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Abstract

Developments in the global electronics industry are typically monitored by tracking indicators that span a whole spectrum of activities in the sector. However, these indicators invariably give mixed signals at each point in time, thereby hampering efforts at prediction. In this paper, we propose a unified framework for forecasting the global electronics cycle by constructing a VAR model that captures the economic interactions between leading indicators representing expectations, orders, inventories and prices. The ability of the indicators to presage world semiconductor sales is first demonstrated by Granger causality tests. The VAR model is then used to derive the dynamic paths of adjustment of global chip sales in response to orthogonalized shocks in each of the leading variables. These impulse response functions confirm the leading qualities of the selected indicators. Finally, out-of-sample forecasts of global chip sales are generated from a parsimonious variant of the model viz., the Bayesian VAR (BVAR), and compared with predictions from a univariate benchmark model and a bivariate model which uses a composite index of the leading indicators. An evaluation of their relative accuracy suggests that the BVAR's forecasting performance is superior to both the univariate and composite index models.

Key Words and Phrases: Leading indicators; Global electronics cycle; VAR; Forecasting

1 Introduction

The semiconductor industry sets the pace of global economic growth, more so than any other single sector, and its vitality is a leading indicator of the world's economic health. As fundamental building blocks of final electronic products, semiconductors (also known as chips) are used as inputs in a wide variety of sectors such as information and communication technology, consumer electronics, as well as the industrial and transportation sectors. Thus, chips serve as a cornerstone to the global electronics industry. A key characteristic of the semiconductor industry is the acceleration of technology which renders each new generation of semiconductors obsolete fairly quickly.[2] Consequently, product cycles are short and this, in turn, results in a compression of the overall global electronics cycle. At the same time, the commoditization of semiconductors—whereby an innovation initially generating high profits plunges in value as the technology for producing it becomes widespread and standardized—brings on wide fluctuations in the electronics industry.

The inherent volatility of the global electronics cycle is most vividly illustrated by the information technology boom during the 1990s, followed by the bursting of the technology bubble in late 2000. It is evident that worldwide economic growth, particularly the domestic business cycles of economies that are heavily reliant on

[2] The semiconductor industry is driven by Moore's Law which says that the number of transistors on a chip doubles every 18 to 24 months, resulting in ever faster and cheaper semiconductors.

electronics exports, is severely impacted by such swings in electronics demand. It follows that close monitoring of the electronics industry is essential for assessing the health of the world economy, which means that timely and accurate forecasts of the global electronics cycle are indispensable.

Developments in the semiconductor industry have typically been monitored by tracking a host of diverse indicators, such as those measuring expectations, investments, orders, inventories, production, shipments, prices and profits. As these indicators span a whole spectrum of activities, they invariably give mixed signals at each point in time, thereby hampering efforts to predict world electronics activity. Apart from product cycles, global electronics demand can also be affected by other factors and the predictive value of each indicator might vary depending on which causal factors are pre-eminent in a particular cyclical episode. There is, therefore, a need for a systematic examination of the predictive potential of each indicator. Yet, the approach that has been adopted to circumvent the problem of mixed signals in electronics indicators—and for that matter, in leading indicators of the economy—is to aggregate them to form a composite index. For instance, the *Monetary Authority of Singapore* has developed an electronics composite leading index comprising five indicators to forecast Singapore's domestic electronics output and exports (Ng et al., 2004), while *Gartner Research* has a composite index of semiconductor market leading indicators for predicting growth in the world semiconductor industry.

In this paper, we propose a unified framework for forecasting the global electronics cycle by constructing a vector autoregressive (VAR) model which incorporates a set of leading indicators identified from a longer list of electronics series. To the best of our knowledge, this has hitherto not been done in the literature. Given the endogeneity of and dynamic interactions between the economic variables influencing the world electronics cycle, forecasting within a VAR framework may confer advantages. Firstly, it frees us from the implicit assumption made in the index approach of a single common factor underlying the movements in electronics indicators. Secondly, the flexibility of the VAR model means that it can accommodate the different lead times of indicators, which might partially account for the conflicting signals received.

We initially use the VAR model to perform Granger causality tests that demonstrate the ability of the selected leading indicators to presage world semiconductor sales—the variable we are interested in forecasting. Following this, the VAR is used to derive impulse response functions which trace out the dynamic effects on chip sales of orthogonalized shocks to the electronics indicators. To circumvent the overparameterization problem typical of VAR forecasting models, we next employ a parsimonious Bayesian VAR (BVAR) model to generate out-of-sample forecasts of global semiconductor sales using our leading series. Finally, the predictive accuracy of the BVAR is evaluated against a benchmark univariate model and a model which uses a composite index constructed from the leading indicators.

