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Forecasting macroeconomic variables using data of different periodicities[1]

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Abstract

A formal statistical method is used in this study to combine forecasts from a quarterly macroeconometric model for Taiwan with monthly time series forecasts. Three monthly models, i.e. vector autoregressive (VAR), Bayesian vector autoregressive (BVAR) and Autoregressive integrated moving average (ARIMA) were alternately applied to examine whether a superior monthly model can achieve better quarterly forecasts. For variables that are observed both quarterly and monthly, combined forecasts are generally found to be superior to the macro forecasts but inferior to the monthly ones. With respect to variables that are available only quarterly, results in this study indicate that the gain in forecasting accuracy due to the inclusion of the monthly data is substantial even when no monthly information is available for the quarter.

Keywords: Combining forecasts; VAR model; BVAR model; ARIMA model; Macro model

1. Introduction

Macroeconomic forecasters generally have at their disposal a collection of time series observed with varying sampling frequencies. Conventional forecasting methods use time series having a common sampling frequency. Since most macroeconometric models focus primarily on the data in the national income and product accounts (NIPA) that are prepared at quarterly intervals, other monthly or higher frequency data apparently ought to be aggregated before entering the quarterly model.

In using a macroeconometric model for forecasting the national economy, practitioners are tied to the schedule for preparing and releasing the NIPA. In most countries, the lag is about one and a half months after the end of a calendar quarter. Taiwan is not an exception. For example, Taiwan statistical forecasting agency, Directorate-General of Budget, Accounting and Statistics (hereafter, DGBAS), releases the GNP of the last quarter on the second Friday of the second month of the quarter. Consequently, as a quarterly econometric model is initiated to project the current quarter, the monthly data in the current quarter of some other variables also

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become available. As the monthly measurements normally provide valuable information regarding the future economic movements, it seems sensible to use this additional information.

In practice this is achieved by adjusting the constant term of relevant equations (or using a non-zero error term) to make the model outcome agree with the new information. Such a procedure to alter a model's solution is often referred to as 'judgmental modification' and is subject to criticism as being unscientific or ad hoc. Recently, Klein and Sojo (1989), Donihue (1993), Corrado and Greene (1988), Corrado (1986), Fuhrer and Haltmaier (1988), Donihue and Howrey (1992), Greene et al. (1986), Howrey et al. (1991) and others proposed an alternative method for incorporating the high frequency information into the forecasting process which can replace the use of judgmental adjustments. Their method first involves constructing quarterly and monthly models. Next their difference is interpreted as the information contained in the monthly data but not in the quarterly data. The quarterly macroeconometric model considered is designed primarily for 'medium-run' forecasting and policy simulations. Its equations therefore generally have a solid theoretical base and exhibit desirable medium-run equilibrium properties, but place less emphasis on short-run forecasting accuracy. The monthly model, in contrast, is designed for short-run forecasting using a mixture of behavioral and time series equations, and for incorporating monthly information, whenever available. The combination of the two forecasting models, which differ significantly in structure and exploit different kinds of information, would be expected to yield lower forecast errors.

However, Granger and Ramanathan (1984), Fuhrer and Haltmaier (1988) and Shen and Liou (1994) show that combined forecasts do not outperform the individual forecast all the time or even on average outside the sample. That is, the theoretical benefits from combining forecasts do not always occur in practice. The discrepancy between empirical studies and theories probably results from the additional parameter uncertainties introduced with estimated combination weights which are not taken into consideration by the theory. Thus, whether high frequency information can improve the quarterly forecast in reality becomes a matter for empirical investigation.

The purpose of this paper is to examine, using Taiwan's data, whether or not the monthly information can be used to improve the quarterly forecast. As previous studies of pooling forecasts for different frequencies generally focus on the developed countries, the case of a developing country, Taiwan, is adopted here as an alternative example. Shen and Liou (1994) studied whether monthly information can actually improve the quarterly forecasts of Taiwan's economy. In their study, a small quarterly econometric model containing 14 behavioral equations, and two monthly time series models, a vector autoregressive (VAR) model and a Bayesian vector autoregressive (BVAR) model are considered. The forecast performance is evaluated on the out-of-sample forecast error of the next period. The methods of exploiting monthly information to improve the quarterly forecasts differ according to the type of endogenous variables: common and non-common variables, where the former are those variables having both high and low frequency data, and the latter are those having only low frequency data. The model C of Granger and Ramanathan (1984) (hereafter, GR) is employed to merge monthly and quarterly forecasts of common variables through a traditional regression approach, whereas a stepwise method (as explained in Section 3) is adopted to select the monthly information useful to improve the forecasts of non-common variables. Shen and Liou (1994) conclude that the accuracy of combined forecasts for common variables is not better than that of the component forecasts all the time or even on average. However, forecasts of non-common variables are significantly improved. Also, a better monthly model increases the performance of the combined forecasts vis-à-vis that of their components in common variables.

In this study, some extensions are made to the work of Shen and Liou (1994) to examine whether their conclusions are robust or not.

