provides a better or as good prediction in comparison with the authoritative forecasts from leading market information providers. The NDBVAR model's good performance in both cases and updated data (2000-2003) make it appropriate to say that our outcome is robust. These results also prove the feasibility of our method, and shed 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 the 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; and, finally, a real-time forecasting adjustment is strongly advocated, that is, under acceptable budget constraint, practitioners should modify their forecasts frequently to adapt to the changing environment.

Of course, our results are based on experiments on two empirical cases and may not be generally applicable; however, we do believe that our results from deliberately examining these two cases are credible, and it is fair to say that our forecasting method has merits in at least some circumstances. On the other hand, since our method is based on a commonly used non-informative prior, the predictive advantage of our NDBVAR forecasts is unlikely a result of calibration.

In our view, the variable selection and range forecasting will be two interesting topics waiting for future researchers to explore. Although the variables used in this study are selected by clustering effect, other variables like macroeconomic variables could be very meaningful and are worthy of consideration. Although we considered only point forecasts (conditional mean) in this paper, we recognize that range forecasting is another important and meaningful direction. For example, researchers can use the 95% confidence interval as the forecast range and examine the percentage of realized data falling in that range. We leave this possibility to future study.

Notes

1 According to Porter (1998), an industrial cluster comprises upstream industries, downstream industries, and peripheral industries in a production chain that spans from materials to final products.

2 We recognize that our variable selection could be somewhat subjective. An alternative and objective approach to search for endogenous variables is using the Granger's causality (e.g., Hsu et al., 2003). However, we did not want to include less explanatory variables, especially in a Bayesian structure.

3 Logarithmic transformation can be found in Kadiyala and Karlsson (1997) and Simpson et al. (2001). Preliminary deseasonalization can also be found in Doan, Litterman, and Sims (1984), Kumar et al. (1995), Dua and Ray (1995), Ravishanker and Ray (1997), Salazar and Weale (1999), Marchetti and Parigi (2000), and Simpson et al. (2001).

4 There are two kinds of multi-step ahead forecasting, the static one and dynamic one. In static forecasting, people use parameters estimated based on t-1 to t-w, but put actual data t+1 to t-s-1 into the model for advanced forecasts (t+2 thru t+s).

5 In Hsu et al. (2003), the LBVAR models do perform better in Theil U in their empirical study of 1998-2000. We attribute the bad Theil U performance of LBVAR forecasts to the Internet Bubble Burst in 2001-2002 and the recession in the information technology markets since 2000. Both events make the prediction job more difficult.

6 Comparing the proposed model with other industrial surveys and forecasting reports was also found in Litterman (1986), Mills and Pepper (1999), Marchetti and Parigi (2000). However, their studies were dealing with economic indicators, and ours is about industrial production of specific industries.

7 ITRI has played an important role in developing Taiwan's semiconductor industry as noted previously. ITRI is also a leading institute in providing market information of technology industries.

8 In some years, III reported only the growth rate of separate sectors (desktop, laptop, PDAs or so) in computer manufacturing industry. In that case, we used the weighted average growth rate of those sectors as III's prediction.

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