2 Leading Indicator Selection

The first task in forecasting the global electronics cycle is to search for plausible leading indicators. We began with a list of indicators that covers, *inter alia*, US time series on electronics new orders, inventories, shipments, and the ratios formed from them. Also included in the list are producer prices for dynamic random access memory (DRAM), the Institute of Supply Management's (ISM) manufacturing Purchasing Managers' Index (PMI), the North American book-to-bill ratio for semiconductor equipment and Nasdaq stock prices, all of which are widely used as de facto leading indicators of the global electronics cycle by private sector analysts. In addition, US corporate profits and private fixed investment in information processing equipment, and in computers and peripherals, were also considered as possible proxies of the final end-user demand for electronics (for details on the series covered and the selection process, refer to Ng et al., 2004).

The selection of leading indicators from the pool of electronics related variables at our disposal could be a potentially daunting exercise. Assuming that four indicators are to be picked from fifteen series, there are over 1300 combinations of indicators to choose from. We resolved the conundrum by appealing to the classical criteria used by researchers at the National Bureau of Economic Research (NBER) to select leading indicators for the macroeconomy. These include 'economic significance', 'currency' and 'conformity' (Zarnowitz, 1992, pp. 317–319). We ensured that the first criterion is satisfied i.e., there should be an economic reason for why an indicator leads. Accordingly, US shipments of electronics was dropped as it appears by definition to be more nearly coincident with the global electronics cycle. The PMI also did not qualify as a leading indicator because the share of electronics production in US manufacturing output is fairly small. The currency criterion, interpreted as a timeliness constraint, meant that quarterly time series should be eschewed in favour of monthly ones, thereby precluding the selection of the profits and investment series as leading indicators.

As a measure of an indicator's conformity, we calculated its cross correlation coefficients at various lead times with the coincident indicator of the electronics cycle used in our study—global semiconductor sales (CHIP). This indicator represents world billings or shipments of semiconductor products, as reported by the Semiconductor Industry Association (SIA) at its website (we have seasonally adjusted the raw data using the Census X-12 multiplicative method). We chose to use global chip sales as the coincident series because it is commonly viewed as the best available indicator of the unobserved state of the world electronics sector.[3] The conformity criterion, taken together with the need to ensure timeliness, further eliminated electronics series that exhibited statistically insignificant correlations or short leads of less than three

[3]Some might argue that the use of a coincident index of world electronics activity, analogous to the one developed for the US technology cycle by Hobijn et al. (2003), is preferable to relying on a single indicator. However, the construction of such an index is beyond the scope of this paper.

months, resulting in the eventual selection of four time series as putative leading indicators of the global electronics cycle. In arriving at our set of indicators, we made the decision to: (a) include US new orders of electronics, a series that conforms weakly to global chip sales but possesses a strong economic rationale as a leading indicator (see the discussion below); and (b) exclude the book-to-bill ratio of chip equipment, a series that fully satisfied the selection criteria but nonetheless performed poorly in subsequent analyses. It appears that the information content of the book-to-bill ratio, which tends to be driven by the semiconductor product cycle, is duplicated by the selected electronics series.

The identified leading indicators are the Nasdaq composite index (NASDAQ), US new orders of computers and electronic products (NO), the ratio of US manufacturers' shipments of electronics to inventories (SI)[4], and the US producer price index for DRAM (PPI). The Nasdaq index was downloaded from Datastream, the seasonally adjusted new orders, shipments and inventories series from the Census Bureau website (series codes are A34SNO, A34SVS and A34STI respectively), and the PPI from the Bureau of Labour Statistics website (the series code is PCU33441333344131A101). The overlapping sample period of these monthly datasets is 1992:2–2004:1, which is therefore the time period used in the paper.

[4]In its latest revisions to the historical data, the Census Bureau has excluded semiconductors from the new orders series but included them in the shipments and inventory series. We would have preferred to use indicators with a consistent coverage had they been available.

We end this section with a brief discussion of the economic rationales behind our chosen set of leading indicators that draws on ideas in Zarnowitz (1992) and de Leeuw (1991). The Nasdaq stock price index is a proxy for firms' expectations about future electronics activity. At the root of the leading relationship is the market's sensitivity to the discounted future earnings of technology firms that supply to world markets, which are ultimately dependent on the final demand for electronics products. A drawback of stock prices, however, is that they tend to be affected by other factors, including speculation, thus occasionally giving rise to false signals.