First, their small quarterly macroeconometric model is expanded to a medium-sized one containing 34 behavioral equations and 25 identities. This makes our quarterly model closer to that of the DGBAS, whose model contains a total of 132 equations (Ho, 1991). More importantly, the larger model includes more endogenous variables on which the conclusions of Shen and Liou (1994) can be tested. Second, a stepwise technique to select useful monthly information is employed for all common variables. Shen and Liou (1994) showed that model C of GR does not significantly raise the forecasting accuracy of combined forecasts in common variables but the stepwise method performed well in non-common variables. Using the stepwise method for all endogenous variables would, therefore, be a logical next step. Third, three (rather than two) monthly time series models, VAR, BVAR and ARIMA are employed to investigate whether a better monthly model could actually reduce the forecast error of combined forecasts. We expect their contributions to the quarterly forecasting accuracy to correspond with their forecasting accuracy.

2. Model linkage–theoretical consideration

This section discusses how quarterly and monthly models are linked. The notion is relatively simple. One-step-ahead forecasts of quarterly data are first generated from both quarterly and monthly models. Next, these forecasts are used to calculate the weights of the quarterly and monthly models in the combining equations. The combined forecasts are then obtained and are just the weighted average of quarterly and monthly forecasts. Very precise forecasts should, theoretically, have more weight than less precise forecasts. The process is referred to as model linkage and is explained in detail below.

Following the notation of Greene et al. (1986), the structural form of a quarterly linear forecasting model is written as

$$CY_t = AY_{t-1} + BX_t + U_t \tag{1}$$

where Y_t is a $G \times 1$ vector of endogenous variables valued at time t, X_t is a $N \times 1$ vector of exogenous variables valued at time t, A, B and C are conformable matrices of structural parameters and U_t is a $G \times 1$ vector of disturbances with mean zero and covariance matrix Σ_{uu}.

The reduced form used for forecasting is written as

$$Y_t = PY_{t-1} + QX_t + V_t \tag{2}$$

where $P = C^{-1}A$, $Q = C^{-1}B$ and $V_t = C^{-1}U_t$. The one-quarter-ahead forecast of Y_t, given Y_{t-1} and X_t, is:

$$\hat{Y}_t = PY_{t-1} + QX_t \tag{3}$$

so that

$$Y_t = \hat{Y}_t + V_t \tag{4}$$

where $V_t \sim N(0, \Sigma_w)$.

Next, the construction of the monthly models uses time series approaches in order to capture the momentum among variables. If a flow variable is used, the monthly forecasts are made for the unobservable months in the quarter and are then properly aggregated into a quarterly forecast. If a stock variable is used, the monthly forecasts are averaged. Using flow variables as illustrative examples, the manner of aggregation of monthly forecasts into a quarterly one depends on the amount of extra information we have. If no monthly information is available, the 1-, 2- and 3-month ahead forecasts are aggregated into a quarterly forecast. However, only forecasts of the second and third months of that quarter are required if the information of the first month is known. The quarterly forecast of a flow variable is therefore obtained by summing up 1 month of actual observation and 2 months of forecasts. The first and the second months of actual observations and the forecast of the third month are summed into a quarterly forecast if 2 months are available.

More specifically, let $y_{t,\,g}(i)$ denote the gth variable in Y_t for month i of quarter t. The i-month forecast of $y_{t,\,g}(i)$ is denoted as $\tilde{y}_{t,\,g}(i)$. Assuming that $y_{t,\,g}(i)$ is a flow variable hereafter, the quarterly forecast based on the monthly model for gth endogenous variable is thus written as

$$\tilde{Y}_{t,g} = \sum_{i=1}^{3} \tilde{y}_{t,g}(i) \tag{5}$$

Let $\tilde{Y}_t$ be the collection of H quarterly forecasts derived from the monthly model, where H is the number of common variables, thus

$$\tilde{Y}_t = [\tilde{Y}_{t,1}, \tilde{Y}_{t,2}, \ldots, \tilde{Y}_{t,H}]'$$

denotes the $H \times 1 (H \leq G)$ vector of 'outside information' forecasts. Namely, monthly information offers extra information for the quarterly forecasts. Because only part of the variables are available monthly, a 'selection' matrix denoted by θ is employed to pick out the H element of Y_t corresponding to $\tilde{Y}_t$ (recall that Y_t contains both common and non-common variables)

$$\theta Y_t = \tilde{Y} + W_t \tag{6}$$

where W_t is a $H \times 1$ vector of disturbances with mean zero and covariance matrix Σ_{WW}.

The difference between the one-quarter ahead forecasts of quarterly and monthly models is

$$\begin{aligned} Z_t &= \tilde{Y}_t - \theta \hat{Y}_t \\ &= \theta V_t - W_t \,. \end{aligned} \tag{7}$$

This forecast discrepancy represents the information contained in the monthly model but not in the quarterly model or vice versa. The use of mixed frequency data to improve upon macroeconomic forecasts is justified by the following theorem.