New orders of electronics is synonymous with demand and serve as an indicator of the early stage in the production process. This indicator might be expected to lead electronics activity because it usually takes time to translate an order into actual production and sales, and works especially well as a leading indicator if firms in the semiconductor industry adopt 'just-in-time' manufacturing technologies. In reality, firms do anticipate future sales, so that unexpected changes in orders rather than new orders *per se* are likely to be more highly correlated with global chip sales.

By itself, the level of inventories has a propensity to lag the electronics cycle. But when it is considered in relation to sales as in the shipment-inventory ratio, the series becomes a leading indicator. Inventory changes help firms smooth production by acting as a buffer to unexpected fluctuations in demand. For example, an increase in electronics orders or shipments could be met by a temporary drawdown in inventories before production is adjusted, causing the shipment-inventory ratio to rise. Indeed, anecdotal evidence suggests that the elimination of excess inventory in a downturn is a pre-requisite for sustained increases in semiconductor prices and sales. Chip prices respond in turn to both anticipated and unforeseen imbalances in demand and supply, making them a leading indicator in much the same way as the prices of sensitive materials.

3 A VAR Analysis of Electronics Leading Indicators

In this section, we carry out empirical analyses to demonstrate the leading qualities of the identified electronics indicators. The indicators were first converted into natural logarithms to stabilize their variances and mitigate departures from normality. We investigated the integration properties of the transformed series by applying the DF-GLS unit root test developed by Elliot, Rothenberg and Stock (1996), in conjunction with the modified AIC for selecting the lag length proposed by Ng and Perron (2001). The DF-GLS test is an asymptotically more powerful variant of the well known Augmented Dickey-Fuller (ADF) test that is obtained from generalized least squares detrending.

The results are shown in Table 1. Without exception, the data series were found to be integrated of order one. Given this, we checked for cointegration between the leading and coincident indicators using Johansen's trace test with five lags and an unrestricted constant (lag length selection is considered below). The trace statistic for the null hypothesis that there is a single cointegrating relationship in the data is 43.01, making it impossible to reject the hypothesis even at the 10% significance level. In the light of these findings, the empirical analyses are performed in the framework of a vector autoregression (VAR) in levels given by:

$$\mathbf{y}_t = \boldsymbol{\tau} + \mathbf{\Pi}_1 \mathbf{y}_{t-1} + \cdots + \mathbf{\Pi}_k \mathbf{y}_{t-k} + \boldsymbol{\varepsilon}_t, \qquad t = 1, 2, ..., T \tag{1}$$

where $\mathbf{y}_t = (NASDAQ,\ NO,\ SI,\ PPI,\ CHIP)'$, the $\mathbf{\Pi}_i$ are fixed (5×5) matrices of parameters, $\boldsymbol{\tau}$ is a (5×1) vector of constants and $\boldsymbol{\varepsilon}_t \sim MN(0, \mathbf{\Sigma})$ is multivariate normal white noise with zero mean.

Table 1: Unit Root Tests

Indicator	Lag Length	τ^{GLS}	5% Critical Value
NASDAQ	1	-1.260	-2.977
NO	2	-0.850	-2.965
SI	5	-1.879	-2.924
PPI	1	-2.632	-2.977
CHIP	5	-1.755	-2.924

Notes: The tests are for the logarithms of series, with a trend included. Critical values are from Cheung and Lai (1995).

Subject to a maximum of 13 lags, the Akaike information criterion (AIC) and the final prediction error criterion (FPE) selected an optimal lag length of 5 while the Schwarz information criterion (SIC) picked 2 lags. However, the white noise assumption was violated when only 2 lags were used in the VAR model; in particular, the residuals exhibited autocorrelation and most of them—including those belonging to the chip sales equation—were not normally distributed, rendering post-estimation inferences invalid. By contrast, including 5 lags in the VAR eliminated serial correlation and only the residuals in the DRAM price equation failed the Jarque-Bera normality test. We therefore set $k = 5$ in the analyses that follow.

3.1 Causality Tests

The standard Granger causality test entails specifying the VAR in (1) and testing to see if the subset of coefficients associated with a given leading indicator is jointly and significantly different from zero in the equation for global chip sales. Under the assumption of stationarity of variables and the null hypothesis of no Granger causality, the Wald test statistic follows a χ^2 distribution with m degrees of freedom in large samples, m being the number of zero restrictions imposed. In the presence of cointegrated regressors, as exemplified by our set of electronics indicators, Sims, Stock and Watson (1990) prove that causality tests based on levels estimation of the VAR model continue to be asymptotically valid.

On performing the Granger tests, we found that the null hypothesis of non-causality can be rejected at the 10% significance level or better for three out of the four electronics indicators—the Nasdaq stock index ($\chi^2_5 = 17.33$, p-value $= 0.004$), the shipment-inventory ratio ($\chi^2_5 = 12.23$, p-value $= 0.032$) and the DRAM chip price ($\chi^2_5 = 9.52$, p-value $= 0.09$). US new orders of electronics, with a χ^2_5 statistic of 3.98 and corresponding p-value of 0.552, do not Granger-cause global chip sales, a result which might be explained by the dual observations that semiconductors are excluded from the orders series and the shipments of electronics industries which do not produce to order are counted as part of new orders. Despite these statistical inadequacies, further evidence is presented in the next sub-section to verify the leading ability of the new orders indicator.

3.2 Impulse Response Analysis

The second use to which we put the VAR model is the derivation of impulse response functions, which show the dynamic effects on global chip sales of innovations to the leading series. Traditionally, impulse response analysis in leading indicator research has been carried out using the methodology of bivariate transfer function models (Koch and Rasche, 1988; Veloce, 1996). We prefer to adopt a VAR approach because it accounts for the endogeneity of the electronics variables and also captures the economic interactions between the leading and coincident indicators.

The impulse response functions generated by the VAR model will only be meaningful if innovations to the variables in the system are serially and mutually uncorrelated. Granted this, the innovations can be interpreted as unanticipated shocks to the leading indicators. Justifying the causal ordering with the the previous section's discussion on the economic rationales of the leading indicators, we orthogonalize these shocks by resorting to a Choleski decomposition of the estimated variance-covariance matrix of the VAR residuals.

In theory, if the individual series have distinct lead times over global chip sales, the contemporaneous correlations between their residuals will be small and alternative causal orderings will yield impulse responses that look alike. This is in fact true for the majority of the empirical correlations. In any event, we tried putting the Nasdaq index after the new orders series on the grounds that the share prices of technology firms might well react to the release of new data on electronics demand, but this makes virtually no difference to the results. Similarly, switching the positions of the shipment-inventory ratio and chip prices in the system leave the impulse response functions qualitatively unchanged.[5]

The estimated impulse response functions are depicted in Figures 1–4. We bootstrapped the VAR residuals to obtain robust standard errors for the impulse responses

[5] In addition, we obtained very similar patterns from generalized impulse response functions, confirming the robustness of our analysis.

from 1000 replications and then used them to construct the one-standard error bands shown in the figures, as recommended by Sims and Zha (1999). In every case, unanticipated shocks to the leading indicators produce statistically significant movements in world semiconductor sales. The time horizon over which the dynamic adjustment paths of chip sales are plotted following the innovations to each of the leading series extends to 24 months, by which time the responses are in general insignificantly different from zero.

All the graphs share the hump-shaped feature so often observed in the impulse response functions reported in business cycle studies. In our context, this characteristic demonstrates the leading qualities of the electronics indicators. In particular, the impulse response in Figure 2 tracing out the impact on semiconductor sales of an orthogonalized shock to US new orders is consistent with our conjecture that only unexpected changes in orders will lead the electronics cycle. The indicators differ, however, on the number of months it takes for the dynamic response of global chip sales to reach a peak, which gives us an idea of the average lead in a series. The estimated impulse responses indicate that the average leads for the Nasdaq index and the shipment-inventory ratio are the longest, at 8–10 months. The lead times for new orders and DRAM prices, at 3 and 2 months respectively, are shorter. In sum, the orthogonalized impulse response functions from the VAR model confirm that all the selected indicators presage world electronics activity, albeit with different lead times.