Theorem 1. Greene et al. (1986). Given the system

$$Y_t = \hat{Y}_t + V_t \qquad V_t \sim N(0, \Sigma_{VV})$$

$$\theta Y_t = \tilde{Y}_t + W_t \quad W_t \sim N(0, \Sigma_{WW})$$

and the information vector

$$Z_t = \tilde{Y}_t - \theta \hat{Y}_t$$

the optimal combined forecast of the quarterly and monthly data is

$$\bar{Y}_t = \hat{Y}_t + K Z_t \tag{8}$$

where

$$K = \Sigma_{ZV} \Sigma_{ZZ}^{-1} \tag{9}$$

$$\Sigma_{ZZ} = \theta \Sigma_{VV} \theta' + \Sigma_{WW} - \theta \Sigma_{VW} - \Sigma_{WV} \theta' \tag{10}$$

$$\Sigma_{ZV} = \theta \Sigma_{VV} - \Sigma_{WV} \tag{11}$$

The coefficients matrix K, which is equivalent to the regression coefficients of regressing quarterly residuals V on Z, is of dimension $G \times H$. Since Z contains all outside information from monthly data, a regression of the residual errors of, say, the ith equation in the V on the 'entire' information vectors is suggested by the above theorem. This implies that, for example, not only monthly information of consumer price index (CPI), but also the remaining outside information, e.g. interest rate, imported price, money supply, is also helpful for reducing forecasting error of quarterly CPI. It also suggests that the forecasting errors on non-common variables, such as GNP, can be reduced from the use of outside information. The concept of employing outside information to improve quarterly forecasts of both common and non-common variables makes a sharp contrast to the model C of GR, which utilizes only 'own' outside information. More specifically, GR's model C can be expressed as follows.

$$Y_{t,j} = k_{t-1,0} + k_{t-1,1} \tilde{Y}_{t,j} + k_{t-1,2} \hat{Y}_{t,j} + \epsilon_t \tag{12}$$

where $Y_{t,j}$ is the jth 'common' variable, $\hat{Y}_{t,j}$ and $\tilde{Y}_{t,j}$ are the corresponding quarterly and monthly forecasts and the parameters $k_{t-1,i}$ are estimated by a regression up to time $t-1$, and re-estimated once the new forecasting residuals are available. The combined forecast in model C is a weighted average of the two competing forecasts, with weights being determined by their own forecasting precisions. That is, each common variable is simply regressed on its own monthly and quarterly forecasts without resorting to other outside information. This also implies that model C cannot be applied to non-common variables since the variables do not have corresponding monthly forecasts. Thus, our approach, which includes entire outside information, is a generalization of GR's model C in terms of exploiting outside information. In other words, the left hand side of Eq. (12) becomes

$$Y_{t,j} = k_{t-1,0} + k_{t-1,1}\tilde{Y}_{t,1} + \dots + k_{t-1,H}\tilde{Y}_{t,H} + k_{t-1,H+1}\hat{Y}_{t,j} + \epsilon_t \quad (13)$$

where $Y_{t,j}$ can be either a common or non-common variable and $\tilde{Y}_{t,j}$ is the forecast of the jth monthly variable. The parameter $k_{t-1,j}$ is obtained from the same regression up to time $t-1$, not time t. Next, a combined forecast is made given current quarterly and monthly forecasts. The parameter is re-estimated once the new forecasts are available. The parameters obtained here are the same as the jth row of K obtained in (9).

Using entire outside information, though appealing, has its limitation. The $\hat{Y}_{t,j}$, which is the series of one-step-ahead quarterly forecasts, typically contains no more than 30 observations and the first 12, say, observations are used for constructing the first K. In our model, one-step-ahead forecasts from macro and monthly models extend from 1985:1 to 1992:2. The first 12 observations are used to obtain the first K. Thus, it is impossible to use entire outside information for 13 variables. Thus, the degrees of freedom are quickly absorbed if the entire H outside information is used as regressors to estimate the first K. To remedy this problem, the most useful outside information should be picked up when estimating $k_{t-1,j}$, the ith row of K. Since theories do not offer any guidance on how to extract the relevant outside information, the stepwise method is thus employed on (13) for each endogenous variable to select the most useful outside information.

3. Taiwan's quarterly macroeconomic model

DGBAS is a government forecasting agency. The agency prepares its forecasts of GNP, CPI, etc., on the second Friday of the second month of the quarter and presents these reports to a committee that has the authority to determine the final figure of all the forecasts. The committee, comprised of governmental officials and experienced economists, discusses the adequacy of the forecasts based on the current economic situation. The forecasts are modified, if deemed necessary, by the constant adjustment process introduced in the introduction and the committee announces the final version of the forecasts before 5:00 pm.

The DGBAS normally updates its macro model annually. In recent years, rapid financial deregulation, the collapse of communist countries and increasing fiscal deficits, have forced the DGBAS to modify its model more frequently to reflect the changing environment. The new version of DGBAS's model focuses on the determination of interest rate, exports to and imports from mainland China, and the approach for financing government expenditures. The conventional Keynesian labor market and production function remained unchanged.

Investigating the potential gain in forecasting accuracy resulting from the use of outside information requires constructing a simplified version of the DGBAS quarterly macroeconometric model of Taiwan. DGBAS's macroeconomic model consists of approximately 132 equations based on the textbook 'income–expenditure model', which includes commodity market, money market, labor market, foreign market and production function (Ho, 1993). The DGBAS's model is closed with identities so that the resulting dynamic simultaneous equation system determines all of the components.