Figure 1: Impulse Response of Global Chip Sales to Nasdaq Shock

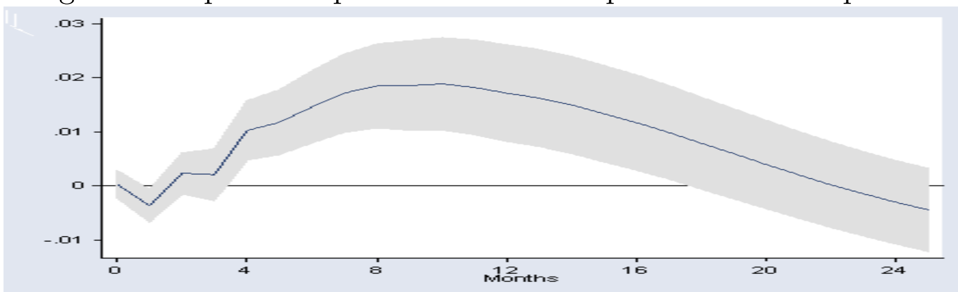


Figure 2: Impulse Response of Global Chip Sales to New Orders Shock

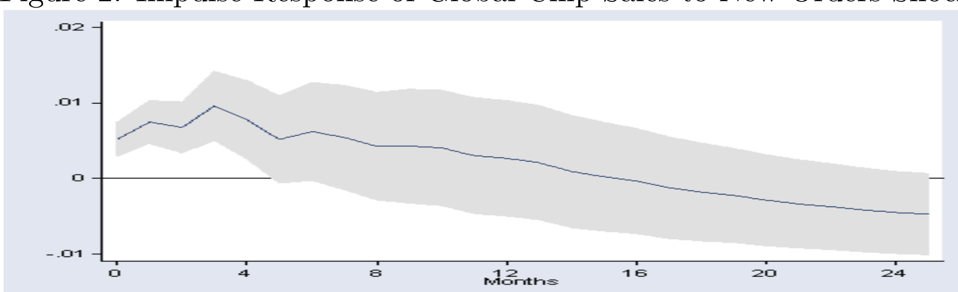


Figure 3: Impulse Response of Global Chip Sales to Shipment-Inventory Shock

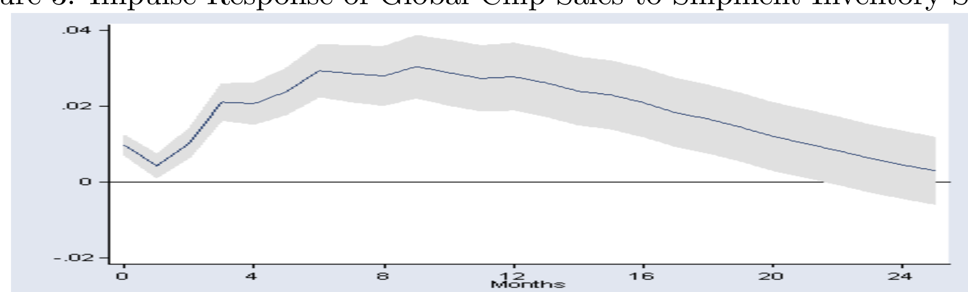
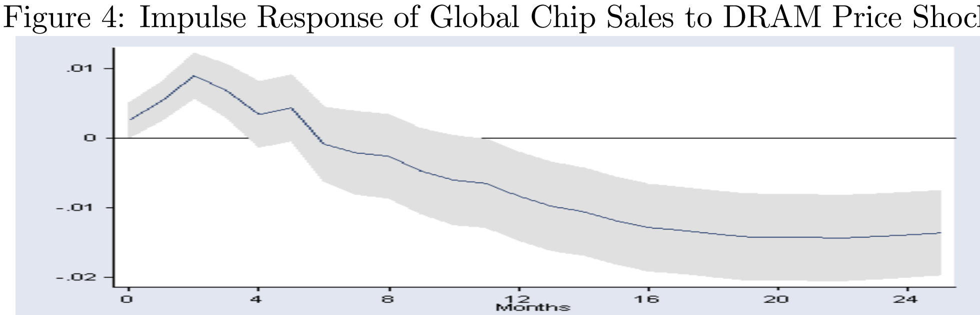


Figure 4: Impulse Response of Global Chip Sales to DRAM Price Shock



4 Forecast Performance of BVAR Model

We proceed in this section to forecast the global electronics cycle within the VAR framework by first explaining the need to adopt a BVAR forecasting model incorporating our four leading indicators. We next describe the alternative models with which the predictive performance of the BVAR is compared and then present the results of several forecast evaluation exercises.

4.1 The Competing Models

A well-known problem afflicting VAR models is the "curse of dimensionality", or tendency for them to be overparameterized in view of the large number of coefficients to be estimated and the limited degrees of freedom typically available for economic data. Even with just five variables as in our model, this problem will potentially lead to unreliable *ex ante* forecasts of global chip sales. To circumvent this difficulty, we employ for prediction purposes a parsimonious variant of the VAR model that retains its flexibility viz., the Bayesian VAR popularized by Doan, Litterman and Sims (1984). We found that forecasts from the VAR model are strictly dominated by those from the BVAR, as one would expect from the more efficient parameter estimates yielded by Bayesian methods. Consequently, we do not report the forecasting results for the unrestricted VAR model to conserve space.

The BVAR's parsimony comes from its application of the so-called 'Minnesota prior' to each equation of the levels VAR in (1): (i) the coefficient on the first lag of the dependent variable is given a prior mean of one; (ii) all the other lag parameters are given zero prior means; and (iii) the constant term is assigned a 'flat' or uninformative prior. In other words, the prior distributions are formulated in such a way as to nudge each dependent variable in the system towards a random walk with drift—a reasonable restriction to impose on the integrated time series we deal with. Furthermore, the standard deviation of the prior distribution for the coefficient on lag k of variable j in equation i is specified as follows:

$$s_{ijk} = \frac{g \cdot w \cdot \sigma_i}{k \cdot \sigma_j}, \qquad w = 1 \text{ if } i = j; \quad k = 1, ..., 5 \tag{2}$$

σ_i/σ_j is a scaling factor that is substituted with estimated standard errors from univariate autoregressions on the electronics variables. In our BVAR model, the prior standard deviations of the autoregressive parameters decay in a harmonic pattern as the lag length increases. The values of the two hyperparameters g and w, representing the overall tightness of the prior on the first lag of each dependent variable and the relative tightness of the prior on the lags of the other endogenous variables respectively, were chosen on the basis of out-of-sample forecast performance. After conducting a grid search over the range of values from 0.1 to 0.9 and relying on the root mean square prediction error (RMSE) as the objective function to be minimized, we settled for $g = 0.3$ and $w = 0.9$.

We will compare the predictive performance of the BVAR with two alternative models of chip sales. The first is the univariate autoregressive (AR) process, which is a frequently used benchmark model. The presence of a unit root in the sales series suggests modelling in logarithm first differences, and the following AR model of order 5 was found to fit the data well:

$$\triangle y_t = \tau + \sum_{k=1}^{5} \phi_k \triangle y_{t-k} + \varepsilon_t \tag{3}$$

The forecasts of chip sales from this model were converted into levels for comparison with the VAR model.

The second forecasting model we consider is a bivariate specification involving a composite index derived from the leading indicators. As mentioned at the beginning, it is customary to combine leading series into a composite index to give a summary measure of their movements. Using the methodology employed by The Conference Board for compiling the US Leading Index, we constructed a similar index for the global electronics cycle.[6] No cointegration was detected between this leading index (z_t) and global chip sales (y_t), motivating us to build a bivariate VAR model in the

[6] This entails the computation of symmetrical month-to-month percentage changes in each indicator, followed by a standardisation process to prevent the more volatile series from dominating the rest. These are then summed to yield the monthly percentage changes in the composite index, thus effectively assigning equal weights to each component. Finally, the index levels are derived recursively after setting the first month's value of the index to 100 (for further details, see the December 1996 issue of *Business Cycle Indicators*).

logarithm differences of these two series.[7] Both the AIC and the FPE selected an optimal lag length of 4 for the leading index model, hence we estimate these two equations:

$$\begin{aligned} \triangle y_t &= \tau_1 + \sum_{k=1}^{4} \phi_{1k} \triangle y_{t-k} + \sum_{k=1}^{4} \alpha_{1k} \triangle z_{t-k} + \varepsilon_{1t} \\ \triangle z_t &= \tau_2 + \sum_{k=1}^{4} \phi_{2k} \triangle y_{t-k} + \sum_{k=1}^{4} \alpha_{2k} \triangle z_{t-k} + \varepsilon_{2t} \end{aligned} \tag{4}$$

For the purpose of evaluating each model's forecast performance, we divided our data set into two parts. The first spans the period from 1992:3 to 2003:1 and was used only for estimation; the remaining 12 data points, spanning 2003:2 to 2004:1, were used for post-sample prediction. We do not use a longer post-sample prediction period in view of the shortness of the data series as well as the size of the BVAR model. Forecast horizons of 1, 3 and 6 months are considered. Reflecting what a forecaster would be able to do in practice, we estimated all the models recursively so that the prediction for time $t + h$ is always computed with data up to time t.

In addition to the RMSE, we also report the mean absolute prediction error (MAE) measure of forecast accuracy for the competing models. The results from the univariate autoregression serve as a yardstick against which we measure the predictive abilities of the other two models; that is, we compute the ratio of the latter's RMSE or MAE to those of the AR model at every forecast horizon. Whenever the relative

[7] We did not set up a BVAR for the leading index since the overfitting problem for a bivariate model is much less severe.