Our model only contains 34 behavioral equations and 25 identities but reflects the basic features of the parent model. Appendix A lists the 88 variables included in our model, 13 of which are available monthly. They are CPI, WPI, PM, PX, TDR1M, TDR1Y, M1B, QM, XG, MG, WG, NF and NUU. These 13 variables, which are available both monthly and quarterly, have been referred to as common variables.

The quarterly model is first estimated over the period 1971:1–1984:4. One-quarter-ahead forecasts are then made for every endogenous variable. Next, the ending period moves forward one quarter and the structural model is re-estimated (but not re-specified) before the new set of one-quarter-ahead forecasts are generated. The above steps are repeated until the end of data, i.e. 1992:2. Hence, the forecasts of all endogenous variables extend from 1985:1 to 1992:2. The model is first estimated by ordinary least squares. A correction was included using the Cochrane–Orcutt technique where the Durbin–Watson statistic revealed a first order autocorrelation. Detailed results are not reported but are available upon request.

4. Monthly model

For the variables available monthly, three types of time series models, VAR, BVAR and ARIMA, are considered.

An unrestricted VAR can be expressed as follows

$$Y_t = D_t + \sum_{j=1}^{m} B_j Y_{t-j} + C_i SD_t + \eta_t \qquad (14)$$

where

Y_t = an $H \times 1$ vector of the values of all of the variables in the system at time t.

D_t = an $H \times 1$ vector representing the constant term.

SD_t = an $H \times 11$ vector representing the 11 seasonal dummies.

C_i = an $H \times H$ matrix of coefficients on the seasonal dummies.

B_j = an $H \times H$ matrix of coefficients on the $t-j$ lagged values of Y_t.

$E(\eta_t \eta_s') = \Sigma$ if $t = s$, and 0 otherwise

The Bayesian version of the VAR differs from the unrestricted version by incorporating the forecaster's prior beliefs regarding the most likely values of the Bs. Prior beliefs are embodied in the estimation procedure by maximizing the likelihood function weighted by the probability density function of the parameters, given the forecaster's priors about the values of the parameters. The distributions of the parameters are assumed to be normal and, therefore, can be completely defined by means and variances. Thus, each parameter is assigned a prior mean and variance. The key to the systematic assignment of means and variances is the so-called Minnesota prior, which is briefly discussed in Appendix B. The prior mean of the coefficient on the own first lag of each variable is 1, and on all of the other own lags and on all cross lags are 0 (see Doan et al., 1984; Litterman, 1986).

For the VAR and BVAR modellings, the 13 common variables were divided into two groups, each group modelled separately. The first one consists of variables closely related to the financial market, including CPI, WPI, PM, PX, TDRIM, TDR1Y, M1B and QM. The second one, corresponding to the real sector, consists of XG, MG, WG, NF and NUU. See Appendix A for the meaning of each variable. While the reason for this classification is the requirement that both systems are supposed to be modest in size, the distinctions are based on the variable's economic feature.

Once the prior mean and variance are specified, the lag length should be determined next, and after proper diagnostic checking, it was selected to be 2. A constant and seasonal dummies are also included. To save space, the estimation results are not reported but are available upon request.

The ARIMA modelling for the 13 variables used the Box–Jenkins approach. Their estimation results are also not reported but are available upon request.

Monthly projections were generated from each type of model starting from the first month of 1985. The forecasting periods of the monthly models are the same as those of the quarterly model, except that the horizon for each forecast covers 3 months, 2 months and 1 month, respectively, depending on the amount of monthly information available in the forecasted quarter. For the zero-month-information forecasts, forecasts of first, second and third months of the quarter are made respectively, and are then aggregated into quarterly forecasts. For the 1-month information, forecasts of only second and third months of the quarter are required. For the 2-month information, forecasts of only the third month are made.

5. Forecasting results

The quarterly forecast errors for the period ranging from 1985:1 through 1988:4, as obtained from the quarterly and monthly models, respectively, are initially substituted into equation (9) to determine the first set of 'K' coefficients. As discussed in Section 3, this is equivalent to estimating (13) in addition, the procedure to select the useful information vector is a stepwise regression. Note that the weights K are not fixed, but are re-estimated each time as the new sets of quarterly forecasts are obtained. A sequence of one-quarter-ahead combined forecasts are generated for the period 1989:1 to 1992:2.

The criteria employed in this study to assess the quality of the forecasts are the root mean squared percentage error (RMSPE) and the mean absolute error (MAE), which are defined as

$$RMSPE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\frac{(Y_t - Y_t^*)^2}{Y_t}}$$

and

$$MAE = \frac{\Sigma |Y_t - Y^*|}{T} \quad (15)$$

respectively, where Y_t is the actual quarterly data, Y_t^* is the corresponding quarterly forecast obtained from either the structural, the monthly or the combined models and T is the number of forecasts used.

Table 1 presents the RMSPE results using the ARIMA monthly models. This table contains the forecasting results with 0-, 1- and 2-month outside information available.