RMSE or MAE of the BVAR or leading index model is smaller (larger) than one, its forecasting performance is better (worse) than the benchmark model.

4.2 Forecast Evaluation

Table 2 reports the relative RMSE and MAE associated with the out-of-sample forecasts of global chip sales generated from the BVAR and leading index models. The inclusion of information from the leading indicators in the BVAR and index forecasting models clearly leads to substantial improvements in predictive accuracy over the univariate AR model. This result holds across all three forecast horizons, notwithstanding the fact that ARIMA models are known to produce very accurate forecasts in the short term. As for the relative predictive performances of the BVAR and index models, we observe that the former consistently outperforms the latter in terms of both the RMSE and MAE criteria over the entire range of forecasting horizons.

Table 2: Forecast Performance of BVAR and Index Models

	Relative RMSE		Relative MAE	
Forecast Horizon	BVAR	Index	BVAR	Index
1 month	0.784	0.946	0.801	0.971
3 months	0.621	0.863	0.530	0.708
6 months	0.559	0.708	0.541	0.583

Note: Relative RMSE or MAE is expressed as a ratio to the univariate AR model.

To ascertain if the differences in predictive accuracy found between the models are statistically significant, we conduct formal tests of forecast performance based on the Diebold-Mariano (1995) test statistic. In particular, we employ the following small sample version (DM) proposed by Harvey, Leybourne and Newbold (1997):

$$\begin{aligned} DM &= \sqrt{\frac{T+1-2h+h(h-1)/T}{T}} \frac{\bar{d}}{\sqrt{V(\bar{d})}} \\ V(\bar{d}) &= \frac{1}{T}\left(\hat{\gamma}_0 + 2\sum_{k+1}^{h-1}\hat{\gamma}_k\right) \end{aligned} \tag{5}$$

where T is the number of forecasts made, h is the forecast horizon in months, $\bar{d}$ is the sample mean of the differences between the squared or absolute forecast errors from any two competing models, $V(\bar{d})$ is the approximate asymptotic variance of $\bar{d}$, and $\hat{\gamma}_k$ is the estimated kth order autocovariance of the forecast error differences. The DM statistics for the alternative models are shown in Table 3 and compared with the one-tailed critical values from the t-distribution with $T-1$ degrees of freedom.

Table 3: Predictive Accuracy Tests

	$h=1$		$h=3$	
	Sq. Errors	Abs. Errors	Sq. Errors	Abs. Errors
BVAR vs AR	-1.97^{**}	-1.26	n.a.	-4.29^{**}
Index vs AR	1.04	1.14	-0.04	-0.35
BVAR vs Index	-1.02	-1.01	0.01	-1.57^{*}

Note: * and ** denote significance at the 10% and 5% level respectively.

It is evident from the table that where the 1-month ahead forecasts are concerned, there is generally no appreciable differences in forecast performance between the three competing models as all but one of the test statistics turned out to be insignificant. The notable exception is the DM statistic for squared forecast errors generated by the BVAR and AR models, providing evidence that the former significantly outperforms the benchmark model even at a short forecast horizon. At the 3 months horizon, the two significant DM statistics for absolute forecast errors indicate that the BVAR model again delivers significantly more accurate predictions than the univariate AR and index models. In contrast, the hypothesis of equal predictive ability between the index and benchmark models cannot be rejected at the 10% significance level for both measures of forecast accuracy at the same horizon.

The DM test statistics are undefined for most of the 6-months ahead forecast errors (and also in the case of the differences between the 3-months ahead squared forecast errors from the BVAR and AR models). This is because $V(\bar{d})$ took on a negative value in each instance, requiring the evaluation of the square root of a negative number in equation (5). In such pathological situations, Diebold and Mariano (1995) suggest that the null hypothesis of equal forecast accuracy be rejected. Given the sizable gains in the corresponding measures of forecast accuracy (Table 2), this automatically implies that the univariate model is inferior to the leading index and BVAR models for forecasting 6 months ahead.

Finally, we turn to forecast encompassing tests to determine whether the forecasts generated by the AR and index models embody useful information about future semiconductor sales absent in those produced by the BVAR model. Forecast encompassing is closely related to forecast combination (Chong and Hendry, 1986). Denoting the composite forecast error by ε_t (assumed to be a white noise term) and the two forecast error series by $e_{it}, i = 1, 2$, we run the following OLS regression

$$e_{1t} = \lambda(e_{1t} - e_{2t}) + \varepsilon_t \tag{6}$$

Under the null hypothesis that the first forecast encompasses the second, $\lambda = 0$. A t-test based on heteroskedasticity and autocorrelation-consistent methods is applied as our test for encompassing and the results in probability form are summarized in Table 4.