For most of the common variables, import (IM) and import price indices (PM), and import and export of merchandise (MG and XG) being the notable exceptions, the ARIMA fittings yield smaller RMSPEs than those of the structural projections. The reason for this outcome may be the drastic change in the trading patterns that Taiwan has confronted in recent years. Since the third quarter of 1986, the New Taiwan dollar appreciated from 40:1 to 25:1 in 1990 with respect to the US dollar. This appreciation slowed down exports to the US but accelerated imports from the US. Meanwhile, exports to the Southeast Asia, mainland China, Hong Kong and European countries substantially increased. As a result, projections using a time series model, which assumes a fixed or slowly evolving pattern in a series, may miss the target. The results suggest that univariate ARIMA models may need to be re-specified (which is costly) when the sample size is increased, especially during periods of significant economic structural changes.

The forecasting accuracies of the combined forecasts are examined next. As shown in Table 1, combined forecasts of common variables do not always yield lower RMSPEs than their components, regardless of the monthly forecasting models. Forecasts generated by the combined model are generally found to be superior to those generated by the structural one but inferior to those generated by the monthly one, even when no monthly information is available, thereby reflecting the greater short-run forecasting accuracy of the monthly model. These results support previous empirical evidence that the combined forecasts do not outperform all their components all of the time or even on average with respect to common variables (Granger and Ramanathan, 1984; Fuhrer and Haltmaier, 1988).

A comparison between the results of the macro model and the pooled one show that outside information is useful in reducing macro forecasting errors. With no monthly information available, the pooled forecast yields substantial gains in forecasting accuracy. When 1-month information is released, the forecasting accuracies are further improved; however, the additional gains appear to be limited. When 2 months of information are available, remarkable improvements are found in forecasts of exports and imports of merchandise (MG and XG), wage rate (WG) and labor force (NF). Similar results are observed when other monthly models are adopted.

The combined forecasts results of non-common variables are also encouraging. The RMSPEs of the majority of variables are re-

Table 1
ARIMA models: root mean square percentage errors (RMSPE)

	Quarterly macro model	0-month information		1-month information		2-month information	
		Monthly ARIMA model	Combined ARIMA model	Monthly ARIMA model	Combined ARIMA model	Monthly ARIMA model	Combined ARIMA model
cpi	5.57	0.99	4.42	0.71	4.37	0.61	4.38
wpi	2.17	1.02	1.12	0.64	1.33	0.48	1.52
pm	1.97	4.14	3.90	3.71	3.65	3.80	3.74
px	4.18	4.67	5.63	4.28	4.63	4.10	4.49
tdrlm	20.39	16.45	18.60	10.68	17.29	7.52	17.67
tdrly	8.76	10.06	9.27	6.60	6.67	4.96	6.09
mlb	13.86	6.74	8.88	5.61	8.81	5.34	8.66
qm	5.99	5.11	10.28	4.14	10.44	3.71	10.32
xg	4.38	7.00	4.13	4.33	3.80	2.70	2.52
mg	4.24	6.78	4.68	5.68	4.18	2.92	2.82
wg	12.02	10.44	5.63	10.36	8.18	4.56	2.63
nf	0.77	0.92	0.59	1.12	0.51	1.47	0.39
nuu	11.31	12.33	13.80	8.45	12.09	5.39	11.49
cf	1.46		1.69		1.72		1.62
pcf	5.23		2.38		2.12		2.01
cfn	6.17		2.81		3.67		2.50
co	8.34		7.68		6.94		6.55
pco	4.74		1.75		1.83		1.84
con	10.73		10.47		7.31		9.12
cg	7.00		4.33		6.51		4.02
pcg	6.27		4.76		6.11		4.46
ig	3.24		1.86		2.01		1.58
pig	3.11		1.60		1.82		1.89
pipc	1.23		1.52		1.32		0.94
ipc	1.25		1.34		1.11		0.87
ibf	23.37		12.85		20.78		22.07
pibf	2.14		1.52		1.35		1.68
ibfn	22.96		13.52		16.25		22.57
exg	4.29		5.40		4.31		3.42
exs	6.73		7.16		9.99		6.51
ex	4.06		5.27		4.00		3.25
pex	2.18		2.28		2.15		1.42
exn	5.34		6.10		5.91		3.68
img	3.93		5.49		8.72		4.97
ims	6.93		6.51		7.13		6.43
pim	2.36		1.92		4.40		3.41
im	3.59		5.29		4.71		4.53
imn	3.89		5.68		7.07		6.23
fia	6.76		1.62		3.27		3.68
pfia	6.28		1.09		1.01		0.75
gnp	2.84		2.26		2.95		4.55
gdp	2.90		2.79		3.03		4.20
pgdp	4.67		1.34		1.60		1.46
gdpn	5.81		3.05		4.39		3.96
pgnp	4.70		1.25		1.54		1.42
gnpn	5.68		2.98		4.27		3.88
ydd	5.83		7.14		5.57		6.29

Table 1 (*continued*)

	Quarterly macro model	0-month information		1-month information		2-month information	
		Monthly ARIMA model	Combined ARIMA model	Monthly ARIMA model	Combined ARIMA model	Monthly ARIMA model	Combined ARIMA model
ne	0.86		1.10		0.92		1.57
taxd	25.62		30.37		26.89		26.59
taxdn	25.81		31.80		31.74		24.24
taxi	8.15		12.53		9.65		9.63
taxin	8.81		13.88		13.41		8.44
ptaxi	3.12		2.99		3.04		2.84
j	6.28		105.25		73.24		87.11
pj	5.86		6.13		3.57		2.60
d	1.97		2.29		1.92		2.06
k	0.22		0.16		0.26		0.19
m2	2.46		3.60		2.57		2.05
subb	3.22		9.17		6.19		3.07

duced even when no monthly information is available. This is important since many non-common variables play a prominent role in policy suggestions (for instance, GNP and GDP). Thus, improving their forecasting accuracies is a primary governmental concern. The pooled forecasts using 1-month information do not exhibit an overwhelming gain over those which have no monthly information. Also, some unfavorable results arise with more monthly information. The forecasting accuracies of some non-common variables deteriorate when 2 months of information is employed. This deterioration may be caused by the monthly ARIMA model in which the 2-month information forecasts become relatively less accurate than those based on 1-month information for trade-related variables. However, the exact transmission channel by which outside information affects non-common variables is unclear. Nevertheless, as will be shown in Table 3, the more monthly information is used, the better the performance of the combined forecasts.

The forecasting results for the monthly VAR model are similar to those of the ARIMA model in many respects and consequently not shown here. Poor forecasts are made for trade-related variables and the RMSPE of most variables decreases but increases for some variables when more monthly information is available. The only noted exception is that monthly forecasts of the VAR model display a strong superiority to those of the ARIMA model in predicting 1-month and 1-year interest rates. The combined VAR forecasts of the same variables also demonstrate a better performance than those of the combined ARIMA forecasts. Thus, a better monthly forecast is probably more helpful with respect to improving the macro forecasting accuracies. Since, in general, similar patterns are given by the BVAR models, the results are not discussed here.

The MAE results reported in Table 2 also reveal that three monthly forecasts of import and export prices (PM and PX), and import and export of merchandise (MG and XG) exhibit a larger deviation from actual value than those of the macro model. Further, for both common and non-common variables, stronger evidence is provided in this table that combined forecasts outperform the macro forecasts. However, the MAEs reported here are affected by the magnitude of the variables, thus the comparison across variables is not meaningful.

A comparison between macro and combined forecasts is highlighted in Table 3. This table reveals that combined forecasts are better than macro forecasts in terms of the RMSPE and the MAE. These figures offer a quick impression of the usefulness of monthly models and outside

Table 2
ARIMA models: mean absolute error (MAE)

	Quarterly macro model	0-month information		1-month information		2-month information	
		Monthly ARIMA model	Combined ARIMA model	Monthly ARIMA model	Combined ARIMA model	Monthly ARIMA model	Combined ARIMA model
cpi	2.40	0.95	2.03	0.81	2.03	0.70	2.03
wpi	1.34	0.93	0.87	0.73	0.95	0.63	1.03
pm	1.15	1.83	1.60	1.76	1.55	1.77	1.57
px	1.76	1.80	1.88	1.74	1.75	1.73	1.67
tdrlm	1.12	0.90	0.96	0.73	0.93	0.58	0.90
tdrly	0.79	0.64	0.73	0.53	0.53	0.45	0.57
mlb	468.70	340.66	344.46	315.73	347.28	296.08	350.00
qm	466.28	449.35	602.67	408.09	611.95	388.44	608.80
xg	138.80	179.89	124.09	136.84	118.27	110.04	94.72
mg	128.87	160.08	124.70	148.16	118.80	104.03	95.35
wg	3.93	4.02	2.49	3.97	3.18	2.31	1.61
nf	6.92	8.00	6.20	8.98	5.80	11.01	4.95
nuu	0.38	0.37	0.39	0.32	0.34	0.27	0.37
cf	44.08		43.08		43.48		41.45
cfn	89.87		56.46		65.13		55.60
cg	86.89		68.20		79.24		68.10
co	170.07		138.69		141.35		129.46
con	196.90		169.45		149.41		154.63
ig	35.94		25.32		26.65		24.40
pcf	2.21		1.34		1.28		1.22
pcg	2.37		2.01		2.27		2.03
pco	2.17		1.08		1.15		1.15
pig	1.79		1.17		1.16		1.22
ex	141.76		139.94		132.36		118.05
exg	139.82		141.86		132.95		114.41
exs	44.08		41.88		46.45		38.28
ibf	125.75		96.60		113.84		116.17
ibfn	132.69		104.82		109.53		126.37
ipc	21.77		22.20		21.37		19.68
pibf	1.36		1.06		1.03		1.12
pipc	0.96		1.04		0.98		0.88
exn	154.75		143.96		149.15		111.23
fia	38.03		16.89		19.58		19.31
im	121.61		142.87		133.16		114.69
imn	121.28		132.15		147.08		127.75
img	113.59		128.74		150.98		108.73
ims	67.00		53.77		60.67		54.86
pex	1.19		1.16		1.14		0.93
pim	1.27		1.07		1.67		1.54
gdp	151.34		126.75		144.07		169.29
gdpn	207.97		160.12		173.35		169.90
gnp	152.66		125.30		143.84		170.74
gnpn	207.97		160.12		173.35		169.00
ne	7.14		7.51		7.22		8.93
pfia	2.59		0.97		0.90		0.79
pgdp	2.17		1.04		1.04		1.03
pgnp	2.18		1.01		1.03		1.01