Table 4: Forecast Encompassing Tests

	$h = 1$			$h = 3$			$h = 6$		
	BVAR	Index	AR	BVAR	Index	AR	BVAR	Index	AR
BVAR	1.00	0.00	0.01	1.00	0.01	0.00	1.00	0.02	0.01
Index	0.99	1.00	0.45	0.08	1.00	0.01	0.99	1.00	0.01
AR	0.37	0.01	1.00	0.73	0.12	1.00	0.73	0.95	1.00

Note: Each entry is the p-value of the null hypothesis that the forecasts generated from a model listed in a column encompasses the forecasts of a model in a row.

The superiority of the BVAR approach to forecasting the electronics cycle is further reinforced by the encompassing analysis. The test results reveal that the BVAR forecasts at every horizon encompass those of the univariate and leading index models at the 5% significance level while the converse is not true. The failure of the forecasts from the latter two models to encompass the BVAR forecasts suggests that the individual leading indicators have useful predictive content. Not surprisingly, the index model also encompasses the univariate model for the 6-months as well as 3-months ahead forecasts, the last result contradicting the finding of the Diebold-Mariano test.

Overall, the relative ranking of the three competing models we considered is clear-cut. Although incorporating information from the leading indicators tends to improve the forecast accuracy of both the BVAR and index models *vis-à-vis* the AR model, the BVAR is unambiguously the best-performing model. The BVAR's reliance on a diversified set of leading electronics indicators instead of a composite index avoids the problems associated with index construction such as the use of equal weights for the component indicators. Its excellent forecasting performance can be attributed to the economic interactions between the variables in each equation of the model (as reflected in the loose value of 0.9 selected for the relative tightness hyperparameter). By virtue of this rich dynamic structure and efficient estimation techniques, the BVAR can accommodate the different lead times of indicators without sacrificing parsimony at the same time, thereby resulting in gains to forecasting accuracy in practice.

5 Conclusion

In this study, we identified from a list of frequently monitored electronics indicators four monthly leading series that are economically significant and show the potential to presage global semiconductor sales. These are the Nasdaq composite index, US new orders of electronics, the US electronics shipments to inventories ratio, and DRAM chip prices. We then construct for this set of leading indicators and our chosen coincident indicator of the global electronics cycle, world semiconductor sales, a VAR model that reflects the dynamic interactions in the electronics market. Besides providing a natural framework for performing Granger causality tests which establish the leading qualities of most of the selected indicators, the VAR system is also used to characterize the dynamic paths of adjustment of global chip sales in response to orthogonalized shocks in each of the leading series. These impulse response functions with their hump-shaped features confirm that our chosen set of electronics indicators presage the world electronics cycle by distinct lead times.

From a methodological point of view, the principal objective of adopting a VAR approach is to provide a unified framework for forecasting the global electronics cycle with leading indicators, without having to make the restrictive assumption of a single common factor underlying the movements in the indicators. To this end, post-sample predictions of global chip sales were generated from a Bayesian VAR model and their accuracy compared with forecasts from two alternative models—a univariate

AR model and a model which uses a composite index constructed from the same set of leading indicators. An evaluation based on standard measures of forecast accuracy and formal tests of predictive ability and forecast encompassing suggests that the BVAR model's forecasting performance is superior to those of the univariate and composite index models.

Our results are in contrast to recent studies that compare the relative forecasting efficacy of leading index and BVAR or VAR models, and find that index models generally predict better (Camba-Mendez et al., 2001; Bodo et al., 2000). This finding is presumably due to the fact that some of the conflicting signals provided by leading indicators are manifestations of measurement errors and random disturbances in the data, which tend to cancel out and lead to noise reduction when a composite index is employed. We show in this paper, however, that the gains to forecasting from using a flexible and parsimonious BVAR can outweigh the benefits of noise reduction when dynamic interactions between economic indicators with different lead times are important.

Although we conclude that the proposed BVAR model incorporating our set of identified leading indicators is ideally suited for forecasting the global electronics cycle, there is scope for further work. For instance, one might want to consider the ability of the model to anticipate turning points in the global electronics cycle. Forecasters in the electronics industry might be more interested in predicting the timing of peaks and troughs rather than in the type of quantitative forecasts that we focused on in this paper. We did not address this issue partly because of the paucity of turning points in our relatively short sample period, but also due to the inherent difficulty of defining cyclical turning points. Nonetheless, future research along these lines is warranted.

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