Table 2 (*continued*)

	Quarterly macro model	0-month information		1-month information		2-month information	
		Monthly ARIMA model	Combined ARIMA model	Monthly ARIMA model	Combined ARIMA model	Monthly ARIMA model	Combined ARIMA model
ydd	181.91		192.94		166.70		176.48
d	36.75		36.32		33.58		32.84
j	29.15		33.22		34.33		30.70
pj	2.34		1.69		1.57		1.29
taxi	86.43		93.39		89.36		89.85
taxd	150.14		149.88		141.98		137.40
taxdn	160.41		161.96		157.04		140.56
ptaxi	1.63		1.25		1.32		1.32
taxin	90.93		97.65		103.08		82.53
k	122.94		99.47		119.03		104.60
m2	353.57		365.68		335.47		293.33
subb	6.36		7.24		7.02		5.37

information in improving macro forecasts. However, interpretation of the results should be done cautiously since the figures do not provide any information concerning the significance of the improvement.

In Table 3, the numbers improve when more monthly information is released, suggesting that the forecasting accuracies are better when more information is available. Further, the three monthly models appear equally useful in improving macro forecasts, with the BVAR model performing slightly better than the other two. The above results are strengthened if the forecasting criterion is based on MAE, thereby suggesting that the combined forecasts are less biased than macro forecasts.

6. Conclusion

A unified framework for incorporating timely monthly information as well as forecasts into quarterly model-based projections was presented in this study. More endogenous variables than in the past literature are considered to investigate whether monthly models and selection methods

Table 3
Number of variables for which combined forecasts outperform the macro forecasts (common and non-common variables)

	0-month		1-month		2-month	
	Common	Non-common	Common	Non-common	Common	Non-common
(a) ARIMA models						
RMSPE	9	33	11	35	11	40
MAE	10	42	12	43	12	45
(b) VAR models						
RMSPE	10	38	10	38	11	43
MAE	12	41	12	45	13	45
(c) BVAR models						
RMSPE	10	35	11	38	12	41
MAE	12	40	12	43	12	44

Figures denote the number of cases for which the combined forecasts outperform the macro forecasts.
There are 13 common and 46 non-common variables in total.

can play an influential role in improving combined forecasts. An empirical study was performed through linking the modified DGBAS quarterly model and three alternative monthly models: VAR, BVAR and ARIMA.

The results indicate that the potential gain in forecasting accuracy achievable through the use of high frequency information is not trivial. In particular, four points can be summarized as follows.

First, with respect to common variables, combined forecasts do not outperform all their components all of the time or even on average. Combined forecasts are generally found to be superior to the macro forecasts but inferior to the monthly ones.

Second, with respect to non-common variables, the theoretically predicted superiority in the combined forecasts does occur. The gains in forecasting accuracies derived from the monthly model are substantial, even when no monthly information is available.

Third, on average, increased amounts of outside information do help improve the performance of the combined forecasts. However, the combined forecasts are occasionally less accurate when more outside information is available. The exact transmission channel by which outside information affects the combined forecasts remains unclear. We think this is an issue worthy of future investigation.

Fourth, combined forecasts are much superior to macro forecasts in terms of the mean-absolute-error criterion. Also, the three monthly models appear equally useful in improving macro forecasts with the BVAR performing slightly better than the VAR and ARIMA models.

Appendix A

Table A1
Description of the variables

Type	Mnemonic	Variable description	Unit	Source
B	CF	Private food consumption expenditure	Million 1986 NT$	QNIS
I	CG	Government consumption expenditure	Million 1986 NT$	QNIS
B	CO	Private non-food consumption expenditure	Million 1986 NT$	QNIS
B	CPI	Consumer price index	1986 = 100	QNIS
B	D	Consumption of fixed capital	Million 1986 NT$	QNIS
E	DEVIPI	Industrial countries' industrial population	1985 = 100	IFS
E	DEVPX	Industrial countries' export unit value	1985 = 100	IFS
E	E	Exchange rate	NT$/US$	FSM
I	EX	Export of goods and services	Million 1986 NT$	QNIS
B	EXG	Exports of goods (national income base)	Million NT$	QNIS
B	EXG	Exports of service (national income base)	Million NT$	QNIS
I	FIA	Net factor income from abroad	Million 1986 NT$	QNIS
I	GDP	Gross domestic product	Million 1986 NT$	QNIS
I	GNP	Gross national product	Million 1986 NT$	QNIS
B	IBF	Gross fixed investment by private sector	Million 1986 NT$	QNIS
I	IG	Gross fixed investment by Government	Million 1986 NT$	QNIS
I	IM	Imports of goods and services	Million 1986 NT$	QNIS
B	IMG	Imports of goods (national income base)	Million NT$	QNIS
B	IMS	Imports of services (national income base)	Million NT$	QNIS
I	IPC	Gross fixed investment by public enterprise	Million 1986 NT$	QNIS
I	J	Increase in stocks	Million 1986 NT$	QNIS
I	K	Capital stock	Million 1986 NT$	QNIS
B	M1B	Money supply M1B (end of month)	Million NT$	FSM
1	M2	Money supply M2 (end of month)	Million NT$	FSM
B	MG	Imports of goods (custom base)	Million 1986 NT$	MSEI

E	N15	Civilian population aged 15 years and over	1000 Persons	MBMS
I	NE	Employment	1000 Persons	MBMS
B	NF	Labor force	1000 Persons	MBMS
B	NUU	Unemployment rate	%	MBMS
B	PCF	Implicit price deflator for CF$	1986 = 100	QNIS
B	PCG	Implicit price deflator for CG$	1986 = 100	QNIS
B	PCO	Implicit price deflator for CO$	1986 = 100	QNIS
B	PEX	Implicit price deflator for EX$	1986 = 100	QNIS
I	PGDP	Implicit price deflator for GDP$	1986 = 100	QNIS
I	PGNP	Implicit price deflator for GNP$	1986 = 100	QNIS
B	PIBF	Implicit price deflator for IBF$	1986 = 100	QNIS
B	PFIA	Implicit price deflator for FIA$	1986 = 100	QNIS
B	PIG	Implicit price deflator for IG$	1986 = 100	QNIS
B	PIM	Implicit price deflator for IM$	1986 = 100	QNIS
B	PIPC	Implicit price deflator for IPC$	1986 = 100	QNIS
B	PJ	Implicit price deflator for J$	1986 = 100	QNIS
B	PM	Import price index	1986 = 100	CPSM
E	POILSAR	Crude oil price by Saudi Arabia	US$/barrel	
B	PTAXI	Implicit price deflator of TAXI$	1986 = 100	QNIS
B	PX	Export price index	1986 = 100	CPSM
B	QM	Quasi money (end of month)	Million NT$	FSM
E	REDISC	Rediscount rate	% per annum	FSM
E	RM	Reserve money (end of month)	Million NT$	FSM
I	SUBB	Subsidies	Million 1986 NT$	QNIS
I	TAXD	Direct tax	Million 1986 NT$	QNIS
I	TAXI	Indirect tax	Million 1986 NT$	QNIS
B	TDR1Y	Time deposit interest rate, 1 year	%	FSM
B	TDR1M	Time deposit interest rate, 1 month	%	FSM
E	WCMPI	World non-fuel commodity price	1985 = 100	QNIS
B	WG	Average monthly earning for manufacturing	1986 = 100	MBEPS
B	WPI	Wholesale price index	1986 = 100	CPSM
B	XG	Exports of goods (custom base)	Million 1986 NT$	MSEI
I	YDD	Disposable income	Million 1986 NT$	QNIS

Types. B, behavior equation; I, identity; E, exogenous.

A variable, X, expressed in 1986 NT$ is represented as $X\$$.

Sources: CPSM, *Commodity-price Statistics Monthly* in Taiwan area, the Republic of China, Directorate-General of Budget, Accounting and Statistics, Executive Yuan, ROC; MBMS, *Monthly Bulletin of Manpowers Statistics*, Taiwan area, Republic of China, DGBAS; QNIS, *Quarterly National Income Statistics* in Taiwan area, the Republic of China, DGBAS; MBEPS, *Monthly Bulletin of Earnings and Productivity Statistics*, Taiwan area, Republic of China, DGBAS; MSEI, *Monthly Statistics of Exports and Imports*, Taiwan area, the Republic of China, the Department of Statistics, Ministry of Finance; FSM, *Financial Statistics Monthly*, Taiwan area, the Republic of China, Economic Research Department, The Central Bank of China; IFS, *International Financial Statistics*, IMF.

Appendix B. Minnesota prior

The Minnesota system of priors has been made conveniently operational in a RATS V. 4.10 software program in which four sets of parameters, referred to as hyperparameters, are chosen to specify the prior variances in a BVAR system (see Doan, 1992). The hyperparameters that specify the variances around the prior means correspond to elements in the following expression.

$$S(i,k,j)=\frac{\gamma g(j)f(i,k)}{s_i/s_k}$$

where

$S(i, k, j)$ = the standard deviation of the prior distribution of the coefficient on lag j of the variable k in equation i.

s_i = the standard error of a univariate autoregression on equation i. The ratio s_i/s_k scales the standard deviations to correct for the different magnitudes of the variables in the system.

$f(i, k)$ = a parameter specifying the tightness on variable k in equation i relative to variable i. By definition $f(i, i) = 1$ and $f(i, k) \leq 1$ for $i \neq k$.

$g(j)$ = a function that determines the tightness on lag j relative to lag j relative to lag $j-1$.

γ = a parameter that determines the overall tightness of the variances.

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